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Analysis of Consumer Preference Structure with Threshold Effect Using Discrete Choice Model and Neural Network

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Abstract

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The purpose of this dissertation is to provide insights into combining discrete choice model and artificial neural network in the context of analyzing consumer preference structure. The recent efforts in the academia has provided many possibilities in the integration of the two fields, yet there are still many more to be made. This dissertation first observes consumer preference with a behavioral discrete choice model, the threshold model, in order to observe whether there are minimal perceptible thresholds that the consumers need to surpass in order to respond with a change in their utility. Threshold is a powerful tool for decision-makers, as it can capture how much the level of the attribute of a product or a service needs to be changed for the consumers to feel a change in their preference structure. Then this dissertation utilizes a hybrid form of neural network, which brings together two neural networks, the Convolutional Neural Network and Dense Neural Network in linear and non-linear forms, respectively, and adds an additional convolution filter to capture the effect of thresholds. The model is tested in the empirical analysis, which aims to compare two different strategies for promoting the diffusion of discrete choice models. The findings indicate that thresholds do exist in the consumers' preference structure, which allows the implications for decision-makers, in terms of which aspect of a product or service they need to prioritize in order to maximize the effects.

Keywords: Discrete choice model, Behavioral model, Threshold model, Neural network, Convolutional Neural Network, Consumer preference, Consumer choice

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Chapter 1. Introduction

1.1 Research Background

Over the course of the last half a century, the field of discrete choice models have evolved greatly. Consequently, as technology started to advance rapidly, new products and markets emerged sporadically, which gave the consumers a wide variety of alternatives to choose from. This has resulted in a completely different paradigm in the traditional mainstream economics, the neoclassical economics. In the field, consumers are assumed to maximize utility based on the information given and rational preferences. However, this has received wide criticisms, stemming from cognitive psychology that under the surface, humans are not rational beings, and we are bound to act according to our behavior and different decision processes (Kitamura, 1990; Tversky & Kahneman, 1974). Many factors affect the behavior and decision process of individuals, and these factors are dynamic and change continuously (Cantillo et al., 2006). These changes can come in macroscopic scale or microscopic scale, and it has now become more important than ever for decision makers, in both public and private sectors, to establish the behavior of individuals in respect to the changes. Moreover, not everyone is endowed with reliable and complete information, so the amount of knowledge is not complete, and therefore must rely on their own decision-making process when the time comes to make a choice. Sometimes, this may depend on the individual's reference point or their indifference to the small perceivable changes.

This has led to the need for researchers to understand the heterogeneity of the consumers. In the last couple decades, consumer heterogeneity has been dealt with using distributional approaches. The heterogeneity can be understood through stochastic terms in utility coefficients, assuming that the utility of respondents is influenced by random terms and has different values in utility coefficients grouped with individuals that have the same choice behavior or similar individual characteristics, or both.

With the development of advanced statistical techniques allowed by the advancement in computing power, this phenomenon has led to the birth of another recent mainstream economics in recent years, the behavioral economics, where researchers streamline their focus into modeling the actual behaviors of the consumers to understand the heterogeneity in the decision-making process. Some consumers may act according to their loss-aversion tendencies and some consumers may act to minimize the potential regret that arouses from their decisions.

Another noteworthy movement in the field of economics is the emergence of machine learning via Artificial Neural Networks (ANN). The power of ANN models lies in the fact that they can process any time of input data, may it be texts, voices, photos, and numbers, due to their universal function approximator. This has naturally permeated into the field of economics, and it has become a popular area of research to improve the predictive ability of the existing models. However, the crucial downside of the machine learning models came to light, which is the interpretability of the machine learning models, which gave the labeling term ‘black box model.’ In order to enhance and equip the models with the power to explain causal relationships, many researchers are proactively attempting many different approaches.

The above phenomenon and aspects are where the objective of this study stems from. To further the understanding of the behavior of the consumers, this study explorers another key aspect relative to the choice process, which is the potential existence of limits, boundaries or cut-offs of perceptions and appraisal of attributes by individuals that can vary within the population. This is referred to as thresholds. Thresholds have been treated in the context of non-compensatory choice such as in the Elimination by Aspects model (Tversky, 1972). Thresholds have also been incorporated as minimum perceptible changes in attributes, but they have mainly been modeled in the context of making consecutive choices, which limits the models from products and services which are not yet launched in the market (Cantillo et al., 2006).

Moreover, due to the restraints in the interpretability of machine learning models, the behavioral aspects of consumers have rarely been explored.

1.2 Research Objective

The objective of this dissertation is to explore the behavioral aspects of consumers in a more realistic context, where consumers not only has reference points, but are also indifferent to any small changes in the level of the products or services that they are using. Moreover, this dissertation further explores the behavioral aspects in machine learning context, mainly to provide the means of maintaining the interpretability of the traditional models and also propose a method to embed behavioral aspects in the model, bridging the gap between the two fields of studies.

First, this dissertation suggests a method to model thresholds in the context of reference points unlike previous studies which analyzes threshold effects through consecutive choices. For example, consumers may not feel the need to change their regular product even though its price increases by a small amount, as the utility gained from staying with the product outweighs the utility from switching to the other product, and the usage from the regular product has formed their standard or reference points. The specification of the model with reference points allows the evaluation of products and services that are relatively new to the market and also allow their behavior to be dependent on another aspect of their behavior.

Secondly, this dissertation suggests a hybrid approach to replicating discrete choice model as a neural network model. This is achieved through utilizing techniques suggested by previous studies by dividing the deterministic term of the utility into theory-driven part and data driven part by utilizing Convolutional Neural Network (CNN) and Dense Neural Network (DNN). This dissertation further expands the model to adopt multiple convolutional filters to replicate hierarchical form of estimation models.

Lastly, through empirical analysis, the performance and the implications of the models are compared, to present an example how threshold models can be used in policy context.

1.3 Research Outline

This study is organized as follows. Previous literature on discrete choice model, compensatory and non-compensatory models, neural networks, and activation functions will be examined in Chapter 2. In Chapter 3, the methodologies used in this dissertation will be discussed. The empirical study is conducted in Chapter 4, where the proposed models of this dissertation will be tested with the data on Electric Vehicle (EV) and its infrastructure. Lastly, the discussion of the findings of this dissertation will be carried out in Chapter 5.

Chapter 2. Literature Review

2.1 Discrete Choice Model

2.1.1 Multinomial Logit Model

The discrete choice models have been widely used in the context of consumer choice, consumer preference, and consumer decision making, in terms of single choice, multiple-choice, rank-ordered and rating, which was first proposed by McFadden (1974) with the Multinomial Logit Model (MNL). Discrete choice experiment is a methodology widely used to evaluate consumer's acceptability and their welfare towards goods, service, or policies (Train, 1999; McFadden & Train, 2000). Specifically, discrete choice experiment with the stated preference (SP) approach provides hypothetical alternatives composed of core attributes to survey respondents, who then either rank the alternatives in the most preferred order or select the most preferred alternative (Hall et al., 2018). In addition to SP data, revealed preference (RP) data also enables the analysis of consumer preference toward each attribute (Kim et al., 2019). Discrete choice models are based on random utility theory, and the random utility model is derived under the assumption of the utility maximization behavior of individuals (McFadden, 2001). Specifically, if a respondent faces multiple alternatives, he or she chooses the alternative that provides the greatest utility (Hall et al., 2004).

In the MNL model, a consumer chooses the best alternative based on the deterministic part a researcher can observe and an unobserved, random part. Since there are unobservable parts in the individual's utility, U_{njt} , which denotes the utility of individual n choosing j in choice situation t can be split into two parts: V_{njt} represents the deterministic part, while ε_{njt} denotes the stochastic part of the utility. The structure of a consumer's utility is as follows:

$$U_{njt} = V_{njt} + \varepsilon_{njt} \quad \text{Eq. 1}$$

where n represents the consumers making the choice, j the alternative, and t the choice situation.

The logit model, which is the basic model of discrete choice models, assumes that the error term, ε_{njt} , follows type 1 extreme value distribution. The logit model is characterized by independence of irrelevant alternatives (IIA) due to the assumption of the distribution of error terms (Train, 2009). The IIA indicates that the ratio of the choice probability between different alternatives is always consistent, even if a new alternative is introduced or a correlation exists between two alternatives. This is a strong restriction toward the substitution and correlation between the alternatives and is extremely unrealistic (Train, 2009). These restrictions have led to the development of various general and realistic models, such as nested logit model, probit model, and mixed logit model, which can mitigate IIA restrictions.

$$U_{njt} = \sum \beta_{njt} x_{njt} + \varepsilon_{njt} \quad \cdots\cdots\cdots \text{ Eq. 2}$$

where β_{njt} represents the marginal utility of consumer n.

Based on this framework, the choice probability of consumer n choosing alternative i can be estimated according to Eq. (4):

$$\begin{aligned} P_{ɜ} &= \Pr(U_{ɜ} > U_{nj} \quad \forall \mathrm{j} \neq i) = \Pr(V_{ɜ} + \varepsilon_{ɜ} > V_{nj} + \varepsilon_{ɜ} \quad \forall \mathrm{j} \neq i) \\ &= \Pr(\varepsilon_{nj} - \varepsilon_{ɜ} < V_{ɜ} - V_{ɜ} \mathrm{j} \neq i) \end{aligned} \quad \cdots\cdots\cdots \text{ Eq. 3}$$

The stochastic term $\varepsilon_{ɜ}$ in Eq. (4) has the same structure as the cumulative density function, indicating that the probability density function of $\varepsilon_{ɜ}$ can be calculated by integrating $f(\varepsilon_{ɜ})$. Therefore, the final formulation of the discrete choice model can vary depending on the definition of $f(\varepsilon_{ɜ})$.

2.1.2 Mixed Logit Model

Although similar to the MNL, the Mixed Logit Model (MXL) relieves some of the constraints of the MNL model for the main purpose of modeling the heterogeneity of the utility structure of the individual consumers. Whereas the MNL model assumes that each individual has the same utility towards each attribute, the MXL model assumes a distribution based on the attribute parameters estimated for the alternative. Also, the researcher is given the freedom to assume the distribution for the individuals for each attribute, making the model highly flexible relative to other discrete choice models. Although a normal distribution is most frequently assumed, other distributions including log-normal, truncated, or censored normal distribution, can also be used according to the context and the circumstances.

The utility function of the MXL is presented in Eq. (5), where the consumer utility U_{njt} consists of determinant V_{njt} and a stochastic random term ε_{njt}, which, similar to the MNL model, is assumed to follow the Type I extreme value distribution. However, the preference parameter β_n takes into account individual heterogeneity, following normal distribution with mean b and variance W (McFadden & Train, 2000).

$$U_{nj} = V_{nj} + \varepsilon_{nj} = \sum_k \beta_{nk} x_{jk} + \varepsilon_{nj},\ \beta_{nk} \sim N(b, W) \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \text{Eq. 4}$$

The choice probability of the mixed logit model is as shown in Eq. (6). Here, the choice probability is an integral form of the multinomial logit probability, $L_{nit}(\beta_n)$, where the density function of β_n is assumed to follow the $f(\beta_n \mid b,W)$ distribution.

$$P_{nit} = \int L_{nit}(\beta_n) f(\beta_n \mid b,W) d\beta_n$$
$$L_{nit}(\beta_n) = \frac{e^{V_{nit}}}{\sum_j e^{V_{njt}}} = \frac{e^{\beta_n' x_{nit}}}{\sum_j e^{\beta_n' x_{njt}}} \quad \cdots\cdots\cdots\cdots\cdots\cdots \text{Eq. 5}$$

where the likelihood function of consumer n choosing alternative i in choice situation t is denoted as $y_{nit} = 1$, and otherwise $y_{nit} = 0$. Consumer n's likelihood function is described by the following equation:

$$P_n = \int \prod_t \prod_i \{L_{nit}(\beta_n)\}^{y_{nit}} f(\beta_n \mid b,W) d\beta_n$$
$$Likelihood = \prod_{n=1}^{N} P_n = \int \prod_{n=1}^{N} \prod_t \prod_i \{L_{nit}(\beta_n)\}^{y_{nit}} f(\beta_n \mid b,W) d\beta_n \quad \cdots\cdots\cdots \text{Eq. 6}$$

2.2 Consumer Preference in the Context of Behavior

As technology advances rapidly, consumers have gained access to vast amounts of information, products, and services, making their decision-making process more complicated. Scientists are studying consumer decision-making and how to incorporate it into models. There are two main types of consumer decision-making models: compensatory and non-compensatory. Compensatory models assume that consumers take all attributes of a product into consideration before making a decision, while non-compensatory models believe that consumers only look at certain attributes. Non-compensatory models include conjunctive, disjunctive, lexicographic, and elimination by aspect models (Cantillo & Ortúzar, 2005). The conjunctive model states that a product must meet all minimum attribute requirements to be considered by a consumer. The disjunctive model, a less stringent version, says a product is viable if it meets some of the minimum requirements, based on the satisfaction of important attributes. The elimination by aspects (EBA) model eliminates options that don't meet certain attribute levels, until only one option remains. In the EBA model, consumers prioritize attributes and set minimum values. The lexicographic model has consumers prioritize attributes and make decisions based on the most important one. The reference-dependent model, developed by Kahneman and Tversky (1979), takes into account different reactions to positive and negative outcomes and separates attributes into Gain and Loss domains. The Gain domain consists of attributes preferred over the current status and the Loss domain includes attributes not preferred. The random regret model, introduced by Loomes & Sugden (1982), evaluates consumer preferences based on the difference in attribute levels between the chosen and unchosen options. These models are summarized in Table 1 (Tversky, 1972; Chorus et al., 2014).

2.2.1 Threshold in Choice Models

Threshold models were originally created based on the idea that there are potential limitations, boundaries, or cutoff points in the perception and evaluation of attributes during the choice process. These limits can vary among individuals and the threshold effect is the main component of the models used in this dissertation. One type of threshold is inertia, habit, or resistance to change, where individuals can form habits that make them reluctant to change their behavior. This can result in the same behavior being maintained even after a change, as changing their usual choice requires both physical and psychological effort and costs. If at an initial time t, an individual used alternative A_r with an associated utility U_{rqt}, then the relationship between the chosen alternative and the other alternatives would be $U_{rqt} \geq U_{iqt} \forall A_i \in A_q$. However, the level of certain attributes can change at $t+1$, causing the utility of another alternative to exceed the utility of A_r, but the individual continues choosing the initial option. This phenomenon can be explained by the theory that a consumer will only switch from the initial alternative A_r to alternative A_j if $U_{jq(t+1)} - U_{rq(t+1)} \geq \delta_{rjq(t+1)}$, where $\delta_{rjq(t+1)}$ is a threshold that reflects the consumer's reluctance to change or the inertia effect. Typically, a positive threshold reflects the impact of transaction costs or inertia, but it may be negative if there is a strong inclination towards change or an excessive reaction to the presence of a completely new option.

In the field of transportation, it has been commonly observed that daily travel patterns are repeated in a certain pattern for individuals as time passes by (Pendyala et al., 2000), indicating that travel behavior may be habit-forming or influenced by inertia. Behavioral scientists generally postulate that individuals are adaptable and will tend to stay with previous choices that are more comfortable and less risky for them if the cost of searching for and implementing new alternatives is too high or uncertain, representing their tendencies to stay with the status quo (Payne et al., 1993; Verplaken et al., 1997). The concept of inertia in the context of travel behavior has been developed quite a long time ago, but it continues to be a significant issue because of its impact on transport policies (ex. changing the pattern of vehicle use) (Goodwin, 1977).

The notion of inertia in decision making is complicated by various factors, such as factors that influence choice over different time frames, such as car accessibility or ownership of public transport season tickets. Inertia can also be seen in stated preference (SP) surveys, where the preferred choice from revealed preference (RP) data is used to create the set of options in the stated preference survey. The study of inertia in discrete choice modeling has been addressed using flexible dynamic models with a focus on panel data analysis, where decisions are based on previous choices (Heckman, 1981). The multinomial probit model was used for panel data analysis by Daganzo and Sheffi (1979, 1982), and the method was applied to a two-period panel data set by Johnson and Hensher (1982). According to their model, the utility of the individual in a certain period depends on the choice made in the previous period:

$$U_{jqt} = \theta_t X_{jqt} + \phi U_{jq(t-1)}, \quad \cdots\cdots \text{Eq. 7}$$

where θ_t is distributed normally and ϕ is a habit parameter. The larger the ϕ, the higher the chance of the previous choice being repeated. If that is the case, the threshold for inertia, as defined above in terms of the previous choice A_r, would be as follows:

$$\delta_{rjq} = \phi(U_{rq(t-1)} - U_{jq(t-1)}), \quad \cdots\cdots \text{Eq. 8}$$

Furthermore, in the context of marketing, Guadagni and Little (1983) introduced a model for capturing consumer inertia or brand loyalty through exponential smoothing. They took a different approach and formulated the utility function as follows:

$$U_{jqt} = \theta_t X_{jqt} + \rho L_{jqt} + \epsilon_{jqt} \quad \cdots\cdots \text{Eq. 9}$$

where L_{jqt} is the loyalty or the tendency to stay to alternative A_j, an inertia indicator, defined as:

$$L_{jqt} = \gamma L_{jq(t-1)} + (1-\gamma)\,\mathrm{Y}_{jq(t-1)} \quad \cdots\cdots \text{Eq. 10}$$

where γ is a smoothing parameter and $Y_{jq(t-1)}$ is a dummy variable that takes the value of 1 if A_j was chosen at time $(t-1)$ or 0 if it was not.

Ben-Akiva and Morikawa (1990) developed a method for modeling changes in behavior using a mix of revealed preference (RP) and stated preference (SP) data. They introduced a threshold parameter for the stated intention, but it was complicated by the modal constants. Hirobata and Kawakami (1990) created a binary model to predict how changes in transportation services will affect travelers' mode of transportation, taking into account resistance to change. They proposed two different specifications for the inertia threshold: one that treated inertia as a constant like Ben-Akiva and Morikawa (1990) and another that saw the inertia threshold as a function of the attribute levels prior to the transport service change, expressed as:

$$\delta_{tq} = \alpha \, \Delta \, X_{q(t-1)} \cdots\cdots \text{Eq. 11}$$

where $\Delta \, X_{q(t-1)}$ is the vector of attribute differences between the current and alternative modes before the change and α is a parameter vector to be estimated. The main limitation to this model is the choice is binary and the thresholds are not considered to be stochastic.

Swait et al. (2004) suggested a method to measure the models of discrete choice that take into account previous behavior and earlier evaluations of attributes in a temporal context. They defined the utility of alternative A_j at time t as a function of the product of utilities in the current and previous periods:

$$\hat{V}_{jqt} = \prod_{s=0}^{t} \alpha_{js} \exp(\hat{V}_{jqt-s}), \cdots\cdots \text{Eq. 12}$$

where α denotes weights associated with previous periods. Cantillo and Ortuzar (2005) formulated a general random specification for inertia that is a function of the earlier valuation of alternatives, the set of objectives motivating, and the conditions characterizing the choice process. The following describes the inertia threshold at $t+1$:

$$\delta_{rjq}^{t+1} = \lambda_q(\phi\varphi_{jq}^{t+1} + (V_{rq}^t - V_{jq}^t)) \cdots\cdots \text{Eq. 13}$$

where $V_{rq}^t - V_{jq}^t$ is the difference between the utilities of alternatives r and j at the initial time period. ϕ is the vector of parameters affecting the set socio-economic characteristics and objectives motivating the choice φ_{jq}^{t+1} at the current time period. λ_q is a parameter reflecting the individual preferences that vary randomly among individuals. When it is above 0, then inertia, or resistance to change, exists, while a value equal to zero indicates no resistance. As such, when inertia is equal to 0, the person was not satisfied with the previous choice and wants a change.

Thresholds are also defined as minimum perceptible changes, which only occur above a certain level, whereas those below it would not cause any consumer reaction. Therefore, if X^t is the value that attribute X takes at time t, then the change in utility of a consumer will only be perceived between t and $t+1$ when $|\Delta X^t| = |X^{(t+1)} - X^t| > \delta$ (Cantillo et al., 2006). Krishnan (1977) introduced an early threshold model in the binary logit model. This model only considered the threshold as the minimum perceivable difference in the total utility function rather than in individual attributes. Later, Swait (2001) improved on this by proposing an extension to the traditional utility maximization framework that took into account individual attribute perception by incorporating cut-offs in the utility functions.

Thresholds serve as the acceptance or rejection criteria for options. This concept is evident in Tversky's EBA model (1972), which assumes that individuals have a ranking of attributes and minimum acceptable thresholds for each of them. The decision-making process starts with the most significant attribute and its threshold is retrieved, eliminating all alternatives with attribute values below the threshold. This is repeated for the remaining attributes, following their order of importance, until only one alternative meets all threshold requirements. If multiple options meet all threshold restrictions, the preferred one may be selected based on compensatory decision-making.

Krishnan (1977) was the first to propose a model using this concept, incorporating the minimum perceivable difference in a binary logit model, but not focusing on each attribute's individual worth. Han et al. (2001) later presented a model that included reference price effects and set up the utility function as follows:

$$U_{jqt} = \theta X_{jqt} + \beta_{loss}(P_{jt} - RP_{jqt})I_{jqt,loss}(\cdot) + \beta_{gain}(RP_{jqt} - P_{jt})I_{jqt,gain}(\cdot) + \epsilon_{jqt} \quad \cdot \text{Eq. 14}$$

where P_{jt} is the selling price of the alternative and the indicator function, and $I(\cdot)$ is equal to 1 when the difference between the selling and reference price exceeds 0. Furthermore, Han et al. (2001) formulated thresholds with deterministic and random components, which can be expressed as follows:

$$\tau_{jqt} = \alpha Z_{jqt} + \zeta_{jqt} \cdots\cdots \text{Eq. 15}$$

Table 1. Decision Rules in Choice Model

Decision Rule	Mathematical Formulation of Decision Rule
Elimination-by-aspects	$y_i = 1 \ \leftrightarrow$ $x_{im} \geq \tilde{x}_m, \quad {}^{\forall}m$ $\tilde{x}_m$: aspiration level for m-th attribute
Lexicographic	$y_i = 1 \ \leftrightarrow$ $x_{im} = \max_{\forall j \in C}\left[x_{jm}\right]$

Reference Dependent

$$y_i = 1 \leftrightarrow V_i \geq V, \ ^{\forall} j \in C$$

$$V_i = \sum_m \begin{pmatrix} -\vec{\beta}_m \max\left[0, \bar{x}_m - x_{im}\right] \\ +\vec{\beta}_m \max\left[0, x_{im} - \bar{x}_m\right] \end{pmatrix}$$

$\bar{x}_m$: Reference of m-th attribute

Random Regret (I)

$$y_i = 1 \leftrightarrow \mathrm{R}_i \leq R_j, \ ^{\forall} j \in C$$

$$R_i = \max_{j \neq i} \left(\sum_m \max\left[0, \beta_m \left(x_{jm} - x_{im}\right)\right] \right)$$

Random Regret (II)

$$y_i = 1 \leftrightarrow \mathrm{R}_i \leq R_j, \ ^{\forall} j \in C$$

$$R_i = \sum_m \sum_{j \neq i} \log\left[1 + \exp\left(\beta_m \left(x_{jm} - x_{im}\right)\right)\right]$$

Threshold (JND)

$$y_i = 1 \leftrightarrow V_i \geq V, \forall j \in C$$

$$V_i = \sum_m \begin{pmatrix} -\beta_m Max\left(\left|\Delta \hat{X}_{kjq}^t\right| - \delta_{kq}, 0\right) \\ +\beta_m Max\left(\left|\Delta \hat{X}_{kjq}^t\right| - \delta_{kq}, 0\right) \end{pmatrix}$$

δ_{kq}: Threshold of k^{th} attribute for q individual

2.3 Modeling Consumer Choice: Machine Learning

2.3.1 General Form of Artificial Neural Network

Artificial neural networks (ANNs) are one of the most widely used frameworks machine learning studies that replicates the functioning of our actual brain networks. Unlike other algorithms, ANNs are capable of learning tasks without being explicitly programmed, much like the human brain. ANNs were developed initially as a non-linear algorithm that modeled the human brain's processes mathematically (McCulloch and Pitts, 1943). The learning performance improved with the development of the perceptron, which allowed for repeated learning and weight adjustment (Rosenblatt, 1957). The real-world application of ANNs began with the development of the multi-layer perceptron (Minsky and Papert, 1986). The multi-layer ANN is the basic structure of current ANNs, allowing for the stacking of multiple layers to form a learning network that adjusts its weights to minimize output error. With multi-layer neural networks, layers were designated based on their function, with the first layer, where data enters the network, being the input layer; the layer where the output or prediction value is produced, being the output layer; and any layers in between being designated as hidden layers.

An Artificial Neural Network (ANN) performs tasks using artificial neurons, which are interconnected and represent the synapses of a biological brain. The signals transmitted between neurons are computed using a non-linear function, and their strength is determined by the weight of the signal. During the learning process, the weights of the signals are adjusted based on the training data. The neurons are then grouped into layers, and the number of layers can be adjusted according to the complexity of the learning process. The data enters the network through the input layer, and the signals from the input layer travel through the hidden layers to reach the final output layer.

The ANN model can be categorized based on the type of learning process, which typically involves feed-forward and backpropagation methods. In the feed-forward model, the values are transferred from the input to the hidden layers without any circulating paths, while in the backpropagation model, the weights are updated by computing the error between the predicted and actual output values (Svozil et al., 1997; Hecht-Nielsen, 1989).

The most common type of artificial neural network is the multi-layer feed-forward neural network. In an artificial neural network, there are three types of units involved: input, hidden, and output layers. In a typical network, the information is transferred from input to output layers. The input layer receives the initial input data, which is then passed on to the next layer. The output of each layer becomes the input of the following layer.

The training of a neural network involves computing the weights within the network. This starts with randomly assigning the connection weights when the input and target outputs are introduced into the network. Next, the network calculates an output and compares it to the actual output data to determine the error. The error is then used to adjust the connection weights of the nodes by transmitting the error in a backward direction from the output layer. This results in the network trying to minimize the mean squared error and enhance the prediction accuracy by finding the optimal adjustment of the inter-neuron weights.

2.3.2 Convolutional Neural Network (CNN)

The CNNs are similar to traditional ANNs in that they are consisted of self-optimizing neurons. Each neuron still receives an input and performs an operation, just like in traditional ANNs. The entire network still represents a single perceptual score function, and the loss functions associated with the classes are still present in the last layer. The tips and tricks for traditional ANNs are also applicable to CNNs.

The main difference between CNNs and traditional ANNs is that CNNs are used primarily in image recognition. This allows for image-specific features to be used as input data in the network architecture, making it more suitable for image-focused tasks while reducing the required parameters.

CNNs have been successful in processing images and other types of data, with a convolutional layer containing filters that extract the characteristics of the input data. The local features are then extracted by a pooling layer. The basic architecture of a CNN consists of three layers: convolutional, pooling, and fully connected, with input data being passed through a convolutional filter to extract characteristics.

The example CNN can be divided into four key areas of functionality. The input layer holds the image's pixel values, similar to other forms of ANNs. In the convolutional layer, the output of neurons is determined by calculating the scalar product between the weights and the region connected to the input volume. The rectified linear unit (ReLU) is used to apply an activation function, such as the sigmoid, element-wise to the output produced by the previous layer. The 2D convolutional filter is calculated using the following equation.

$$Y_{i+1} = (Y_i \times F) + b = \sum_{N}^{-N}\sum_{M}^{-M}(Y_i \times F) + b, \quad \text{Eq. 16}$$

where Y_i and Y_{i+1} are the data before and after passing through the convolution filter, respectively; F is the filter, and b the bias.

The pooling layer reduces the spatial dimensions of the input, reducing the number of parameters in the activation. It extracts information from the feature map and reduces its dimensions, typically using either average or maximum pooling. Maximum pooling extracts the maximum value within a filter kernel in the feature map. The resulting geometry from the filter kernel is obtained through this operation.

$$A = [a_{ij}](i, j \le n) \quad \text{Eq. 17}$$

$$\text{maxpooling}(A) = \max(a_{ij}), \quad \text{Eq. 18}$$

where A is the filter kernel and a_{ij} is an element of the filter kernel.

Lastly, the fully connected layers in this architecture perform the same functions as those in a standard artificial neural network (ANN) and aim to produce class scores for classification. It is recommended to use ReLU activation between the layers to enhance performance.

The convolutional layer, as the name suggests, is a crucial component in the functioning of a Convolutional Neural Network (CNN). This layer uses learnable kernels that are small in spatial dimensions but cover the entire depth of the input. During processing, the convolutional layer slides each filter across the spatial dimensions of the input to generate a 2D activation map. As the filter moves, a scalar product is calculated for each value in the kernel by taking the center element of the kernel and computing a weighted sum of itself and surrounding pixels. This allows the network to learn kernels that activate in response to specific features at certain spatial positions of the input, resulting in activations.

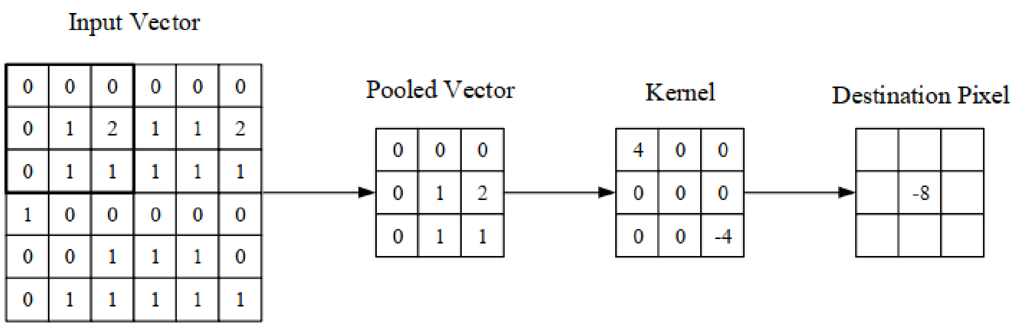

Figure 1. Visual representation of the process of CNN

Each kernel generates a corresponding activation map, which is stacked along the depth dimension to form the complete output of the convolutional layer.

As aforementioned, training ANNs on inputs such as images results in models that are too large to be efficiently trained. This is due to the fully connected nature of standard ANN neurons. To overcome this, each neuron in a convolutional layer is only connected to a small region of the input volume, referred to as the neuron's receptive field size. The depth of the connection is nearly always equal to the depth of the input.

For instance, if the input to the network is a 64 × 64 × 3 (RGB) image, and the receptive field size is set to 6 × 6, each neuron in the convolutional layer would have 108 weights (6 × 6 × 3). This is compared to the 12,288 weights in each standard neuron in other forms of ANNs. The complexity of the model can also be reduced through output optimization with the help of three hyperparameters: depth, stride, and zero-padding.

The stride in which the depth of the input is set to place the receptive field can also be defined. A stride of one, for instance, would result in a heavily overlapped receptive field producing large activations. On the other hand, setting the stride to a higher value would decrease the overlap and produce an output with lower spatial dimensions.

The purpose of pooling layers is to decrease the dimensionality of the representations and simplify the model's complexity. Typically, max pooling layers with a 2x2 kernel and a stride of 2 are used, reducing the activation map to a quarter of its original size while maintaining the depth. This scales the activation map down to 25% of the original size whilst maintaining the depth volume at its standard size. There are only two generally used methods of max pooling. The commonly used methods of max pooling include setting both the stride and filter to 2x2, or using overlapping pooling with a stride of 2 and a kernel size of 3. Note that larger kernel sizes can negatively affect the model's performance. Additionally, CNNs can include general pooling layers with pooling neurons that perform operations like L1/L2 normalization and average pooling.

In the fully connected layer, the neurons are directly connected to the neurons in the adjacent layers, with no connections to the neurons within the same layer. This setup is similar to the arrangement of neurons in conventional artificial neural networks (ANNs).

2.3.3 Activation Functions of Artificial Neural Network

The activation function is a crucial aspect of artificial neural networks (ANNs) alongside the nodes and layers. In creating an ANN, designing the neuron models is key as neurons are the fundamental units in biological neural networks. The activation function of a node decides the output that is generated given an input in the ANN model. As learning occurs, the activation function modifies the weights and bias, transforming from 0 to 1. There are two types of activation functions: linear and non-linear. However, only non-linear activation functions are effective for building complex networks with limited number of nodes.

The linear activation function is clear and direct, as it assumes a linear relationship between the input and output. However, its simplicity makes it unsuitable for analyzing complex data, as it cannot capture the complexity of various parameters. On the other hand, non-linear activation functions are widely used to model and generalize the complexity of data for producing an output. These functions come in different forms, based on their range or curve shape, with the most common being sigmoid or logistic, tanh, ReLU, and Softplus.

Table 2. Types of Activation Function

Type	Equation	Derivative
Linear/Identity	$f(x) = x$	$f'(x) = 1$
Binary Step	$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x \neq 0 \\ ? & \text{for } x = 0 \end{cases}$
Logistic/sigmoid	$f(x) = \sigma(x) = \frac{1}{1+e^{=x}}$	$f'(x) = f(x)(1 - f(x))$
Tanh	$f(x) = \tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{=x}}$	$f'(x) = 1 - f(x)^{2}$
Softmax	$f(y_i) = \frac{e^{y_i}}{\sum_j e^{y_j}}$ where $j \neq i$	$f'(x) = f(x_j)(1 - [f(x_i)])$
SoftPlus	$f(x) = \ln(1+e^{x})$	$f'(x) = \frac{1}{1+e^{=x}}$
Rectified Linear Unit (ReLU)	$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ \text{x} & \text{for } x \geq 0 \end{cases}$	$f'(x) = \begin{cases} 0 & \text{for } x \leq 0 \\ 1 & \text{for } x > 0 \end{cases}$

Leaky Rectified Linear Unit (LReLU)	$f(x)=\begin{cases} x & if \quad x \geq 0 \\ 0.01x & if \quad x<0 \end{cases}$	$f'(x)=\begin{cases} 1 & if \quad x>0 \\ 0.01 & otherwise \end{cases}$
Parametric Rectified Linear Unit (PReLU)	$f(x)=\begin{cases} x & if \quad x \geq 0 \\ ax & if \quad x<0 \end{cases}$	
Randomized Rectified Linear Unit (RReLU)	$f(x)=\begin{cases} x & if \quad x \geq 0 \\ \alpha x & if \quad x<0 \end{cases}$	$\alpha \sim U(A,B), A<B and A,B \in [0,1)$
Exponential Linear Unit (EReLU	$f(y_i)=\begin{cases} x & if \quad x \geq 0 \\ \alpha(e^x-1) & if \quad x<0 \end{cases}$	$f'(x)=\begin{cases} 1 & if \quad x>0 \\ \alpha e^x & if \quad x \leq 0 \end{cases}$
Multiple Parametric Exponential Linear Unit (MPELU)	$f(y_i)=\begin{cases} x & if \quad x>0 \\ \alpha(e^{\beta x}-1) & if \quad x \leq 0 \end{cases}$	

The sigmoid or logistic activation function, which is the most widely used activation function, is a smooth, S-shaped function that outputs values ranging from 0 to 1. Its formula is as follows:

$$f(x)=\frac{1}{1+e^{-x}} \qquad \text{Eq. 19}$$

Despite the ease of computing its derivatives, the sigmoid function is rarely used in deep neural networks as it leads to zero gradient in the limit, causing difficulties in training deep neural network models. This is particularly relevant when the sigmoid function is utilized in the output layer.

$$\lim_{x \to +\infty} f'(x) = 0 \quad \text{and} \quad \lim_{x \to -\infty} f'(x) = 0 \qquad \text{Eq. 20}$$

The optimization of the loss function leads to the derivatives of the sigmoid function becoming close to zero in the saturation area, leading to reduced contributions in the early layers. This is known as the vanishing gradient, and is typically a problem in networks with more than five layers (Glorot & Bengio, 2010; Han & Moraga, 1995).

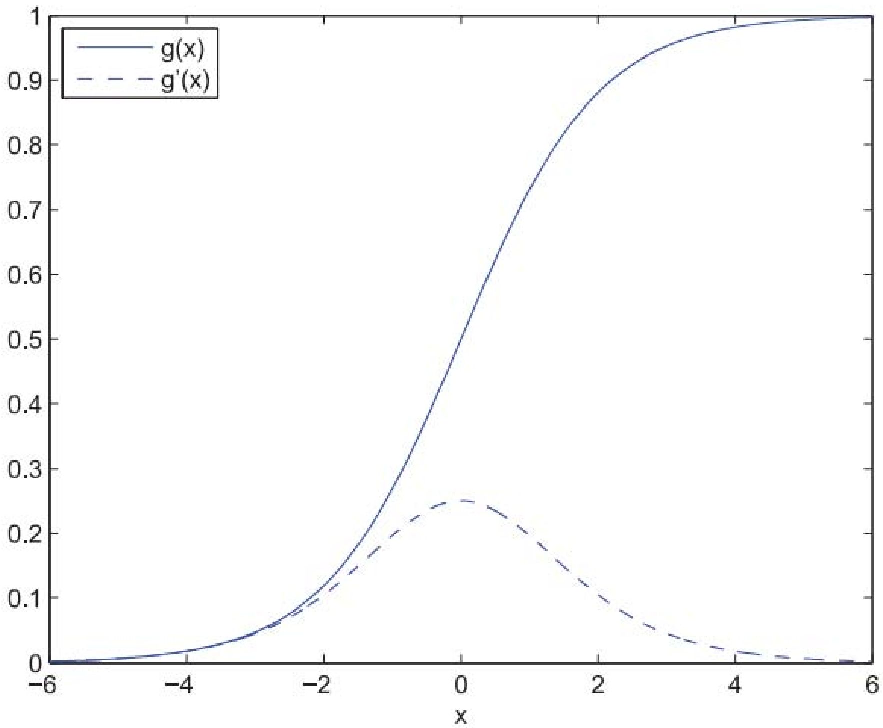

Figure 2. Shape of sigmoid function and its derivative

The tanh function, also known as the hyperbolic tangent function, extends the sigmoid function in an S-shape and outputs values between -1 and 1. It is defined as the ratio of the sine function and the cosine function.

$$\tan h(x) = \frac{\sin h(x)}{\cos h(x)} = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \qquad \text{Eq. 21}$$

Being similar to the sigmoid function, the tanh function can be deducted from the sigmoid function:

$$\tan h(x) = 2sigmoid(2x) - 1 \cdots\cdots \text{Eq. 22}$$

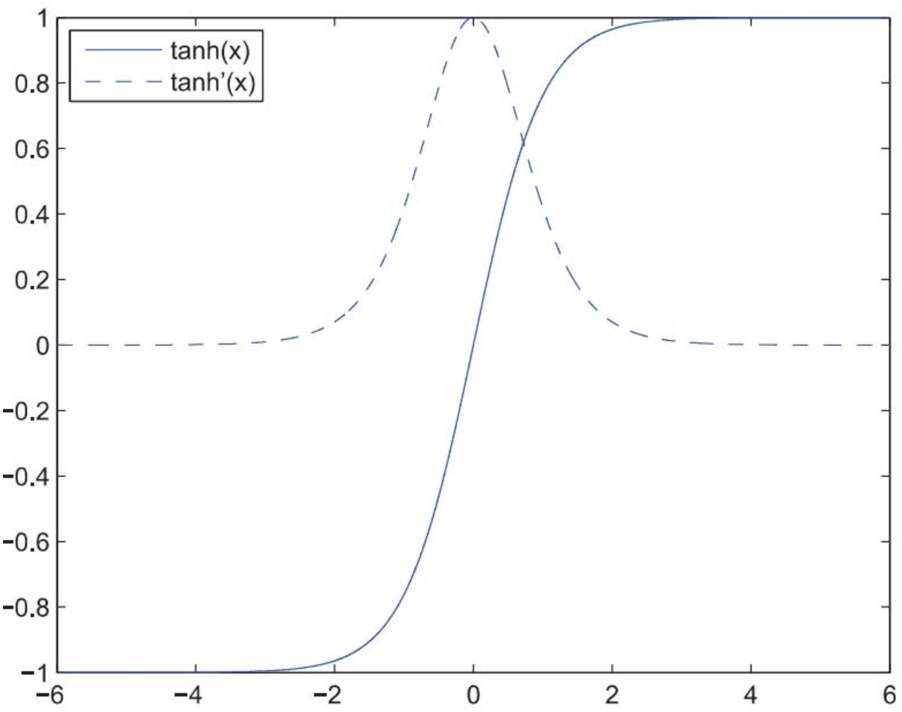

Figure 3. Shape of hyperbolic tangent function and its derivative

Like the sigmoid function, the tanh function is also differentiable, but it similarly encounters the issue of the vanishing gradient. The sigmoid and tanh functions have the possibility of producing a vanishing gradient, which arises from inputting a large number of information. The problem becomes evident especially when the researcher uses many number of layers in the network, and consequently, the gradient between the layers become too small to be trained by the network. The gradient of a neural network is calculated using backpropagation, which involves computing the derivatives of the network as it moves backward from the final layer to the initial layer. According to the chain rule, the derivatives of each layer are multiplied as the network moves back, to obtain the derivatives of the initial layer. However, if the gradient becomes too small at a certain hidden layer, the next derivative may become exponentially small, which could leave the weights and biases without being updated. Thus, small gradients can interfere with the training process and the performance of the model overall (Hochreiter, 1998). To avoid this computational challenge and the vanishing gradient problem, different activation functions have been developed.

The ReLU function, which is a rectified linear unit activation function, has become a popular choice in artificial neural network modeling. This is due to insights from neuroscience suggesting that activation functions in the brain can be modeled with rectifiers. Unlike the sigmoid and tanh functions, where over half of the neuron units are activated simultaneously, in the brain only a small percentage (1-4%) of neurons are activated at once, leading to the need for a change in the neural network design.

Unlike the sigmoid function, ReLU has a value between 0 and ∞, meaning that it is half rectified from 0. The derivative is a constant when the input is $x > 0$. The definition and derivative of ReLU are as follows:

$$f(x) = \max(0, x) = \begin{cases} x & if \quad x \geq 0 \\ 0 & if \quad x < 0 \end{cases} \qquad \text{Eq. 23}$$

$$f(x) = \max(0, x) = \begin{cases} 1 & if \quad x \geq 0 \\ 0 & if \quad x < 0 \end{cases} \qquad \text{Eq. 24}$$

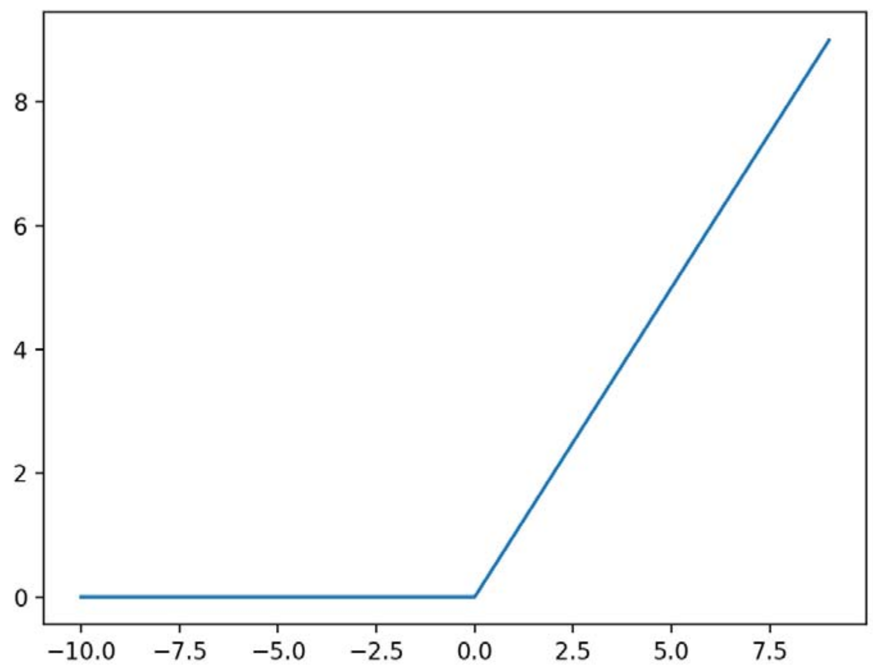

Figure 4. Shape of ReLU activation function

Compared to the sigmoid or tanh activation functions, using the ReLU activation function has many advantages, including its computational simplicity and reduced risk of vanishing gradients. Unlike sigmoid or tanh functions that require computation of exponential functions, the ReLU function only involves a simple calculation. Networks with ReLU functions also converge much faster during training with gradient descent compared to those with saturating activation functions. The ReLU function also enables networks to easily obtain sparse representations, where the output is 0 when the input is less than 0, leading to sparse activation of neuron units and improved efficiency in data learning. When the input is $x \geq 0$, the features of the data can largely be retained. Finally, deep neural networks with ReLU activation functions can perform optimally without undergoing any unsupervised pre-training in supervised tasks using large, labeled data sets.

However, the ReLU function's assumption of setting all negative values to 0 can lead to many activations in the layers becoming 0. This is because the gradient is 1 for all positive values and 0 for negative values, which can result in relative weights not being updated and cause some neurons to "die" by never being activated when needed. This issue is known as the "dying ReLU problem". To address this, the leaky ReLU function was created as a modification of ReLU, assigning non-zero slopes to negative values. The form of the leaky ReLU varies depending on the assignment of values lower than 0. The leaky ReLU function and its derivative are generally defined as follows (Maas et al., 2013):

$$f(x) = \max(0, x) = \begin{cases} x & if \quad x \geq 0 \\ 0.01x & if \quad x < 0 \end{cases} \quad \text{Eq. 25}$$

$$f'(x) = \begin{cases} 1 & if \quad x > 0 \\ 0.01 & otherwise \end{cases} \quad \text{Eq. 26}$$

The parametric leaky ReLU (PReLU) model assumes the same functional form except that it defines the value of α as learned during training in the back-propagation process (Sun & Yu, 2016).

$$f(x) = \begin{cases} x & if \quad x \geq 0 \\ ax & if \quad x < 0 \end{cases} \quad \text{Eq. 27}$$

To summarize, ReLU, leaky ReLu, and PReLU can be distinguished according to the following conditions:

$$\begin{array}{l} \text{If } \alpha_i = 0, \text{ ReLU} \\ \text{If } \alpha_i > 0, \text{ LeakyReLU} \\ \text{If } \alpha_i \text{ can be learned, PReLU} \end{array} \quad \text{Eq. 28}$$

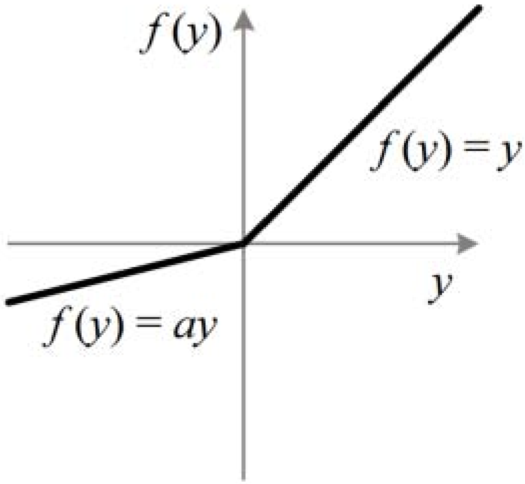

Figure 5. Shape of PReLU activation function

The Randomized Rectified Linear Unit (RReLU) is another variation of the ReLU activation function. Unlike leaky ReLU, where the slope for negative values is set as a constant or learnable parameter, in RReLU the slope is randomly assigned within a specified range during the training phase, and then fixed during the testing phase. The definition of RReLU is:

$$f(x) = \begin{cases} x & if \quad x \geq 0 \\ \alpha x & if \quad x < 0 \end{cases} \quad \cdots\cdots \text{Eq. 29}$$

where

$$\alpha \sim U(A, B), A < BandA, B \in [0,1) \quad \cdots\cdots \text{Eq. 30}$$

In the training set, α is a random number sampled from the uniform distribution $U(A,B)$. In the testing set, the average of all parameters α in the training set is taken and the parameter is set as $(A+B)/2$.

In order to get the activation means closer to zero to decrease the bias shift effect of a ReLU function, the Exponential Rectified Linear Unit (ELU) was proposed with $\alpha > 0$, where the definition and derivative is defined as:

$$f(y_i) = \begin{cases} x & if \quad x \geq 0 \\ \alpha(e^x - 1) & if \quad x < 0 \end{cases} \qquad \text{Eq. 31}$$

$$f'(x) = \begin{cases} 1 & if \quad x > 0 \\ \alpha e^x & if \quad x \leq 0 \end{cases} \qquad \text{Eq. 32}$$

The drawback of ELU and LReLU is that searching for α is time consuming. Therefore, the following Parametric Exponential Linear Unit was proposed (Li et al., 2018):

$$f(y_i) = \begin{cases} x & if \quad x > 0 \\ \alpha(e^{\beta x} - 1) & if \quad x \leq 0 \end{cases} \qquad \text{Eq. 33}$$

2.3.4 Fundamental Difference Between Machine Learning and Discrete Choice Model

Although many researches now attempt to formulate consumer preference structure through machine learning, seemingly making it as if the two fields are closely related. However, discrete choice models and machine learning are fundamentally different. Discrete choice models are based in economic theories. Therefore, it is referred to as knowledge driven or theory driven. Also, as is the case for all economic models, the pinnacle of discrete choice model is its interpretability that comes with the accumulated theories and techniques including the Random Utility Theory, simulation techniques such as Markov Chain, and assumptions of distributions of variables.

Table 3. Comparison between Logit and Machine Learning Models

Type	Logit Models	Machine-learning Models
Model formulation	$U_{njt} = V(x_{njt}, s_{njt}) + \varepsilon_{njt} = \beta'_{njt} + x_{njt} + \alpha'_{njt} s_{nt} + \varepsilon_{njt}$ $P_{nit} = \int L_{nit}(\beta_n) f(\beta_n \mid b, W) d\beta_n$ $L_{nit}(\beta_n) = \frac{e^{V_{nit}}}{\sum_j e^{V_{njt}}} = \frac{e^{\beta'_n x_{nit}}}{\sum_j e^{\beta'_n x_{njt}}}$	$Y = f(Z \mid \theta), Y \in \{1, \ldots, K\}$
Commonly used models	Multinomial Logit, Mixed Logit, Nested Logit	NB, CART, BAG, BOOST, RF, SVM, NN
Prediction type	Class probability	Classification
Model topology	Layer structure	Layer structure, Tree structure, Case-based

		reasoning, etc.
Optimization method	Maximum likelihood estimation, Simulated maximum likelihood, Bayesian estimation	Back propagation, gradient descent, recursive partitioning, structured risk minimization, etc.
Evaluation criteria	Log-likelihood, AIC, BIC	Resampling-based measures
Variable importance	Relative importance (RI)	Variable importance
Variable effects	Sign and magnitude of β coefficients	Partial dependence plots

Machine learning models are considered data-driven, lacking a theoretical foundation or prior knowledge. Instead, they rely solely on the data they are trained on and prioritize performance and prediction accuracy. As a result, some researchers argue that machine learning models cannot be replaced by traditional models, as they operate differently.

Despite the differences between machine learning models and traditional models, efforts are still being made to replicate the latter. Neural networks have become increasingly popular due to their ability to identify complex relationships between variables. In the marketing industry, ANNs are used for a variety of tasks including market segmentation, predicting market response, forecasting sales, and predicting consumer choices. The use of ANNs to determine the effect of marketing variables and to estimate price elasticities has grown significantly over time (Dasgupta et. al., 1994; Thieme et al., 2015).

Studies have shown that machine learning models have the ability to supersede traditional models in terms of performance, however, they lack interpretability and do not provide insight into the cause-and-effect relationships.

Studies have shown that machine learning models have the potential to surpass traditional models in performance, but they lack interpretability and provide limited insight into the causal relationships. To address this, some researchers have combined the elements of discrete choice models and neural networks to create hybrid models. One such example is the NN-MNL model introduced by Bentz and Merunka (2000), which follows a two-step process of estimating a NN model to identify non-linear effects in the utility function and then modifying the MNL model to incorporate these effects through new variables.

Sifringer (2018) aimed to combine the predictive power of NN with the interpretability of DCM by linking the mathematical derivation of the multinomial logit model to the NN equivalent. This enabled the formation of a connection between the linear and non-linear parts by using unused variables in DCM in the non-linear layer through a Dense Neural Network (DNN).

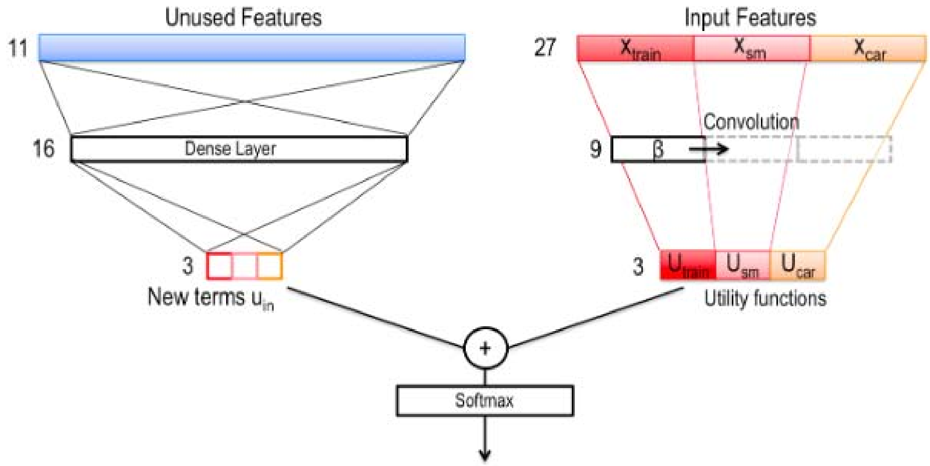

Figure 6. The schematic of Learning Multinomial Logit (L-MNL) Model (Sifringer et al., 2018)

Subsequently, Sifringer et al. (2020) advanced the previous work by introducing two new hybrid models, the Learning Multinomial Logit (L-MNL) and Learning Multinomial Nested Logit (L-NL) models. The models feature a linear layer representing the systematic part of the utility function, and a non-linear dense layer that learns a representation term from a set of additional socio-demographic variables for which no prior relationship is assumed. The present study is largely based on this work, and the methodology will be explained in more detail in the following chapter.

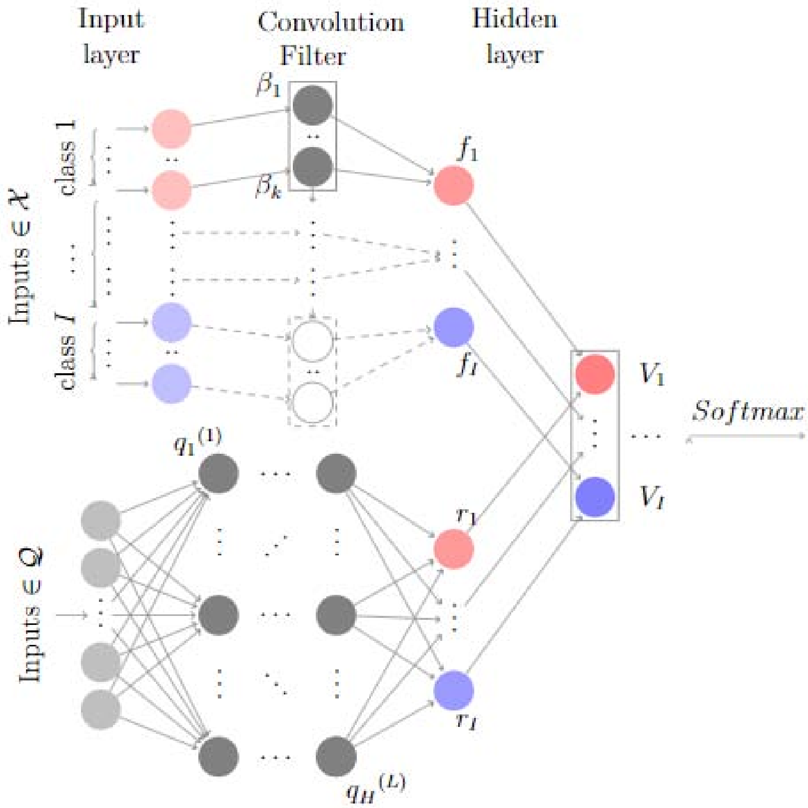

Figure 7. The schematic of Learning Multinomial Logit (L-MNL) Model

(Sifringer et al., 2020)

Wong and Farooq (2021) created the Residual Logit Model (ResLogit), which combines a Deep Neural Network (DNN) with a Multinomial Logit (MNL) model. This model outperformed previous ones and provided more interpretability, as the residual network's parameters can be used to uncover valuable economic indicators. Arkoudi et al. (2021) also proposed a DCM that is based on neural network with fully interpretable parameters. They were able to derive such parameters by introducing an embedding layer as part of the model's architecture that can effectively encode discrete input variables with high cardinality into alternative-specific continuous values.

Figure 8. The architecture of Embeddings Multinomial Logit (E-MNL) Model (Arkoudi et al., 2021)

2.4 Result of Literature Review

As mentioned in the previous section, many researches have shown great performances. However, machine learning models are still criticized for only having predictive abilities when in real life, interpretability also matters greatly. On the other hand, researchers in traditional academic fields, mainly economics, still dwell around machine learning because of the powerful predictive capacity of the neural network models. Also, because machine learning models lack interpretability, there have been many restrictions in replicating behavioral models of discrete choice models, which is another prominent area of research in modern day economics that stems from the prospect theory.

According to the review of the previous studies, it has come to light that in order to enhance the interpretability and embed behavioral characteristics of the existing models, and if the two models cannot replace each other, they should be combined. This study follows the framework of the previous literature that employed hybrid model approach, where the model maintains the interpretability of the discrete choice model by formulating one part of the neural network as linear and the other part as non-linear. Many efforts have already been taken in that aspect, but this study attempts to provide further development and open the doors to providing additional options to explore the various aspects of choice models. Specifically, this study will attempt to implement the concept of thresholds, one of the behavioral models of choice models, into the hybrid neural network model. The attempt to combine neural networks and compensatory/non-compensatory is not the first (West et al., 1997), but it is one of the first attempts to implement it into the hybrid models.

However, in the perspective of the existing choice models, this study attempts to resolve one of the few limitations, the restrictions from accessible data. For example, in the previous literature regarding threshold models, although the threshold levels were stochastic and were distributed randomly throughout the population (Cantillo et al., 2006), the researcher still needed the data on the individuals' reference points (Han et al., 2001).

However, by using the power of neural network models, the threshold levels can be trained by itself without the knowledge and actually provide the clues where the actual reference points of the individuals might be located.

Therefore, this study made a hybrid approach to formulating a model that incorporates the traditional aspects, the linear part, and the data driven aspects, the non-linear part. First, a modified discrete choice model is proposed that implements a decision rule based on thresholds. Then, a neural network approach was taken to separate the utility function of the discrete choice models into the theory-driven part and data-driven part. The theory-driven part maintains the interpretability of the original model, while enhancing the predictive performance of the model through additional neural network that utilizes as much data as possible, which is explained in the following chapter.

Chapter 3. Methodology

3.1 Threshold as ‘Just Noticeable Difference’ in Discrete Choice Model

The methodology used in this study that implements thresholds is based on discrete choice experiment. Although previous behavioral models that utilized discrete choice models have the advantage of observing the asymmetric preference structure of the consumers, recent studies have examined the possibility of the existence of thresholds in addition to reference effects. In short, threshold posits that there is a certain region in consumers’ preference, where their utility does not change despite the changes in attribute levels. This phenomenon is referred to as “just noticeable difference.” In fact, the concept of thresholds is not a completely new idea. It was first introduced in psychological experiments, and the concept was developed by classical economists, who analyzed consumer choice of goods using indifference curves. Slutsky (1952) discovered that between any two bundles of goods, consumers had three attitudes: 1) X is preferred to Y 2) Y is preferred to X 3) is indifferent to both X and Y. Krishnan (1977) introduced this concept to the field of discrete choice experiment, specifically designing the choice situation to include a third alternative in addition to two normal alternatives, to reflect the indifferent attitude.

More recent studies have implemented thresholds as a part of existing discrete choice models. Han et al. (2001) combined reference price effect and threshold effect, suggesting that there is a latitude of acceptance or zone of indifference around the reference point, such that minor changes in price around the reference point do not have any significant impact on consumer choice. In other words, consumers have differential thresholds for gains and losses. Unless the difference between actual and reference price is higher than these thresholds, consumers do not experience any shifts in utility. However, the limitation of this study is that despite the fact that thresholds may exist for any attribute, the study have considered thresholds for only the price attribute. Cantillo et al. (2006) utilized multinomial logit model and structured the threshold to be randomly distributed, to determine how the threshold levels would differ across individuals. The results of the study indicated that where thresholds exist in the population, not taking them into consideration would lead to errors in estimation and prediction. Although this study observed the heterogeneity of the consumers' thresholds, the study did not observe the heterogeneity in the coefficients. Therefore, a model is proposed in this study that incorporates thresholds into mixed logit model, a more advanced model that considers heterogeneity in preferences for each respondent, meaning that it can identify an individual respondent's preference for every attribute.

First, based on the random utility theory, the mixed logit model with random parameters is used to capture the consumers' preferred directions for the attributes of the alternative and each random parameter is set as having a normal distribution to consider the differences in a preferred direction. When using the mixed logit model, individual-level marginal utility can be derived with Bayes' theorem (Hensher & Greene, 2003).

Individual marginal utility shows the direction of consumers' preferences for the increase of the attribute levels. If it is larger than 0, then the consumers prefer the increase of levels, and otherwise, they do not prefer. The random utility model is expressed as Eq. (1). U_{nj} represents the utility respondent *n* gains from their selected alternative *j*.

$$U_{nj} = V_{nj} + \epsilon_{nj} = \beta'_{nk} X_k + \epsilon_{nj},\ \beta_{nk} \sim N(b, W) \quad \cdots\cdots \text{Eq. 34}$$

In Eq. (1), respondent n's utility U_{nj} can be divided into the deterministic term, V_{nj}, and the stochastic term, ϵ_{nj}. Then, the deterministic term can be further expressed as the product of the vector (X_k), which refers to the attribute of the alternatives, and the coefficient vector (β_{nk}). The deterministic term refers to the the attribute of the product that can be explained, and the stochastic term refers to the uncertainties. This study assumed that the coefficient followed normal distribution with mean (b) and variance (W), and the stochastic term followed independent and identically distributed type I extreme value distribution.

Secondly, by using individual-level marginal utility (β^1) and the difference between level (x_{jk}) of attribute(k)of alternative(j) and the reference point (r_{nk}) for attribute (k) of respondent (n), the relative attribute levels can be divided into gain and loss domains, as in Eq.(2). If $(x-r)$, or the difference of x_{jk} and r_{nk} has the same sign as β_1, then this means that the respondents prefer the relative attribute levels (considered as gain) and otherwise, they do not (considered as loss). Here, the reference point is obtained as a stated preference data from survey, where the respondents state their expectation towards each of the attributes.

$$\begin{array}{l}\text{Gain, if } (\beta^1_{nk} \geq 0 \,\&\, \mathrm{x}_{jk} \geq r_{nk}) \text{ or } (\beta^1_{nk} < 0 \,\&\, x_{jk} < r_{nk}) \\ \text{Loss, if } (\beta^1_{nk} < 0 \,\&\, \mathrm{x}_{jk} \geq r_{nk}) \text{ or } (\beta^1_{nk} \geq 0 \,\&\, x_{jk} < r_{nk})\end{array} \quad \text{Eq. 35}$$

Thirdly, in addition to the relative attribute levels considered in the conventional reference dependence studies, this study input the threshold levels for each attribute (δ). As mentioned before, consumers do experience shifts in utility only when the difference between the actual attribute level (x) and the reference point (r) is higher than these thresholds. Therefore, the relative attribute levels with thresholds can be divided into gain and loss domains again, as in Eq. (3).

$$\begin{array}{l}\text{Gain, if } (\beta^1_{nk} \geq 0 \,\&\, \mathrm{x}_{jk} \geq r_{nk} \,\&\, 0 \leq \delta_{nk,gain} \leq x_{jk} - r_{nk}) \text{ or } (\beta^1_{nk} < 0 \,\&\, x_{jk} < r_{nk} \,\&\, 0 \leq \delta_{nk,gain} \leq r_{nk} - x_{jk}) \\ \text{Loss, if } (\beta^1_{nk} < 0 \,\&\, \mathrm{x}_{jk} \geq r_{nk} \,\&\, 0 \leq \delta_{nk,loss} \leq x_{jk} - r_{nk}) \text{ or } (\beta^1_{nk} \geq 0 \,\&\, x_{jk} < r_{nk} \,\&\, 0 \leq \delta_{nk,loss} \leq r_{nk} - x_{jk})\end{array} \quad \text{Eq. 36}$$

Finally, the influence of relative attribute levels with thresholds on the utility of respondent n can be modeled as Eq. (4). The deterministic term of the utility function was split into traditional term, which is the first term in the equation, and the modified terms, which include the remaining terms. The traditional term reflects the attributes that do not consider the reference and threshold effects, while the modified terms reflect those that consider the reference and threshold effects.

$$V_{nj} = \beta'_{nk} X_{nk} \\ + \beta_{gain} \cdot \| x_{jk} - r_{nk} | - \delta_{nk,gain} | \cdot I\{(\beta^1_{nk} \geq 0 \,\&\, 0 \leq \delta_{nk,gain} \leq x_{jk} - r_{nk}) \text{ or } (\beta^1_{nk} < 0 \,\&\, 0 \leq \delta_{nk,gain} \leq r_{nk} - x_{jk})\} \\ + \beta_{loss} \cdot \| x_{jk} - r_{nk} | - \delta_{nk,gain} | \cdot I\{(\beta^1_{nk} < 0 \,\&\, 0 \leq \delta_{nk,gain} \leq x_{jk} - r_{nk}) \text{ or } (\beta^1_{nk} \geq 0 \,\&\, 0 \leq \delta_{nk,gain} \leq r_{nk} - x_{jk})\} \quad \text{Eq. 37}$$

By substituting Eq. (4) into Eq. (1), the final form of the utility function can be expressed as Eq. (5).

$$U_{nj} = \beta'_{nk} X_{nk} \\ + \beta_{gain} \cdot \| x_{jk} - r_{nk} | - \delta_{nk,gain} | \cdot I\{(\beta^1_{nk} \geq 0 \,\&\, 0 \leq \delta_{nk,gain} \leq x_{jk} - r_{nk}) \text{ or } (\beta^1_{nk} < 0 \,\&\, 0 \leq \delta_{nk,gain} \leq r_{nk} - x_{jk})\} \quad \text{Eq. 38} \\ + \beta_{loss} \cdot \| x_{jk} - r_{nk} | - \delta_{nk,gain} | \cdot I\{(\beta^1_{nk} < 0 \,\&\, 0 \leq \delta_{nk,gain} \leq x_{jk} - r_{nk}) \text{ or } (\beta^1_{nk} \geq 0 \,\&\, 0 \leq \delta_{nk,gain} \leq r_{nk} - x_{jk})\} \\ + \epsilon_{nj}$$

In general, threshold levels are usually unknown to the researcher, as the consumers are unaware of its existence and magnitude themselves (Cantillo et al., 2006). Therefore, in the utility model, the threshold terms are stochastically defined by individual characteristics (Z_{nk}) and the absolute difference between the actual attribute level (x_{jk}) and the reference point (r_{nk}) as shown in Eq. (6). This phenomenon is complicated because consumers do not appraise a product or service just once, but their evaluation of them can accumulate over time and exceed the threshold, or a change in their behavior and taste might occur, which would cause a change in their threshold levels. Therefore, in the general case thresholds are treated as dynamic which depends on the characteristics of the individuals and consequently distributed randomly within the population (Georgescu-Roegen, 1958).

$$\delta_{nk} = | x_{jk} - r_{nk} | \times \rho_{nk} Z_{nk} + \xi_{nj}, \quad \xi_{nj} \sim \mathrm{N}(0, \Sigma) \quad \text{Eq. 39}$$

In this study, Markov Chain Monte Carlo (MCMC) Gibbs sampler is used in Bayesian estimation procedure by the following order.

$$\begin{aligned} &\rho \mid \Sigma, \beta_n \\ &\Sigma \mid \beta_n, \rho \\ &\beta_n \mid \rho, \Sigma \end{aligned} \quad \text{Eq. 40}$$

3.2 Hybrid Formulation of CNN and DNN

Based on the literature review, this study applies advanced utility specification to form a hybrid model consisting of both a discrete choice model and machine learning. Divided utility specification is deployed into the interpretable and data driven (learning) parts (Sifringer et al., 2020). The main goal of research in machine learning to try to implement machine learning into the traditional econometric models to avoid losing interpretability of the machine learning model as much as possible. Machine learning has widely been regarded as 'black box' models, where the coefficients were unable to be derived and interpreted, which is the fundamental aspect of an economic model. Therefore, in recent years many hybrid models have appeared that formulate the model in a way that could still be interpreted through various assumptions.

A neural network consists of a function that maps the input space to an output of interest through the medium known as the hidden layers ($h^{(j)}$):

$$U = h^{(L)} q^{(L-1)},$$
$$with \quad q^{(j)} = h^{(j)}(q^{(j-1)}), \ \forall j = 1, ..., \mathrm{L}, \quad \text{......................................} \text{Eq. 41}$$

where $q^{(0)} = x$ and L is the last representation layer.

This study utilizes a CNN to retrieve the MNL formulation. What differentiates CNN from other NN models is that the weights of CNN are represented by a convolutional filter that connects one layer $h^{(j)}$ to the following hidden layers or the output layer by applying a convolution. Convolution is commonly used in the area of image processing, where a filter with a fixed number of weights is applied to an equal number of inputs by multiplying the terms together and then summing them over to obtain a single new value. A new image is obtained by sliding the filter over all the input data, a process referred to as the stride. In the case of this study, the model employs CNN model without applying the filter out of the boundaries, reducing the size from one layer to the next, referred to as the paddling. In other words, the layers are directly connected. Therefore, the value of a neuron i in the next layer $(j+1)$ can be written as:

$$h_i^{(j+1)} = g\left(\sum_{k=0}^{d} h_{(s\cdot i+k)}^{(j)} \beta_k^{(j)} + \alpha_i^{(j)}\right), \quad \text{...} \text{Eq. 42}$$

where $\{\beta_1, ..., \beta_d\} = \boldsymbol{\beta}$ is the filter size $(1 \times d)$, s the stride of the convolution, α_i a bias term, and $g(\cdot)$ an activation function.

The MNL formulation is retrieved by employing only a single layer, setting the activation function to identity $(g(x)=x)$ and the stride s to d. This differs from the general formulation, as the nodes are directly connected between each layer 1 to 1. The original deterministic term of the utility function can be obtained this way.

Finally, the probability function, which much resembles that of the discrete choice model, can be obtained by using a SoftMax activation layer as follows:

$$(\boldsymbol{\sigma} \mid (V_n))_i = \frac{e^{(V_{in})}}{\sum_{j \in C_n} e^{(V_{jn})}}, \quad \cdots\cdots \text{Eq. 43}$$

which can be identified as the same probability function of the MNL.

The output of the network then goes through a loss function:

$$H_n(\sigma, y_n) = -\sum_{i \in C_n} y_{in} \log[\sigma_i(V_n)] \quad \cdots\cdots \text{Eq. 44}$$

Minimizing the above equation is equivalent to maximizing the log likelihood function when summed over all individuals, n.

As mentioned above, in this study, the deterministic part of the utility function is divided into two parts as follows:

$$V_{in} = f_i(X_n, \beta) + r_i(Q_n, w), \cdots \text{Eq. 45}$$

where $f_i(X_n;\beta)$ is the interpretable part driven by theory and knowledge, and as a result the function is now defined so that the unknown parameters (β) are an interpretable by its attributes; $r_i(Q_n;w)$ is the data-driven learning part, learned from set of socio-demographic variables where no previous relationship is assumed in any case.

Substituting Eq. 16 into the utility function gives the following:

$$U_n = f_i(X_n, \beta) + r_i(Q_n, w) + \epsilon_n \cdots \text{Eq. 46}$$

Intuitively, this indicates that the data driven or learning part, $r_i(Q_n;w)$, is taken out of the residual of the function, which enhances the performance of the model, such that:

$$\overline{\epsilon}_{in} = r_i(Q_n, w) + \epsilon_{in} \cdots \text{Eq. 47}$$

A similar formulation has been proven to be highly effective through the use of a residual network (He et al., 2016).

The likelihood of selecting the choice alternative i for individual n given the values of the model parameters, attributes, and influencing variables can be expressed as follows:

$$P_n(i) = \frac{e^{f_i(X_n,\beta)+r_i(Q_n,w)}}{\sum_{j\in C_n} e^{f_j(X_n,\beta)+r_j(Q_n,w)}} \quad \text{Eq. 48}$$

Regarding the learning part, $r_i(Q_n;w)$, this study used a Dense Neural Network (DNN), where r_{in} is the resulting function of a DNN with L layers of H neurons and a single output per utility function:

$$r_{in} = \sum_{k=1}^{H} w_{ik}^{(L)} g(q_n^{(L-1)} w_k^{(L-1)} + \alpha_k^{(L-1)}) + \alpha_i^{(L)}, \quad \text{Eq. 49}$$

where $g(\cdot)$ is the ReLU activation function.

The schematic of the model is visualized in Figure 3.

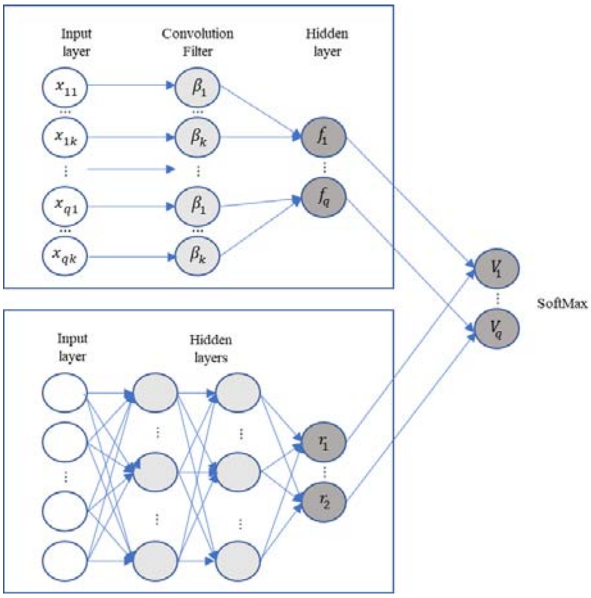

Figure 9. Hybrid machine learning model schematic

Here, what distinguishes the hybrid model from the traditional models is that the connection between the input to the convolution layer is not fully connected, and that they are matched 1:1 between the weight and the variable of the input layer (Sifringer et. al., 2020). This leads to some concerns that, as the nodes are not fully connected, the model might sacrifice some of the advantages of a neural network model. However, as can be seen in the results in a later chapter, the addition of variables into the DNN enhanced the prediction accuracy of the model.

In addition, in order to formulate a threshold model with machine learning, this study added another convolution layer to the theory driven part of the utility function. The filter is set to a 1 x 1 size with the stride set to 1. The ReLU activation function is used. By formulating the model in this way, the disadvantage is a loss of the ability to capture the asymmetric structure of preference. However, as in the case of evaluating thresholds, it is to the researcher's interest to observe the range where the utility of the consumers does not change, i.e., the indifference zone, and the range where the utility starts to increase. Therefore, this study implemented the ReLU function to capture the threshold effect. Consequently, the likelihood of selecting the choice alternative i for individual n, visualized in Figure 4, is as follows:

$$P_n(i) = \frac{e^{f_i(X_n,\beta,\delta)+r_i(Q_n,w)}}{\sum_{j\in C_n} e^{f_j(X_n,\beta,\delta)+r_j(Q_n,w)}} \quad \cdots\cdots \text{Eq. 50}$$

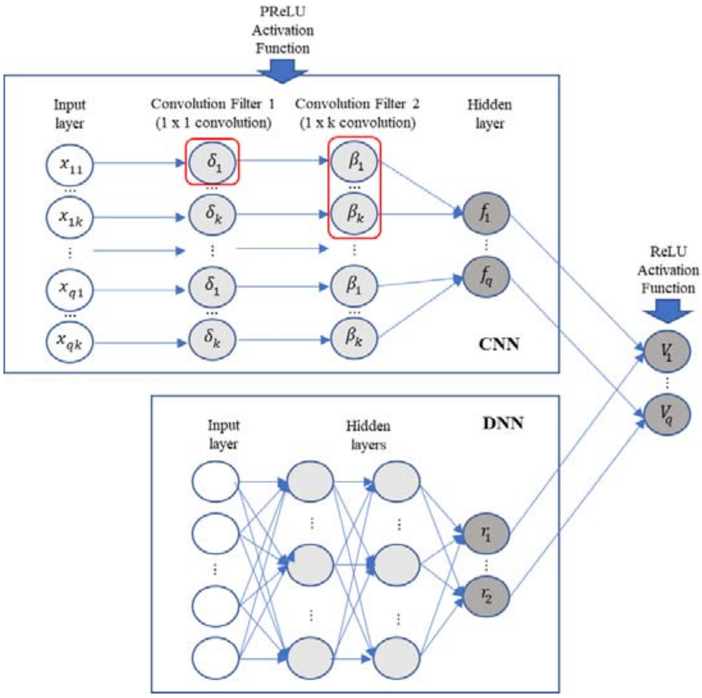

Figure 10. Hybrid machine learning model schematic with 2 convolution filters

One of the major challenges in training a neural network is deciding how much and how well to train the model. When the model is not trained enough, then the model will underfit the training and test sets of data. On the other hand, when the model is trained too much, it will be vice versa, where the mode is overfit and result in poor performance on the test set. Therefore, a compromise needs to be made to train on the training dataset until the performance on the test dataset starts to degrade. This method is referred to as early stopping which is intuitively very simple, but it has shown high performance and it has been widely used to train neural networks (Prechelt, 1998; Raskutti et. al., 2014).

One of the approaches to solve the problem is treating the number of training epochs as a hyperparameter, training the model repeatedly with different number of epochs, and selecting the number of epochs that finally presents the best results. The disadvantage of this approach is that it requires the manual work of the researcher to train and discard multiple models, which can be highly inefficient computationally and defeats the purpose of using machine learning models.

The alternative approach to early stopping method is to start the training process with a large number of epochs. Once the dataset starts to get trained, the model is evaluated on a holdout validation dataset after each epoch. If the performance of the model on the validation dataset starts to degrade, then the training process is stopped. The reason behind it is that when the training process stops, it means that the loss starts to increase, or the accuracy begins to decrease. The early stopping method has been widely used to prevent overestimation in neural network models.

Chapter 4. Empirical Studies

4.1 Background

In an effort to curb the upcoming of the global warming, governments around the globe has gathered to adopt the Paris Agreement 2015, which became the guiding principle of environmental policies. The Agreement requires all countries to implement their own GHG reduction targets, and South Korea has also set a 37% reduction in GHG emissions compared to BAU by 2030 as its national target. However, despite the countries' efforts to reduce greenhouse gas emissions through regulations, the GHG emission continues to be a serious issue, especially in the transportation sector from internal combustion engines (ICEVs). More than 95% of the vehicles registered around the globe are gasoline and diesel vehicles, accounting for more than 50% of crude oil use.

As the demand for a dramatic change to this landscape rapidly increased, governments across the globe initiated several notable changes. Most notably, European countries have adopted the Alternative Fuel Infrastructure Directive, setting the standard of charging infrastructure and recommending that at least 1 charging station be installed for every 10 registered EVs. The Korean government has also joined this rally and imposed key regulations. In February 2021, the government announced the "4th Basic Plan for Environment Friendly Vehicles." In this plan, the government revealed its ambitious goals to reduce the GHG emission level in the transportation sector by 24% and achieve the rollout of 7.85 million alternative fuel vehicles (AFVs) by the year 2030. Also, the government has expanded the charging infrastructure, and as a result, South Korea currently has the highest ratio of public charging infrastructure per registered EV (0.5) compared to the global average (< 0.1) (IEA, 2021). Additionally, the government has also funded R&D to drastically reduce the charging time and ultimately aims to remove any barriers that hinder consumers from purchasing EV until 2030. However, despite the effort, the government fails to meet its policy target each year. As the diffusion of EVs is already behind schedule, many are now arguing that the government should uptake a new strategy, to divide and conquer by prioritizing the aspect that would boost the penetration rate of EVs in short term, on either the quantity of the infrastructure or the quality of the infrastructure.

Given the context, there is a need to analyze consumer preference to catalyze the process. Consumer choice has widely been studied in terms of their utility, under the assumption that consumers make choices that brings them maximum satisfaction. Because consumer data for innovative products introduced in the market is not readily available, researchers can use product attributes for virtual alternatives to analyze consumer preferences (Train, 2009). In this study, key characteristics of EVs, such as price, fuel cost, maximum distance, charging/fueling time, and accessibility to charging stations are used in the survey. The traditional models that encompass this assumption are structured in the way that the utility of the consumers immediately increase with the immediate change in the attribute levels. However, recent studies on behavioral economics have discovered that individual consumers rarely change their behavior immediately when the attribute levels of products or services change, as can be seen in Elimination by Aspects Model (Tversky, 1972). More recently, this is explained as the potential existence of limits, boundaries or cutoff points that can vary within the population, which is referred to as thresholds (Cantillo and Ortúzar, 2005).

4.2 Research Goal

Unlike other studies on consumer preference for EVs, this study performs a consumer utility analysis and examine the effect of thresholds for EVs and its core attributes by setting the consumers' expected future purchase of vehicles. In particular, by using the thresholds that can analyze not only attributes with the same preference direction but also the cutoff points, the model captures consumer behavior at a higher dimension. This study further carries out simulation analysis to examine the future market share of EV market as the infrastructure and charging time improve and compares the policies that can accelerate the diffusion of EVs.

4.3 Empirical Analysis Framework

In order to derive both methodological and policy implications, this study has utilized total of 4 models including traditional models and proposed models. 1) Mixed Logit Model (MXL) 2) Threshold Model (TL) 3) Hybrid Neural Network Model (HNNM) 4) Threshold Hybrid Neural Network Model (THNNM). To directly compare the results and the performance of each model, this study employed the same data set for all four models, which will be described later in this chapter. The overall framework of is presented below.

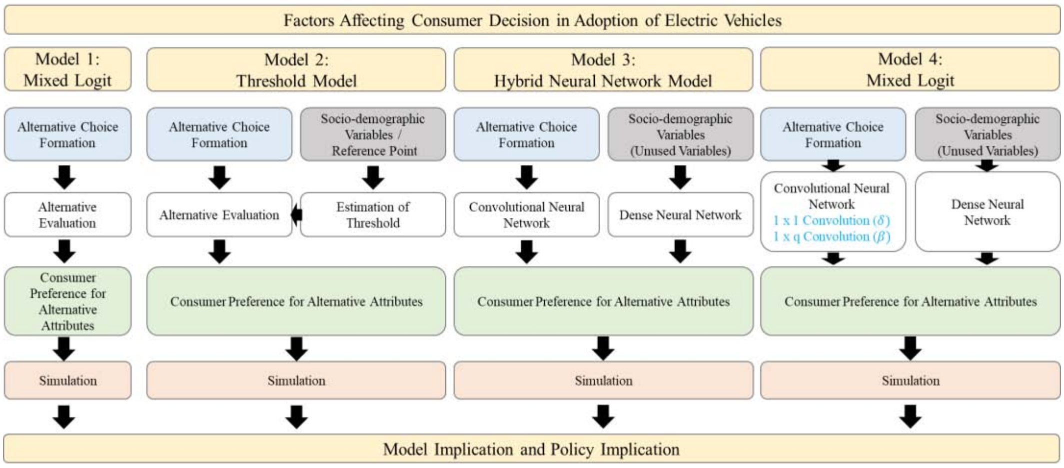

Figure 11. Framework of the Empirical Study

4.4 Data and Model

To carry out the estimation of the model, maximum likelihood estimation (MLE), a traditional estimation method, can be used to estimate the coefficients of each attribute. However, the calculation process of MLE is complex and can seldom have problems in locating the maximum likelihood value depending on the initial value. Therefore, this study used the Bayesian estimation method. The method carries the advantages of consistency and efficiency in more flexible conditions that the MLE (Edwards and Allenby, 2003). The Bayesian estimation method uses attribute coefficient, the prior distribution for marginal utility and the posterior distribution of the likelihood function.

The data used in the analysis of this research was obtained from an experimental survey conducted against 665 people by Gallup Korea in May 2019. The survey was carried out in the largest regions in Korea with the highest number of populations: Seoul, five largest metropolitan cities, and several new towns in Gyeonggi Province. The survey respondents were aged between 20 and 59, who were selected accounting for the minimum driving age and the requirement of understanding a survey concerning purchase of the next vehicle.

The sample was allocated based on the characteristics of the population, using demographics such as gender and age. Called purposive quota-sampling, it ensures that component ratio of the actual population is maintained (Sudman, 1966). The demographic characteristics of the survey respondents are provided in Table 1. The reference points for vehicle properties were set to expectations for future purchase of vehicles rather than past experience and present-day status. The reasoning behind this was that the market of EVs and FCEVs is not fully mature, and the number of owners of such vehicles were not sufficient to represent the population. Moreover, a discrepancy can occur where the consumers' reference point may differ between the vehicles they own right now and what they expect to purchase in the future, due to the expensive and durable characteristics of vehicles. Therefore, future expectation was set as the reference point for the main attributes of a vehicle in this study.

Table 4. Characteristics of survey respondents

Group	Number of respondents (%)

Sex	Male	337 (50.7%)
	Female	328 (49.3%)
Age	20 to < 30	152 (22.9%)
	30 to < 40	160 (24.0%)
	40 to < 50	177 (26.6%)
	50 to <60	176 (26.5%)
Region	Seoul	271 (40.7%)
	Busan	91 (13.7%)
	Incheon	85 (12.8%)
	Daegu	69 (10.4%)
	Daejeon	41 (6.2%)
	Gwangju	42 (6.3%)
	Gyeonggi	66 (9.9%)
Average Monthly House Income (thousand KRW)	< 4,000	102 (15.3%)
	4,000 to < 5,000	131 (19.7%)
	5,000 to < 6,000	168 (25.3%)
	6,000 to < 7,000	139 (20.9%)
	≥ 7,000	125 (18.8%)

The attributes of vehicles used in this study were based on the attributes used in previous studies, and the attribute levels were set according to the current level of technology. In choosing the number of attributes to be used, maximum of eight are recommended, as higher number of attributes can lead to fatigue in the survey respondents. Therefore, this study used seven attributes as shown in Table 2, which best represents the core factors considered when purchasing vehicles. All other attributes are assumed to be the same across the respondents (Moon et al., 2018). Then, the total number of alternatives is 8,640, with all attributes at each level $(5\times3\times4\times3\times3\times4\times4)$ $(5 \times 3 \times 4 \times 3 \times 3 \times 4 \times 4)$. As presenting all number of possible alternatives is time consuming and costly, orthogonal design was then used to produce 32 alternative cards. Then, the cards were divided into 8 choice sets, each containing 4 alternatives. Respondents were therefore asked to answer eight choice problems, selecting each alternative that would provide them with the highest utility.

Table 5. Attributes and levels used in the discrete choice experiment

No.	Attributes	Description	Levels
1	Fuel type	The type of fuel needed to power up the vehicle	gasoline, diesel, LPG, hybrid, EV, HFCV
2	Charging/fueling time (minutes)	The duration of fully charging/fueling the vehicle when empty. For fuel types other than EV, fuel time was fixed to 5 minutes.	5, 15, 25
3	Fuel cost (KRW/10km)	The cost for driving 10km	500, 1,000, 1,500, 2,000
4	Maximum Distance (km)	Maximum distance a vehicle can travel on full fuel/charge	400, 600, 800

5	Vehicle body type	Type of vehicle distinguished by its size	(sub) compact, large/luxury, SUV/RV
6	Accessibility (%)	The level of gas stations is set as 100%, and accessibility of fueling station for each fuel type is defined in proportion to that number	10, 40, 70, 100
7	Purchase cost (ten thousand KRW)	The price a consumer pays to purchase a vehicle	1,500, 3,500, 5,500, 7,500

The example of the choice set and the example of the survey is as follows. The respondents are presented with 8 choice sets with 4 alternatives each. Here, the combination of the attribute levels does not reflect those of the real market levels. The combinations are hypothetical, which accounts for the trade-offs among the attribute levels within the same alternative.

Table 6. Example of conjoint survey and its alternatives and attribute levels

Attributes	**Alternative A**	**Alternative B**	**Alternative C**	**Alternative D**
Fuel type	EV	Diesel	Gasoline	LPG
Charging/fueling time (minutes)	5 minutes	5 minutes	5 minutes	5 minutes
Fuel cost	1,000 won/ 10km	1,000 won/ 10km	500 won/ 10km	1,500 won/ 10km
Maximum Distance	800 km	600 km	800 km	800 km

Vehicle body type	SUV/ RV	Large sedan	Small sedan	SUV/RV
Accessibility	70% (of gas stations)	100% (of gas stations)	100% (of gas stations)	70% (of gas stations)
Purchase cost	15 mil KRW	15 mil KRW	75 mil KRW	15 mil KRW

According to the previous literature on choice modelling, it is recommended to use the status quo or the no-choice alternative in the analysis is highly important for multiple reasons, one of them being whether there is status-quo bias, which is the tendency of a decision-making to favor a previously chosen alternative more than they should have, had it not been chosen in the past (Maniquet & Nosratabadi, 2022). Therefore, this study received responses to the experiment as a 2-part response: First the respondents choose an alternative along with the no-choice alternative, and secondly, the no-choice alternative is excluded from the choice set, and the respondents were asked to choose one of the other four alternatives. Instead of using the responses that include no-choice alternative, this study used the data that excludes the alternative, as including the data caused problems in relation to the interpretation of the no-choice alternative in the neural network models. Moreover, the Threshold Model is flexible that it allows thresholds to be estimated for only the selected attributes, but this is not possible for neural network models, hence the no-choice alternative was not used in this study.

Also, to obtain the reference point levels to be used in the estimation process as part of the indicator function in the Threshold Model, this study directly asked the respondents of the survey the expected levels of the vehicle attributes of their next purchase, *a priori* to the conjoint survey as follows. It was specified that the respondents must respond with the expected attribute levels for their *next* purchase of a vehicle. The threshold levels were never collected from the survey, and was obtained only via estimation process.

Table 7. Survey questions for reference point

Q. If you were to purchase a vehicle in the future, please respond to what you would expect for each attribute of the vehicle	
Attributes	**Expected attribute level**
Fuel type	1. Gasoline 2. Diesel 3. LPG 4. Hybrid 5. EV 6. HFCEV
Charging/fueling time (minutes)	For EV, within _______ minutes (5 minutes for all other fuel types by default)
Fuel cost	Within ________ won /10 km
Maximum Distance	More than ______ km per full charge/fuel
Vehicle body type	1. Compact, small sedan 2. Large sedan 3. SUV/ RV
Accessibility	More than _______% compared to the current number of gas stations
Purchase cost	Within ________ won

Additionally, for the estimation of the machine learning models, this study used various socio-demographic variables additional to those used to estimate the thresholds in discrete choice model as follows. Variables were selected based on the relationship to the respondent's basic demographic characteristics, characteristics related to their attitude and behavior towards the environment that could impact their choice towards environmentally friendly vehicle, and driving habits.

Table 8. Socio-demographic variables used in neural network models

Variables	
Demographic	Age
	Gender
	Ownership of vehicle
	License
	Household income
	Driving distance per month
	Education level
Environment	Aware of emission level
	Considers the environmental impact of vehicles
	Plans to purchase eco-friendly vehicle in the future
Driving habit	Leisure
	Commute
	Business
	Daily (shopping, etc.)

4.5 Estimation Results

This study analyzed consumer preference towards new vehicle purchases based on total of 4 models. The results are presented in consecutive order from Table 5. The combined results are presented at the end of this section.

Table 9. Estimation results of individual-level marginal utility for Mixed Logit Model

Variables		Mean	Std. D
Fuel types	Diesel	-0.4518^{***}	0.4444
	LPG	-0.5495^{***}	0.0264
	Hybrid	0.2551^{***}	0.2264
	Electric	0.3633^{***}	0.8412
	Hydrogen	-0.6580^{***}	0.4793
Vehicle body type	Large	-0.5075	0.0248
	SUV	-0.1281	0.1984
Charging/fueling time		-0.2047^{***}	0.0045
Fuel Cost		-0.0621^{**}	0.0882
Maximum Distance		0.0792^{***}	0.1243
Accessibility		0.0182^{***}	0.0065
Price		-0.5798^{***}	0.3832

***, **, and * indicates statistical significance at the 1%, 5%, and 10% level

As presented in Table 5, other than vehicle body types, marginal utilities of all attributes were significant. The estimation results of each attribute are as follows. In the case of fuel types, the consumers generally preferred gasoline vehicles over hydro fuel cell, diesel, and LPG vehicles, but preferred hybrid and electric vehicles over gasoline vehicles. Even though electric and hydro fuel cell vehicles are under the same environment friendly vehicle fleet, the preference structure of the consumers displayed clear difference according to fuel types. On the other hand, vehicle body type did not have significant impact on the consumers' vehicle choice process. This can be interpreted as consumers having different taste of vehicle size across different demographic characteristics.

Consumers' preference increases when charging/fueling time decreases, when fuel cost decreases, when maximum driving distance increases, when accessibility increases, and finally when the price of the vehicle decreases.

Table 10. Estimation results of individual-level marginal utility for Threshold Model

Variables		Mean	Std. D
Fuel types	Diesel	-0.2838***	0.1575
	LPG	-0.4099***	0.1545
	Hybrid	0.5119**	0.1460
	Electric	0.8599***	0.2470
	Hydrogen	-0.8920***	0.1614
Vehicle body type	Large	0.2475	0.1381
	SUV	0.3086	0.1142

Charging/fueling time	Gain	2.3429***	0.3174
	Threshold	15 minutes	
	Loss	-3.1713***	0.7904
	Threshold	-	
Fuel Cost	Gain	1.1358***	0.0855
	Threshold	-	
	Loss	-0.9216***	0.0824
	Threshold	1,400 won / 10 km	
Maximum Distance	Gain	2.2573***	0.5085
	Threshold		
	Loss	-2.3552***	0.4475
	Threshold	-	
Accessibility	Gain	2.4556***	0.3858
	Threshold	49%	
	Loss	-2.6211***	0.3649
	Threshold	12%	
Price	Gain	1.7587***	0.0874
	Threshold	33 mil won	
	Loss	-1.7809***	0.0730
	Threshold		

***, **, and * indicates statistical significance at the 1%, 5%, and 10% level

Overall, excluding vehicle body types, marginal utility of all attributes was significant under 1% significance level. The estimation results of each attribute are as follows. In the case of fuel types, the consumers generally preferred gasoline vehicles over hydro fuel cell, diesel, and LPG vehicles, but preferred hybrid and electric vehicles over gasoline vehicles. Even though electric and hydro fuel cell vehicles are under the same environment friendly vehicle fleet, the preference structure of the consumers displayed clear difference according to fuel types. On the other hand, vehicle body type did not have significant impact on the consumers' vehicle choice process. This can be interpreted as consumers having different taste of vehicle size across different demographic characteristics.

Among the five attributes, for charging time, fuel cost, and price, the change in utility according to the decrease in the attribute level is the marginal utility in the gain territory and the change in utility according to the increase in the attribute level is the marginal utility in the loss territory. On the other hand, for maximum distance and accessibility attributes, the marginal utility is presented as the opposite as the previous three attributes. To our expectation, as charging time, fuel cost, or price decreased or maximum distance or accessibility increased, the utility of the consumers increased in the gain territory. Unlike the previous two attributes (fuel type and vehicle body type), the preference of each attribute was analyzed based on reference dependence tendencies for the remaining attributes. As the consumers evaluate alternatives based on their reference points, marginal utility is estimated for gain and loss territories.

This study compared and analyzed two strategies for the penetration and diffusion of electric vehicles, the reduction of charging time through development of charging technology and expansion of charging infrastructure. To this end, the estimated thresholds for charging time and accessibility were compared in the following Table 12. Only the threshold in the gain region was reported because the focus of this study is to observe the increase in utility as the level of the attributes are improved. Also, for the other attributes, when the estimation result of the thresholds exceeded the range of the attribute levels of the study, then it was assumed that the respondents do not have any thresholds towards that that attribute. According to the analysis of the effect of demographic characteristics on thresholds based on Eq. (6), the residents in non-capital areas were more sensitive to the increase in accessibility. In other words, the thresholds for accessibility were lower for residents in non-capital areas than those residing in capital region.

Table 11. Threshold results

	Charging time	Accessibility
Threshold_gain	15 minutes	49%
Non-capital residents	1.0631***	-1.1267***
Monthly income level	-1.2701***	0.0186

Next, this study employed a hybrid neural network model to as an attempt to improve the performance of the existing discrete choice models without losing interpretability.

Therefore, this study combined CNN, which was formulated as the discrete choice model, and DNN, which fully takes advantage of neural network, using 14 variables to enhance the performance accuracy of the model. The loss graph and the estimation result is as follows:

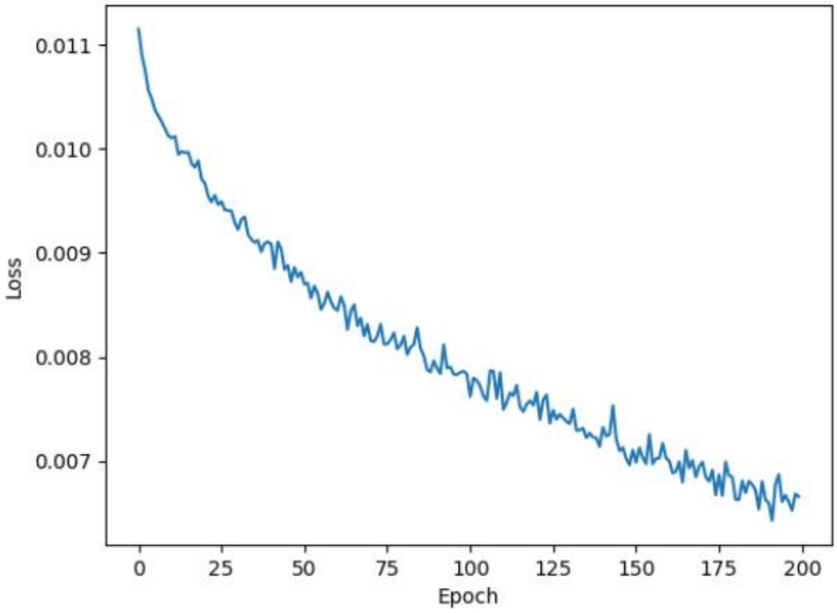

Figure 12. Loss function graph of hybrid neural network model

Table 12. Hybrid Neural Network Model Results

Variables		Mean
Fuel types	Diesel	-0.0810
	LPG	-0.1085
	Hybrid	0.2228

	Electric	0.2625
	Hydrogen	0.0947
Vehicle body type	Large	0.2613
	SUV	0.0968
Charging/fueling time		-0.0048
Fuel Cost		-0.0344
Maximum Distance		0.0170
Accessibility		0.0006
Price		-0.2818

The result of the model was highly similar to that of mixed logit model. First, in the case of fuel types, electric vehicle was the most preferred type followed by hybrid and gasoline. Diesel, LPG, and hydrogen fuel cell vehicles were shown to be less preferred than gasoline. The consumers' preference increases as charging/fueling time, fuel cost and price of the vehicle decreases, whereas the preference increases when maximum distance and accessibility increases.

Next, for the Threshold-Hybrid Neural Network model, to check for the best performance condition, this study tested out different number of hidden layers and number of epochs. As the linear portion of the model is restricted in adjusting the number of layers, as it is not fully connected, only the number of layers in the non-linear portion of the model was adjusted. The number of epochs applies to the entire model. Refer to Appendix for the entire set of visual materials.

Table 13. Model Validation

Number of hidden layers	No. of epoch	Early stop epoch	Best valid loss	Training Accuracy	Test Accuracy
1	100	6	49.6423	0.7416	0.8000
	200	25	62.6436	0.7628	0.7964
	300	132	50.6153	0.7416	0.8000
2	100	86	50.8474	0.7516	0.8115
	200	199	49.2336	0.7504	0.8100
	300	14	57.5333	0.7540	0.7300
3	100	32	59.2954	0.7558	0.7200
	200	82	62.29	0.7628	0.7800
	300	65	56.2335	0.7504	0.7500
4	100	42	59.2954	0.7558	0.7233
	200	97	62.6870	0.7628	0.6800
	300	238	57.3057	0.7522	0.7400
5	100	100	57.3449	0.7522	0.7400
	200	76	62.6869	0.7628	0.6800
	300	8	55.1200	0.7487	0.7600

6	100	24	50.6346	0.7416	0.800
	200	55	64.0436	0.7628	0.6800
	300	57	50.8517	0.7416	0.800
7	100	21	57.7908	0.7540	0.7300
	200	35	62.6870	0.7628	0.6800
	300	14	52.8519 9	0.7451	0.7800

In order to choose the best performing model, this study tested the number of layers from 1 to 7 and number of epochs from 100 to 300. The general pattern of the test indicates that running the model with 300 epochs generally led to the overfitting of the model and 200 epochs showed better performance on average, as shown below.

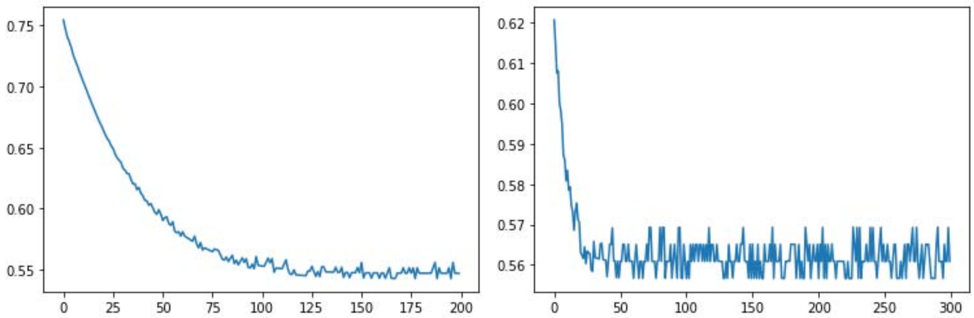

Figure 13. Comparison of loss function between 3 layers with 200 epochs (left) and 3 layers with 300 epochs (right)

Also, as the number of layers increased, the models showed a pattern of being overfit and the test accuracy turned out to be lower than the training accuracy, suggesting that using a smaller number of layers was better in terms of performance.

The best performing model was selected based on the Best valid loss and test accuracy. Additionally, as this study implemented the early stop algorithm to prevent the overfit of the data, it was also assumed that if the early stop epoch is too early, then the model has been overfit and was thus rejected. According to the test results, the model with 2 layers with 200 epochs showed the best performance. Although the test accuracy was 81% and not the highest among the test sets, the early stop epoch for the model was 199, almost close to 200, the best valid loss value was relatively low compared to other test sets. For example, the loss graphs of the model with 2 layers and 200 epochs shows a smooth curve, while the model with 5 layers and 100 epochs show a sharp drop in the early epochs. Also, considering that the validation loss, number of epoch, and accuracies of the former model outperformed the latter model, the former was chosen as the analysis model of this study. The comparison of the two loss graphs is as below.

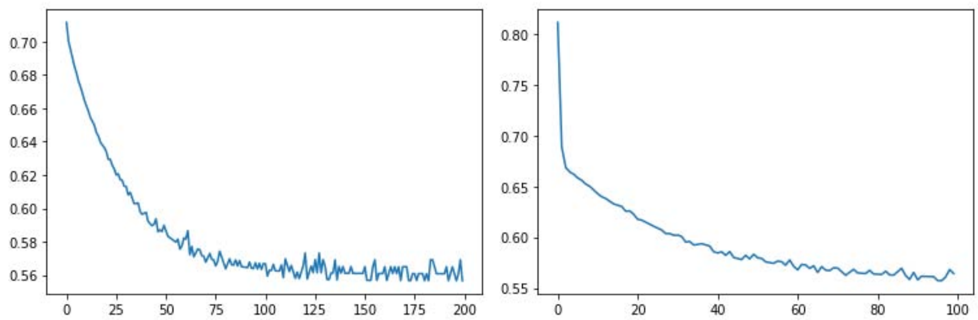

Figure 14. Comparison of loss function between 2 layers with 200 epoch (left) and 5 layers with 100 epoch (right)

Table 14. Threshold-Hybrid Neural Network Model Results

Variables		Mean	
Fuel types	Diesel	-0.2800	
	LPG	0.1348	
	Hybrid	0.1267	
	Electric	0.4411	
	Hydrogen	-0.8268	
Vehicle body type	Large	0.1443	
	SUV	0.1122	
Charging/fueling time	gain	-0.1608	
	Threshold		14.61 minutes
	Loss	-0.1608	
	Threshold		19.76 minutes
Fuel Cost	Gain	-0.2393	
	Threshold		1,003 won/10km
	Loss	-0.2393	
	Threshold		1,570won/10km
Maximum Distance	Gain	0.7477	
	Threshold		7,686 km
	Loss	0.7477	
	Threshold		5,466 km
Accessibility	Gain	1.4124	

	Threshold		72%
	Loss	1.4124	
	Threshold		47%
Price	Gain	-0.8249	
	Threshold		37.7 million won
	Loss	-0.8249	
	Threshold		58.6 million won

***, **, and * indicates statistical significance at the 1%, 5%, and 10% level

The result of the Threshold-Hybrid Neural Network Model presented slightly different result that other models. First, in the case of fuel types, all fuel types other than diesel were shown to be preferred than gasoline vehicles. All other attributes showed the same direction for both models.

The use of PReLU activation function allows parametric formulation of the model, allowing the thresholds to be trained on both the gain and loss domain. According to the results, thresholds existed for all continuous attributes. The threshold for the gain of the threshold was 14.61 minutes and loss 19.76 minutes, indicating that the consumers do not experience any changes in utility between approximately 15 minutes to 20 minutes of charging time, i.e., they will start to feel an increase in their utility when the charging time decreases below the 15-minute threshold. For accessibility, the threshold for gain was 72%, meaning that the respondents will feel a change in the utility when the number of charging stations exceeds 72% of the number of current gas stations and feel loss of utility when the level is below 47%. Likewise, to the Threshold Model, it was assumed that thresholds does not exist for the respondents if the threshold value did not fall within the logical range of the attribute levels, but in the case of this empirical analysis, all the threshold levels were within the range of the attribute levels.

Another interesting point to notice here is that this study initially collected the reference points of each individuals via survey, meaning that they specifically stated their expected levels of the attributes, which will be referred to as the *stated reference point*. Then for Threshold Model, the reference point data was directly used in the model. In the neural network model, the reference point data is not used, but intuitively, it can be assumed that the reference point falls within the range of the gain and loss thresholds as thresholds are dependent on reference points. For purpose of comparison, the unknown reference point level will be referred to as *latent reference point*. However, in some cases according to the results of the neural network model, the stated reference point did not fall within the range of the thresholds. For example, for charging time, the stated reference point of the individuals was 9.3 minutes, and the latent reference point is in the range between 14.61 minutes and 19.76 minutes. This indicates that the reference point or the standard of the individuals towards the attribute levels differs between the survey data and the estimated result. Although it cannot be determined whether which is more accurate in the scope of this study, this adds to one of the benefits of the proposed neural network model as in can present the range where the latent reference points of the individuals are located.

Table 15. Predictive accuracy of the two models

	Mixed Logit	Threshold Model	HNNM	T-HNNM
Accuracy	65%	68%	78%	81%

Next, to compare the performance capability of the four models used in the empirical study, the predictive accuracies of the models are presented in Table 16 above. As in previous studies, discrete choice models have shown an accuracy in the 60% range (Zhao et al., 2019). Both hybrid neural networks were superior in terms of predictive accuracy with 78% and 81% accuracy respectively.

Table 16. Combined results of the estimation models

Variables		Mixed Logit (SD)	Threshold (SD)	Hybrid Neural Network	Threshold Hybrid Neural Network
Fuel types	Diesel	-0.4518*** (0.4444)	0.2838*** (0.1575)	-0.0810	-0.2800
	LPG	-0.5495*** (0.0264)	-0.4099*** (0.1545)	-0.1085	0.1348
	Hybrid	0.2551*** (0.2264)	0.5119** (0.1460)	0.2228	0.1267
	Electric	0.3633*** (0.8412)	0.8599*** (0.2470)	0.2625	0.4411
	Hydrogen	-0.6580*** (0.4793)	-0.8920*** (0.1614)	0.0947	-0.8268

Vehicle body type	Large	-0.5075 (0.0248)	0.2475 (0.1381)	0.2613	0.1443
	SUV	-0.1281 (0.1984)	0.3086 (0.1142)	0.0968	0.1122
Charging/fueling time	Mean	-0.2047*** (0.0045)		-0.0048	0.1608
	Gain		2.3429*** (0.3174)		14.61 minutes
	Threshold		15 minutes		- 0.1608
	Loss		-3.1713*** (0.7904)		19.76 minutes
	Threshold		-		0.2393
Fuel Cost	Mean	-0.0621** (0.0882)		-0.0344	1,003 won/10km
	Gain		1.1358*** (0.0855)		-0.2393
	Threshold		-		1,570won/10km
	Loss		0.9216*** (0.0824)		0.7477
	Threshold		1,400 won / 10 km		7,686 km
Maximum Distance	Mean	0.0792*** (0.1243)			-0.7477
	Gain		2.2573*** (0.5085)	0.0170	5,466 km
	Threshold				1.4124
	Loss		2.3552*** (0.4475)		72%
	Threshold				-1.4124

Accessibility	Mean	0.0182*** (0.0065)		0.0006	47%
	Gain		2.4556*** (0.3858)		0.8249
	Threshold		49%		37.7 million won
	Loss		-2.6211*** (0.3649)		-0.8249
	Threshold		12%		58.6 million won
Price	Mean	-0.5798*** (0.3832)			-0.2800
	Gain		1.7587*** (0.0874)	-0.2818	0.1348
	Threshold		33 mil. won		0.1267
	Loss		-1.7809*** (0.0730)		0.4411
	Threshold				-0.8268

***, **, and * indicates statistical significance at the 1%, 5%, and 10% level

4.6 Simulation

As aforementioned, the purpose of this study is to compare the performance of the proposed models in the context of the two potential strategies the government can implement to achieve the goal of electric vehicle penetration rate. The Korean government has also joined the global rally of decreasing the level of emission in the transportation sector and imposed key regulations. The effort has continued in the last 10 years, but most notably, in February 2021, the government announced the “4th Basic Plan for Environment Friendly Vehicles." In this plan, the government revealed its ambitious goals to reduce the GHG emission level in the transportation sector by 24% and achieve the rollout of 7.85 million alternative fuel vehicles (AFVs) by the year 2030. However, there are many criticisms towards the effort and many doubts. The Korean government has invested nearly 4 trillion won but has failed to achieve its target goal. Among the 4 trillion won, most of the budget has been allocated to purchase subsidies, surmounting to 82% and 18% for subsidies for installing charging stations. But the result fell far short from the policy target. For example, the target rollout was 65,000 EVs in the year 2020, but the actual rollout was only 48.2% of the target at 31,000 vehicles. Therefore, although the government plans to deviate the budget of purchase subsidies to other areas, many specialists still advocate that there is a need to focus on deviating from the initial course of solely providing cash in exchange to vehicle purchases and focus on the fundamentals on how to persuade the consumers to purchase environment-friendly vehicles. The aspect that has been much of the issue regarding the use of EVs is the condition and the environment of charging the vehicles. Most of the complaints from the use of EVs are related to charging, notably the duration of the time it takes to charge, the queue in line, and the lack of infrastructure.

Therefore, based on the assumption that the budget is not of the utmost importance in the diffusion of EVs, this study has set up two scenarios to analyze the effects of thresholds to compare the effects of two aspects of charging infrastructure of EVs. The two strategies are 1) R&D investment to decrease charging time and 2) expansion of charging infrastructure. To satisfy our research purpose, this paper has set two scenarios accordingly as below to analyze the market share of electric vehicles according to the change in the attribute levels of charging time and accessibility. The baseline scenario was set to current levels of the attributes

The scenarios to be examined in this study is as follows:

Scenario 1: the average charging time reaches 10 minutes by the year 20
25 and 5 minutes by the year 2030

Scenario 2: The accessibility of the charging infrastructure reaches 75%
by the year 2025, and 150% by the year 2030.

Table 17. Baseline scenario

Attributes	Gasoline	Diesel	LPG	Hybrid	EV	FCEV
Diesel	0	1	0	0	0	0
LPG	0	0	1	0	0	0
Hybrid	0	0	0	1	0	0
Electric	0	0	0	0	1	0
Hydrogen	0	0	0	0	0	1
Sedan	1	1	1	1	1	1
SUV	0	0	0	0	0	0
Fueling time (minutes)	5	5	5	5	30	10
Fuel Cost (Won/10km)	1,199	862.69	866.06	865.94	451.27	825.62

Maximum Distance (km)	800	800	700	800	600	400
Accessibility	100	100	17.2	100	10.8	0.08
Price	2,504	2,563	2,239	2,866	3,489	5,084

Table 18. Baseline probability

Alternative	Choice Probability
Gasoline	27.43%
Diesel	22.57%
LPG	10.08%
Hybrid	29.12%
EV	8.39%
FCEV	2.40%

First, Figure 20 and Figure 21 represent the market share of each fuel type as the level of charging time and accessibility of charging stations improves by the year 2030. As can be witnessed, in the case of charging time, the market share of EV immediately starts to increase as soon as charging time starts to decrease. On the other hand, in the case of accessibility, the market share of EV only increases by a slight amount over the span of the decade.

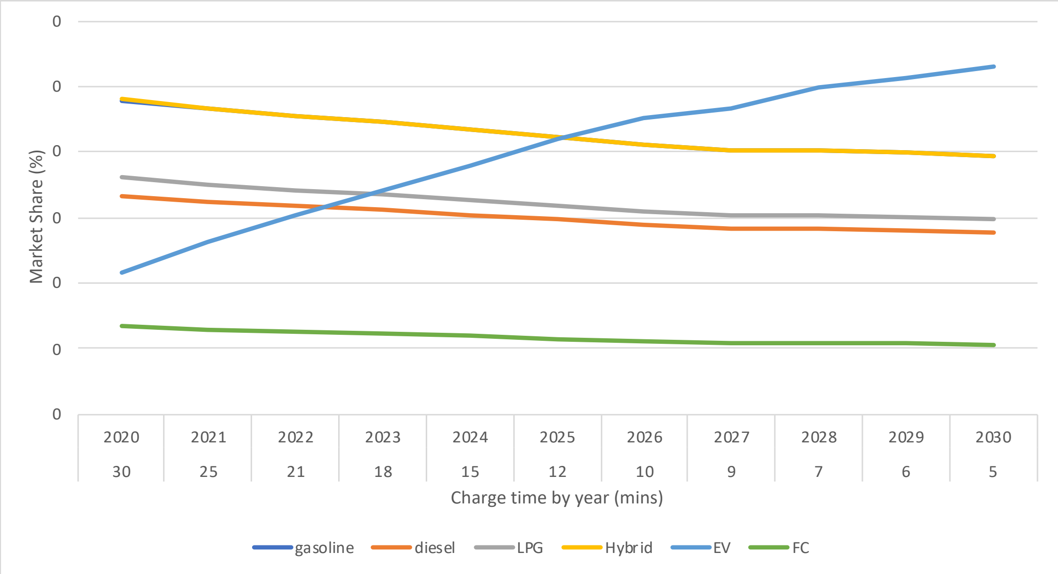

Figure 15. Market share by fuel type with the development of charging time (Mixed Logit Model)

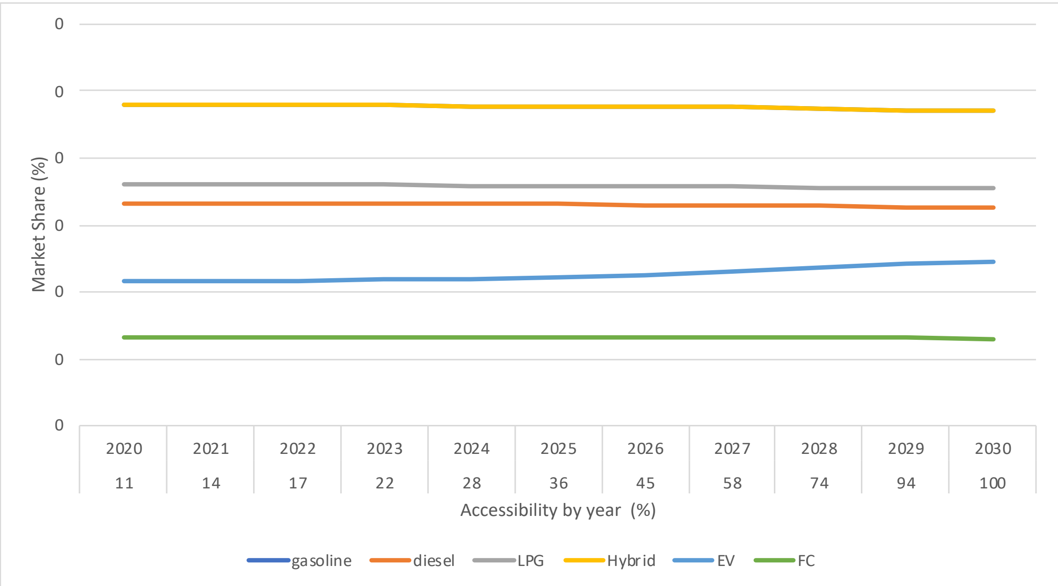

Figure 16. Market share by fuel type with the development of accessibility (Mixed Logit Model)

However, this does not necessarily mean that the mixed logit model is at a disadvantage, as it reflects the strong preference of consumers for shorter charging time. This would mean that if the duration does indeed fall to 5-minute level, the market share of electric vehicles would drastically increase.

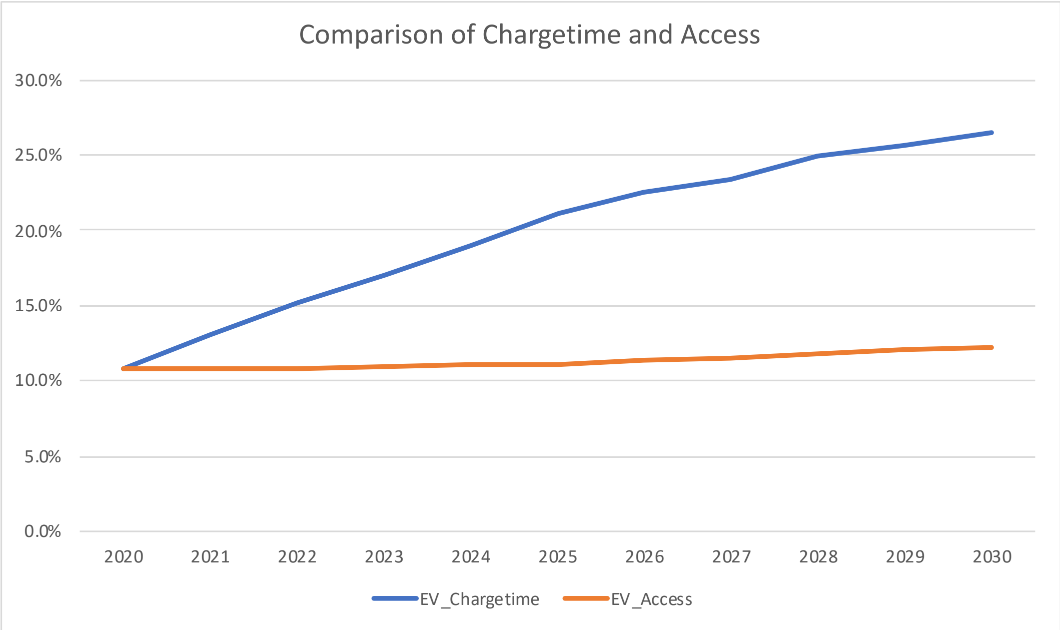

Figure 17. Comparison of market share between charge time and accessibility (Mixed Logit Model)

However, the research question of this study focuses on whether this perfectly reflects a real-life scenario that is likely to be the case. For example, would consumers really not experience a change in their utility when the accessibility to charging stations improve by nearly a 10-fold over the decade? Although mixed logit model is considered to be a powerful tool to forecast future market share, there are still critics that point out that the model can sometimes be overestimated according to the survey data. Therefore, the purpose of this research was to formulate a behavioral model that implements thresholds

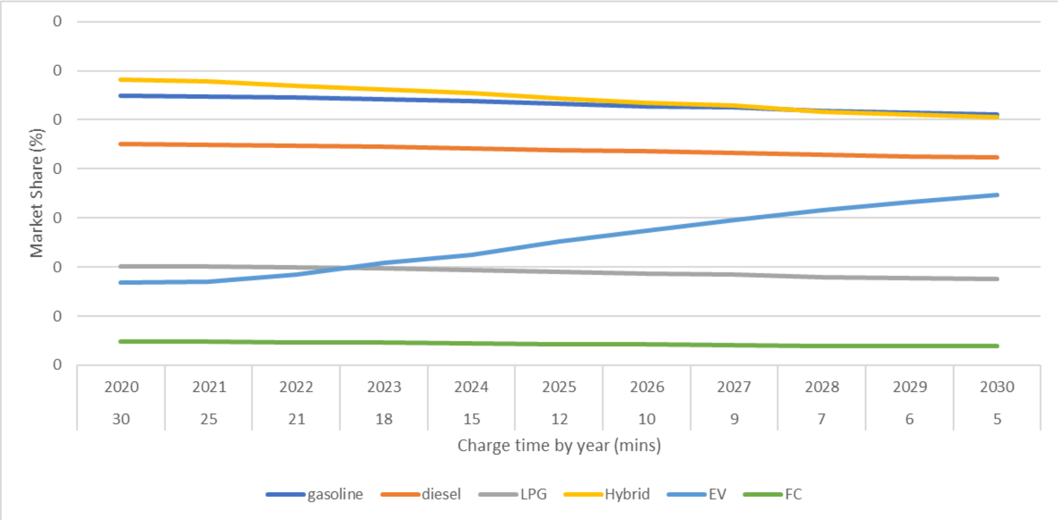

Figure 18. Market share by fuel type with the development of charging time (Threshold Model)

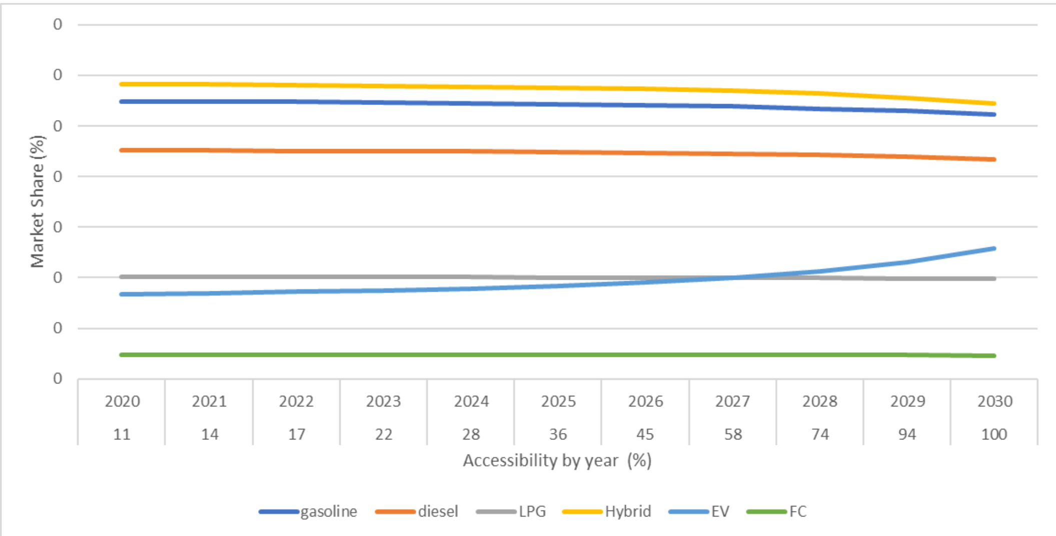

Figure 19. Market share by fuel type with the development of accessibility (Threshold Model)

Figure 23 and Figure 24 each shows the market share of each fuel type according to the decrease in charging time of electric vehicles and increase in level of accessibility. First, in the case of Figure 9, it can be witnessed that the level of charging time decreases to 20 minutes by the year 2022 to surpass the market share of LPG vehicles. The market share continues to increase as charging time decreases, taking the most market share from hybrid vehicles. When charging time becomes 5 minutes with rapid advancement in technology by the year 2030, the market share of electric vehicles becomes approximately 18%.

Next, in the case of Figure 10, the level of accessibility to charging infrastructure expands beyond 50% after the year 2026, surpassing the market share of LPG vehicles. The market share of electric vehicles continues to rapidly increase, and when the level of charging infrastructure equals the number of gas stations in the year 2030, the market share of electric vehicles reaches approximately 15%. Combining the results of the two scenario analyses, one notable result is that the growth rate of the electric vehicle is relatively constant for the decrease in charging time, while the growth rate of the market share according to the expansion of accessibility starts to rapidly increase from the year 2027 when the level of accessibility exceeds 60% under the influence of thresholds.

Additionally, when the two results are compared as in Figure 25, interestingly enough, the threshold for accessibility comes into effect and the two lines cross each other. This indicates that in the short-term perspective, the decrease in charging time attributed to faster market penetration than the expansion of charging stations. However, in the long-term perspective, the market share of electric vehicles between the two scenarios grows further apart, where accessibility exercises more impact to market penetration closing in on the government target when the level of accessibility reaches 250%.

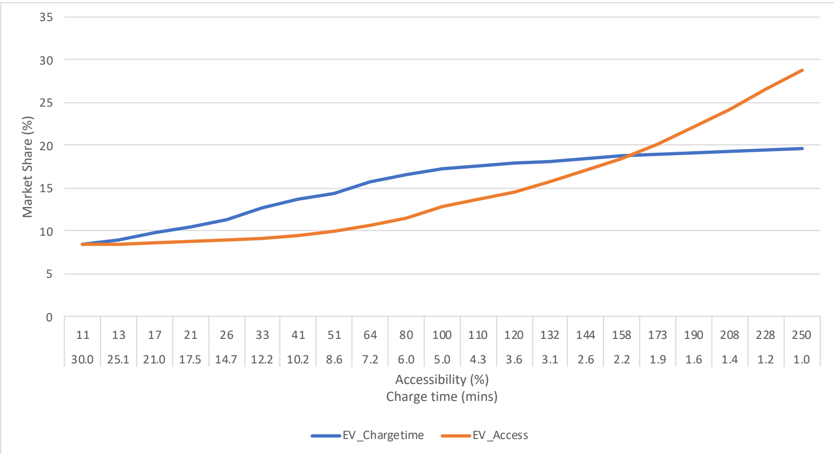

Figure 20. Comparison of long-term simulation results of accessibility and charge time

Chapter 5. Conclusion

5.1 Concluding Remarks and Contribution

This study proposed a new hybrid neural networks model that incorporates behavioral aspects neural network model. In order to achieve the research goal, this study first explored the behavioral dimension of consumers and formulated a discrete choice model that includes threshold effect. Then, with the recent hybrid models in the field of neural networks, this study incorporated the concept of thresholds as an additional convolutional layer in a model that incorporates CNN as linear and DNN as non-linear parts.

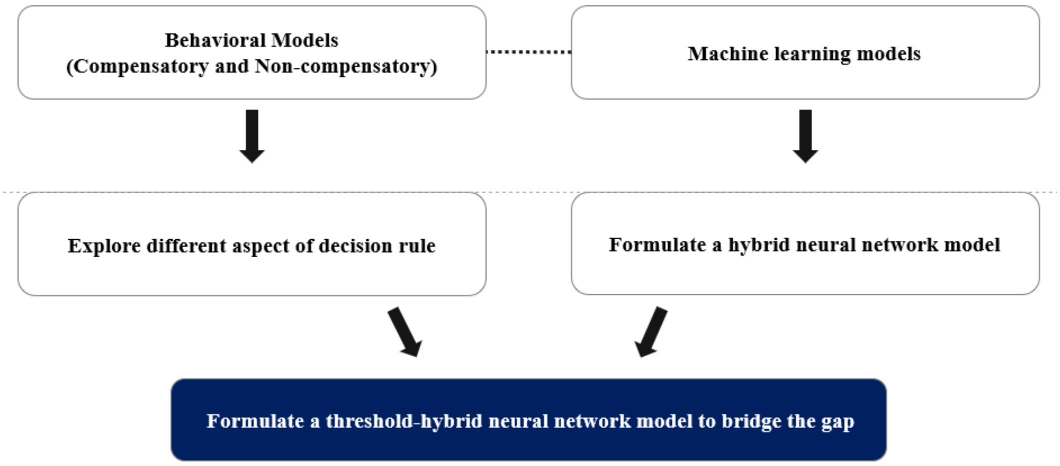

Figure 21. The concept of the model of this study

This study implemented the concept of just noticeable difference or threshold into discrete choice models to analyze consumer preference and simulate future market share of EVs. This is not the first attempt, but previous studies have only examined the effect of thresholds on price related attributes or failed to fully consider the heterogeneity in consumers. This study advanced the threshold model by incorporating thresholds for all attributes for all individuals, estimated in the manner of hierarchical Bayesian estimation method. This allowed the model to draw from the distribution to estimate the precise threshold values for all attributes. The results indicated that although thresholds did not exist for all attributes, thresholds that were estimated provided fruitful implications to understanding the preference structure of the individuals. Namely, thresholds existed for both charging time and accessibility attributes, which was the focus of the empirical study, indicating that the utility of the consumers increased after a shorter range of improvements in the levels of charging time attribute, while the utility of the consumers increased in the longer term for improvements in accessibility.

Secondly, this study achieved the research goal of incorporating the concept of threshold into the existing hybrid neural network models as an additional convolutional layer. Although there would have been better ways to go about it, such as incorporating thresholds as conditions for convolution of the filters, the study still was successful in training the data to locate the threshold points of the data. The results of the Threshold-Hybrid Neural Network model generally performed better than the discrete choice models, with higher predictive accuracy.

The limitation of this study is as follows. According to the previous literature on choice modelling, it is recommended to use the status quo or the no-choice alternative in the analysis is highly important for multiple reasons, one of them being whether there is status-quo bias, which is the tendency of a decision-making to favor a previously chosen alternative more than they should have, had it not been chosen in the past (Maniquet & Nosratabadi, 2022). Therefore, this study received responses to the experiment as a 2-part response: First the respondents choose an alternative along with the no-choice alternative, and secondly, the no-choice alternative is excluded from the choice set, and the respondents were asked to choose one of the other four alternatives. Instead of using the responses that include no-choice alternative, this study used the data that excludes the alternative, as including the data caused problems in relation to the interpretation of the no-choice alternative in the neural network models.

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Appendix 1: Model Validation

Layers = 1

Epoch = 100

Epoch 6: Train Loss: 0.5907, Train Acc: 0.7416, Valid Loss: 0.4964, Valid Acc: 0.8
Save model, Best valid loss: 49.64233794808388

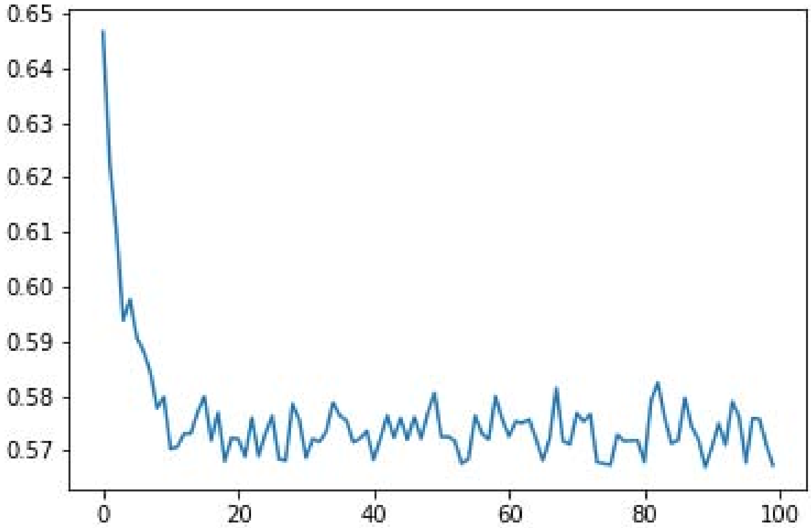

Figure Appendix 1.1. Loss function for 1 layer, 100 epochs

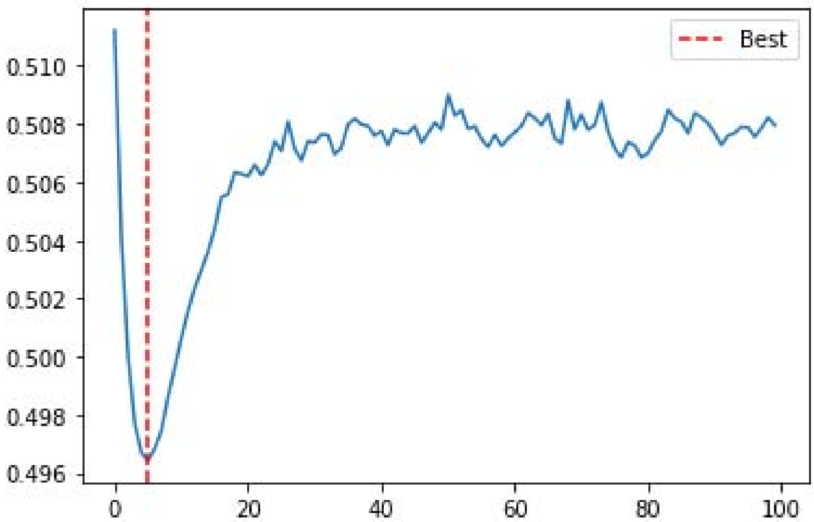

Figure Appendix 1.2. Early Stiop for 1 layer, 100 epochs

Layers = 1

Epoch = 200

Epoch 25: Train Loss: 0.5643, Train Acc: 0.7628, Valid Loss: 0.7964, Valid Acc: .68

Save model, Best valid loss: 62.64360550045967

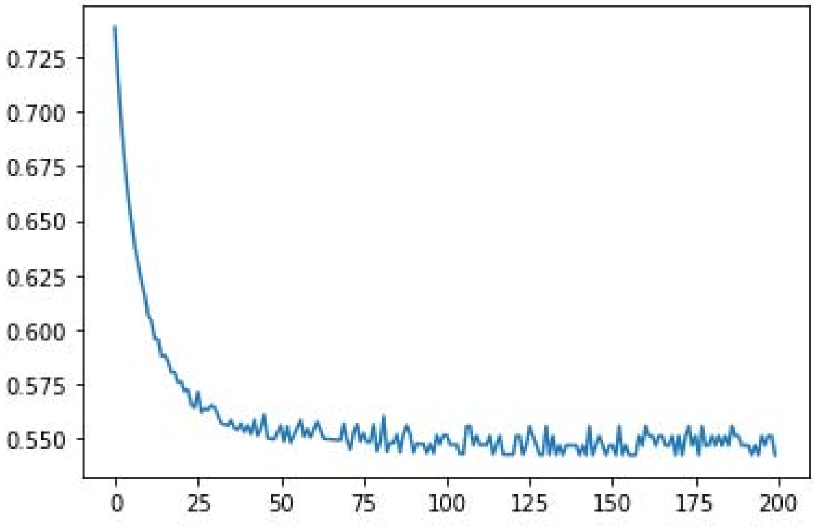

Figure Appendix 1.3. Loss function for 1 layer, 200 epochs

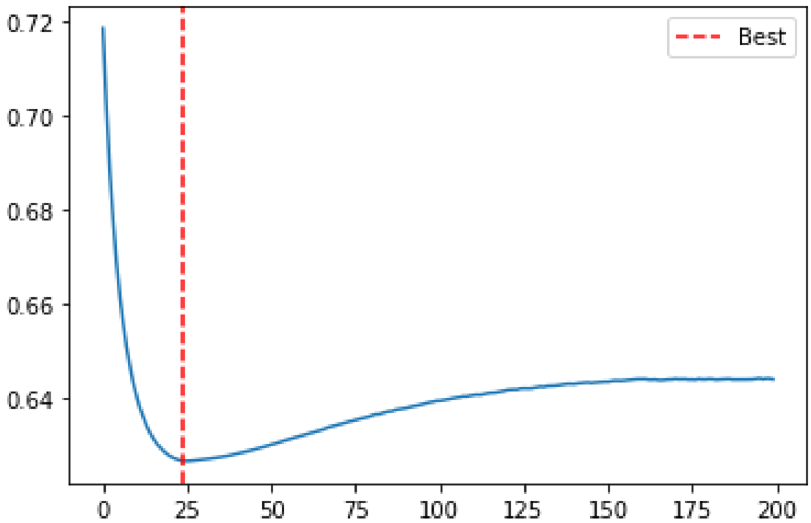

Figure Appendix 1.4. Early Stop for 1 layer, 200 epochs

Layers = 1

Epoch = 300

Epoch 132: Train Loss: 0.5748, Train Acc: 0.7416, Valid Loss: 0.5062, Valid Acc: .8

Save model, Best valid loss: 50.61527119576931

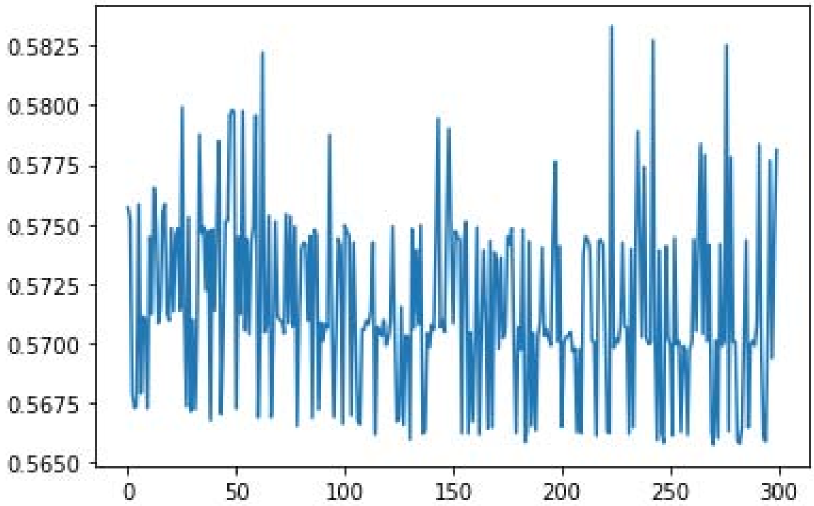

Figure Appendix 1.5. Loss function for 1 layer, 300 epochs

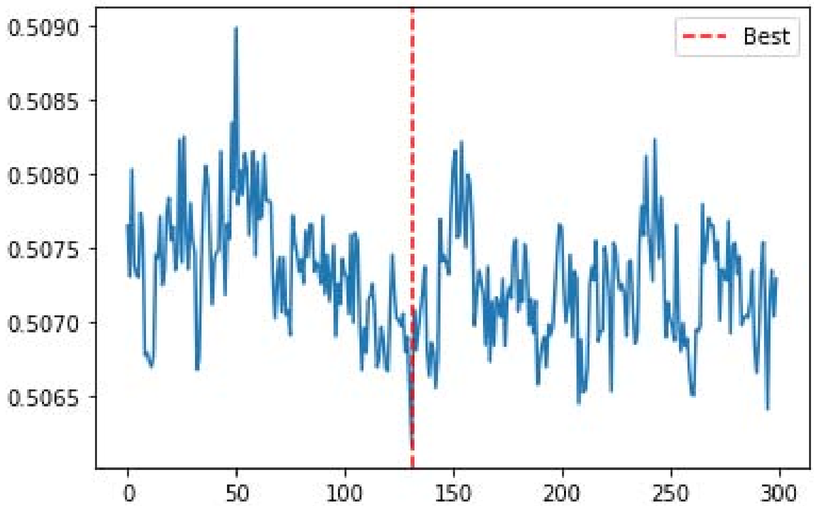

Figure Appendix 1.6. Early Stop for 1 layer, 300 epochs

Layers = 2

Epoch = 100

Epoch 86: Train Loss: 0.5764, Train Acc: 0.7416, Valid Loss: 0.5085, Valid Acc: 0.8

Save model, Best valid loss: 50.84741874039173

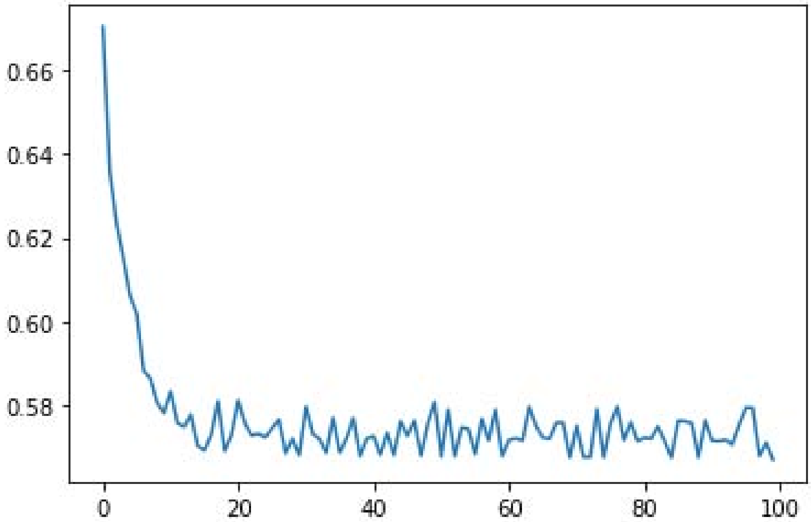

Figure Appendix 1.7. Loss function for 2 layer, 100 epochs

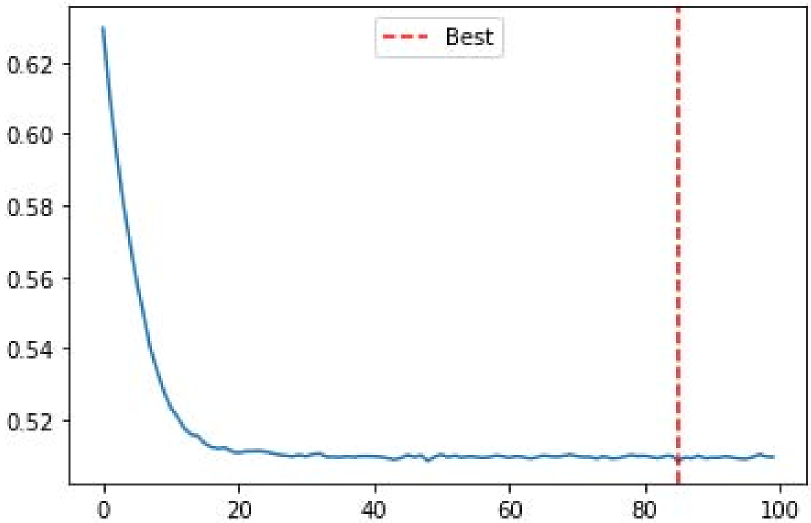

Figure Appendix 1.8. Early Stop for 2 layer, 100 epochs

Layers = 2

Epoch = 200

Epoch 199: Train Loss: 0.5692, Train Acc: 0.7504, Valid Loss: 0.5623, Valid Acc: 0.75

Save model, Best valid loss: 56.233616918325424

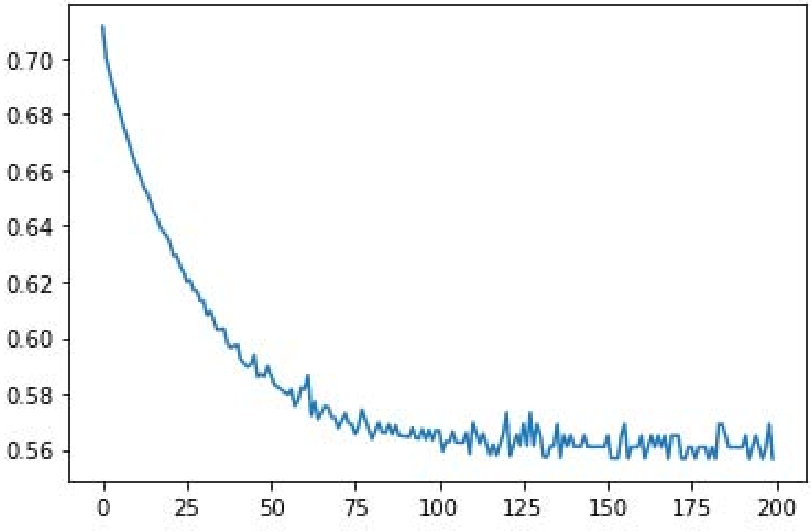

Figure Appendix 1.9. Loss function for2 layer, 200 epochs

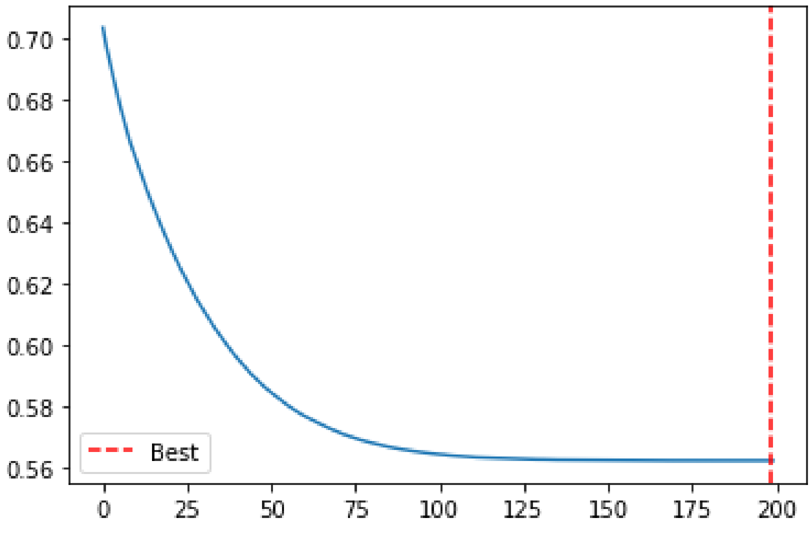

Figure Appendix 1.10. Early Stop for 2 layer, 200 epochs

Layers = 2

Epoch = 300

Epoch 14: Train Loss: 0.565, Train Acc: 0.754, Valid Loss: 0.5753, Valid Acc: 0.73

Save model, Best valid loss: 57.53332984447479

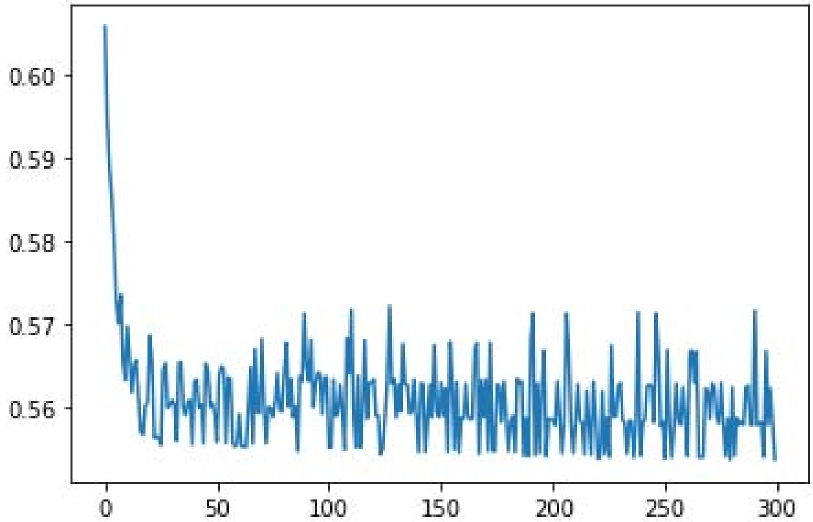

Figure Appendix 1.11. Loss function for 2 layer, 300 epochs

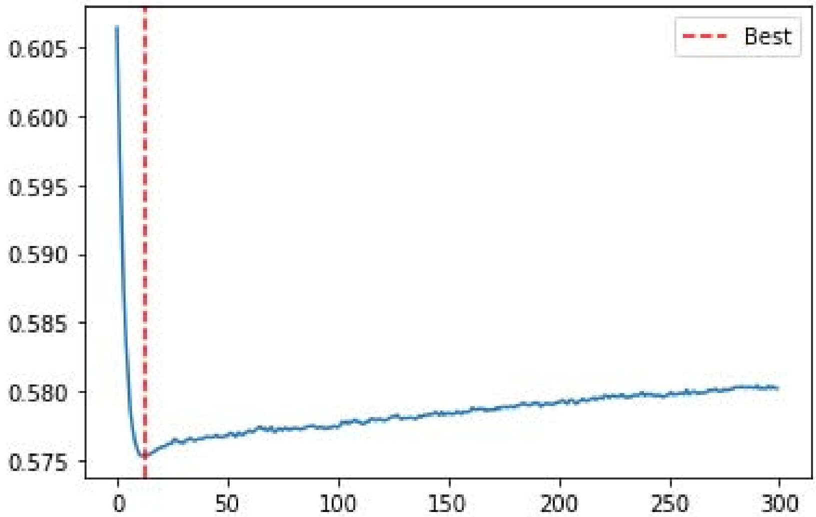

Figure Appendix 1.12. Early Stop for 2 layer, 300 epochs

Layers = 3

Epoch = 100

Epoch 32: Train Loss: 0.5551, Train Acc: 0.7558, Valid Loss: 0.593, Valid Acc: 0.72

Save model, Best valid loss: 59.29541540145874

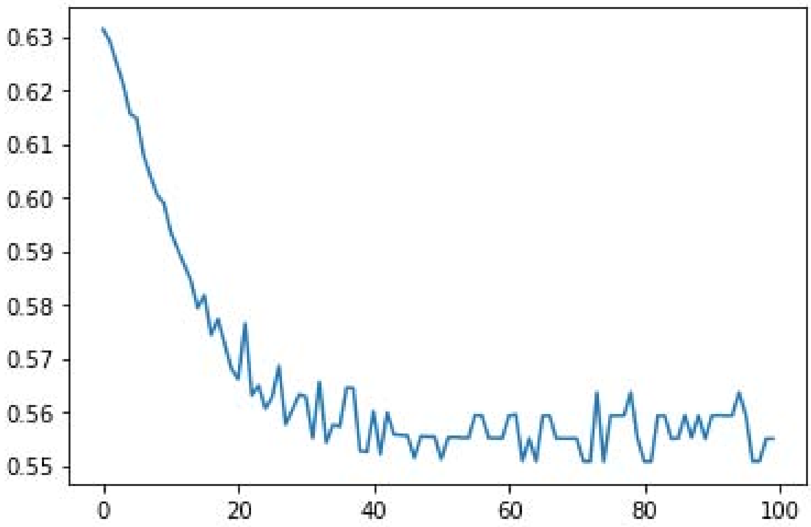

Figure Appendix 1.13. Loss function for 3 layer, 100 epochs

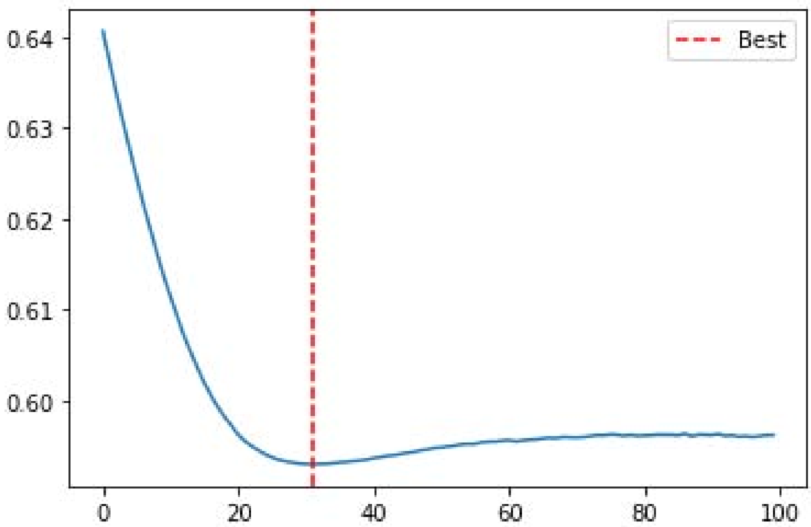

Figure Appendix 1.14. Early Stop for 3 layer, 100 epochs

Layers = 3

Epoch = 200

Epoch 77: Train Loss: 0.5669, Train Acc: 0.7628, Valid Loss: 0.7964, Valid Acc: 0.68

Save model, Best valid loss: 62.68702256679535

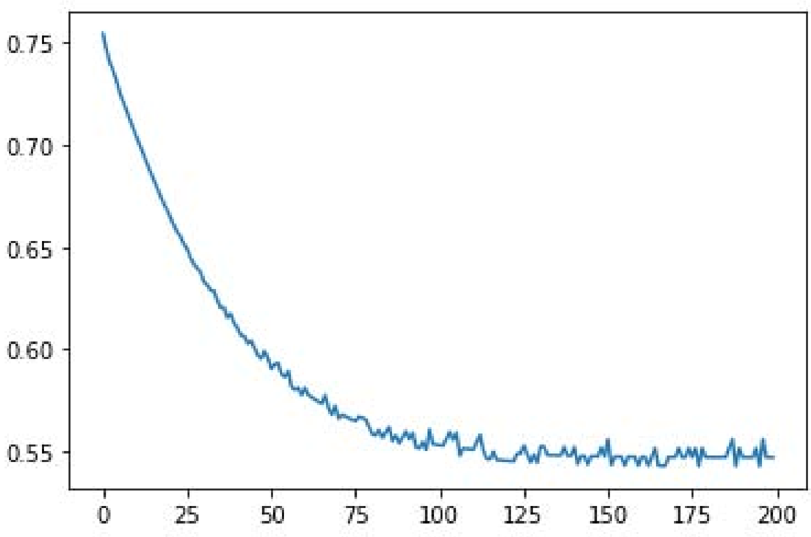

Figure Appendix 1.15. Loss function for 3 layer, 200 epochs

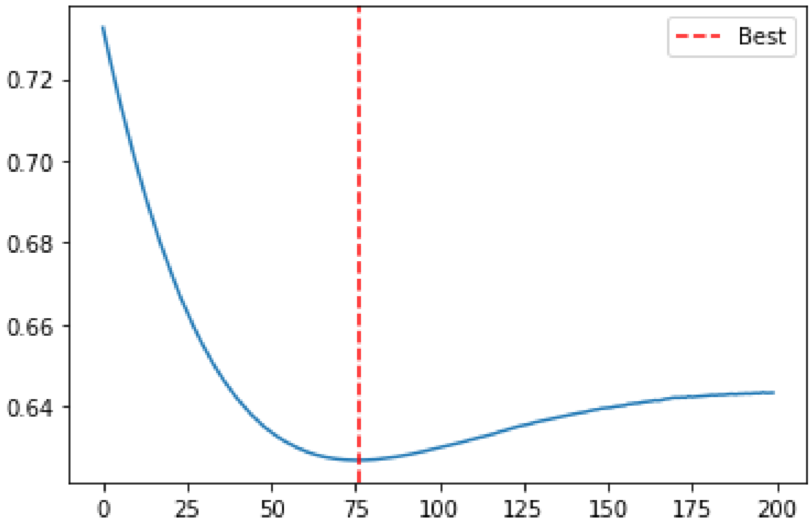

Figure Appendix 1.16. Early Stop for 3 layer, 200 epochs

Layers = 3

Epoch = 300

Epoch 65: Train Loss: 0.5566, Train Acc: 0.7504, Valid Loss: 0.5623, Valid Acc: 0.75

Save model, Best valid loss: 56.23351112008095

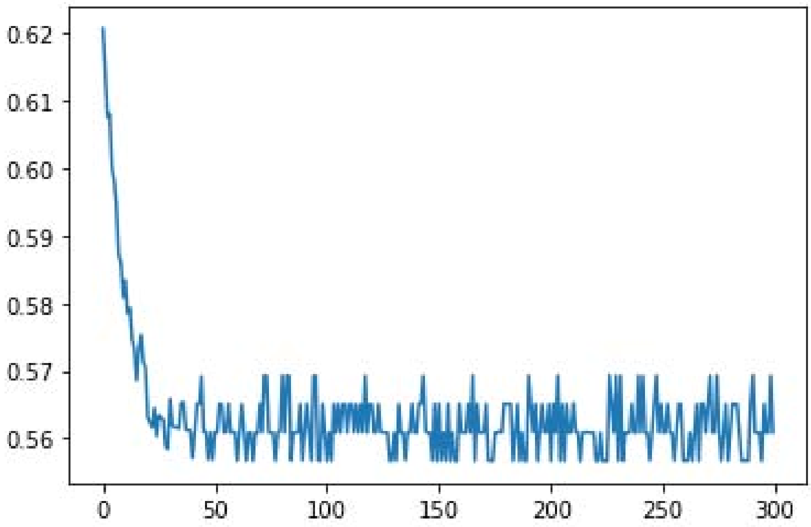

Figure Appendix 1.17. Loss function for 3 layer, 300 epochs

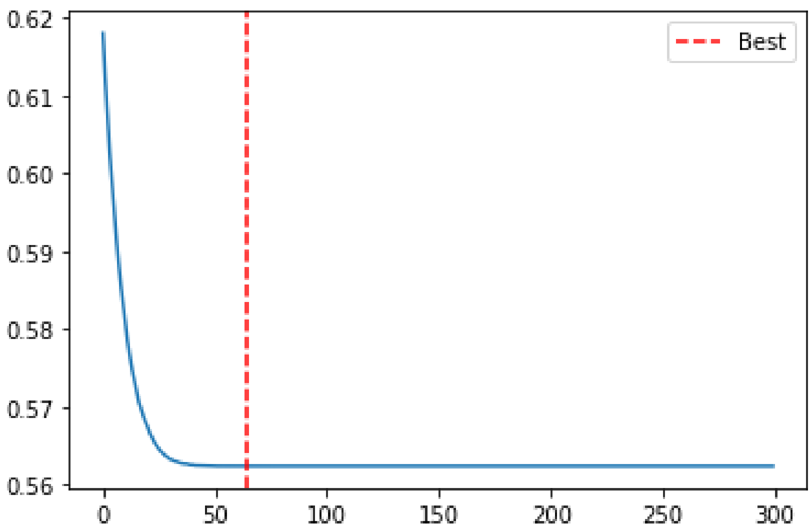

Figure Appendix 1.18. Early Stop for 3 layer, 300 epochs

Layers = 4

Epoch = 100

Epoch 42: Train Loss: 0.5623, Train Acc: 0.7558, Valid Loss: 0.593, Valid Acc: 0.72

Save model, Best valid loss: 59.295369386672974

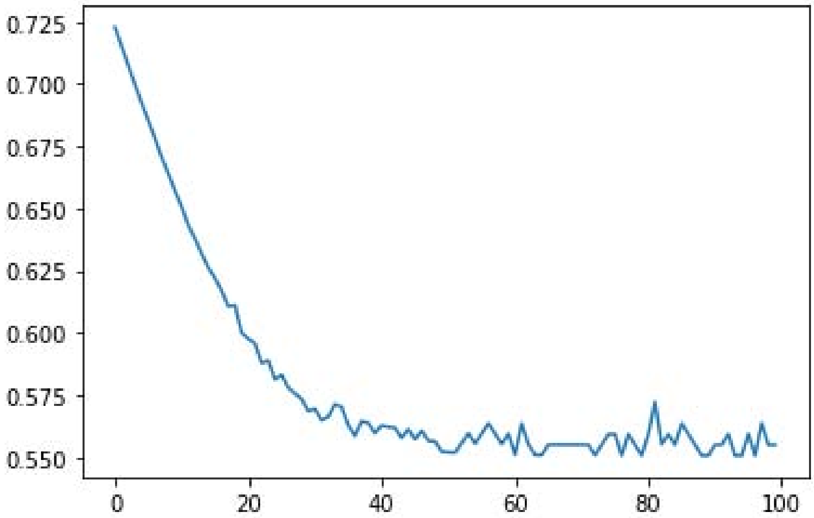

Figure Appendix 1.19. Loss function for 4 layer, 100 epochs

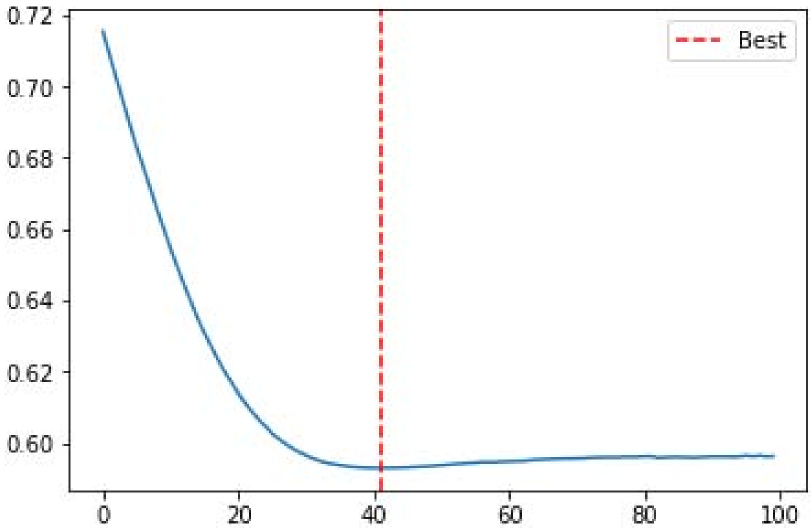

Figure Appendix 1.20. Early Stop for 4 layer, 100 epochs

Layers = 4

Epoch = 200

Epoch 97: Train Loss: 0.5674, Train Acc: 0.7628, Valid Loss: 0.7964, Valid Acc: 0.68

Save model, Best valid loss: 62.68706953525543

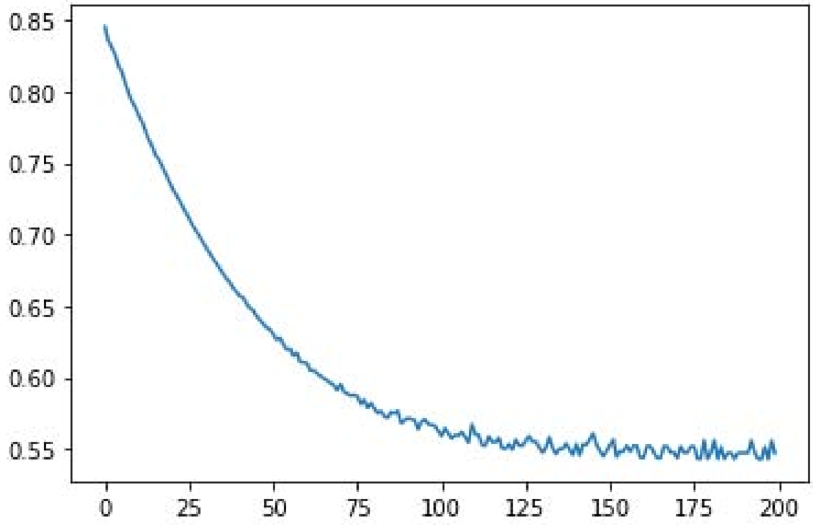

Figure Appendix 1.21. Loss function for 4 layer, 200 epochs

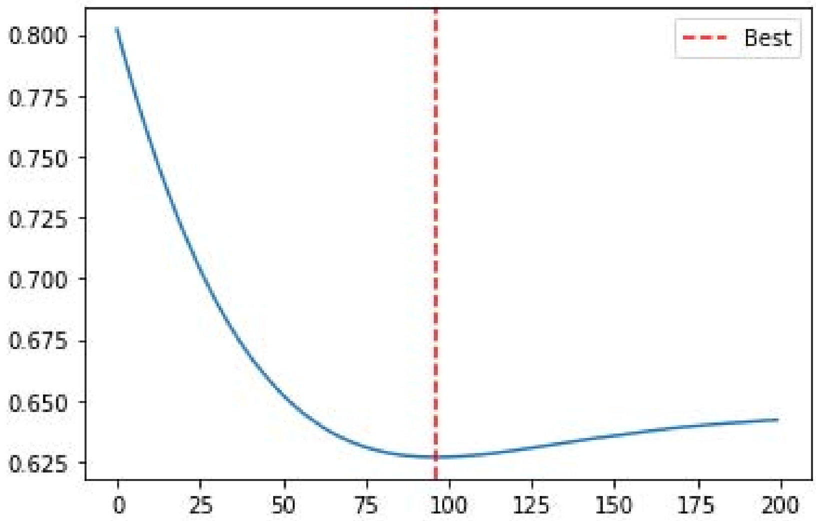

Figure Appendix 1.22. Early Stop for 4 layer, 200 epochs

Layers = 4

Epoch = 300

Epoch 238: Train Loss: 0.5564, Train Acc: 0.7522, Valid Loss: 0.5731, Valid Acc: 0.74

Save model, Best valid loss: 57.305710792541504

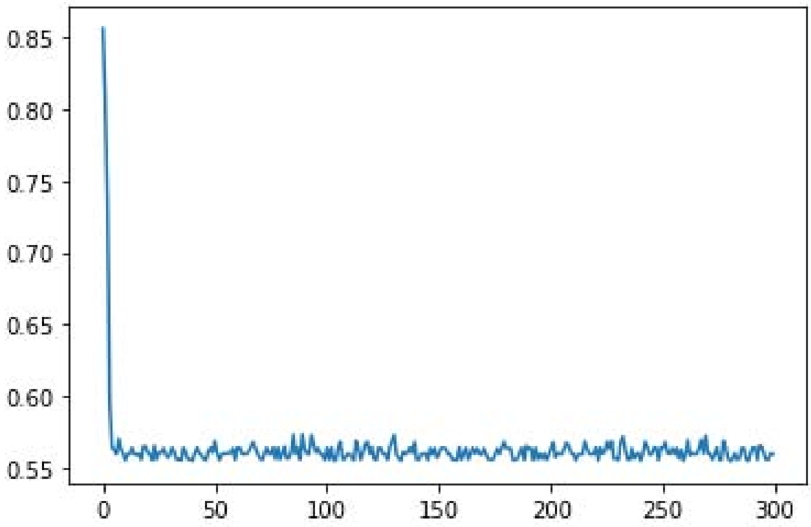

Figure Appendix 1.23. Loss function for 4 layer, 300 epochs

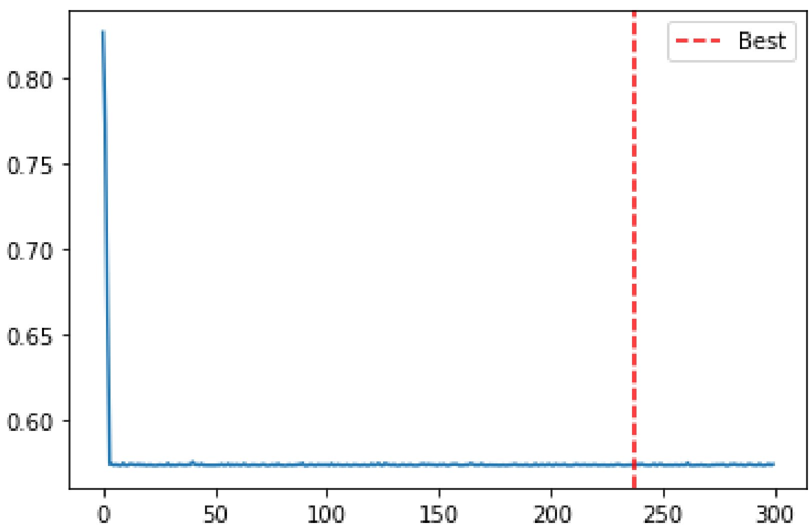

Figure Appendix 1.24. Early Stop for 4 layer, 300 epochs

Layers = 5

Epoch = 100

Epoch 100: Train Loss: 0.5644, Train Acc: 0.7522, Valid Loss: 0.5734, Valid Acc: 0.74

Save model, Best valid loss: 57.34490090608597

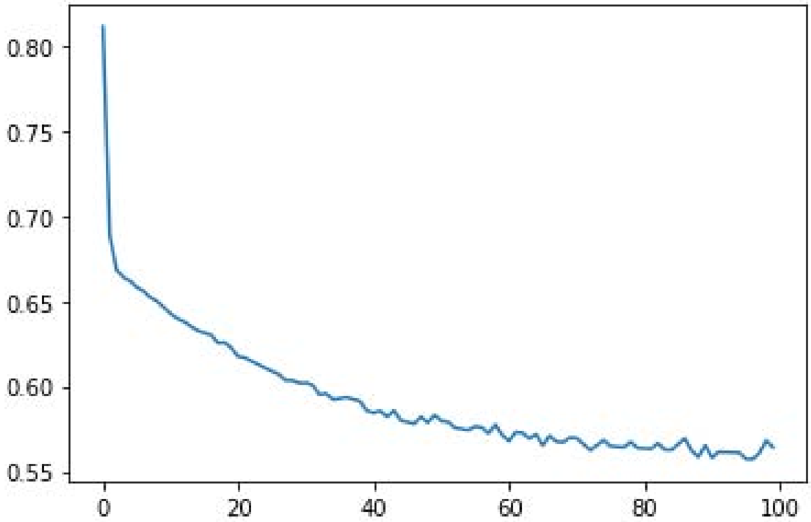

Figure Appendix 1.25. Loss function for 5 layer, 100 epochs

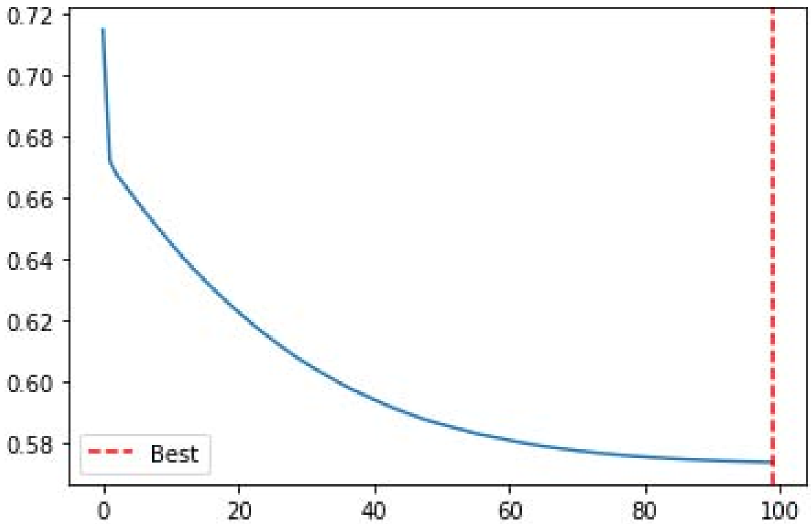

Figure Appendix 1.26. Early Stop for 5 layer, 100 epochs

Layers = 5

Epoch = 200

Epoch 76: Train Loss: 0.5702, Train Acc: 0.7628, Valid Loss: 0.7964, Valid Acc: 0.68

Save model, Best valid loss: 62.686986804008484

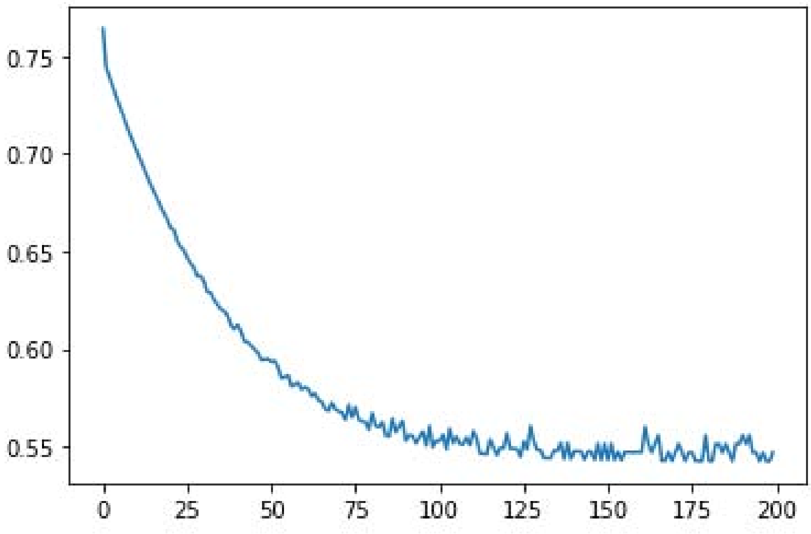

Figure Appendix 1.27. Loss function for 5 layer, 200 epochs

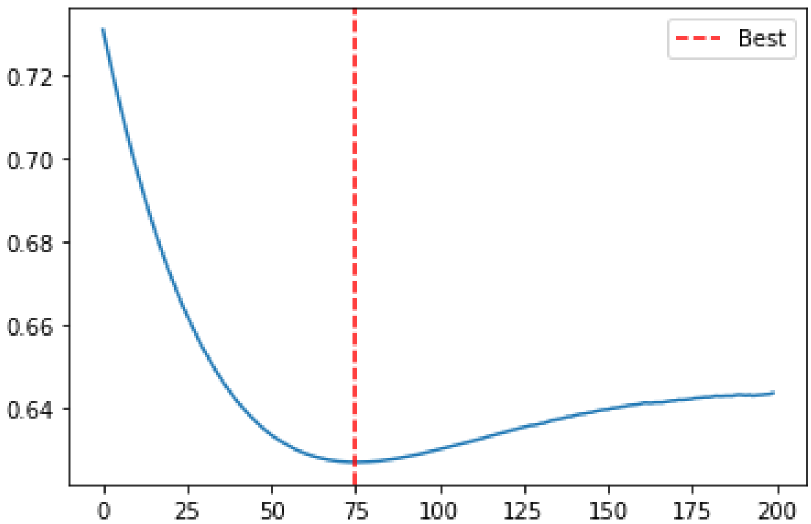

Figure Appendix 1.28. Early Stop for 5 layer, 200 epochs

Layers = 5

Epoch = 300

Epoch 8: Train Loss: 0.5605, Train Acc: 0.7487, Valid Loss: 0.5512, Valid Acc: 0.76

Save model, Best valid loss: 55.12002617120743

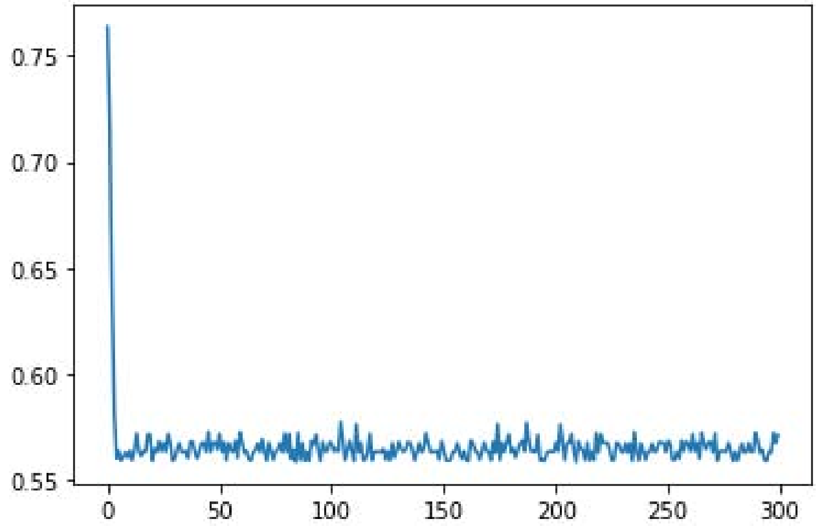

Figure Appendix 1.29. Loss function for 5 layer, 300 epochs

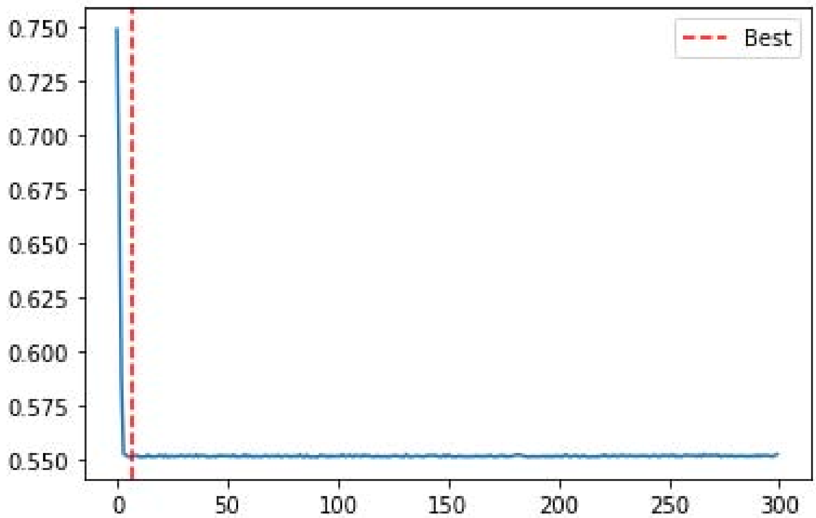

Figure Appendix 1.25. Early Stop for 5 layer, 300 epochs

Layers = 6

Epoch = 100

Epoch 24: Train Loss: 0.5712, Train Acc: 0.7416, Valid Loss: 0.5063, Valid Acc: 0.8

Save model, Best valid loss: 50.63462734222412

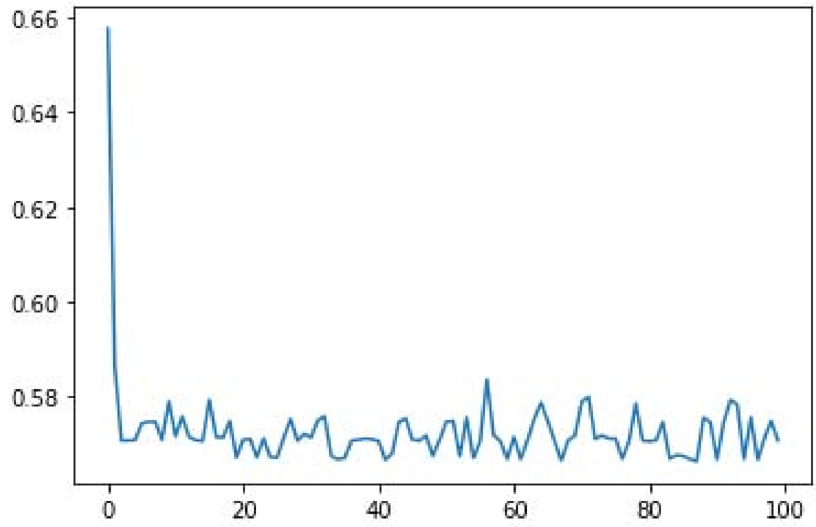

Figure Appendix 1.31. Loss function for 6 layer, 100 epochs

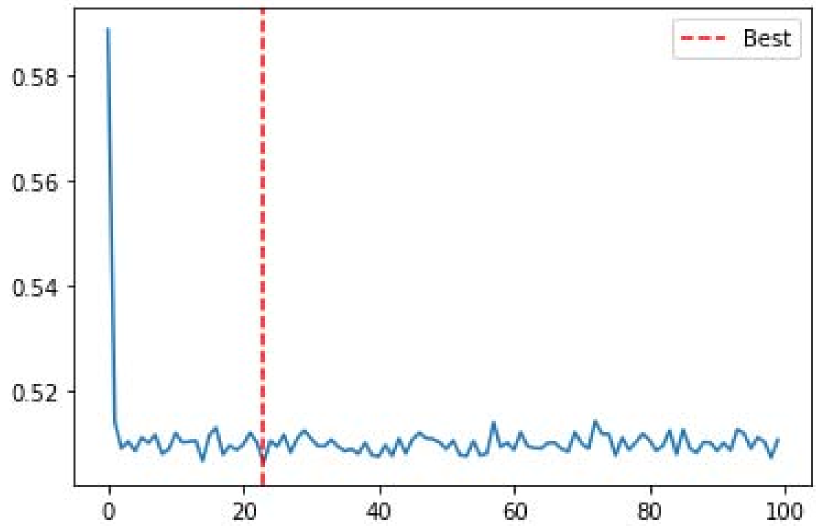

Figure Appendix 1.32. Early Stop for 6 layer, 100 epochs

Layers = 6

Epoch = 200

Epoch 55: Train Loss: 0.5483, Train Acc: 0.7628, Valid Loss: 0.7964, Valid Acc: 0.68

Save model, Best valid loss: 64.04361641407013

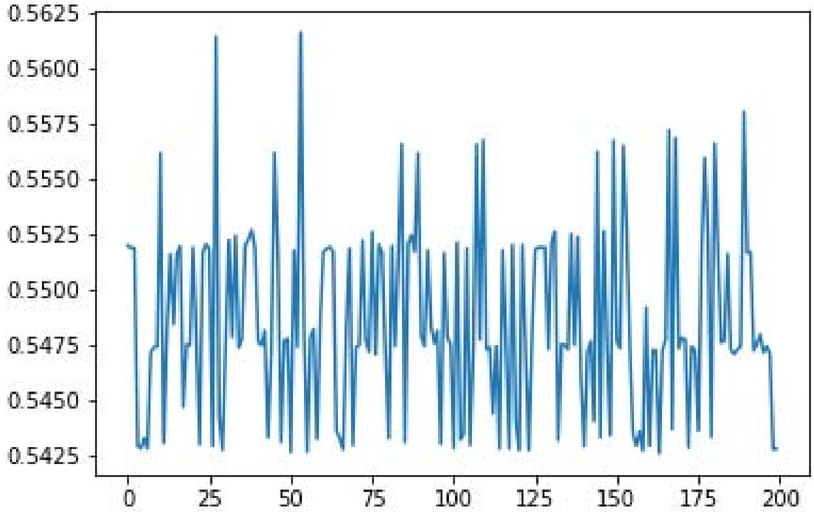

Figure Appendix 1.33. Loss function for 6 layer, 200 epochs

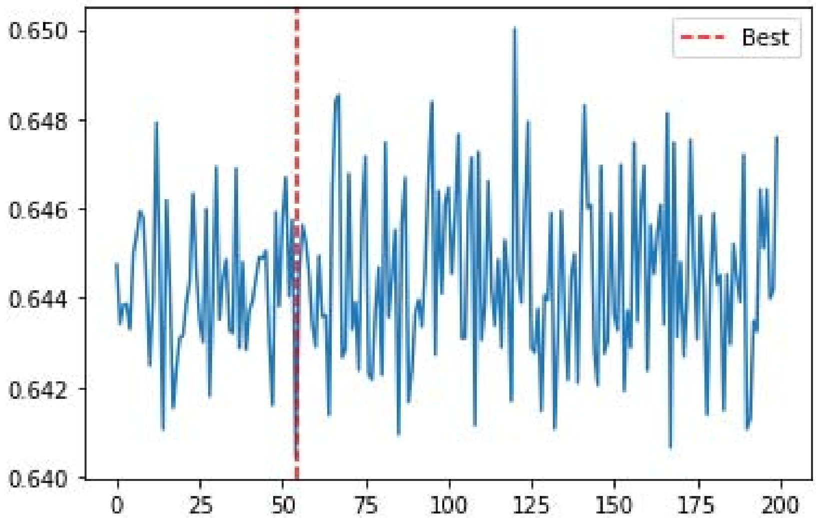

Figure Appendix 1.34. Early Stop for 6 layer, 200 epochs

Layer = 6

Epoch = 300

Epoch 57: Train Loss: 0.5699, Train Acc: 0.7416, Valid Loss: 0.5085, Valid Acc: 0.8

Save model, Best valid loss: 50.851761773228645

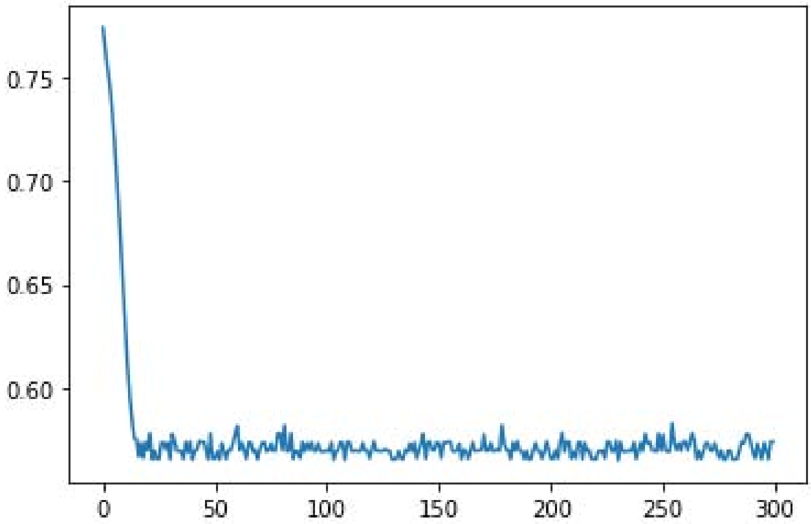

Figure Appendix 1.35. Loss function for 6 layer, 300 epochs

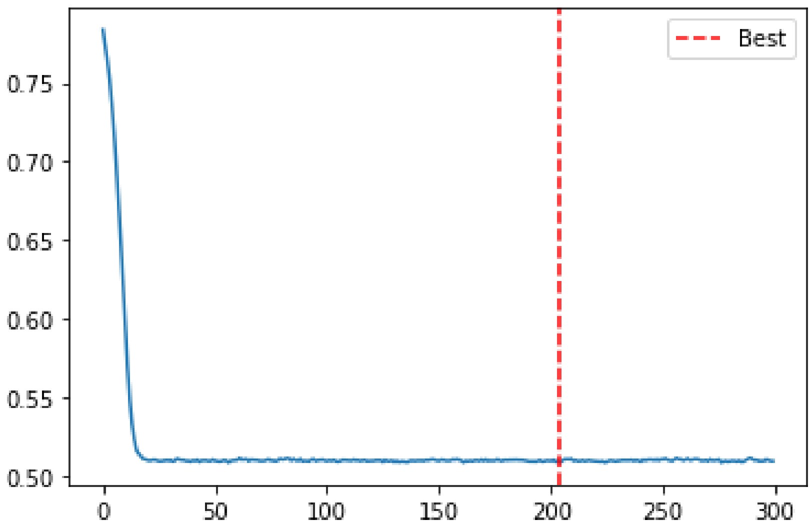

Figure Appendix 1.36. Early Stop for 6 layer, 300 epochs

Layer = 7

Epoch = 100

Epoch 21: Train Loss: 0.5588, Train Acc: 0.754, Valid Loss: 0.5779, Valid Acc: 0.73
Save model, Best valid loss: 57.79086282849312

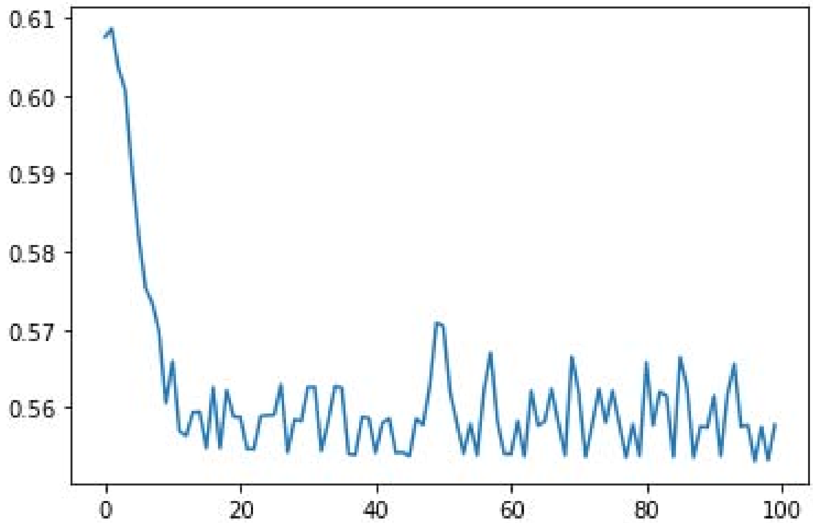

Figure Appendix 1.37. Loss function for 7 layer, 100 epochs

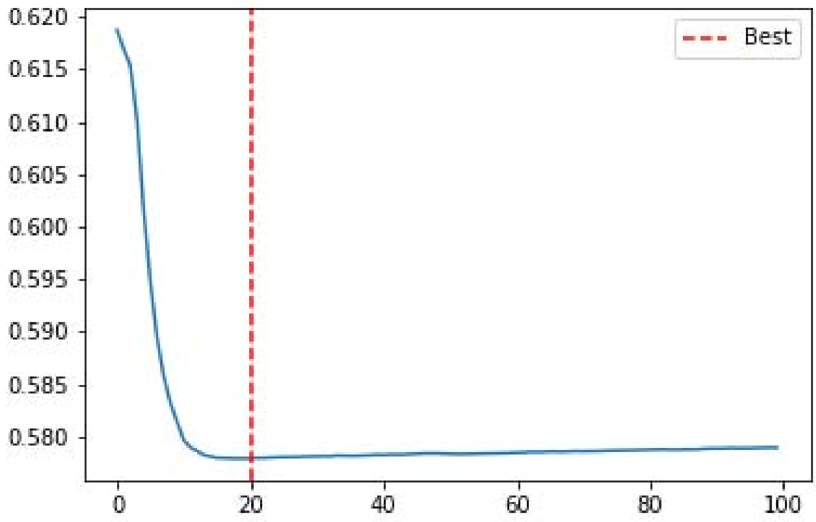

Figure Appendix 1.38. Early Stop for 7 layer, 100 epochs

Layer = 7
Epoch = 200

Epoch 35: Train Loss: 0.567, Train Acc: 0.7628, Valid Loss: 0.7964, Valid Acc: 0.68
Save model, Best valid loss: 62.68703269958496

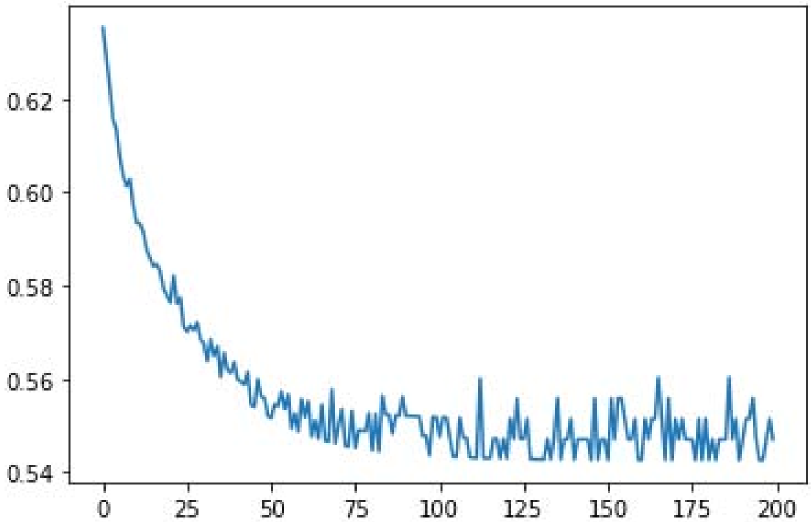

Figure Appendix 1.39. Loss function for 7 layer, 200 epochs

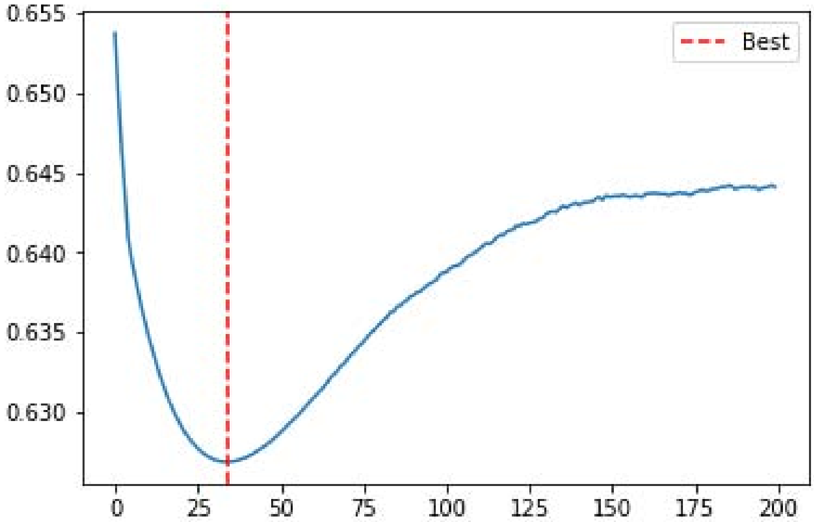

Figure Appendix 1.40. Early Stop for 7 layer, 200 epochs

Layer = 7
Epoch = 300

Epoch 14: Train Loss: 0.573, Train Acc: 0.7451, Valid Loss: 0.5285, Valid Acc: 0.78
Save model, Best valid loss: 52.85199749469757

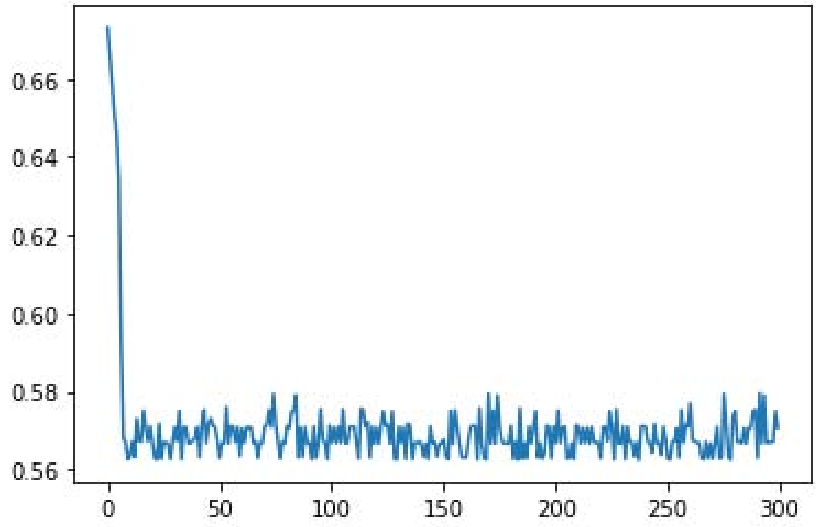

Figure Appendix 1.41. Loss function for 7 layer, 300 epochs

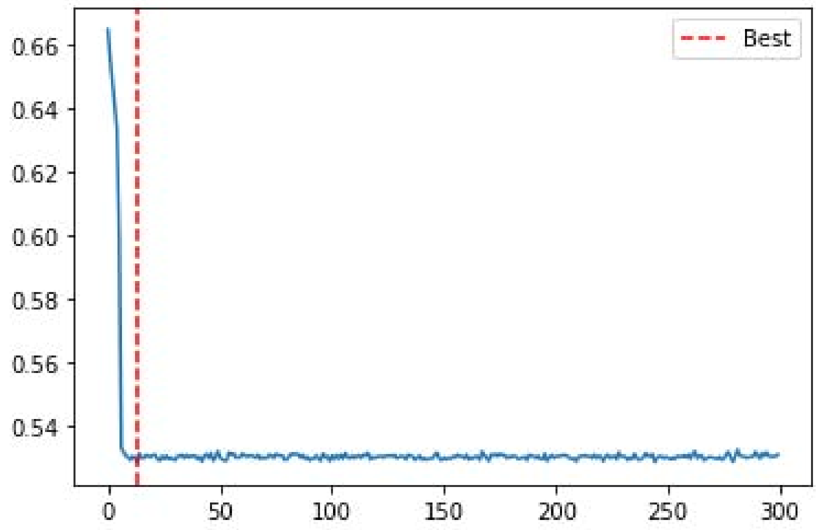

Figure Appendix 1.42. Early Stop for 7 layer, 300 epochs

Appendix 2: Survey

I. 자동차 유형별 선호도

다음은 자동차의 여러 속성과 속성별 수준에 대한 설명입니다. 다음 제시한 속성 설명을 잘 숙지하시고 응답해 주시기 바랍니다.

▣ 자동차 속성 및 수준 설명문

속성			속성 설명 및 수준
1. 연료 종류(유종)		설명	**차량의 연료종류는 휘발유, 경유, LPG, 하이브리드, 전기, 수소연료전지로 구분됨** - **휘발유, 경유** 차량은 일반적으로 액체연료인 유류만을 연료로 이용하는 내연기관차임 - **LPG** 차량은 기체연료를 액화한 액화석유가스를 연료로 이용하는 내연기관차임 - **하이브리드** 차량은 휘발유/경유를 주 연료로 하며, 엔진 이용 시 발생하는 에너지를 활용해 전기모터를 함께 이용하는 차량임. **전기** 차량은 전기만을 연료로 이용하는 차량임 - **수소연료전지** 차량은 수소가 주 연료이며, 공기 중의 산소와 화학 반응하여 전력을 만들어 내는 차량임
		수준(6개)	① 휘발유 ② 경유 ③ LPG ④ 하이브리드 ⑤ 전기 ⑥ 수소연료전지
전기차만 해당	1-1. 충전시간	설명	**1회 완전 급속 충전 시 걸리는 총 시간**
		수준(3개)	① 5분 ② 15분 ③ 25분
2. 연료 비용(연비)		설명	**10Km 주행 시 소요되는 비용** (연료비용은 국내운행 차량의 월평균 주행거리 1300km를 적용하여 계산함)
		수준(4개)	① 500원/10km (65,000원/월) ② 1,000원/10km (130,000원/월) ③ 1,500원/10km (195,000원/월) ④ 2,000원/10km (260,000원/월)
3. 최대주행가능거리		설명	**1회 완전 주유/충전 시 운행할 수 있는 최대 주행 가능 거리**
		수준(3개)	① 400km ② 600km ③ 800km
4. 차종		설명	**차량의 크기, 배기량 등에 따라 경차·소형차, 준중형차·중형차, 대형차, SUV·RV로 구분 가능함** - **경차**는 **기아 모닝, 쉐보레 스파크** 등의 차량이 포함되며, **소형차**는 **기아 프라이드, 현대 엑센트** 등의 차량이 포함됨. **준중형차**는 **기아 K3, 현대 아반떼** 등의 차량이 포함됨 - **중형차**는 **기아 K5, 현대 소나타**와 같은 차량이 포함되며, **대형차**는 **기아 K9, 현대 에쿠스** 등의 차량이 포함됨 - **SUV**는 Sports Utility Vehicle의 줄임말로, **기아 스포티지, 현대 투싼, 산타페** 등의 차량이 포함되며, **RV**는 Recreational Vehicle의 줄임말로 **기아의 카니발과 같은 다인 승합차**가 포함됨
		수준(3개)	① 경차·소형차·준중형차 ② 중형차·대형차 ③ SUV·RV
5. 주유/충전소 접근 용이성		설명	**현재 이용 가능한 전체 주유소 수 대비, 해당 차량의 주유/충전이 가능한 주유/충전소의 비율**
		수준(4개)	① 100% (전체 주유소 수에 비해 100% 수준) ② 70% (전체 주유소 수에 비해 70% 수준) ③ 40% (전체 주유소 수에 비해 40% 수준) ④ 10% (전체 주유소 수에 비해 10% 수준)
6. 차량 가격		설명	**차량 등록세, 취득세 등 구매 과정 중 세금을 포함한 차량 구매에 소요되는 총 비용을 의미함** (현재 국내 등록세는 차량 가격의 3~5%, 취득세는 차량 가격의 2% 수준임)
		수준(4개)	① 1,500만원 ② 3,500만원 ③ 5,500만원 ④ 7,500만원

1. 다음 페이지부터 설명 드린 7개의 속성을 조합하여 구성한 **가상의 자동차 유형의 선호를 묻는 질문 6개가 제시됩니다.**
2. 귀하께서는 유형별 자동차 속성 수준을 잘 확인하시고,
   ① 제시된 4가지 유형의 자동차 중, **선호하는 순서대로 1~4까지의 순위를 응답**
   ② 선호하는 자동차 없음/현재 자동차 이용이 포함된 5개의 자동차 유형 중, **가장 선호하는 유형 하나에 O표**해 주십시오.
3. 각 유형에 제시된 7가지 속성 이외의 **다른 모든 자동차 속성은 서로 동일**한 것으로 가정하고 응답해주십시오.

문1. **(전체 응답자)** ① 제시된 4개의 가상의 자동차 유형 중, 귀하의 **선호 순위를 1위부터 4위까지 응답**해 주시고,
② 비선택을 포함한 **5개의 가상의 자동차 유형 중, 가장 선호하는 유형 하나에 응답(단답)**해 주십시오.

■ **자동차 선호도 질문 1**

속성	유형 A	유형 B	유형 C	유형 D	비선택
1. 연료 종류	전기	경유	휘발유	LPG	(자동차가 있는 경우) 현재 주이용 자동차 유지 / (자동차가 없는 경우) 구매하지 않음
1-1. 충전시간	5분	5분	5분	5분	
2. 연료비용	1,000원/10km	1,000원/10km	500원/10km	1,500원/10km	
3. 최대주행가능거리	800km	600km	800km	800km	
4. 차종	SUV·RV	중형차·대형차	경차·소형차·준중형차	SUV·RV	
5. 주유/충전 접근성	70% (전체 주유소 수 대비 70% 수준)	100% (전체 주유소 수 대비 100% 수준)	100% (전체 주유소 수 대비 100% 수준)	70% (전체 주유소 수 대비 70% 수준)	
6. 차량가격	1,500만원	1,500만원	7,500만원	1,500만원	
① 1위~4위 선호순위	위	위	위	위	
② 가장 선호하는 유형 (5개 중 하나에 ○표)	유형 A	유형 B	유형 C	유형 D	비선택

■ **자동차 선호도 질문 2**

속성	유형 A	유형 B	유형 C	유형 D	비선택
1. 연료 종류	LPG	LPG	전기	수소연료전지	(자동차가 있는 경우) 현재 주이용 자동차 유지 / (자동차가 없는 경우) 구매하지 않음
1-1. 충전시간	5분	5분	25분	5분	
2. 연료비용	500원/10km	1,000원/10km	2,000원/10km	2,000원/10km	
3. 최대주행가능거리	600km	600km	600km	800km	
4. 차종	SUV·RV	경차·소형차·준중형차	경차·소형차·준중형차	중형차·대형차	
5. 주유/충전 접근성	40% (전체 주유소 수 대비 40% 수준)	10% (전체 주유소 수 대비 10% 수준)	40% (전체 주유소 수 대비 40% 수준)	100% (전체 주유소 수 대비 100% 수준)	
6. 차량가격	7,500만원	3,500만원	1,500만원	7,500만원	
① 1위~4위 선호순위	위	위	위	위	
② 가장 선호하는 유형 (5개 중 하나에 ○표)	유형 A	유형 B	유형 C	유형 D	비선택

■ **자동차 선호도 질문 3**

속성	유형 A	유형 B	유형 C	유형 D	비선택
1. 연료 종류	전기	하이브리드	수소연료전지	경유	(자동차가 있는 경우)재 주이용 자동차 유지 / (자동차가 없는 경우) 구매하지 않음
1-1. 충전시간	15분	5분	5분	5분	
2. 연료비용	1,000원/10km	1,500원/10km	2,000원/10km	500원/10km	
3. 최대주행가능거리	800km	400km	600km	800km	
4. 차종	중형차·대형차	SUV·RV	경차·소형차·준중형차	경차·소형차·준중형차	
5. 주유/충전 접근성	40% (전체 주유소 수 대비 40% 수준)	100% (전체 주유소 수 대비 100% 수준)	100% (전체 주유소 수 대비 100% 수준)	10% (전체 주유소 수 대비 10% 수준)	
6. 차량가격	5,500만원	3,500만원	3,500만원	5,500만원	
① 1위~4위 선호순위	위	위	위	위	
② 가장 선호하는 유형 (5개 중 하나에 ○표)	유형 A	유형 B	유형 C	유형 D	비선택

■ 자동차 선호도 질문 4

속성	유형 A	유형 B	유형 C	유형 D	비선택
1. 연료 종류	휘발유	경유	하이브리드	수소연료전지	(자동차가 있는 경우) 현재 주이용 자동차 유지 / (자동차가 없는 경우) 구매하지 않음
1-1. 충전시간	5분	5분	5분	5분	
2. 연료비용	1,500원/10km	500원/10km	1,500원/10km	1,500원/10km	
3. 최대주행가능거리	600km	400km	800km	800km	
4. 차종	중형차-대형차	중형차-대형차	경차-소형차-준중형차	SUV-RV	
5. 주유/충전 접근성	70% (전체 주유소 수 대비 70% 수준)	40% (전체 주유소 수 대비 40% 수준)	40% (전체 주유소 수 대비 40% 수준)	10% (전체 주유소 수 대비 10% 수준)	
6. 차량가격	3,500만원	3,500만원	5,500만원	3,500만원	
① 1위~4위 선호순위	위	위	위	위	
② 가장 선호하는 유형 (5개 중 하나에 O표)	유형 A	유형 B	유형 C	유형 D	비선택

■ 자동차 선호도 질문 5

속성	유형 A	유형 B	유형 C	유형 D	비선택
1. 연료 종류	휘발유	전기	하이브리드	수소연료전지	(자동차가 있는 경우) 현재 주이용 자동차 유지 / (자동차가 없는 경우) 구매하지 않음
1-1. 충전시간	5분	25분	5분	5분	
2. 연료비용	1,000원/10km	1,500원/10km	2,000원/10km	1,500원/10km	
3. 최대주행가능거리	400km	600km	600km	400km	
4. 차종	SUV-RV	중형차-대형차	SUV-RV	중형차-대형차	
5. 주유/충전 접근성	40% (전체 주유소 수 대비 40% 수준)	10% (전체 주유소 수 대비 10% 수준)	10% (전체 주유소 수 대비 10% 수준)	40% (전체 주유소 수 대비 40% 수준)	
6. 차량가격	7,500만원	7,500만원	5,500만원	5,500만원	
① 1위~4위 선호순위	위	위	위	위	
② 가장 선호하는 유형 (5개 중 하나에 O표)	유형 A	유형 B	유형 C	유형 D	비선택

■ 자동차 선호도 질문 6

속성	유형 A	유형 B	유형 C	유형 D	비선택
1. 연료 종류	수소연료전지	휘발유	하이브리드	휘발유	(자동차가 있는 경우) 현재 주이용 자동차 유지 / (자동차가 없는 경우) 구매하지 않음
1-1. 충전시간	5분	5분	5분	5분	
2. 연료비용	500원/10km	500원/10km	1,000원/10km	1,000원/10km	
3. 최대주행가능거리	600km	800km	800km	600km	
4. 차종	SUV-RV	중형차-대형차	중형차-대형차	SUV-RV	
5. 주유/충전 접근성	40% (전체 주유소 수 대비 40% 수준)	10% (전체 주유소 수 대비 10% 수준)	40% (전체 주유소 수 대비 40% 수준)	100% (전체 주유소 수 대비 100% 수준)	
6. 차량가격	1,500만원	1,500만원	3,500만원	5,500만원	
① 1위~4위 선호순위	위	위	위	위	
② 가장 선호하는 유형 (5개 중 하나에 O표)	유형 A	유형 B	유형 C	유형 D	비선택

■ 자동차 선호도 질문 7

속성	유형 A	유형 B	유형 C	유형 D	비선택
1. 연료 종류	전기	LPG	전기	경유	(자동차가 있는 경우) 현재 주이용 자동차 유지 / (자동차가 없는 경우) 구매하지 않음
1-1. 충전시간	5분	5분	15분	5분	
2. 연료비용	500원/10km	1,500원/10km	500원/10km	2,000원/10km	
3. 최대주행가능거리	400km	400km	400km	800km	
4. 차종	SUV·RV	경차·소형차·준중형차	경차·소형차·준중형차	SUV·RV	
5. 주유/충전 접근성	100% (전체 주유소 수 대비 100% 수준)	100% (전체 주유소 수 대비 100% 수준)	70% (전체 주유소 수 대비 70% 수준)	70% (전체 주유소 수 대비 70% 수준)	
6. 차량가격	5,500만원	1,500만원	3,500만원	3,500만원	
① 1위~4위 선호순위	위	위	위	위	
② 가장 선호하는 유형 (5개 중 하나에 O표)	유형 A	유형 B	유형 C	유형 D	비선택

■ 자동차 선호도 질문 8

속성	유형 A	유형 B	유형 C	유형 D	비선택
1. 연료 종류	수소연료전지	경유	하이브리드	LPG	(자동차가 있는 경우) 현재 주이용 자동차 유지 / (자동차가 없는 경우) 구매하지 않음
1-1. 충전시간	5분	5분	5분	5분	
2. 연료비용	1,000원/10km	1,500원/10km	1,000원/10km	2,000원/10km	
3. 최대주행가능거리	400km	600km	400km	400km	
4. 차종	경차·소형차·준중형차	경차·소형차·준중형차	경차·소형차·준중형차	중형차·대형차	
5. 주유/충전 접근성	10% (전체 주유소 수 대비 40% 수준)	70% (전체 주유소 수 대비 70% 수준)	70% (전체 주유소 수 대비 70% 수준)	70% (전체 주유소 수 대비 70% 수준)	
6. 차량가격	1,500만원	7,500만원	7,500만원	5,500만원	
① 1위~4위 선호순위	위	위	위	위	
② 가장 선호하는 유형 (5개 중 하나에 O표)	유형 A	유형 B	유형 C	유형 D	비선택

H. 자동차 이용행태

먼저, 귀하(댁)의 자동차 보유 현황 및 운전 행동을 묻는 질문입니다.

문1. **(전체 응답자) 현재 귀하나 귀댁에서는 자동차를 보유**하고 있습니까?

1. 예 (있다)
2. 아니오 (없다) → **다음 페이지 문2.로 이동하십시오**

문1-1. **(문1.에서 1. 현재 보유차량 있다에 응답한 응답자)**
현재 보유 차량과 이전 **차량의 구매 시점은 언제**입니까?

현재 보유 차량	이전 구매 차량
□□□□ 년	□□□□ 년 0. 이전 차량 없었음 (현재 차량이 처음 구매차량)

문1-2. **(문1.에서 1. 현재 보유차량 있다에 응답한 응답자)** 현재 귀댁에서 **보유하고 있는 자동차의 사양을** 응답해 주십시오.

	항목	주이용 자동차 (자동차를 보유한 응답자 모두 응답)	부이용 자동차 (자동차를 2대 이상 보유한 경우만 응답)
	1. 제조년도	□□□□ 년	□□□□ 년
	2. 국산차/수입차 여부	① 국산차 ② 수입차	① 국산차 ② 수입차
	3. 자동차 모델명 (구체적으로 응답해 주십시오.)	□	□
	4. 차종	① 경차 ② 소형차 ③ 준중형차 ④ 중형차 ⑤ 대형차 ⑥ SUV/RV	① 경차 ② 소형차 ③ 준중형차 ④ 중형차 ⑤ 대형차 ⑥ SUV/RV
	5. 유종	① 휘발유 ② 경유 ③ LPG ④ 하이브리드 ⑤ 전기 ⑥ 수소	① 휘발유 ② 경유 ③ LPG ④ 하이브리드 ⑤ 전기 ⑥ 수소
	6. 신차/중고차 구입 여부	① 신차 ② 중고차	① 신차 ② 중고차
	7. 구입가격 (단위 : 백만원)	□□ 천 □ 백	□□ 천 □ 백
	8. 1리터당 주행거리(연비) [전기차는 kWh당, 수소차는 kg당]	□□ km	□□ km
	9. 연평균 주행거리	□□ 만 □ 천km	□□ 만 □ 천km
	10. 일주일 평균 주행거리	□□□ km	□□□ km
일주일 평균 주행거리 중 용도별 주행거리의 비중을 10-1 ~ 10-5에 응답해 주시기 바랍니다.			
용도별 주행거리의 비중	10-1. 출퇴근용	□□□ %	□□□ %
	10-2. 사업용/업무용	□□□ %	□□□ %
	10-3. 레저 및 장거리 여행용	□□□ %	□□□ %
	10-4. 가정/일상 생활용(쇼핑 등)	□□□ %	□□□ %
	10-5. 기타	□□□ %	□□□ %
	합계	1 0 0 %	1 0 0 %

문2. **(전체 응답자)** 다음 용도별로 귀하께서 활용하는 **이동수단 이용현황을 응답**해 주십시오.

	출퇴근용	사업용/업무용	레저 및 장거리 여행용	가정/일상 생활용 (쇼핑 등)
주이용 이동수단	① 자동차(자가) ② 카풀 ③ 카셰어링 (쏘카) ④ 버스/지하철 ⑤ 택시 ⑥ 철도 ⑦ 걷기 등 기타	① 자동차(자가) ② 카풀 ③ 카셰어링 (쏘카) ④ 버스/지하철 ⑤ 택시 ⑥ 철도 ⑦ 걷기 등 기타	① 자동차(자가) ② 카풀 ③ 카셰어링 (쏘카) ④ 버스/지하철 ⑤ 택시 ⑥ 철도 ⑦ 걷기 등 기타	① 자동차(자가) ② 카풀 ③ 카셰어링 (쏘카) ④ 버스/지하철 ⑤ 택시 ⑥ 철도 ⑦ 걷기 등 기타
이동수단 이용주기	① 매일 ② 1주일에 ( )회 정도 ③ 1개월에 ( )회 정도	① 매일 ② 1주일에 ( )회 정도 ③ 1개월에 ( )회 정도	① 매일 ② 1주일에 ( )회 정도 ③ 1개월에 ( )회 정도	① 매일 ② 1주일에 ( )회 정도 ③ 1개월에 ( )회 정도
1회 이동시 평균 이동거리	km	km	km	km
이동 시기 (평일/주말)	① 주로 주말에 ② 주로 평일에	① 주로 주말에 ② 주로 평일에	① 주로 주말에 ② 주로 평일에	① 주로 주말에 ② 주로 평일에
월 평균 소득 대비 지불비용	%	%	%	%

문3. **(전체 응답자)** 귀하께서는 자동차를 선택하실 때 아래의 **자동차 속성이 얼마나 중요**하다고 생각하십니까?

	전혀 중요하지 않다	중요하지 않은 편이다	보통이다	다소 중요하다	매우 중요하다
1. 자동차 주행 시 나오는 **소음**	1	2	3	4	5
2. **주유 및 충전 비용**	1	2	3	4	5
3. 주유 또는 충전을 위해 기다리는 **시간**	1	2	3	4	5
4. 트렁크 여유 **공간**	1	2	3	4	5
5. **부품 결함**으로 인한 **자동차 고장 확률**	1	2	3	4	5
6. 자동차 내 **소프트웨어 업데이트**	1	2	3	4	5
7. **최대 주행 가능 속도**	1	2	3	4	5
8. 스마트 **안전 경보 시스템**	1	2	3	4	5
9. **셀프 주유 및 충전** 가능 여부	1	2	3	4	5
10. **외부 공기 정화 기능**	1	2	3	4	5

문4. **(전체 응답자) 차세대자동차(전기차, 수소차) 위험성 및 환경문제 인식**에 대해 귀하와 가장 가까운 번호에 O표해 주십시오.

	전혀 그렇지 않다 ◀			보통이다			▶ 매우 그렇다
1. 차세대자동차를 운전하는 것은 **잠재적인 위험이 따를 것**이다	1	2	3	4	5	6	7
2. 전반적으로 **차세대자동차의 안정성이 내연기관차보다 낮다**	1	2	3	4	5	6	7
3. 차세대자동차를 운전하는 것은 **불확실성이 따를 것**이다	1	2	3	4	5	6	7
4. 차세대자동차는 홍보와 달리 **성능이 기대 이하일 것**이다	1	2	3	4	5	6	7
5. 소비자는 **구매하는 제품의 환경적 영향에 관심**을 가져야 한다	1	2	3	4	5	6	7
6. 소비자는 **환경을 오염시키는 제품에 더 높은 가격을 지불**해야 한다	1	2	3	4	5	6	7
7. 정부는 **환경 프로그램 지원에 더 많은 돈을 투자**해야 한다	1	2	3	4	5	6	7
8. 정부는 **친환경 기술 연구에 보조금을 지원**해야 한다	1	2	3	4	5	6	7

문5. **(전체 응답자)**
귀하께서는 아래의 **자동차 운행 관련 환경 피해 및 수송부문 에너지/환경 관리 정책**에 대해 얼마나 알고 계십니까?

	전혀 모른다 1	모르는 편이다 2	보통이다 3	아는 편이다 4	매우 잘 안다 5
1. 자동차 운행으로 인한 **환경오염 비용의 개념**	1	2	3	4	5
2. 자동차 운행에 따른 **온실가스(CO_2) 배출량**	1	2	3	4	5
3. 자동차 운행에 따른 **미세먼지 배출량**	1	2	3	4	5
4. 2030년 **수송부문 온실가스 감축 목표치**	1	2	3	4	5
5. 고농도 **미세먼지 비상저감 조치 시 자동차 운행 제한** 제도	1	2	3	4	5
6. **노후 경유차 운행제한** 제도	1	2	3	4	5
7. 유류비 내 **세금 구성 항목**	1	2	3	4	5
8. 유류비 내 **세금 비중**	1	2	3	4	5
9. 유류비 내 세금의 **재정 쓰임 현황**	1	2	3	4	5
10. **LPG 연료**에 대한 **이용자 제한 정책**	1	2	3	4	5
11. **LPG 연료 화물차** 신규 **구입시 보조금** 지원	1	2	3	4	5
12. 타 유종 대비 **LPG 차량**의 **온실가스 및 미세먼지 배출량**	1	2	3	4	5
13. 전기차 및 수소차 **구입 보조금**	1	2	3	4	5
14. 전기차 및 수소차 **충전 요금**	1	2	3	4	5
15. 전기차 및 수소차 **충전 인프라 현황**	1	2	3	4	5

문6. **(전체 응답자)** 귀하께서 **예상하시는 향후 차량 구매 시점은 언제**입니까?

약 [ ][ ] 년 후

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0. 구매의향 없음

문7. **(전체 응답자)** 만약, 귀하께서 **향후 차량을 구매한다면, 자동차의 각 속성별로 기대하는 수준**을 응답해 주십시오.

자동차 속성	기대하는(원하는) 자동차 속성 수준 응답란
1. 연료 종류 (중복응답 가능)	1. 휘발유 2. 경유 3. LPG 4. 하이브리드 5. 전기 6. 수소연료전지
1.1. 충전시간	전기차 충전시 최대 [ ][ ][ ] **분 이내**
2. 연료비용	최대 [ ][ ][ ][ ] **원/10㎞ 이내**
3. 최대주행가능거리	1회 완전 주유/충전 시 최소 [ ][ ][ ][ ] **㎞ 이상**
4. 차종 (중복응답 가능)	1. 경차·소형차·준중형차, 2. 중형차·대형차, 3. SUV·RV
5. 주유/충전 접근성	현재 전체 주유소 수 대비 최소 [ ][ ][ ] **% 이상**
6. 차량가격	최대 [ ][ ][ ][ ][ ] **만원 이내**

Abstract (Korean)

본 연구의 목적은 소비자의 선호구조를 분석하기 위해 이산선택모형과 신경망 모형을 통합하여 각 분야에 새로운 가능성을 제시하는 것이다. 최근들어 소비자행동과 신경망 분야는 서로의 장단점을 보완하기 위해 많은 연구들이 진행되어 왔지만 아직까지 충분한 연구가 진행되었다고 보기는 어렵다. 따라서 본 연구는 첫째로 행동학적 요소를 도입한 이산선택 모형을 사용하여 소비자들의 이질적 선호구조를 분석하였다. 구체적으로, 소비자들이 효용의 변화를 느끼기 위해 넘어야 하는 임계점을 도입한 임계점 모형을 사용하였으며, 이를 통해 제품 또는 서비스의 속성 수준이 어느 수준까지 개선되어야 소비자들의 효용이 증가하는지를 알아볼 수 있었다. 둘째로, 본 연구는 합성곱 신경망과 심층 신경망, 두 개의 신경망을 혼합한 하이브리드 형태의 신경망 모형을 사용하여 소비자 선호구조를 분석하였고, 합성곱 신경망에 기존에는 시도되지 않았던 추가적인 합성곱 필터를 추가하여 소비자들의 임계점을 도출하였다. 실증 분석에서는 본 연구에서 제안한 모형으로 전기차 인프라에 대한 소비자의 선호를 분석하였으며, 이를 통해 전기차 보급 목표 달성을 위해 인프라 수준이 얼만큼 개선되어야 하는지를 모형 결과를 통해 확인할 수 있었다. 연구 결과에 의하면 소비자들은 선호 구조에 임계점이 존재하며, 이는 정책효과를 극대화하기 위해 제품, 서비스,

정책의 어떤 요인을 우선시해야 하는지에 대해 의사결정자들에게 시사점을 제공한다.

주요어 : 이산선택모형, 행동모형, 임계점, 신경망, 소비자선호, 소비자선택
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