Merchant Segmentation and Churn Analysis

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Problem Statements

Using dummy future data, how can we identify different kinds of businesses in the sample? Generate assignments for each merchant.

- **Given:** Limited info on merchants
- **Deliverable:** Segment customers for deeper analysis
- **Process:**
  - Merchants are unlabeled
    --> Unsupervised learning
    - Clustering is best approach here
  - Normalize data
  - Dummy encode any categorical into numerical type
  - Elbow method to find optimal # of clusters
  - K-means clustering
  - Analyze resulting clusters
  - Generate hypotheses about clusters
  - EDA to dive deeper and test hypotheses
  - Connect merchant findings to business recommendations

We want to identify and predict churn.

a) come up with a concrete definition for churn
b) identify merchants that have already churned in the dataset
c) build a model to predict which active merchants are most likely to churn in the near future.

- **Given:** Churn = customers leaving, want to reduce churn
- **Deliverable:** Identify who has churned, predict who will churn
- **Process:**
  - Clearly define what churn is
  - Define time period and assumptions
  - Normalize data
  - Dummy encode categorical into numerical type
  - Generate a method for finding who churned month-to-month
  - Run classification model
  - Interpret accuracy
  - Dive deeper to determine important features
  - Connect churn findings to business recommendations

Customer Segmentation

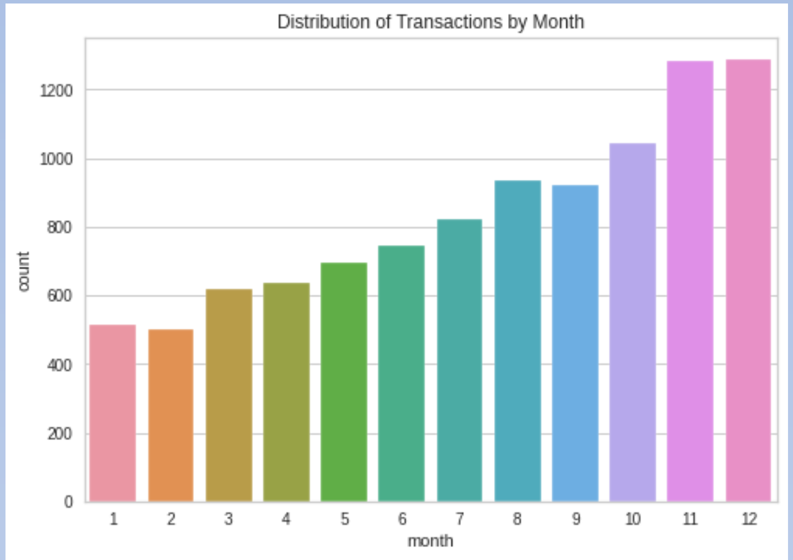
Overview

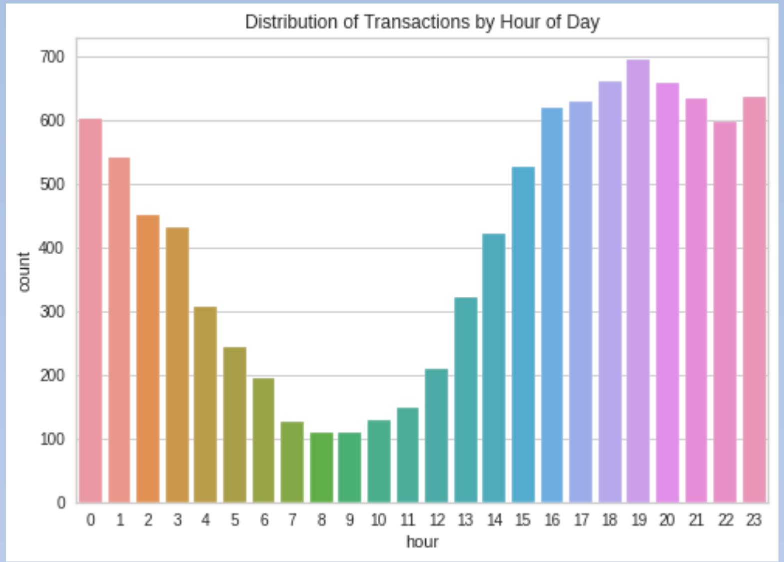
<u>Distribution:</u>

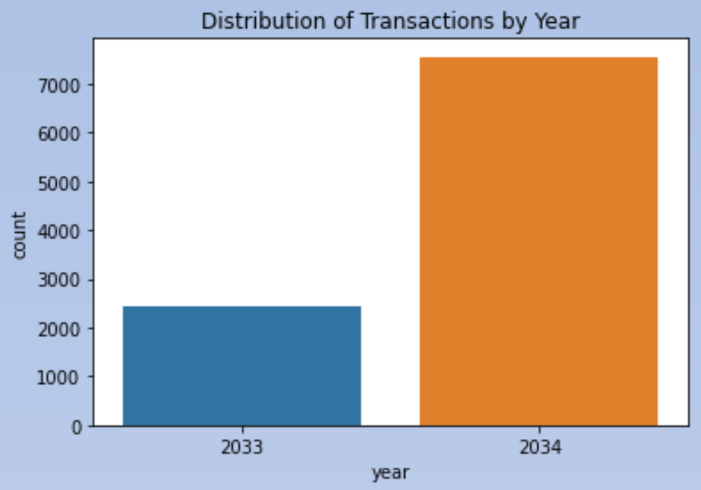
- Transaction amounts ranged from **$2.01 - $260,000+**
- **1,513,719 transactions** made at **14,351 different merchants** during this 2-year period
  - **Less than one transaction per merchant per day**, on average

    -> how can we increase this metric?
- Few outliers, mostly transactions of less than **$100,000**

Exploratory Data Analysis







- More transactions in later months
    - Bias from large number of new merchants acquired in late 2033/2034?
    - Holidays?

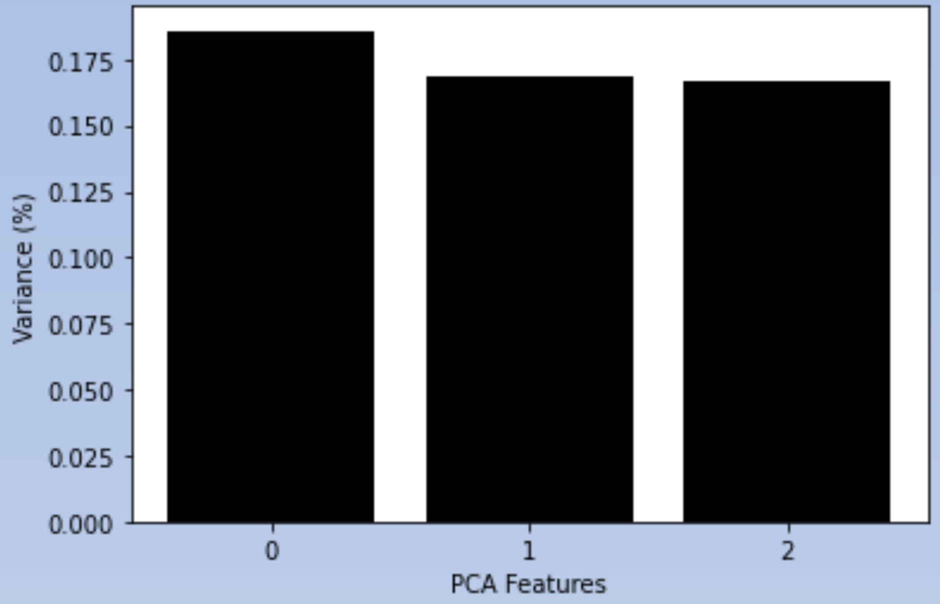
- Transactions ramp up during work hours, as expected
- Also more transactions after-hours
    - International merchants?
    - Restaurants, clubs, **e-commerce**, etc.?

- Business ramped up in 2034
    - **3x** the number of transactions, velocity ↑
- **Check customer churn, retention, and acquisition to investigate deeper**

Model Preparation

merchant	amount_dollars	year	month	day	hour
faa029c6b0	63.49	2034	6	17	23
ed7a7d91aa	38.54	2034	12	27	0
5608f200cf	7.89	2034	4	30	1
15b1a0d61e	44.52	2034	9	16	1
4770051790	202.03	2034	7	22	16
...	...	...	...	...	...
aaa631d7ca	105.18	2034	11	26	10
47b468a8c4	52.53	2034	7	31	2
e4c027a857	140.53	2034	4	23	17
2c328165ea	5.29	2034	10	26	2
6044a863a1	83.92	2034	11	2	3

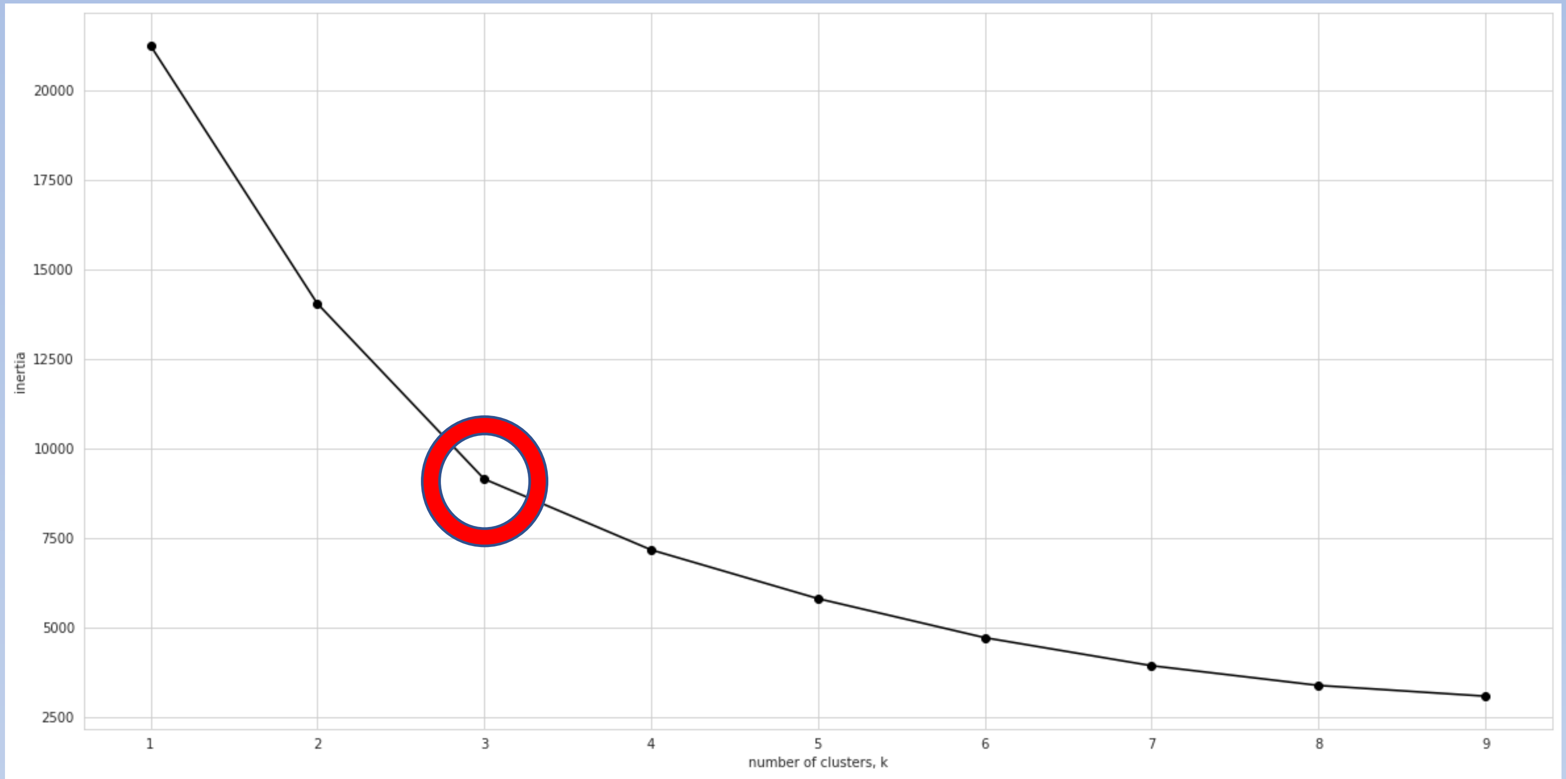
- Split ‘time’ column to look across various granularities
  - But added more dimensionality



- Normalized numerical data before performing Principal Component Analysis (PCA)
- PCA to reduce dimensionality
- First 3 components explain roughly **50%** of variance

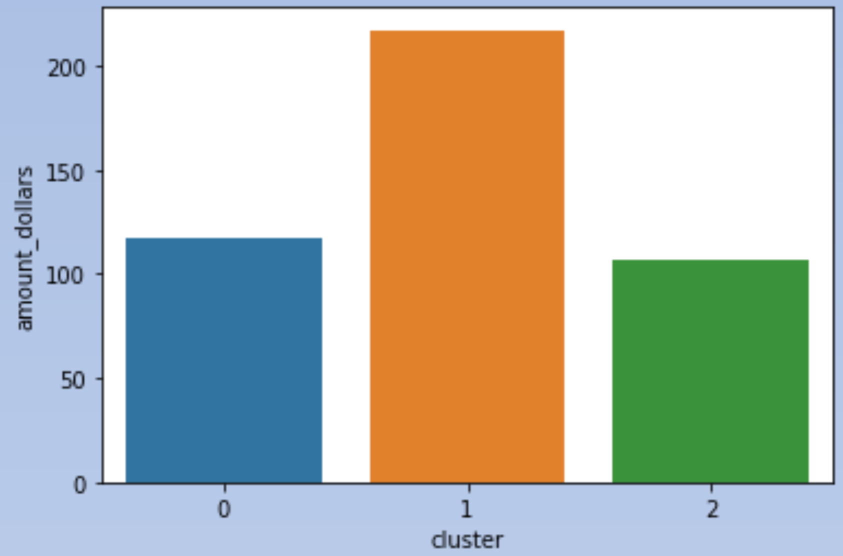
Model

- Merchants are not labeled or grouped
- Need to perform unsupervised learning
  -> **K-means clustering**
  - Cluster merchants and investigate discerning attributes across clusters using their averages
- Used ‘elbow method’ to find optimal number of clusters
  - Segment merchants into **three** clusters
- Converted merchant names into numerical data for the model
- Mapped cluster labels back to data frame
  - Each merchant has an associated cluster now and is labeled



Model Results

cluster	amount_dollars	year	month	day	hour
0	117.382975	2033.952357	6.740750	20.164470	18.144450
1	217.184228	2033.923565	6.702913	10.268532	7.696279
2	107.031430	2033.229610	9.861229	15.702744	13.208736



<u>Cluster 0:</u>

- Merchants process most transactions after regular business hours
- Relatively similar transaction sizes to cluster 2 merchants

<u>Cluster 1:</u>

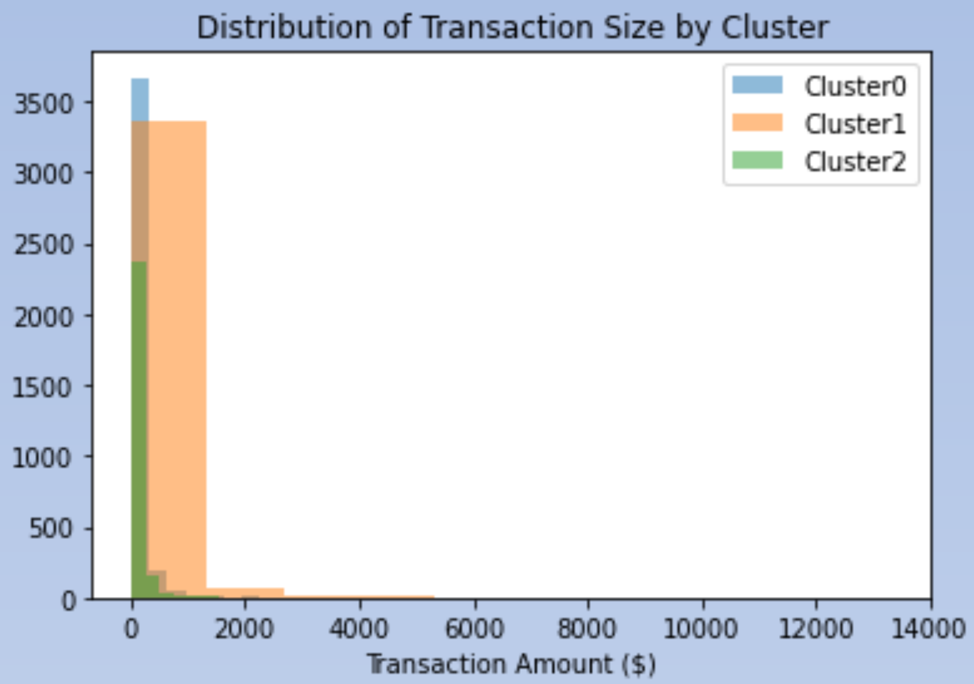
- Merchants' average transactions are ~ **2x** larger
- Merchants process most transactions in the morning
  - see distribution of rest of hours

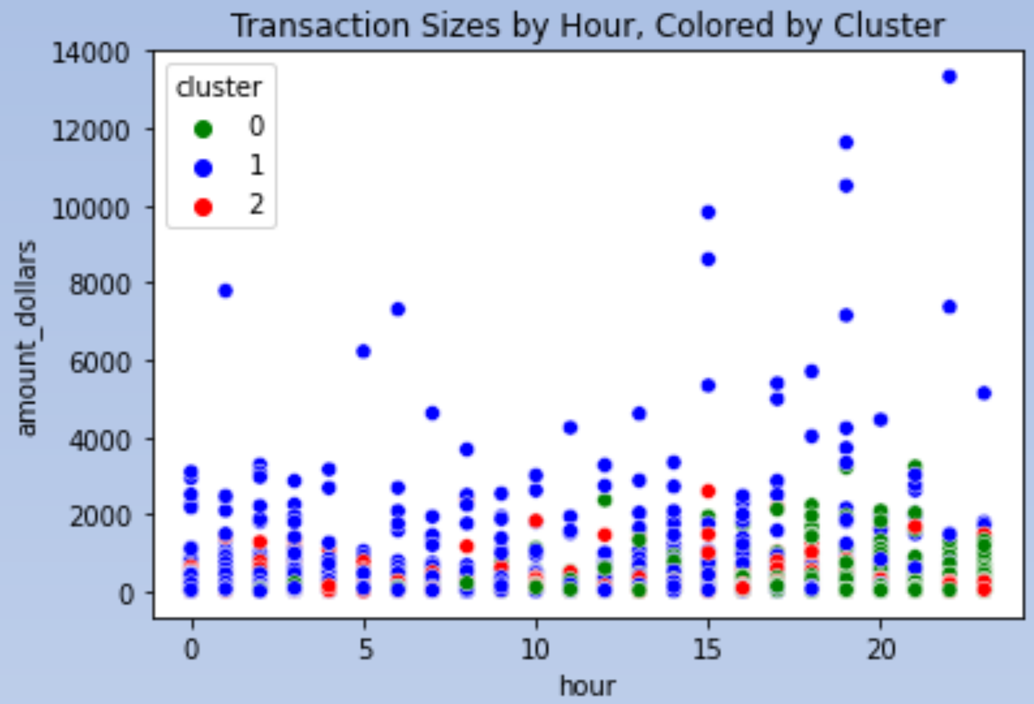
<u>Cluster 2:</u>

- Merchants process most transactions in the early afternoon
- Merchants process the smallest transactions, mostly in 2033
  - Have these merchants churned already in 2034?

- Cluster 0 and 1 merchants processed many more transactions in 2034
- Are these merchants newer than those in cluster 2, or just doing better?
  - Cluster 0 is newer, cluster 1 is doing better

Cluster Analysis





- Cluster 1 merchants have a large spread of transaction sizes, can process around the clock
  - Split amounts into buckets to see how much of each size?
- Cluster 2 merchants mainly process smaller transactions

- Cluster 0 merchants process after-hours too, but much smaller transactions

- Cluster 1 merchants process the largest amount of big transactions

Recommendations

Cluster 0: Newer Merchants

- These are merchants who started in late 2033 / early 2034
- Accept transactions around the clock
- High volume merchants, although deal with relatively smaller transactions
- **They are viewed as a promising opportunity to grow** with them as they scale to handle larger transactions

Recommendation:

- Offer on-boarding to get them up to speed
- Good support to keep them feeling valued

Cluster 1: Big Merchants

- Very profitable merchants
- Big Merchants process the largest and the most amounts of transactions, around the clock
- Big Merchants also process, therefore sell, a wide range of items
- **Focus on retaining these merchants as best as possible**

Recommendation:

- Provide competitive exclusive crypto rewards programs
- Ensure customer support and experience is top-notch

Cluster 2: Unprofitable Merchants

- These are smaller, older merchants who process small transactions and are at high risk of churning
  - Some already did by 2034
- **If start-up, re-engage for potential future opportunities**

Recommendation:

- A/B tests with re-engagement, come back based on new features/promotion?
- Surveys about experience
- See which product they were using

Churn Analysis

What is Churn?

- Churn is essentially **the loss of a customer**
  - E.g., given merchant was active from start until March 2033, but not in April 2033 or beyond
- Up to **5x** more expensive to acquire new customers than to retain customers (Forbes)
- We want to keep churn below a certain threshold
  - **Keeping churn low increases customer retention and keeps revenue streams healthy**

- Churn rate = # of merchants who churned / # of active merchants at beginning of period
- Retention rate = 100% - churn rate

- Analyzing Subset: Q4 2034 (October – December 2034)
  - Representative of busiest months, with most recent merchant data
  - Assume findings from subset represents those from entire dataset

By The Numbers

Churn:

- **Churn Rate = 90%**
- High churn -> not always bad, but investigate
- **Is it ‘positive’ churn?**
    - Bad fit, unprofitable merchants, etc.
- 325 merchants churned between Oct and Nov 2034
- 350 merchants churned between Nov and Dec 2034

Acquisition:

- High churn but high acquisition too -> **leaky bucket effect**
- **Acquisition Rate = 99.3%**
    - **Net + 136 new merchants** in Q4
        - 749 -> 885 active merchants

merchant	churn
53b3fbeae2	0
524efc3692	1
0646c31f12	1
53b3fbeae2	0
e5393f7993	1
...	...
207cc1c4a7	0
eb772f6014	0
d087d4c321	0
a26684af60	1
062de5273b	0

Data frame showing each merchant has an associated churn label

Churn Prediction Model

Predicted Result	0	1
Actual Result		
0	267	31
1	26	166

	precision	recall	f1-score	support
0	0.92	0.89	0.91	301
1	0.85	0.89	0.87	207
accuracy			0.89	508
macro avg	0.89	0.89	0.89	508
weighted avg	0.89	0.89	0.89	508

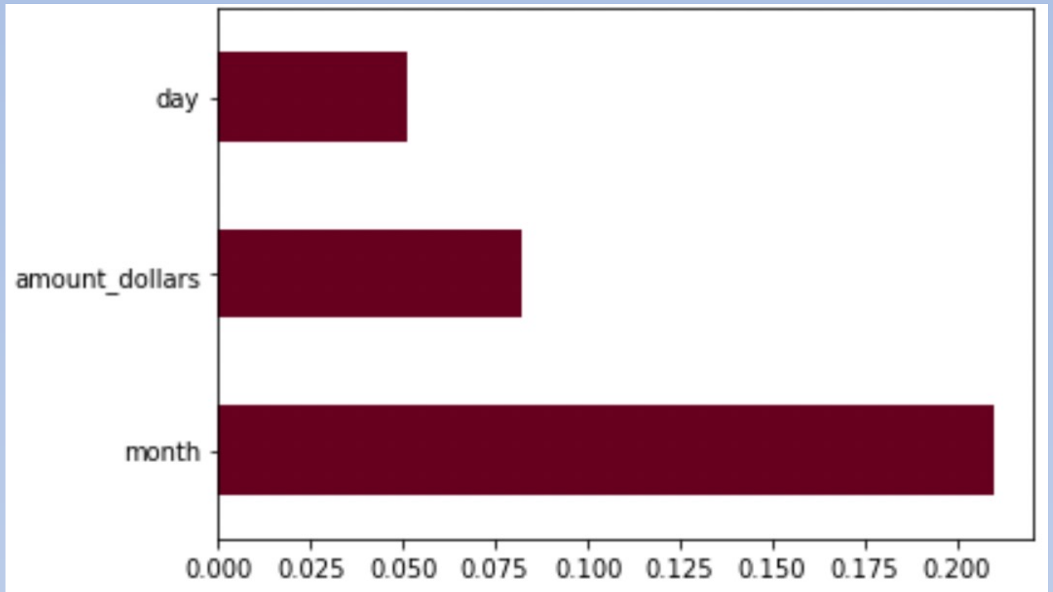
0.8917322834645669

- To predict whether a merchant will churn or not is a binary classification problem
  - Random Forest Classifier
  - Need to convert merchant to a numerical data type for model

Results:

- **89% accuracy**
  - High F_1 and recall while still maintaining high precision

What Impacts Churn?



- We see the importance (~ **20%**) that **month of transaction** demonstrates in predicting churn
- This model could be used to help predict customer churn based on different transaction attributes such as the month and transaction amount
  - May not be easy to implement, maintain, or interpret on a large scale, though…
    - **Model drift with more merchants scaling up?**

Recommendations

- **Follow-up surveys to discover if dissatisfaction is why churn is high**
  - Competitors, missing expectations, too expensive, sub-par customer service, etc.?
- Which clusters do churned merchants belong to?
  - **Cascade with customer segmentation analysis**
  - How many were profitable cluster 1 merchants?
- **Perform a conjoint study to find merchants' feature preferences**
- **Anomaly detection when churn is too high**
  - Live track and alert when a certain churn threshold has been reached in a specified timeframe

<u>For retaining customers:</u>

- Create marketing campaigns to upsell those currently using services

<u>For expanding merchant base:</u>

- Increase marketing budget
- Provide a cheaper subscription method to lower monthly costs for smaller merchants to be more inclusive
- A/B test with different re-engagement methods
- Adjust cost / profit margins potentially, if a big enough issue, to stay competitive

Thank You!

Questions