

Consumer Behaviour in Retail: Next Logical Purchase using Deep Neural Network

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Abstract

Predicting future consumer behaviour is one of the most challenging problems for large scale retail firms. Accurate prediction of consumer purchase pattern enables better inventory planning and efficient personalized marketing strategies. Optimal inventory planning helps minimise instances of Out-of-stock/ Excess Inventory and, smart Personalized marketing strategy ensures smooth and delightful shopping experience. Consumer purchase prediction problem has generally been addressed by ML researchers in conventional manners, either through recommender systems or traditional ML approaches. Such modelling approaches do not generalise well in predicting consumer purchase pattern. In this paper, we present our study of consumer purchase behaviour, wherein, we establish a data-driven framework to predict whether a consumer is going to purchase an item within a certain time frame using e-commerce retail data. To model this relationship, we create a sequential time-series data for all relevant consumer-item combinations. We then build generalized non-linear models by generating features at the intersection of consumer, item, and time. We demonstrate robust performance by experimenting with different neural network architectures, ML models, and their combinations. We present the results of 60 modelling experiments with varying Hyper-parameters along with Stacked Generalization ensemble [24] and F_1 -Maximization framework. We then present the benefits that neural network architectures like Multi Layer Perceptron, Long Short Term Memory (LSTM), Temporal Convolutional Networks (TCN) [13] and TCN-LSTM [12] bring over ML models like Xgboost [4] and RandomForest.

1 Introduction

Consumer behaviour insights have always been one of the key business drivers for retail, specially given fast changing consumer needs. Existing trend, competitor pricing, item reviews, sales and marketing are some of the key factors driving today's consumer world in retail. While very little information is available on future variabilities of the above factors, what retailers have is large volumes of transactional data. Retailers use conventional techniques with the available data to model consumer purchase [5]. While these help in estimating purchase pattern for loyal consumers and high selling items with reasonable accuracy, they don't perform

well for the long tail. Since multiple parameters interact non-linearly to define consumer purchase pattern, traditional models are not sufficient to achieve high accuracy across thousands to millions of consumers.

In many of the retail/e-retail brands, short term (2-4 weeks ahead) inventory planning is done on the basis of consumer purchase pattern. Also, certain sales and marketing strategies like Offer Personalization, personalized item recommendations are made leveraging results of consumer purchase predictions for the near future. Given that every demand planner works on a narrow segment of item portfolio, there is high variability in choices that different planners recommend. Also, given their busy schedule, they have very less interaction moments to discuss their views and insights over their recommendations. Hence, subtle effects like cannibalization [20], and item-affinity remains unaccounted. Such inefficiencies lead to gap between consumer needs and item availability, resulting in the loss of business opportunities in terms of consumer churn, out-of-stock, and excess inventory.

In this paper, we apply multiple deep learning architectures along with tree based machine learning algorithms to predict the next logical item purchase at consumer level. We showcase the performance of individual models with varying hyper-parameter configurations along with the results of stacked generalization ensemble [24] (algorithmic combination of predictions from different models) and F_1 -maximization (optimal purchase probability cut-off at consumer level). In the next section 2, we briefly discuss research work related to the problem in hand. Section 3 explains the overall methodology adopted to solve the problem. It lays out neural network architectures and various algorithmic variants applied to the problem. Section 4 describes the experiments performed, and results obtained in different modelling setups.

2 Related Work

In the past few years, various machine learning methods for predicting consumer purchase pattern have been analyzed in the academia field and few of them are often used by ML practitioners. In most cases those approaches are based on extracting consumer's latent characteristics from its past purchase behavior and applying statistical and ML based formulations [6, 5]. Some of previous studies have analyzed

the use of random forest and Xgboost techniques in order to predict consumer retention, where past consumer behavior was used as potential explanatory variable for modelling such patterns. In one such study [15], the authors develop a model for predicting whether a consumer performs a purchase in prescribed future time frame based on historical purchase information such as the number of transactions, time of the last transaction, and the relative change in total spending of a consumer. They found gradient boosting to perform best over test data. We propose neural network architectures with entity embeddings [9] which outperforms the gradient boosting type of models like Xgboost [4].

From Neural Network architectures perspective, close to our work is Deep Neural Network Ensembles for Time Series Classification [8]. In this paper, authors show how an ensemble of multiple Convolutional Neural Networks can improve upon the state-of-the-art performance of individual neural networks. They use 6 deep learning classifiers including Multi Layer Perceptron, Fully Convolutional Neural Network, Residual Network, Encoder [19], Multi-Channels Deep Convolutional Neural Networks [28] and Time Convolutional Neural Network [27]. The first three were originally proposed in [23]. We propose the application of such architectures in the consumer choice world and apply the concept of entity embeddings [9] along with neural network architectures like Multi Layer Perceptron, Long Short Term Memory (LSTM), Temporal Convolutional Networks (TCN) [13] and TCN-LSTM [12].

3 Methodology

In our framework, we treat each relevant consumer-item as an individual object and shape them into weekly time series data based on historical transactions, where the target value at each time step (week) takes a binary input, 1/0 (purchased/non purchased). *Relevancy* of the consumer-item refers to the items transacted by the consumer during training time window. *Postive samples* (purchased/1) are the weeks where consumer did transact respective item, whereas *Negative samples* (non purchased/0) are the weeks where the consumer didnot buy that item. We apply sliding windows testing routine in order to generate out of time results. The time series is split into 4 parts - train, validation, test1, and test2 as shown in Table 1. All our models are built in a multi-object fashion, which allows the gradient movement to happen across all consumer-item combinations in batches. This enables cross-learning to happen across consumers and increases the number of training samples for model robustness. We then perform Feature Engineering over the data to generate multiple types of features. Below are some of the feature groups we experimented with:

- **Datetime:** Transactional metrics at various temporal cuts including week, month and quarter. Datetime related features capturing seasonality and trend.
- **Consumer-Item Profile:** Transactional metrics at different granularities including consumer, item, consumer-item, department, aisle, etc. The metrics include Time since first order, Time since last order, time gap between orders, Reorder rates, Reorder frequency, Streak - user

Table 1: Modelling data splits

| Data Split | Specifications | Consumer-Item combinations | Max Time-Series length |
|------------|---|----------------------------|------------------------|
| Train | Model training | 50,872 | 46 weeks |
| Validation | Hyper-Parameter Optimization | 50,888 | 2 weeks |
| Test1 | Stacked Generalization, F ₁ Maximization | 50,899 | 2 weeks |
| Test2 | Reporting Accuracy Metrics | 50,910 | 2 weeks |

purchased the item in a row, Average position in the cart, Total number of orders.

- **Consumer-Item-Time Profile:** Transactional metrics at the intersection of consumer, item and time. Interactions capturing consumer behaviour towards items for the given time period.

The model we needed to build, thus, should learn to identify similarly behaving time series across latent parameters, and take into account consumer and item variations in comparing the time series. In our framework, a row in time series is represented by

$$y_{cit} = f(i_t, c_t, \dots, c_{t-n}, i_{c_t}, \dots, i_{c_{t-n}}, d_t, \dots, d_{t-n}) \quad (1)$$

where y_{cit} is purchase prediction for consumer 'c' item 'i' at time 't'. i_t is attribute of the item 'i' like category, department, brand, color, size, etc. c_t is attribute of the consumer 'c' like age, sex and transactional attributes. i_{c_t} is transactional attributes of the consumer 'c' towards item 'i'. d_t is derived from datetime to capture trend and seasonality. Finally, n is the number of time lags.

3.1 Loss Function

Since we are solving Binary classification problem, Binary Cross-Entropy/Log Loss seemed most logical loss function for training the models. Below is the formula to calculate Binary Cross-Entropy:

$$H_p = -\frac{1}{N} \sum_{i=1}^N y_i \cdot \log(p(y_i)) + (1 - y_i) \cdot \log(1 - p(y_i)) \quad (2)$$

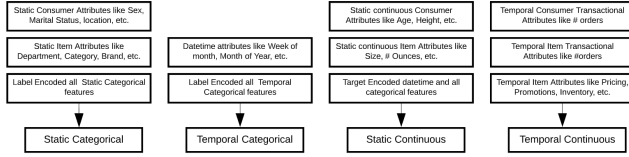
here H_p represents computed loss, y_i is the target value (label), and $p(y_i)$ is the predicted probability against the target. The BCELoss takes non-negative values. We can infer from Equation 2 that Lower the BCELoss, better the Accuracy.

3.2 Model Architectures

As mentioned above, traditional machine learning models are not really a suitable choice for modelling f Equation 1 due to non-linear interaction of the features. Hence, we work with tree based models like RandomForest, Xgboost [4] to Deep learning models ranging from Multi Layer Perceptron (MLP), Long Short Term Memory (LSTM) and Temporal Convolutional Networks (TCN). Architectures of MLP, LSTM, TCN [13] and TCN-LSTM [12] models are shown in Figure 2, Figure 3, Figure 4 and Figure 5, and have been explained below.

- **Entity Embeddings + Multi Layer Perceptron:** (MLP) Figure 2 is the simplest form of deep neural networks and was proposed in [23] as a baseline architecture for Time Series classification. The architecture contains three hidden layers fully connected to the output of its previous

Figure 1: Data classification for DNN Architectures



layer. The final layer is the sigmoid layer to generate probabilities. One disadvantage is that since the input time series is fully connected to the first hidden layer, the temporal information in a time series is lost [7].

- **Entity Embeddings + Long Short Term Memory: (LSTM)** Figure 3 is an architecture comprising of 2 LSTM layers combined with entity embeddings. This combination flows into 3 fully connected ReLU based layers yielding to dense layer which has sigmoid activation.
- **Entity Embeddings + Temporal Convolutional Network: (TCN)** Figure 4, originally proposed in [13], is considered a competitive architecture yielding the best results when evaluated over our experimental dataset. This network is comprised of 3 dilated Convolutional network combined with entity embeddings. Similar to LSTM, this architecture, after convolving and concatenation flows into 3 fully connected ReLU based layers yielding to dense layer which has sigmoid activation.
- **Entity Embeddings + Long Short Term Memory-Temporal Convolutional Network: (TCN-LSTM)** Figure 5 inherits the properties of LSTM and TCN in a fully connected network.

As described in data classification Figure 1, the data was divided into following groups:

- **Static Categorical:** These are categorical features which do not vary with time. This includes the consumer attributes like sex, marital status and location, different item attributes like category, department and brand.
- **Temporal Categorical:** These are categorical features which vary with time. It includes all the datetime related features like week, month of year, etc.
- **Static Continuous:** These features are static but Continuous. This includes certain consumer attributes like age and weight, item attributes like size, and certain derived features like target encoded features.
- **Temporal Continuous:** These are time varying Continuous features. All consumer and item related traditional attributes like number of orders, add to cart order, etc. falls under this bucket.

As mentioned, in all the above described neural network architectures, we learn the embeddings [9] of the categorical features during training phase. We embed these attributes in order to both compress their representations while preserving salient features, and capture mutual similarities and differences.

Figure 2: Multi Layer Perceptron (MLP)

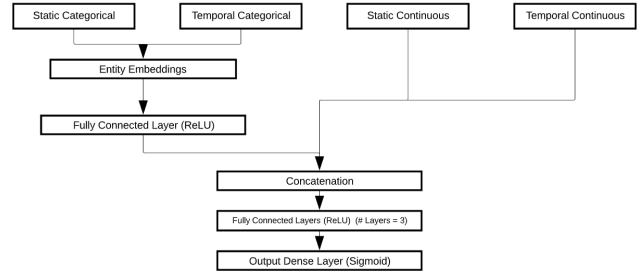
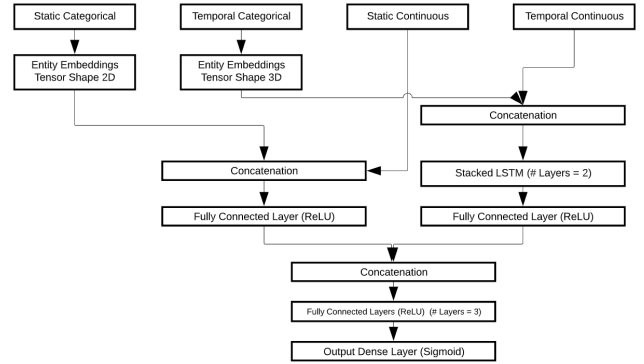


Figure 3: Long Short Term Memory (LSTM)



The consumer purchase pattern has huge variation in terms of time of purchase (weekday/weekends), cadence of purchase (days to months), purchased item types (dairy/meat/grocery/apparels/etc.) and brand loyalty (tendency to substitute items). Given such huge variance it becomes imperative to cross learn consumer behaviour from like consumer groups. To learn such relationships its very important to capture non-linear relationship between target and regressors at the most granular level. Tree based and Deep learning models are chosen for their ability to model feature interactions even if transient in time, so that they capture non-linearity well.

Tree based models and MLP are trained in such a way where lagged values of time varying features are used to capture temporal dependencies. LSTM, TCN and TCN-LSTM models are trained using entire life-cycle data of a time series (Consumer-Item) in sequential manner. We use lagged values of temporal features for multiple time steps, lagged values combined with offsets in the form of statistical rolling operations like mean, median, quantiles, variance, kurtosis and skewness over varying lag periods are used for feature generation. More details around dataset and features are explained in section 4.

3.3 Hyperparameter Tuning

Hyper-parameters of tree based models are optimized using Bayesian Hyper-parameter Optimization Technique [2]. We use documented best practices in deep learning along

Figure 4: Temporal Convolutional Network (TCN)

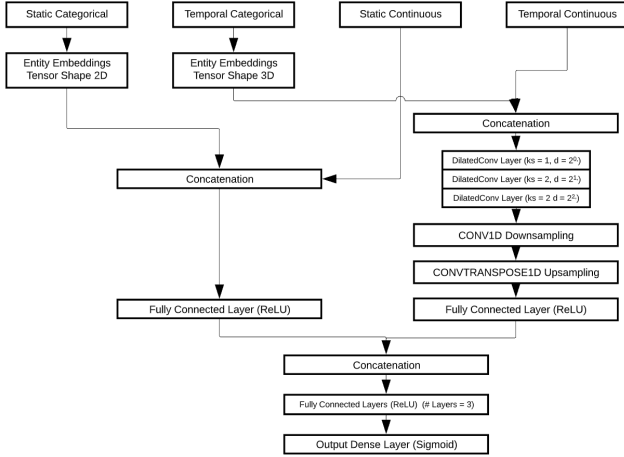
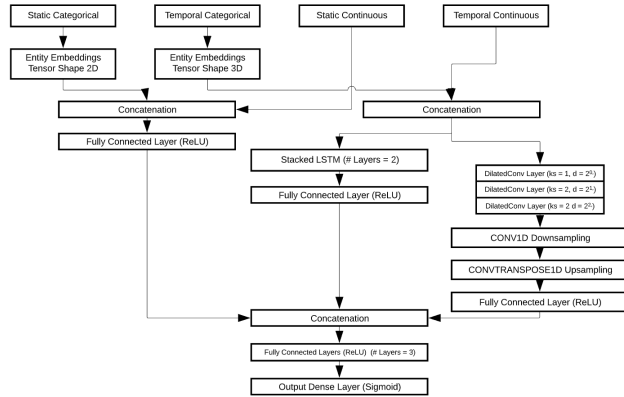


Figure 5: TCN-LSTM



with some experiments and domain understanding to choose model hyperparameters like learning rate. All hyperparameter optimization was performed over Validation dataset. We list some of the params along with the values we used for Deep learning models.

- **Optimizer Parameters:** RMSProp [1] and Adam were used as different trial configurations. The learning rate was experimentally tuned to $1e-3$. We also did weight decay of $1e-5$ which helped a bit in model Regularization.
- **Scheduler Parameters:** Cyclic [21] and ReduceLROnPlateau [26] Learning rates were used as different trial configurations. we used $1e-3$ as max lr and $1e-6$ as base lr for Cyclical learning rate along with the step size being the function of length of train loader. ReduceLROnPlateau was tuned for $1e-6$ as min lr.
- **SWA:** Stochastic Weight Averaging (SWA) [11] is used to improve generalization across Deep Learning models. SWA performs an equal average of the weights traversed by SGD with a modified learning rate schedule. We used $1e-3$ as SWA learning rate.

- **Parameter Average:** This applies weighted average over the parameter weights of n best performing epochs (local minimas) from state dictionary post completion of training.

Apart from the above parameters we also iterated enough to tune network parameters like number of epochs, batch size, number of Fully Connected Layers, number of LSTM layers, convnet parameters (kernel size, dilations, padding) and embedding sizes for the categorical features. Binary Cross-Entropy/Log Loss 2 was used as loss function for all the models. For sequence model [22], we also incorporated Dropout [10] and BatchNorm [18] as regularization parameters.

As mentioned above, we used Bayesian Hyper-parameter Optimization (Hyperopt) [2] for hyper-parameter tuning with 100 trials. Some of the hyper-parameters we used for Machine learning models are :

- **Learning Rate:** Range set to vary between $1e-2$ to $5e-1$.
- **Max Depth:** Range set from 2 to 12 at step of 1.

Apart from these, Regularization parameters like Reg Lambda, Min Sample Leaf was also optimized for using Hyperopt.

Deep learning models are built using deep learning framework PyTorch [16], and are trained on GCP instance containing 6 CPUs and a single GPU. scikit-learn [17] is used for Tree based models like RandomForest and Xgboost [4]. For Neural Network Architectures, we save the state dictionary of the best checkpoint which contains the learned weights of Entity Embeddings and all other network layers. This increases the efficiency of the model training time, as we don't need to retrain the model everytime a new consumer-item comes, and, learned embeddings and other state dictionary can enable inference over the same. We built a total of 60 models, 12 different param configurations for each of 4 Deep Learning models and 6 best trials for each of 2 Machine Learning models as shown in Table 2.

3.4 Stacked Generalization Ensemble

Stacked Generalization Ensemble or Stacking [24] is a method used to combine predictions from different models algorithmically. We used Weighted K-Best as Stacker model for combining k models (candidates) out of total 60 from Table 2. Test1 BCELoss was used as metric to compute weight for each of the 60 candidates. We iterated with different values of k ranging from 3 to 25. For Stacking, we computed Weighted Average of prediction probabilities from k individual models for Train, Validation, Test1 and Test2 for each time steps. Above phenomenon of stacking can be represented as:

$$y_{cit} = \sum_{j=1}^k w_j \times p_{cit_j} \quad (3)$$

where y_{cit} is the stacked probability for consumer 'c' item 'i' at time 't'. k represents the number of candidates shortlisted for stacking and p_{cit_k} represents the prediction probability for consumer 'c' item 'i' at time 't' by k^{th} model. w_k is the candidate weight of k^{th} model.

3.5 F₁-Maximization

Post generation of the consumer-item probabilities, we optimize for the purchase cut-off probability based on probability distribution of a time step at consumer level using F₁-Measure [14]. To illustrate above, let's say we generated purchase probabilities for n_i items of b_i actually purchased items for consumer c_i . Let Actual items purchased by consumer c_i at a time step be $[Ia_1, Ia_2, \dots, Ia_{b_i}]$ whereas items for which the model generated probabilities for the consumer c_i at that time step be $[Ip_1, Ip_2, \dots, Ip_{n_i}]$.

$$A_{c_i} = [a_1, a_2, \dots, a_{n_i}] \quad \forall a_j \in \{0,1\} \quad (4)$$

$$P_{c_i} = [p_1, p_2, \dots, p_{n_i}] \quad \forall p_j \in [0,1] \quad (5)$$

A_{c_i} represents the actuals for consumer c_i , with a_j being 1/0 (purchased/non purchased). P_{c_i} represents the predicted probabilities for consumer c_i for respective item, with p_j being probability value. As mentioned above n_i is the total items model generated purchase probabilities for.

$$D(P_{c_i}) : P_{c_i}^{1 \times n_i} \rightarrow P_{c_i}'^{1 \times n_i} : p_j' = \begin{cases} 1 & p_j \geq Pr_{c_i} \\ 0 & p_j < Pr_{c_i} \end{cases} \quad (6)$$

$$P_{c_i}' = [p_1', p_2', \dots, p_{n_i}'] \quad \forall p_j' \in \{0,1\} \quad (7)$$

$$k_i = \sum_{j=1}^{n_i} p_j' \quad (8)$$

Pr_{c_i} is the probability cut-off to be optimized for consumer c_i . Decision rule D converts probabilities P_{c_i} to binary predictions P_{c_i}' such that if p_j is less than Pr_{c_i} then p_j' equals 0 else 1. k_i is the total number of predictions which Decision rule D converted to 1 or in other words number of predictions which model predicted as purchase.

$$V_{Pr_{c_i}} = P_{c_i}' \times A_{c_i}^T \Rightarrow \begin{pmatrix} p_1' & \dots & p_{n_i}' \end{pmatrix} \times \begin{pmatrix} a_1 \\ \dots \\ a_{n_i} \end{pmatrix} \quad (9)$$

$V_{Pr_{c_i}}$ represents the number of items with purchase probabilities greater than Pr_{c_i} which were actually purchased (True Positives). Now using the below formulae we calculate Precision, Recall and F₁-score for consumer c_i .

$$Precision_{c_i} = \frac{V_{Pr_{c_i}}}{k_i} \quad \text{and} \quad Recall_{c_i} = \frac{V_{Pr_{c_i}}}{b_i} \quad (10)$$

$$F1_{c_i} = \frac{2 \times Precision_{c_i} \times Recall_{c_i}}{Precision_{c_i} + Recall_{c_i}} \Rightarrow 2 * \frac{V_{Pr_{c_i}}}{k_i + b_i} \quad (11)$$

$F1_{c_i}$ becomes the value to be maximised at optimal Pr_{c_i} for consumer c_i . We solve the above Optimization function over test1 probability distribution at a consumer level to find optimal probability cut-off Pr_{c_i} . Final purchase predictions are based on the cut-off value generated at consumer level.

4 Experiments and Results

We use transactional data from instacart kaggle challenge to train all our models. As can be seen in Figure 6 data has transactional details including consumer id, item id, order id, add to cart order, date of transaction, aisle id and department id. Also, from Table 1, we can see that we utilize 1 year data

which gets split into train, validation, test1 and test2. We generate consumer-item-week level data with purchase/ non purchase being the target. We use the above data to generate consumer-item purchase predictions for 2 time steps in the future (2 weeks in our case).

4.1 Experiment Setups

We started with exploratory data analysis, looking at the data from various cuts and trying to study the variations of the features with target. Some of them include looking at the density of consumers with different basket sizes Figure 8, orders placed for items across departments Figure 7, variation of reorder probability with add to cart order Figure 9, order probability variations at different temporal cuts like week, month and quarter, transactional metrics like total orders, total reorders, recency, gap between orders, at both consumer and item levels. We then performed multiple experiments with above features and different hyper-configurations to land at reasonable parameters to perform our experiments and present results.

4.2 Results and Observations

Tables 3 and 4 show the experimental results obtained across models with different hyper-configurations. Table 3 contains the Deep Learning Experiment setup results and Table 4 has Machine Learning model results. From model performance perspective, it is observed that TCN showed the best Accuracy score at test2, with most of the other Deep Learning models having comparable scores. Also, from Table 5 we see that all the Deep Learning models outperform Machine Learning models including Xgboost and RandomForest both in terms of Accuracy and Generalization. This table has the average of BCELoss across 3 best trials, and it can be observed that TCN has the lowest BCELoss, which translates into best Accuracy. From hyper-parameter configuration perspective we observe that RMSprop and CyclicLR emerged as the clear winners as Optimizer and Scheduler respectively from Table 3. 7 out of 12 times, we found this combination (out of 3 possible combinations) generating the best result.

We also present the effectiveness of combining predictions in the form of stacking. From Table 6, we can see the results of stacking at different values of K, for Weighted K-Best model setups. We realised the best outcome at K = 3, which led to a better score compared to any individual model. In Figure 10, we can see the probability distributions post stacking for both labels of the target. Finally we apply F₁-Maximization over stacked probability values so as to generate binary predictions(1/0 referring to Purchase/Non Purchase). F₁-Score Optimizer helps strike a balance between Precision and Recall [3]. Post F₁-Maximization we observe that Precision, Recall and F₁-Score are close enough for all data splits, as can be seen in Table 7. We scored **0.4109** over unseen data (Test2) from Table 7 as F₁-Score with the described framework.

Table 2: Model Specifications

| Model Type | Trials | Model Hyper-Parameters | Loss Functions |
|--------------|--------|---|----------------|
| MLP | 12 | Optimizer, Scheduler, SWA, Parameter Averaging, Feature Groups, FC Layers | BCELoss |
| LSTM | 12 | Optimizer, Scheduler, SWA, Parameter Averaging, Feature Groups, FC Layers, LSTM Layers | BCELoss |
| TCN | 12 | Optimizer, Scheduler, SWA, Parameter Averaging, Feature Groups, FC Layers, Convolution Parameters | BCELoss |
| TCN-LSTM | 12 | Optimizer, Scheduler, SWA, Parameter Averaging, Feature Groups, FC Layers, LSTM, Convolution Parameters | BCELoss |
| Xgboost | 6 | Learning rate, Tree Depth, Regularization parameters | BCELoss |
| RandomForest | 6 | Tree Depth, Evaluation Metrics, Regularization parameters | BCELoss |

Figure 6: Sample Dataset

| user_id | order_id | product_id | add_to_cart_order | order_number | date | product_name | aisle_id | department_id | aisle | department |
|---------|----------|------------|-------------------|--------------|----------|---|----------|---------------|------------------------|------------|
| 1 | 2539329 | 196 | 1 | 1 | 01/01/18 | Soda | 77 | 7 | soft drinks | beverages |
| 1 | 2539329 | 14084 | 2 | 1 | 01/01/18 | Organic Unsweetened Vanilla Almond Milk | 91 | 16 | soy lactosefree | dairy eggs |
| 1 | 2539329 | 12427 | 3 | 1 | 01/01/18 | Original Beef Jerky | 23 | 19 | popcorn jerky | snacks |
| 1 | 2539329 | 26088 | 4 | 1 | 01/01/18 | Aged White Cheddar Popcorn | 23 | 19 | popcorn jerky | snacks |
| 1 | 2539329 | 26405 | 5 | 1 | 01/01/18 | XL Pick-A-Size Paper Towel Rolls | 54 | 17 | paper goods | household |
| 1 | 2398795 | 196 | 1 | 2 | 16/01/18 | Soda | 77 | 7 | soft drinks | beverages |
| 1 | 2398795 | 10258 | 2 | 2 | 16/01/18 | Pistachios | 117 | 19 | nuts seeds dried fruit | snacks |
| 1 | 2398795 | 12427 | 3 | 2 | 16/01/18 | Original Beef Jerky | 23 | 19 | popcorn jerky | snacks |
| 1 | 2398795 | 13176 | 4 | 2 | 16/01/18 | Bag of Organic Bananas | 24 | 4 | fresh fruits | produce |
| 1 | 2398795 | 26088 | 5 | 2 | 16/01/18 | Aged White Cheddar Popcorn | 23 | 19 | popcorn jerky | snacks |
| 1 | 2398795 | 13032 | 6 | 2 | 16/01/18 | Cinnamon Toast Crunch | 121 | 14 | cereal | breakfast |

Table 3: BCELoss of Test2 for 12 Trials of Deep Learning Models

| Trial | Optimizer | Scheduler | SWA | Parameter Avg | MLP | LSTM | TCN | TCN-LSTM |
|-------|-----------|-------------------|-------|---------------|---------------|---------------|---------------|---------------|
| 1 | RMSprop | ReduceLROnPlateau | True | False | 0.0276 | 0.0306 | 0.0249 | 0.0307 |
| 2 | RMSprop | CyclicLR | True | False | 0.0708 | 0.0269 | 0.0269 | 0.0348 |
| 3 | Adam | ReduceLROnPlateau | True | False | 0.0295 | 0.0303 | 0.0667 | 0.0337 |
| 4 | RMSprop | ReduceLROnPlateau | False | False | 0.0297 | 0.0275 | 0.0364 | 0.0759 |
| 5 | RMSprop | CyclicLR | False | False | 0.0250 | 0.0306 | 0.0600 | 0.0286 |
| 6 | Adam | ReduceLROnPlateau | False | False | 0.0360 | 0.0302 | 0.0590 | 0.0309 |
| 7 | RMSprop | ReduceLROnPlateau | False | True | 0.0293 | 0.0432 | 0.0453 | 0.0381 |
| 8 | RMSprop | CyclicLR | False | True | 0.0245 | 0.0378 | 0.0569 | 0.0262 |
| 9 | Adam | ReduceLROnPlateau | False | True | 0.0700 | 0.0491 | 0.0610 | 0.0382 |
| 10 | RMSprop | ReduceLROnPlateau | True | True | 0.0356 | 0.0364 | 0.0238 | 0.0309 |
| 11 | RMSprop | CyclicLR | True | True | 0.0420 | 0.0377 | 0.0284 | 0.0269 |
| 12 | Adam | ReduceLROnPlateau | True | True | 0.0321 | 0.0306 | 0.0547 | 0.0305 |

Table 4: BCELoss of Test2 for 6 best Trials of ML Models

| Trial | Hyper-Parameter | Xgboost | RandomForest |
|-------|-----------------|---------------|---------------|
| 1 | HyperOpt | 0.0332 | 0.0526 |
| 2 | HyperOpt | 0.0364 | 0.0479 |
| 3 | HyperOpt | 0.0347 | 0.0416 |
| 4 | HyperOpt | 0.0364 | 0.0449 |
| 5 | HyperOpt | 0.0335 | 0.0459 |
| 6 | HyperOpt | 0.0339 | 0.0578 |

Table 5: BCELoss mean of top 3 trials across data splits

| Model Type | Val BCELoss | Test1 BCELoss | Test2 BCELoss |
|--------------|---------------|---------------|---------------|
| MLP | 0.0405 | 0.0289 | 0.0256 |
| LSTM | 0.0373 | 0.0293 | 0.0282 |
| TCN | 0.0368 | 0.0292 | 0.0251 |
| TCNLSTM | 0.0368 | 0.0304 | 0.0273 |
| Xgboost | 0.0352 | 0.0318 | 0.0335 |
| RandomForest | 0.0437 | 0.0389 | 0.0441 |

4.3 Industrial Applications

The Next Logical Purchase framework has multiple applications in retail/e-retail industry. Some of its applications include

- **Personalized Marketing:** With prior knowledge of next logical purchase, accurate item recommendations and optimal offer rollouts can be made at consumer level to pro-

vide a seamless and delightful consumer experience.

- **Inventory Planning:** Short Term Inventory Planning (2-4 weeks) is largely dependant over consumer preference in near future. Solution of the current problem can assist planners in better inventory planning.
- **Assortment Planning:** In retail stores, consumer choice study can be used to optimize the store layout with right product placement over right shelf.

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