Customer Purchase Journey Prediction (CPJP)

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https://github.com/adityasumbaraju/aditya_portfolio/tree/main/Customer_Purchase_Journey_Prediction

Customer Purchase Journey Prediction

Business Problem

Customer purchasing predictions are standard for many companies, including large and small-scale businesses. It is always an advantage to an organization that contains data wealth, and this will help them predict the possible purchasing behavior of a given customer. And it also allows clients to make informed decisions on maintaining inventory and providing customer recommendations on items, customer promotions, and predicting the customer's interests in buying a similar product from its competitor. In this case study, I would analyze and demonstrate some of these metrics on a publicly available dataset and develop an ML model using RNN to predict the future long-term purchasing in the form of customer lifetime values.

Background

In recent years analyzing shopping baskets has become quite appealing to retailers. Advanced technology made it possible to gather information on their customers and what they buy. Electronic point-in sales increased the use and application of transactional data in the next basket analysis. Analyzing purchase behavior patterns allows retailers to understand customers' purchase behavior, which helps to adjust promotions, store settings and serve customers better. Transactional data is used in mining information on co-purchases and adjusting promotion and advertising accordingly.

Accurate "customers' purchase behavior" will enable next-generation e-commerce predictive shopping and logistics. I would be applying the deep learning technology behind the next basket prediction. Retail domain E-commerce online sales are predicted to double in the following three years, and it will be known for Covid-19 years. The pandemic accelerated this trend, and now even groceries are going online, for example, amazon fresh. As per the experts, this process is considered to be irreversible. Groceries have many repetitive purchases occurring that generate buyer behavior patterns in time, and respective patterns can be identified by machine learning models and subsequently be used to predict from the purchase transactions data.

Customers' purchase Journey prediction has been a primary ML topic for retailers for quite some time. Experts forecasted that machine learning would predict the next purchase to change e-commerce forever in the next year. This forecast did not materialize, and even seven years later, machine learning models are not good enough to make the next basket prediction which can be useful enough. Some estimate that even 60% prediction accuracy can enable predictive shopping, and Amazon is already experimenting with so-called anticipatory shipping.

Data Explanation

Data Source Urls:

- https://www.kaggle.com/chiranjivdas09/ta-feng-grocery-dataset
- https://stackoverflow.com/questions/25014904/download-link-for-ta-feng-grocery-dataset

About Data: The Ta Feng Grocery Dataset

Column definition: Transaction date and time, Customer ID, Age Group, PIN Code (Region), Product subclass, Product ID, Amount, Asset, Sales price

Fields of the Dataset are:

- Transaction date and time
- Customer ID
- Age: 10 possible values

- Residence Area: 8 possible values
- Product subclass
- Product ID
- Amount
- Asset
- Sales price

The Ta Feng Grocery Dataset is a supermarket dataset containing

- 817741 transactions from November 2000 until the end of Feb 2001.
- The data set contains information about 119578 shopping baskets that belong to 32266 unique users.
- In total, 1129939 items were purchased from available 23812 products.

Implementation Plan

The implementation plan contains the below steps to accomplish the project

- Business understanding
- Data Preparation
- Exploratory data analysis
- Data prep for Modeling
- Modeling
- Model evaluation

Methods

I would be using a simple recurrent neural network with 250 hidden units with Relu activation using L1 regularization and loss of mean square error to predict an accurate model using the CRISP-DM method. Below are the phases I would be targeting to achieve a better model.

- **Business understanding**: I would be focusing on case study objectives and requirements from a business perspective. This is a valuable phase to create a preliminary plan and move with the subsequent stages.
- **Data Understanding**: Dataset is already identified to proceed with the case study. All I need to do is to identify data anomalies, detect interesting subsets from the hypothesis.
- **Data Preparation**: This phase covers the data wrangling scenarios to construct the final dataset from the raw dataset.
- **Modeling**: The customer shopping is generally recorded as a transaction, summarizing the purchase at each visit. The customer shopping pattern can be modeled as a time series since the transactions are happening over time. After computing the RFM values for the respective customer to the desired date, the proposed simple RNN model will be trained for RFM prediction. I would be using a simple recurrent neural network with 250 hidden units with Relu activation using L1 regularization and loss of mean square error.
- **Evaluation**: As I have considered, RNN is the best suitable method for my use case. I will be publishing the Accuracy results of the simple RNN model
- **Deployment**: Publish final results and conduct a case study retrospect on what went well and required to build the Model better.

Analysis

Illustrations

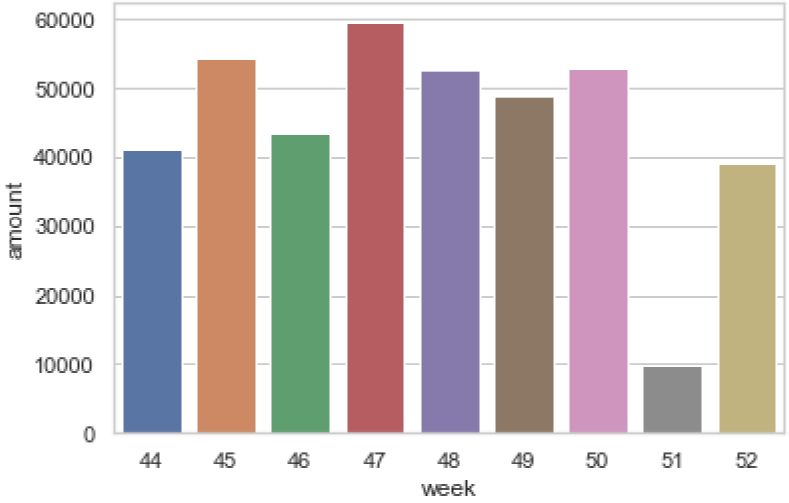


Illustration 1: Weekly Transactions Nov/Dec 2000

Observation: It is evident that Thanksgiving week accounted for more sales when compared to other weeks. We can see a dip in week 51, and sales look normal in week 52. It is tough to identify the root cause for the drop in week 51 sales from the limited dataset, but we can have a strong assumption by comparing weeks 51 and 52 that inventory refresh could have caused a dip in week 51 sales.

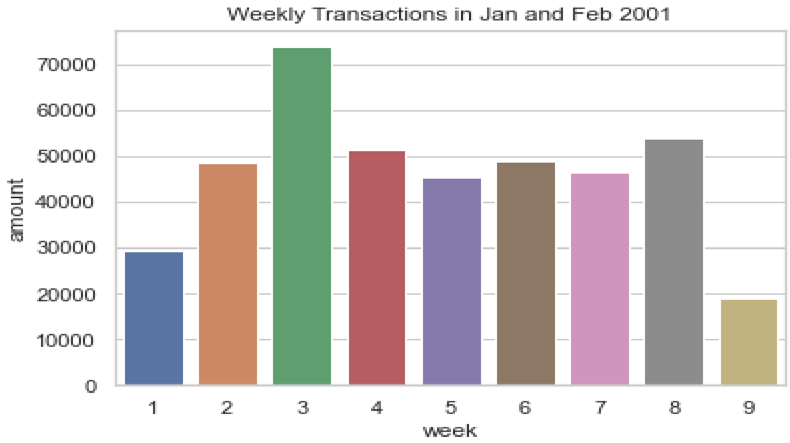


Illustration 2: Weekly Transactions Jan/Feb 2001

Observation: January 3rd week accounts for more sales than the first week. Ideally, Jan 1st week.2nd and 3rd week are considered peak seasons in the retail domain.

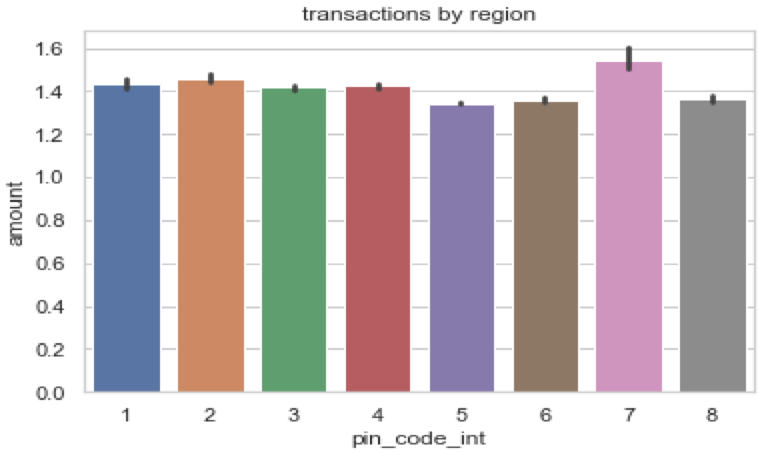


Illustration 3: Transactions by Regions

Observation: Region 7 is contributing more sales followed by 2 and 1. I think we need to apply more marketing strategies in region 5 to boost sales.

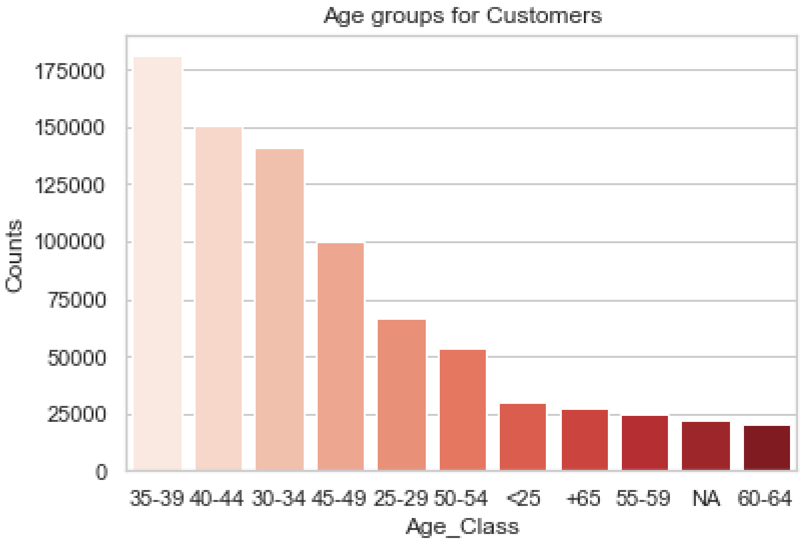


Illustration 3: frequent shoppers w.r.t age groups

Observation: The frequent shoppers come from the age ranges of 30 to 44; this would seem consistent for a grocery store. If you are a young adult shopper, usually young adults tend to shop more compared to other age groups. Presumably, older adults only need to buy for themselves and their partners.

Exploratory Data Analysis:

Behavioral customer segmentation is based on three metrics:

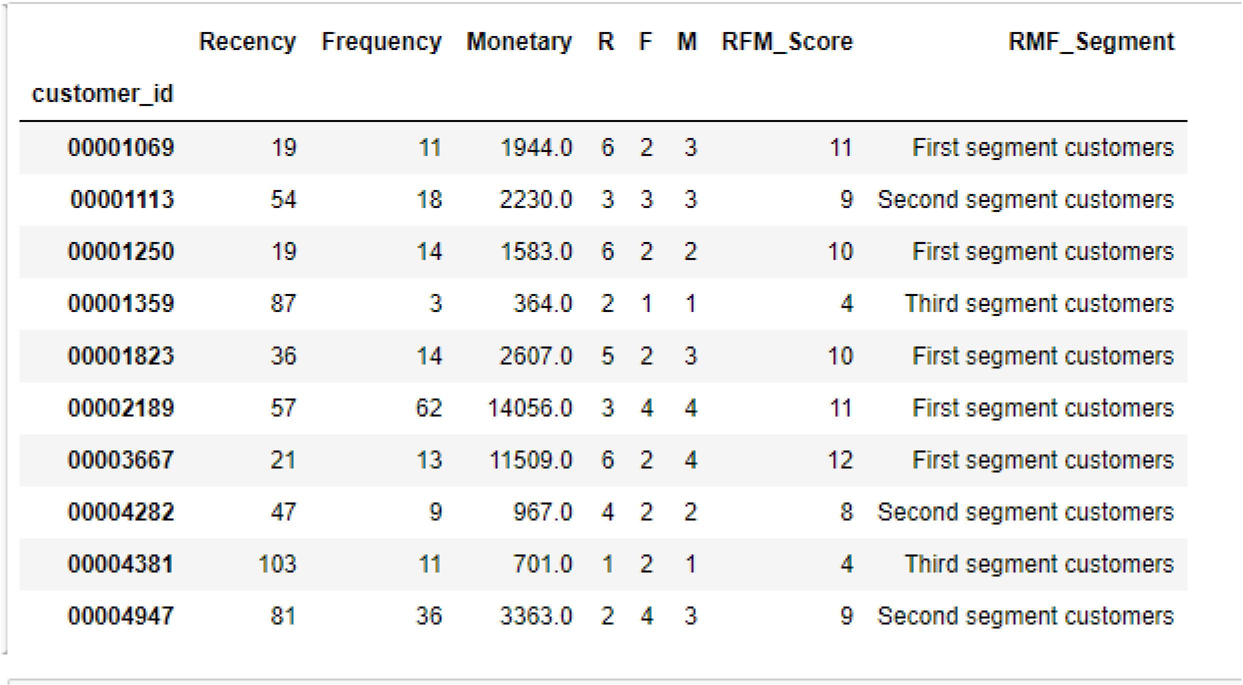
- Recency (R): How many days since customer's last purchase. This model works better for the shorter date range since last purchased.

- Frequency (F): How many purchases the customer has done

- Monetary Value (M): Measures how much the customer has spent.

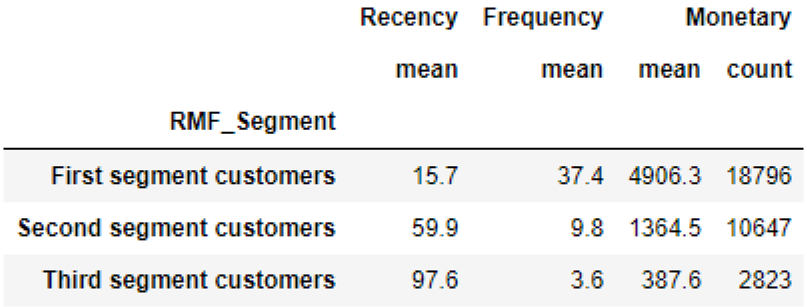
RFM variables are useful for beginning to classify users based on their behavior over time.

Impact of RFM scores:



	Recency	Frequency	Monetary	R	F	M	RFM_Score	RMF_Segment
customer_id								
00001069	19	11	1944.0	6	2	3	11	First segment customers
00001113	54	18	2230.0	3	3	3	9	Second segment customers
00001250	19	14	1583.0	6	2	2	10	First segment customers
00001359	87	3	364.0	2	1	1	4	Third segment customers
00001823	36	14	2607.0	5	2	3	10	First segment customers
00002189	57	62	14056.0	3	4	4	11	First segment customers
00003667	21	13	11509.0	6	2	4	12	First segment customers
00004282	47	9	967.0	4	2	2	8	Second segment customers
00004381	103	11	701.0	1	2	1	4	Third segment customers
00004947	81	36	3363.0	2	4	3	9	Second segment customers

EDA 1: RFM Detailed Scores



	Recency	Frequency	Monetary	
	mean	mean	mean	count
RMF_Segment				
First segment customers	15.7	37.4	4906.3	18796
Second segment customers	59.9	9.8	1364.5	10647
Third segment customers	97.6	3.6	387.6	2823

EDA 2: RFM aggregated Scores

Observation: EDA 2 represents RFM scores that are easier to read table summarized by the relative RFM score as shown in EDA 1. The customers with high RFM scores are more important customers to the business. Group customers based on RFM score to classify customers into First Segment, Second Segment, and Third segments for more straightforward interpretation.

- First Segment customers= RFM Score equal or greater than 9
- Second Segment customers = RFM Score between 4 and 9
- Third Segment customers = Anything else

Modeling

In the process of Model creation and evaluation, I just pass all the features that could help to possibly inform the prediction along with split values of Customer ID and R, M, F values. These values are passed into a function that splits the Customer IDs into separate integer values, just in case there truly are features within the Customer ID that can inform RFM prediction. The next step was to turn the data into an array format and normalize the data since the RMF values and features were all on different scales. The data is split into training and testing sets in order to pass them into the Model. As mentioned previously, the model type was a Simple Recurrent Neural Network with 250 hidden units with Relu activation using L1 regularization and a loss of Means Squared Error.

Customer Purchase Journey Prediction

Hyperparameters

1. SimpleRNN

2. Relu activation

3. 250 hidden units

4. L1 regularization at 0.0001

5. MSE loss

6. Batch size 120

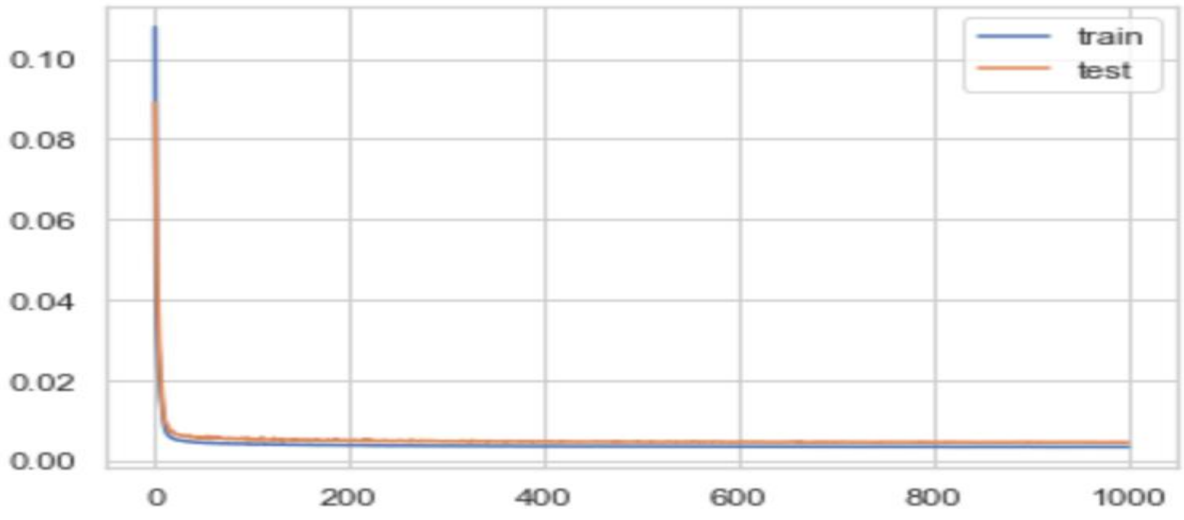
7. Shuffle=True

8. 1000 epochs

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 simple_rnn (SimpleRNN)      (None, 11)                330

 dense (Dense)               (None, 250)               3000

 dense_1 (Dense)             (None, 11)                2761

=================================================================
Total params: 6,091
Trainable params: 6,091
Non-trainable params: 0
_________________________________________________________________
```

Customer Purchase Journey Prediction

Model Stats:



```
Epoch 996/1000
32/32 [==============================] - 0s 2ms/step - loss: 0.0035 - mae:
0.0202 - acc: 0.7266 - val_loss: 0.0046 - val_mae: 0.0233 - val_acc: 0.788
9
Epoch 997/1000
32/32 [==============================] - 0s 2ms/step - loss: 0.0036 - mae:
0.0208 - acc: 0.7165 - val_loss: 0.0047 - val_mae: 0.0227 - val_acc: 0.880
7
Epoch 998/1000
32/32 [==============================] - 0s 2ms/step - loss: 0.0035 - mae:
0.0201 - acc: 0.7181 - val_loss: 0.0047 - val_mae: 0.0227 - val_acc: 0.927
5
Epoch 999/1000
32/32 [==============================] - 0s 2ms/step - loss: 0.0036 - mae:
0.0208 - acc: 0.7207 - val_loss: 0.0047 - val_mae: 0.0234 - val_acc: 0.817
0
Epoch 1000/1000
32/32 [==============================] - 0s 2ms/step - loss: 0.0035 - mae:
0.0205 - acc: 0.7224 - val_loss: 0.0047 - val_mae: 0.0241 - val_acc: 0.678
3
```

The results show an overall accuracy of 72%. Accuracy of the model is consistently above 70%.

Assumptions and Limitations

Although customer behavior prediction is computationally efficient and straightforward, several significant limitations exist. Since there is no available data on households and individual consumers, interdependencies across purchases of individual consumers or households are neglected. In other words, due to data restrictions, homogeneity across purchases is assumed. Personal household-level data would be very beneficial for the analysis. A combination of insights on product dependencies and household level data could help retailers better pricing and promotion decisions for different customer segments. My area of interest is investigating sequences of purchases and events concerning the customer.

Assuming the sequential time series analysis would be an appropriate technique to use while dealing with anonymous transactions. Please note that anonymous transactions do not unveil information on consumer behavior. Availability of household data would be very beneficial for the second research question. A model-based approach can be used for prediction and forecasting. Running a multinomial logistic regression with more independent variables would effectively predict product choice. Having non-anonymous household data also allows applying techniques like clustering, decision trees, or artificial neural networks to provide more insightful information on the consumers and their preferences.

Challenges

- Data contains Chinese characters; I have imported the data using ISO-8859-1.
- Anticipating whitespaces in data and need to work on data alignment.

- Incorrect variable types.
- Python package-related issues.
- There is no detailed data description; it doesn't contain currency details for the sales price and the units used for the variables "amounts" and "Assets."
- I am relying on the Kaggle dataset as this is usually clean, and I anticipate no missing or insufficient data that needs to be substituted with dummy data.
- Since the data is not current, Modeling and forecasting may not apply to the present-day scenarios.

Recommendations

Future Uses:

Retailers can use the insights gained from the next basket analysis in several ways, including:

1. **Cross-Sell**: Group products that customers frequently purchase together in the store's product placement.
2. **Campaigns & Promotions (Marketing)**: Target marketing campaigns to customers and entice them to purchase related products for recently purchased items.
3. **Online shopping websites**: Provide recommendations that are associated with frequently purchased products. For example, Amazon and BestBuy display the message "Customers who purchased this product also viewed this product…" right after adding the items to the basket.
4. **Bioinformatics:** discovering co-occurrence relationships among patients' diagnosis and active pharmaceutical ingredients prescribed to different patient groups.
5. **Manufacturing**: predictive analysis of equipment failure

6. **Customer purchase behavior:** Tying up customer purchase data with demographic and household income.

In the current trend, organizations are discovering ways of using purchase prediction analysis to gain valuable insights into pattern associations and hidden relationships. The market leaders such as Amazon, BestBuy, Walmart continue to explore the technique's value. A predictive version of next basket analysis makes in-roads across many sectors to identify sequential purchases.

Ethical Assessment

The project reminds me of a rational maxim, "good ethics is good business"; Does it mean that unethical conduct is penalized in the Retail-Ecomm domain and ethical conduct rewarded? It is proved that, in many circumstances, firms may be immune to marketplace sanctions and more inclined towards customer retention. It is worth examining the conditions under which the organizations are called to task "the indefinite campaigns" or reward the existing consumers, i.e., as reflected in consumer attitudes toward the brand, the organization, and purchase intentions. This includes investigating the relationship between shopping experience and consumer purchasing behavior. Different algorithms may give other output for a given dataset, provided their limitation is associated with the individual machine learning models. This seems to be a potential problem in choosing a model for my use-case, and I would pick the best-suited algorithm based on its characteristics.

Importantly, I would seek customers' consent before using the customer data in predictive modeling applications that drive the marketing strategies.

Conclusion

This work aims to automate Marketing campaigns using customer segmentation data as an input. The purpose is to simplify the Marketing team's job by avoiding analyzing thousands of rules associating customers with their next item. Recurrent Neural Networks make it easy to find the sequential patterns that return the most probable item sequence. We can retain the customers based on the model-based recommendations by sending appropriate promotional emails. The experiment results depict that RNNs can efficiently predict RFM values of customers. This Model is more likely to be used in recommender systems for next basket recommendation, promotional offers, loyalty programs management, and customer retention programs.

Appendix

The data set contains information about 119578 shopping baskets belonging to 32266 unique users. In total, 1129939 items were purchased from available 23812 products.

Features:

- transaction_dt
- customer_id
- age_group
- pin_code
- product_subclass
- product_id

Customer Purchase Journey Prediction

- amount
- asset
- sales_price
- frequency
- recency
- monetary

Additional features:

- Week_number
- Total_sum
- Age_group
- Unit_price
- Log_unit_price

Hyperparameters

1. SimpleRNN

2. Relu activation

3. 250 hidden units

4. L1 regularization at 0.0001

5. MSE loss

6. Batch size 120

7. Shuffle=True

8. 200 epochs

Indexed terms:

- Customer Behaviour Prediction
- Deep Learning, Recurrent Neural Networks
- Recency Frequency Monetary (RFM)

10 Questions:

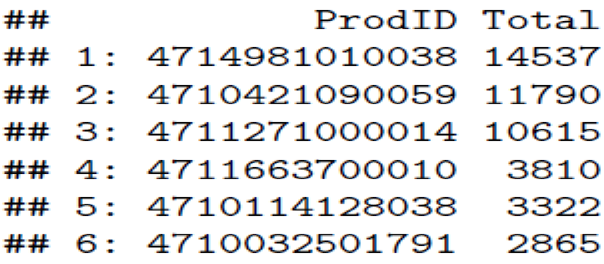
1. **How this Model does help in marketing strategies?**

   Frequent itemset mining leads to discovering associations and correlations among items in large transactional or relational data sets. The discovery of exciting correlation relationships among vast amounts of business transaction records can help in business decision-making processes such as cross-marketing, catalog design, and customer shopping behavior analysis.

2. **How do end-users access the results?**

   In real-time, this Model is subjected to run every day after the previous day batch is complete in the production environment. The ETL process loads the prediction results for a given customer in a Date_Key stacked Type-1 table. It helps marketing Analysts to advertise end-user strategically.

3. From EDA, What are the best-selling products?



```
##              ProdID Total
## 1: 4714981010038 14537
## 2: 4710421090059 11790
## 3: 4711271000014 10615
## 4: 4711663700010  3810
## 5: 4710114128038  3322
## 6: 4710032501791  2865
```

4. Why use a Recurrent Neural Network?

RNNs have received the most success when working with sequences of words and paragraphs, generally called natural language processing.

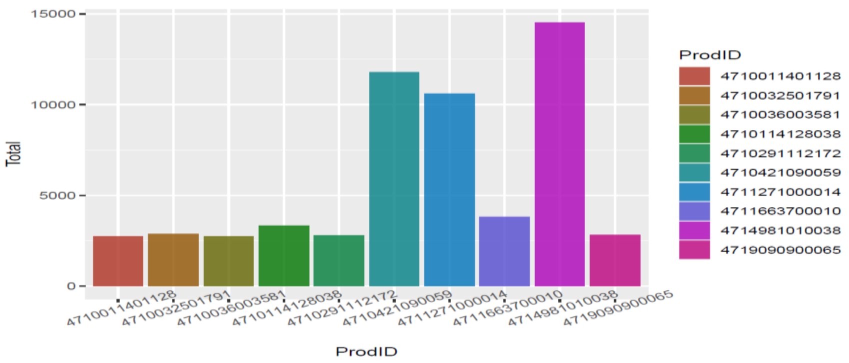
This includes both text and spoken language sequences represented as a time series. They are also used as generative models that require a sequence output with text and applications such as generating handwriting.

RNNs are used for:

- Text data
- Speech data
- Classification prediction problems
- Regression prediction problems
- Generative models

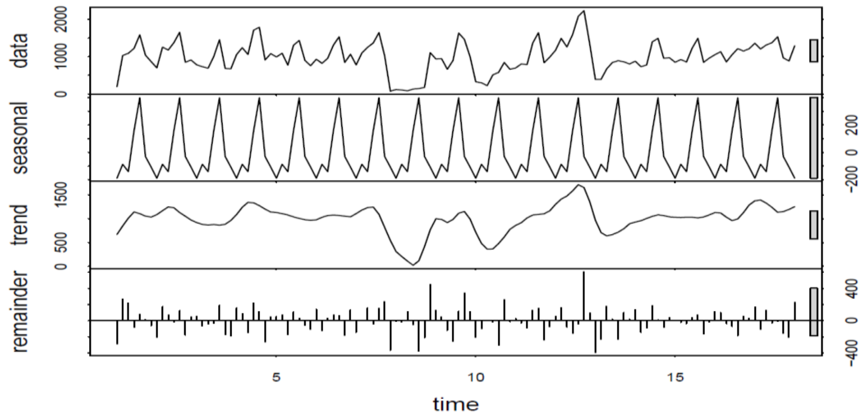
5. What is the sales trend for my best-selling products?

The below analysis is made using R programming. Artifacts are available on Github.



6. **What evidence or rationale supports your findings?**

    - The sales totals for the Top Selling Products by Region
    - The timer series analysis for the different Product IDs



7. **How would you go about designing an operational solution?**

    Automate data extraction from the required source and maintain the data in SCD type 2 table format. Create an OLAP layer for reporting needs.

8. **How would you go about estimating the time/cost/skills needed to build something?**

    - Obtain information about the type, access, and location of the involved Database systems
    - Obtain information about the size and complexity of the data to be processed
    - Obtain information about the requirements for the format and frequency of reporting.

9. **What modeling techniques are applied?**

   RNN – Recurrent Neural Network; RNNs were designed to work with sequence prediction problems.

10. **List the existing applications that use this Model, if any?**

    Amazon, BestBuy, and Walmart use this Model as a recommendation engine.

References:

Smartbridge, (2021, January 12). *Market basket analysis 101: Anticipating customer behavior*. Smartbridge. Retrieved December 19, 2021, from https://smartbridge.com/market-basket-analysis-101/

Kordik, P. (2020, November 14). *Deep learning for recommender systems: Next Basket Prediction and sequential product recommendation*. Medium. Retrieved December 19, 2021, from https://medium.com/recombee-blog/deep-learning-for-recommender-systems-next-basket-prediction-and-sequential-product-recommendation-796228b34dee

Cavique, L. (2006). *(PDF) next-item discovery in the Market Basket Analysis*. Next-Item Discovery in the Market Basket Analysis. Retrieved December 19, 2021, from https://www.researchgate.net/publication/224693768_Next-Item_Discovery_in_the_Market_Basket_Analysis

Singh, S. (2021, May 26). *Predicting purchases with Market Basket analysis*. Medium. Retrieved December 19, 2021, from https://medium.com/geekculture/predicting-purchases-with-market-basket-analysis-d6ad2152bf6e

Guidotti, R., Rossetti, G., Pappalardo, L., Giannotti, F., & Pedreschi, D. (1970, January 1). *[PDF] next basket prediction using recurring sequential patterns: Semantic scholar*. Next Basket Prediction using Recurring Sequential Patterns. Retrieved December 19, 2021, from https://www.semanticscholar.org/paper/Next-Basket-Prediction-using-Recurring-Sequential-Guidotti-Rossetti/b59d6ee45a50a5f5dc7be654cb706897e4ff147c

H. Salehinejad and S. Rahnamayan, "Customer shopping pattern prediction: A recurrent neural network approach," 2016 IEEE Symposium Series on Computational Intelligence (SSCI), 2016, pp. 1-6, doi: 10.1109/SSCI.2016.7849921.

Loshin, D. (2013). *Market basket analysis*. Market Basket Analysis - an overview | ScienceDirect Topics. Retrieved January 8, 2022, from https://www.sciencedirect.com/topics/computer-science/market-basket-analysis