iMentor Project

•••

December 15, 2016
Team Awesome

iMentor Background

Who?

iMentor is a non-profit organization that facilitates mentoring relationships to ensure more students from low-income communities enroll and graduate from college.

Where?

Serves more than 6,000 students through its direct-service programs in New York City, Chicago, and the Bay Area

How?

By partnering with public high schools, the program matches students with mentors for the majority of their high school career.

- Weekly messages and chat conversation
- Monthly in-school meetings and many more!

Problem Statement:
Mentor persistence

With the ultimate goal of college completion, one of the iMentor's Core Metrics of quality is Mentors under the program execution rubric. A mentor dropping out of the program before its full length could impact the mentee's success in the program.

Understanding the problem

High dropout in year 2-3

iMentor's own analysis revealed that a significant percentage of mentors do not complete the 3- or 4-year mentoring commitment, with most dropping out over the second and third year.

2 Program Types

- College Ready (4-year program)
- College Transition (3-year program)

Any indicators?

- Mentors demographic attributes
- Mentors behavior: message frequencies, responsiveness and length

Project objective:

Establish a successful framework for repeatable and continued analysis of possible indicators of mentors dropout

In scope

The analysis will cover:

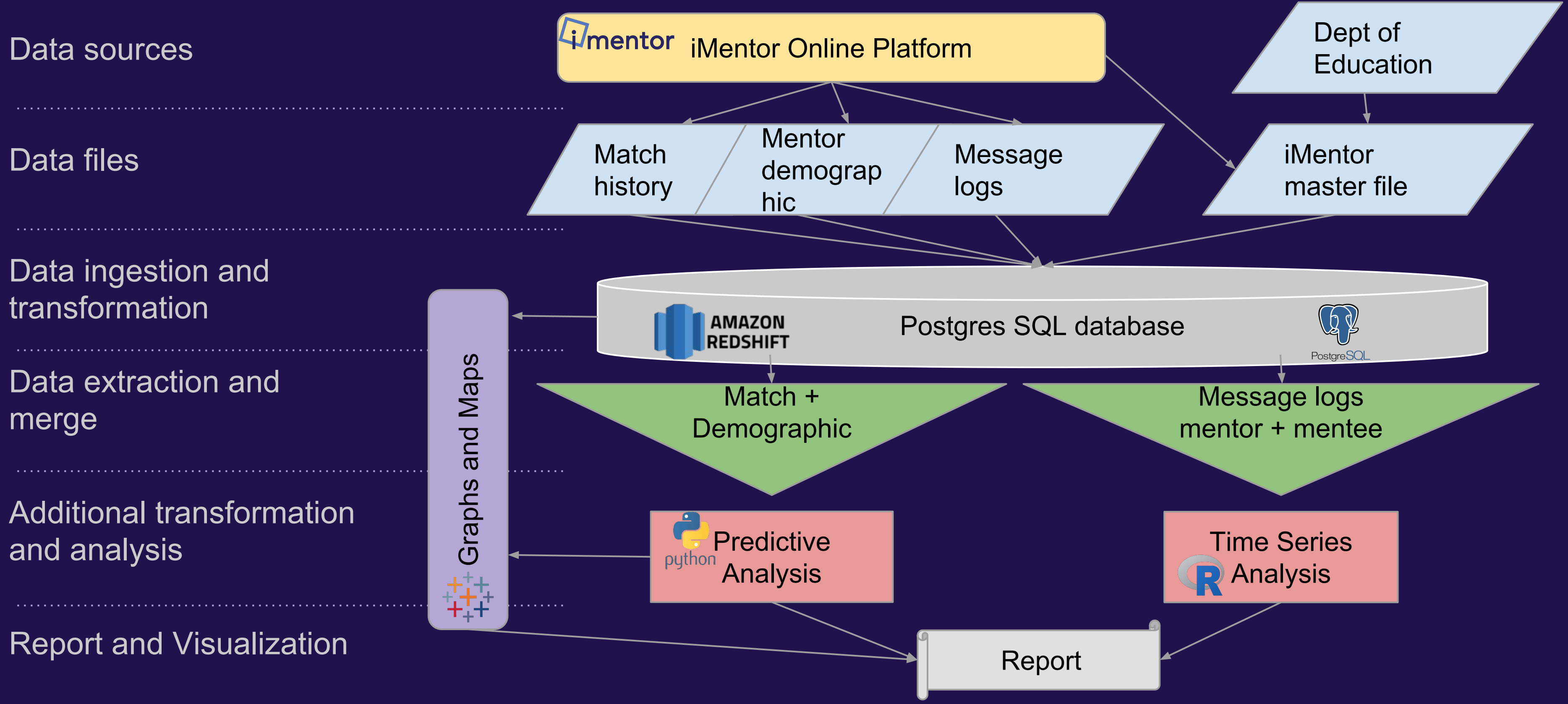
- Mentors demographic information
- Message log data for one school year 15-16 i.e. excludes the content of messages
- Mentors participating in iMentor NYC only

Note 1: Additional datasets are still processed in our ETL since will be used in the future analysis.

Note 2: Further data is recommended to be included as a next step of this project.

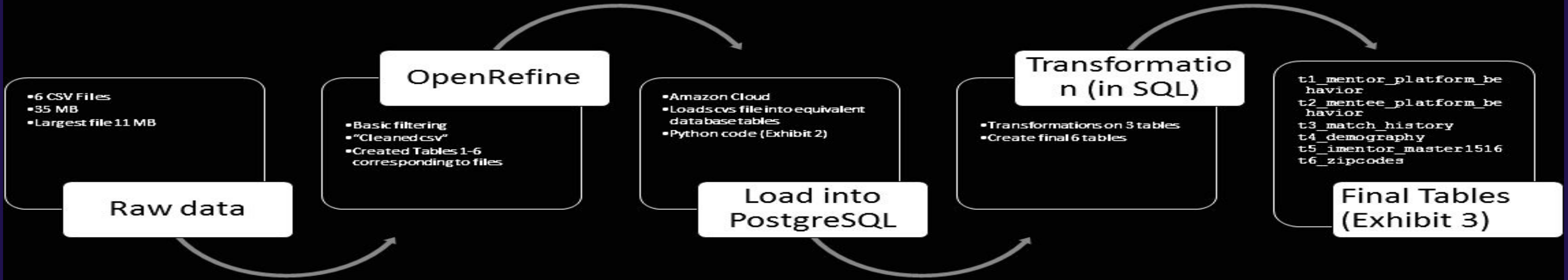
1. Analysis Framework

Framework Chart



2. Data Processing

Extract - Load -Transform



Raw data

- 6 CSV Files
- 35 MB
- Largest file 11 MB

OpenRefine

- Basic filtering
- "Cleaned csv"
- Created Tables 1-6 corresponding to files

Load into PostgreSQL

- Amazon Cloud
- Loads cvs file into equivalent database tables
- Python code (Exhibit 2)

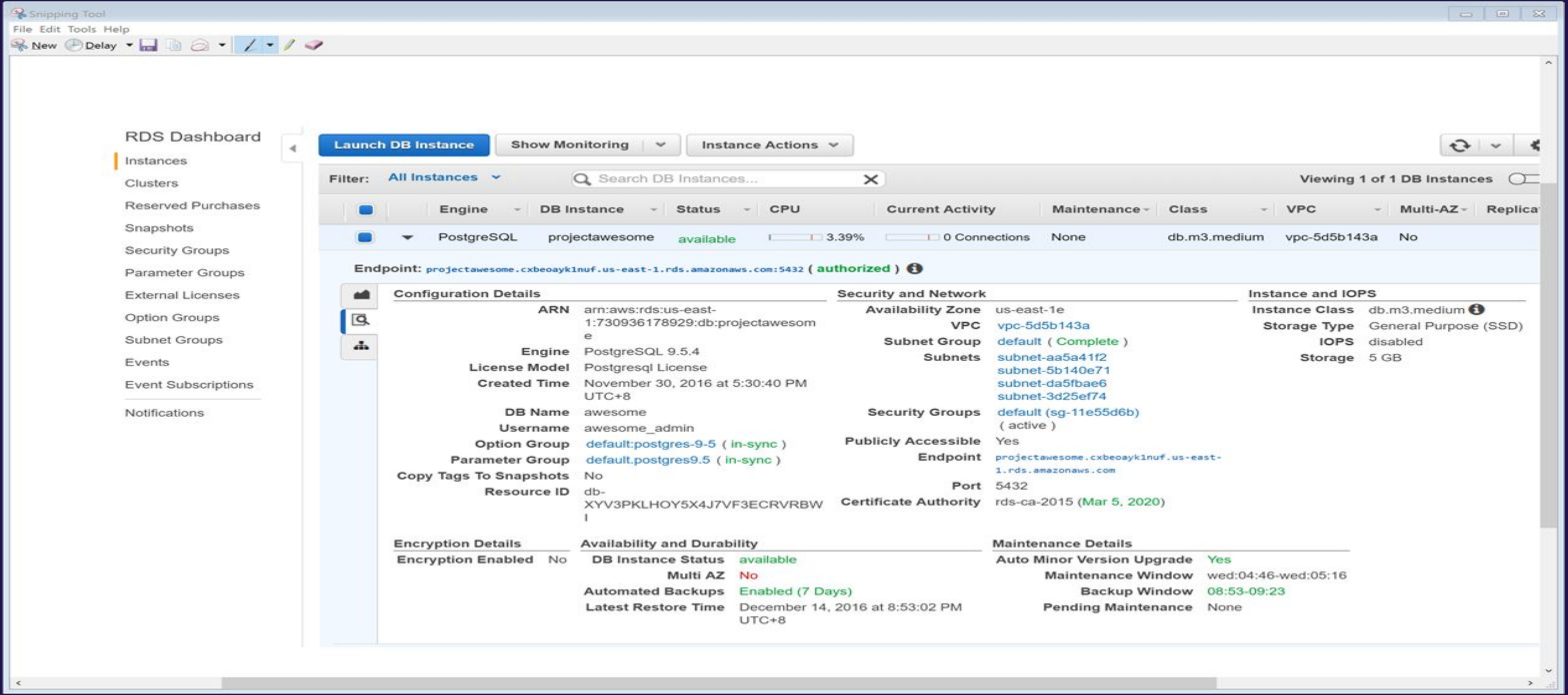
Transformation (in SQL)

- Transformations on 3 tables
- Create final 6 tables

Final Tables (Exhibit 3)

t1_mentor_platform_behavior
t2_mentee_platform_behavior
t3_match_history
t4_demography
t5_imentor_master1516
t6_zipcodes

Our Database on Amazon



	Engine	DB Instance	Status	CPU	Current Activity	Maintenance	Class	VPC	Multi-AZ	Replica
■	PostgreSQL	projectawesome	available	3.39%	0 Connections	None	db.m3.medium	vpc-5d5b143a	No	

Endpoint: projectawesome.cxbeoayk1nuf.us-east-1.rds.amazonaws.com:5432 (authorized)

Configuration Details

ARN	arn:aws:rds:us-east-1:730936178929:db:projectawesome
Engine	PostgreSQL 9.5.4
License Model	Postgresql License
Created Time	November 30, 2016 at 5:30:40 PM UTC+8
DB Name	awesome
Username	awesome_admin
Option Group	default:postgres-9-5 (in-sync)
Parameter Group	default.postgres9.5 (in-sync)
Copy Tags To Snapshots	No
Resource ID	db-XYV3PKLHOY5X4J7VF3ECRVRBWI

Security and Network

Availability Zone	us-east-1e
VPC	vpc-5d5b143a
Subnet Group	default (Complete)
Subnets	subnet-aa5a41f2 subnet-5b140e71 subnet-da5fbae6 subnet-3d25ef74
Security Groups	default (sg-11e55d6b) (active)
Publicly Accessible	Yes
Endpoint	projectawesome.cxbeoayk1nuf.us-east-1.rds.amazonaws.com
Port	5432
Certificate Authority	rds-ca-2015 (Mar 5, 2020)

Instance and IOPS

Instance Class	db.m3.medium
Storage Type	General Purpose (SSD)
IOPS	disabled
Storage	5 GB

Encryption Details

Encryption Enabled	No

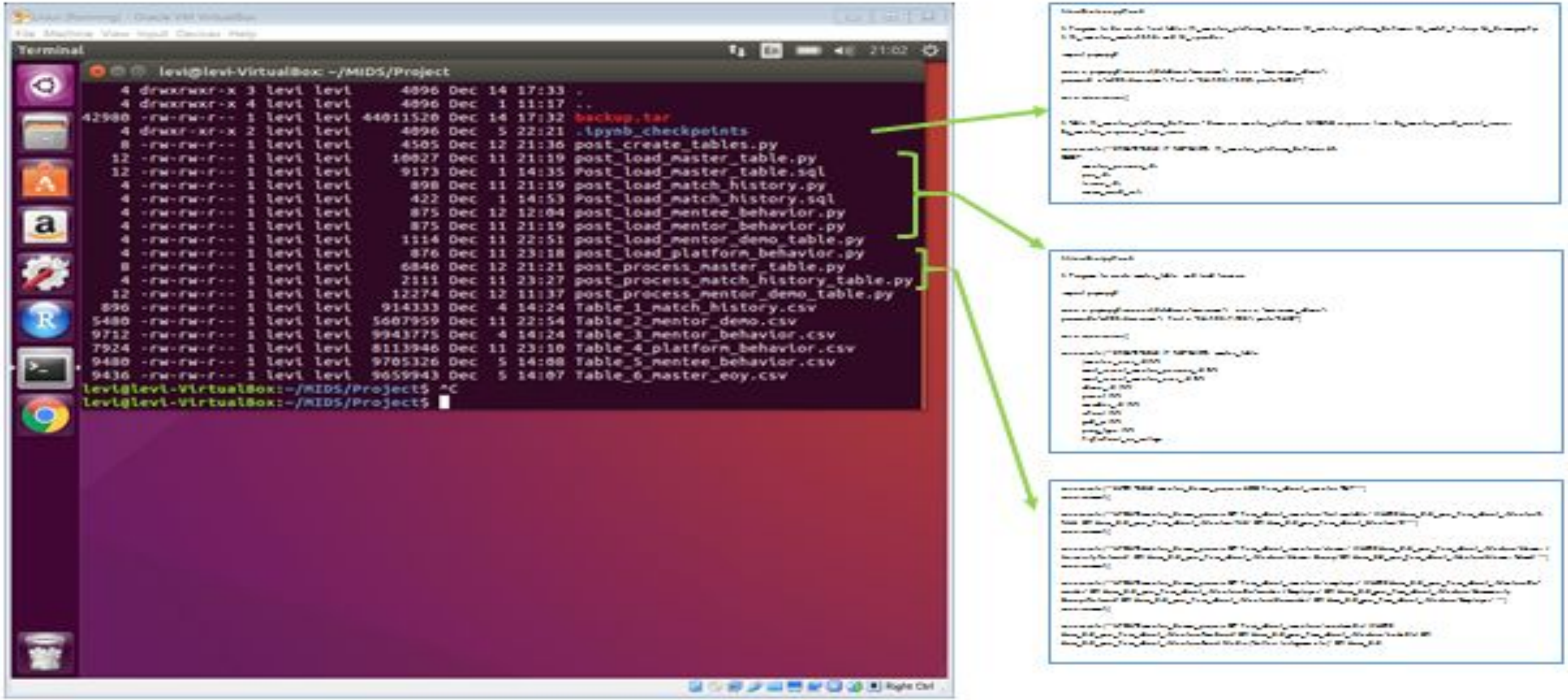
Availability and Durability

DB Instance Status	available
Multi AZ	No
Automated Backups	Enabled (7 Days)
Latest Restore Time	December 14, 2016 at 8:53:02 PM UTC+8

Maintenance Details

Auto Minor Version Upgrade	Yes
Maintenance Window	wed:04:46-wed:05:16
Backup Window	08:53-09:23
Pending Maintenance	None

Data Processing App (10 sub-programs)



```
    4 drwxrwxr-x 3 levi levi     4096 Dec 14 17:33 .
    4 drwxrwxr-x 4 levi levi     4096 Dec  1 11:17 ..
42980 -rw-rw-r-- 1 levi levi 44011520 Dec 14 17:32 backup.tar
    4 drwxr-xr-x 2 levi levi     4096 Dec  5 22:21 .ipynb_checkpoints
    8 -rw-rw-r-- 1 levi levi     4505 Dec 12 21:36 post_create_tables.py
   12 -rw-rw-r-- 1 levi levi    10027 Dec 11 21:19 post_load_master_table.py
   12 -rw-rw-r-- 1 levi levi     9173 Dec  1 14:35 Post_load_master_table.sql
    4 -rw-rw-r-- 1 levi levi      898 Dec 11 21:19 post_load_match_history.py
    4 -rw-rw-r-- 1 levi levi      422 Dec  1 14:53 Post_load_match_history.sql
    4 -rw-rw-r-- 1 levi levi      875 Dec 12 12:04 post_load_mentee_behavior.py
    4 -rw-rw-r-- 1 levi levi      875 Dec 11 21:19 post_load_mentor_behavior.py
    4 -rw-rw-r-- 1 levi levi     1114 Dec 11 22:51 post_load_mentor_demo_table.py
    4 -rw-rw-r-- 1 levi levi      876 Dec 11 23:18 post_load_platform_behavior.py
    8 -rw-rw-r-- 1 levi levi     6846 Dec 12 21:21 post_process_master_table.py
    4 -rw-rw-r-- 1 levi levi     2111 Dec 11 23:27 post_process_match_history_table.py
   12 -rw-rw-r-- 1 levi levi    12274 Dec 12 11:37 post_process_mentor_demo_table.py
  896 -rw-rw-r-- 1 levi levi   914333 Dec  4 14:24 Table_1_match_history.csv
 5480 -rw-rw-r-- 1 levi levi  5607959 Dec 11 22:54 Table_2_mentor_demo.csv
 9712 -rw-rw-r-- 1 levi levi  9943775 Dec  4 14:24 Table_3_mentor_behavior.csv
 7924 -rw-rw-r-- 1 levi levi  8113946 Dec 11 23:10 Table_4_platform_behavior.csv
 9480 -rw-rw-r-- 1 levi levi  9705326 Dec  5 14:08 Table_5_mentee_behavior.csv
 9436 -rw-rw-r-- 1 levi levi  9659943 Dec  5 14:07 Table_6_master_eoy.csv
levi@levi-VirtualBox:~/MIDS/Project$ ^C
levi@levi-VirtualBox:~/MIDS/Project$ 
```

Schema (Final Tables)

3. Mentor demographic data
Predictive Analysis

Key Findings

- Formal closure and dropout mentors group size significantly differ by program type
- Demographic attributes are not sufficient alone to accurately predict probability of whether a mentor will drop out

Program Types

Figure 1 - entire match history

4-yr program mentor dropout > formal closure

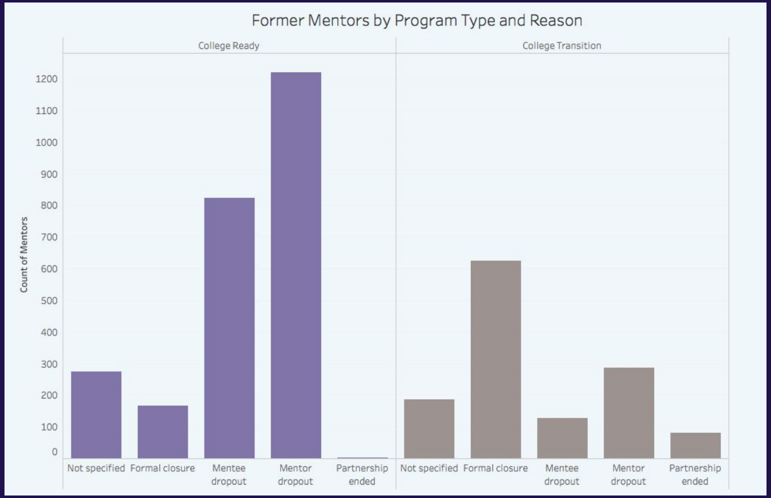
3- yr program mentor dropout < formal closure

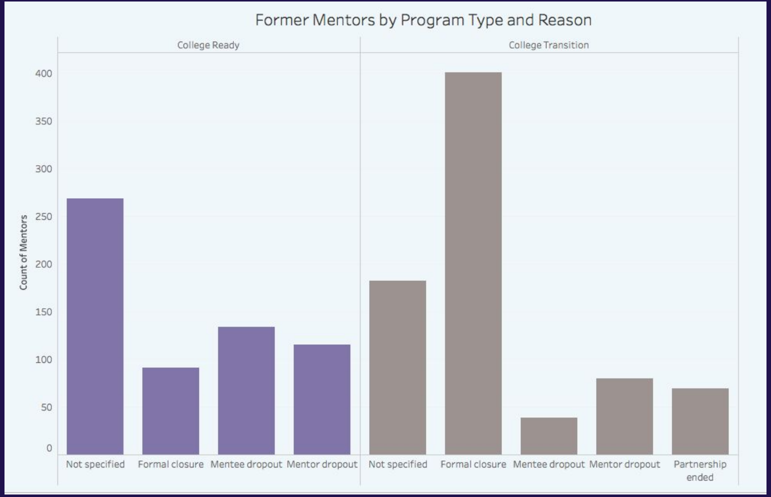
Figure 2 - 2012 match start year

4-yr program mentor dropout > formal closure

3- yr program mentor dropout < formal closure

Observation: There are more mentor dropouts than formal closure for 4-yr program and the opposite case for 3-yr program. However in case of 4-yr program, such difference narrows for 2012 match start year cohort which covers a period of at least 4 years to 2016 data collection year.





Question:

Can mentors demographics attributes be indicators of mentor dropouts?

Method:

Predictive analysis by training mentors demographic attributes in a classification model

Mentors Demographic Attributes

List of attributes in the predictive analysis of dropouts:

- Age at match
- Gender
- Marital status
- Racial group
- Career
- Level of education
- Parent college degree
- Have children
- How heard about iMentor

Note: some variables which contain overlapping characteristics (e.g. occupation vs. career) have been removed.

Figure A. Dropout and Demographic features correlation matrix

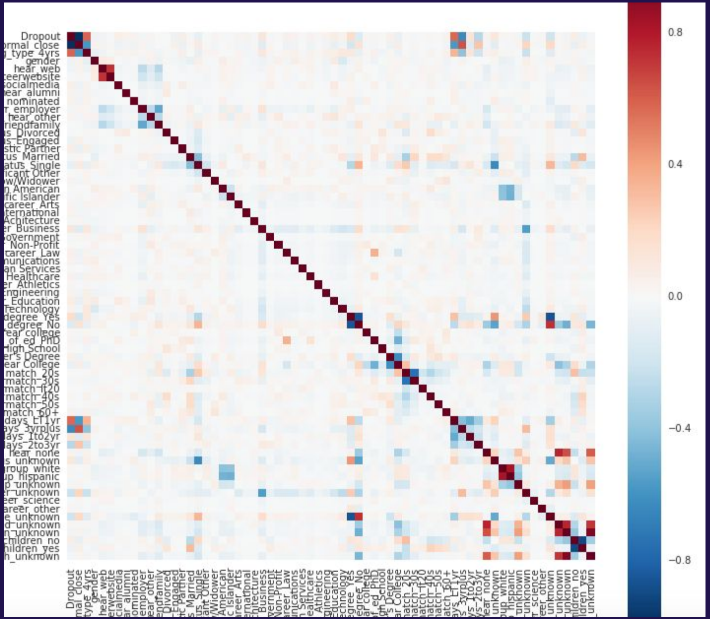


Figure A shows that not a lot of demographic attributes of mentors have a strong relationship with mentors dropouts

Predictive Analysis - Model

Algorithms used:

- Unsupervised learning (PCA and clustering): not intuitive and lower accuracy
- ✓ Decision Tree: easier to understand and better accuracy

Note: some bootstrapping techniques were used to balance out the number of dropouts and formal closure in the dataset

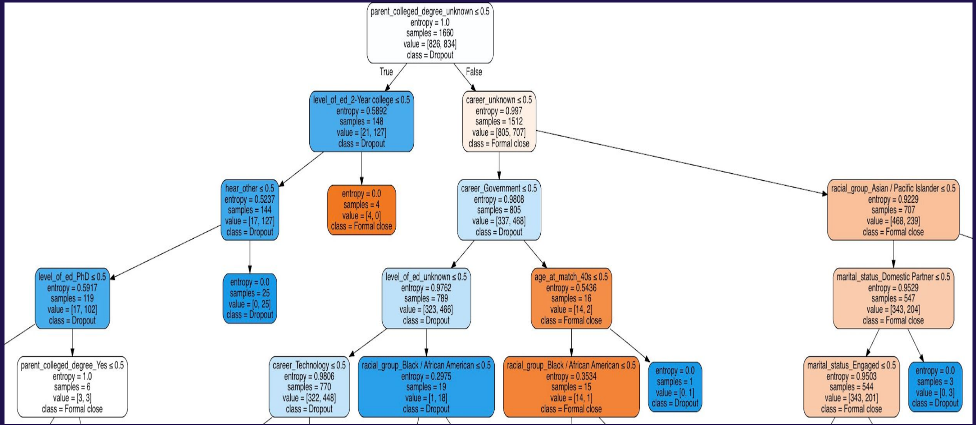


Figure 3 Extract of Decision Tree

Predictive analysis - Findings

Top 10 most important predictive indicators:

- Career - not specified
- Parent college degree - not specified
- Heard iMentor from employer
- Level of education - 2-yr college
- Career in Government
- Racial group - African American
- Racial group - Asian
- Career in Tech
- Level of education - not specified
- Age at match - 30's

Model accuracy: 65%

The low accuracy possible explanation:

- Demographic attributes of mentors alone can only partially explain mentors likelihood of dropping out. As next step, features other than demographics will need to be explored and added to the current model
- Small number of formal closure (i.e. the opposite label of mentor dropout) in the dataset in the 4 yr-program can weaken the predictive power of the model

Predictive analysis - Possible Uses

- Predict dropout probability of current mentors and detect potential group likely to dropout
    - Can be visualized on a map by school - see Figure B - Tableau demo (note mentors mailing zip code was used since school zip codes were not available)
- Better understand factors related to mentors dropout to help better mentor recruitment
- The prediction of mentors dropouts can also help for mentors population projection and resource planning

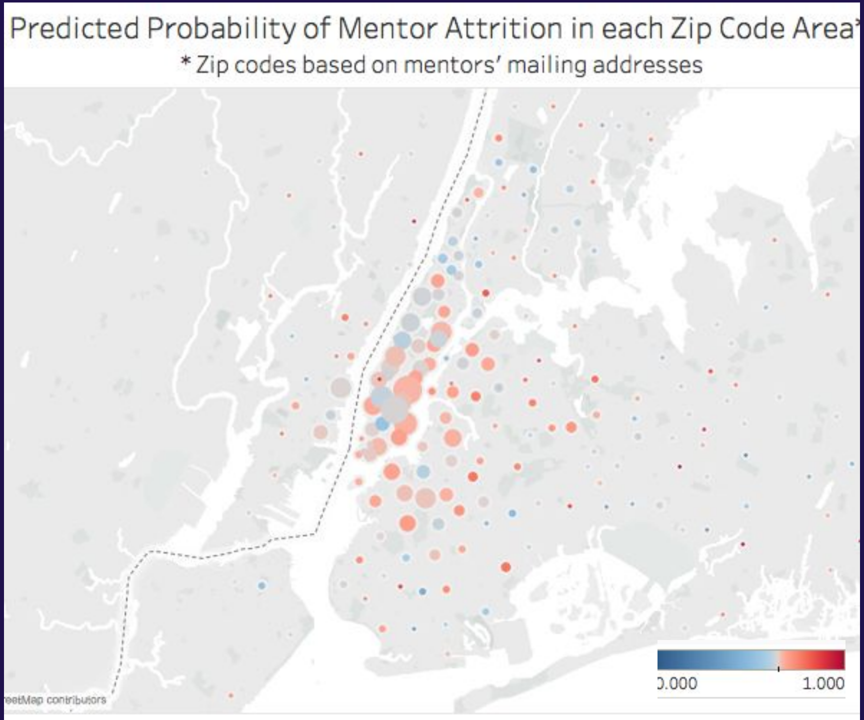

Predicted Probability of Mentor Attrition in each Zip Code Area*
* Zip codes based on mentors' mailing addresses
).000
1.000
reetMap contributors

Figure B Map of mentors likelihood to drop out

4. Message traffic data
Time Series Analysis

Key Findings

- No readily apparent behaviors distinguishing dropout mentors from other groups
- Patterns suggesting decreasing mentor engagement over time

Message Traffic Data Description

- Identifier for what week / lesson sequence each message was for
- Time stamp for login and send
- Message length
- Mentor, mentee, and pair identifiers
- School year 2015-2016
- Dataset for mentee and mentor messages, both with about 90,000 observations

Mentor Groups

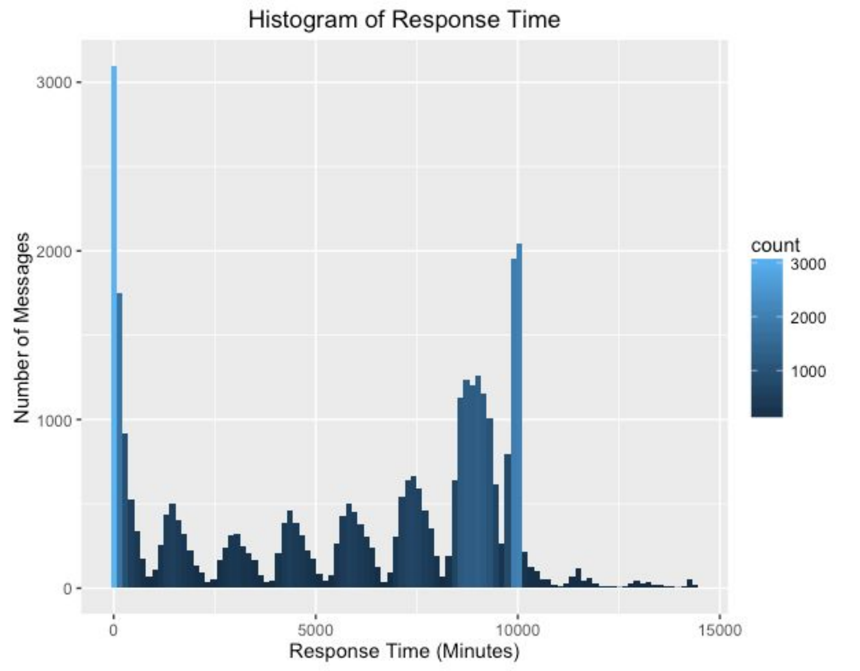
- Mentor dropout
- Formal closures (program completion)
- Mentee dropout
- Open matches

Methodology

- Compare metrics across groups
- Standardize measures calculating z score for each observation relative to mean and standard deviation for that particular mentor
- Group by message sequence to observe trends leading up to match closure or end of observations

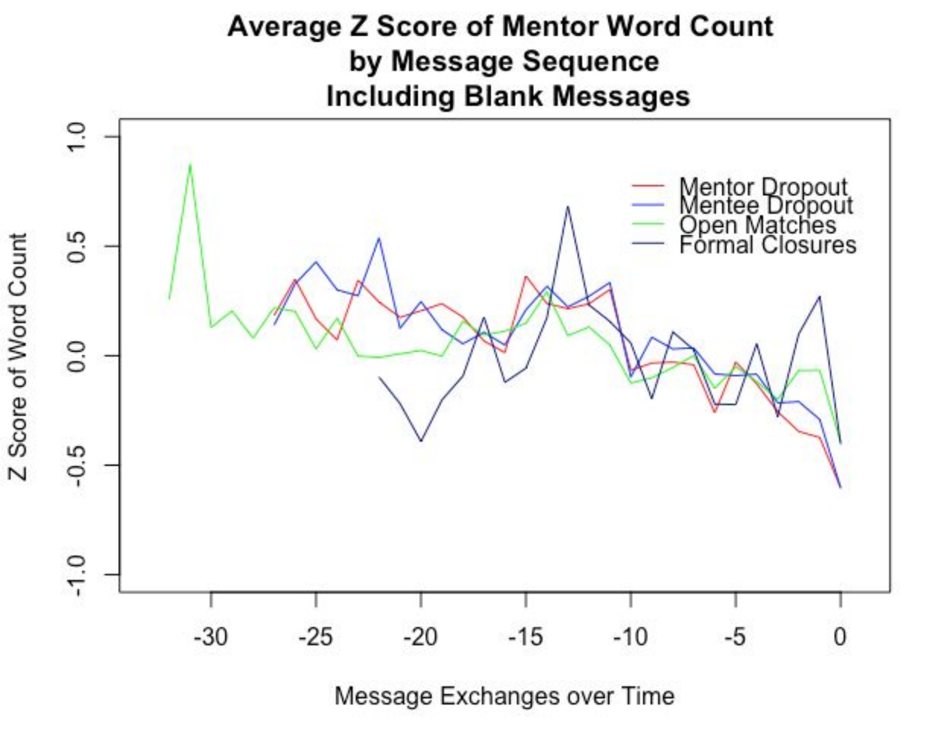
Response Time

- Large number of mentors who respond quickly each week
- Large spike as mentors rush to respond at the end of each week
- Hoped to see more last minute responses for dropout mentors, but the distribution looked similar for all mentor groups



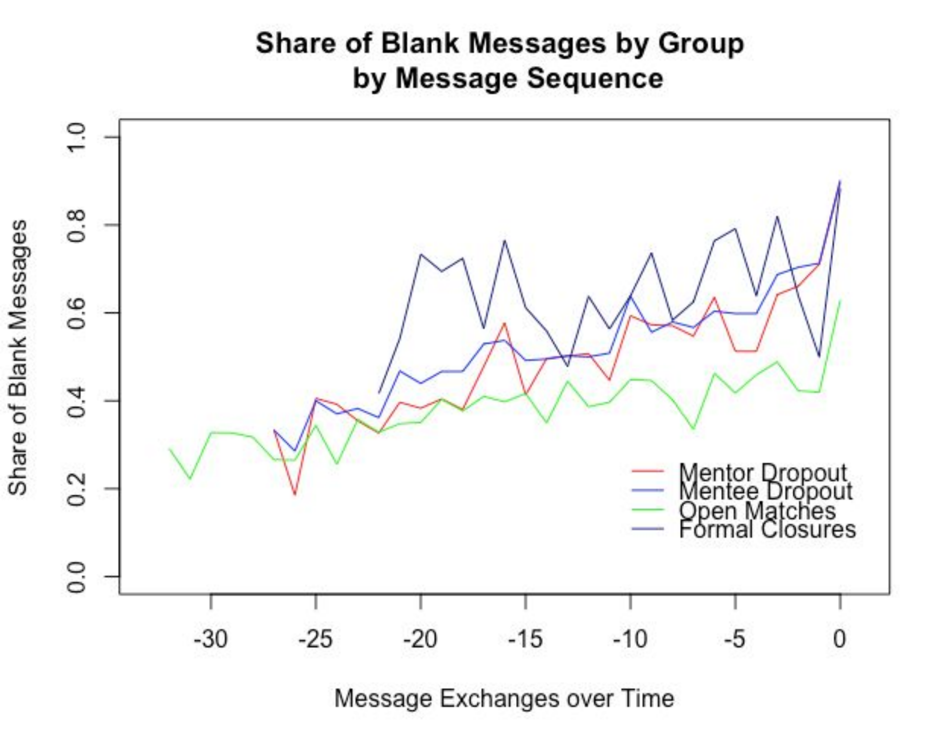
Word Count

- Mentors write on average about two and a half times as many words as mentees, with mean message length for mentors of 191 words and 74 words for mentees.
- Word count trends downward as mentors spend a longer time in the program



Blank Messages

- Very distinct increase in blank messages over time for all groups
- At least 40% of messages were blank for all groups
- Strangely, formal closures had highest prevalence of blank messages, difference was statistically significant at the p < .001 level using pairwise t-test with Bonferroni correction



Conclusion

- No strong indicators found to differentiate dropouts from formal closure:
    - Demographic attributes can partially train a prediction model but additional features should be added to complete the model
    - Message traffic analysis is based on one school year. Analysis over several years may reveal distinctions between dropouts and mentors who reach completion of the program

Proposed Next Steps

Data Architecture & Processing

- Will need to work with raw files that are used to generate the master data file.
- Need ability to "customize" tables for analysis -- data is currently heavily filtered manually
- Message logs and content will increase rapidly over time. May need to investigate Hadoop for stability
- Push demographics analysis back to cloud, create/update mentor dropout table with Bayesian statistics? For visualization

Proposed Next Steps

Demographics Analysis

- Combine demographic attributes of mentors with features that reflect mentors behavior within program (e.g. message frequencies), mentors interaction and relationship with mentees (same interests, hobbies, family background, racial group, languages, etc.) and other features (proximity of work/home to school, etc.)

Proposed Next Steps

Messages & Logs

- Analyze patterns in chat, could be some interaction with blank messages
- If changes are made to the program, repeat analysis to see if they seem to improve mentor engagement
- Find out whether mentors begin to feel some fatigue over time
  - How do we explain consistent mentor disengagement?

The Team

Nicholas Chen

Time Series Analysis Lead

Message traffic analysis

Stephanie Fan

Data Visualization Lead

Tableau expert

Hyera Moon

Predictive Analysis Lead

Mentor demographic data analysis

Leslie Teo

ETL Lead

Data architecture, storage and retrieval expert