Sep-2023

Homicide over the past decade
Project-4 Group-1
SMU Data Science Bootcamp

Meet Our Team

Project Team Student Members :

- Carlos Delarosa
- Raj Agrawal
- Ann Ly
- John Banowsky

Faculty :

- Alex Booth - Instructure
- Sherhone Grant - TA
- Sean Fleming - SSM

AGENDA

- Introduction
- Inspiration to select data
- About Data
- Analysis
  - Website
  - Data cleaning
  - Machine-learning
  - Tableau

Project Title & Description

- **Title - “Homicides over the past decade”**
- We have selected above as our Title / theme to perform the data analysis
- PROJECT 4 - Our main purpose is to use a standard dataset and utilize various tools that we learn so far i.e. – machine learning, Tableau
  - Ability to connect to a file set
  - Ability to fetch data and organize them with various useable data frame
  - Perform supervised model / predictions
  - To use correlation and create various Bar, Donut, line charts using Tableau
- **Data Collection-** The Washington Post collected data on more than 52,000 criminal homicides over the past decade in 50 of the largest American cities. The data included the location of the killing, whether an arrest was made and, in most cases, basic demographic information about each victim. Reporters received data in many formats, including paper, and worked for months to clean and standardize it, comparing homicide counts and aggregate closure rates with FBI data to ensure the records were as accurate as possible.

INSPIRATION

Why did you decide to use that topic? Inspiration, etc.

- **Carlos –** My inspiration is to analyzing a homicides dataset to investigate how victim age influences arrest outcomes in cases
- **Raj –** To learn more about homicides dataset and related investigation, and used acquired knowledge of the data science bootcamp for the data analysis. Eventually, participate in the volunteer program to help community to serve better.
- **Ann –** I am interested in knowing more about the shared factors among all the homicide cases.
- **John –** Homicides are never a good thing. Having a better understanding of which populations are affected will help us better address homicide to protect these demographics.

DATA

Homicides – Dataset from Kaggle
https://www.kaggle.com/datasets/joebeachcapital/homicides

Population Data – Datasets from US Census

https://www.census.gov/data/datasets/time-series/demo/popest/intercensal-2000-2010-cities-and-towns.html

https://www.census.gov/programs-surveys/popest/technical-documentation/research/evaluation-estimates/2020-evaluation-estimates/2010s-cities-and-towns-total.html

CENSUS DATA CLEANING

SubEst2010.csv

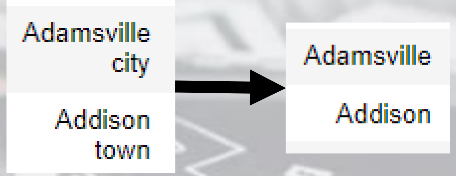
```
RangeIndex: 81625 entries, 0 to 81624
Data columns (total 20 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   SUMLEV             81625 non-null  int64
 1   STATE              81625 non-null  int64
 2   COUNTY             81625 non-null  int64
 3   PLACE              81625 non-null  int64
 4   COUSUB             81625 non-null  int64
 5   NAME               81625 non-null  object
 6   STNAME             81625 non-null  object
 7   ESTIMATESBASE2000  81625 non-null  int64
 8   POPESTIMATE2000    81625 non-null  int64
 9   POPESTIMATE2001    81625 non-null  int64
 10  POPESTIMATE2002    81625 non-null  int64
 11  POPESTIMATE2003    81625 non-null  int64
 12  POPESTIMATE2004    81625 non-null  int64
 13  POPESTIMATE2005    81625 non-null  int64
 14  POPESTIMATE2006    81625 non-null  int64
 15  POPESTIMATE2007    81625 non-null  int64
 16  POPESTIMATE2008    81625 non-null  int64
 17  POPESTIMATE2009    81625 non-null  int64
 18  CENSUS2010POP      81625 non-null  int64
 19  POPESTIMATE2010    81625 non-null  int64
dtypes: int64(18), object(2)
memory usage: 12.5+ MB
```

SubEst2020.csv

```
RangeIndex: 81415 entries, 0 to 81414
Data columns (total 24 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   SUMLEV              81415 non-null  int64
 1   STATE               81415 non-null  int64
 2   COUNTY              81415 non-null  int64
 3   PLACE               81415 non-null  int64
 4   COUSUB              81415 non-null  int64
 5   CONCIT              81415 non-null  int64
 6   PRIMGEO_FLAG        81415 non-null  int64
 7   FUNCSTAT            81415 non-null  object
 8   NAME                81415 non-null  object
 9   STNAME              81415 non-null  object
 10  CENSUS2010POP       81415 non-null  object
 11  ESTIMATESBASE2010   81415 non-null  int64
 12  POPESTIMATE2010     81415 non-null  int64
 13  POPESTIMATE2011     81415 non-null  int64
 14  POPESTIMATE2012     81415 non-null  int64
 15  POPESTIMATE2013     81415 non-null  int64
 16  POPESTIMATE2014     81415 non-null  int64
 17  POPESTIMATE2015     81415 non-null  int64
 18  POPESTIMATE2016     81415 non-null  int64
 19  POPESTIMATE2017     81415 non-null  int64
 20  POPESTIMATE2018     81415 non-null  int64
 21  POPESTIMATE2019     81415 non-null  int64
 22  POPESTIMATE042020   81415 non-null  int64
 23  POPESTIMATE2020     81415 non-null  int64
dtypes: int64(20), object(4)
memory usage: 14.9+ MB
```

all_pop_data.csv

- Dropped 2000-2006 and 2018-2020
- Changed STNAME (state name) from full name to 2-letter abbreviation
- Edited cities in the NAME column to match the 50 cities from the homicide_data.csv



- Merged the two files together using City and State.

CENSUS DATA CLEANING

	NAME	STNAME	LOCATION	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
0	Alabama	AL	Alabama, AL	4672840	4718206	4757938	4779736	4799642	4816632	4831586	4843737	4854803	4866824	4877989
1	Abbeville	AL	Abbeville, AL	2784	2742	2714	2688	2694	2645	2629	2610	2602	2587	2578
5	Adamsville	AL	Adamsville, AL	4633	4594	4558	4522	4474	4453	4430	4399	4371	4335	4304
9	Addison	AL	Addison, AL	750	752	759	758	750	745	744	742	734	734	728
13	Akron	AL	Akron, AL	395	384	369	356	347	347	344	338	338	335	332

DATA CLEANING for MACHINE LEARNING

homicide_data.csv

	uid	reported_date	victim_last	victim_first	victim_race	victim_age	victim_sex	city	state	lat	lon	disposition
0	Alb-000001	20100504	GARCIA	JUAN	Hispanic	78	Male	Albuquerque	NM	35.095788	-106.538555	Closed without arrest
1	Alb-000002	20100216	MONTOYA	CAMERON	Hispanic	17	Male	Albuquerque	NM	35.056810	-106.715321	Closed by arrest
2	Alb-000003	20100601	SATTERFIELD	VIVIANA	White	15	Female	Albuquerque	NM	35.086092	-106.695568	Closed without arrest
3	Alb-000004	20100101	MENDIOLA	CARLOS	Hispanic	32	Male	Albuquerque	NM	35.078493	-106.556094	Closed by arrest
4	Alb-000005	20100102	MULA	VIVIAN	White	72	Female	Albuquerque	NM	35.130357	-106.580986	Closed without arrest

- Fixed spelling and typing errors in specific instances.
- Dropped victim_last and victim_first
- Dropped data that did not have full demographic information
- Changed dispositon to a binary “Arrest Made” or “No Arrest”
- Split “reported_date” into year, month, day of week, and season.
- Merged city and state columns into LCOATION

Dallas, TX, Phoenix, AZ, Kansas City, MO, where dropped entirely.

Original Homicide Count: 52179
Count of Usable Data: 47478

DATA CLEANING for MACHINE LEARNING

Merged “homicide_data.csv” and “all_pop_data.csv”

- Filtered the population data to the 50 cities in homicide data.
- Used a melt function to return the populations for each city by year.

	NAME	STNAME	LOCATION	YEAR	POPULATION
0	Birmingham	AL	Birmingham, AL	2007	218880
1	Fresno	CA	Fresno, CA	2007	477659
2	Long Beach	CA	Long Beach, CA	2007	460328
3	Los Angeles	CA	Los Angeles, CA	2007	3751872
4	Oakland	CA	Oakland, CA	2007	383500

- Merged on LOCATION
- Saved as a new csv file “ml_clean_homicide_data.csv”

uid	disposition	victim_sex	victim_race	victim_age	age_range	reported_date	reported_year	reported_month	reported_weekday	season	city	state	lat	lon	LOCATION	POPULATION
Alb-000001	No Arrest	Male	Hispanic	78	65+	5/4/2010	2010	May	Tuesday	Spring	Albuquerque	NM	35.0957885	-106.5385549	Albuquerque, NM	545852
Alb-000002	Arrest Made	Male	Hispanic	17	0-17	2/16/2010	2010	February	Tuesday	Winter	Albuquerque	NM	35.0568104	-106.715321	Albuquerque, NM	545852
Alb-000003	No Arrest	Female	White	15	0-17	6/1/2010	2010	June	Tuesday	Summer	Albuquerque	NM	35.086092	-106.695568	Albuquerque, NM	545852
Alb-000004	Arrest Made	Male	Hispanic	32	30-44	1/1/2010	2010	January	Friday	Winter	Albuquerque	NM	35.0784929	-106.5560938	Albuquerque, NM	545852

DATA CLEANING for TABLEAU

Same

- Fixed spelling and typing errors in specific instances.
- Dropped victim_last and victim_first
- Changed dispositon to a binary “Arrest Made” or “No Arrest”
- Split “reported_date” into year, month, day of week, and season.
- Merged city and state columns into LCOATION

Different

- Did not drop because of incomplete demographic information
- Kept Dallas, TX, Phoenix, AZ, and Kansas City, MO
- Saved as a new csv file “tbl_no_drop_homicide_data.csv”

- Used the population and homicides per year to calculate homicides per 100,000 population
- Saved as a new csv file “tbl_homicide_count_per_100000.csv”

	LOCATION	reported_year	uid	POPULATION	homicides_per_100000
0	Albuquerque, NM	2010	45	545852	8.243993
1	Albuquerque, NM	2011	38	552105	6.882749
2	Albuquerque, NM	2012	46	555074	8.287183
3	Albuquerque, NM	2013	33	557547	5.918784
4	Albuquerque, NM	2014	28	557566	5.021827

PLANNING

Color palette

- Mixed selection – light / gray / additional

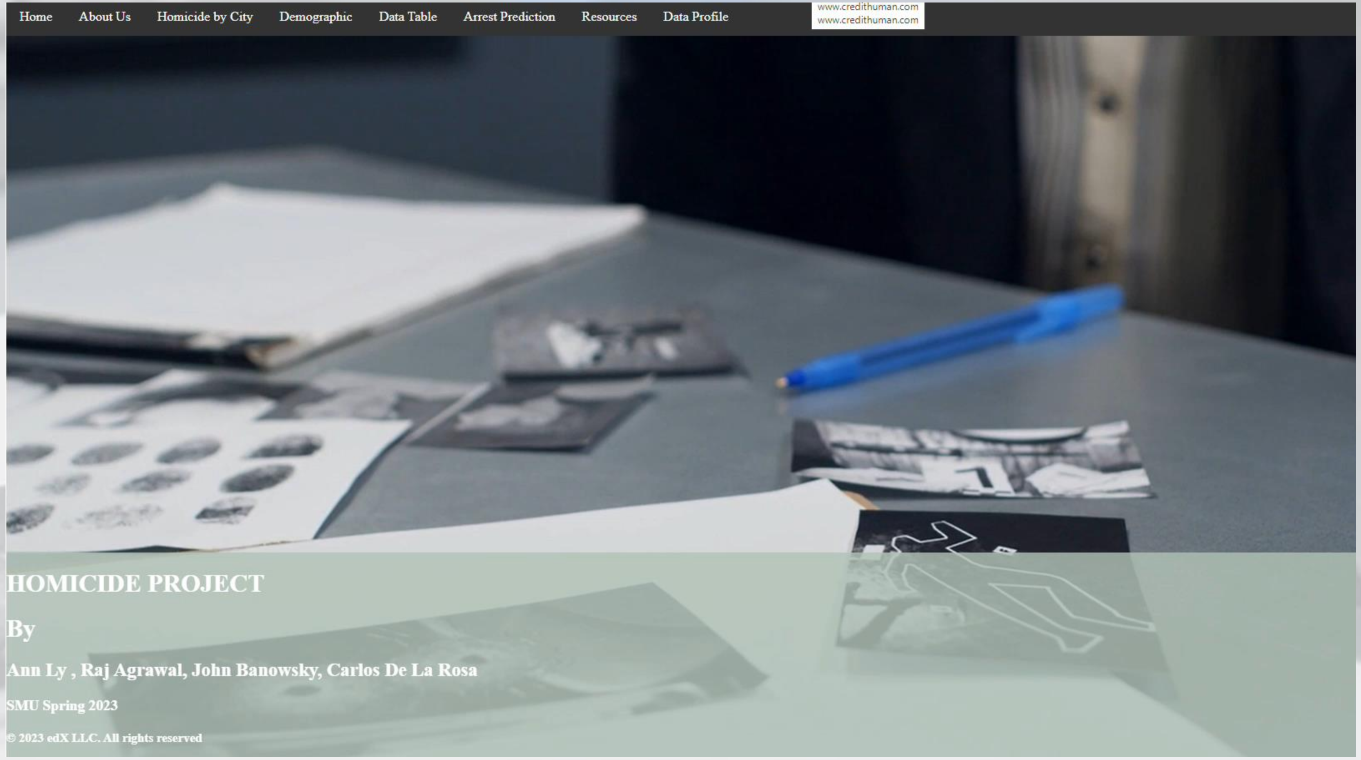
Expected Outcome - of the data analysis

- What are at least THREE research questions you want to explore/answer in this data source?
  - How race / age data summaries
  - Homicide over a period of time
  - Census data merge with homicide data to see population / demographic
- Additional Research Questions to Answer
  - Per 100,000 rate of homicides

WEBSITE DEVELOPMENT

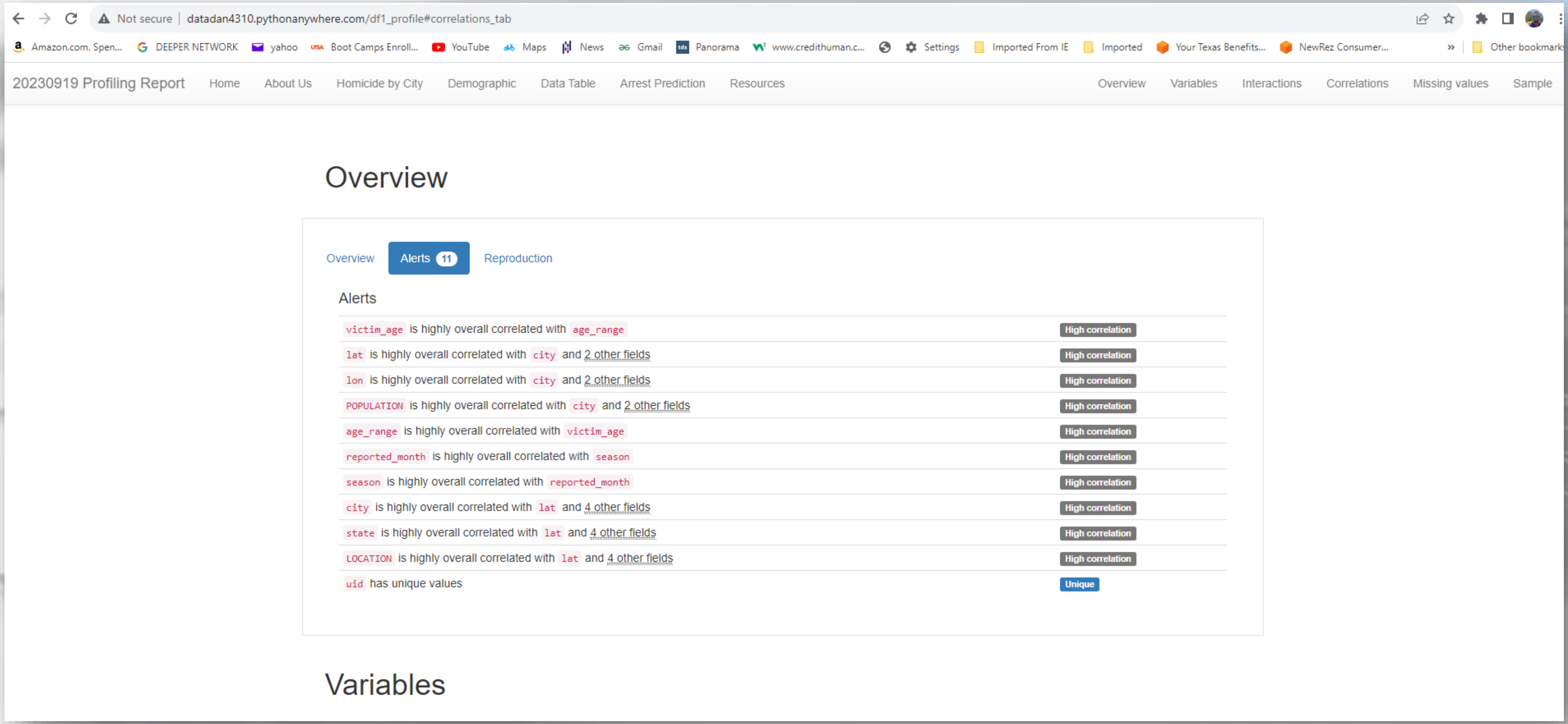
- Capturing the audience attention with a video background
- Respecting the Topic with the tones of color

```
<ul class="navbar">
  <li><a href="/">Home</a></li>
  <li><a href="/about_us">About Us </a></li>
  <li><a href="/tableau">Homicide by City</a></li>
  <li><a href="/tableau1">Demographic</a></li>
  <li><a href="/datatable">Data Table</a></li>
  <li><a href="/ml_form">Arrest Prediction</a></li>
   <li><a href="/resources">Resources</a></li>
  <li><a href="/df1_profile">Data Profile</a></li>
</ul>



<!-- video background -->
<video autoplay muted loop id = "bgvideo">
<source src ="static/assets/background.mp4" type="video/mp4">
Your browser does not support html5 video.
</video>
</body>
```



WEBSITE DEVELOPMENT

- Embedding Ydata for dataset profiling
- Overview of our dataset



WEBSITE DEVELOPMENT

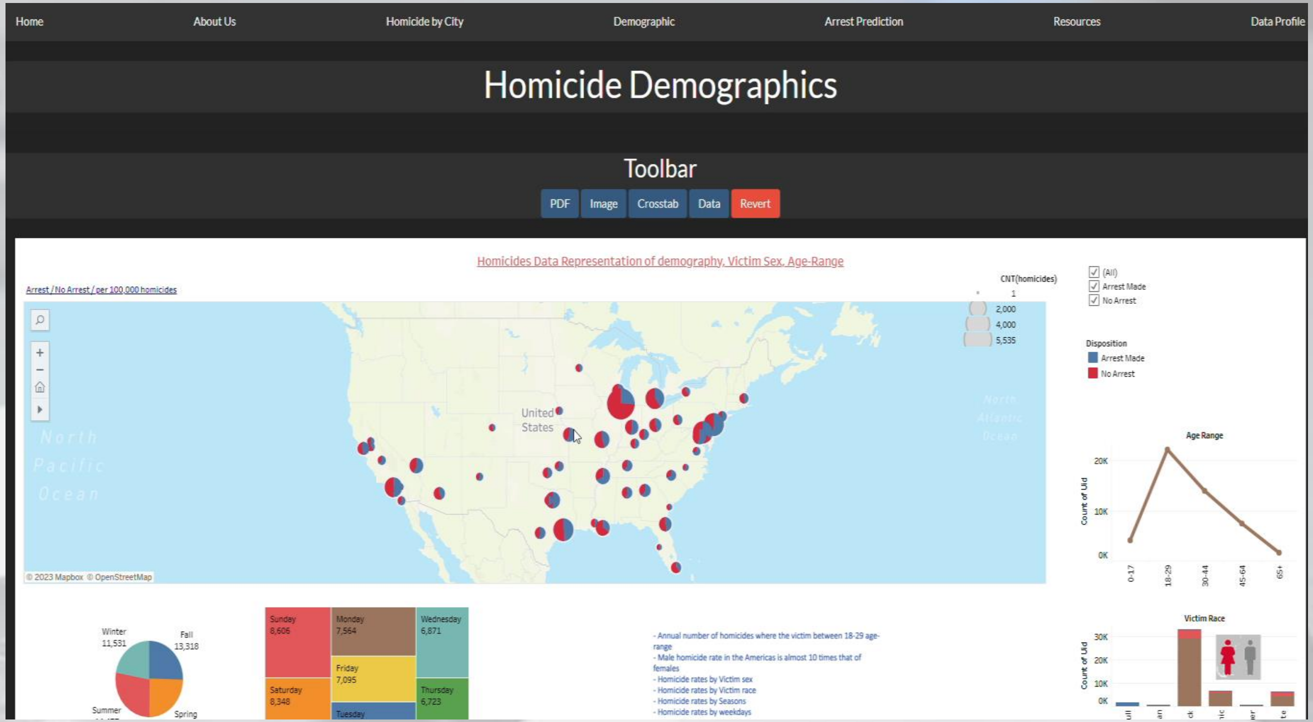
- Calling API

static > js > JS tableau_1.js > ready() callback > click() callback

You, yesterday | 1 author (You)

```javascript
var viz;

$(document).ready(function() {
    initializeViz();

    $("#pdf").click(function() {
        exportPDF();
    });
    $("#image").click(function() {
        exportImage();
    });
    $("#crosstab").click(function() {
        exportCrossTab();
    });
    $("#data").click(function() {        You, 6 days ago • website with tableau …
        exportData();
    });
    $("#revert").click(function() {
        revertAll();
    });
});

function initializeViz() {
    var placeholderDiv = document.getElementById("tableauViz");
    var url = "https://public.tableau.com/views/SMU_Proj4_Group1_homicides_TD2/Dashboard1";
    var options = {
        width: placeholderDiv.offsetWidth,
        height: placeholderDiv.offsetHeight,
        hideTabs: true,
        hideToolbar: true,
```

- Tableau page



WEBSITE DEVELOPMENT

- Prediction form Challenges

```python
@app.route("/makePredictions", methods=["POST"])
def make_predictions():
    content = request.json["data"]
    print(content)
    # return(jsonify({"ok": True}))# test the readin of the logic.js file

    # parse
    year = int(content["year"])
    age = int(content["age"])
    population = int(content["population"])
    sex = content["sex"]
    race = content["race"]
    month = content["month"]
    weekday = content["weekday"]
    season = content["season"]
    city = content["city"]
    state = content["state"]

    preds = modelHelper.makePredictions(year,age,population,sex,race,month,weekday,season,city,state)
    return(jsonify({"ok": True, "prediction": str(preds)}))
```

```javascript
// Perform a POST request to the query URL
$.ajax({
    type: "POST",
    url: "/makePredictions",
    contentType: 'application/json;charset=UTF-8',
    data: JSON.stringify({ "data": payload }),
    success: function(returnedData) {
        // print it
        console.log(returnedData);

        if (returnedData["prediction"] === "1") {
            $("#output").text("Arrest made!");
        } else {
            $("#output").text("No Arrest made!");
        }

    },
    error: function(XMLHttpRequest, textStatus, errorThrown) {
        alert("Status: " + textStatus);    You, 4 days ago •
        alert("Error: " + errorThrown);
    }
});
```

```python
    inp["victim_age"] = age
    inp["reported_year"] = year
    inp["POPULATION"] = population
    inp[f"victim_sex_{sex}"] = 1
    inp[f"victim_race_{race}"] = 1
    inp[f"reported_month_{month}"] = 1
    inp[f"reported_weekday_{weekday}"] = 1
    inp[f"season_{season}"] = 1
    inp[f"city_{city}"] = 1
    inp[f"state_{state}"] = 1

    inp = pd.DataFrame([inp])
    rtn = lgbm_model.predict_proba(inp)[0]
    return rtn
```

MACHINE LEARNING

```python
#Read in the data
df = pd.read_csv("ml_clean_homicide_data.csv", encoding = 'latin1')
df
```

	uid	disposition	victim_sex	victim_race	victim_age	age_range	reported_date	reported_year	reported_month	reported_weekday	season	
0	Alb-000001	No Arrest	Male	Hispanic	78	65+	2010-05-04	2010	May	Tuesday	Spring	Albuquer
1	Alb-000002	Arrest Made	Male	Hispanic	17	0-17	2010-02-16	2010	February	Tuesday	Winter	Albuquer
2	Alb-000003	No Arrest	Female	White	15	0-17	2010-06-01	2010	June	Tuesday	Summer	Albuquer
3	Alb-000004	Arrest Made	Male	Hispanic	32	30-44	2010-01-01	2010	January	Friday	Winter	Albuquer
4	Alb-000005	No Arrest	Female	White	72	65+	2010-01-02	2010	January	Saturday	Winter	Albuquer
...	...	...	...	...	...	...	...	...	...	...	...	
47473	Was-001380	Arrest Made	Male	Black	29	18-29	2016-09-08	2016	September	Thursday	Fall	Washing
47474	Was-001381	No Arrest	Male	Black	19	18-29	2016-09-13	2016	September	Tuesday	Fall	Washing
47475	Was-001382	No Arrest	Male	Black	23	18-29	2016-11-14	2016	November	Monday	Fall	Washing
47476	Was-001383	No Arrest	Male	Black	24	18-29	2016-11-30	2016	November	Wednesday	Fall	Washing
47477	Was-001384	Arrest Made	Male	Black	17	0-17	2016-09-01	2016	September	Thursday	Fall	Washing

47478 rows × 17 columns

Read in the CSV file for machine learning

```python
selected_cols = ['victim_age', 'victim_race', 'victim_sex', 'reported_weekday', 'reported_month', 'reported_year', 'season', 'cit
                 'state', 'POPULATION', 'disposition']
df1 = pd.DataFrame(df[selected_cols])
df1
```

	victim_age	victim_race	victim_sex	reported_weekday	reported_month	reported_year	season	city	state	POPULATION	disposition
0	78	Hispanic	Male	Tuesday	May	2010	Spring	Albuquerque	NM	545852	No Arrest
1	17	Hispanic	Male	Tuesday	February	2010	Winter	Albuquerque	NM	545852	Arrest Made
2	15	White	Female	Tuesday	June	2010	Summer	Albuquerque	NM	545852	No Arrest
3	32	Hispanic	Male	Friday	January	2010	Winter	Albuquerque	NM	545852	Arrest Made
4	72	White	Female	Saturday	January	2010	Winter	Albuquerque	NM	545852	No Arrest
...	...	...	...	...	...	...	...	...	...	...	...
47473	29	Black	Male	Thursday	September	2016	Fall	Washington	DC	687576	Arrest Made
47474	19	Black	Male	Tuesday	September	2016	Fall	Washington	DC	687576	No Arrest
47475	23	Black	Male	Monday	November	2016	Fall	Washington	DC	687576	No Arrest
47476	24	Black	Male	Wednesday	November	2016	Fall	Washington	DC	687576	No Arrest
47477	17	Black	Male	Thursday	September	2016	Fall	Washington	DC	687576	Arrest Made

47478 rows × 11 columns

Select columns from the DF that will be use for machine learning and put them in a DataFrame

MACHINE LEARNING

```python
#Arrest = 1 , No arrest = 2
df1["disposition"] = df1["disposition"].apply(lambda x: 1 if x == "Arrest Made" else 0)
df1
```

	victim_age	victim_race	victim_sex	reported_weekday	reported_month	reported_year	season	city	state	POPULATION	disposition
0	78	Hispanic	Male	Tuesday	May	2010	Spring	Albuquerque	NM	545852	0
1	17	Hispanic	Male	Tuesday	February	2010	Winter	Albuquerque	NM	545852	1
2	15	White	Female	Tuesday	June	2010	Summer	Albuquerque	NM	545852	0
3	32	Hispanic	Male	Friday	January	2010	Winter	Albuquerque	NM	545852	1
4	72	White	Female	Saturday	January	2010	Winter	Albuquerque	NM	545852	0
...	...	...	...	...	...	...	...	...	...	...	...
47473	29	Black	Male	Thursday	September	2016	Fall	Washington	DC	687576	1
47474	19	Black	Male	Tuesday	September	2016	Fall	Washington	DC	687576	0
47475	23	Black	Male	Monday	November	2016	Fall	Washington	DC	687576	0
47476	24	Black	Male	Wednesday	November	2016	Fall	Washington	DC	687576	0
47477	17	Black	Male	Thursday	September	2016	Fall	Washington	DC	687576	1

47478 rows × 11 columns

```python
#value counts for disposition
df1.disposition.value_counts()
```

```
0    24258
1    23220
Name: disposition, dtype: int64
```

"We have designated 'disposition' as the target variable for our machine learning task. Consequently, we transformed the values in this column into a binary format, where 1 represents 'arrest made' and 0 signifies 'no arrest'."

```python
#Counting the unique values and values counts for each of the categorical columns in the DF
cat_cols = df1.select_dtypes(exclude=[np.number]).columns

# value counts
for col in cat_cols:
    print(df1[col].nunique())
    print(df1[col].value_counts())
    print()
```

```
White        6259
Asian         676
Other         664
Name: victim_race, dtype: int64

2
Male      40387
Female     7091
Name: victim_sex, dtype: int64

7
Sunday       7850
Saturday     7619
Monday       6853
Friday       6446
Tuesday      6331
Wednesday    6256
Thursday     6123
Name: reported_weekday, dtype: int64
```

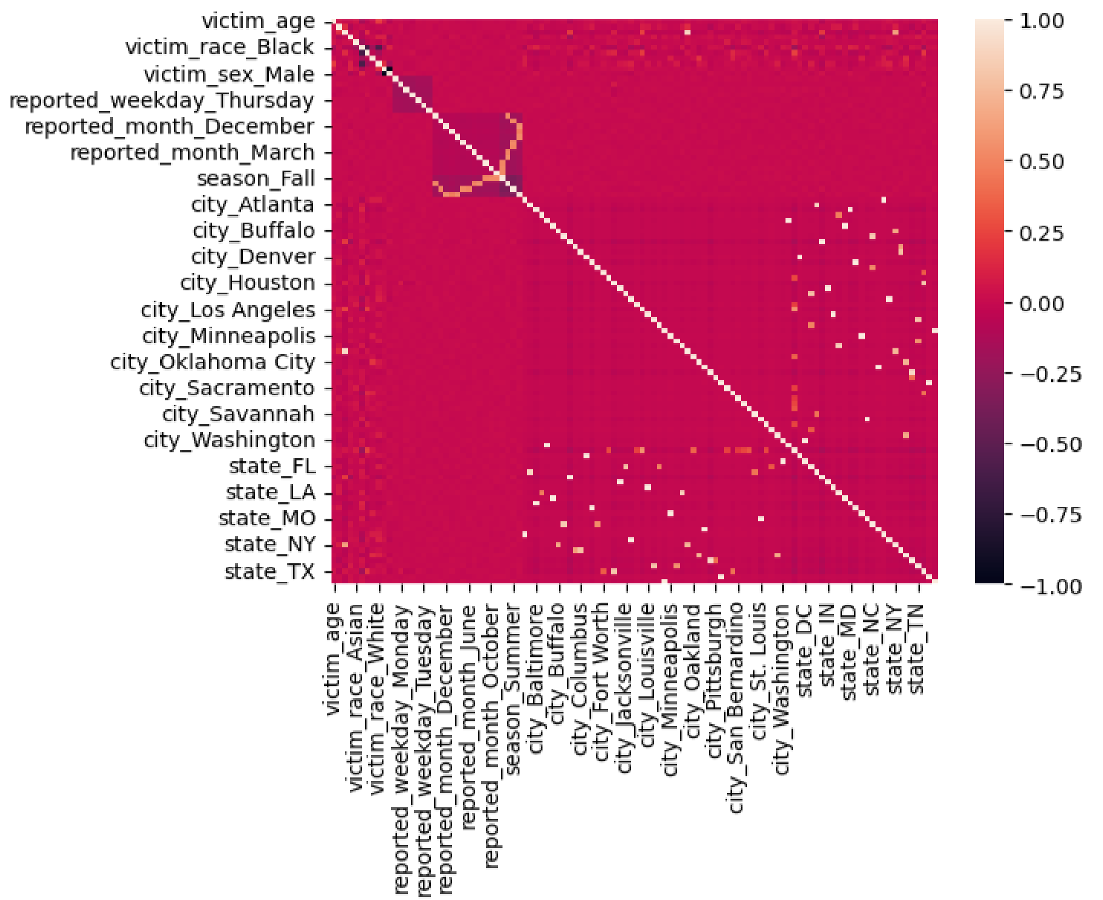
```python
#One hot coding
df2 = pd.get_dummies(df1)
df2
```

	victim_age	reported_year	POPULATION	disposition	victim_race_Asian	victim_race_Black	victim_race_Hispanic	victim_race_Other	victim_race_White
0	78	2010	545852	0	0	0	1	0	0
1	17	2010	545852	1	0	0	1	0	0
2	15	2010	545852	0	0	0	0	0	1
3	32	2010	545852	1	0	0	1	0	0
4	72	2010	545852	0	0	0	0	0	1
...	...	...	...	...	...	...	...	...	...
47473	29	2016	687576	1	0	1	0	0	0

Count the unique values of each categorical column in the DF, followed by applying One Hot Coding to these columns.

MACHINE LEARNING

```python
# plotting the heatmap and correlation
corrs = df2.corr()
sns.heatmap(corrs)
plt.show()
```




```python
#checking the correlation between the variables and target (disposition)
abs(corrs["disposition"]).sort_values(ascending=False)
```

```
disposition                  1.000000
city_Chicago                 0.162975
state_IL                     0.162975
victim_race_White            0.106228
victim_sex_Female            0.102491
                               ...
reported_weekday_Saturday    0.000664
reported_weekday_Wednesday   0.000546
state_MN                     0.000473
city_Minneapolis             0.000473
city_Jacksonville            0.000296
Name: disposition, Length: 108, dtype: float64
```

The correlation between disposition and all other variables:

- Chicago: 16%
- IL: 16%
- Victim Race: white: 11%
- Victim_sex: Female: 10%

MACHINE LEARNING

```
# Create our train/test set
X = df2.drop(columns=["disposition"])
y = df2["disposition"]

X_train, X_test, y_train, y_test = train_test_split(X,
                                                    y,
                                                    random_state=42,
                                                    stratify=y, test_size = 0.2)

print(X_train.shape, y_train.shape)
print(X_test.shape, y_test.shape)
```

```
(37982, 107) (37982,)
(9496, 107) (9496,)
```

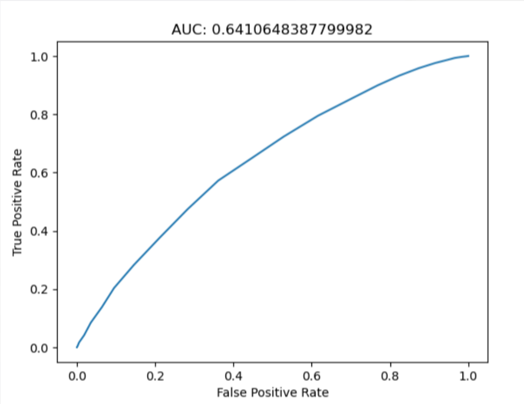
```
def doMLClassification(model, X_train, y_train, X_test, y_test):
    # fit the model
    model.fit(X_train, y_train)

    # predict the model
    train_preds = model.predict(X_train)
    test_preds = model.predict(X_test)
    test_proba = model.predict_proba(X_test)[:,1]

    # make some pretty graphs
    print("TRAINING SET METRICS")
    print(confusion_matrix(y_train, train_preds))
    print(classification_report(y_train, train_preds))
    print()
    print("TESTING SET METRICS")
    print(confusion_matrix(y_test, test_preds))
    print(classification_report(y_test, test_preds))

    # ROC Curve
    auc = roc_auc_score(y_test, test_proba)
    fpr, tpr, thresholds = roc_curve(y_test, test_proba)
    plt.plot(fpr, tpr)
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title(F"AUC: {auc}")
    plt.show()
```

- Set “disposition” as the target variable: Y
- Create out train/test set using train_test_split function
- Fit the model

MACHINE LEARNING

```
# init the model
knn = KNeighborsClassifier(n_neighbors=25)
doMLClassification(knn, X_train, y_train, X_test, y_test)
```

```
TRAINING SET METRICS
[[13083  6323]
 [ 7177 11399]]
              precision    recall  f1-score   support

           0       0.65      0.67      0.66     19406
           1       0.64      0.61      0.63     18576

    accuracy                           0.64     37982
   macro avg       0.64      0.64      0.64     37982
weighted avg       0.64      0.64      0.64     37982


TESTING SET METRICS
[[3099 1753]
 [1986 2658]]
              precision    recall  f1-score   support

           0       0.61      0.64      0.62      4852
           1       0.60      0.57      0.59      4644

    accuracy                           0.61      9496
   macro avg       0.61      0.61      0.61      9496
weighted avg       0.61      0.61      0.61      9496
```



KNN Model:

Precision

Arrest(1): 60% in testing vs. 65% in training model

No Arrest(0): 61 % vs. 65% in training model

Recall:

Arrest: 57% in testing vs. 61% in training model

No Arrest: 64% in testing vs. 67% in training model

F1: Arrest: 59% in testing vs. 63% in training model

No Arrest: 62% in testing vs. 66% in training model

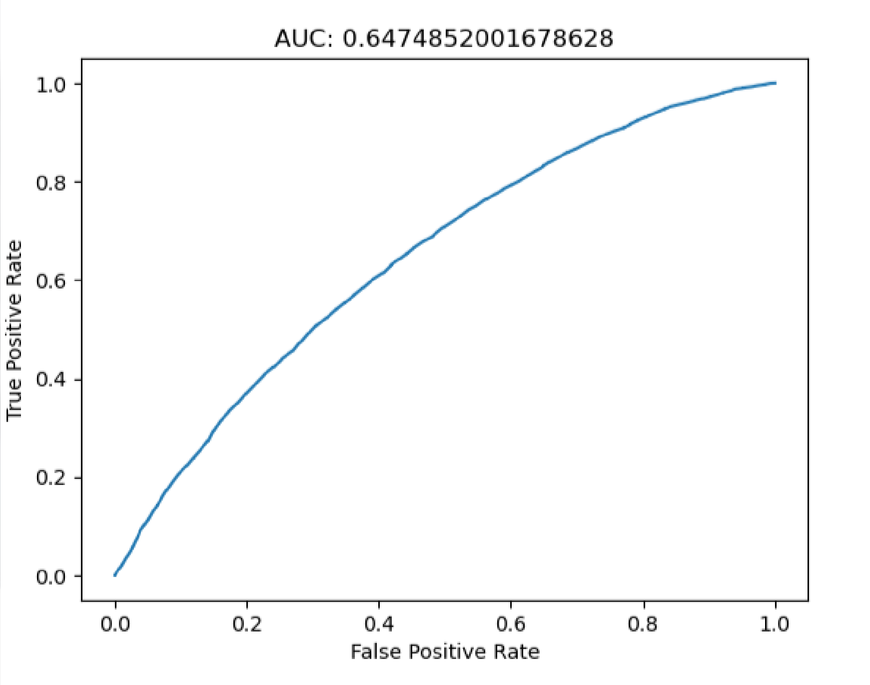
Accuracy: 61% for testing model and 64% for training set.

AUC score is 64% ---- the model is performing slightly better than random guessing, but it’s still not providing a strong level of discrimination between all the classes.

MACHINE LEARNING

```python
# init the model
rf = RandomForestClassifier(random_state=42)
doMLClassification(rf, X_train, y_train, X_test, y_test)
```

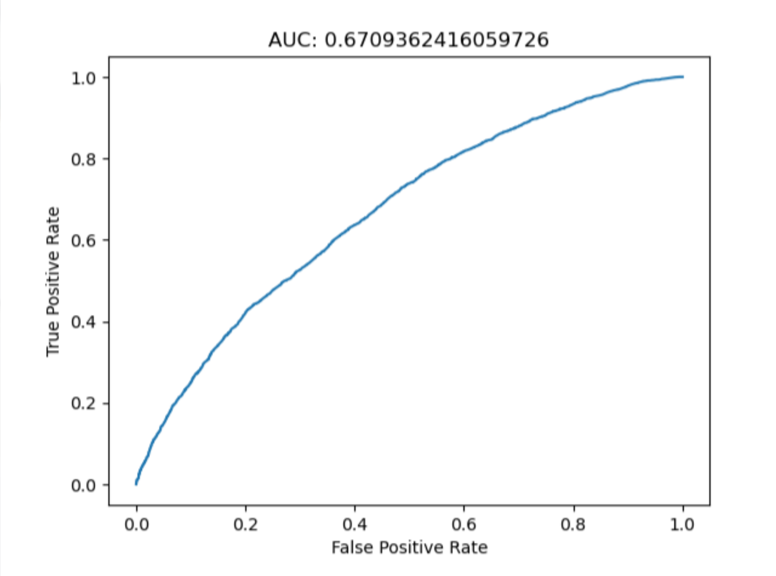
```
TRAINING SET METRICS
[[19300   106]
 [  157 18419]]
              precision    recall  f1-score   support

           0       0.99      0.99      0.99     19406
           1       0.99      0.99      0.99     18576

    accuracy                           0.99     37982
   macro avg       0.99      0.99      0.99     37982
weighted avg       0.99      0.99      0.99     37982


TESTING SET METRICS
[[2876 1976]
 [1791 2853]]
              precision    recall  f1-score   support

           0       0.62      0.59      0.60      4852
           1       0.59      0.61      0.60      4644

    accuracy                           0.60      9496
   macro avg       0.60      0.60      0.60      9496
weighted avg       0.60      0.60      0.60      9496
```



Data indicating overfitting for the training set data metrics.
Testing model's performance is very low, accuracy score of only 60%
AUC 64% -- still not a good model for classification and predicting outcome.

```python
#init the model
ada = AdaBoostClassifier(random_state=42)
doMLClassification(ada, X_train, y_train, X_test, y_test)
```

```
TRAINING SET METRICS
[[12422  6984]
 [ 7283 11293]]
              precision    recall  f1-score   support

           0       0.63      0.64      0.64     19406
           1       0.62      0.61      0.61     18576

    accuracy                           0.62     37982
   macro avg       0.62      0.62      0.62     37982
weighted avg       0.62      0.62      0.62     37982


TESTING SET METRICS
[[3107 1745]
 [1875 2769]]
              precision    recall  f1-score   support

           0       0.62      0.64      0.63      4852
           1       0.61      0.60      0.60      4644

    accuracy                           0.62      9496
   macro avg       0.62      0.62      0.62      9496
weighted avg       0.62      0.62      0.62      9496
```



MACHINE LEARNING

ADA Model:

Precision

Arrest(1): 62% in testing vs. 61% in training model

No Arrest(0): 62 % vs. 63% in training model

Recall:

Arrest: 60% in testing vs. 61% in training model

No Arrest: 64% in testing vs. 64% in training model

F1: Arrest: 60% in testing vs. 61% in training model

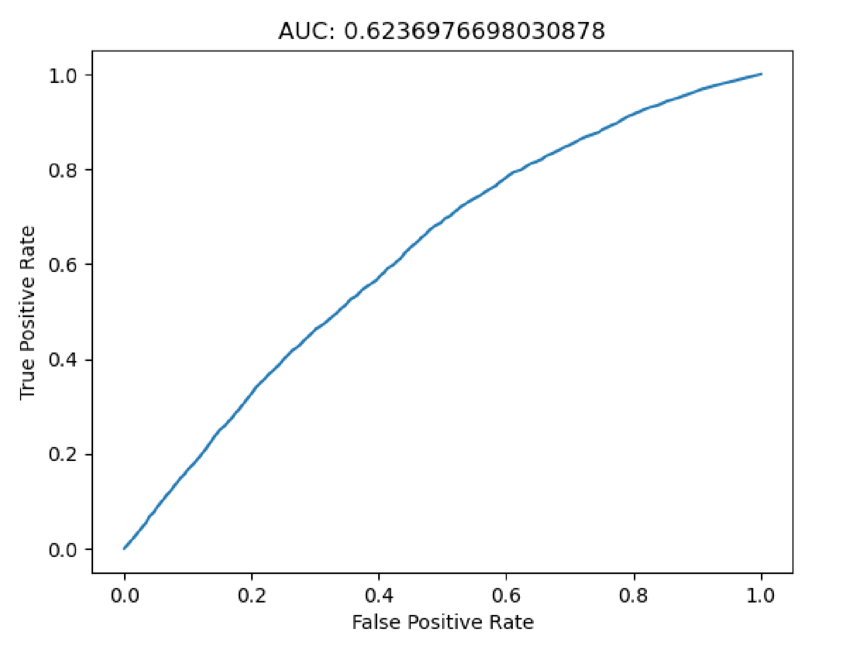
No Arrest: 63% in testing vs. 64% in training model

Accuracy: 62% for both testing and training models

The AUC score is 67% ---- the model performs significantly better than random guessing. This suggests that the model has some effectiveness in making predictions.

```
# init the model
et = ExtraTreesClassifier(random_state=42)
doMLClassification(et, X_train, y_train, X_test, y_test)
```

```
TRAINING SET METRICS
[[19401     5]
 [  258 18318]]
              precision    recall  f1-score   support

           0       0.99      1.00      0.99     19406
           1       1.00      0.99      0.99     18576

    accuracy                           0.99     37982
   macro avg       0.99      0.99      0.99     37982
weighted avg       0.99      0.99      0.99     37982


TESTING SET METRICS
[[2842 2010]
 [1901 2743]]
              precision    recall  f1-score   support

           0       0.60      0.59      0.59      4852
           1       0.58      0.59      0.58      4644

    accuracy                           0.59      9496
   macro avg       0.59      0.59      0.59      9496
weighted avg       0.59      0.59      0.59      9496
```



MACHINE LEARNING

ExtraTrees Model:

Training model suggest overfitting

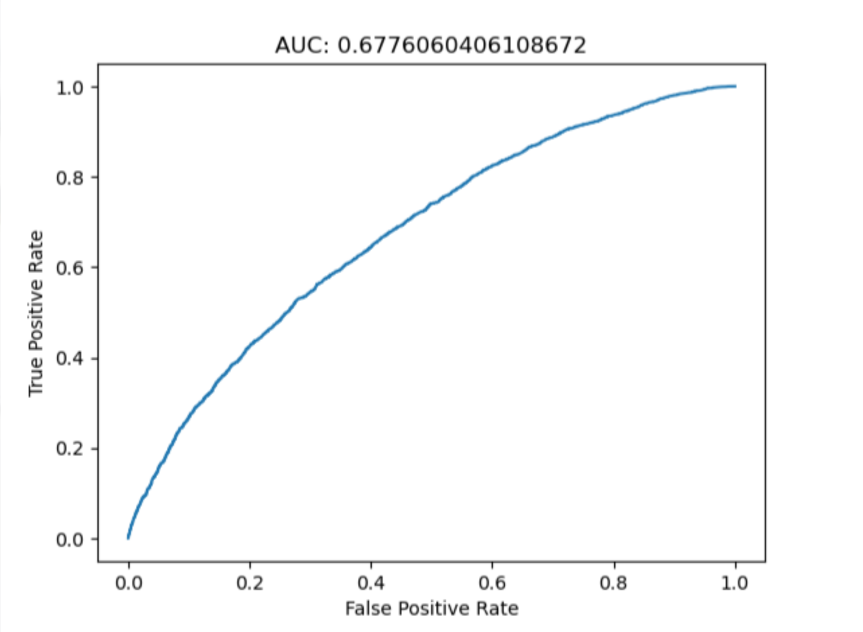
Testing model score are low in precision, recall, f1 and accuracy.

AUC of only 62%.

Not a good model.

MACHINE LEARNING

```
# init the model
gb = GradientBoostingClassifier(random_state=42)
doMLClassification(gb, X_train, y_train, X_test, y_test)

TRAINING SET METRICS
[[12619  6787]
 [ 7069 11507]]
              precision    recall  f1-score   support

           0       0.64      0.65      0.65     19406
           1       0.63      0.62      0.62     18576

    accuracy                           0.64     37982
   macro avg       0.63      0.63      0.63     37982
weighted avg       0.64      0.64      0.64     37982


TESTING SET METRICS
[[3110 1742]
 [1825 2819]]
              precision    recall  f1-score   support

           0       0.63      0.64      0.64      4852
           1       0.62      0.61      0.61      4644

    accuracy                           0.62      9496
   macro avg       0.62      0.62      0.62      9496
weighted avg       0.62      0.62      0.62      9496
```



GradientBoostingClassifier Model:

Precision

Arrest(1): 62% in testing vs. 63% in training model

No Arrest(0): 63% in both models

Recall:

Arrest: 60% in testing vs. 61% in training model

No Arrest: 64% in testing vs. 64% in training model

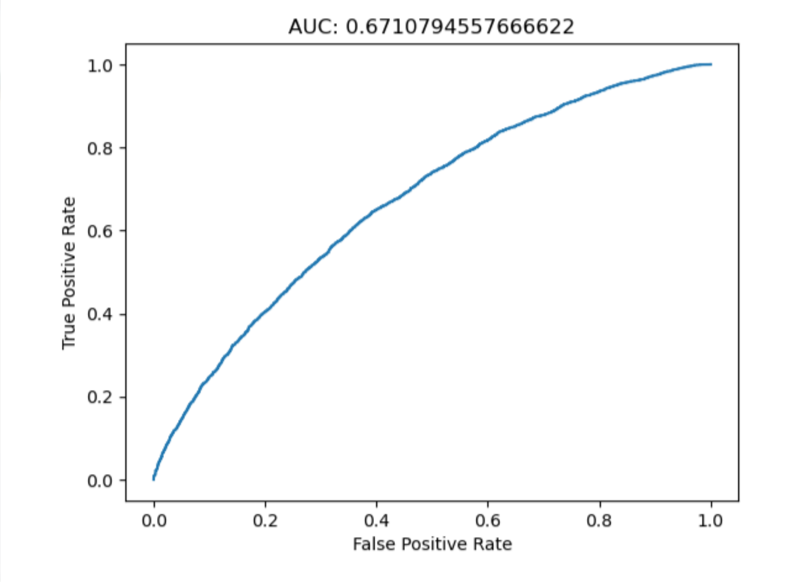
F1: Arrest: 61% in testing vs. 62% in training model

No Arrest: 63% in testing vs. 64% in training model

Accuracy: 62% for testing and 64% training models

The AUC score is 68% ---- the model performs significantly better than random guessing. This suggests that the model is effectiveness in making predictions.

```
]:  # init the model
    xgb = XGBClassifier(random_state=42)
    doMLClassification(xgb, X_train, y_train, X_test, y_test)

TRAINING SET METRICS
[[14182  5224]
 [ 5525 13051]]
              precision    recall  f1-score   support

           0       0.72      0.73      0.73     19406
           1       0.71      0.70      0.71     18576

    accuracy                           0.72     37982
   macro avg       0.72      0.72      0.72     37982
weighted avg       0.72      0.72      0.72     37982


TESTING SET METRICS
[[3117 1735]
 [1832 2812]]
              precision    recall  f1-score   support

           0       0.63      0.64      0.64      4852
           1       0.62      0.61      0.61      4644

    accuracy                           0.62      9496
   macro avg       0.62      0.62      0.62      9496
weighted avg       0.62      0.62      0.62      9496
```



MACHINE LEARNING

XGB

Precision

Arrest(1): 62% in testing vs. 71% in training model

No Arrest(0): 63 % vs. 72% in training model

Recall:

Arrest: 61% in testing vs. 70% in training model

No Arrest: 64% in testing vs. 73% in training model

F1: Arrest: 61% in testing vs. 71% in training model

No Arrest: 64% in testing vs. 71% in training model

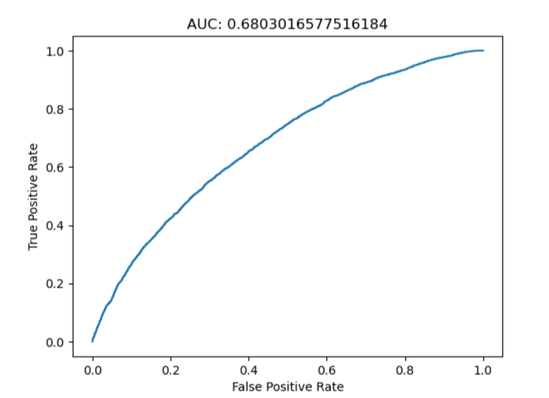
Accuracy: 62% for testing and 72% for training models

The AUC score is 67% ---- the model performs significantly better than random guessing. This suggests that the model has some effectiveness in making predictions.

MACHINE LEARNING

```
# init the model
lgbm = LGBMClassifier(random_state=42)
doMLClassification(lgbm, X_train, y_train, X_test, y_test)
```

```
[LightGBM] [Warning] Found whitespace in feature_names, replace with underlines
[LightGBM] [Info] Number of positive: 18576, number of negative: 19406
[LightGBM] [Warning] Auto-choosing row-wise multi-threading, the overhead of testing was 0.001127 seconds.
You can set `force_row_wise=true` to remove the overhead.
And if memory is not enough, you can set `force_col_wise=true`.
[LightGBM] [Info] Total Bins 564
[LightGBM] [Info] Number of data points in the train set: 37982, number of used features: 107
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.489074 -> initscore=-0.043712
[LightGBM] [Info] Start training from score -0.043712
TRAINING SET METRICS
[[12876  6530]
 [ 6231 12345]]
              precision    recall  f1-score   support

           0       0.67      0.66      0.67     19406
           1       0.65      0.66      0.66     18576

    accuracy                           0.66     37982
   macro avg       0.66      0.66      0.66     37982
weighted avg       0.66      0.66      0.66     37982


TESTING SET METRICS
[[3048 1804]
 [1746 2898]]
              precision    recall  f1-score   support

           0       0.64      0.63      0.63      4852
           1       0.62      0.62      0.62      4644

    accuracy                           0.63      9496
   macro avg       0.63      0.63      0.63      9496
weighted avg       0.63      0.63      0.63      9496
```



LGBM Classifier:

Precision

Arrest(1): 62% in testing vs. 65% in training model

No Arrest(0): 64 % vs. 67% in training model

Recall:

Arrest: 62% in testing vs. 66% in training model

No Arrest: 63% in testing vs. 66% in training model

F1: Arrest: 62% in testing vs. 66% in training model

No Arrest: 63% in testing vs. 67% in training model

Accuracy: 63% for testing and 66% for training models

The AUC score is 68% ---- the model performs significantly better than random guessing. This suggests that the model has some effectiveness in making predictions.

```
import pickle

filename = 'model.pkl'

# Save the model to a file
with open(filename, 'wb') as file:
    pickle.dump(lgbm, file)
```

We picked LGBM to do hyperparameter tuning and K fold cross-validation.

We also need to deploy this model for the prediction tab on our website, so we saved the model as a pickle file.

HYPER PARAMETER TUNING: GRIDSEARCHCV

```
from sklearn.model_selection import GridSearchCV
```

```
# Define the hyperparameter grid for Gridsearchcv
param_grid = {
    'n_estimators': [100, 200, 300],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 4],
    'colsample_bytree': [0.8, 1.0],
    'subsample': [0.8, 1.0]
}

# Initialize GridSearchCV
grid = GridSearchCV(lgbm, param_grid, cv=5, scoring='accuracy', verbose=2)

# Perform the grid search
grid_result = grid.fit(X_train, y_train)
grid_result
```

We used GridSearchCV to perform hyper parameter tuning on LGBM model. The accuracy turned out to be 63%, same as the original model.

```
print("Best_params:", grid_search.best_params_)
print( "Best_estimator:" , grid_search.best_estimator_)
print("Best Score:", round(grid_search.best_score_, 2))
```

```
Best_params: {'colsample_bytree': 1.0, 'learning_rate': 0.1, 'max_depth': 4, 'n_estimators': 300, 'subsample': 0.8}
Best_estimator: LGBMClassifier(max_depth=4, n_estimators=300, random_state=42, subsample=0.8)
Best Score: 0.63
```

MACHINE LEARNING – CROSS VALIDATION, KFOLD

```python
from lightgbm import LGBMClassifier
from sklearn.model_selection import cross_val_score, KFold

# Initialize the LightGBM classifier
lgbm = LGBMClassifier()

# Define the number of folds for cross-validation
num_folds = 5

# Initialize a KFold object
kf = KFold(n_splits=num_folds, shuffle=True, random_state=42)

# Perform k-fold cross-validation
cv_scores = cross_val_score(lgbm, X, y, cv=kf, scoring='accuracy')

# Print the cross-validation scores
print(f'Cross-Validation Scores: {cv_scores}')
print(f'Mean Accuracy: {cv_scores.mean()}')
```

```
Cross-Validation Scores: [0.61973463 0.63142376 0.63363521 0.62474987 0.63475513]
Mean Accuracy: 0.6288597199874186
```

We use Cross validation, and Kfold to calculate the average accuracy of the LGBM classifier, the result is still 63%.

DATA VISULASIZATION - TABLEAU

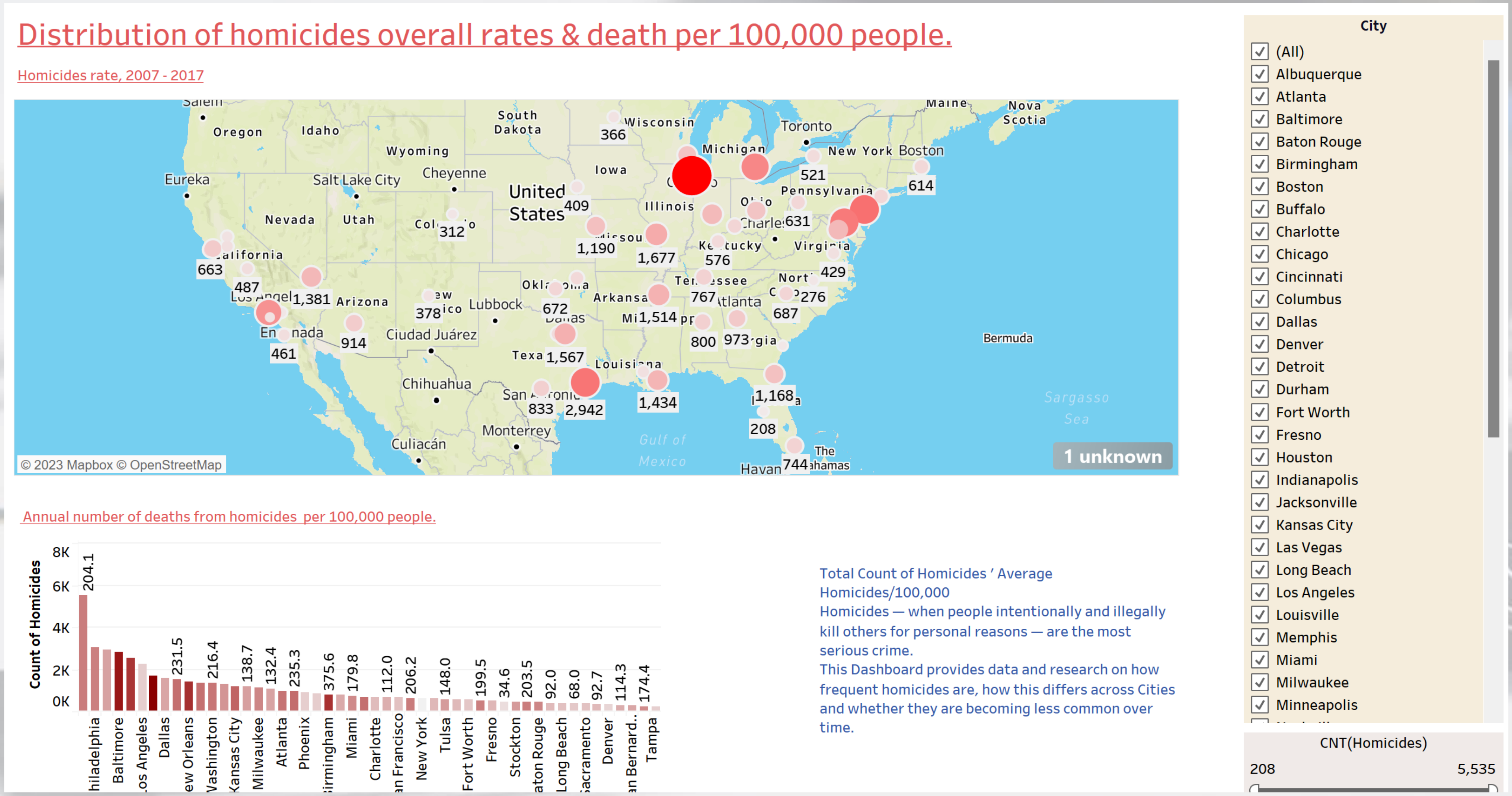


Tableau dashboard – main page explains about distributions of the homicides across US cities. The dashboard has filters based on Cities & a range of count of homicides

DATA VISULASIZATION - TABLEAU

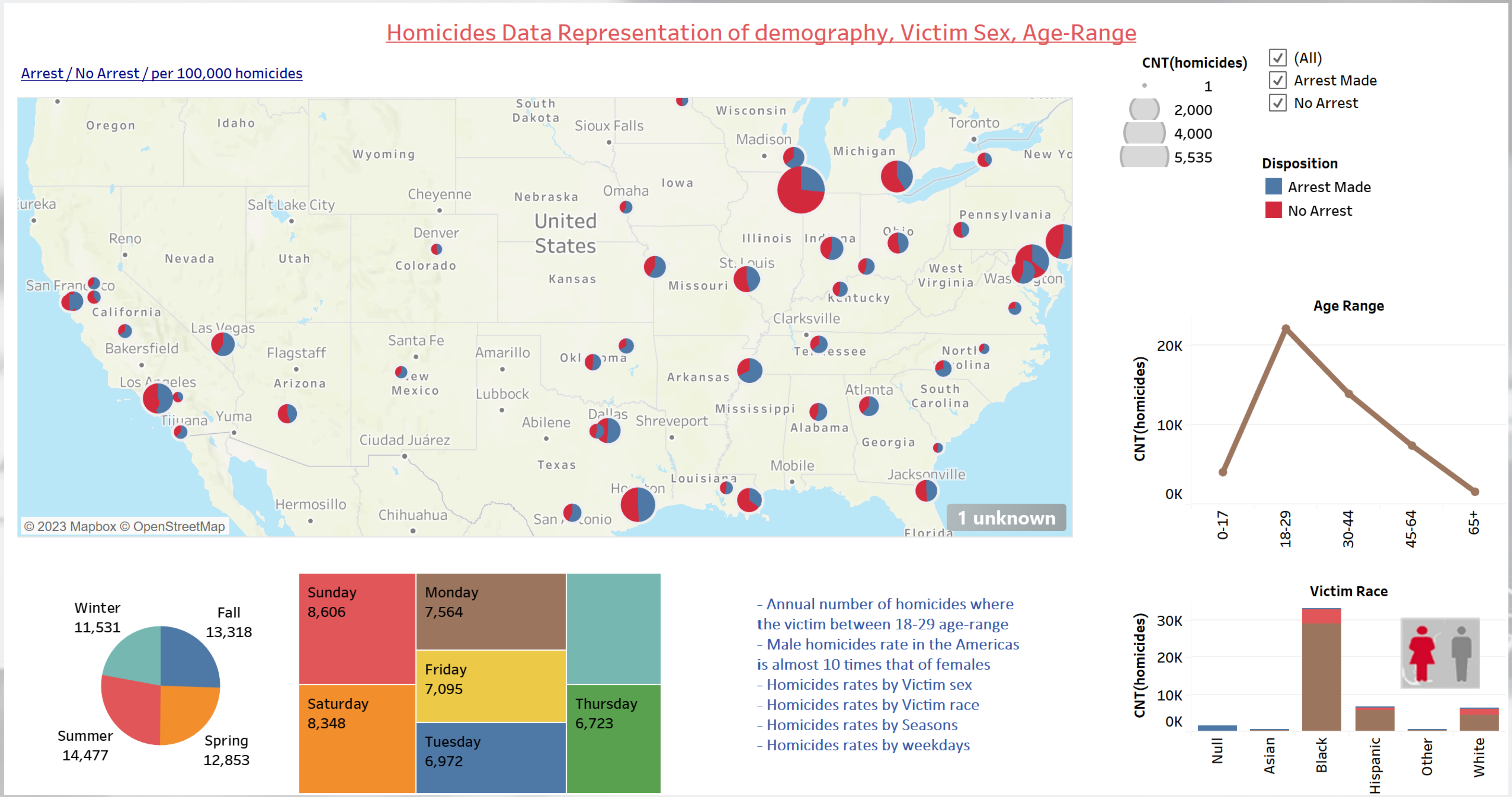


Tableau dashboard – second page explains demography wise distributions of the homicides across US cities. The dashboard has filters based on "Arrest" "no arrest" & a range of count of homicides

Q&A