Stuart Ogawa (Mentor) Kevin Pierce Chris Nishimura

Recommendation Monkey

Data and Decisions Sponser: Bill.com **Team Inspector Royale** CS 189 Jianwen Su Chandra Krintz Mason Corey











Derek Garcia **Project Lead** Noa Kim Scribe Database Carson Coley Front-End Jonas Zhang Statistics

Joe Zhuang Backend





Challenge

Architect and develop a scalable data science lab to analyze, predict, and recommend the most promising U.S. small and medium size industries and businesses to pursue

Data Set Characteristics

- 10.4m real transactions representing \$36B in business transactions
- 5 years of financial transactions (2015 to 2019)
- 100K+ entities and 100's of Dun and Bradstreet industries

What We Did and How We Did It

Fall 2021 - "Build the Model T" and drive it around the block

- Design the architecture/code from scratch
- Test lab against 4M record data set

Winter 2022 - "Build the Ferrari" and race it

- Refactor lab for scalability
- Created a Platform
- Test lab against 10M record data set

"Bill.com is going to immediately use this scalable data science lab platform and continue to extend and scale this lab into the AWS EC2 Cloud" -stu ogawa

System Architecture



Refactored Jupyter User Experience

- Easier user experience navigation
- Quicker results and recommendations
- Faster computations
- Improves efficiency of statistical algorithms
- Visualization of results more user-friendly



Business Archetype Selection

Selection of Industries in Archetype

3.5 CPU vs GPU "head to head" compute experiment



Hardware

CPU: 10M records processed in 10 minutes GPU: 10M records processed in 1 minute

- Dell laptop (2015),
 - AMD 4 core CPU
 - 16GB of RAM
 - GTX 6 core GPU
 - 4GB of RAM
 - 500GB SSD
- PyTorch ver. 1.10.1
- GPU has 10x reduction in compute time = superior hardware for scalability
- K-means computation for one industry takes ~300ms via optimization

3.3 & 3.4: Derivative Analysis on Middle Cluster of K-means



^{7558 41397 86289 134026 146683 139358 233199 296549 256388 362344 373995 384758 395154 395156 39518 397549 413271 415263 428218 434503 441466 445613 453505 453848 483230 489525 523309} SENDER D

X-axis = Vendor ID Y-axis = Net change in Trans Velocity/Acceleration



- 1st graph = change in trans amt over time
- 2nd graph = change in trans velocity over time
- We can see which vendors are increasing at an increasing rate = potential for exponential growth

Results 3 - Predict which vendors/customers increasing at an increasing rate

- Time Series moving average for long term trends
 - Four-year data forecast two-year transactions

Business recommendation: use these top 20 business vendors as a "seed" / training data to perform subsequent machine learning and deep learning predictions



SARIMA: "moving-average" machine learning model for predicting transaction amounts of an industry

1st Step:

Train model w/ 3 years of data

- Blue -> training data
- Green -> model's prediction
- Orange -> actual values
- Grey -> upper/lower bounds





4. Prioritize and Recommend Vendor/Customers pairs with top subscription revenue

- top ten vendors with subscription based revenue
 used LAG FUNCTION
 - Between 25-35 days, +or- 10% difference in transaction amount

Business recommendation: use the top 20 business vendors as training data to perform subsequent machine learning



2. Regression Analysis for Best Fitting Function & Future Prediction

Use Polyfit to find best fitting function with designated order/derivative

Predict future performance of a certain industry





Special thanks:



Kevin Pierce **Tech Advisor** Stu Ogawa Mentor



Chris Nishimura Tech Advisor



