# 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:

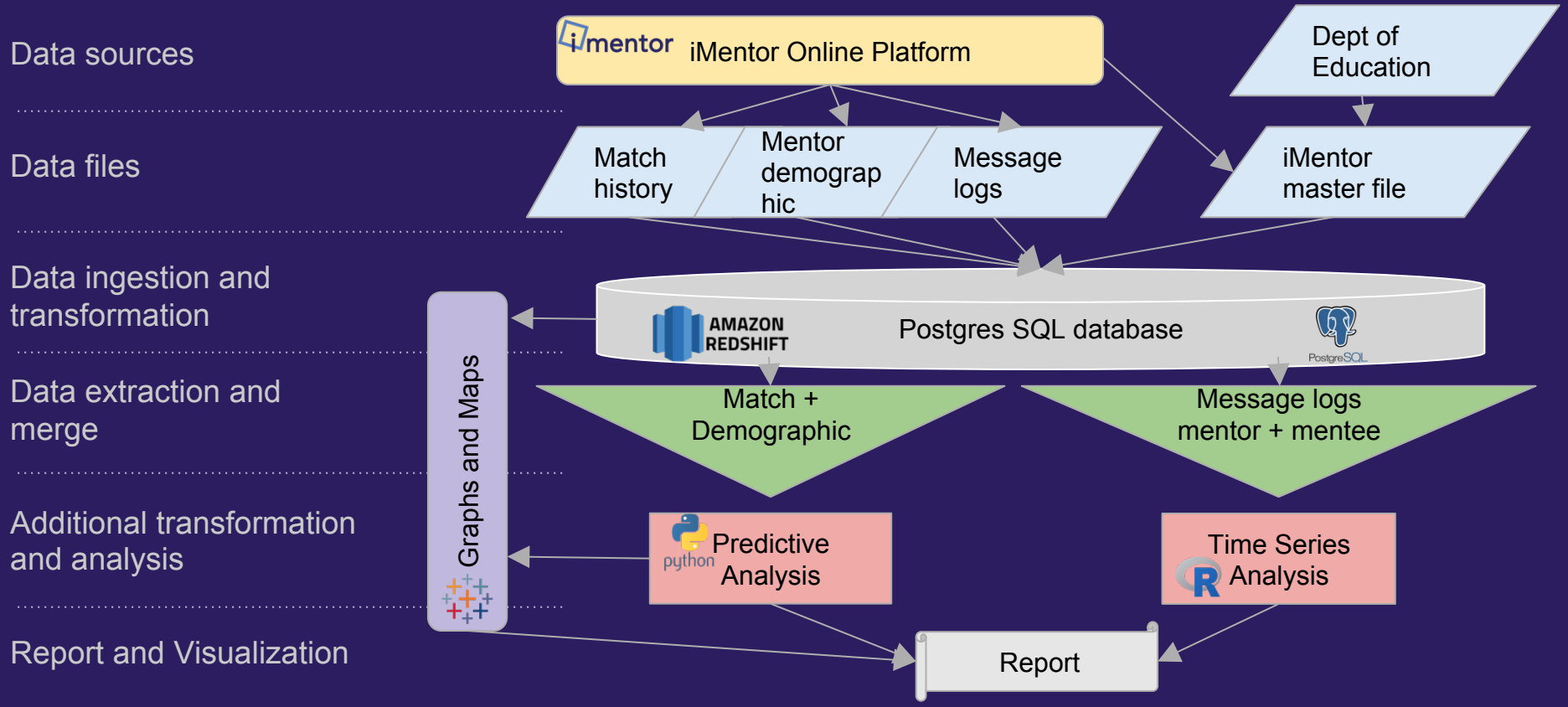
- Mentors demographic information
- Message log data for one school year 15-16 i.e. excludes the content of messages
- Mentors participating in iMentor NYC only

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.

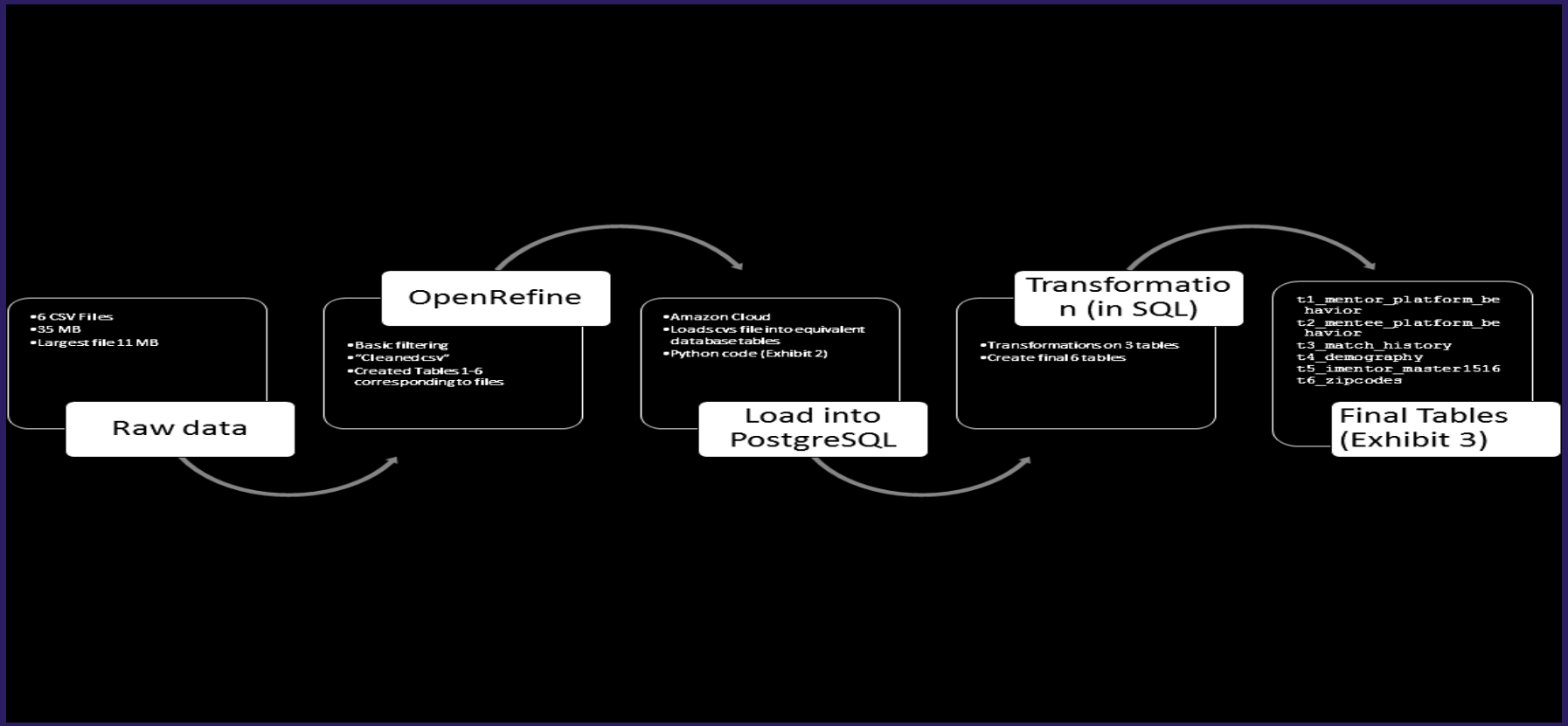
# 1. Analysis Framework

# Framework Chart

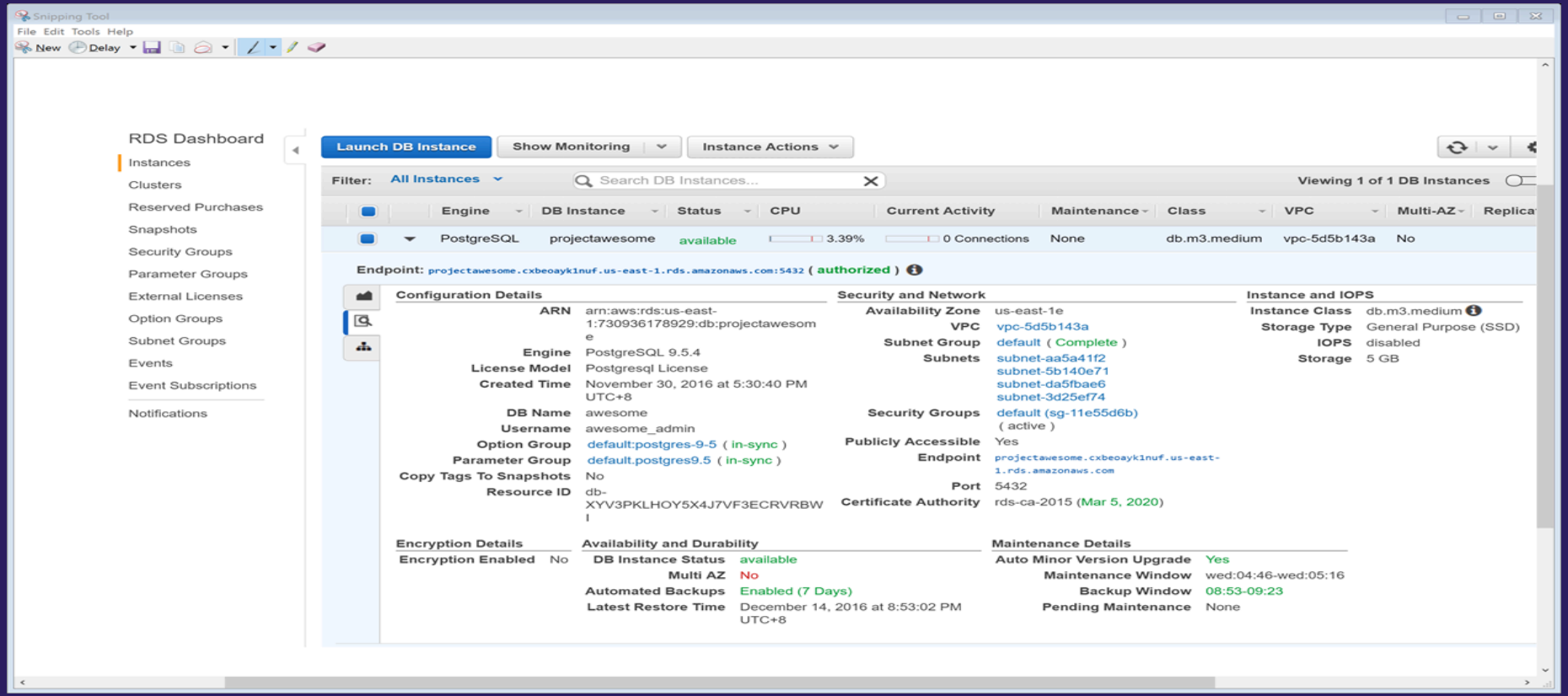


# 2. Data Processing

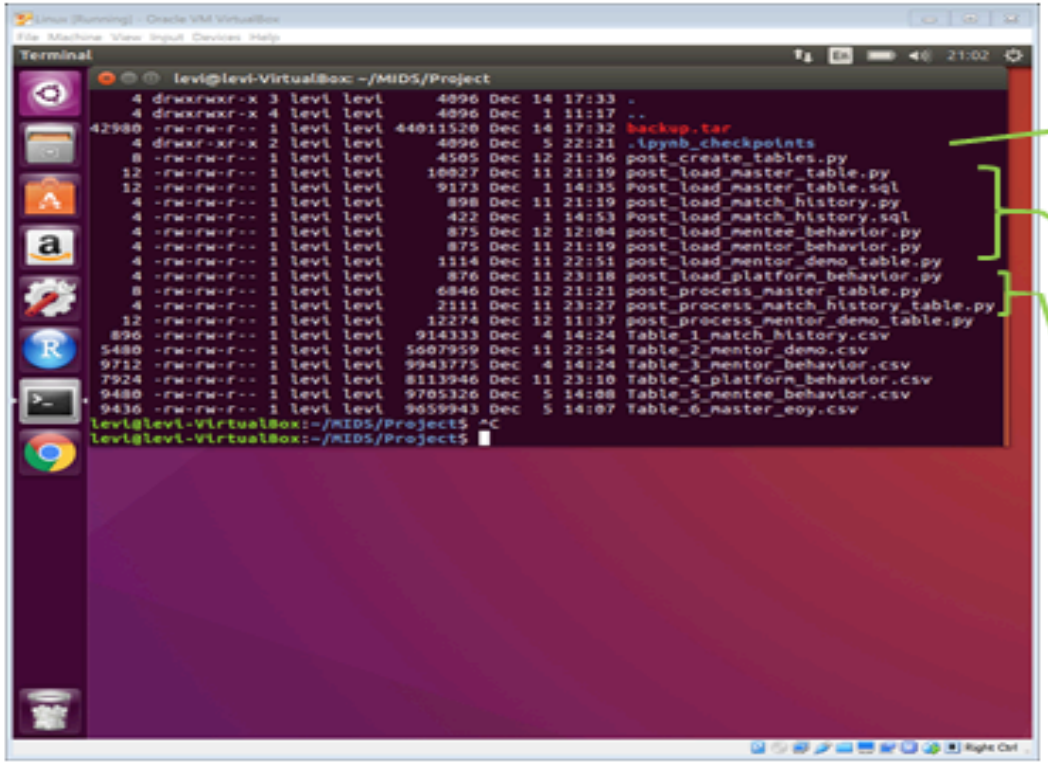
# Extract - Load -Transform



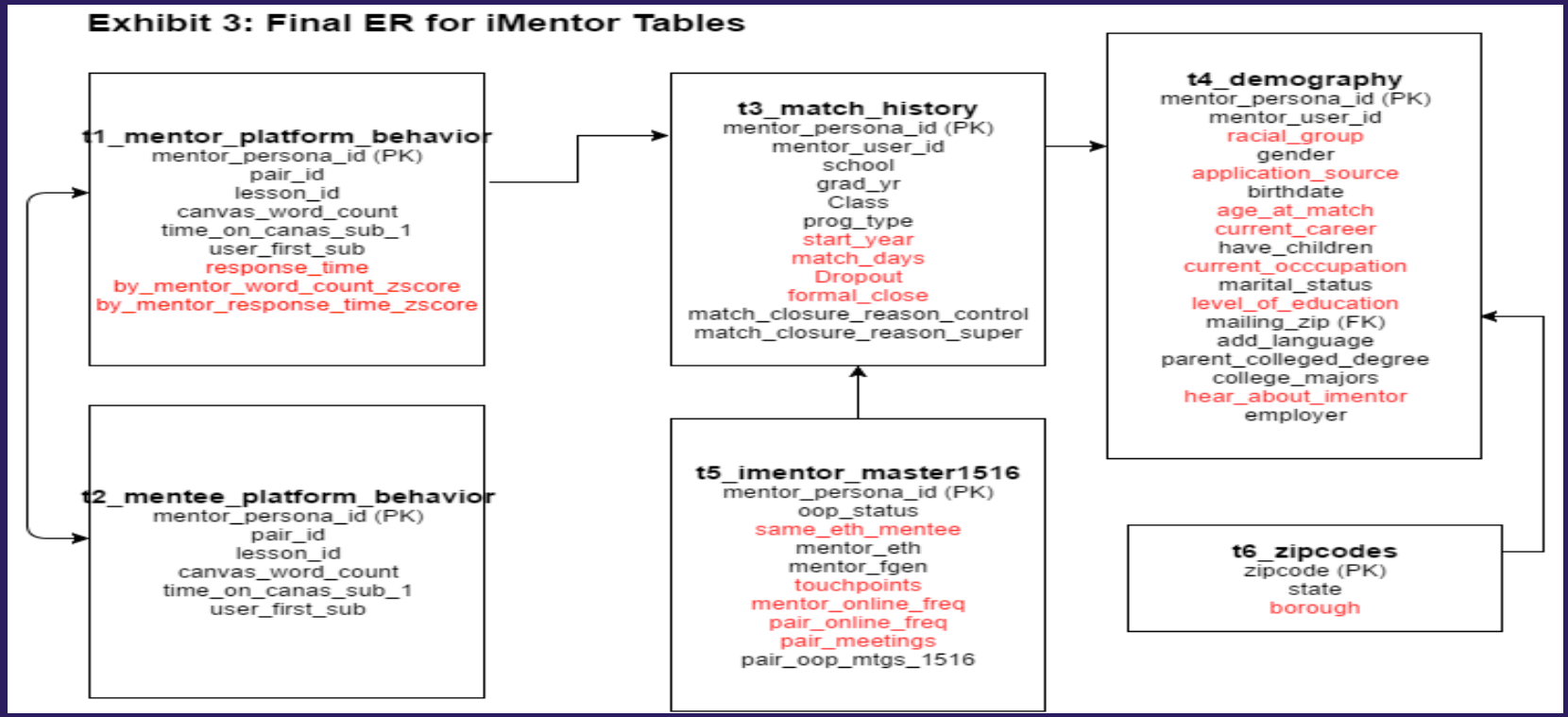
# Our Database on Amazon



# Data Processing App (10 sub-programs)



# 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

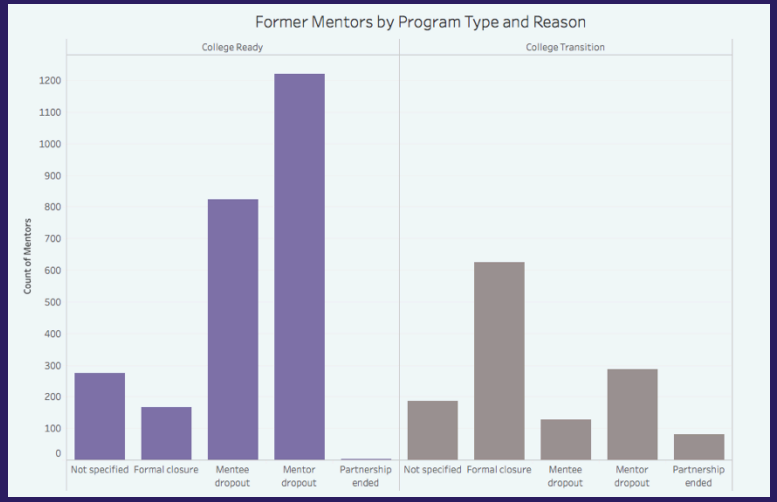
3- yr program mentor dropout < formal closure

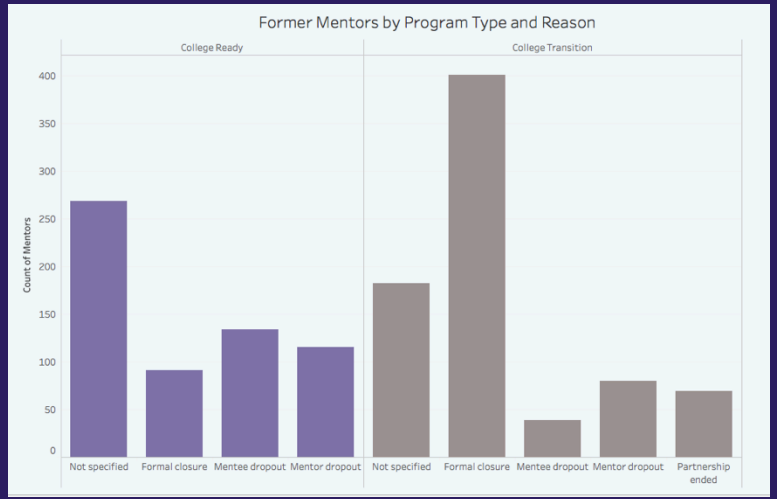
## Figure 2 - 2012 match start year

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

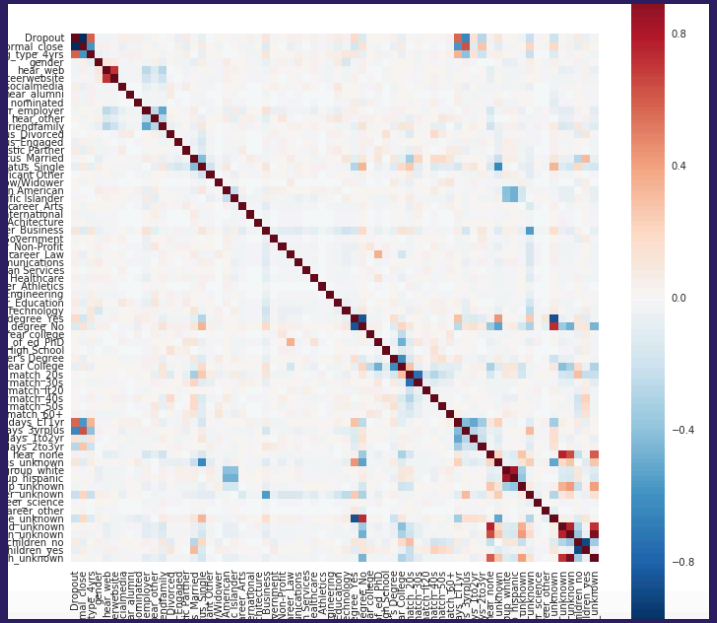



Figure A shows that not a lot of demographic attributes of mentors have a strong relationship with mentors dropouts

# 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

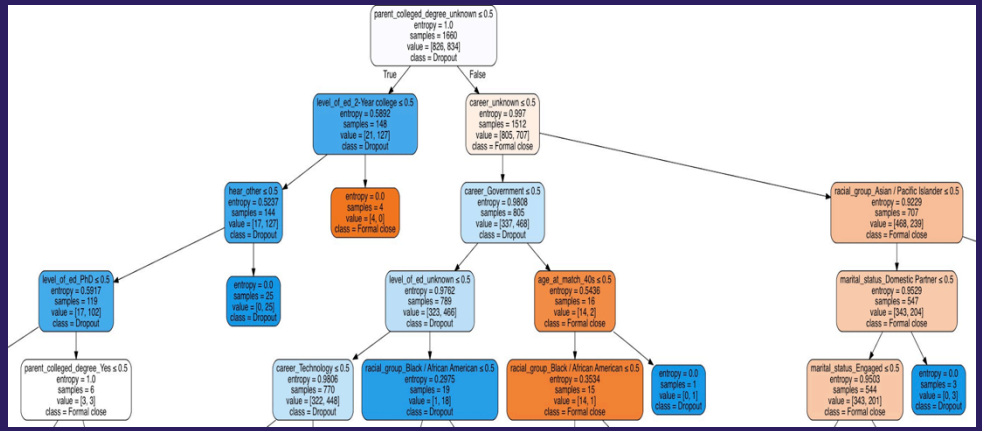



Figure 3 Extract of Decision Tree

# Predictive analysis - Findings

**Top 10 most important predictive indicators:**

1. Career - not specified
2. Parent college degree - not specified
3. Heard iMentor from employer
4. Level of education - 2-yr college
5. Career in Government
6. Racial group - African American
7. Racial group - Asian
8. Career in Tech
9. Level of education - not specified
10. 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

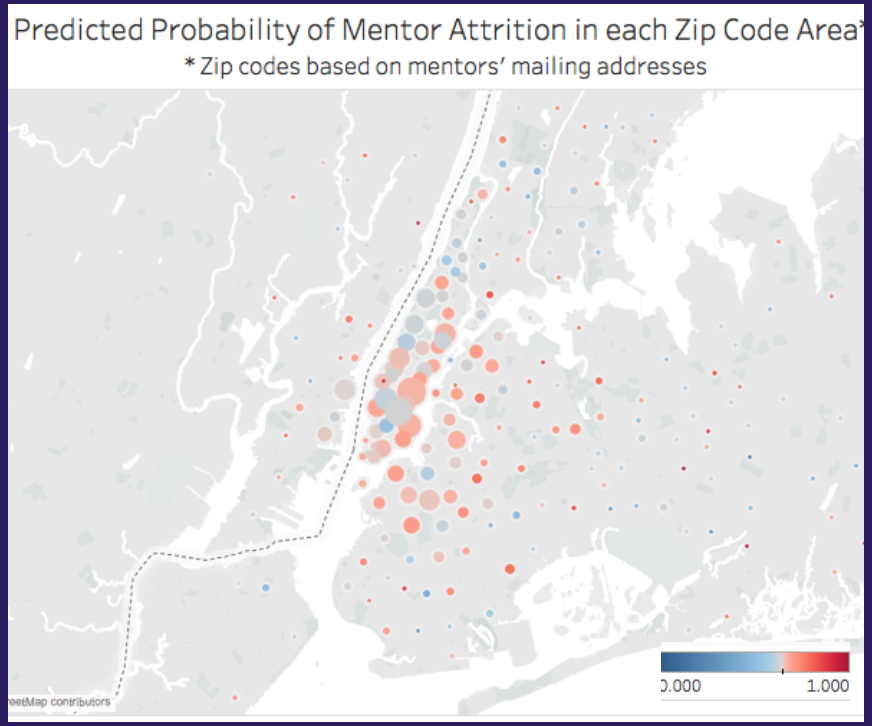



Figure B Map of mentors likelihood to drop out

# 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

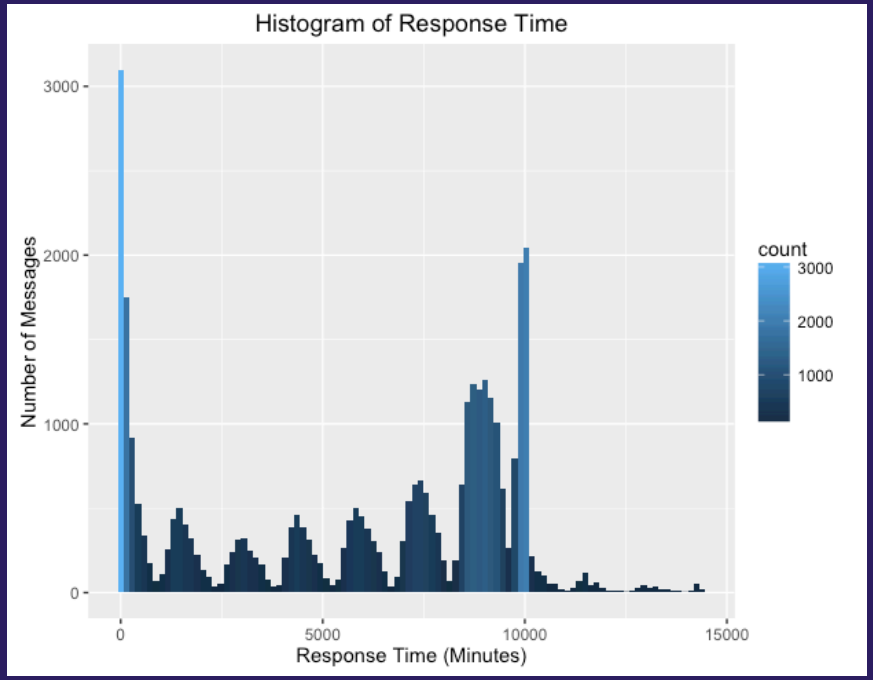
- Mentor dropout
- Formal closures (program completion)
- Mentee dropout
- Open matches

# 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

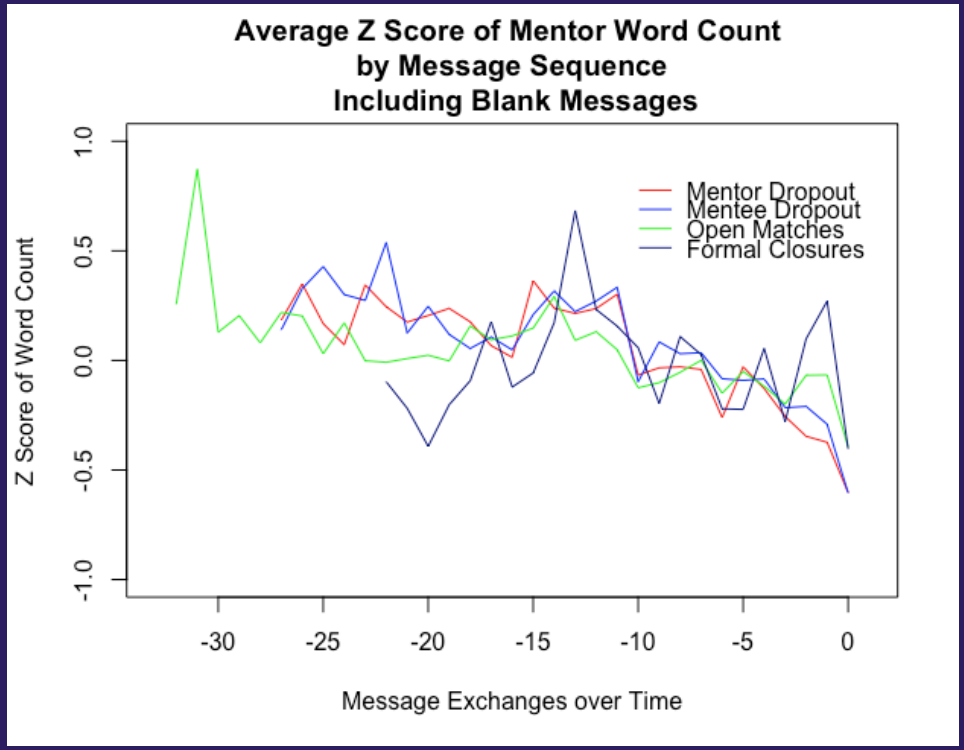
# Response Time

- 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



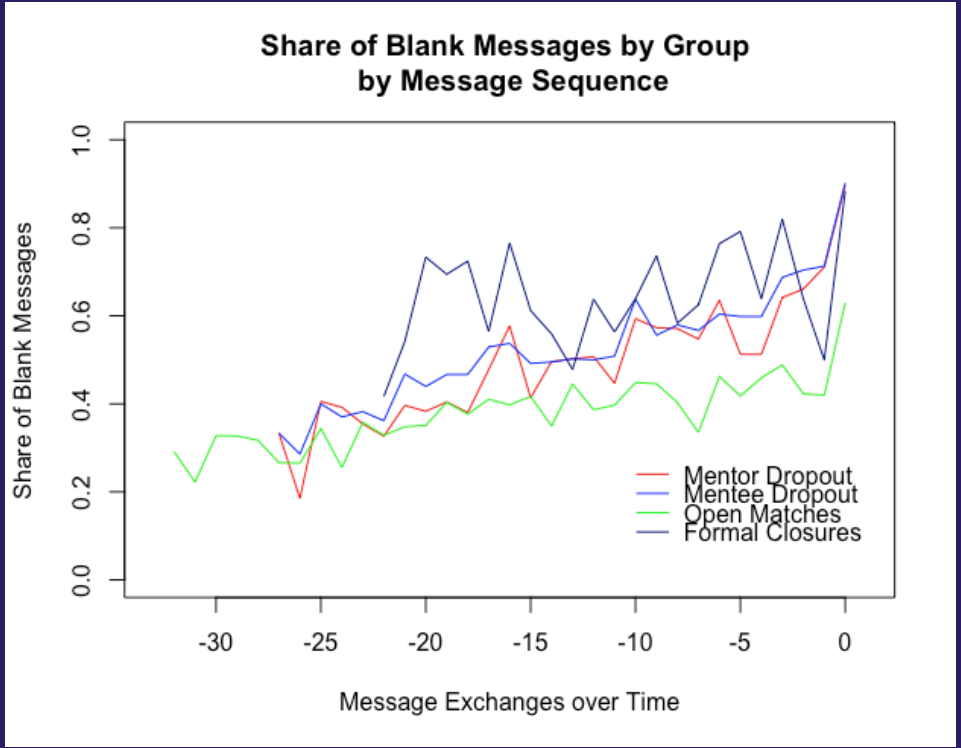
# Word Count

- 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

# 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

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