CSCI-P556: Applied Machine Learning

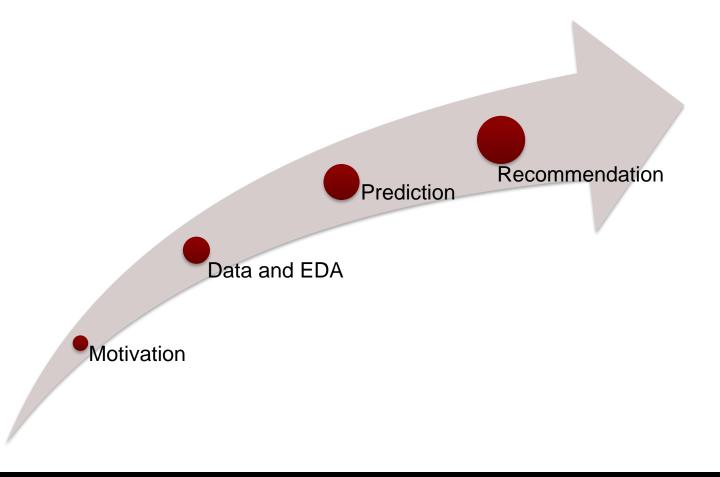
Instacart – Customer Cart Prediction and Recommendation

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Project pipeline



Motivation

For the brand-

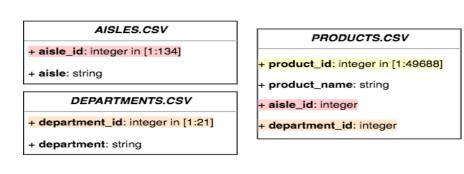
- Gain more users
- Provide delightful shopping experience to increase customer retention

For the users-

- Save time and effort in shopping
- Discover new and better products through recommendations

Data

- The Instacart Online Grocery Shopping Dataset 2017
 - Relational Datasets describing customer orders
 - 3.3 million orders for ~50k products



```
ORDER_PRODUCTS__PRIOR.CSV

+ order_id: integer

+ product_id: integer

+ add_to_cart_order: integer

+ reordered: boolean 0-1

ORDER_PRODUCTS__TRAIN.CSV

+ order_id: integer

+ product_id: integer

+ add_to_cart_order: integer

+ reordered: boolean 0-1

SAMPLE_SUBMISSION.CSV

+ order_id: integer

+ product_id: integer

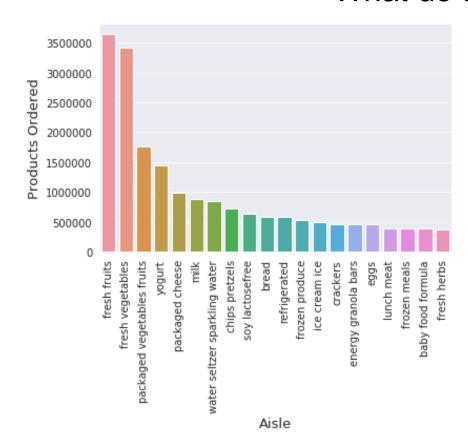
+ product_id: integer
```

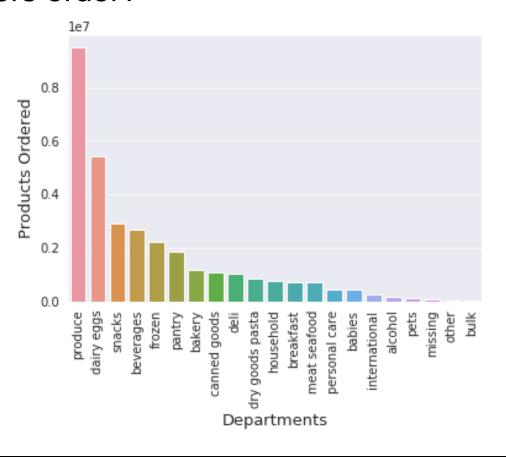
```
+ order_id: integer
+ user_id: string
+ eval_set: prior / train / test
+ order_number: integer
+ order_dow: integer in [1:7]
+ order_hour_of_day: integer in [0:23]
+ day_since_prior_order: integer in [0:30] or NA
```

Image source: https://www.kaggle.com/c/instacart-market-basket-analysis/discussion/33128#183176

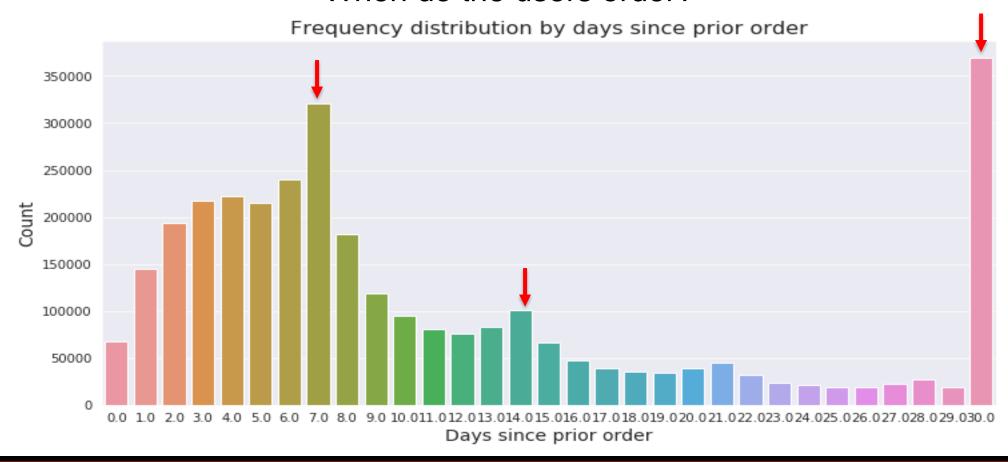


What do the users order?

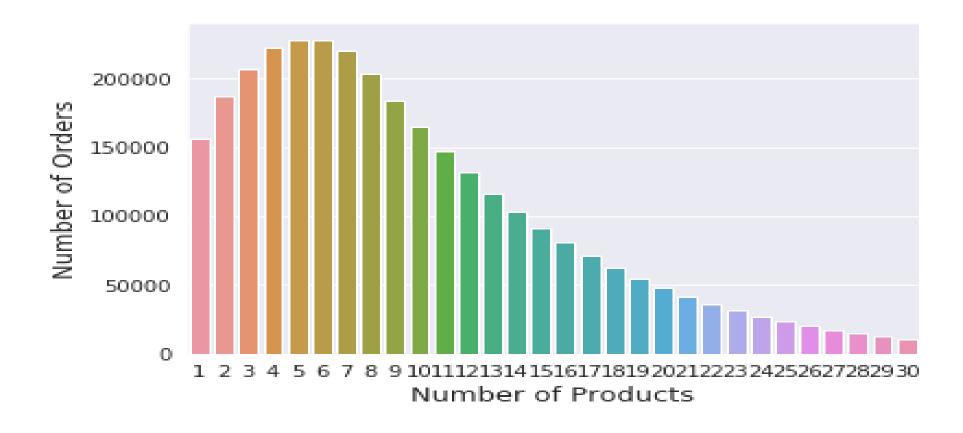




When do the users order?



How much do the users order?



Prediction

Prediction – Feature Engineering

* Existing features

User Related user_total_orders User_total_items Total_distinct_items User_avg_days_bw_orders user_avg_basket User_total_buy_max	Product related features Product_orders Product_reorders Product_reorder_rate Aisle_id* Department_id*				
Order related features Order_dow* Order_hour_of_day* Days_since_prior_order* Days_since_ratio	User_X_Product related features UP_chance_ratio UP_reorder_rate UP_chance UP_orders_since UP_chance_vs_bought UP_drop_chance UP_orders UP_orders UP_orders_ratio				

Prediction – What will the user order?

- Algorithms: XGBoost and Light GBM
 - 1. Faster training speed and higher efficiency.
 - 2. Lower memory usage.
 - 3. Better accuracy.
 - 4. Support of parallel and GPU learning.
 - 5. Capable of handling large-scale data.
- Model Building: We have trained model on user's last order (eval_set = train).
 However, the featured created used the data from prior data set too.
- Feature selection: We have used in-build method of light gbm and xgboost to find feature importance

Prediction – What will the user order?

Output Format:

	order_id	products
0	2774568	17668 21903 39190 47766 18599 43961 23650 24810
1	1528013	8424 21903 38293
2	1376945	33572 17706 28465 27959 44632 24799 34658 1494
3	1356845	11520 14992 49683 30489 7076 22959 37687 28134
4	2161313	11266 196 10441 12427 37710 14715 27839

• Results:

Model	Light GBM	XGBoost		
Baseline Model CV Accuracy	0.1599	0.2015		
Tuned CV Accuracy	0.4412	0.3965		
Kaggle Accuracy	0.3809	0.3786		

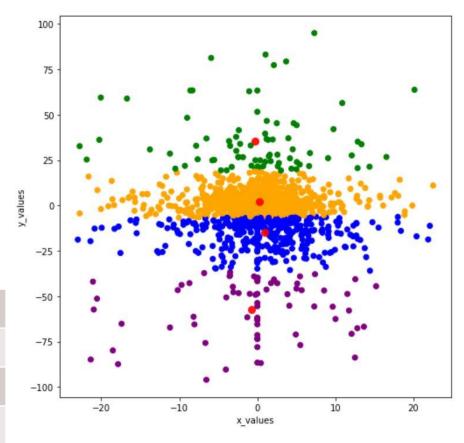
The highest accuracy in Kaggle was 0.4091

Clustering

Clustering - KMeans

- Segmentation of customers is performed on the frequency of products bought from an aisle
- Original idea of segmenting on frequency of pairs of products did not work because of high number of product pairs(large data)
- Cluster found to give the most popular products for a customer, this is used for the recommendations given

Cluster 0 •	Fresh Fruits
Cluster 1 •	Fresh Vegetables
Cluster 2 •	Fresh Vegetables
Cluster 3 •	Yogurt



Recommendation

Apriori

Support: This is the percentage of orders that contains the item set

Confidence: It measures the percentage of times that item B is purchased, given that item A was purchased.

Lift: Lift indicates whether there is a relationship between A and B, or whether the two items are occurring together in the same orders simply by chance

	itemA	itemB	freqAB	supportAB	freqA	supportA	freqB	supportB	confidenceAtoB	confidenceBtoA	lift
0	Yogurt, Sheep Milk, Strawberry	Blueberry Sheep Milk Yogurt	5	0.012986	5	0.012986	6	0.015583	1.000000	0.833333	64.173333
2	Bamba Peanut Snack	Bissli Pizza Flavor Snack	4	0.010389	5	0.012986	5	0.012986	0.800000	0.800000	61.606400
213	Iced Bhakti Chai Coffee Blend	Apple Mango Passion Fruit Fruit Snack	6	0.015583	7	0.018180	6	0.015583	0.857143	1.000000	55.005714
232	Tai Pei Chicken Chow Mein	Chicken Egg Rolls	6	0.015583	7	0.018180	6	0.015583	0.857143	1.000000	55.005714
241	Filet Mignon Canine Cuisine Wet Dog Food	Dog Food With Beef in Meaty Juices	5	0.012986	7	0.018180	5	0.012986	0.714286	1.000000	55.005714

Recommendation

We are using Light GBM, Apriori and Clustering to recommend products

- Step 1 When user logs in: When user logs in, we can recommend products based on their transactional history. We are using LGBM to find products to recommend
- Step 2 When user add products to cart: After user has added product to the cart, we can suggest products which they are likely to buy with the current product. For this we are using apriori and customer segmentation. As Instacart suggest 11 products, we are also recommending 11 products – 9 from apriori and 2 from clusters

Related Items



\$4.49 Fairlife Whole Ultra-Filtered Milk 52 fl oz



\$3.29 Simple Truth Whole Milk Ultra-Pasteurized

(+)



\$4.49 Fairlife 2% Reduced Fat Ultra-Filtered Milk 52 fl oz



\$5.89 Simple Truth Whole Vitamin D Milk



\$4.69 Fairlife 2% Reduced Fat Ultra-Filtered Milk 52 fl oz



Recommendation

- Accuracy: For every product we are recommending 11 other products. If user
 actually bought one or more recommended products then we will consider the
 recommendation as success. Accuracy for an order will be total success/total
 products ordered. Final accuracy is mean of accuracy for all the orders
- Results: We are a accuracy of 9.6% which means that 1 in every 10 recommendation will have a product which is actually purchased by the user
- **Improvement:** Running apriori algorithm on entire dataset and clustering users by product pairs can improve the accuracy significantly