Predicting Race In Law Enforcement Killings In the US

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Problem Statement

- Fatal Encounters is an organization that compiles and publishes data on individuals that have been killed by the police, with an observation for each person.
- The current database includes details surrounding each incident, as well descriptive and identifying information for each person.
- One of these features is the racial identity of the victims, and currently, of the ~32,000 observations, approximately 8,300 observations fall into the "Race Unspecified" category.
- Fatal Encounters has already created a model which, in two separate features, imputes the racial identity value and provides a corresponding probability of its strength of accuracy.

Problem Statement

- Goal: create a model which predicts the correct racial classification for individuals in the dataset who are categorized as "Race Unspecified" more accurately than the current model Fatal Encounters uses.

Name	Age	Gender	Race	Race with imputations	Imputation probab
Bradley G. Pullman	48	Male	Race unspecified	European-American/White	0.950023321
Jose Hernandez	62	Male	Race unspecified	Hispanic/Latino	0.95506125
William Graziano	57	Male	Race unspecified	European-American/White	0.939858242
Jamie Lamar Darley	33	Male	Race unspecified	European-American/White	0.961589767
James R. Best	45	Male	Race unspecified	European-American/White	0.960406969
Jack D. Beegle	27	Male	Race unspecified	European-American/White	0.994435149
Joshua Kyle Priest	33	Male	Race unspecified	European-American/White	0.864845571
Nicole Ann Stephens	30	Female	Race unspecified	European-American/White	0.822036834
Christopher Lee Sauseda	34	Male	Race unspecified	Hispanic/Latino	0.853798999
Daniel Hernandez Bravo	28	Male	Race unspecified	Hispanic/Latino	0.998428486
Jose Reyna Lozano	38	Male	Race unspecified	Hispanic/Latino	0.925737052
Isaac Andre Renfro	26	Male	Race unspecified	European-American/White	0.926463207

Background Information

- Racial discrimination in law enforcement responses in the US remains a discernible phenomenon and pressing issue.
- Once racial values imputations are near true accuracy, the dataset can be used to provide better insights about the nature of racial discrimination in American policing practices.
- In turn, these insights can hopefully contribute to addressing systemic racism in law enforcement responses across the US.
- Chosen for importance & relevance, personal passion, availability of supplementary data, comprehension of applicability, and clearly defined objective.

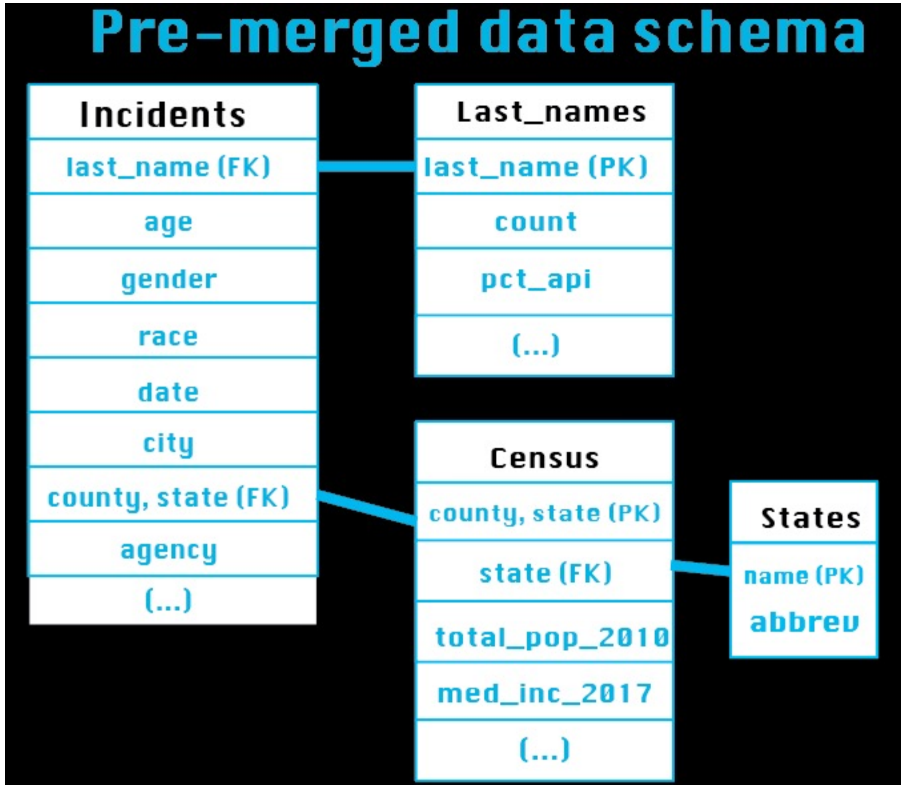
Meta Data I

DataFrames Content Overview

name	columns	rows	description	example
Incidents	32	30,413	Details surrounding each incident, identifying information for each person.	Name, gender, age, race, city, state, county, date
Census	178	3,168	Various demographic info on county basis	Tot_pop_2010, med_inc_2017, pct_ain_2015
Last Names	151,063	10	Aggregated last names at birth (2011) including racial composition	Pct_api, pct_blck, pct_his
States	2	50	State names in full and abbreviated formats	Name, code

Relational DataFrames

- 4 DataFrames
- 3 Primary Keys
- 3 Foreign Keys
- *States DataFrame to simplify "county, state" feature creation



Data Cleaning

- Dropping columns and rows
- Checking nulls
  - Dropping columns with too many
  - Imputing for numericals
  - Dropping rows
- Checking unique values
  - Dropping categoricals with too many
  - Checking for categorical/numeric conflation with smaller values
- Creating features
  - Last Name
  - County, State
  - Agency
  - Date
  - Dummifying categoricals
- Formatting column names
- Inner merging

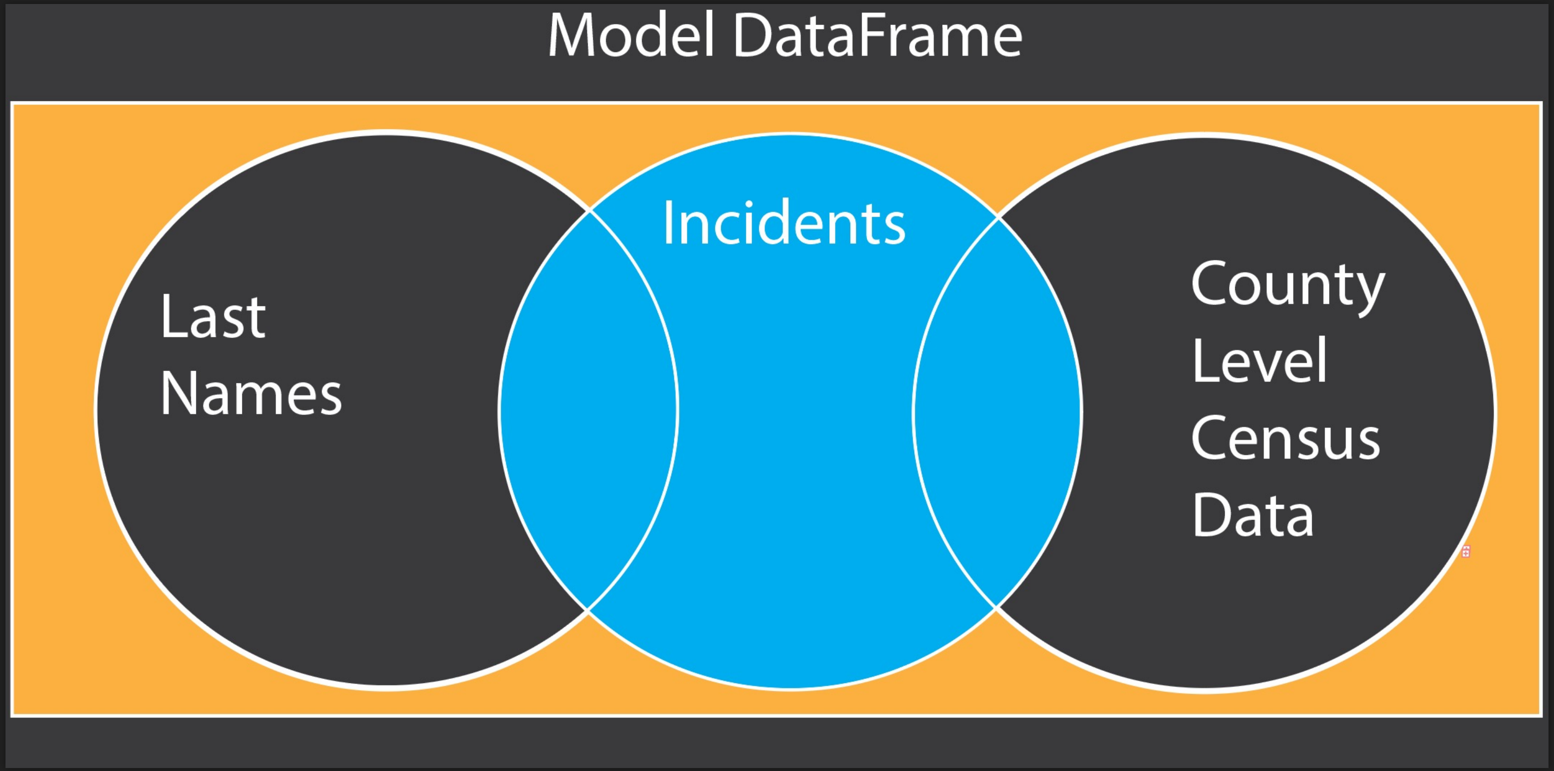
Merged DataFrame Structure

Excluded:
- Counties with no incidents
- Individuals with last names not in eponymous database.

26007 rows × 273 columns

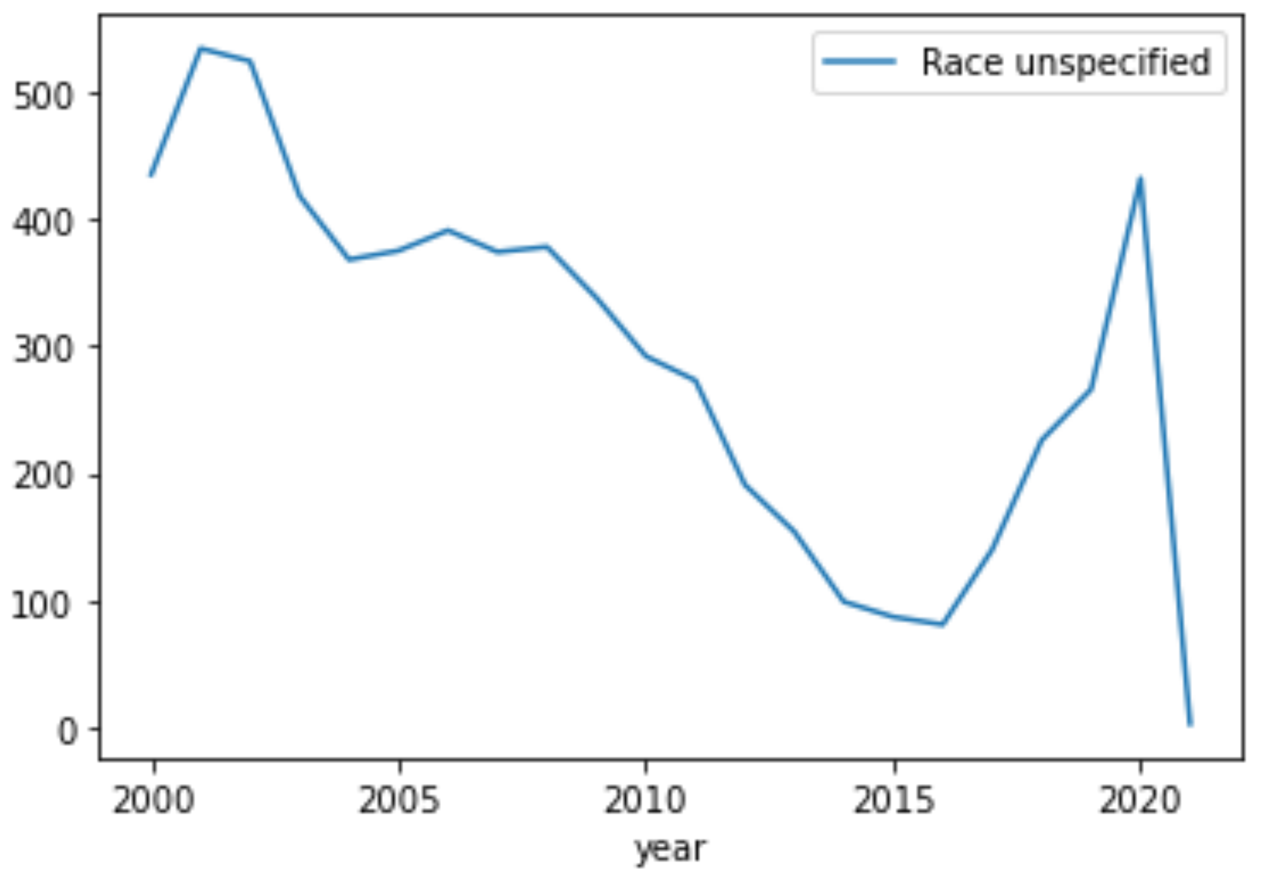
Training Set:
Race Cat. (Labeled)
19628 rows × 272 columns

Testing Set:
Race Unspec. (Unlabeled)
6379 rows × 272 columns



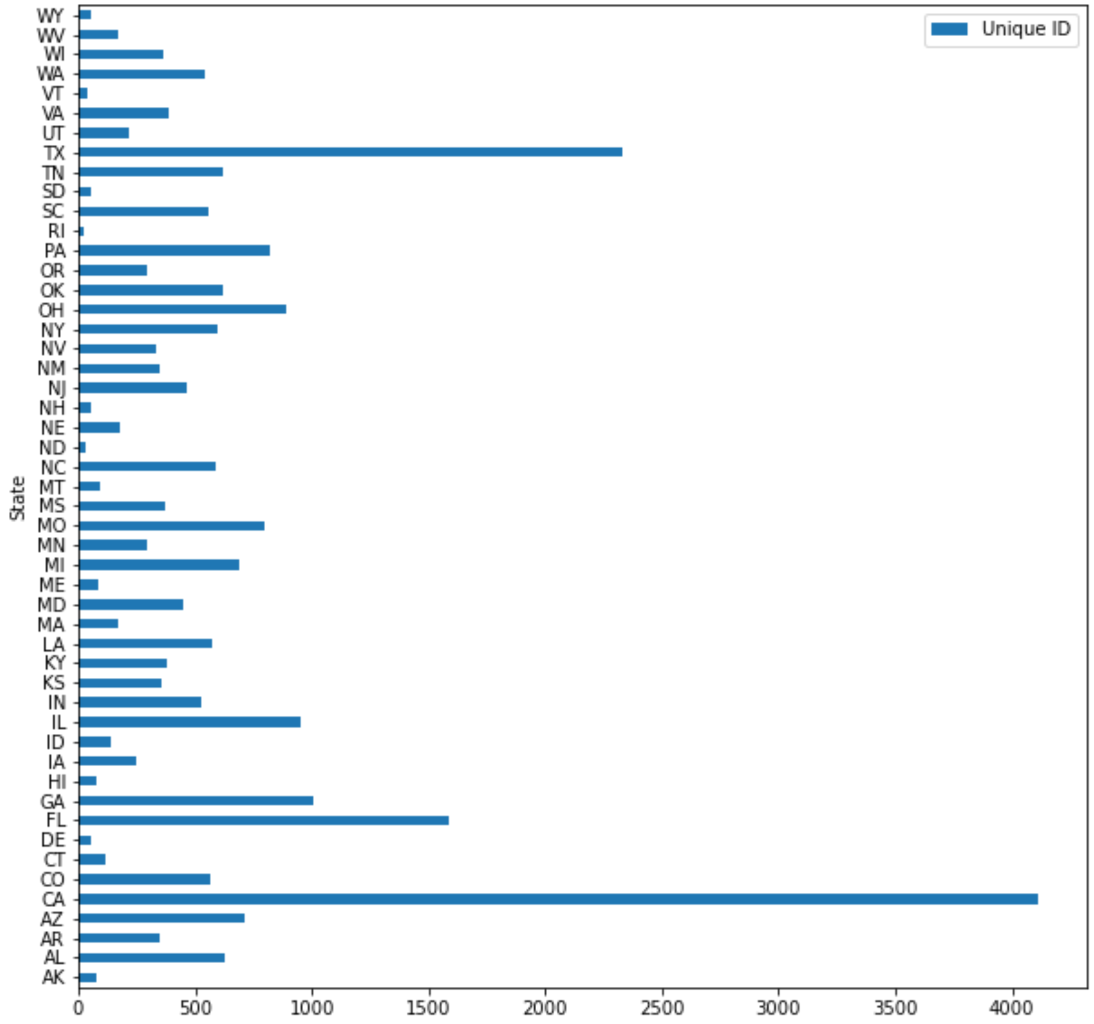
EDA

- Total number of incidents labeled 'Race unspecified' from 2000 to present.
- Peaks in early 2000's
- Trough in mid 2010's
- Rapidly rising
- Incomplete data 2021



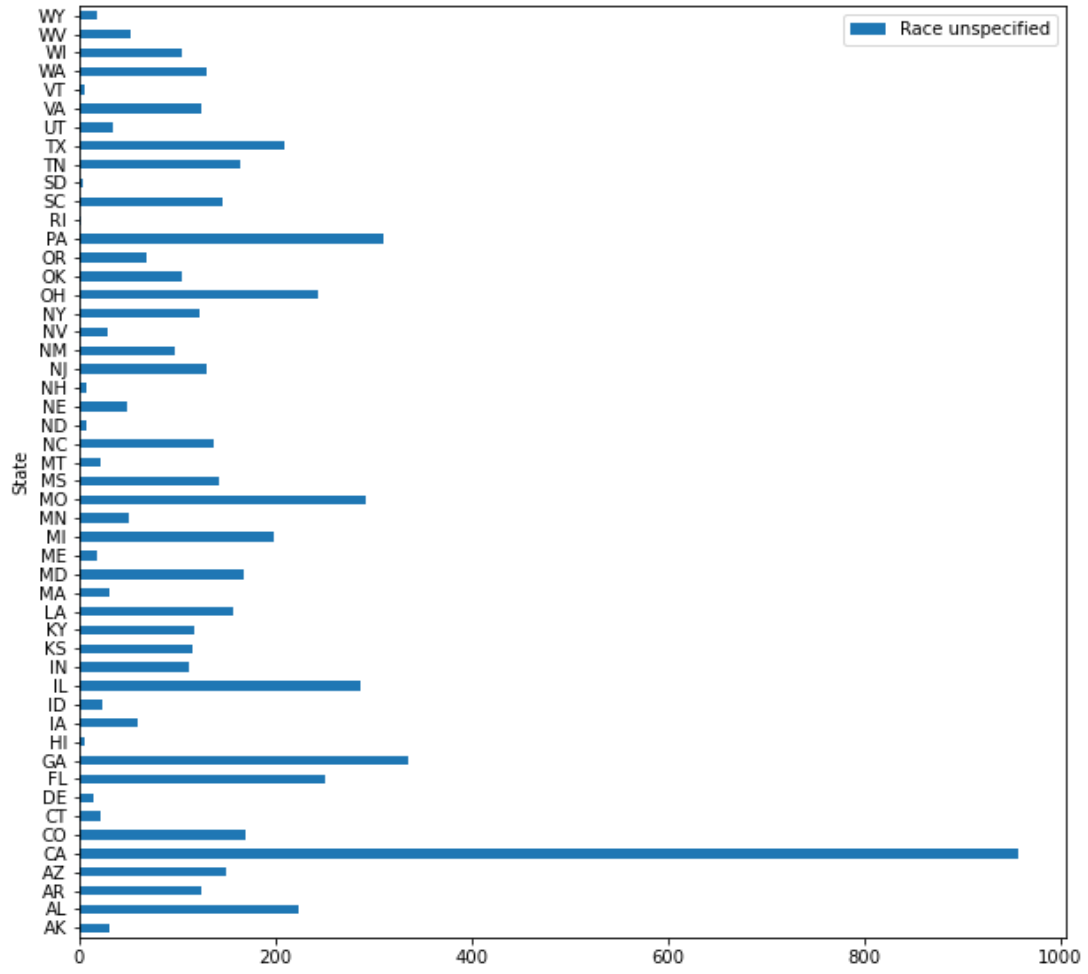
EDA

- Total number of incidents is loosely proportionate to state total population.
- California has the most total number of incidents, perhaps outsize.
- New York is a good exception.



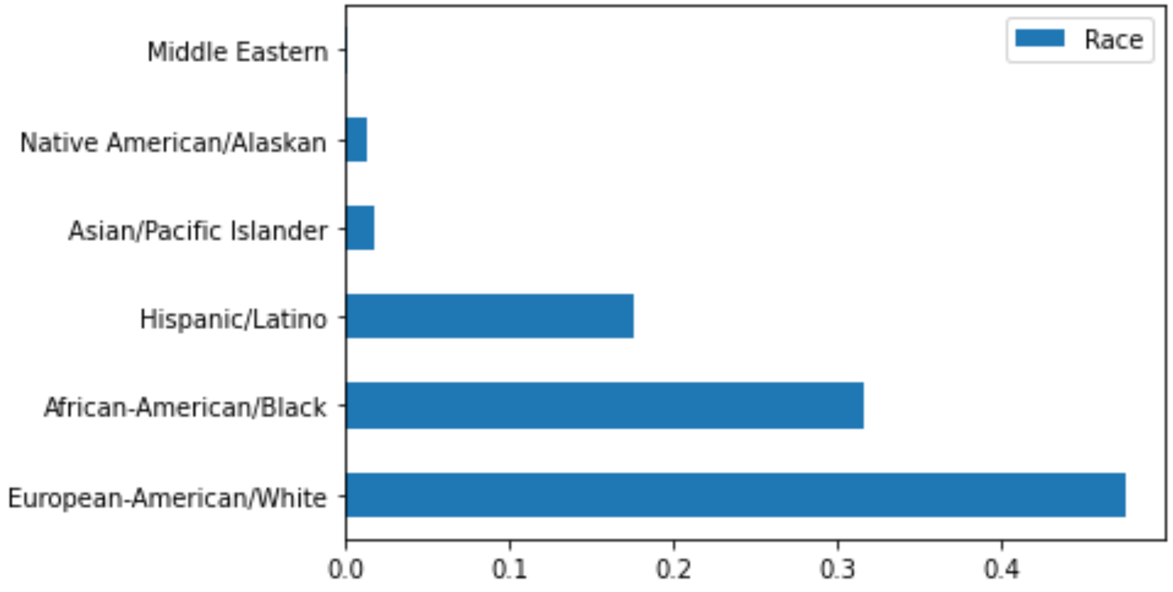
EDA

- Number of incidents where race is unspecified is not proportionate to state total population.
- California still leads in volume.
- Texas comes and Florida both come after Georgia, Pennsylvania, and Missouri.



Baseline Scores

European-American/White	0.475596
African-American/Black	0.316334
Hispanic/Latino	0.176075
Asian/Pacific Islander	0.018035
Native American/Alaskan	0.012686
Middle Eastern	0.001274



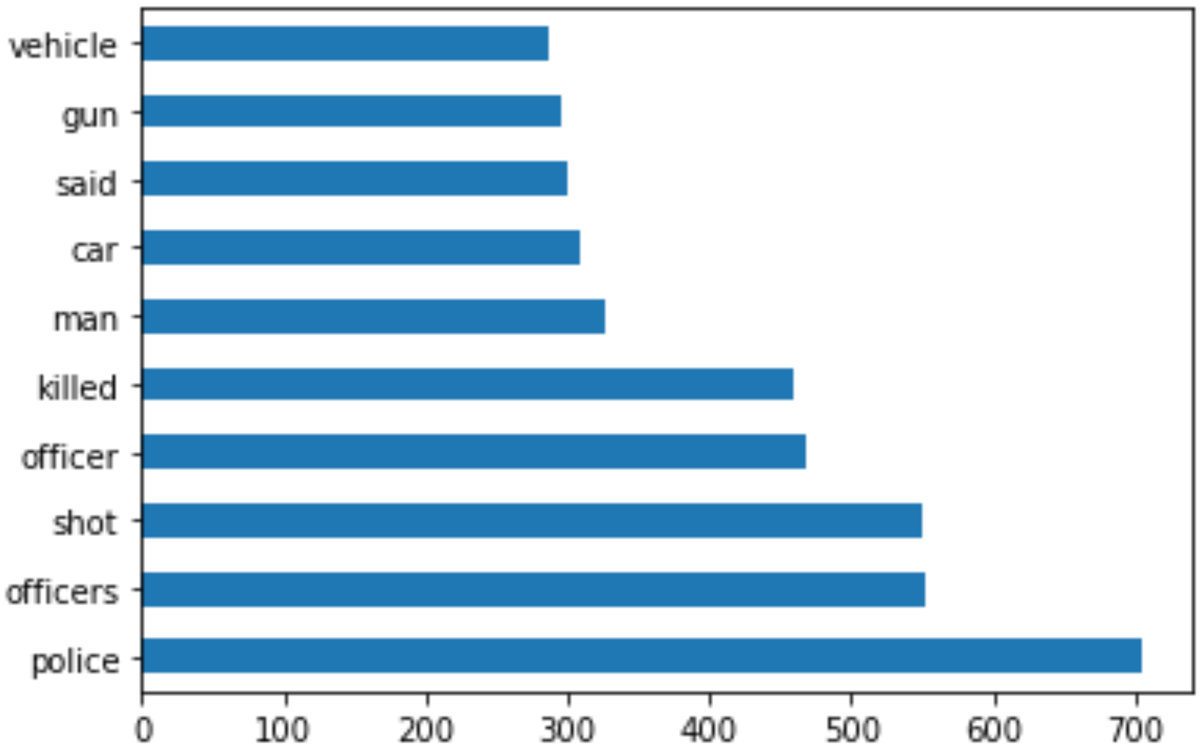
Models

- All of the models hit a ceiling with their accuracy scores around 0.80
- Tree based models seemed to very well on training data, but lost some testing accuracy
- Gradient Boost had the highest scores, and was slightly overfit
- ADA Boost had the worst scores, but was the least overfit

Name	Train	Test
Logistic Regression	0.82	0.80
Ridge Classifier	0.81	0.80
KNN	0.74	0.70
Decision Tree	0.99	0.71
Random Forest	0.86	0.79
Bagging Classifier	0.98	0.78
Support Vector Machine	0.84	0.79
ADA Boost	0.67	0.67
Extra Trees	0.99	0.77
Gradient Boost	0.85	0.80
XGBoost	0.97	0.80

Logistic Regression with TFIDF

- TFIDI: stop_words='english', strip_accents = 'ascii'
- 10 most common words in description column
- Text only: 0.81 train, 0.64 test
- Test plus: 0.99 train, 0.72 test



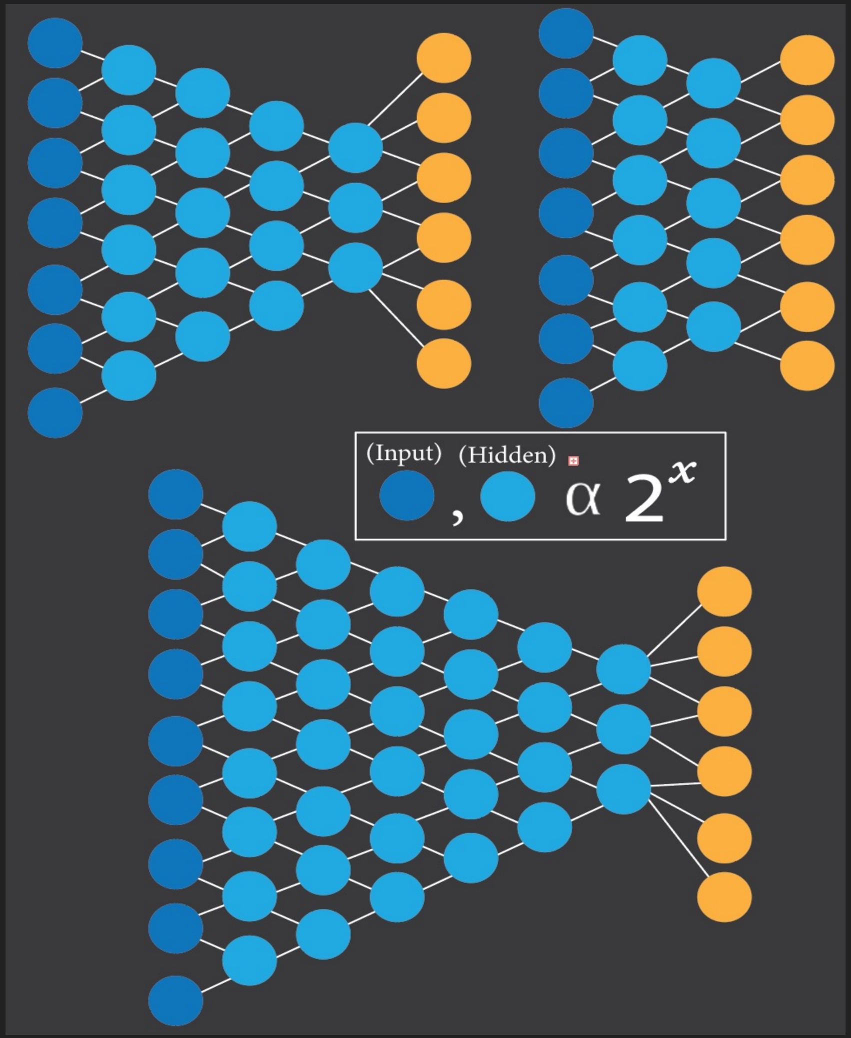
TFIDF Coefficients

- Most predictive value: names common among black-Americans, latino-Americans and white-Americans
- Least predictive value: odd verbs, oxycontin, ‘28’

word	coefficient_value
brown	2.478846
johnson	2.402715
williams	2.358154
jackson	2.187326
washington	2.114714
davis	2.113919
rodriguez	-2.084456
martinez	-2.048479
robinson	2.000967
jones	1.972671

word	coefficient_value
screamed	-0.000016
jerrick	-0.000029
roach	-0.000041
aiming	0.000067
lapsed	0.000141
describes	-0.000143
oxycontin	0.000154
paranoid	0.000201
28	-0.000219
fell	0.000221

Neural Networks

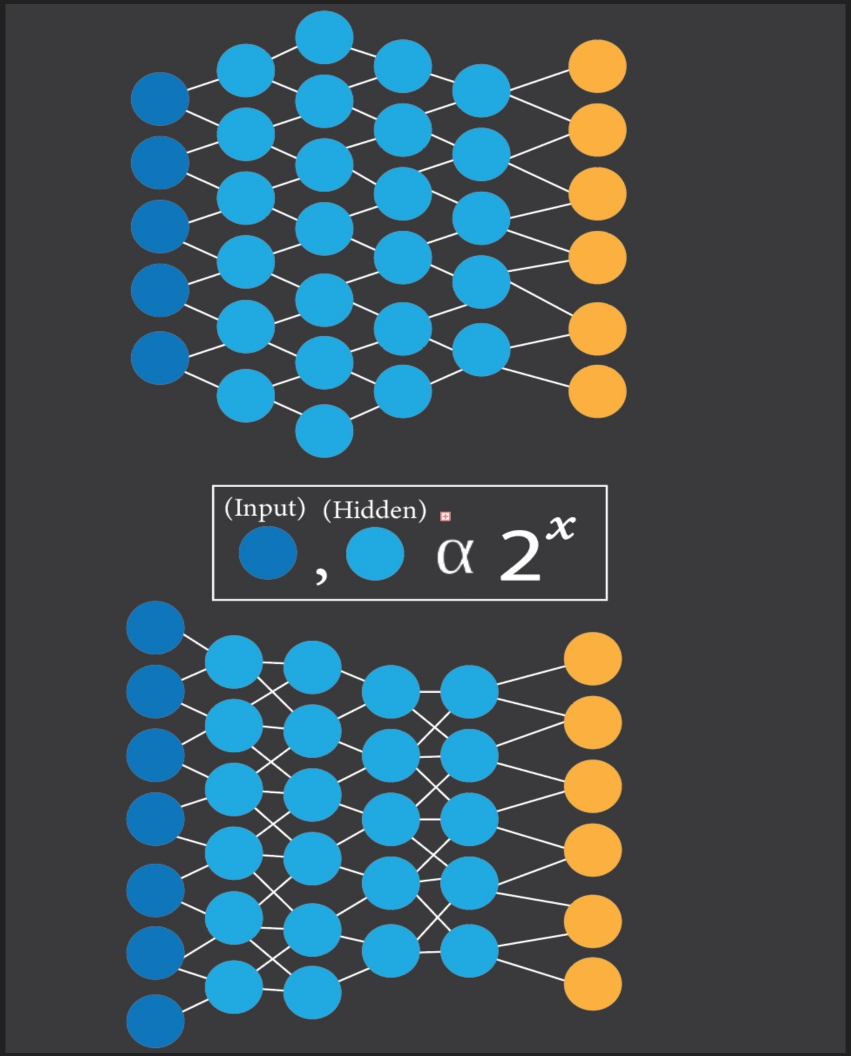


Loss range:
Categorical Crossentropy

Training: 0.53 - .40
Testing: 0.58 - 0.51

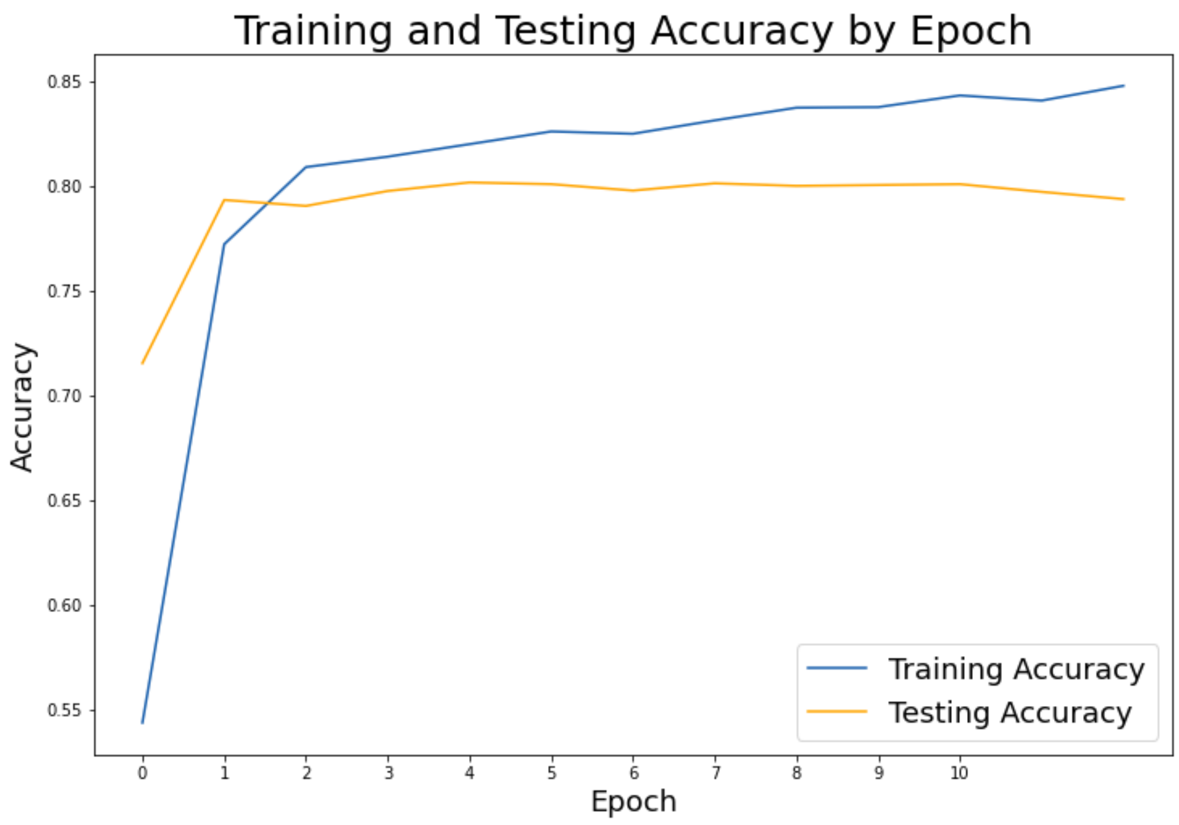
Metric range:
Accuracy:

Training: 0.80 - 0.86
Testing: 0.72 - 0.79



Neural Networks

- 5 Dense Layers
- Softmax activation function
- Early Stopping
- 11 Epochs
- Loss: 0.40
- Val loss: 0.54
- Training: 0.85
- Testing: 0.79



Unsupervised Learning

- 0: 0.32
- 3: 0.26
- 4: 0.23
- 5: 0.12
- 1: 0.05
- 2: 0.02

Racial Cat.	0	1	2	3	4	5
AA	0.09411765	0.14414414	0.22047244	0.33619702	0.58906752	0.34685864
API	0.00392157	0.01201201	0.08661417	0.01546392	0.00192926	0.0104712
EUR	0.85441176	0.40840841	0.20472441	0.52806415	0.34662379	0.34816754
HIS	0.04362745	0.42342342	0.48818898	0.1185567	0.06173633	0.29057592
MID	-	-	-	0.00057274	-	0.0039267
NAT	0.003921	0.0120120	-	0.00114548	0.0006430	-

Confusion Matrix

- Accuracy: 0.82
- Recall Score: 0.80
- Precision: 0.80
- F1: 0.80

Interpreting coefficients

- Portions of black American having a particular last name or living in a particular county were both important features when predicting race.
- Demographic features such as portion of Americans identifying as two or more races, and househould density.
- County based economic data such as unemployment, total sales, count non-farm businesses, and federal spending.
- State location: Florida and Georgia

0	name_pct_black	2.381574
1	unemployed_2017	2.023155
2	sales_2007	1.925037
3	private_nonfarm_estblhments_2009	1.845359
4	fed_spending_2009	1.818185
5	pop_black_2010	1.791341
6	persons_per_household_2017	1.673634
7	two_plus_races_2010	1.655088
8	State_FL	1.531944
9	State_GA	1.526401

Model Performance Comparison

Normalized Value Counts of Predictions

Average Imputed Probability

Trevor: 0.82

Fatal Encounters: 0.84

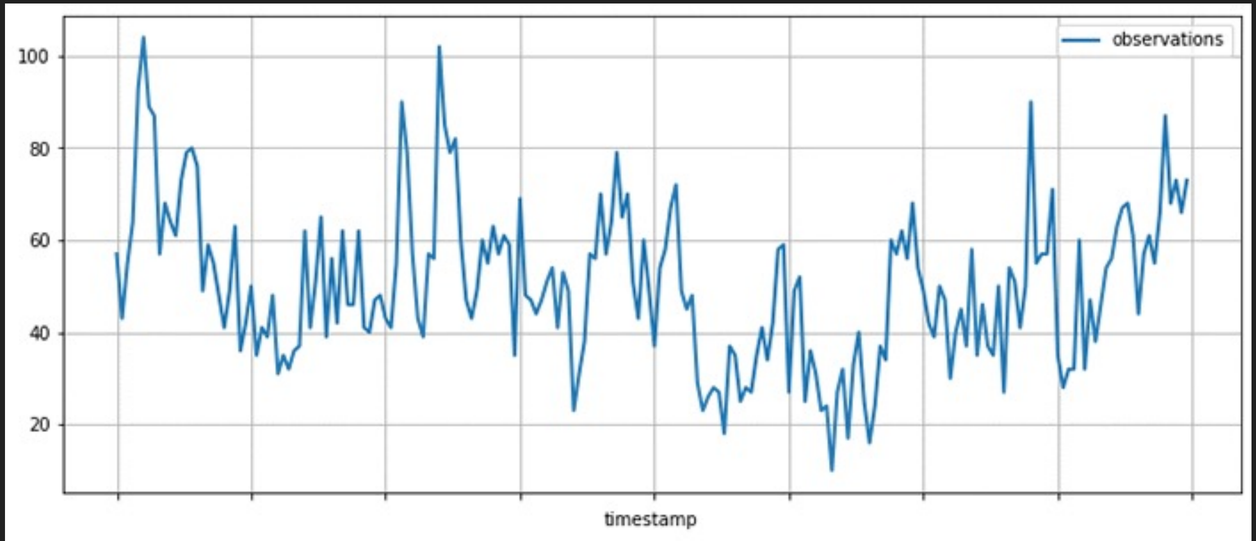
Racial Cat.	Trevor	F.E.	Baseline
European-American/White	0.55	0.63	0.47
African-American/Black	0.31	0.22	0.31
Hispanic/Latino	0.12	0.13	0.17
Asian/Pacific Islander	0.01	0.01	0.01
Native American/Alaskan	0.001	N/A	0.01
Middle Eastern	0.001	N/A	0.001

Conclusions

- The racial distribution of a last name is the probably the most powerful predictor of race.
- On average our model predicted race with slightly less confidence than the Fatal Encounters Model.
- Taking the most confident prediction from both datasets provides the best dataset.

Project Future

- More data:
  - More levels of geographic census info
    - ZIP
    - State
    - City
  - More/all years
  - More names (or workaround)
  - Create more features
- Hyperparameter tuning
- Regularization
- RNN with TFIDF
- Time Series



Thank you!

- Jessica Li
- Dr. Anderson Prewitt
- Gwen Rathgeber
- Heather Robbins
- Supportive course mates