Multitask Learning Deep Neural Network to Combine Revealed and Stated Preference Data

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Abstract

It is an enduring question how to combine revealed preference (RP) and stated preference (SP) data to analyze travel behavior. This study presents a new approach of using multitask learning deep neural network (MTLDNN) to combine RP and SP data and incorporate the traditional nest logit approach as a special case. Based on a combined RP and SP survey in Singapore to examine the demand for autonomous vehicles (AV), we designed, estimated and compared one hundred MTLDNN architectures with three major findings. First, the traditional nested logit approach of combining RP and SP can be regarded as a special case of MTLDNN and is only one of a large number of possible MTLDNN architectures, and the nested logit approach imposes the proportional parameter constraint under the MTLDNN framework. Second, out of the 100 MTLDNN models tested, the best one has one shared layer and five domain-specific layers with weak regularization, but the nested logit approach with proportional parameter constraint rivals the best model. Third, the proportional parameter constraint works well in the nested logit model, but is too restrictive for deeper architectures. Overall, this study introduces the MTLDNN model to combine RP and SP data, relates the nested logit approach to the hyperparameter space of MTLDNN, and explores hyperparameter training and architecture design for the joint demand analysis.

Keywords: Multitask Learning, Machine Learning, Deep Neural Network, Revealed Preference, Stated Preference

1. Introduction

In demand analysis, two types of data are widely used: revealed preference (RP) and stated preference (SP) data. RP data are commonly thought as more reliable because they represent the real behavior, and SP data are necessary when researchers seek to understand the effects of new attributes, the new value ranges, or new alternatives. A common challenge in the transportation field is the demand prediction of a new travel mode, either technically new such as autonomous vehicle, or practically new such as a new subway line in regions without prior subway systems. Facing these challenges, researchers need to make full use of all possible information, typically including both RP and SP data. Ben-Akiva and Morikawa [1] [2] combined RP and SP by using a nested logit approach [1] More precisely, it is a method of pooled estimation with heteroscedasticity across

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[1] We call it an approach because it is not exactly a nested logit model. People make two choices respectively in RP and SP, rather than one choice, which is the assumption in standard nested logit model.

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While this modeling idea has been used for decades and becomes standard in textbooks, the nested logit structure can be behaviorally restrictive and pose intractable optimization challenges. In this paper we will demonstrate the possibility of using deep neural network (DNN) to combine RP and SP data considering this heteroscedasticity.

We present a multitask learning deep neural network (MTLDNN) method to combine RP and SP for travel demand analysis. The architecture of MTLDNN typically starts with shared layers and ends with domain-specific layers, based on the insight that shared layers reflect the similarity across RP and SP domains and domain-specific layers represent the separate RP and SP information. We have designed the hyperparameter space of MTLDNN models with seven dimensions, among which the most important one is whether the proportional parameter constraint is imposed. This constraint is derived from the nested logit approach, which assumes the proportional scales of random utility terms between RP and SP data. In total, we estimated 100 MTLDNN architectures and the nested logit approach is only one special case with the sparsest structure and the weakest regularization of all the MTLDNN architectures. The model with the highest prediction accuracy has one shared layer and five domain-specific layers, but the model representing the nested logit approach rivals it.

This paper makes three contributions. First, it presents the first research of using the MTLDNN framework to combine RP and SP data for travel demand analysis. The MTLDNN framework is more general than the nested logit approach and is flexible with a great number of possible architecture designs. Second, in contrast to the many DNN studies in demand analysis that use only the default parameters, this study demonstrates the importance of hyperparameter search and architecture design of DNN, which is particularly valuable in the context of RP and SP combination to achieve high prediction accuracy. Lastly, we point out that the behavioral insights such as proportional scales of random utility terms can function as one hyperparameter dimension in MTLDNN framework.

The paper is organized as the following. We will first review past studies, discussing RP and SP estimation, multitask learning, and representation learning of DNN. In the third section, we will discuss the setup of our MTLDNN, along with the connection to the nested logit approach. The fourth section shows the results of hyperparameter training. The last section concludes this study.

2. Literature Review

RP and SP data are both widely used for choice analysis. While many studies used RP and SP data separately, several studies have argued for the benefits of combining RP and SP data, and particularly for the scenarios in which new attributes, new attribute ranges, or new alternatives need to be tested. Ben-Akiva and Morikawa modeled the behavior of switching from old travel modes to new ones by using the information from SP survey. Polydoropoulou and Ben-Akiva used nested logit model to combine RP and SP. Their models assumed shared parameters between RP and SP, differing by a scale factor due to the different scales of random utility terms. This approach became the standard practice of combining RP and SP datasets widely used in later studies on travel mode choices and beyond travel mode choice, it has also been applied to other types of behaviors, such as exit choice of pedestrian crowd evacuees, choice of alternative-fuel vehicles, and choice of ecological services.
We propose that from a machine learning perspective, combining RP and SP can be seen as a multitask learning (MTL) problem because RP and SP predictions can be treated as two separate but highly related tasks. MTL has been developed in machine learning community for many years with numerous applications. The early MTL research focused on how to convexify the MTL problem so that the optimization problem becomes tractable [11]. Recent MTL work has been mainly based on the DNN framework: a typical MTLDNN architecture starts with general purpose layers and ends with domain-specific layers associated with the respective tasks [12] [13]. The typical MTLDNN architecture reflects both the similarity and the difference between two different domains: shared layers transform all the inputs in the same way, and the domain-specific layers respect the differences in the two domains. Since MTLDNN models are under the DNN framework, convexity of the optimization problem becomes less a concern, but instead, how to regularize and design the MTLDNN architecture is one key consideration. For instance, studies either used distance constraints or shared Bayesian priors between task-specific layers in MTLDNN so that diverse tasks are related in certain ways [13].

The joint estimation of different tasks has been theoretically discussed and widely used for decades. Combining RP and SP by nested logit model is one good example of joint estimation [2] [1]. Researchers have shown that people may simultaneously decide their job and residence locations [14]; automobile ownership and usage [15]; activity schedule and travel behavior [16]; automobile numbers and mode choice [17]; travel mode and trip chain [18]; and vehicle miles travelled and mode choice [8]. The initial motivation of joint estimation was to address the endogeneity problem, as illustrated in Train’s study [17]. Nowadays researchers are free to expand the possibilities of joint estimation to all the related behavioral decisions, including travel mode, travel frequency, scheduling, route choice, activity types, residential location, car ownership, and other travel or activity variables. Note that simultaneous decisions are not the same as similar decision domains. The prerequisite of MTLDNN is that several domains share some commonalities. The joint estimation methods implicitly assume certain degree of commonalities between these simultaneous decisions, and therefore MTLDNN can be applied. Joint estimations can also be applied to the same classification tasks in different time periods or cities.

While the joint estimation idea underlying MTLDNN has a long history, the underpinning DNN structure is different from traditional models because the DNN framework incorporates extraordinary flexibility of architecture design and powerful capacity of representation learning. Compared to traditional statistical approaches that pre-impose feature engineering procedures, the DNN uses generic purpose hidden layers, such as Rectified Linear Units, to learn feature representations [19]. This generic feature representation of DNN is theoretically proved as an universal approximator [20] and the DNN models empirically outperformed 17 families of 179 classifiers in 121 datasets for two-alternative choice tasks [21]. In the transportation field, researchers have shown the power of using DNN in empirical studies for travel behavior and demonstrated the relationship between DNN and choice models [22] [23] [24]. While the sources of DNNs generalization capacity remain theoretically unclear, many studies suggest that the powerful representation learning can be one reason. Several recent convolutional neural network papers show that the hidden layers of DNN can be semantically meaningful after a long training time [25] [26]. These findings suggest that the MTLDNN framework can outperform traditional nested logit approach in combining RP and SP when the true data generating process (DGP) deviates from a linear feature structure significantly.

The paper only focuses on using MTLDNN to address one of the many concerns
in combining across RP and SP data, namely, the heteroscedasticity across RP and SP domains (the nested logit approach can be seen as a pooled estimation with heteroscedasticity across RP and SP domains). Even though the DNN models are powerful in their representation learning capacity, it remains an open question whether the MTLDNN can address other concerns involved in combining RP and SP data, including heterogeneity of model coefficients across individuals [27], state-dependence of SP coefficients on RP coefficients [28], and panel structure between RP and SP domains [10]. These aspects of combining RP and SP can be modeled using mixed logit model with delicate statistical specification [28] [10] and we conjecture that better DNN architecture designs are necessary to take these statistical concerns into account in the MTLDNN framework—important questions for future research.

Lastly, MTLDNN is one particular architecture of DNN, so it broadly relates to neural architecture search (NAS) and hyperparameter optimization (HPO) [29] [30]. Most important development of DNN depends on novel DNN architectures [31] [32]. It is possible to make the architecture searching automatic by using Gaussian process or reinforcement learning to reduce human efforts [33] [34]. In this study, we only explore the architectures of the standard MTLDNN with some exploration into other hyperparameters, but the algorithmic perspective of neither NAS nor HPO is our key focus. This study uses the benchmark random search for the hyperparameter training, since it is more effective and efficient than grid search [35] [36].

3. MTLDNN Architecture for Combining RP and SP Data

The example prototype architecture of MTLDNN is visualized as Figure 1, which has \( M (= 3) \) hidden layers shared by RP and SP, and \( N (= 3) \) domain-specific hidden layers for RP and SP respectively. The input features go through \( M \) layers of shared transformation, which learn abstract and generalizable information that fit both RP and SP domains. The \( N \) domain-specific layers adjust the shared information to fit different tasks. In our specific example, the outputs of RP and SP are different: RP has four travel mode alternatives: walking, bus, ridesharing, and driving, and SP has five alternatives with the autonomous vehicles (AV) being the fifth alternative. In this MTLDNN framework, the depths of shared layers and domain-specific layers are two important hyperparameters. This study tests \( M = 0, 1, 2, 3, 4, 5 \), and \( N = 1, 2, 3, 4, 5 \). Other hyperparameters include the imposition of proportional parameter constraint or not (True/False), \( L_1 \) regularization strength, number of iterations, number of neurons in each layer, and the size of mini batch. We developed 100 groups of hyperparameters in the hyperparameter space using random searching, the benchmark method used in hyperparameter optimization [35]. Most of the hyperparameters are commonly used in DNN, except for the proportional parameter constraint, which is the focus in our study since it represents the same constraint as in the nested logit method of combining RP and SP [7] [6]. The detailed information of the hyperparameter space is included in Appendix I.

Mathematically, we use \( \{X, P(X)\} \) to denote the generator, and \( \{Y, P(Y|X)\} \) to denote the information from the model. While theoretically any component in \( \{X, P(X)\} \) and \( \{Y, P(Y|X)\} \) may differ across the RP and SP tasks [37], we only focus on the case in which \( \{X_{RP}, P(X_{RP})\} = \{X_{SP}, P(X_{SP})\} \), but the choice sets of \( Y_{RP} \) and \( Y_{SP} \) are different and \( P(Y_{RP}|X_{RP}) \neq P(Y_{SP}|X_{SP}) \). The operations applied to input features \( X \) by hidden layers are denoted as
Figure 1: MTLDNN Architecture ($M = 3; N = 3$)
Each $g^i$ represents one hidden layer in the MTLDNN, and it takes the form $g^i(u) = ReLU(W^i u + b^i)$. The empirical risk minimization (ERM) of this neural network is:

$$\min_{W,b} E(W,b) = \min_{W,b} \sum_{t \in RP,SP} \sum_{n} L(y_{n,t}, G_t(x; W, b)) + \gamma ||W||_1$$

(2)

The $l_1$ norm regularization is used because we aim to control generalization errors. The $L()$ is the cross-entropy loss function.

3.1. Proportional Parameter Constraint: Relationship to Nested Logit Approach of Combining RP and SP

The proportional parameter constraint in the MTLDNN model represents the essence of the nested logit approach of combining RP and SP [7] [6]. The nested logit approach assumes that the decision making tasks of RP and SP are similar except for the bias term and the scale of the unobserved errors. Since the scales of the unobserved random utility terms in the decision-making with random utility maximization (RUM) can be transformed to the scale of coefficients, we impose the proportional parameter constraint in MTLDNN as the equivalence to the nested logit approach. Formally, the deterministic utilities $G_{RP}$ and $G_{SP}$ in traditional nested logit approach take this linear form:

$$G_{RP}(x) = g^1_{RP}(x) = x^T w_{RP} + b_{RP}$$

$$G_{SP}(x) = g^1_{SP}(x) = x^T w_{SP} + b_{SP}$$

(3)

with $w_{RP} = \mu w_{SP}$ as the proportional parameter constraint. This traditional nested logit approach can be visualized in a DNN format in Figure 2a, with $M = 0$ shared hidden layer, $N = 1$ domain-specific layer, and proportional parameter constraint between RP-specific and SP-specific layers. Figure 2a is exactly the same as Equation 3 because the RP-specific layer represents $W_{RP}$ and the SP-specific layer represents $W_{SP}$. One simple extension of this Figure 2a is Figure 2b, which adds one shared layer before the domain-specific layer. Figure 2b is a more reasonable model when we expect that the raw input features need to be transformed before entering the RP and SP models. Actually in the typical modeling practices, researchers often transformed features in a way to reflect their domain-knowledge, such as using the quadratic or interaction terms instead of linear terms. Overall, the nested logit approach of combining RP and SP is one particular case of MTLDNN with very shallow shared and domain-specific layers and the proportional parameter constraint.

We need to clarify four points concerning this proportional parameter constraint. First, while the non-convex ERM problem in MTLDNN creates modeling concerns, the approach of combining RP and SP using the nested logit approach has the similar problem. A simple logistic regression has convex ERM, so its optimization has good properties. But the proportional parameter constraint makes the optimization non-convex. Suppose the choice probabilities in RP and SP follow:

$$P_{ni,t} = \frac{e^{V_{ni}^t}}{\sum_{j \in B_k} e^{V_{nj}^t}} = \frac{e^{x^T_{ni} w_t + b_t}}{\sum_{j \in B_k} e^{x^T_{nj} w_t + b_t}}$$

(4)
in which \( t \in \text{RP,SP} \). Common assumption is \( w_{RP} = \mu w_{SP} \). The empirical risk minimization problem is as following.

\[
E(w, b) = - \sum_{n} \log(P_{ni,t}) = - \sum_{n, t \in \text{RP,SP}} \log(P_{ni,t}) = \\
- \sum_{n} \sum_{i} y_{ni}(x_{ni}^{T}w_{RP} + b_{RP} - \log(\sum_{j} x_{nj}^{T}w_{RP} + b_{RP})) = \\
- \sum_{n} \sum_{i} y_{ni}(x_{ni}^{T}w_{SP} + b_{SP} - \log(\sum_{j} x_{nj}^{T}w_{SP} + b_{SP})) \\
= - \sum_{n} \sum_{i} y_{ni}(x_{ni}^{T}\mu w_{SP} + b_{SP} - \log(\sum_{j} x_{nj}^{T}\mu w_{SP} + b_{SP})) \\
- \sum_{n} \sum_{i} y_{ni}(x_{ni}^{T}w_{SP} + b_{SP} - \log(\sum_{j} x_{nj}^{T}w_{SP} + b_{SP}))
\]

The last equality holds after the proportional parameter constraint between RP and SP is used. It is important to note that Equation 5 becomes non-convex in joint \( \mu \) and \( w \) because \( \mu w \) form is not a convex function. It makes the problem intractable. Therefore, usually researchers estimated \( w \) and \( \mu \) sequentially or simultaneously without global optimum as the guarantee.

Second, the proportional parameter constraint is more straightforward when the choice
sets of RP and SP are the same, because the constraint can be exactly used. But in our case where the choice sets of RP and SP are different (which is often the case in applications where new technologies or business models are introduced), this proportional parameter constraint can not be directly used. Accordingly we modified this constraint such that only the corresponding RP and SP coefficients are subject to this proportional parameter constraint, and the one additional column of $W_{SP}$ associated with AV is set to be free in estimation. Third, this proportional parameter constraint essentially comes from the heteroscedasticity assumption in error terms of the choice models, implying a covariance matrix of the error terms with elements on only its main diagonal. Hence our study does not capture a full covariance matrix structure, which is often modeled by mixed logit model. Fourth, proportional parameter constraint is only one of many ways to regularize the two domain-specific layers. For instance, researchers can impose $l_2$ distance between the two domain-specific layers or use a shared Bayesian prior as a constraint. The reason we opted for proportional parameter constraint is its underlying behavioral assumption and its correspondence to the traditional nested logit approach.

4. Data

This study uses the online survey data collected in Singapore employing a professional survey company Qualtrics.com. The survey consisted of one section of revealed preference (RP) survey, one section of stated preference (SP) survey, and one section for socioeconomic variables. The survey started with a RP survey, in which all respondents reported the home and working locations and their current travel mode. After obtaining the geographical information, our algorithm computed walking time, waiting time, in-vehicle travel time, and travel cost of each travel mode based on the origin and destination provided by participants and the price information collected from official data sources in Singapore. The information gathered from the RP survey was then used for generating SP scenarios automatically, which were the bulk of the survey. While the AV mode did not exist in the RP survey, it was introduced in the SP survey, so there were five alternatives of travel mode in SP: walking, public transit, driving, ride sharing, and AVs. The SP survey followed the standard orthogonal design. Each attribute took three levels of values with the medium level equal to the value revealed in the RP survey so that the values were realistic and understandable to participants, and the other two levels were adjusted by multiplying the medium value by certain constants. The value range of time and cost of the AV mode resembled that of the ride sharing mode. The complete SP survey contained 54 combinations of attribute values, among which seven were randomly chosen for each individual to elicit responses. In total, we gathered 1,592 RP choice answers and 8,418 SP choice answers. Both datasets had 25 explanatory variables including age, income, gender, travel costs, travel times, and the chosen travel mode as the dependent variable.

This RP and SP data were respectively split into three sets: training, validation, and testing sets with the ratio of 6 : 2 : 2. We used the training set to train each individual model, and compared the prediction accuracy across 100 MTLDNN models by using cross-validation. Tensorflow was used to build and estimate MTLDNNs. The results of hyperparameter training are reported in Section 5.
5. Findings

Table 1 reports the five MTLDNN models with the highest average prediction accuracy in Panel 1 and the five with the lowest average prediction accuracy in Panel 2. Column 1 of Table 1 reports the value of prediction accuracy, which is averaged over RP and SP and five cross-validation. The rest of the columns of Table 1 report the hyperparameters associated with the specific prediction accuracy.

| Prediction Accuracy | M Share | N Specific | Param Constraint | l1 Const | Number of Iterations | Number of Neurons | Size of Mini Batch |
|---------------------|---------|------------|------------------|----------|----------------------|-------------------|-------------------|
| Panel 1: Five MTLDNN Architectures with Highest Average Prediction Accuracy |
| 0.591 | 1.0 | 5.0 | False | 0.01 | 20000 | 25 | 500 |
| 0.589 | 0.0 | 1.0 | True | 0.00 | 20000 | 100 | 200 |
| 0.587 | 4.0 | 3.0 | False | 0.01 | 20000 | 25 | 100 |
| 0.576 | 1.0 | 1.0 | False | 0.00 | 2000 | 300 | 100 |
| 0.56  | 4.0 | 2.0 | False | 0.01 | 10000 | 500 | 200 |
| Panel 2: Five MTLDNN Architectures with Lowest Average Prediction Accuracy |
| 0.208 | 2.0 | 3.0 | True | 0.001 | 500 | 500 | 200 |
| 0.225 | 3.0 | 4.0 | True | 0.01 | 500 | 500 | 500 |
| 0.225 | 2.0 | 3.0 | True | 0.001 | 1000 | 100 | 500 |
| 0.228 | 5.0 | 2.0 | True | 0.01 | 500 | 300 | 100 |
| 0.232 | 2.0 | 3.0 | True | 0.001 | 1000 | 25 | 200 |

Table 1: Hyperparameter Training Examples

Table 1 yields three findings. First, the model with the highest prediction accuracy is the one with 1 shared layer and 5 domain-specific layers and weak regularization. Some transformation of the raw inputs indeed help prediction, which is in line with our intuition and the traditional approach of engineering features before feeding into the models. Second, somewhat surprisingly, the MTLDNN model mimicking the traditional nested logit approach also performs very well. Its prediction accuracy ranks as the second out of the 100 models. The average RP and SP prediction accuracy is 58.9% only 0.2% lower than the highest. Note that the standard derivation of the five estimations of the best model is 2.3%, which is much larger than the 0.2% gap between the best and the second best models. Hence we conclude that the traditional nested logit approach can rival the best prediction model, which suggests that the classical behavioral insights about different scales of random utility have described true models well. But since we only searched 100 sets of hyperparameters, we cannot be sure how the ultimate best model would perform. Suppose we had explored deeper architectures and finer hyperparameter space, it is possible some DNN architectures could significantly outperform all current models. Third, comparing Panel 1 and 2, we could conclude that the proportional parameter constraint seems too restrictive especially when models become deep. All the MTLDNN architectures with the lowest prediction accuracy have the proportional parameter constraints.

These results suggest that the traditional nested logit approach is a viable alternative in combining RP and SP, particularly when the sample size is not very large. Given that a thorough hyperparameter search of deep MTLDNNs requires the definition of hyperparameter space, specifying searching rules, and a lot of computation to estimate each model, the simple alternative of using the nested logit approach is practical and computationally efficient. The high prediction accuracy of the nested logit approach suggests

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*We opted to average over RP and SP so that it is possible to define the unique ranking of all models. Otherwise we had to identify the Pareto frontier of RP and SP prediction accuracy.*
the validity of the underlying behavioral assumption: RP and SP decision-making rules may differ mostly by the scale of the random utility, or at least this proportional random utility assumption can approximate the true decision-making rule well.

To further examine the role of depth and the proportional parameter constraint, we visualized their relationship in Figure 3 and 4. Figure 3 represents the relationship between average prediction accuracy (y-axis) and the number of total layers (x-axis), with green colors representing the models without the proportional parameter constraint and red ones representing those with the constraint. The dash curves in Figure 3 are the average prediction accuracy categorized by the existence of proportional parameter constraint. Figure 4 is similar to Figure 3 except that the y-axis represents prediction accuracy of RP and SP respectively.

![Figure 3: Average Prediction Accuracy and Hyperparameters](image)

The results in Figure 3 and 4 echo the findings in Table 1 with more details. The proportional parameter constraint effectively differentiates between the models with high and low prediction accuracy. The proportional parameter constraint is too restrictive in the deep architectures. However, this distinction does not exist when the architecture is very shallow. When the MTLDNN has only one domain-specific layer, the prediction accuracies of the models with and without this constraint are similar. In fact, conditioning on shallow architectures, the prediction accuracy does not vary much with any of the hyperparameters. On the contrary, when MTLDNN becomes deeper, the variation of prediction accuracy becomes much larger, ranging from about 20% to 60%. Certain
MTLDNN architectures outperform the traditional one layer MTLDNN with proportional parameter constraint, but it requires thorough hyperparameter search to identify the specific MTLDNN architecture and hyperparameters. In addition, the benefit of depth is unclear. In fact, the two dash lines have a mild downward slope within the range from 3 to 9. This mild downward slope also exist in the separate RP and SP prediction accuracies in Figure 4. Figure 3 and 4 also illustrate the importance of hyperparameter search in general, particularly on how to specify useful hyperparameter dimensions. Both figures show that the prediction accuracy ranges from 20% to 60%; even for those models without proportional parameter constraint, the prediction accuracy ranges from 40% to 60%. It indicates that the naive application of DNN without a careful hyperparameter search in this RP and SP case will not generate desirable results.

6. Discussion

This study introduces a MTLDNN framework to combine RP and SP for demand analysis and explained the relationship between the MTLDNN framework and the nested logit approach. It is driven by the practical importance of predicting the demand of new product and the theoretical interest of using new deep learning models for classical questions.  

This study reports three main findings. First, the proposed MTLDNN structure works for the joint analysis of RP and SP data. It is an intuitive framework that starts with general-purpose layers to reflect the shared feature transformation and ends with domain-specific layers to fit different classification tasks; it is a flexible framework since it incorporates the traditional nested logit approach of combining RP and SP as one special

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It is important to differentiate average and maximum prediction accuracy. While the average prediction accuracy goes down as depth increases, the maximum prediction accuracy of different depths does not have a clear trend.

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case and it has the potential to incorporate many other data formats and hyperparameter dimensions. Second, after searching through the high-dimensional parameter space, we found that the MTLDNN architecture with one shared layer and five domain-specific layers performs the best, and the traditional nested logit approach rivals the highest prediction accuracy. Third, among all the hyperparameter dimensions, the proportional parameter constraint based on utility theory functions well in very shallow architecture, but is too restrictive in deep architectures.

The prediction accuracy of the best MTLDNN model selected based on our hyperparameter search is quite close to that of the DNN model representing the traditional nested logit model. This reveals several crucial facts about using DNN for demand analysis. While many DNN applications simply use the default hyperparameters for training, our result shows that hyperparameter search is really necessary to identify good, or even just acceptable, DNN models. A DNN model without careful hyperparameter selection can be much worse than traditional models. Our experiment seems to suggest that the depth of DNN architecture does not matter much beyond certain levels, and we are very curious whether it is generally true in demand analysis or just specific to our small data set. Overall, how to choose hyperparameter space and DNN architecture is a generic challenge. Besides the common dimensions of hyperparameters, this study uses one behavioral assumption as one hyperparameter dimension, which is the proportional scale effects of the random utility in decision-making rules. We argue that this idea can be expanded to include other behavioral insights as additional dimensions of hyperparameter search.

Many limitations remain in this MTLDNN framework, partially due to the generally insufficient research on the relationship between DNN and statistical concerns. For instance, RP and SP can be related as a panel structure since the unobserved random utility can be correlated; or RP and SP both have inherent preference heterogeneity across individuals. Many statistical discussions involve the covariance structure of the random utility terms, which are not well represented in the DNN model at least not in an obvious way. It is critical in future research to explore how to use DNN to address statistical concerns such as heterogeneity and endogeneity. This study chose the proportional parameter constraint thanks to its close relationship to the traditional nested logit approach, but other constraints with behavioral considerations are possible. Some natural extensions of this study include how to apply this MTLDNN to other types of joint estimations, such as travel mode and auto choice, activity schedule and travel behavior, job and residence locations, or the same choices across different cities, time periods, or research procedures. While this study only used MTLDNN to combine two domains RP and SP, it can be extended to scenarios in which the number of domains is larger than two. There are many opportunities for researchers to use this MTLDNN framework for other types of applications. With the flexibility and the power of deep MTLDNN architectures, we believe that these further applications can improve demand prediction and provide new insights into travel behavior analysis.

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4The deep DNN architecture is superior when the data has hierarchical representation such as images, but may not be very effective when variables are socio-economic variables.
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Appendix I: Hyperparameter Space

Table 2 summarizes the hyperparameter space we explored in this paper.

| Hyperparameter Dimensions | Values |
|---------------------------|--------|
| Shared M                  | [0, 1, 2, 3, 4, 5] |
| Domain-specific N         | [1, 2, 3, 4, 5] |
| Proportional parameter constraint | [True, False] |
| l1 constant               | [1e-10, 1e-3, 1e-2] |
| n iteration               | [500, 1000, 2000, 5000, 10000, 20000] |
| n hidden                  | [25, 50, 100, 200, 300, 500] |
| n mini batch              | [50, 100, 200, 500] |

Table 2: Hyperparameter space of MTLDNN

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