An intelligent shopping list based on the application of partitioning and machine learning algorithms

Nadia Tahiri[§][*], Bogdan Mazoure[‡], Vladimir Makarenkov[§]

Abstract—A grocery list is an integral part of the shopping experience of many consumers. Several mobile retail studies of grocery apps indicate that potential customers place the highest priority on features that help them to create and manage personalized shopping lists. First, we propose a new machine learning model written in Python 3 that predicts which grocery products the consumer will buy again or will try to buy for the first time, and in which store(s) the purchase will be made. Second, we introduce a smart shopping template to provide consumers with a personalized weekly shopping list based on their shopping history and known preferences. As the explanatory variables, we used available grocery shopping history, weekly product promotion information for a given region, as well as the product price statistics.

Index Terms—Machine Learning, Prediction, Long short-term memory, Convolutional Neural Network, Gradient Tree Boosting, F_1, Python, Sklearn, Tensorflow

Introduction

A typical grocery retailer offers consumers thousands of promotions every week to attract more consumers and thus improve its economic performance [TTR16]. The studies by Walters and Jamil (2002, 2003) ([WJ02] and [WJ03]) report that about 39% of all items purchased during a grocery shopping are weekly specials, and about 30% of consumers surveyed are very sensitive to the product prices, buying more promotional items than regular ones. With the recent expansion of machine learning methods, including deep learning, it seems appropriate to develop a series of methods that allow retailers to offer consumers attractive and cost-effective shopping baskets, as well as to offer tools to create smart personalized weekly shopping lists based on the purchase history, known preferences, and weekly specials available in local stores.

A grocery list is an integral part of the shopping experience of many consumers. Such lists serve, for example, as a reminder, a budgeting tool, or an effective way to organize weekly grocery shopping. In addition, several mobile retail studies indicate that potential customers place the highest priority on features that help them to create and manage personalized shopping lists interactively [NPS03] and [SZA16].

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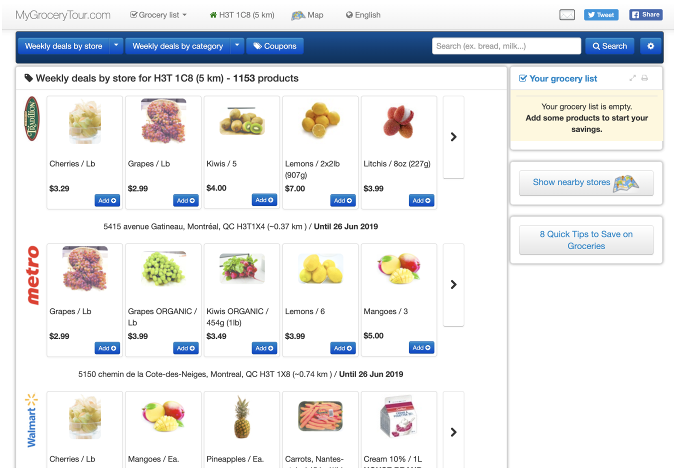

MyGroceryTour.com
Grocery list
H3T 1C8 (5 km)
Map
English
Tweet
Share
Weekly deals by store
Weekly deals by category
Coupons
Search (ex. bread, milk...)
Search
Weekly deals by store for H3T 1C8 (5 km) - 1153 products
Your grocery list
Your grocery list is empty.
Add some products to start your savings.
Show nearby stores
8 Quick Tips to Save on Groceries
Cherries / Lb $3.29 Add
Grapes / Lb $2.99 Add
Kiwis / 5 $4.00 Add
Lemons / 2x2lb (907g) $7.00 Add
Litchis / 8oz (227g) $3.99 Add
5415 avenue Gatineau, Montréal, QC H3T1X4 (~0.37 km) / Until 26 Jun 2019
metro
Grapes / Lb $2.99 Add
Grapes ORGANIC / Lb $3.99 Add
Kiwis ORGANIC / 454g (1lb) $3.49 Add
Lemons / 6 $3.99 Add
Mangoes / 3 $5.00 Add
5150 chemin de la Cote-des-Neiges, Montreal, QC H3T 1X8 (~0.74 km) / Until 26 Jun 2019
Walmart
Cherries / Lb
Mangoes / Ea.
Pineapples / Ea.
Carrots, Nantes-
Cream 10% / 1L

Fig. 1: *Screenshot of the MyGroceryTour.ca website for the postal code H3T 1C8 in Montreal. The website has been created to test our new machine learning model. It has been written in JavaScript, Bootstrap, and Python.*

Problem statement and proposal

In this section, we present the problem statement and describe the considered machine learning architecture. First, by using a Canadian grocery shopping database *MyGroceryTour.ca*[1] (see Figure 1), we partitioned consumers into classes based on their purchase histories. Then, this classification was used at the prediction stage. Since the real consumer data contained thousands of individual articles, we regrouped the products by their categories. A principal component analysis (linear and polynomial PCA [Jol11]) was first carried out to visualize the raw data and select the number of the main components to use when partitioning consumers into classes. The application of efficient partitioning methods, such as K-means [Jai10] and X-means [PM+00], allowed us to determine the number of classes of consumers, as well as their distribution by class. We used the Calinski-Harabazs cluster validity index [CH74] to determine the number of cluster in K-means. The Silhouette index [RPJ87] could be also used for this purpose.

Second, we developed a statistical model to predict which products previously purchased by a given consumer will be present in his/her next order. By using explanatory variables, such as available grocery shopping histories, information on the current promotions in stores of a given region, and commodity price

1. MyGroceryTour.ca

statistics, we developed a machine learning model which is able to:

i. Predict which groceries the consumer will want to buy again or will try to buy for the first time, as well as in which store(s) (within the area they usually shop in) the purchase(s) will be made;
ii. Create a smart shopping list by providing the consumer with a weekly shopping list, customized based on his/her purchase history and known preferences.

This list also includes recommendations regarding the optimal quantity of every product suggested. We also calculate the consumer's optimal weekly commute using the generalized travelling salesman algorithm (see Figure 2).

An F_1 statistics maximization algorithm [NCLC12] (see the Statistics section), based on dynamic programming, was used to achieve the objective (i). This will be of major interest to retailers and distributors. A deep learning method [GBC16], based on Recurrent Neural Networks (RNN) and Convolutional Neural Network (CNN), both implemented using the TensorFlow library [HLYX18], was used to achieve the objective (ii). Those implementations can provide significant benefits to consumers.

Our prediction problem can be reformulated as a binary prediction task. Given a consumer, the history of his/her previous purchases and a product with its price history, predict whether or not this product will be included in the grocery list of the consumer. Our approach applies a generative model to process the existing data, i.e., first-level models, and then uses the internal representations of these models as features of the second-level models. RNNs and CNNs were used at the first learning level and forward propagation neural networks (Feed-forward NN) was used at the second learning level.

Thus, depending on the user's u and the user's purchase history ($shop_{t-h:t}$, $h > 0$), we predict the probability that the product i is included in the current shopping basket $_{t+1}$ of u.

Dataset

In this section, we discuss the details of our synthetic and real datasets, the latter obtained from our website *MyGroceryTour.ca.*

Features

To perform the prediction only the features we found to be significant, such as *distance*, *special* rate, *products*, and *store*, were considered. All features used in our study are presented below:

- **user_id**: the user ID. We anonymized all data used in our study. $user\_id \in \underbrace{\{1 \cdots 374\}}_{\text{reals}} \cup \underbrace{\{375 \cdots 1,374\}}_{\text{generated}}$
- **order_id**: unique number of the basket. $order\_id \in \mathbb{Z}$
- **store_id**: unique number of the store. $store\_id \in \{1 \cdots 10\}$
- **distance**: distance to the store. $distance \in \mathbb{R}^+$
- **product_id**: unique number of the product. $product\_id = 49,684$. We tested our model with 1,000 products only (out of 49,684 products), which belonged to 5 out of the 24 available categories, i.e. *Fruits-Vegetables*, *Pasta-Flour*, *Organic Food*, *Beverages*, and *Breakfast*; the rest of the categories were not considered in our tests.
- **category_id**: unique category number for a product. $category\_id \in \{1 \cdots 24\}$
- **reorder**: the reorder is equal to 1 if the product has been ordered by this user in the past, 0 else. $reorders \in \{0,1\}$
- **special**: discount percentage applied to the product price at the time of purchase. $special \in \{[0\%,15\%[, [15\%,30\%[, [30\%,50\%[, [50\%,100\%[\}$

In total, we processed the data of 1374 users (i.e., consumers). Among them, we had 374 real users and 1000 users whose behaviour was generated following the distribution of real users (see Figure 3) and the consumer statistics available in the report by Statistics Canada (2017). The product categories were available for each product. So, the product category was one of the explanatory variables used in the model. In total, we considered 5 (of 24) product categories. The current version of our model does not allow a new product to be bought by the user (i.e., every user can only buy products that were present in at least one of its previous shopping baskets). The user IDs were not sequential because we only considered real users having a sufficient number of previous shopping baskets available (>50 baskets). The average basket size was also used to predict the content of the current basket size for each user.

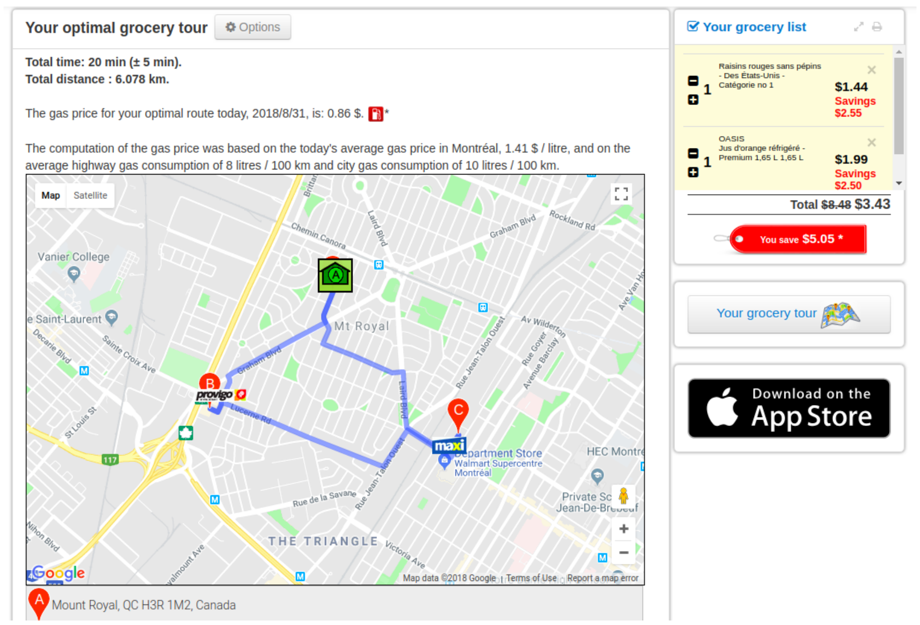
Two types of features, categorical and quantitative variables, were present in our data. Only the *distance* and *special* features were quantitative variables, the rest of them were categorical. To manage the categorical variables, we applied a hashing scheme to deal with large scale categorical features. The hash function takes into account the input and output vector length. We used the *LabelEncoder* function of the *scikit-learn* package of Python (version 3).

Consumer profile

According to Statistics Canada there exist 3 consumer profiles (see [WJ03], [WJ02], and [TNTK16]). The first profile represents consumers who buy only promotional items. The second profile represents consumers who always buy the same products (without considering promotions). Finally, the third profile represents consumers who buy products whether they are in special or not. On our model, we plan to consider this information and make the prediction more personalized with respect to the consumer's profile.

Data Synthesis

Since the real dataset was not large enough to apply the appropriate machine learning methods, its size was increased by adding simulated data following the distribution of real data. The original dataset was composed of 374 users. It may be not enough to apply an appropriate machine learning method, and 1000 simulated users were added to our dataset. Thus, 72.7% of our data were simulated (1000 out of 1374 user histories were simulated). Here, we describe the simulated part of our dataset, and present in detail the results of the simulation step. For *store_id*, we started with an initial store and changed stores based on the proportion of common products between baskets. If we assume that the store coordinates are normally and independently distributed $\mathcal{N}(0,\sigma^2)$, the distance between this store and the consumer home located at the origin $(0,0)$ follows a Rayleigh distribution [KR05] with the σ parameter. Finally, we increased the value of the *special* random variable. Its value has been drawn from a Boltzmann distribution [AAR+18]. We made sure that the generated baskets followed the same distribution that the original basket in terms of the basket size (see Figure 3).



Your optimal grocery tour

Total time: 20 min (± 5 min).
Total distance : 6.078 km.

The gas price for your optimal route today, 2018/8/31, is: 0.86 $.*

The computation of the gas price was based on the today's average gas price in Montréal, 1.41 $ / litre, and on the average highway gas consumption of 8 litres / 100 km and city gas consumption of 10 litres / 100 km.

Mount Royal, QC H3R 1M2, Canada

Your grocery list

1	Raisins rouges sans pépins - Des États-Unis - Catégorie no 1	$1.44 Savings $2.55
1	OASIS Jus d'orange réfrigéré - Premium 1,65 L 1,65 L	$1.99 Savings $2.50

Total ~~$8.48~~ $3.43

You save $5.05 *

Fig. 2: Screenshot of the MyGroceryTour.ca website displaying an optimal shopping journey calculated using the generalized travelling salesman algorithm.

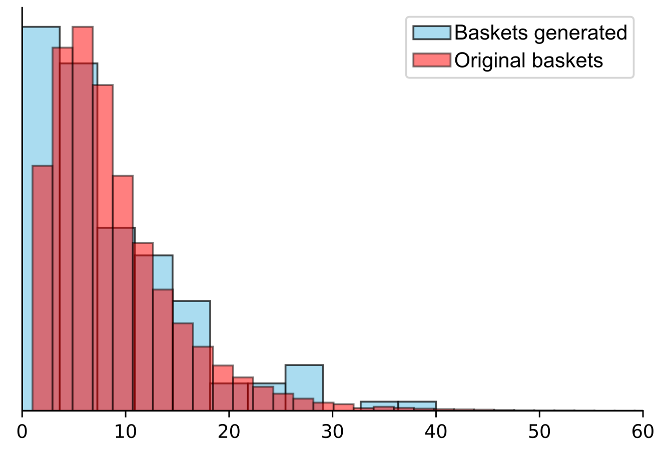


Fig. 3: *Difference in the basket size distribution between **Baskets generated** in blue and **Original baskets** in red.*

Preprocessing dataset

Initially, the data were saved in CSV files and stored in a MySQL database taking 1.4 GB of disk space. Then, the data were organized in a dataframe and processed using our Python script. We launched the preprocessing data tasks on the servers of Compute Canada. This step was carried out using 172 nodes and 40 cores with an Intel Gold 6148 Skylake CPU(2.4 GHz), and NVidia V100SXM2(16 GB of memory). We preprocessed the user data, the product data, and the department data. The preprocessing had a 48 hour limit and used 32 GB of the RAM memory.

Models

In this section, we present the workflow (see Figure 4) and the models we used. The graphical representation of the workflow in

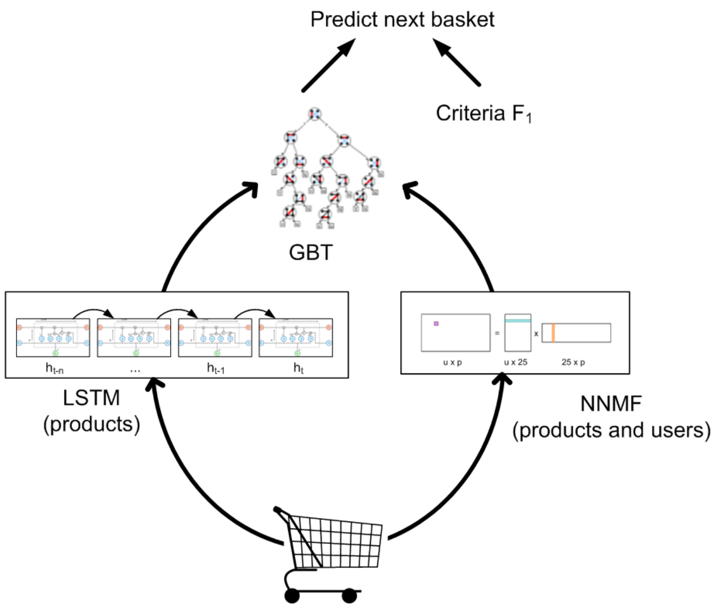


Fig. 4: *The graphical illustration of the proposed model intended to predict the content of the current grocery basket. At the first level of the model the LSTM and NNMF networks were used. At the second level of the model, the GBT model was applied. Finally, at the last step we predicted the current grocery basket using F_1.*

Figure 4 allowing one to predict the current consumer's basket using the three following models: LSTM, NNMF, and GBT (see the next section).

Long short-term memory (LSTM) network

The LSTM [HS97] is a recurrent neural network (RNN) that has an input, a hidden memory block, and an output layer. The memory block contains 3 gate units namely the input, forget, and output with a self-recurrent connection neuron [HS97].

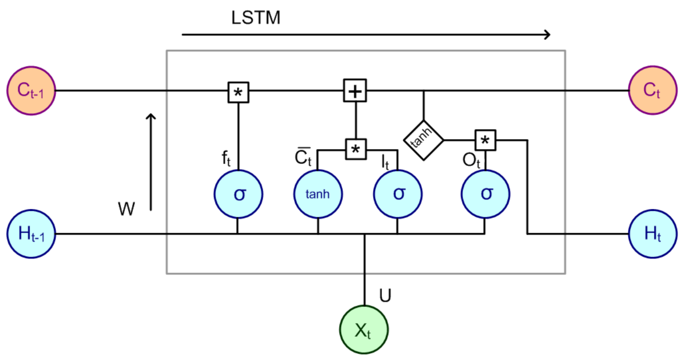


Fig. 5: This figure shows a chain-structured LSTM network. An LSTM architecture contains the forget, learn, remember, and uses gates that determine the importance of the input data. In the LSTM unit represented in this figure, there are four different functions: sigmoid (σ), hyperbolic tangent (tanh), multiplication ($*$), and sum ($+$), making it easier to update the weights during the backpropagation process. Here X_t denotes the input vector, H_{t-1} is the previous cell output, C_{t-1} is the previous cell memory, H_t is the current cell output, C_t is the current cell memory. f_t is the forget gate with sigmoid function sigma, $\overline{C_t}$ and I_t corresponds to the input gate with tanh function, and finally O_t is the output gate with sigma function.

- **Input gate** learns what information is to be stored in the memory block.
- **Forget gate** learns how much information from the memory block should be retained or forgotten.
- **Output gate** learns when the stored information can be used.

Figure 5 illustrates the proposed architecture and summarizes the details of our network model.

A combined RNN and CNN network was trained to predict the probability that a given user will order a given product at each timestep. A timestep was defined by the composition of the basket and the store location on the map (see Figure 2). Here, RNN was a single-layer LSTM and CNN was a 6-layer causal CNN with dilated convolutions. The width of the CNN was equal to 1374 (i.e., the number of users), the height was equal to 8 (i.e., the number of features), and the depth was equal to 100 (i.e., the number of orders). The last layer was a fully-connected layer that was making the final classification. The CNN network was used as a feature extractor and the LSTM network as a sequential learner.

Overall characteristics of the neural networks used in our project are as follow:

```
nn = rnn(
 reader=dr,
 log_dir=os.path.join(base_dir,
                      'logs'),
 checkpoint_dir=os.path.join(base_dir,
                             'checkpoints'),
 prediction_dir=os.path.join(base_dir,
                             'predictions'),
 optimizer='adam',
 learning_rate=.001,
 lstm_size=512,
 batch_size=64,
 num_training_steps=300,
 early_stopping_steps=10,
 warm_start_init_step=0,
 regularization_constant=0.0,
 keep_prob=1.0,
 enable_parameter_averaging=False,
 num_restarts=2,
 min_steps_to_checkpoint=100,
 log_interval=20,
 num_validation_batches=4,
)
```

We considered the *Adam* optimizer which is a good default implementation of gradient descent. The learning rate was equal to 0.001 to control how long the weights should be updated in response to the estimated gradient at the end of each batch. The size of the hidden state of an LSTM unit was fixed to 512. Batch size corresponds to the number of samples between updates of the model weights. It was set to 64 during the training process. Also, we set to 4 the number of validation batches. The Tensorflow package was used to implement our *rnn* class that account for the features described in the previous section. The *rnn* class structure was organized using the four following functions: 1) constructor function, 2) loss score function calculation, 3) getter function, and 4) output score function.

```
import TFBaseModel

class rnn(TFBaseModel):
  def __init__(self,
               lstm_size,
               dilations,
               filter_widths,
               skip_channels,
               residual_channels,
               **kwargs):
      ...
  def calculate_loss(self):
      ...
  def get_input_sequences(self):
      ...
  def calculate_outputs(self, x):
     ...
```

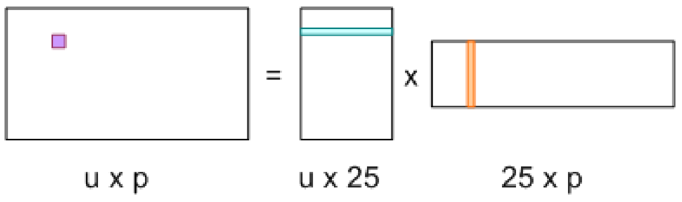


Fig. 6: Decomposition of the user_id (u in Figure) by product_id (p in Figure). The first matrix accounts for the products purchased by the user (i.e. order count), whereas the second and the third matrices account for the representations of the user and the product, respectively.

Non-negative matrix factorization (NNMF) network

Non-negative matrix factorization NNMF [LS01] is a series of algorithms in multivariate analysis and linear algebra in which a matrix X is factorized into two matrices W and H having the property that all three matrices have no negative elements. This non-negativity makes the resulting matrices easier to utilize. We factorize the matrix X (i.e. matrix of *user_id* by *product_id*) into two matrices W (i.e. *user_id*) and H (i.e. *product_id*), so that the matrix representation can be formulated as: $X \approx WH$ (see Figure 6).

NNMF is a powerful machine learning method. It has been proved that NNMF converse to at least a locally optimal solution [LS01]. NNMF is trained on the matrix of the *user*product* counts.

Gradient Boosted Tree (GBT) network

GBT [Fri02] is an iterative algorithm that combines simple parameterized functions with low performance (i.e. high prediction error) to produce a highly accurate prediction rule. GBT utilizes an ensemble of weak learners to boost performance; this makes it a good candidate model for predicting the grocery shopping list. It requires little data preprocessing and tuning of parameters while yielding interpretable results, with the help of partial dependency plots and other investigative tools. Further, GBT can model complex interactions in a simple recommendation system and be applied in both classification and regression with a variety of response distributions, including Gaussian [Car03], Bernoulli [CMW16], Poisson [PJ73], and Laplace [Tay19]. The composition of the shopping history list is not complete in the sense that we do not have the composition of the baskets for each user for all weeks. Finally, missing values in the collected data can be easily managed.

The data were divided into two groups (training and validation sets) which comprised 90% and 10% of the data, respectively. After simulating the dataset, the strategy used was to merge real and simulated data and then split them into two groups (training and validation sets). The test set was composed of both real and simulated data. The final model included two neural networks and a GBT classifier. Once trained, it was used to predict in "real time" the content of the current grocery basket, based on the history of purchases and the current promotions in neighbouring stores. In fact, the "real time" does not mean "second-by-second", but rather "day-by-day". We scheduled it using the crontab tool. Based on the validation loss function, we removed the following parameters from our input data: 1) LSTM Category and 2) LSTM size of the next basket.

The last layer included a GTB classifier used to predict the products that will be purchased during the current week. GBT model was modelled using "by user" and "by order" frameworks. The classifier contained two classes: 0 (i.e. the product will be bought) and 1 (i.e. the product won't be bought).

First level model (feature extraction)

Our goal was to find a diverse set of representations using neural networks (see Table 1). Table 1 summarizes the top-level models used by the algorithm. We described each type of model used for every representation (e.g. *Products*, *Category*, *Size of the basket*, and *Users*). We estimated the probability of the $product_i$ to be included into the next basket $order_{t+1}$ with $orders_{t-h}$, where t represents the current time, $t+1$ represents the next time, and $t-h$ represents all previous time periods (i.e. time history). We decomposed the matrix {user,product} into two matrices, one corresponding to the user and another to the product. We predicted the probability to have the $product_i$ in the next $order_{t+1}$, taking into account the purchase history of the current user. We used an LSTM network with 300 neurons. Finally, we optimized the size of the next order by minimizing the root mean square error (RMSE).

Latent representations of entities (embeddings)

For each $a \in \mathscr{A}$, an embedding $T : \mathscr{A} \to \mathbb{R}^d$ returns a vector d-dimensionel. If $\mathscr{A} \subset \mathbb{Z}$, T is a matrix $|\mathscr{A}| \times d$ learned by backpropagation. We represented in Table 2 all dimensions of each model used.

Representation	Description	Type
Products	Predict $\mathrm{P}(\mathrm{product}_i \in \mathrm{order}_{t+1})$ with $\mathrm{orders}_{t-h,t}$, $h > 0$.	LSTM (300 neurons)
Categories	Predict $\mathrm{P}(\exists i : \mathrm{product}_{i,t+1} \in \mathrm{category}_r)$.	LSTM (300 neurons)
Size	Predict the size of the order_{t+1}.	LSTM (300 neurons)
Users Products	Decomposed $V_{(u\times p)} = W_{(u\times d)} H^T_{(p\times d)}$	Dense (50 neurons)

__TABLE 1:__ Top-level models used. The figure shows the representation, the description, and the type of products, the categories, the size of baskets, and the matrix users/products.

Model	Embedding	Dimensions
LSTM Products	Products	$49,684 \times 300$
LSTM Products	Categories	24×50
LSTM Products	Categories	$50 \to 10$
LSTM Products	Users	$1,374 \times 300$
NNMF	Users	$1,374 \times 25$
NNMF	Products	$49,684 \times 25$

__TABLE 2:__ Dimensions of the representations learned by different models at the first level of the model.

Second level model: Composition of baskets

The resulting basket was chosen according to the final reorganization probabilities, selecting the subset of products with the expected maximum F_1 score, see [LEN14] and [NCLC12]. This score is frequently used when the relevant elements are scarce.

$$\max_{\mathscr{P}} \mathbb{E}_{p' \in \mathscr{P}}[F_1(\mathscr{P})] = \max_{\mathscr{P}} \mathbb{E}_{p' \in \mathscr{P}} \left[\frac{2\sum_{i\in\mathscr{P}} \mathrm{TP}(i)}{\sum_{i\in\mathscr{P}}(2\mathrm{VP}(i) + \mathrm{FN}(i) + \mathrm{FP}(i))} \right],$$

where True Positive $(TP) = \mathbb{I}[\lfloor p(i) \rceil = 1]\mathbb{I}[R_i = 1]$, False Negative $(FN) = \mathbb{I}[\lfloor p(i) \rceil = 0]\mathbb{I}[R_i = 1]$, False Positive $(FP) = \mathbb{I}[\lfloor p(i) \rceil = 1]\mathbb{I}[R_i = 0]$ and $R_i = 1$ if the product i was bought in the basket $p' \in \mathscr{P}$, else 0.\ We used $\mathbb{E}_X[F_1(Y)] = \sum_{x\in X} F_1(Y = y|x)P(X = x)$

Statistics

Here, we present the results obtained using the proposed method. The *F-measure* (see Equation 1) metric was used to evaluate the performance of the method.

Statistical score

F-measure, or F_1, is a well-known and reliable evaluation statistic (see [JOA05]). The F_1 value of 1 means perfect accuracy.

$$F - measure = F1 = \frac{2 \times Precision \times Recall}{(Precision + Recall)} \quad (1)$$

Python Script

The final reorder probabilities were computed as the weighted average of the outputs from the second-level models. The final basket was chosen by using these probabilities and selecting the product subset with a maximum expected F1-score. In our implementation, we used *f1_optimizer* implemented in **F1Optimizer** package. The implementation of [NCLC12] is available in [F1Optimizer]. The select_products function in Python script was the following:

```python
from f1_optimizer import F1Optimizer

def select_products(x):
 series = pd.Series()

```

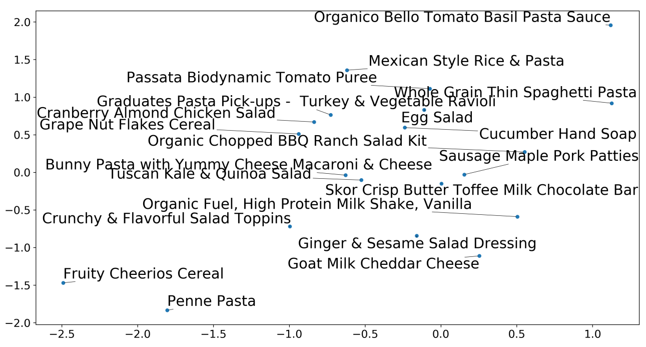


Fig. 7: *Embeddings of 20 random products projected into 2 dimensions.*

```
for prod in x['product_id'][x['label'] > 0.5:
  if prod != 0:
   true_products = [str(prod)].values]
  else:
   true_products = ['None'].values]

if true_products:
 true_products = ' '.join(true_products)
else:
 true_products = 'None'

prod_preds_dict = dict(zip(x['product_id'].values,
                           x['prediction'].values))
none_prob = prod_preds_dict.get(0, None)
del prod_preds_dict[0]

other_products = np.array(prod_preds_dict.keys())
other_probs = np.array(prod_preds_dict.values())

idx = np.argsort(-1*other_probs)
other_products = other_products[idx]
other_probs = other_probs[idx]

opt = F1Optimizer.max_expectation(other_probs,
                                  none_prob)

best_prediction = ['None'] if opt[1] else []
best_prediction += list(other_products[:opt[0]])

if best_prediction:
 predicted_products = ' '.join(map(str,
                               best_prediction))
else:
 predicted_products = 'None'

series['products'] = predicted_products
series['true_products'] = true_products

return true_products, predicted_products, opt[-1]
```

Results

Figure 7 illustrates PCA of 20 random products projected into 2 dimensions. These results show clearly the presence of the cluster of products, including the Pasta sauce and Pasta group articles. This embedding plot was generated with 20 random products. Some trends can be observed here, but there are also some exceptions, as it often happens with real data. In Table 2, Pasta Group was included into the product Categories. In fact, this result can help identify the consumer buying behaviour.

PCA was performed to visualize the clustering of 20 selected products. It was used to show that some products are frequently

Product	F_1
Gogo Squeez Organic Apple Strawberry Applesauce	0.042057
Organic AppleBerry Applesauce on the Go	0.042057
Carrot And Celery Sticks	0.042057
Gluten Free Peanut Butter Berry Chewy	0.042057
Organic Italian Balsamic Vinegar	0.049325
Diet Cranberry Fruit Juice	0.599472
Purified Water	0.599472
Vanilla Chocolate Peanut Butter Ice Cream Bars	0.599472
Total 0% with Honey Nonfat Greek Strained Yogurt	0.590824
Total 0% Blueberry Acai Greek Yogurt	0.590824

TABLE 3: *The average value of F_1 for all products considered.*

Product	Number of baskets
Banana	6138
Strawberries	3663
Organic Baby Spinach	1683
Limes	1485
Cantaloupe	1089
Bing Cherries	891
Small Hass Avocado	891
Organic Whole Milk	891
Large Lemon	792
Sparkling Water Grapefruit	792

TABLE 4: *The 10 most popular products included in the predicted baskets. The top products were taken from a subset comprising 2% of all available products.*

bought together with the other products. Such a clustering was not used explicitly in our model, by an artificial network model is supposed to capture and take it into account implicitly in order to provide a better prediction. F_1 in Figure 8 (a) shows that the profiles of all promotions are similar. In the perspective, it would be interesting to include in our model the product weight based on some additional available statistics. For example, according to Statistics Canada - 2017, only 5% of all specials had a rebate of 50% and larger, whereas 95% of them had a smaller rebate. The use of theses weights could make the model more robust.

Figure 8 (b) indicates that all stores follow similar profiles in our model.

This plot presents the distribution of the F1-score results with respect to the promotions and stores. We can observe that the distributions of the promotions and stores are very similar. Finally, this plot suggests the absence of the bias for these two model parameters. Figure 9 and Table 3 report the values of the F_1 metric for the products whose inclusion into the consumer's basket was either very easy or very hard to predict. The first group of products includes the articles of restriction regimes such as *diet cranberry fruit juice*, *purified water*, and *total 0% blueberry acai greek yogurt.*

Table 3 presents only the products with the five highest and the five lowest values of *F_1* (the average, in this case, was taken over all users who purchased these products).

We also evaluated the prediction quality of our model (see Section 'Statistic scores') using the *sklearn* metrics (see below):

```
from sklearn.metrics import make_scorer,
                            accuracy_score,
                            f1_score,
                            recall_score
```

The results reported in Table 5 suggest that a better model accuracy was obtained when the original dataset of 374 real users was enriched by 1,000 artificial users. The accuracy of 49% was

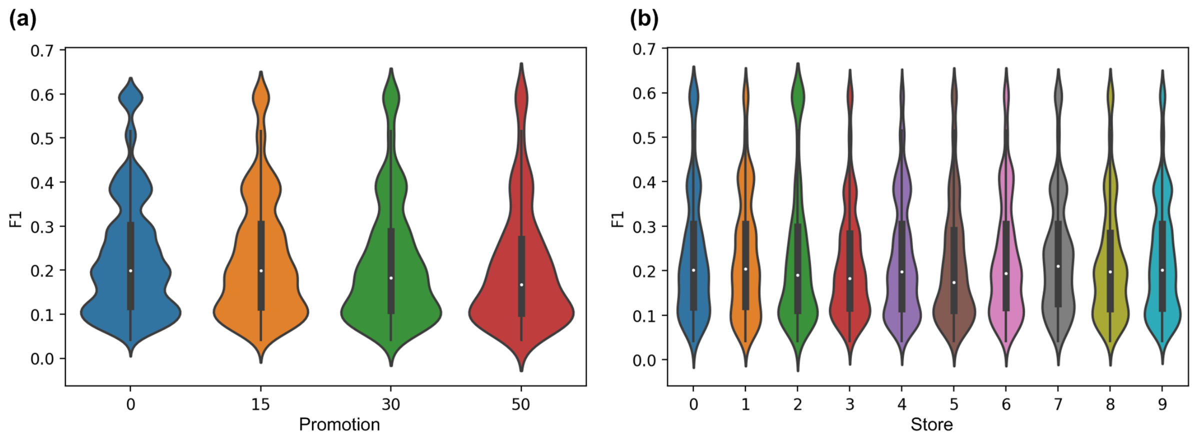


Fig. 8: *Distribution of F_1 measures against rebates (a), and stores (b).*

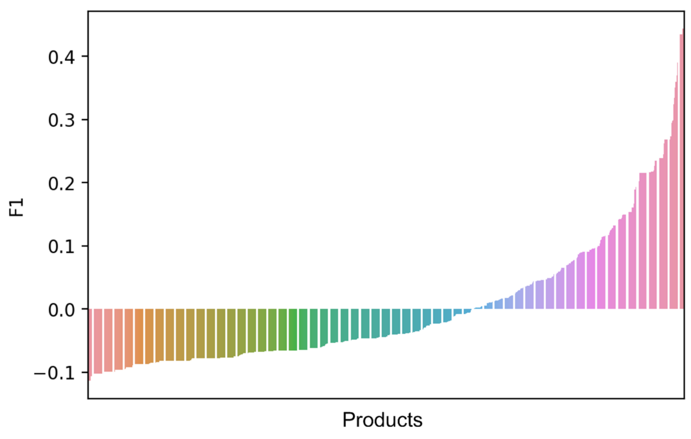


Fig. 9: *Distribution of the F_1 scores relative to the products around average.*

Statistics score	Real data	Real and augmented data
Accuracy	0.27	0.49
Precision	0.27	0.49
Recall	0.51	0.7
F-measure	0.22	0.37

TABLE 5: *Statistical scores results obtained for real data, and for real + artificial augmented data. The table clarifies the impact of using augmented data instead in addition to the real ones.*

obtained for the augmented dataset, compared to the accuracy of 27% for the original dataset.

Conclusions and Future Work

We analyzed grocery shopping data generated by the users of the site *MyGroceryTour.ca*. We developed a new machine learning model to predict which grocery products the consumer will buy and in which store(s) of the region he/she will do grocery shopping. We created an intelligent shopping list based on the shopping history of each consumer and his/her known shopping preferences. The originality of the approach, compared to the existing methods, is that in addition to the purchase history we also considered the promotions available, possible purchases in different stores, and the distance between these stores and the consumer's home.

We have modelled the habits of the MyGroceryTour.ca site consumers using deep neural networks. Two types of neural networks were applied at the learning stage: Recurrent neural networks (RNN) and Forward-propagating neural networks (Feed-forward NN). The value of the F_1 statistic that represents the quality of the model needs could be increased in the future by considering additional explanatory features and product weights. The constant influx of new data on *MyGroceryTour* will allow us to improve the model's results.

In the future, we plan to predict the grocery store that will be visited next, and include the recommended product quantities in the basket proposed to the user.

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Abbreviations

- CNN - Convolutional Neural Network
- GBT - Gradient Tree Boosting
- LSTM - Long Short-Term Memory
- ML - Machine Learning
- NN - Neural Networks
- NNMF - Non-Negative Matrix Factorization
- PCA - Principal Component Analysis
- RMSE - Root Mean Square Error
- RNN - Recurrent Neural Networks

References

[AAR+18] Amin, Mohammad H., Evgeny Andriyash, Jason Rolfe, Bohdan Kulchytskyy, and Roger Melko. *Quantum boltzmann machine*. Physical Review X, 8(2):021050, 2018. DOI: https://doi.org/10.1103/PhysRevX.8.021050

[Car03] Rasmussen, Carl Edward. *Gaussian processes in machine learning*. In Summer School on Machine Learning, pp. 63:71. Springer, Berlin, Heidelberg, 2003. DOI: https://doi.org/10.1007/978-3-540-28650-9_4

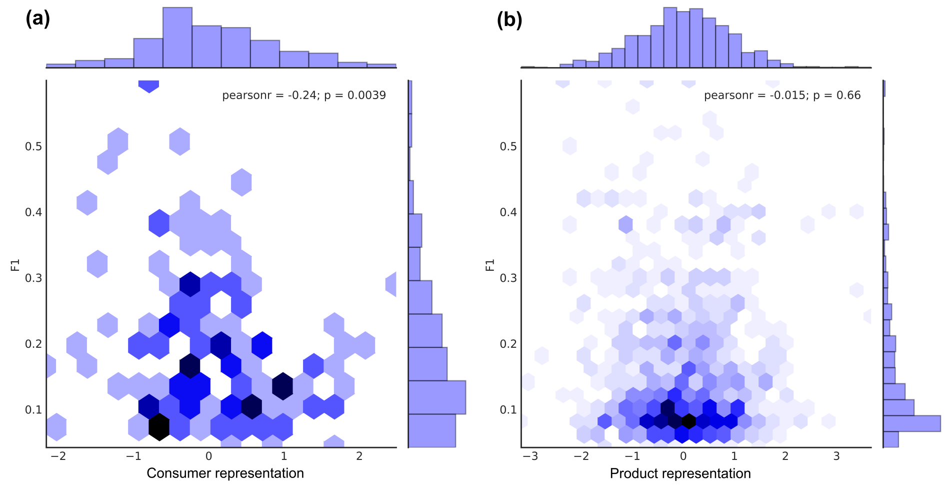

Fig. 10: *Distribution of the F_1 scores with respect to the consumers and products.*

[CH74] Caliński, T. and Harabasz, J., 1974. *A dendrite method for cluster analysis*. Communications in Statistics-theory and Methods, 3(1), pp.1-27. DOI: https://doi.org/10.1080/03610917408548446

[CMW16] Maddison, Chris J., Andriy Mnih, and Yee Whye Teh. *The concrete distribution: A continuous relaxation of discrete random variables*. arXiv preprint arXiv:1611.00712, 2016. https://arxiv.org/pdf/1611.00712.pdf

[F1Optimizer] Kaggle post, *F1-Score Expectation Maximization in $O(n^2)$*, 2017. https://www.kaggle.com/mmueller/f1-score-expectation-maximization-in-o-n

[Fri02] Jerome H. Friedman. *Stochastic gradient boosting*. Computational Statistics & Data Analysis, 38(4):367–378, 2002. DOI: https://doi.org/10.1016/S0167-9473(01)00065-2

[GBC16] Ian Goodfellow, Yoshua Bengio, and Aaron Courville. *Deep learning*. MIT press, 2016.

[HLYX18] Hao, L., Liang, S., Ye, J. and Xu, Z., 2018. *TensorD: A tensor decomposition library in TensorFlow*. Neurocomputing, 318, pp. 196-200. DOI: https://doi.org/10.1016/j.neucom.2018.08.055

[HS97] Sepp Hochreiter and Jurgen Schmidhuber. *Long short-term memory*. Neural computation, 9(8):1735–1780, 1997. DOI: https://doi.org/10.1162/neco.1997.9.8.1735

[Jai10] Anil K Jain. *Data clustering: 50 years beyond k-means*. Pattern recognition letters, 31(8):651–666, 2010. DOI: https://doi.org/10.1016/j.patrec.2009.09.011

[JOA05] Joachims, T., 2005. *A support vector method for multivariate performance measures*. In Proceedings of the 22nd international conference on Machine learning (pp. 377-384). ACM. DOI: https://dl.acm.org/citation.cfm?doid=1102351.1102399

[Jol11] Ian Jolliffe. *Principal component analysis*. Springer, 2011. DOI: https://doi.org/10.1007/978-3-642-04898-2_455

[KR05] Debasis Kundu and Mohammad Z Raqab. *Generalized rayleigh distribution: different methods of estimations*. Computational statistics & data analysis, 49(1):187–200, 2005. DOI: https://doi.org/10.1016/j.csda.2004.05.008

[LEN14] Zachary C Lipton, Charles Elkan, and Balakrishnan Naryanaswamy. *Optimal thresholding of classifiers to maximize f1 measure*. In Joint European Conference on Machine Learning and Knowledge Discovery in Databases, pp. 225–239. Springer, 2014. DOI: https://doi.org/10.1007/978-3-662-44851-9_15

[LS01] Lee, D.D. and Seung, H.S. *Algorithms for non-negative matrix factorization*. In Advances in neural information processing systems, pp. 556-562, 2001.

[NCLC12] Ye Nan, Kian Ming Chai, Wee Sun Lee, and Hai Leong Chieu. *Optimizing f-measure: A tale of two approaches*. arXiv preprint arXiv:1206.4625, 2012. https://arxiv.org/ftp/arxiv/papers/1206/1206.4625.pdf

[NPS03] Erica Newcomb, Toni Pashley, and John Stasko. *Mobile computing in the retail arena*. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, pp. 337–344. ACM, 2003. DOI: https://doi.org/10.1145/642667.642670

[PJ73] Consul, Prem C., and Gaurav C. Jain. *A generalization of the Poisson distribution*. Technometrics 15(4):791-799, (1973).

[PM+00] Dan Pelleg, Andrew W Moore, et al. *X-means: extending kmeans with efficient estimation of the number of clusters*. In Icml, volume 1, pp. 727–734, 2000.

[RPJ87] Rousseeuw, P.J., 1987. *Silhouettes: a graphical aid to the interpretation and validation of cluster analysis*. Journal of computational and applied mathematics, 20, pp.53-65. DOI: https://doi.org/10.1016/0377-0427(87)90125-7

[SZA16] Szpiro, S., Zhao, Y. and Azenkot, S. *Finding a store, searching for a product: a study of daily challenges of low vision people*. In Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing, pp. 61-72. ACM, 2016. DOI: https://doi.org/10.1145/2971648.2971723

[Tay19] Taylor, James W. *Forecasting value at risk and expected shortfall using a semiparametric approach based on the asymmetric Laplace distribution*. Journal of Business & Economic Statistics 37(1):121-133, 2019. DOI: https://doi.org/10.1080/07350015.2017.1281815

[TNTK16] Arry Tanusondjaja, Magda Nenycz-Thiel, and Rachel Kennedy. *Understanding shopper transaction data: how to identify crosscategory purchasing patterns using the duplication coefficient*. International Journal of Market Research, 58(3):401–419, 2016. DOI: https://doi.org/10.2501/ijmr-2016-026

[TTR16] Arry Tanusondjaja, Giang Trinh, and Jenni Romaniuk. *Exploring the past behaviour of new brand buyers*. International Journal of Market Research, 58(5):733–747, 2016. DOI: https://doi.org/10.2501/ijmr-2016-042

[WJ02] Rockney Walters and Maqbul Jamil. *Measuring cross-category specials purchasing: theory, empirical results, and implications*. Journal of Market-Focused Management, 5(1):25–42, 2002.

[WJ03] Rockney G Walters and Maqbul Jamil. *Exploring the relationships between shopping trip type, purchases of products on promotion, and shopping basket profit*. Journal of Business Research, 56(1):17–29, 2003. DOI: https://doi.org/10.1016/s0148-2963(01)00201-6