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using Online Review Data: Nonlinear Estimation
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Toshikuni Sato

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Center for Data Science and Service Research
Graduate School of Economic and Management
Tohoku University
27-1 Kawauchi, Aobaku
Sendai 980-8576, JAPAN

Investigating the Impacts of Customer Experience and Attribute Performances on Overall Ratings using Online Review Data: Nonlinear Estimation and Visualization with a Neural Network

Toshikuni Sato[†]

[†]*Graduate School of Economics and Management, Tohoku University*

Abstract

This study investigates interpretable neural networks for marketing and consumer behavior research using customer reviews instead of measurement scales to better understand customer experiences. Service attribute ratings are used to measure attribute performances to compare the influence of customer experience and service performance on overall satisfaction. Although many researchers have investigated word-of-mouth reviews and their practical applications, the detailed contents of those reviews were generally disregarded, possibly because of their high dimensionality. To solve this problem, this study proposes some useful neural-network methods for specifying the expected assumptions based on previous knowledge or theories in consumer behavior research. Because neural networks help estimate nonlinear relationships between objective and predictive variables, a partial dependence plot is used to visualize the estimated functions and marginal effects. Empirical results not only provide a highly accurate neural-network model, they also create better marketing implications.

Keywords: Customer experience, Customer review, Neural networks, Interpretable machine learning, Nonlinear measurement model

1. Introduction

Customer experience, as proposed by Schmitt (1990), has been applied to a wide range of marketing areas, from retail marketing to service design and customer journey (Verhoef et al. 2009; Grewal 2009; Teixeira et al. 2012; Lemon & Verhoef 2016). Experiential marketing aims to provide the desired experience for customers via goods or services based on SEMs (strategic experiential modules), which are constructed around the five aspects of sense, feel, think, relate, and act (Schmitt 1999, p.60-63). To create a better marketing experience, Schmitt (1990) explained the importance of utilizing ExPros (experience providers) that included variables of *communications, visual and verbal identity and signage, product presence, co-branding, spatial environments, electronic media, and people*. Measurement scales have been developed by several researchers (Bustamante & Rubio 2017; Pelleiter & Collier 2018; Bleier et al. 2019; Nikhashemi et al. 2019) to evaluate customer experience. Although measurement scales are useful to understanding customer experience, this study focuses on online reviews obtained from websites and social network services, such as Amazon, Trip Adviser, Facebook, and Twitter.

Word-of-mouth (WOM) marketing is a powerful and important tool for diffusing information about new products, sales, and marketing campaigns (Trusov et al. 2009, Kozinets et al. 2010). However, online customer reviews (OCR) contain information related to customer experience when they consume products and receive services (Chen & Xie 2008). To utilize this kind of free-form textual information, several topic models based on latent dirichlet allocation (LDA) have been proposed for marketing areas (Tirunillai & Tellis 2014, Büschken & Allenby 2016). Deep-learning neural networks for natural language process are also popular (Collobert et al. 2010). Most studies for review data have focused on the relationships among words and terms, such that they adapt morphological analyses to divide text into effective words. They then convert text into high dimensional word data, and machine-learning methods are often used to analyze them. In contrast, many machine-learning methods have performed complicated model estimations known as “black box” (Larasati et al. 2011). It is important to obtain reasonable interpretations from these techniques in social science.

The purpose of this study is to utilize the advantages of machine learning for online review data and to discuss the marketing interpretations of the results. We develop a marketing model for forecasting overall satisfaction using the Rakuten travel dataset (Rakuten, Inc. 2016). For predictors, words in text and attribute ratings are used to measure customer experience and attribute performance, respectively. Additionally, the proposed model adopts the interaction of words, because they represent customer experiences, including perceptions and feelings during travel. It is also important to specify the nonlinear relationship between attribute performance and overall satisfaction (Finn 2011, Falk et al. 2010, Lin et al. 2010, Cheung & Lee 2009, Gómez et al. 2004, Matzler et al. 2004, Anderson & Mittal 2000, Mittal et al. 1998, Brandt 1988).

2. Related Literature

This section reviews two marketing research areas to introduce the role of customer experience in marketing and consumer behavior. The first area includes customer experience studies, which conduct developing measurement scales and testing consumer behavior models. The second area includes online review studies that adopt review data for marketing models.

2.1. Measurement Scales and Models for Customer Experience

Many researchers have measured customer experiences and have investigated its impact on consumer behaviors. Table 1 summarizes representative studies in several areas, where researchers conceptualized customer experience in various unique scopes. Those studies commonly focus on customer feelings, emotions, perceptions, or mental states during their experiences.

Novak et al. (2000) discussed online experiences before Scimitt (1999) conceptualized experiential marketing. Subsequently, the other researchers developed measurement scales based on experience types. To define brand experiences, Brakus et al. (2009) extended three basic experience types: product, shopping and service, and consumption (Hoch 2002, Hui & Bateson 1991, Krein et al. 1992, Holbrook

& Hirschman 1982). For measurements, they defined brand experiences as subjective, internal consumer responses, and behavioral responses. Although they specified four constructs (i.e., sensory, affective, behavioral, and intellectual), Bustamante and Rubio (2017) improved the work of Brakus et al. (2009) by measuring social constructs.

Table 1: Customer experience studies

| Author (year) | Type of CX | Constructs |
|-----------------------------|------------------------------|---|
| Novak et al. (2000) | Online Experience | Flow, Arousal, Challenge, Control, Focused Attention, Interactivity, Speed, Involvement, Importance, Skill, Telepresence, Time Distortion |
| Brakus et al. (2009) | Brand Experience | Sensory, Affective, Behavioral, Intellectual |
| Klaus & Maklan (2012; 2013) | Service Experience | Product experience, Outcome focus, Moments-of-truth, Peace-of-mind |
| Khan & Rahman (2016) | Retail Brand Experience | Brand name influence, Customer billing, order & application forms, Mass media impression, Point-of-sales assistance, Recommendation by a salesperson, Emotional event experience, Brand stories connectedness |
| Bustamante & Rubio (2017) | In-Store Customer Experience | Cognitive, Affective, Physical, Interaction with customers, Interaction with employees, Social |
| Pelletier & Collier (2018) | Experiential Purchases | Fun, Escapism, Servicescape quality, Social congruence, Uniqueness |

For consumer behavior models, many researchers have investigated the relationship between customer experience and satisfaction and loyalty, proposing two different approaches (Bustamante & Rubio 2017). Klaus and Mklan (2012; 2013) examined service experience quality using a formative model and estimated indirect effects of sub-experiential dimensions on satisfaction. Brakus et al. (2009) and Khan and Rahman (2016) assumed direct effect of an essential component of sub-experiential dimensions using a reflective model. Although these methods differed, both approaches leveraged customer experience to derive satisfaction directly or indirectly.

In addition to service experience quality, Klaus and Mklan (2012; 2013) explained the differences of perceived service quality as an overall judgment for excellence or superiority (Parasuraman et al. 1988). They defined customer experience as “a customer’s cognitive and affective assessment of all direct and indirect encounters with a firm relating to their purchasing behavior, triggering an experiential quality” (Klaus & Mklan 2013, p.228; Klaus & Mklan 2012, p.10). Hence, measuring service experience and quality should be distinguished from the measurement scales of perceived service quality (Parasuraman et al. 1985; 1988, Cronin & Tayler 1982) or customers’ evaluation of specific services.

Following Klaus and Mklan (2012; 2013), we specify that customer experience and quality are different measurements from attribute ratings, and they are predictors of overall satisfaction. Additionally, the attribute rating score is used to measure attribute performance, and it is an essential factor of overall satisfaction (Arbore & Busacca 2009, Matzler et al. 2004, Mittal & Kamakura 2001, Mittal et al. 1998, Brandt 1988). Hence, we assume that customer experience can be measured from review texts as cognitive and affective statements of customer experiences, and that attribute ratings for specific services take the place of attribute performances. Figure 1 shows the proposed conceptualized model.

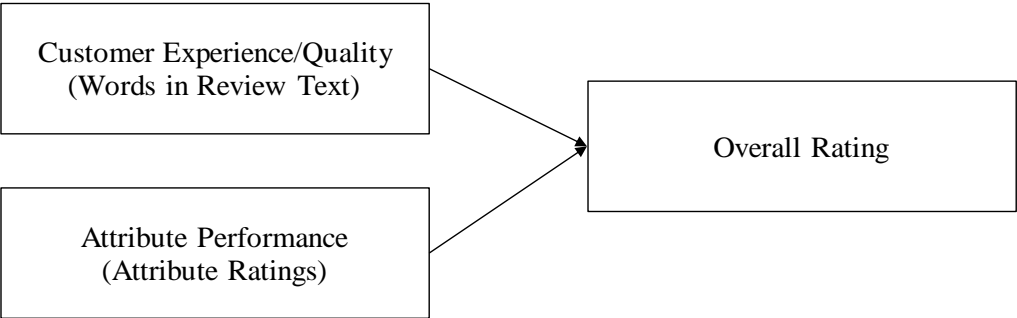


Figure 1: Conceptualized Model

2.2. Measurements of Online Reviews

Table 2 summarizes several studies that investigated the influence of online reviews as marketing variables. Three variables of *valance*, *volume*, and *variance* were used to adopt online review data for marketing models (Kostyra et al. 2016, p.12-13). Chintagunta et al. (2010) investigated the impact of online user reviews on box-office performance using valance, volume, and variance as averages, numbers, and variances, respectively, for movie ratings. They found significant effects of valance; however, they also indicated that volume and variance were not effective predictors. Marchand et al. (2016) measured valance and volume from Twitter WOMs as a microblog and Amazon reviews as an OCR website for video games. They found that OCRs had long-term effects on sales, whereas microblog WOMs were effective during pre-release periods.

Table 2: WOM and OCR studies

| Author (year) | Data Category | Type of WOM Variable | Objective Variable | Method/Model |
|---------------------------|--|--|---|--|
| Chintagunta et al. (2010) | Movie (Yahoo! Movies website) | Valance/Volume/Variance | Total opening earnings | Multiple Regression estimated by GMM (generalized method of moments) |
| Gopinath et al. (2014) | Cell Phone (Howard Forums) | Categorized by Attribute/Emotion/Recommendation with Score (-2~+2 for negative to positive contents) | Sales | DHLM (dynamic hierarchical linear modeling) |
| Ma et al. (2015) | Company in Fortune 500 (Twitter) | Categorized (Compliments/Neutral/Complaints) | Voicing Decision (positive/neutral/negative/no voicing) | HMM (hidden-Markov mode) |
| Kostyra et al. (2016) | eBook Reader (not real data) | Categorized by Valance/Volume/Variance | Choice Probability | Laboratory Experiment and Conjoint Analysis by MMNLM (mixed multinomial logit model) |
| Marchand et al. (2017) | Video Game (Twitter/Amazon) | Valance/Volume | Sales | OLS & 3SLS (three-stage least squares regression) |
| Wang & Chaudhry (2018) | Hotel (TripAdvisor/ Expedia/ Hotels.com/ Orbitz) | Categorized by Negative/Positive | Rating | DID (deference in differences) |

Some studies measured online reviews as a categorical variable. Ma et al. (2014) and Wang and Chaudhry (2018) labeled WOMs as positive, negative, or neutral, based on the rating (e.g., less than 4-star = negative) or WOM contents. They investigated the influence of manager responses (MR), defined

as the act of managers publicly replying to online reviews (Wang & Chaudhry 2018, p.163). Ma et al. (2014) indicated that MRs sometimes created negative effects. Additionally, Wang and Chaudhry (2018) recommended managing negative reviews rather than positive ones, because they found that MRs to positive reviews had negative impacts on later ratings. Kostyra et al. (2016), on the other hand, performed a conjoint experiment to analyze choice probability for eBook readers using categorized averages of ratings (valence), number of reviews (volume), and variance of ratings (variance). Their results indicated that valence and volume had positive effects on the choice probability and willingness-to-pay. Additionally, large level variance had a negative effect. They also found the OCRs decreased the effect of product attributes (e.g., brand, price, and technical features) by comparing two groups: review-provided and other.

Apart from the three measurements and categorizing methods, Gopinath et al. (2014) introduced scoring for WOM contents. They graded WOMs on a scale of -2 to 2 points, based on three aspects: *attribute*, *emotion*, and *recommendation*, following the texts. They found significant effects of these predictors with cell-phone sales. Their results also indicated the importance of paying attention to contents and not just focusing on WOM volume.

2.3. Customer Experience and Online Review Measures

We reviewed the methods of treating online reviews as marketing variables in a previous section, finding three issues in the preset methods. First, volume and variance were not effective in some cases (Chintagunta et al. 2010). Second, many researchers did not consider the detailed contents of online reviews (Gopinath et al. 2014), although, some researchers categorized texts by positive and negative content (Ma et. 2014; Wang & Chaudhry 2018). Third, there were no exact methods used to judge the text contents and words. It is sometimes inconvenient to check all words without using effective guidelines. However, many researchers showed interest in the impact of online reviews and developing better methods to measure them.

In contrast, our research measures customer experience using online reviews. On the other hand, perceived attribute performance is measured using attribute ratings, assuming that the text information in online reviews and their ratings represent a different construct. One possible problem is that the WOM behaviors are driven by customer satisfaction (Klaus & Maklan 2012; 2013). However, the customer describes an event at a point in time when perceptions of their experiences are fresh. Concretely, we prepare two example reviews, as follows:

- i. “I was very satisfied, because the dinner was delicious, and I also like the buffet breakfast. Additionally, the staff was very kind to me.”
- ii. “Bad services” (lowest rating).

These reviews mainly indicate descriptions of experiences, sometimes including a reason. Izogo and Jayawardhena (2018) investigated Facebook WOMs using Netnography, a qualitative research methodology, to study cultures and communities emerging through computer-mediated communications (Kozinets 2002). They indicated that several constructs related to customer experience could be conjectured from WOM sentence expressions. Therefore, we use word information directly from reviews to measure customer experience. Although Sridhar and Srinivasan (2012) adapted a similar method and model as our concept, our study investigates the effects of word frequency on overall ratings and compares them with the effects of each attribute rating.

3. Methods and Model

3.1. Basic Procedure

Our research procedure is as follows:

- i. Make a frequent-term text matrix based on morphological analysis.
- ii. Compare several neural-network models.
- iii. Visualize and estimate the marginal effects of each predictor.

We first adapt morphological analysis to divide text samples into words and count the frequencies of each. Second, we propose interpretable neural-network models and compare their accuracy using training and testing datasets. Finally, we use a partial dependence plot (PDP) (Hastie et al. 2009) to investigate marginal effects and to discuss marketing implications.

3.2. Neural Network as Mental Processing

This section introduces the basic feed-forward neural-network model and its use as a measurement model for mental processing. Figure 2 indicates the neural network as a regression model.

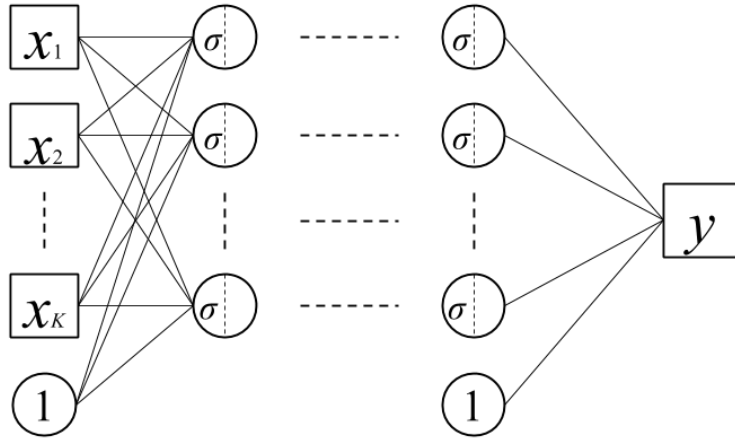


Figure 2: Feed-forward neural-network model

Let $l = 1, \dots, L$ represent the number of layers. The top layer ($l = L$) in the network is express as

$$y_i = f(\mathbf{x}_i; \boldsymbol{\theta}) = \boldsymbol{\beta}^{(L)'} \mathbf{z}_i^{(L-1)} + c^{(L)}, \quad (1)$$

where i is the discrete individual, y_i is the objective variable (output), $\boldsymbol{\beta}^{(L)}$ is the vector of regression coefficients (weight parameters), \mathbf{z}_i is the vector of latent variables, and $c^{(L)}$ is the constant term (bias parameter). $\boldsymbol{\beta}^{(L)}$ and $\mathbf{z}_i^{(L-1)}$ are thus given by

$$\boldsymbol{\beta}^{(L)'} = [\beta_1^{(L)}, \beta_2^{(L)}, \beta_3^{(L)}, \dots, \beta_p^{(L)}], \quad (2)$$

$$\begin{aligned} \mathbf{z}_i^{(L-1)'} &= \left[z_1^{(L-1)}, z_2^{(L-1)}, z_3^{(L-1)}, \dots, z_p^{(L-1)} \right]_i \\ &= \left[g(u_1^{(L-1)}), g(u_2^{(L-1)}), g(u_3^{(L-1)}), \dots, g(u_p^{(L-1)}) \right]_i, \end{aligned} \quad (3)$$

where g is an activation function (e.g., sigmoid), and $u_j^{(L-1)}$ ($j = 1, \dots, p$) is given by

$$\begin{bmatrix} u_1^{(L-1)} \\ u_2^{(L-1)} \\ u_3^{(L-1)} \\ \vdots \\ u_p^{(L-1)} \end{bmatrix}_i = \begin{bmatrix} b_{1,1}^{(L-1)} & b_{1,2}^{(L-1)} & b_{1,3}^{(L-1)} & \dots & b_{1,q}^{(L-1)} \\ b_{2,1}^{(L-1)} & b_{2,2}^{(L-1)} & b_{2,3}^{(L-1)} & \dots & b_{2,q}^{(L-1)} \\ b_{3,1}^{(L-1)} & b_{3,2}^{(L-1)} & b_{3,3}^{(L-1)} & \dots & b_{3,q}^{(L-1)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ b_{p,1}^{(L-1)} & b_{p,2}^{(L-1)} & b_{p,3}^{(L-1)} & \dots & b_{p,q}^{(L-1)} \end{bmatrix} \begin{bmatrix} z_1^{(L-2)} \\ z_2^{(L-2)} \\ z_3^{(L-2)} \\ \vdots \\ z_q^{(L-2)} \end{bmatrix}_i + \begin{bmatrix} c_1^{(L-1)} \\ c_2^{(L-1)} \\ c_3^{(L-1)} \\ \vdots \\ c_p^{(L-1)} \end{bmatrix}. \quad (4)$$

Hence, $u_j^{(L-1)}$ is a latent variable (unit) formed by former latent variables transformed using the activation function. Rewriting Eq. (4), we obtain a simple expression,

$$U_i^{(L-1)} = \mathbf{B}^{(L-1)} \mathbf{z}_i^{(L-2)} + \mathbf{c}^{(L-1)}. \quad (5)$$

In the lowest latent layer ($l = 0$), similarly, we obtain the following equations,

$$\begin{bmatrix} u_1^{(1)} \\ u_2^{(1)} \\ u_3^{(1)} \\ \vdots \\ u_p^{(1)} \end{bmatrix}_i = \begin{bmatrix} b_{1,1}^{(1)} & b_{1,2}^{(1)} & b_{1,3}^{(1)} & \dots & b_{1,q}^{(1)} \\ b_{2,1}^{(1)} & b_{2,2}^{(1)} & b_{2,3}^{(1)} & \dots & b_{2,q}^{(1)} \\ b_{3,1}^{(1)} & b_{3,2}^{(1)} & b_{3,3}^{(1)} & \dots & b_{3,q}^{(1)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ b_{p,1}^{(1)} & b_{p,2}^{(1)} & b_{p,3}^{(1)} & \dots & b_{p,q}^{(1)} \end{bmatrix} \begin{bmatrix} x_1^{(0)} \\ x_2^{(0)} \\ x_3^{(0)} \\ \vdots \\ x_q^{(0)} \end{bmatrix}_i + \begin{bmatrix} c_1^{(1)} \\ c_2^{(1)} \\ c_3^{(1)} \\ \vdots \\ c_p^{(1)} \end{bmatrix}. \quad (6)$$

Then,

$$U_i^{(1)} = \mathbf{B}^{(1)} \mathbf{x}_i^{(0)} + \mathbf{c}^{(1)}. \quad (7)$$

where \mathbf{x}_i is a vector of observable predictors (inputs). Eq. (7) indicates a formative model specification. Therefore, the neural network can be regarded as a type of measurement model in consumer behavior research if we predict some assessments or scores for the psychological constructs of related predictors.

3.3. Skip-Layer Neural Network

Several related networks are used for machine learning. Skip-layer networks (SLNet) and residual learning networks (ResNet) are modeled as follows:

$$f(\mathbf{x}_i; \boldsymbol{\theta}) = \underbrace{\mathbf{x}_{1,i} \boldsymbol{\beta}_1}_{(1) \text{ Skip-Layer}} + \underbrace{NN(\mathbf{x}_i; \boldsymbol{\theta})}_{(2) \text{ Fully connected network}}, \quad (8)$$

$$f(\mathbf{x}_i; \boldsymbol{\theta}) = \underbrace{\mathbf{x}_i \mathbf{I}}_{(1) \text{ Make residual between input and output}} + \underbrace{NN(\mathbf{x}_i; \boldsymbol{\theta})}_{(2) \text{ Fully connected network}}, \quad (9)$$

where \mathbf{I} is a vector whose elements are all ones. ResNet (Eq. 9) is a helpful network used for learning deep neural networks (He et al. 2016). The network of the second term learns the residuals between the objective and predictive variables ($y_i - \mathbf{x}_i \mathbf{I}$). The important difference of these two models and the next three semiparametric models is that the second term contains all predictors. Hence, these two models offer more complicated interpretations.

3.4. Semiparametric Neural Network

The essential problem of neural networks is their interpretability. Generally, network parameters cannot be identified, although the neural network provides better functional approximations. This is known as weight–space symmetry (Bishop 2006), indicating that it is nearly impossible to find unique solutions for parameters. However, Crane–Droesch (2017; 2018) focused on the approximation properties of feed-forward networks and proposed a semiparametric neural network. Let f be a regression function; let NN be a function specified by a fully connected network containing latent variables; let \mathbf{x}_i be the predictor (input) matrix; and let $\boldsymbol{\theta}$ be all parameters containing constant terms and regression coefficients. Crane–Droesch (2017; 2018)’s model (Figure 3) is thus given by

$$f(\mathbf{x}_i; \boldsymbol{\theta}) = \underbrace{\mathbf{x}_{1,i} \boldsymbol{\beta}_1}_{(1) \text{ Specified with linear parameters}} + \underbrace{NN(\mathbf{x}_{2,i}; \boldsymbol{\theta}_2)}_{(2) \text{ Fully connected network except } X_1}, \quad (10)$$

where $\mathbf{x}_{1,i}$ and $\mathbf{x}_{2,i}$ are sub-vectors of \mathbf{x}_i , and $\boldsymbol{\beta}_1$ and $\boldsymbol{\theta}_2 = \boldsymbol{\theta} \setminus \boldsymbol{\beta}_1$ are parameters corresponding to $\mathbf{x}_{1,i}$ and $\mathbf{x}_{2,i}$, respectively. This is similar specification using a partially linear regression model (Robinson 1988); hence, we call this model as partially linear network (PLNet). Crane–Droesch (2017) investigated the estimates for $\boldsymbol{\beta}_1$ using a Monte Carlo simulation, showing its unbiasedness and consistency. Note that the linear part does not contain an intercept, because it cannot be identified separately from the nonlinear function, NN , similar to the partially linear model (Klemelä 2014).

Additionally, Crane–Droesch (2017; 2018) adopted this model for panel data analysis and indicated its better prediction compared with ordinal fixed effect models, lasso regression, random forest, and fully connected neural networks.

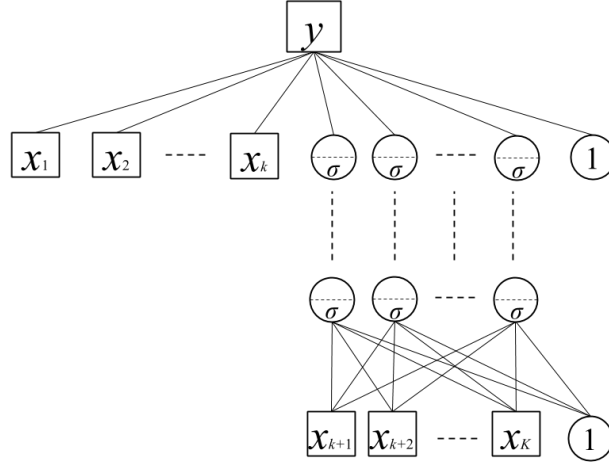


Figure 3: PLNet

In our research, we extend PLNet to a nonlinearity of part or all of $\mathbf{x}_{1,i}$ and propose an additive model learning network (AMNet) (Figure 4), as follows:

$$f(\mathbf{x}_i; \{\boldsymbol{\theta}_d\}) = \sum_{d=1}^K NN_d(\{x_{d,i}, x_{d,i}^2, \dots, x_{d,i}^M\}; \boldsymbol{\theta}_d), \quad (11)$$

where $d = 1, \dots, K$ represents the number of predictors; $m = 1, \dots, M$ is the degree of the polynomial; and NN_d is an independent network of predictor d . This model learns the independent networks constructed by a single predictor with polynomial transformation and approximates the objective variable using the sum of the independent nonlinear function, NN_d . Thus, AMNet is a kind of additive model (Hastie & Tibshirani 1986). In practice, it is possible to combine AMNet, PLNet, and fully connected networks using independent predictors. Similar to the additive model, only one NN_d contains the intercept, but another NN_d does not.

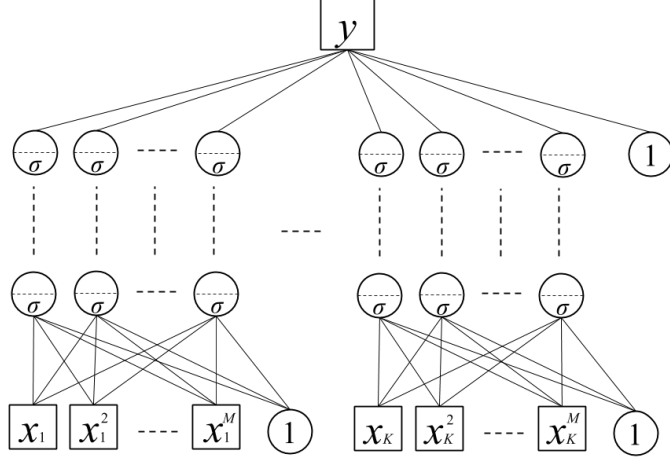


Figure 4: AMNet

If we know the relationship of some predictors from existing knowledge or theories, AMNet can be extended as follows:

$$f(\mathbf{x}_i; \{\boldsymbol{\theta}_g\}) = \sum_{g=1}^G NN_g \left(\left\{ \mathbf{x}_{1,i}^{(g)}, \mathbf{x}_{2,i}^{(g)}, \dots, \mathbf{x}_{k(g),i}^{(g)} \right\}; \boldsymbol{\theta}_g \right), \quad (12)$$

where $g = 1, \dots, G$ is the number of independent predictor groups. For our setting, the review texts and attribute ratings represent a different construct. Thus, this model learns two networks constructed separately of words and rating scores (see Figure 5). This becomes a grouped AMNet (G-AMNet). Finally, Table 3 summarizes those models and their interpretability.

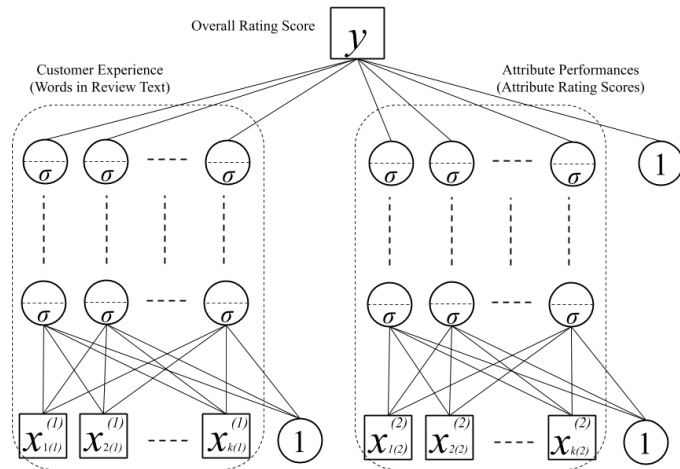


Figure 5: G-AMNet

Table 3: Neural Networks and Interpretability

| Model | References | Interpretability | |
|---|--|------------------|---|
| | | parameter | function |
| Skip-Layer Network (SLNet) | Velten (2009), Venables & Ripley (2002) | impossible | complicated |
| Residual Learning Network (ResNet) | He et al. (2016) | impossible | complicated |
| Partially Linear Neural Network (PLNet) | Crane-Droesch (2017; 2018) | partially | partially linear |
| Additive Model Learning Network (AMNet) | This study | partially | partially linear partially nonlinear |

3.5. Partial Dependence Function and Marginal Effect

The previous section introduced a few interpretable neural networks. However, it is still necessary to investigate the complicated multivariate function or fully connected network in cases such as G-AMNet. Estimating a partial dependence function is useful to solving this problem. The partial dependence function and PDP have been discussed to visualize the results given by some machine-learning methods (e.g., decision trees, random forests, and boosted regression) (Becker et al. 1996; Friedman 2001; Hasite et al. 2009; Greenwell 2017). Klemalä (2014) also discussed PDP in line with nonparametric regressions (Klemalä 2014, p.298-299).

Let $\mathbf{x} = (x_1, \dots, x_d)$ represent the predictors of a regression model whose prediction is $f(\mathbf{x})$. If we divide \mathbf{x} into an interest set, z_S , and its compliment, $z_C = \mathbf{x} \setminus z_S$, then the ‘‘partial dependence’’ of the response on z_S is defined as

$$f_S(z_S) = E\{f(z_S, z_C)\} = \int f(z_S, z_C) p_C(z_C) dz_C, \quad (13)$$

where $p_C(z_C)$ is the marginal probability of z_C : $p_C(z_C) = \int p(\mathbf{x}) dz_S$. Eq. (14) can be estimated from a set training data by

$$\hat{f}_S(z_S) = \frac{1}{n} \sum_{i=1}^n \hat{f}(z_S, z_{i,C}), \quad (14)$$

where $z_{i,C}$ ($i = 1, 2, \dots, n$) are the values of z_C occurring in the training sample. Thus, it averages over the effects of all the other predictors in the model.

To estimate the marginal effect, let $z_{i,z}$ ($i = 1, 2, \dots, n$) denote the estimates ordered points at which the regression function is evaluated. Applying a finite-difference estimate of the derivative to $\hat{f}_S(z_S)$, we obtain

$$\frac{d\hat{f}_S(z_{i,S})}{dz_{i,S}} = \frac{\hat{f}_S(z_{i,S}) - \hat{f}_S(z_{i-1,S})}{z_{i,S} - z_{i-1,S}}. \quad (15)$$

Because it is inconvenient to calculate the derivative from the neural network, we simply estimate the marginal effect from the above equation, like in cases of some nonparametric regressions (Cameron & Trivedi 2005). The partial dependence function indicates an averaged $f(\mathbf{x})$ with respect to z_C at any data points of z_S . Thus, Eq. (15) indicates an averaged change of $f(\mathbf{x})$ when z_S is changed. For example, assuming a simple linear regression, $f(\mathbf{x}) = a + b_1x_1 + b_2x_2 + \dots + b_dx_d$, we obtain $f_S(\mathbf{x}) = a + b_dx_d$ and $df_S(\mathbf{x})/dx_d = b_d$ for $z_S = x_d$. In this case, the marginal effect of Eq. (15) is the same as the analytical solution. Assuming $f(\mathbf{x}) = a + g_1(x_1) + g_2(x_2) + \dots + g_d(x_d)$, which is a simple expression of AMNet, we obtain $f_S(\mathbf{x}) = a + g_d(x_d)$ for $z_S = x_d$, and the marginal effect can be calculated with Eq. (15). Hence, PLNet and AMNet provide a more amenable interpretation compared to the fully connected network.

4. Empirical Applications

4.1. Data Description

The data were provided by Rakuten, Inc. and contains customer reviews and ratings about accommodations in Japan, posted from January 1997 to November 2015 (Rakuten, Inc. 2016). We randomly selected 100,000 samples from the latest 2015 data, because the total sample (over 5 million) was too large. Additionally, we deleted samples missing values and lacking reviews. We finally used 80,000 samples for training data, and the remaining 16,761 were used for test data.

In morphological analysis, we selected the words based on parts-of-speech tags and truncating words whose total frequency was less than 100 to remove unusual words. Outliers (e.g., “am,” “is,” “are,” “do,” or “does”) were also deleted. As a result, a total of 684 words were gathered, including 112 adjectives, 113 adverbs, and 459 verbs. Their frequencies were used to measure customer experience.

For attribute performance, the six variables of attribute rating scores (5 scales) were *Location*, *Room*, *Meal*, *Bathroom* (or *Hot spring*), *Service*, and *Facility and Amenity* (F&A). However, *Meal*, *Bathroom*, and *F&A* scales contain 0 for the guests who did not use those services or for hotels not providing such services. We then make dummy variables (e.g., *no_Meal*, *no_Bathroom*, and *no_F&A*) that take 1 when the ratings of *Meal*, *bathroom*, or *F&A* take 0, respectively. Additionally, because of these dummy variables, *Meal*, *Bathroom*, and *F&A* contain a coefficient dummy variable that takes 1 when *no_Meal*, *no_Bathroom*, and *no_F&A* are 0, respectively, and take 1 otherwise.

For the other predictors, purpose (*Business*, *Leisure*, and *other*) and companion (*Alone*, *Family*, *Colleague*, *Couple*, and *other*) dummy variables are available. Additionally, we extracted the room type from *room names* in the dataset and created a Japanese-styled room dummy variable (*J_room*), which takes 1 for Japanese-styled rooms. Similarly, month dummies were created using character strings of *posted dates* in the dataset. Table 4 displays our arranged dataset.

Table 4: Dataset arrangement

| | Word1 | Word2 | ... | Word684 | Location | Room | Meal | Bathroom | Service | A & F | Business | Leisure |
|-------|-------|-------|-----|---------|----------|------|------|----------|---------|-------|----------|---------|
| User1 | 0 | 0 | | 0 | 4 | 3 | 0 | 3 | 3 | 3 | 0 | 1 |
| User2 | 1 | 0 | | 0 | 4 | 3 | 3 | 2 | 3 | 3 | 1 | 0 |
| User3 | 0 | 2 | | 0 | 4 | 5 | 4 | 4 | 5 | 4 | 0 | 1 |
| User4 | 0 | 0 | | 0 | 5 | 4 | 5 | 4 | 4 | 4 | 0 | 1 |
| User5 | 0 | 1 | | 0 | 5 | 3 | 0 | 3 | 3 | 3 | 0 | 0 |
| User6 | 0 | 0 | | 1 | 5 | 4 | 5 | 4 | 5 | 5 | 0 | 1 |
| ⋮ | ⋮ | ⋮ | | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| ⋮ | ⋮ | ⋮ | | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |

| | Alone | Family | Colleague | Friend | Couple | no_Meal | no_Bath | no_A & F | J_room | Jan | Feb | ... | Oct | Overall(Y) |
|-----|-------|--------|-----------|--------|--------|---------|---------|----------|--------|-----|-----|-----|-----|------------|
| | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | | 0 | 4 |
| | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | | 0 | 3 |
| ... | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | | 0 | 4 |
| | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | | 0 | 5 |
| | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | | 0 | 4 |
| | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | | 0 | 5 |
| | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | | ⋮ | ⋮ |
| | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | | ⋮ | ⋮ |

4.2. Comparative Models and Optimization

We compared the following five models using ordinal linear regression without the words.

$$f_{FCNet} = NN(\text{Words}_{(684)}, \text{Attributes}_{(6)}, \text{DummyVariables}_{(21)}), \quad (16)$$

$$f_{PLNet} = NN(\text{Words}_{(684)}) + \text{Attributes}_{(6)} \boldsymbol{\beta}_1 + \text{DummyVariables}_{(21)} \boldsymbol{\beta}_2, \quad (17)$$

$$\begin{aligned} f_{P-PLNet} &= NN(\text{Words}_{(684)}) \\ &+ \sum_{k=1}^6 \text{Attribute}_k \beta_{1,1}^{(k)} + \text{Attribute}_k^2 \beta_{1,2}^{(k)} + \dots + \text{Attribute}_k^9 \beta_{1,9}^{(k)} \\ &+ \text{DummyVariables}_{(21)} \boldsymbol{\beta}_2, \end{aligned} \quad (18)$$

$$\begin{aligned} f_{I-AMNet} &= NN_0(\text{Words}_{(684)}) \\ &+ \sum_{k=1}^6 NN_k(\text{Attribute}_k, \text{Attribute}_k^2, \dots, \text{Attribute}_k^7) \\ &+ \text{DummyVariables}_{(21)} \boldsymbol{\beta}_2 \end{aligned} \quad (19)$$

$$\begin{aligned} f_{G-AMNet} &= NN_0(\text{Words}_{(684)}) + NN_1(\text{Attributes}_{(6)}) \\ &+ \text{DummyVariables}_{(21)} \boldsymbol{\beta}_2. \end{aligned} \quad (20)$$

$$f_{G-AMNet0} = NN_1(\text{Attributes}_{(6)}) + \text{DummyVariables}_{(21)} \boldsymbol{\beta}_2. \quad (21)$$

For simplicity, we note *purpose*, *companion*, *no meal*, *no bathroom*, *no F&A*, *J_room*, and *month* as dummy variables in the above models. FCNet is a standard feed-forward network, and PLNet sets linear parameters for attribute ratings and dummy variables. P-PLNet contains ninth-degree polynomial terms for each attribute rating, whereas the independent AMNet (I-AMNet) has six networks constructed by seventh-degree polynomial variables for each attribute rating with the word network. Grouped AMNet (G-AMNet) specifies the two networks as customer experience and attribute performance, constructed with words and attribute ratings, respectively. G-AMNet0 is set without the word network to check the importance of words as predictors.

The neural network optimization method uses Adam (Kingma & Ba 2015), and all of the necessary pre-parameter settings follow the default values from the original paper (see Appendix II for a detailed algorithm). This method achieves faster convergence of optimization by adjusting the learning rate with the first and second moments of the gradients. To tune the units, we changed their number from 1 to 10,

and from 10 to 100 by 10s. Then, we chose the unit number for minimum mean squared error (MSE), comparing the MSEs of training and test datasets among the different numbers of units. After unit tuning, we added the latent layer and tuned the unit again. We repeated this process until the MSE stopped improving. Using PLNet, we fixed the units and layers of the word network for the other models. We changed the degree of the polynomial for each attribute rating from 2 to 15 jointly and compared the MSEs. Although each predictor was normalized by dividing each maximum value for efficient learning, we reported the results based on non-normalized parameter estimates. Table 11 in Appendix I summarizes the details of each final network.

4.3. Model and Coefficient Comparison

Table 5 reports the training and test MSEs for each model, showing that G-AMNet achieves the lowest MSE, although, FCNet also shows better prediction when training MSE. Additionally, I-AMNet shows a slightly better prediction capability than P-AMNet.

Table 6 reports the estimates of linear parameters in each model. Note that the blanks in Table 6 indicate the parameter that cannot be identified from the nonlinear part. However, there is a large difference in the estimates for the coefficients of “companion” (i.e., alone, family, colleague, couple). Therefore, we investigate the estimates of G-AMNet to check validity. We repeated the estimation 50 times using different initial values generated from the standard normal distribution and evaluated the series of estimates via mean and standard deviation. The results of the validation for G-AMNet are shown in the G-AMNet (V) column of each Table. From Table 5, G-AMNet provides stable forecasting; however, we found that the estimates for the coefficients of companion depend on the initial values in Table 6.

Table 5: MSE

| Model | LR | FCNet | PLNet | P-PLNet | I-AMNet | G-AMNet0 | G-AMNet | G-AMNet (V) |
|----------|---------|---------|---------|---------|---------|----------|---------|-----------------|
| Training | 0.24730 | 0.20327 | 0.22452 | 0.21942 | 0.21579 | 0.21451 | 0.20321 | 0.20188 (0.001) |
| Test | 0.24367 | 0.22260 | 0.22794 | 0.22063 | 0.21785 | 0.21136 | 0.20704 | 0.20655 (0.001) |

Table 6: Coefficient Estimates

| | PLNet | P-PLNet | I-AMNet | G-AMNet0 | G-AMNet | G-AMNet (V) | Without Words | | | |
|-------------|--------|---------|---------|----------|---------|----------------|--------------------|--------|--------|--------|
| Intersept | | | | | | | -0.166 (0.023) *** | | | |
| Location | 0.116 | | | | | | 0.586 (0.012) *** | | | |
| Room | 0.256 | | | | | | 1.418 (0.012) *** | | | |
| Meal | 0.139 | | | | | | 0.775 (0.012) *** | | | |
| Bathroom | 0.087 | | | | | | 0.445 (0.011) *** | | | |
| Service | 0.269 | | | | | | 1.635 (0.013) *** | | | |
| F & A | 0.095 | | | | | | 0.445 (0.014) *** | | | |
| Business | 0.014 | -0.002 | -0.003 | 0.001 | -0.004 | 0.003 (0.005) | 0.022 (0.009) ** | | | |
| Leisure | 0.024 | 0.011 | 0.010 | 0.006 | 0.004 | 0.011 (0.005) | 0.016 (0.008) * | | | |
| Alone | -0.160 | 0.066 | -0.006 | 0.117 | 0.162 | 0.020 (0.125) | 0.045 (0.020) * | | | |
| Family | -0.177 | 0.054 | -0.016 | 0.099 | 0.145 | 0.004 (0.124) | 0.012 (0.020) | | | |
| Colleague | -0.156 | 0.078 | 0.006 | 0.131 | 0.177 | 0.031 (0.126) | 0.056 (0.022) ** | | | |
| Friend | -0.144 | 0.090 | 0.023 | 0.143 | 0.183 | 0.043 (0.125) | 0.054 (0.021) ** | | | |
| Couple | -0.165 | 0.074 | 0.002 | 0.125 | 0.167 | 0.024 (0.125) | 0.027 (0.021) | | | |
| no_Meal | 0.525 | 0.910 | 0.684 | | | | 0.588 (0.010) *** | | | |
| no_Bathroom | 0.284 | 0.766 | 0.485 | | | | 0.290 (0.012) *** | | | |
| no_F & A | 0.148 | 0.034 | 0.396 | | | | 0.075 (0.021) *** | | | |
| J_room | -0.007 | -0.003 | 0.000 | -0.008 | -0.011 | -0.011 (0.001) | -0.011 (0.005) * | | | |
| Jan | 0.010 | 0.015 | 0.014 | 0.009 | 0.012 | 0.012 (0.001) | 0.002 (0.009) | | | |
| Feb | 0.014 | 0.022 | 0.018 | 0.016 | 0.020 | 0.020 (0.002) | 0.010 (0.009) | | | |
| Mar | 0.005 | 0.010 | 0.010 | 0.010 | 0.012 | 0.011 (0.002) | 0.004 (0.009) | | | |
| Apr | -0.006 | 0.002 | -0.001 | 0.002 | 0.004 | 0.003 (0.002) | -0.009 (0.009) | | | |
| May | 0.020 | 0.021 | 0.022 | 0.019 | 0.017 | 0.018 (0.002) | 0.024 (0.008) ** | | | |
| Jun | 0.020 | 0.025 | 0.023 | 0.024 | 0.025 | 0.023 (0.002) | 0.027 (0.008) ** | | | |
| Jul | 0.012 | 0.014 | 0.013 | 0.016 | 0.013 | 0.013 (0.002) | 0.019 (0.008) * | | | |
| Aug | 0.009 | 0.011 | 0.009 | 0.008 | 0.009 | 0.009 (0.001) | 0.011 (0.008) | | | |
| Sep | 0.007 | 0.008 | 0.008 | 0.006 | 0.006 | 0.008 (0.001) | 0.007 (0.008) | | | |
| Oct | 0.012 | 0.015 | 0.011 | 0.007 | 0.010 | 0.009 (0.001) | 0.014 (0.008) | | | |
| | | | | | | | R2 | Adj.R2 | RSE | |
| | **** | 0.001 | *** | 0.01 | * | 0.05 | . | 0.7217 | 0.7216 | 0.4974 |

4.4. Partial Dependence Functions and Marginal Effects

Table 7 and Figure 6 in Appendix I report the estimated partial dependence functions and marginal effects for the attribute ratings by G-AMNet (V). Table 7 shows that nearly all estimates are stable, although some (e.g., *Meal*, *no_Meal*, *no_bathroom*, and *no_F&A*) depend on initial values. Hence, we plan to address their instability in future studies.

From the results in Table 7 and Figure 6, we found the nonlinear relationships between attribute ratings and overall rating so that the marginal effects of attribute ratings are not constant. The marginal effect decreases until the rating changes to four points in *Room*, *Meal*, *Bathroom*, and *Service*. It also keeps decreasing in *F&A*, whereas it increases in *Location*. When the rating changes from four to five, the marginal effect increases in the former four attributes (*Room*, *Meal*, *Bathroom*, and *Service*). However, it may not provide large contributions to overall rating.

Table 7: Details of estimated marginal effects

| | Location | Room | Meal | Bathroom | Service | F & A |
|-------------------------------------|---------------|---------------|---------------|---------------|---------------|---------------|
| Partially Dependence Function (PDF) | | | | | | |
| 1 | 3.760 (0.034) | 2.987 (0.051) | 3.620 (0.174) | 3.749 (0.077) | 2.606 (0.045) | 3.665 (0.055) |
| 2 | 3.862 (0.022) | 3.610 (0.031) | 3.886 (0.177) | 3.938 (0.039) | 3.555 (0.042) | 3.882 (0.028) |
| 3 | 3.955 (0.022) | 3.920 (0.023) | 4.074 (0.172) | 4.053 (0.029) | 3.937 (0.023) | 4.026 (0.021) |
| 4 | 4.062 (0.021) | 4.123 (0.021) | 4.223 (0.176) | 4.132 (0.034) | 4.109 (0.022) | 4.120 (0.021) |
| 5 | 4.186 (0.020) | 4.338 (0.022) | 4.395 (0.174) | 4.241 (0.030) | 4.338 (0.022) | 4.210 (0.022) |
| Marginal Effect | | | | | | |
| 1-2 | 0.102 (0.025) | 0.623 (0.036) | 0.266 (0.069) | 0.189 (0.053) | 0.949 (0.040) | 0.217 (0.038) |
| 2-3 | 0.093 (0.007) | 0.310 (0.019) | 0.188 (0.012) | 0.115 (0.015) | 0.381 (0.034) | 0.143 (0.016) |
| 3-4 | 0.106 (0.005) | 0.204 (0.008) | 0.150 (0.011) | 0.079 (0.012) | 0.172 (0.012) | 0.094 (0.008) |
| 4-5 | 0.125 (0.004) | 0.215 (0.007) | 0.172 (0.009) | 0.109 (0.015) | 0.229 (0.010) | 0.090 (0.010) |
| | | | no_Meal | no_Bathroom | | no_F & A |
| Partially Dependence Function (PDF) | | | | | | |
| 0 | | | 3.962 (0.168) | 4.065 (0.028) | | 4.078 (0.020) |
| 1 | | | 4.376 (0.415) | 4.449 (0.448) | | 4.583 (0.109) |
| Marginal Effect | | | | | | |
| 0-1 | | | 0.414 (0.582) | 0.385 (0.466) | | 0.505 (0.110) |

Table 8: Top-50 negative and positive marginal effects when the word frequency changes to one from zero

| Negative | | | | Positive | | | |
|---------------------------|-----------|------------------|-----|------------------|-----------|------------------|-----|
| term | POS | Marginal Effects | max | term | POS | Marginal Effects | max |
| never again | Adverb | -0.505 (0.030) | 2 | utilize/use | Verb | 0.144 (0.023) | 2 |
| unfavorable | Adjective | -0.196 (0.029) | 3 | save | Verb | 0.124 (0.021) | 2 |
| sting | Verb | -0.170 (0.023) | 2 | suitable/exactly | Adverb | 0.120 (0.013) | 2 |
| somehow/manage to | Adverb | -0.142 (0.026) | 2 | elaborate | Verb | 0.111 (0.017) | 1 |
| throw | Verb | -0.142 (0.016) | 3 | not crowded | Verb | 0.108 (0.015) | 2 |
| believe | Verb | -0.135 (0.013) | 2 | rather | Adverb | 0.103 (0.016) | 1 |
| raise/wake | Verb | -0.134 (0.020) | 3 | never | Adverb | 0.097 (0.012) | 2 |
| pay | Verb | -0.131 (0.021) | 3 | really/please | Adverb | 0.096 (0.006) | 2 |
| sink | Verb | -0.127 (0.013) | 2 | completely | Adverb | 0.093 (0.012) | 2 |
| return | Verb | -0.124 (0.017) | 3 | excel | Verb | 0.093 (0.009) | 2 |
| arrive | Verb | -0.124 (0.016) | 2 | smooth/slippy | Adverb | 0.091 (0.011) | 3 |
| noisy | Adjective | -0.124 (0.009) | 3 | apparently | Adverb | 0.090 (0.011) | 2 |
| stand/get | Verb | -0.122 (0.011) | 2 | light | Adjective | 0.085 (0.013) | 2 |
| black | Adjective | -0.120 (0.020) | 2 | simmer | Verb | 0.083 (0.014) | 2 |
| give up | Verb | -0.119 (0.014) | 3 | boil | Verb | 0.080 (0.013) | 3 |
| lower/reduce | Verb | -0.119 (0.013) | 2 | spread | Verb | 0.079 (0.014) | 1 |
| offer | Verb | -0.116 (0.014) | 2 | furthermore | Adverb | 0.077 (0.013) | 2 |
| lukeworm | Adjective | -0.116 (0.010) | 2 | stretch | Verb | 0.077 (0.010) | 3 |
| raise/increase | Verb | -0.113 (0.015) | 2 | mostly | Adverb | 0.077 (0.013) | 2 |
| dry | Verb | -0.112 (0.017) | 2 | so/that much | Adverb | 0.077 (0.010) | 2 |
| pay | Verb | -0.112 (0.018) | 9 | really/please | Adverb | 0.076 (0.004) | 3 |
| peel off | Verb | -0.111 (0.013) | 2 | contrary | Adverb | 0.072 (0.019) | 1 |
| wake | Verb | -0.111 (0.012) | 2 | bring/report | Verb | 0.070 (0.014) | 2 |
| hurry | Verb | -0.110 (0.017) | 3 | forcibly | Adverb | 0.070 (0.007) | 2 |
| make a nise | Verb | -0.109 (0.009) | 2 | get bored/tired | Verb | 0.069 (0.007) | 2 |
| strange/suspicious | Adjective | -0.108 (0.019) | 2 | face/touch | Verb | 0.069 (0.016) | 3 |
| horrible | Adjective | -0.108 (0.013) | 5 | take | Verb | 0.069 (0.014) | 3 |
| be cut off | Verb | -0.107 (0.015) | 2 | narrow/limit | Verb | 0.068 (0.013) | 1 |
| go to/visit | Verb | -0.106 (0.015) | 2 | entirely | Adverb | 0.068 (0.016) | 1 |
| float | Verb | -0.105 (0.016) | 2 | pretty/cute | Adjective | 0.066 (0.010) | 3 |
| somehow/manage to | Adverb | -0.104 (0.013) | 2 | take out | Verb | 0.065 (0.016) | 3 |
| cloud/mist | Verb | -0.102 (0.023) | 2 | please | Adverb | 0.065 (0.004) | 2 |
| build up | Verb | -0.102 (0.022) | 3 | can stary | Verb | 0.065 (0.003) | 3 |
| stop | Verb | -0.101 (0.024) | 1 | always | Adverb | 0.064 (0.007) | 2 |
| divide | Verb | -0.100 (0.008) | 2 | sufficiently | Adverb | 0.063 (0.007) | 2 |
| dirty | Adjective | -0.099 (0.010) | 4 | read | Verb | 0.063 (0.013) | 3 |
| have a shower/bath | Verb | -0.099 (0.016) | 4 | pass | Verb | 0.063 (0.019) | 2 |
| at least | Adverb | -0.098 (0.011) | 2 | stick/keep to | Verb | 0.062 (0.015) | 3 |
| clog up/choke | Verb | -0.097 (0.022) | 2 | sometimes | Adverb | 0.062 (0.009) | 2 |
| probably | Adverb | -0.095 (0.015) | 1 | watch | Verb | 0.061 (0.012) | 5 |
| tell | Verb | -0.095 (0.009) | 5 | shrink | Verb | 0.061 (0.013) | 3 |
| smell bad | Adjective | -0.091 (0.006) | 7 | interesting/fun | Adjective | 0.057 (0.007) | 2 |
| with effort | Adverb | -0.091 (0.007) | 3 | squeeze | Verb | 0.057 (0.011) | 4 |
| serious/heavy | Adjective | -0.090 (0.012) | 3 | relatively | Adverb | 0.056 (0.008) | 2 |
| together/at the same time | Adverb | -0.090 (0.012) | 2 | quick | Adjective | 0.056 (0.014) | 2 |
| connect | Verb | -0.090 (0.017) | 3 | remember | Verb | 0.056 (0.016) | 3 |
| decrease | Verb | -0.087 (0.013) | 2 | equip/have | Verb | 0.055 (0.014) | 2 |
| thin/weak | Adjective | -0.084 (0.006) | 3 | unexpectedly | Adverb | 0.055 (0.008) | 2 |
| fall | Verb | -0.084 (0.012) | 4 | keep | Verb | 0.055 (0.011) | 2 |
| later | Adverb | -0.082 (0.018) | 2 | can get/have | Verb | 0.055 (0.006) | 2 |

Table 8 summarizes the top-50 words ordered by the magnitudes of negative and positive marginal effects when the word frequency increases from zero to one. Figure 7 in Appendix I picks up the two words, “unfavorable” and “light,” which are the top negative and positive words among adjectives, respectively. Additionally, the details of estimates for partial dependence functions and marginal effects are reported in Table 9.

In Table 8, we find the asymmetry effect between negative and positive words, so that the marginal effects of negative words are larger than that of positive words. This result indicates that managing the negative customer reviews is more important. This was a similar conclusion of Wang and Chaudhry (2018). Figure 7 and Table 9 indicate that the positive and negative marginal effects decrease with increasing frequencies of “unfavorable” and “light,” respectively. Note that these marginal effects are estimated based on overall rating. For negative words, a negative effect is estimated, because the word might be used frequently in customer reviews with lower overall ratings. Therefore, some words might appear unreasonable.

Table 9: Illustrations of partial dependence functions and marginal effect for words

| Unfavorable | | | | Light | | | |
|-------------|---------------|-----------------|----------------|-------|---------------|-----------------|---------------|
| | PDF | Marginal Effect | | | PDF | Marginal Effect | |
| 0 | 4.082 (0.020) | | | 0 | 4.082 (0.020) | | |
| 1 | 3.886 (0.036) | 0-1 | -0.196 (0.029) | 1 | 4.167 (0.023) | 0-1 | 0.085 (0.013) |
| 2 | 3.682 (0.064) | 1-2 | -0.205 (0.036) | 2 | 4.223 (0.034) | 1-2 | 0.055 (0.017) |
| 3 | 3.541 (0.084) | 2-3 | -0.141 (0.028) | 3 | 4.257 (0.046) | 2-3 | 0.035 (0.016) |
| 4 | 3.461 (0.094) | 3-4 | -0.081 (0.022) | 4 | 4.279 (0.057) | 3-4 | 0.022 (0.013) |
| 5 | 3.415 (0.100) | 4-5 | -0.045 (0.017) | 5 | 4.293 (0.066) | 4-5 | 0.014 (0.010) |

Comparing the marginal effects of attribute ratings and words, the overall ratings seem to be more affected by attribute service performance. However, we found that word frequency was important when the attribute ratings achieved higher points (3–5). Because we assume the review texts represents a customer experience, managers should pay attention to customer experiences, even if they obtain better

service attribute assessments. Additionally, it is effective to overall customer satisfaction to keep providing better experiences so that the customers willingly write positive reviews. Therefore, it is useful to realize improvement by investigating the review text based on the negative words estimated by G-AMNet.

Finally, we select the most effective two words (i.e., “never again” and “unfavorable”) and illustrate an example for a 2-dimensional partial dependence plot. The results are reported in Table 10 and Figure 8. When the frequency of the phrase, “never again,” changes from zero to one, the marginal effects of “unfavorable” decreases. Similarly, increasing the frequency of “unfavorable,” the marginal effect of “never again” decreases. Focusing on the interaction effect, a “never again” and an “unfavorable” easily promote decreasing overall ratings. However, it needs four “unfavorables” to reduce the overall rating by the same magnitude as without a “never again.” For illustration purposes, compare the color of the heat map and the two line graphs in Figure 8. These 2-dimensional PDPs should help obtaining a proper interpretation for interaction effects.

Table 10: Illustrations of 2-dimensional partial dependence functions and marginal effects

| Partial Dependence Function | | | Marginal Effect | | | | | | | |
|-----------------------------|---------------|---------------|--------------------|---------------------|---|----------------|-------------|-----|----------------|----------------|
| | Never_again | | Never_again 0-1 | Never_again (fixed) | | | | | | |
| | 0 | 1 | | 0 | 1 | | | | | |
| Unfavorable | 0 | 4.084 (0.020) | 3.577 (0.034) | Unfavorable (fixed) | 0 | -0.507 (0.031) | Unfavorable | 0-1 | -0.197 (0.029) | -0.115 (0.039) |
| | 1 | 3.888 (0.036) | 3.463 (0.046) | | 1 | -0.425 (0.036) | | 1-2 | -0.205 (0.036) | -0.060 (0.028) |
| | 2 | 3.683 (0.064) | 3.402 (0.067) | | 2 | -0.280 (0.056) | | 2-3 | -0.141 (0.028) | -0.030 (0.018) |
| | 3 | 3.542 (0.084) | 3.372 (0.081) | | 3 | -0.169 (0.065) | | 3-4 | -0.081 (0.022) | -0.016 (0.012) |
| | 4 | 3.461 (0.094) | 3.357 (0.091) | | 4 | -0.104 (0.064) | | 4-5 | -0.045 (0.017) | -0.008 (0.008) |
| 5 | 3.416 (0.100) | 3.348 (0.096) | 5 | -0.067 (0.058) | | | | | | |

5. Conclusions and Future Research

This study proposed a marketing model to estimate the impact of customer experience using a constrained neural network to process online review data. We investigated the relationship of overall ratings with customer experience and attribute performance. G-AMNet achieved better performance

than a fully connected neural network, indicating that different variables types should need to be treated separately when applying neural networks. We attribute this to a technique called “dropout,” which randomly drops units and their connections from the fully connected neural network during training. This makes it possible to improve the accuracy while avoiding overfitting (Srivastava et al. 2014). G-AMNet and the other semiparametric neural networks can be regarded as special cases of dropout.

Social science data is often handled differently from those of natural science or machine learning. Thus, it might be important to consider the model-driven approach of machine-learning algorithms for social science applications. In this study, we assumed that customer reviews and attribute ratings represented a different construct, then the G-AMNet learns the variables as separate networks. Additionally, the PDP estimated by this model provides natural interpretations for customer experience and attribute performance. The results indicate that the impactful words are useful to finding implementations of customer experience and services, and the negative words are especially important, because the customer might be more sensitive to the negative experience than the positive one.

For future research, there are three main limitations and issues. First, it is necessary to develop a measuring and validation method to specify the psychological variables from the text data posted by customers. According to Izogo and Jayawardhera (2018), customer reviews and experiences have a strong relationship. However, there are no systematic methods to measure the constructs from the textual data. Toubia et al. (2019) estimated latent topics based on psychological theory, and Humphreys and Wang (2018) called the latent topic a construct and discussed the applications of LDA in social science. For neural networks, CR and AVE (Sato 2019, Fornell & Larcker 1981) can be extended, because Sato (2019) proposed the construct validation for a nonlinear measurement model and discussed the reliability coefficient with the marginal effect estimation.

Second, the setting of our conceptualized model requires more strict causal relationships, because our model is very simple. For example, the relationship between customer experience and attribute performance should be estimated. However, we did not achieve this with our neural network. Moreover, past reviews might provide customer expectations or ideal points, affecting customer experience.

Therefore, specifying causal relationships among predictors and introducing dynamic effects in the network should improve the accuracy and validity of our model. The heterogeneity of consumers, hotels, and regions having high dimensional word data is an important remaining issue. Additionally, it requires specifying the context of the words and discussing how to find and visualize important interaction effects among the words.

Third, we should investigate the theoretical property of neural networks and apply it to the Bayesian neural-network method (e.g., Gaussian process regression model (Lee et al. 2018)). Because some estimates were unstable in G-AMNet, discovering this reason is very important for neural network interpretations in the social sciences. Additionally, the stochastic model for high dimensional data, such as Gaussian process regression, provides probabilistic inferences for the estimated parameters and functions. This is an advantage of the Bayesian neural network. Combining other Bayesian methods, we expect to resolve the sparsity of marketing data, which does not contain enough data when sorted by individuals.

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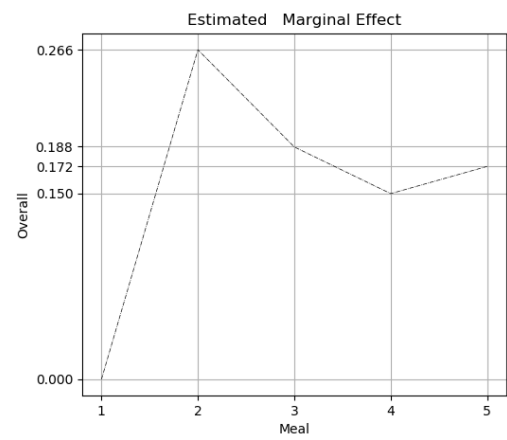
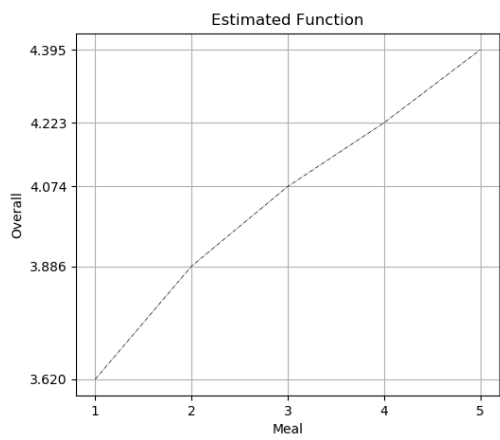
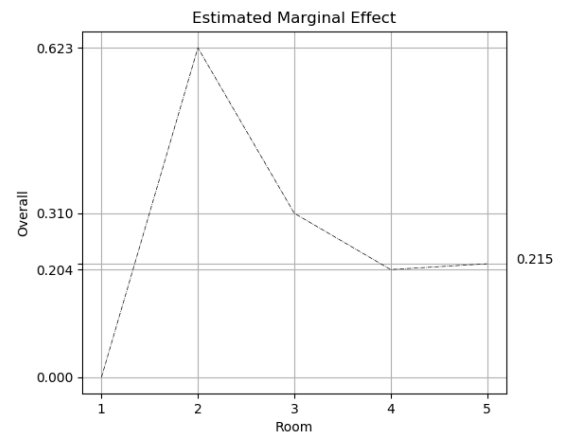
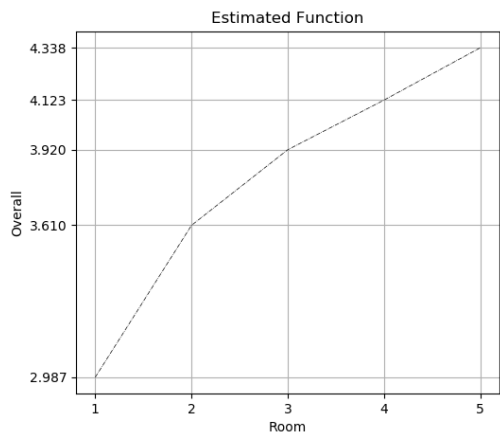
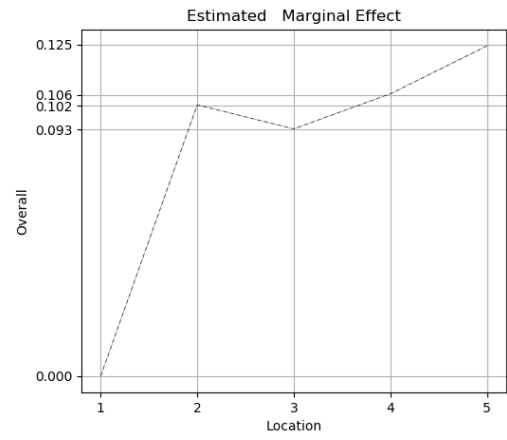
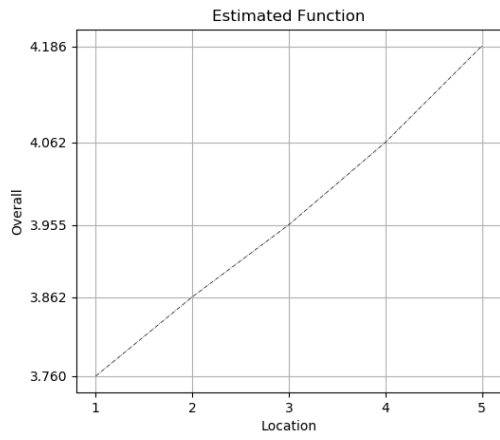
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Appendix I: Other Figures and Tables

Table 11: Details of each network

| Model | Layer (unit or dimension) | | | | | |
|----------|---|-------------------|---|--|-----------------------------------|------------|
| | 0th | 1st | 2nd | 3rd | 4th | 5th |
| FCNet | Words (684) Attribute ratings (6) Dummy Variables (21) | 8 | 9 | 9 | 4 | Output (1) |
| PLNet | Words (684) | 3 | 7 | 8 Attribute Ratings (6) Dummy Variables (21) | Output (1) | |
| P-PLNet | Words (684) | 3 | 7 | 8 9th Degree Polynomial for Each Attribute Rating (54) Dummy Variables (21) | Output (1) | |
| I-AMNet | Words (684) | 3 | 7 7th Degree Polynomial Location (7) 7th Degree Polynomial Room (7) 7th Degree Polynomial Meal (7) 7th Degree Polynomial Bathroom (7) 7th Degree Polynomial Service (7) 7th Degree Polynomial F & A (7) | 8 7 7 7 7 7 7 7 7 7 7 7 | Output (1) | |
| G-ANnet0 | attribute ratings (6) | 70 | 100 | 30 | 40 Dummy Variables (21) | Output (1) |
| G-AMNet | attribute ratings (6) | Words (684) 80 | 3 80 | 7 50 | 8 8 Dummy Variables (21) | Output (1) |

Figure 6: Partial dependence plots and marginal effect of each attribute rating on overall rating



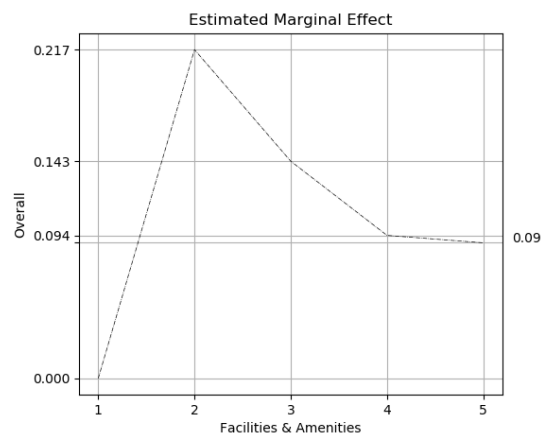
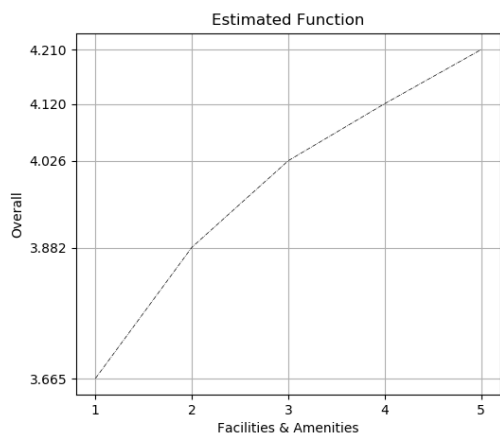
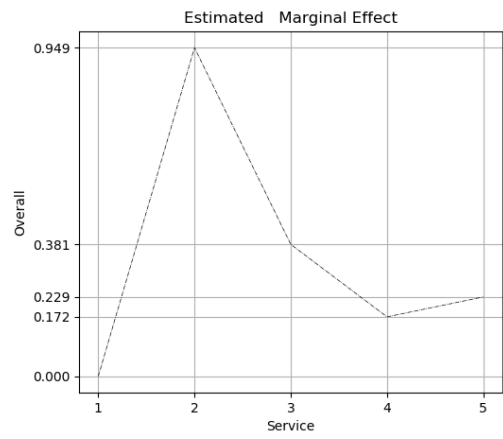
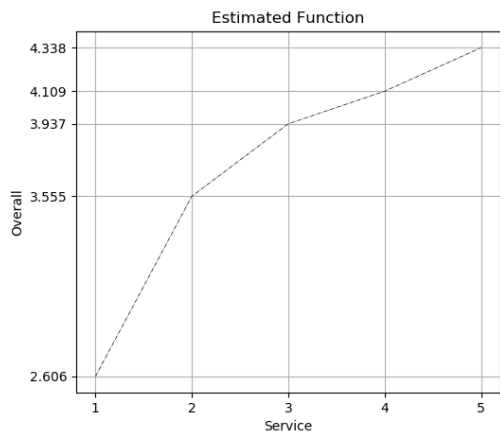
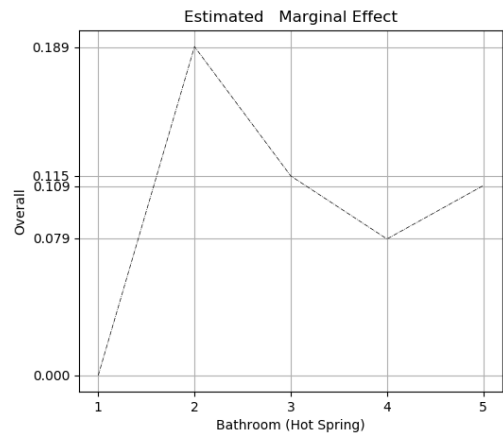
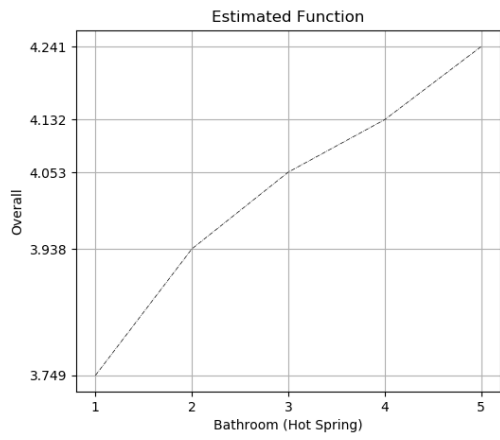


Figure 7: Partial dependence plots and marginal effect of each word on overall rating

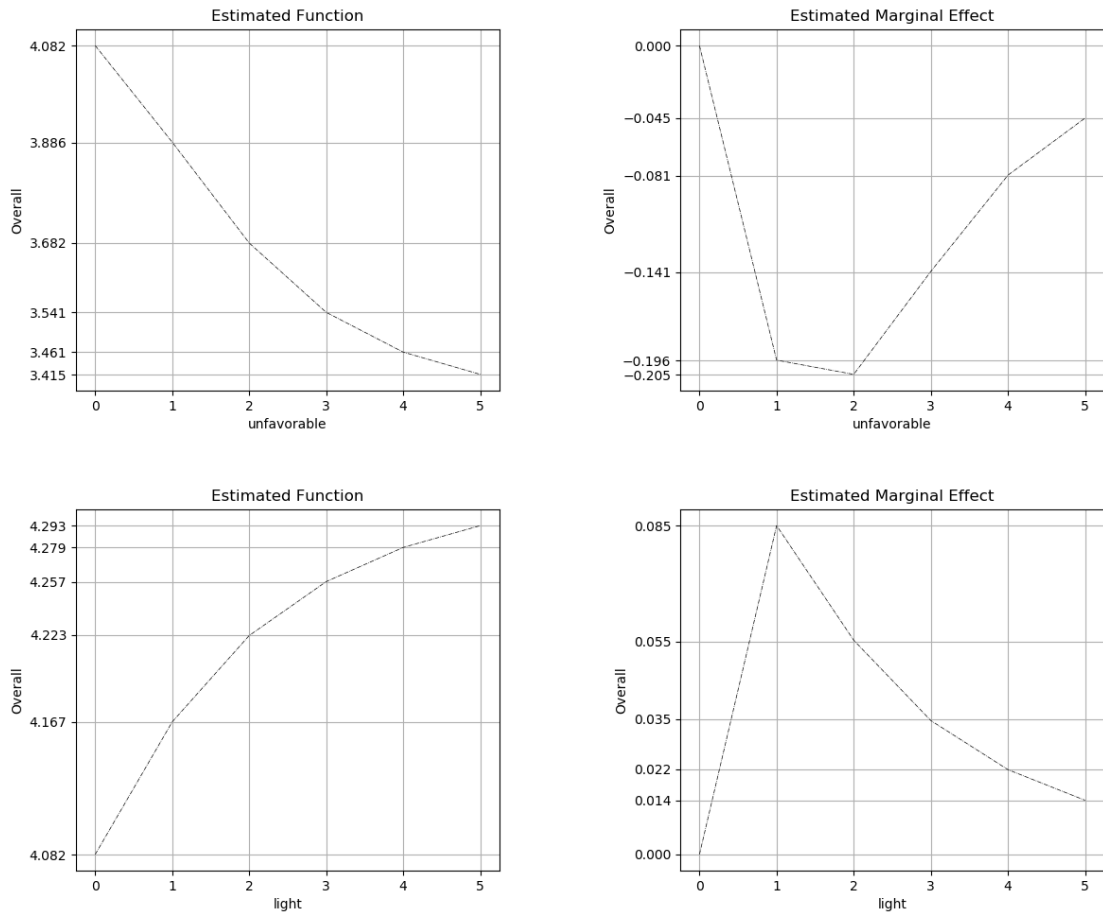


Figure 8: Different kinds of 2-dimensional partial dependence plot example

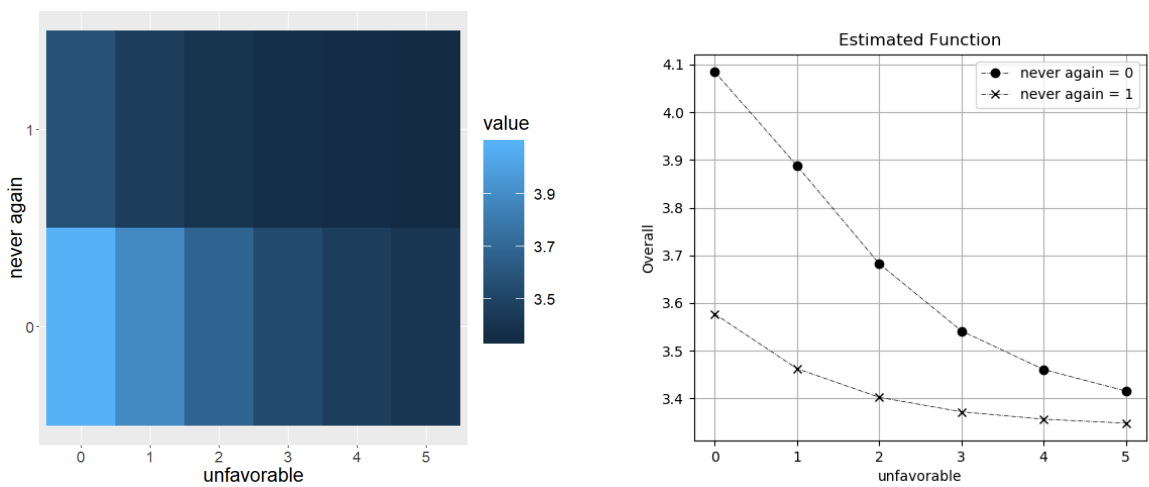


Table 12: Descriptive statistics for each variable

| | mean | | variance | | min | | 1st.q | | median | | 3rd.q | | max | |
|-------------|-----------|---------|----------|---------|-----|-----|-------|-----|--------|-----|-------|-----|-----|-----|
| Overall | 4.084 | (4.076) | 0.889 | (0.894) | 1 | (1) | 4 | (4) | 4 | (4) | 5 | (5) | 5 | (5) |
| Location | 4.193 | (4.202) | 0.720 | (0.714) | 1 | (1) | 4 | (4) | 4 | (4) | 5 | (5) | 5 | (5) |
| Room | 3.937 | (3.935) | 1.007 | (1.016) | 1 | (1) | 3 | (3) | 4 | (4) | 5 | (5) | 5 | (5) |
| Meal | 4.002 | (3.933) | 0.948 | (0.961) | 1 | (1) | 4 | (3) | 4 | (4) | 5 | (5) | 5 | (5) |
| Bathroom | 3.952 | (3.937) | 0.989 | (0.997) | 1 | (1) | 3 | (3) | 4 | (4) | 5 | (5) | 5 | (5) |
| Service | 3.970 | (3.966) | 0.987 | (0.981) | 1 | (1) | 3 | (3) | 4 | (4) | 5 | (5) | 5 | (5) |
| F & A | 3.945 | (3.934) | 0.992 | (1.005) | 1 | (1) | 3 | (3) | 4 | (4) | 5 | (5) | 5 | (5) |
| | frequency | | | | | | | | | | | | | |
| Business | 22781 | (4779) | | | | | | | | | | | | |
| Leisure | 52905 | (11140) | | | | | | | | | | | | |
| Alone | 38330 | (8081) | | | | | | | | | | | | |
| Family | 30257 | (6385) | | | | | | | | | | | | |
| Colleague | 2892 | (595) | | | | | | | | | | | | |
| Friend | 4060 | (828) | | | | | | | | | | | | |
| Couple | 3790 | (726) | | | | | | | | | | | | |
| no_Meal | 23288 | (4835) | | | | | | | | | | | | |
| no_Bathroom | 3707 | (738) | | | | | | | | | | | | |
| no_F & A | 665 | (138) | | | | | | | | | | | | |
| J_room | 15646 | (3373) | | | | | | | | | | | | |
| Jan | 5800 | (1210) | | | | | | | | | | | | |
| Feb | 4880 | (967) | | | | | | | | | | | | |
| Mar | 5449 | (1127) | | | | | | | | | | | | |
| Apr | 4865 | (1052) | | | | | | | | | | | | |
| May | 7857 | (1670) | | | | | | | | | | | | |
| Jun | 7374 | (1553) | | | | | | | | | | | | |
| Jul | 7792 | (1634) | | | | | | | | | | | | |
| Aug | 10960 | (2339) | | | | | | | | | | | | |
| Sep | 9565 | (1946) | | | | | | | | | | | | |
| Oct | 8061 | (1701) | | | | | | | | | | | | |

Appendix II: Details of ADAM

Back propagation with ADAM (Kingma & Ba, 2015; Goodfellow et al., 2016)

Require: L , Network depth

Require: $\mathbf{B}^{(l)}$, $l \in \{1, 2, \dots, L\}$, The weight matrices, vectors, or scalars of the model.

Require: $\mathbf{c}^{(l)}$, $l \in \{1, 2, \dots, L\}$, The bias (constant) parameters of the model.

Require: \mathbf{x} , Input variables.

Require: \mathbf{y} , Output variables.

Require: $n \in \{1, 2, \dots, N_d\}$, Mini-batch size.

Require: α , Step size ($\alpha = 0.001$).

Require: ϵ , Small constant ($\epsilon = 10^{-8}$) used for numerical stabilization.

Require: $\rho_1, \rho_2 \in [0, 1)$, Exponential decay rates for moment estimates ($\rho_1 = 0.9, \rho_2 = 0.999$).

Initialization:

$t \leftarrow 0$ (Initialize time step)

for $l = \{1, 2, \dots, L\}$ **do**

$\mathbf{B}_0^{(l)}, \mathbf{c}_0^{(l)} \leftarrow N(0, 1)$ (Initialize weight and bias parameters applied element-wise.),

$\boldsymbol{\theta}_0^{(l)} = \{\mathbf{B}_0^{(l)}, \mathbf{c}_0^{(l)}\}$ (Combine weight and bias parameters as one matrix or vector.),

$\mathbf{g}_0^{(l)} \leftarrow \mathbf{0}$ (Initialize 1st moment corresponding to the weight and bias parameters),

$\mathbf{h}_0^{(l)} \leftarrow \mathbf{0}$ (Initialize 2st moment corresponding to the weight and bias parameters).

end for

Start Optimization :

while $\boldsymbol{\theta}_t^{(1)}, \boldsymbol{\theta}_t^{(2)}, \dots, \boldsymbol{\theta}_t^{(L)}$ **not converged do**

$t \leftarrow t + 1$ (Iteration number).

Forward computation :

$\mathbf{Z}^{(0)} \leftarrow \mathbf{x}$ (Set input variables).

for $l = \{1, 2, \dots, L\}$ **do**

$$\mathbf{U}^{(l)} = \mathbf{B}_{t-1}^{(l)} \mathbf{Z}^{(l-1)} + \mathbf{c}_{t-1}^{(l)} \mathbf{1}_N, \quad (\text{A.1})$$

$$\mathbf{Z}^{(l)} = \mathbf{g}^{(l)}\{\mathbf{U}^{(l)}\}, \quad (\text{A.2})$$

$\boldsymbol{\theta}_{t-1}^{(l)} = \{\mathbf{B}_{t-1}^{(l)}, \mathbf{c}_{t-1}^{(l)}\}$ (Combine weight and bias parameters as one matrix or vector.).

end for

$\hat{\mathbf{y}} = \mathbf{Z}^{(L)}$ (Compute Predicted Outputs),

$J = L(\hat{\mathbf{y}}, \mathbf{y})$ (Compute Total Loss).

Backward computation :

$$\Delta_t^{(L)} \leftarrow \nabla_{\hat{\mathbf{y}}} L(\hat{\mathbf{y}}, \mathbf{y}) = \hat{\mathbf{y}} - \mathbf{y}. \quad (\text{A.3})$$

for $l = \{L - 1, L - 2, \dots, 1\}$ **do**

$$\Delta_t^{(l)} \leftarrow f'^{(l)}\{\mathbf{U}^{(l)}\} \odot \{\mathbf{B}_{t-1}^{(l+1)} \Delta_t^{(l+1)}\}, \quad (\text{A.4})$$

$$\partial \boldsymbol{\theta}_t^{(l)} = \frac{1}{N_d} \Delta^{(l)} \begin{bmatrix} \mathbf{Z}^{(l-1)} \\ \mathbf{1}_{N_d} \end{bmatrix}^T \quad (\text{Compute gradients on weights and biases}),$$

$$\mathbf{g}_t^{(l)} \leftarrow \rho_1 \mathbf{g}_{t-1}^{(l)} + (1 - \rho_1) \partial \boldsymbol{\theta}_t^{(l)} \quad (\text{Update biased first moment estimate}),$$

$$\mathbf{h}_t^{(l)} \leftarrow \rho_2 \mathbf{h}_{t-1}^{(l)} + (1 - \rho_2) \partial \boldsymbol{\theta}_t^{(l)} \odot \partial \boldsymbol{\theta}_t^{(l)} \quad (\text{Update biased second raw moment estimate}),$$

$$\hat{\mathbf{g}}_t^{(l)} \leftarrow \mathbf{g}_t^{(l)} / (1 - \rho_1^t) \quad (\text{Compute bias-corrected first moment estimate}),$$

$$\hat{\mathbf{h}}_t^{(l)} \leftarrow \mathbf{h}_t^{(l)} / (1 - \rho_2^t) \quad (\text{Compute bias-corrected second raw moment estimate}),$$

$$\boldsymbol{\theta}_t^{(l)} \leftarrow \boldsymbol{\theta}_{t-1}^{(l)} - \alpha \hat{\mathbf{g}}_t^{(l)} / \left(\sqrt{\hat{\mathbf{h}}_t^{(l)}} + \epsilon \right) \quad (\text{Update weights and biases applied element-wise}),$$

$$\{\mathbf{B}_t^{(l)}, \mathbf{c}_t^{(l)}\} = \boldsymbol{\theta}_t^{(l)} \quad (\text{Obtain updated weights and biases}).$$

end while

return $\boldsymbol{\theta}_t^{(1)}, \boldsymbol{\theta}_t^{(2)}, \dots, \boldsymbol{\theta}_t^{(L)}$ (Resulting parameters).

For equations (A.1) and (A.2), let p be a number of unit in the l^{th} layer, and let q be a number of unit in $l - 1^{\text{st}}$ layer, $\mathbf{U}^{(l)}$, defined as:

$$\mathbf{U}^{(l)} = [U_1^{(l)}, \dots, U_{N_d}^{(l)}], \quad (22)$$

where

$$U_n^{(l)} = \mathbf{B}^{(l)} \mathbf{z}_n^{(l-1)} + \mathbf{c}^{(l)}$$

$$\begin{bmatrix} u_1^{(l)} \\ u_2^{(l)} \\ u_3^{(l)} \\ \vdots \\ u_p^{(l)} \end{bmatrix}_n = \begin{bmatrix} b_{1,1}^{(l)} & b_{1,2}^{(l)} & b_{1,3}^{(l)} & \cdots & b_{1,q}^{(l)} \\ b_{2,1}^{(l)} & b_{2,2}^{(l)} & b_{2,3}^{(l)} & \cdots & b_{2,q}^{(l)} \\ b_{3,1}^{(l)} & b_{3,2}^{(l)} & b_{3,3}^{(l)} & \cdots & b_{3,q}^{(l)} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ b_{p,1}^{(l)} & b_{p,2}^{(l)} & b_{p,3}^{(l)} & \cdots & b_{p,q}^{(l)} \end{bmatrix} \begin{bmatrix} z_1^{(l-1)} \\ z_2^{(l-1)} \\ z_3^{(l-1)} \\ \vdots \\ z_q^{(l-1)} \end{bmatrix}_n + \begin{bmatrix} c_1 \\ c_2 \\ c_3 \\ \vdots \\ c_p \end{bmatrix}^{(l)}, \quad (23)$$

and

$$\begin{bmatrix} z_1^{(l)} \\ z_2^{(l)} \\ z_3^{(l)} \\ \vdots \\ z_p^{(l)} \end{bmatrix}_{(n)} = \begin{bmatrix} g^{(l)}(u_1) \\ g^{(l)}(u_2) \\ g^{(l)}(u_3) \\ \vdots \\ g^{(l)}(u_p) \end{bmatrix}_{(n)}, \quad (24)$$

for $n = 1, \dots, N_d$. $g^{(l)}$ is an activation function.

In Eq. (A.3) & (A.4), for the top layer ($l = L$), let $E_n = 1/2 (\hat{y}_n - y_n)^2$ be a loss function for sample n , and put $\hat{y}_n = z_n^{(L)} = u_n^{(L)}$ for a regression setting. Because $d(u_n^{(L)} - y_n)/du_n^{(L)} = 1$,

$$\delta_{1,n}^{(L)} = \frac{\partial E_n}{\partial u_n^{(L)}} = u_n^{(L)} - y_n = z_n^{(L)} - y_n = \hat{y}_n - y_n. \quad (25)$$

Hence,

$$\Delta^{(L)} = [\delta_{1,1}^{(L)}, \delta_{1,2}^{(L)}, \dots, \delta_{1,N_d}^{(L)}]. \quad (26)$$

For the other layers ($l = L - 1, L - 2, \dots, 1$), let r be a unit number in the $l + 1^{\text{st}}$ layer. Then,

$$\delta_{p,n}^{(l)} = \frac{\partial E_n}{\partial u_p^{(l)}} = \sum_r \delta_{r,n}^{(l+1)} \{b_{rp}^{(l+1)} g'(u_p^{(l)})\}. \quad (27)$$

Hence,

$$\Delta^{(l)} = \begin{bmatrix} \delta_{1,1}^{(l)} & \delta_{1,2}^{(l)} & \cdots & \delta_{1,N_d}^{(l)} \\ \delta_{2,1}^{(l)} & \delta_{2,2}^{(l)} & \cdots & \delta_{2,N_d}^{(l)} \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{p,1}^{(l)} & \delta_{p,2}^{(l)} & \cdots & \delta_{p,N_d}^{(l)} \end{bmatrix}. \quad (28)$$

For PLNet and AMNet, consider adding some units or inputs independently in Eq. (A.1), divide

$p = \bar{p} + \tilde{p}$, and $q = \bar{q} + \tilde{q}$, and define Eq. (A.1') as follows:

$$\begin{aligned} U_n^{(l)} &= \mathbf{B}^{(l)} \mathbf{z}_n^{(l-1)} + \mathbf{c}^{(l)} \\ \begin{bmatrix} \bar{U}_{1,n}^{(l)} \\ \tilde{U}_n^{(l)} \end{bmatrix} &= \begin{bmatrix} \bar{\mathbf{B}}^{(l)} & \mathbf{0} \\ \mathbf{0} & \tilde{\mathbf{B}}^{(l)} \end{bmatrix} \begin{bmatrix} \bar{\mathbf{z}}_{1,n}^{(l-1)} \\ \tilde{\mathbf{z}}_n^{(l-1)} \end{bmatrix} + \begin{bmatrix} \bar{\mathbf{c}}_n^{(l)} \\ \tilde{\mathbf{c}}_n^{(l)} \end{bmatrix} \\ \begin{bmatrix} \bar{u}_1^{(l)} \\ \vdots \\ \bar{u}_{\bar{p}}^{(l)} \\ \tilde{u}_{\bar{p}+1}^{(l)} \\ \vdots \\ \tilde{u}_{\bar{p}+\tilde{p}}^{(l)} \end{bmatrix}_n &= \begin{bmatrix} \bar{b}_{1,1}^{(l)} & \cdots & \bar{b}_{1,\bar{q}}^{(l)} & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ \bar{b}_{\bar{p},1}^{(l)} & \cdots & \bar{b}_{\bar{p},\bar{q}}^{(l)} & 0 & \cdots & 0 \\ 0 & \cdots & 0 & \tilde{b}_{\bar{p}+1,\bar{q}+1}^{(l)} & \cdots & \tilde{b}_{\bar{p}+1,\bar{q}+\tilde{q}}^{(l)} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & \tilde{b}_{\bar{p}+\tilde{p},\bar{q}+1}^{(l)} & \cdots & \tilde{b}_{\bar{p}+\tilde{p},\bar{q}+\tilde{q}}^{(l)} \end{bmatrix} \begin{bmatrix} \bar{z}_1^{(l-1)} \\ \vdots \\ \bar{z}_{\bar{q}}^{(l-1)} \\ \tilde{z}_{\bar{q}+1}^{(l-1)} \\ \vdots \\ \tilde{z}_{\bar{q}+\tilde{q}}^{(l-1)} \end{bmatrix}_n + \begin{bmatrix} \bar{c}_1^{(l)} \\ \vdots \\ \bar{c}_{\bar{p}}^{(l)} \\ \tilde{c}_{\bar{p}+1}^{(l)} \\ \vdots \\ \tilde{c}_{\bar{p}+\tilde{p}}^{(l)} \end{bmatrix}^{(l)}. \quad (29) \end{aligned}$$

Hence, the above equation can be regarded as a restricted equation with fixed parameters, and the algorithm will not be changed while keeping the fixed parameters as 0.

Appendix III: Simulation Result for AMNet

We generated 500 (and 100 for test) samples from the following settings and estimated two-layer (input layer + one hidden layer + output layer) AMNet model 100 times.

$$\begin{aligned} y_i &= 0.5 + 0.485 * x_{1,i} + 0.550 * x_{2,i} + \sin(1.643 * x_{3,i}) + \cos(2.735 * x_{4,i}) + \varepsilon_i, \\ \mathbf{x}_i &\sim i.i.d.MVN(\mathbf{0}, I_4), \\ \varepsilon_i &\sim i.i.d.N(0,1). \end{aligned} \quad (30)$$

Activation function is defined as a sigmoid (logistic) function:

$$g(x) = \frac{1}{1 + e^{-x}}. \quad (31)$$

For each optimization, we set epochs = 200 and batch sizes = 50, meaning each epoch uses 50 samples randomly. The probabilistic optimization repeats an optimization until the sum of mini-batches achieves the same number as the sample size, such that it needs $500/50 = 10$ times. This repeats 200 times for convergence of optimization. Before simulation, we generate data from Eq. (29) once and jointly search the degree of the polynomial and the units in the hidden layer. Figure 9 shows the learning history of the MSE. Table 13 indicates the 7th degree, and its unit is the best for testing data. However, the 9th degree unit is better for training data. According to test MSE, we adapt the two-layer AMNet with seven units and use the inputs transformed by the 7th-degree polynomial (Figure 10).

Table 13: MSE of training and test data

| degree & unit | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---------------|--------|--------|--------|--------|--------|--------|--------|
| train | 1.2938 | 1.0858 | 1.0701 | 0.9805 | 1.0295 | 0.9701 | 1.0484 |
| test | 1.3497 | 1.0975 | 1.1488 | 1.0995 | 1.1529 | 1.0311 | 1.1533 |
| degree & unit | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
| train | 0.9673 | 0.9979 | 0.9971 | 1.0560 | 1.0095 | 0.9831 | 1.0007 |
| test | 1.0608 | 1.0863 | 1.1426 | 1.1106 | 1.1397 | 1.1110 | 1.1308 |

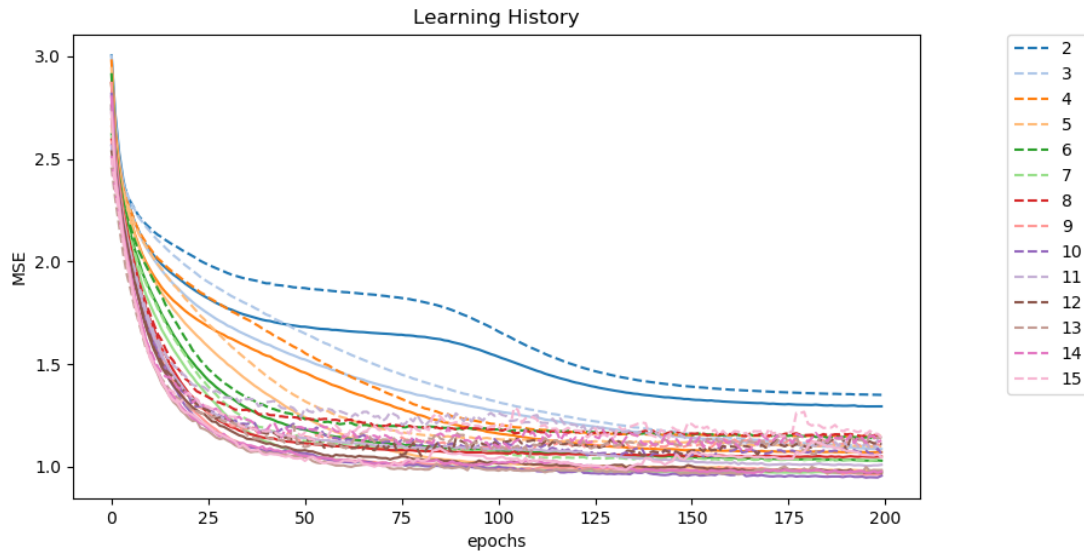


Figure 9: Learning history of AMNet

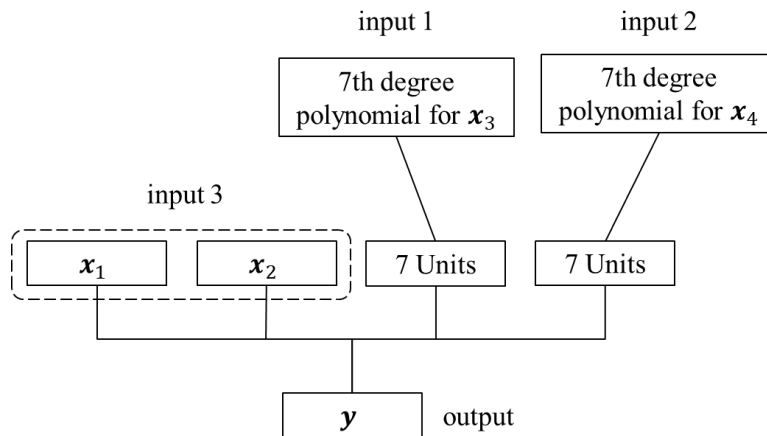


Figure 10: AMNet for simulation study

Table 14 summarizes the result of this simulation study and shows bias and RMSE for betas 1 and 2. A.RMS and A.Corr in Table 14 indicates the average RMS and the correlation coefficient between true and estimated functions. The results indicate that betas 1 and 2 are estimated unbiased, and the sin and cos functions are also estimated closely by each network. We visualize those results in Figure 11.

Table 14: Results of simulation study

| | beta1 | beta2 | sin | cos |
|------|-----------|-----------|--------|-------------|
| True | 0.485 | 0.550 | | |
| Bias | -0.009 | 0.004 | A.RMS | 0.528 0.569 |
| RMSE | (0.042) | (0.045) | A.Corr | 0.951 0.939 |

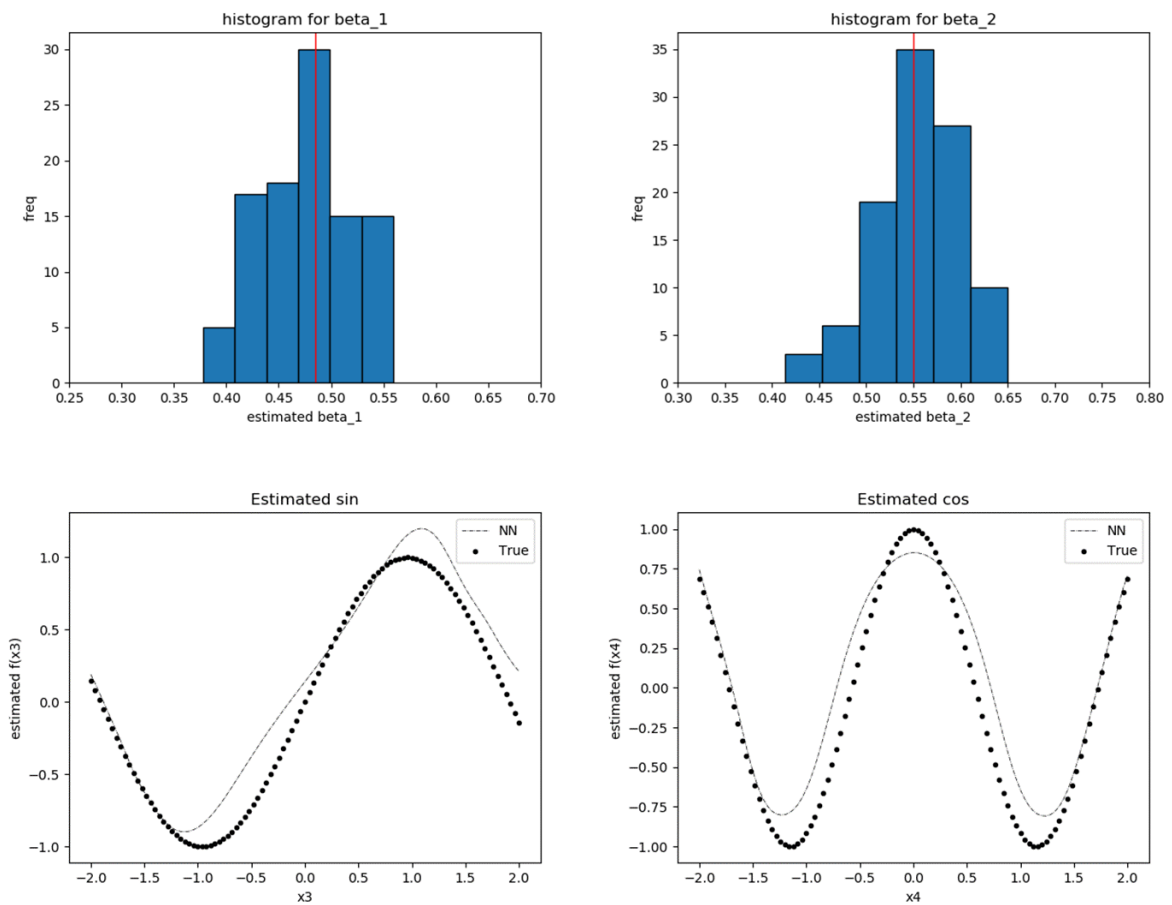


Figure 11: Histograms of estimated betas 1 and 2 (upper side), the plots of true functions, and the average of estimated functions (bottom side)