

# AUSTIN RESTAURANTS HEALTH INSPECTION

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*Project Final Presentation*

*by Nikos Vergos*

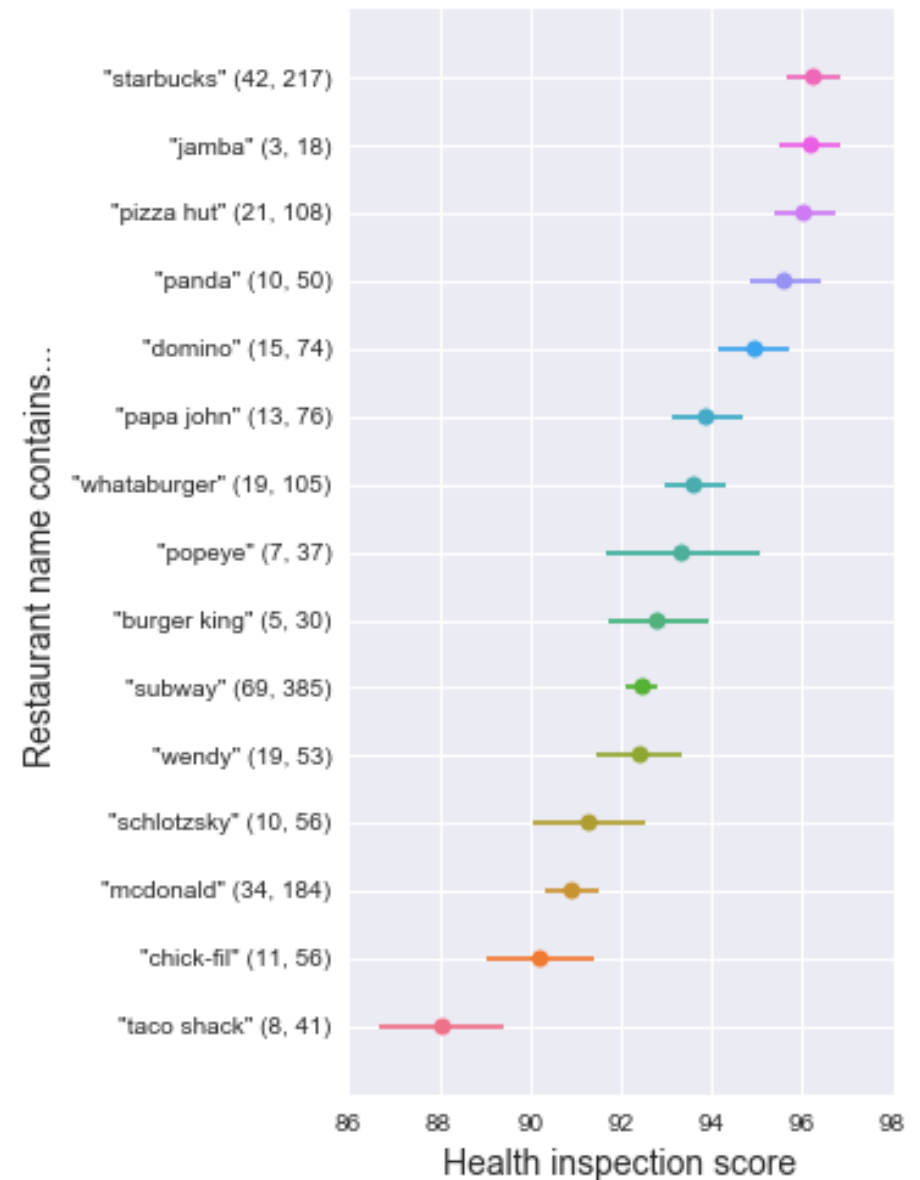
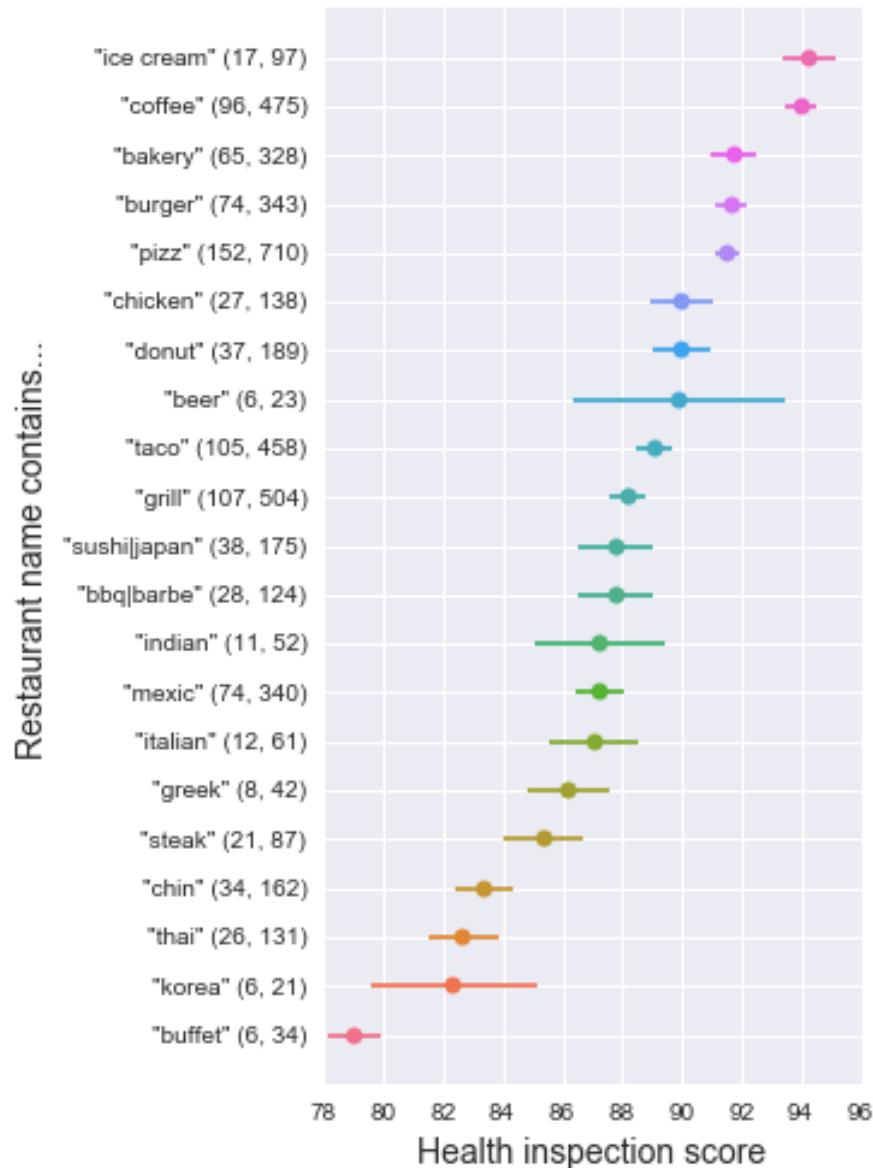
## PREVIOUSLY...

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- Using open data from [data.austintexas.gov](http://data.austintexas.gov)
- Data set: City of Austin/Travis County Restaurant Inspections
  - 22,875 rows (inspections)
  - 4,774 establishments inspected (roughly 2x a year)

# PREVIOUSLY...



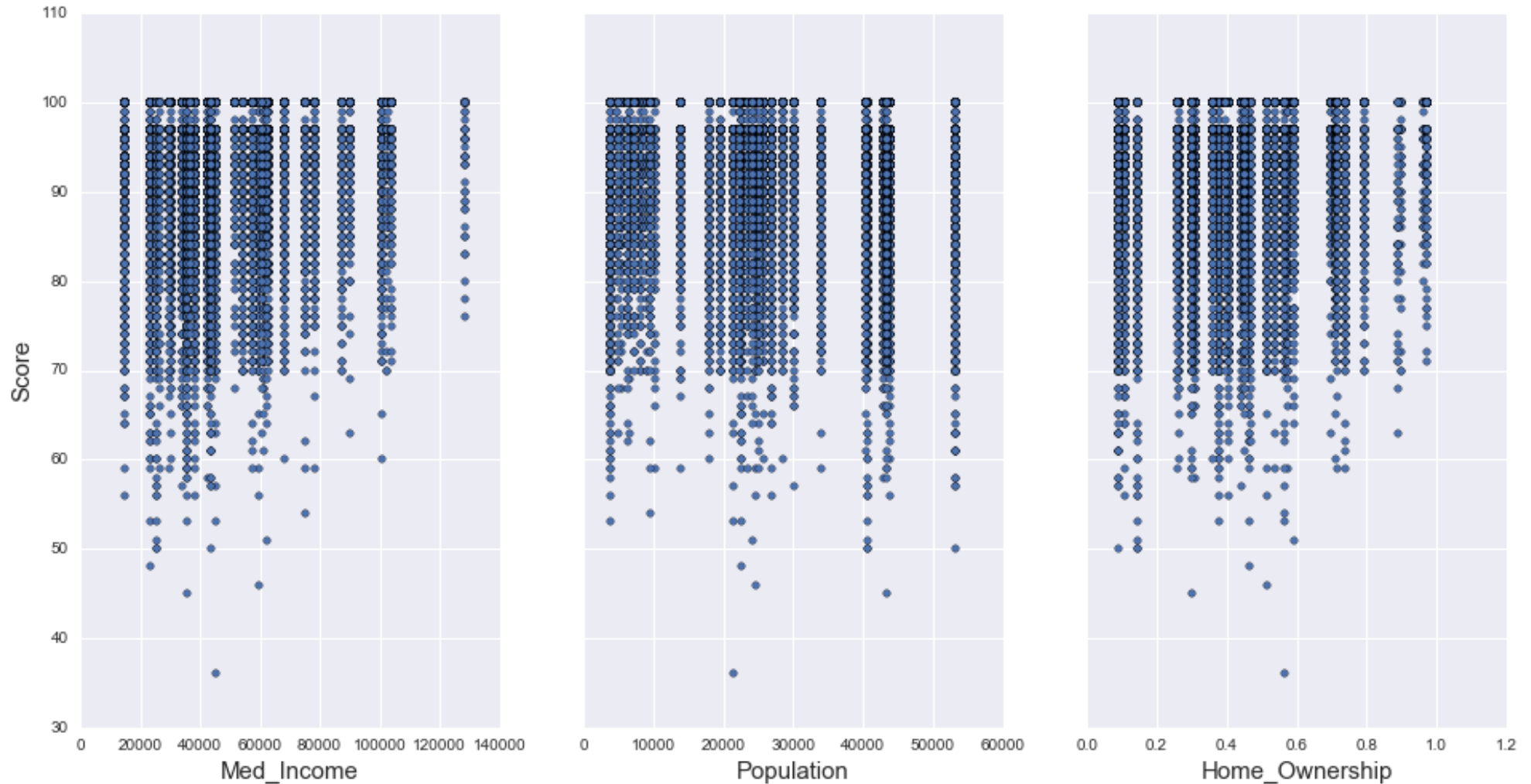
# PROJECT OUTLINE

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- ~~First and foremost: Clean and “enrich” data set~~
- ~~Part I: Exploratory Data Analysis~~
  - ~~Scores distribution~~
  - ~~Correlation among inspections~~
  - ~~Confidence intervals for scores by type of restaurant~~
- Part II: Machine Learning
  - A) [*Supervised*] Classification Algorithms: can we **predict** a restaurant’s performance based on past scores?
  - B) [*Unsupervised*] PCA & k-means clustering: are there any **patterns** in names/addresses? Do they affect the score?
- Part III: Fancy stuff (time permitting)
  - Geocoding - visualizations: Heat maps by zip code / area
  - Linear regression: web scraping for yelp scores, add zip codes’ median income - can I predict health inspection score?

# ADDING NUMERICS



# LINEAR REGRESSION

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# GENERAL ASSEMBLY

- *Attempted to predict score given numerics - terrible idea (2% of variance explained)*
- *Switched to “averaged” data - 36 rows, one per zip code of interest:*
  - *Score vs. Median Income: 40%*
  - *Score vs. Population: 17.4%, negative slope*
  - *Score vs. Home Ownership Percentage: 13.7%*
- *Multiple Linear Regression Model: 49.4% - Almost as good as a coin toss!*
- *No predictions allowed - more of a toy problem*

# LOGISTIC REGRESSION



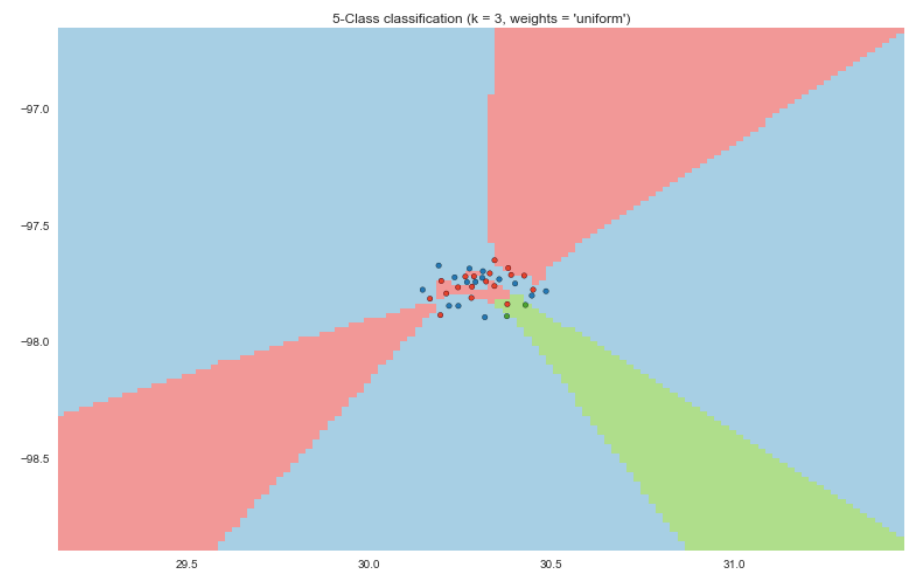
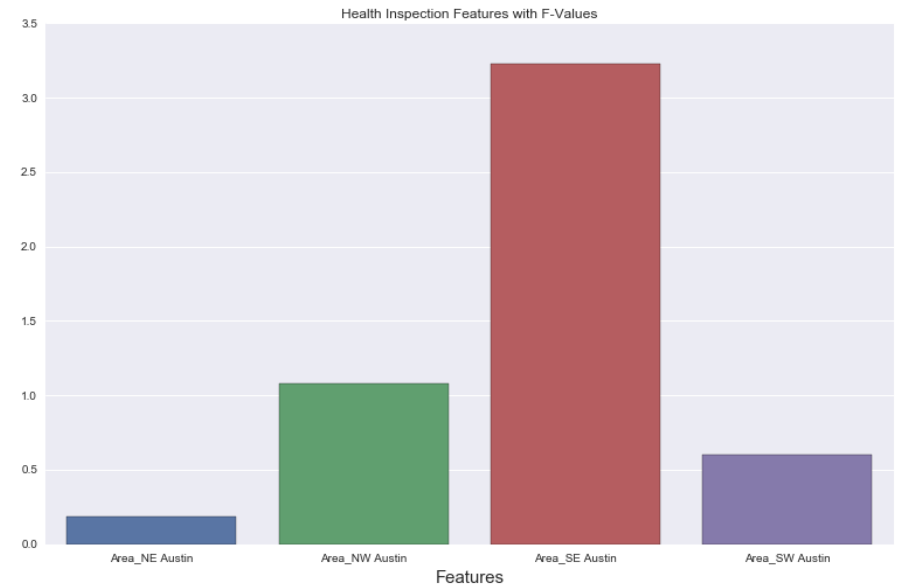
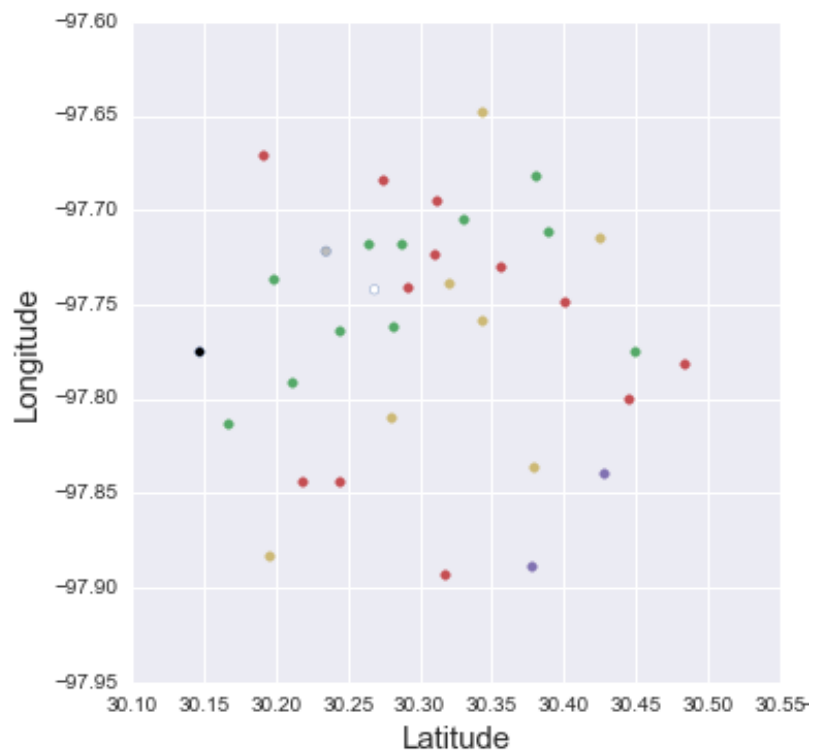
- *Features: City Areas (5)*
- *Target: Pass/Fail*
  - *Also: assigned letter grades (like in New York City)*
  - *Class Imbalance: only 1% of 18610 entries have failing scores*
    - *linear\_model.LogisticRegression(class\_weight='balanced') - 55%*
    - *Oversampling the minority class - 56%*
- *Changing the classification threshold:*

```
The number of restaurants predicted to pass inspection with logistic threshold = 0.5 is 13384
The number of restaurants predicted to pass inspection with logistic threshold = 0.6 is 11999
The number of restaurants predicted to pass inspection with logistic threshold = 0.7 is 5423
The number of restaurants predicted to pass inspection with logistic threshold = 0.8 is 0
The number of restaurants predicted to pass inspection with logistic threshold = 0.9 is 0
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- *Switching to a different prediction target: Letter Grade A or (not A)*

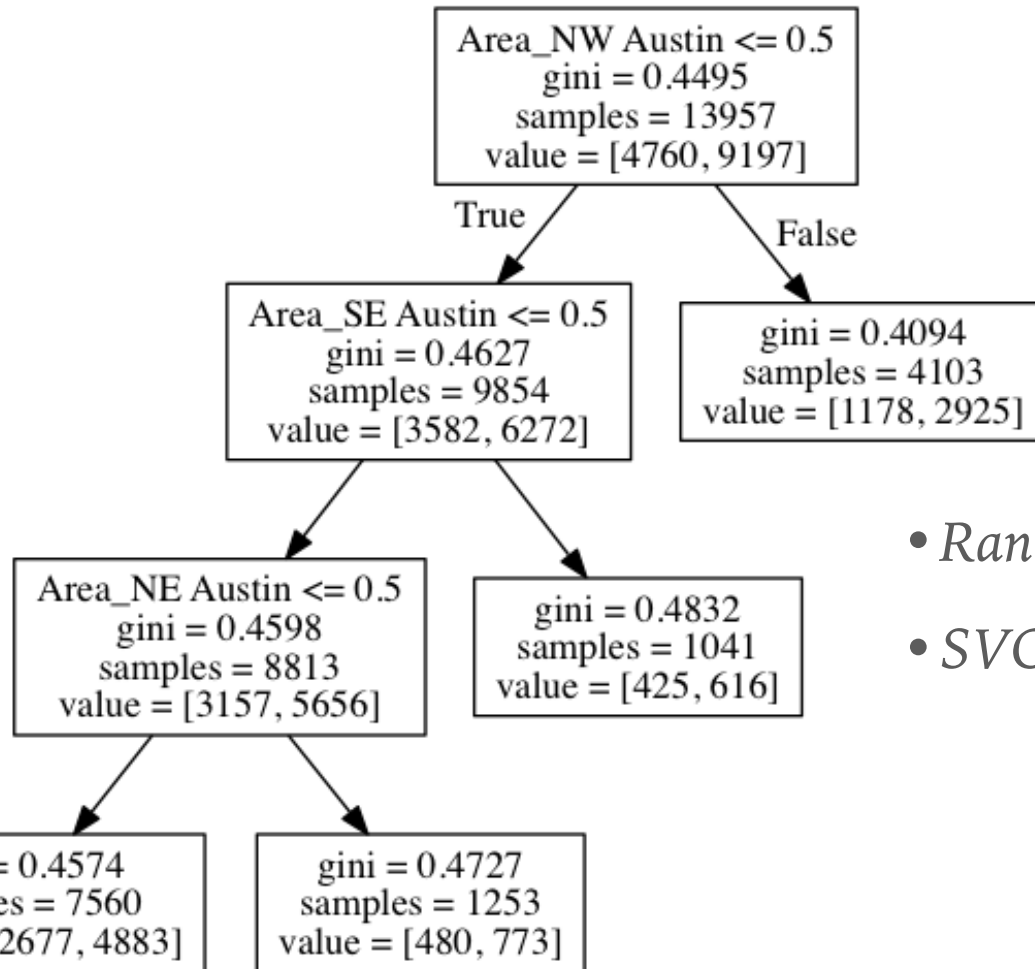
# KNN ON AVERAGE SCORES

- *Score on holdout set: 85%!*
- *A recurring theme:*
- *SE/NW Austin seem to be “important”*





# OTHER CLASSIFIERS



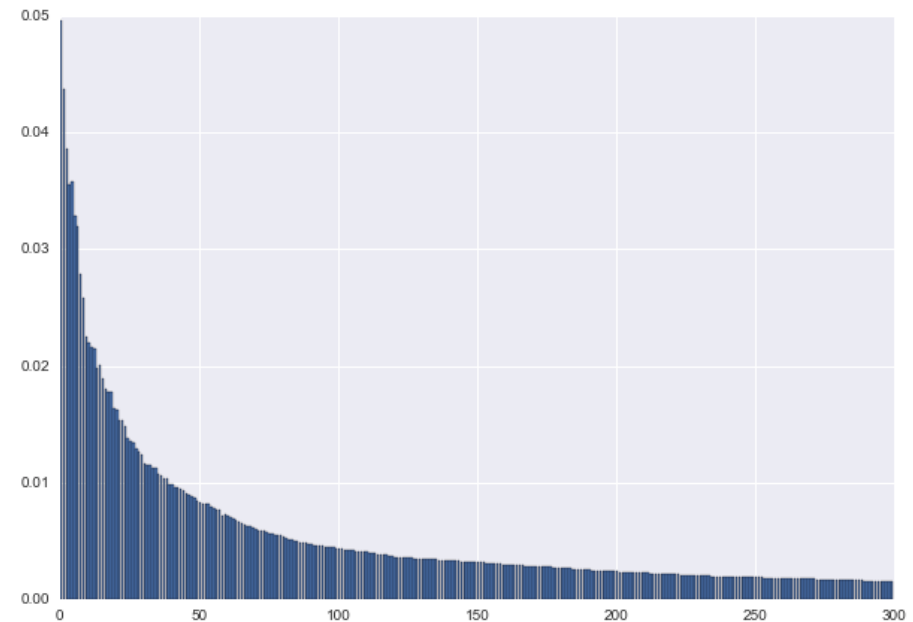
- *Random Forest with 250 trees: 65.8%*
- *SVC: 65.8%*

# TEXT MINING FOR CLASSIFICATION



# GENERAL ASSEMBLY

- *Bag-of-Words model for:*
  - *Restaurant Name ( $\sim 3500$  features): 66.8%*
  - *Street ( $\sim 540$  features): 61.9%*
  - *Using: CountVectorizer, Multinomial Naive Bayes*
- *Dimensionality Reduction: Truncated SVD*
  - *Similar score with 10% of the features!*



# IMPORTANT FEATURES



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Class: A

**austin:** -4.6089, **the:** -4.7837, **elementary:** -4.8022, **food:** -4.8064, **mart:** -4.9958, **cafe:** -4.9958, **pizza:** -5.0059, **coffee:** -5.1214, **market:** -5.1953, **center:** -5.2554, **bar:** -5.3193, **school:** -5.4331, **food mart:** -5.4449, **subway:** -5.5099, **club:** -5.5795, **bakery:** -5.6690, **grill:** -5.6739, **house:** -5.6990, **catering:** -5.7195, **and:** -5.7247, **deli:** -5.7247, **starbucks:** -5.7299, **restaurant:** -5.7892, **foods:** -5.8060, **inn:** -5.8289, **of:** -5.8347, **wl:** -5.8464, **taco:** -5.8523, **child:** -5.8823, **la:** -5.8823

Class: B

**restaurant:** -4.4523, **cafe:** -4.5059, **austin:** -4.6419, **the:** -4.8050, **bar:** -4.8518, **market:** -4.8884, **pizza:** -4.9658, **la:** -4.9658, **food:** -4.9725, **grill:** -5.1414, **el:** -5.1991, **mart:** -5.2876, **taco:** -5.3448, **house:** -5.3746, **subway:** -5.4924, **and:** -5.4924, **mexican:** -5.5271, **in:** -5.5271, **bakery:** -5.5877, **food mart:** -5.6930, **coffee:** -5.8108, **deli:** -5.8265, **taqueria:** -5.8265, **grocery:** -5.8588, **inn:** -5.8921, **kitchen:** -5.9092, **club:** -5.9092, **stop:** -5.9443, **star:** -5.9807, **thai:** -5.9993

Class: C

**restaurant:** -3.9294, **cafe:** -4.3385, **grill:** -4.5645, **the:** -4.5930, **bar:** -4.5930, **la:** -4.5930, **market:** -4.8381, **taqueria:** -4.8568, **el:** -4.8758, **house:** -4.9559, **mexican:** -5.0204, **austin:** -5.0429, **thai:** -5.2435, **and:** -5.3006, **taco:** -5.4257, **food:** -5.4596, **mexican restaurant:** -5.5688, **in:** -5.6488, **bakery:** -5.6488, **cuisine:** -5.6488, **pizza:** -5.6913, **kitchen:** -5.7358, **pho:** -5.7358, **los:** -5.7358, **sushi:** -5.7823, **bar grill:** -5.7823, **meat:** -5.8310, **meat market:** -5.8310, **shop:** -5.9363, **china:** -5.9935

Class: F

**la:** -3.7515, **restaurant:** -3.8002, **market:** -4.3107, **taqueria:** -4.3107, **el:** -4.3107, **austin:** -4.3977, **grill:** -4.5981, **thai:** -4.7158, **meat:** -4.8491, **bar:** -4.8491, **meat market:** -4.8491, **bakery:** -5.1850, **los:** -5.1850, **la michoacana:** -5.1850, **kitchen:** -5.1850, **michoacana:** -5.1850, **cafe:** -5.4077, **cuisine:** -5.4077, **house:** -5.4077, **lion:** -5.6945, **taco:** -5.6945, **mexican:** -5.6945, **taqueria los:** -5.6945, **del:** -5.6945, **el meson:** -5.6945, **and:** -5.6945, **shop:** -5.6945, **buffet:** -5.6945, **vietnamese:** -5.6945, **la catracha:** -5.6945

# HOT OFF THE PRESS!

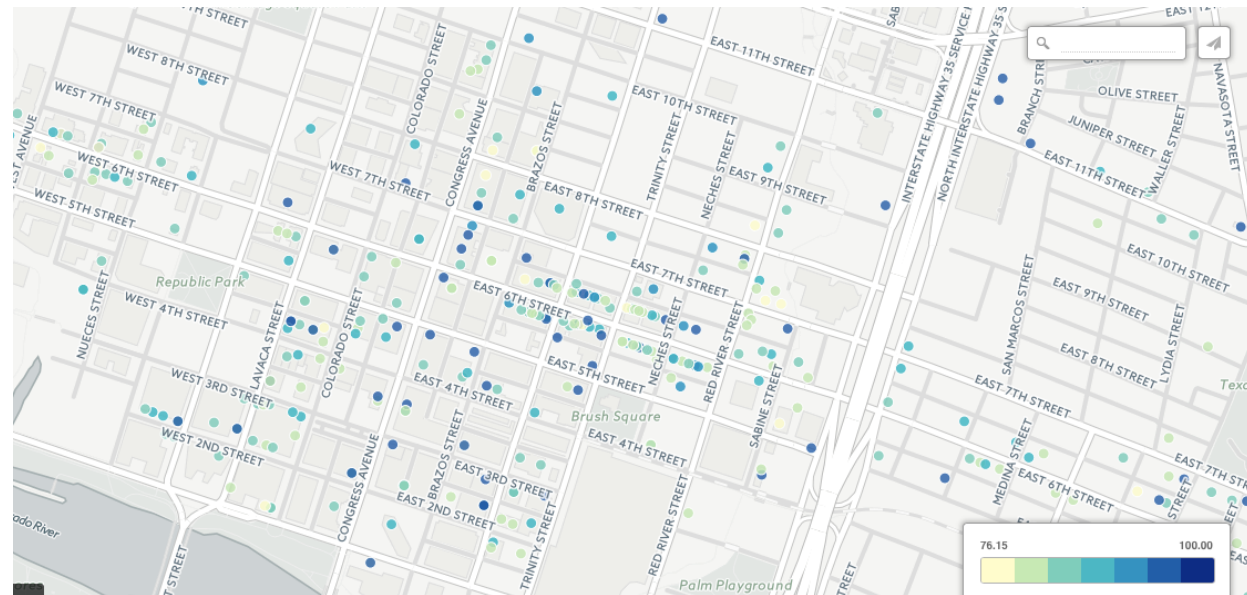
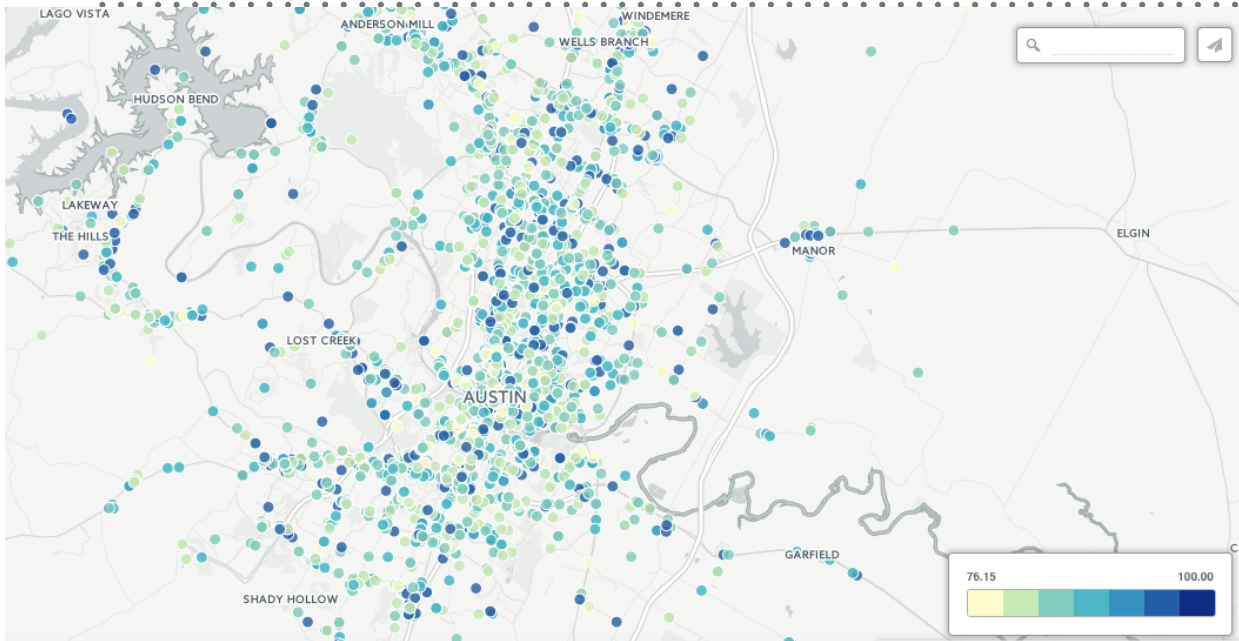


- *Filter out words with len < 3:*

A: catering grill **club subway** market **center coffee** pizza cafe austin  
B: **subway** mexican **taco** house grill **pizza** market austin cafe restaurant  
C: taco **thai** house austin mexican **taqueria** market grill cafe restaurant  
F: kitchen bakery **michoacana** meat **thai** market austin grill **taqueria** restaurant

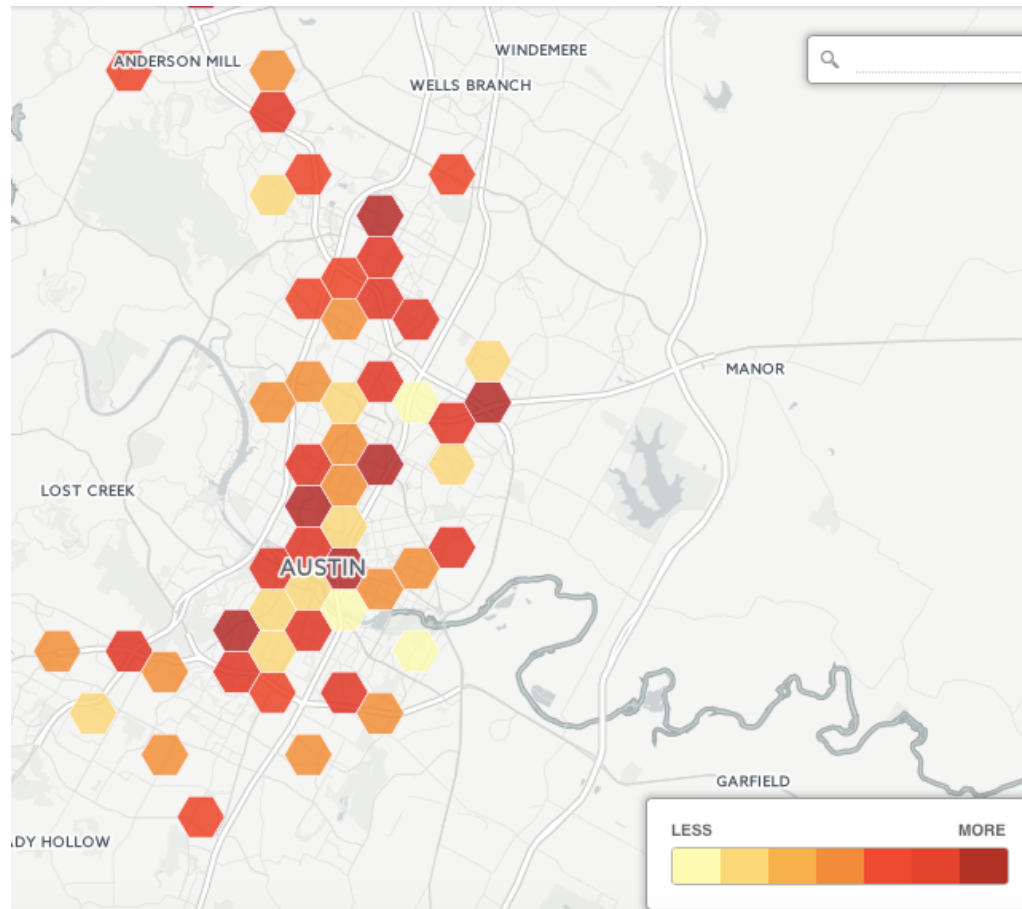
A: **slaughter anderson mopac caves capital** congress william parmer lamar blvd  
B: oltorf riverside springs **capital anderson** parmer congress william blvd lamar  
C: slaughter parmer stassney oltorf riverside springs william congress blvd lamar  
F: **cesar** parmer springs congress martin **anderson** riverside blvd oltorf lamar

# GEOCODING & MAPPING



# GEOCODING & MAPPING

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# CONCLUSION – NEXT STEPS

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# GENERAL ASSEMBLY

- *Austin is very diverse in its neighborhoods*
- *Managed to predict the letter grade of an ungraded restaurant with 60 - 67% accuracy by only knowing the restaurant's area of town and name.*
- *Next: Improve NB Classifier; Try unsupervised learning; clustering of restaurants by name/street*
- *Fork out the \$ for good geocoding of all 19,000 data points (less than \$20)*
  - *Add “neighborhood” data as a better(?) feature than “Area” - “Street”*
- *Publish: <https://github.com/nvergos>, CartoDB ([nvergos.cartodb.com](https://nvergos.cartodb.com))*
- *Do more **Data Science!** (Note to self: next data set should have some non categorical variables)*