# Parking Tickets in Chicago

Predicting Payment

#### **Overview**

- Data from <u>ProPublica</u>
- City of Chicago Parking Tickets
- Passenger Vehicles only
- Multiple decades and has over 50 million observations
- Only analyzing first million

Potential to help allocate city resources/increase revenue

#### **Data**

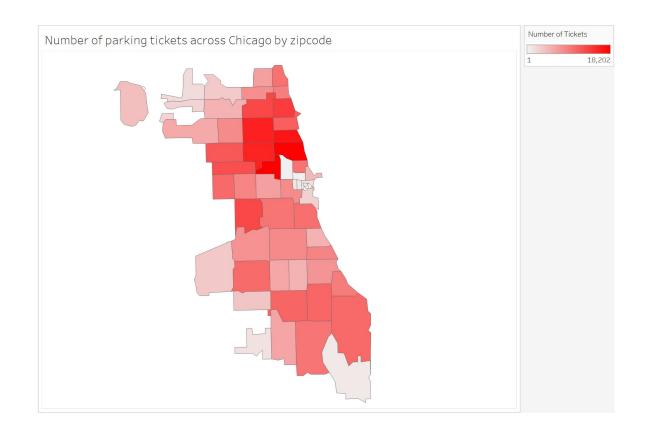
#### **Target: Payment Status**

- Paid if paid
- Not Paid if: Dismissed, Unpaid, Hearing Required, Notice Sent, or Bankruptcy

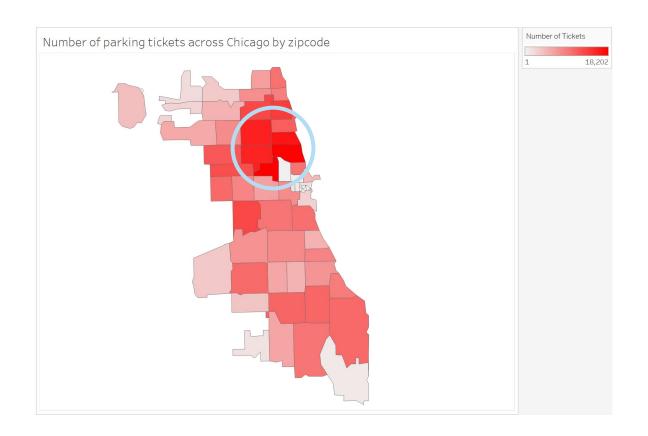
#### **Features for Focus**

- License Plate State
- Geolocation (Latitude/Longitude)
- Fine amount (\$\$\$)
- Violation code (what is the ticket for?)
- Count of license plate appearing in data

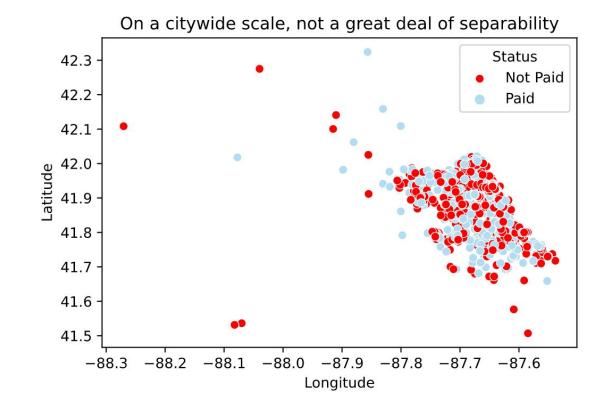
## **EDA**



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## Thoughts on classifying and potential errors

Imbalance of paid tickets to unpaid (two to one): Random Oversample Unpaid
The models in this project classify unpaid tickets as "positive"

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Goal: To separate paid and unpaid tickets as cleanly as possible

Metric: Use AUC score and confirm with confusion matrix

## Baselining

- Simple Logistic models based on each feature for smaller data sample
  - AUC scores near 50%, not much better than coin flip

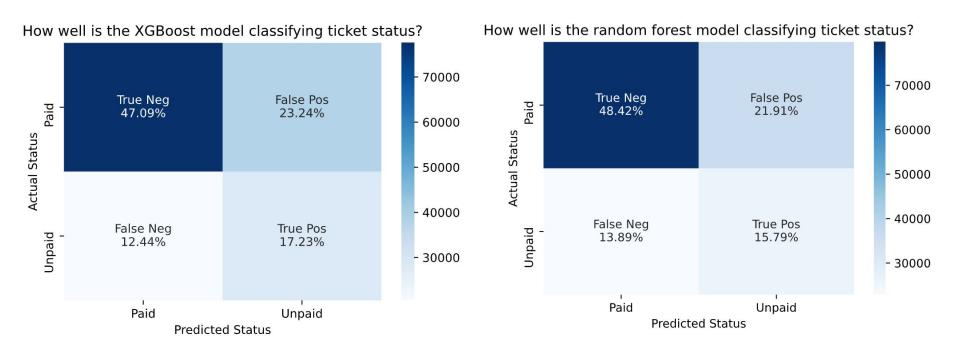
- Simple kNN models similar to above
  - o Performance (speed) is terrible on larger data sets, not worth waiting

Use more features in training logistic, Random Forest, and XGBoost

## The top performing models were

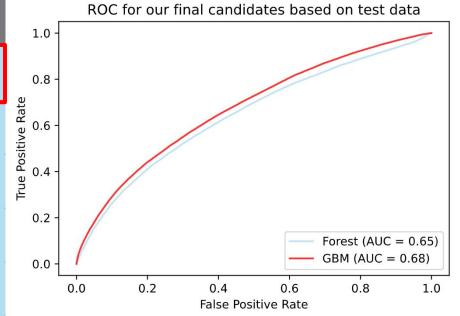
- 1) XGBoost
- 2) Random Forest

#### XGBoost and Random Forest similar on unseen data



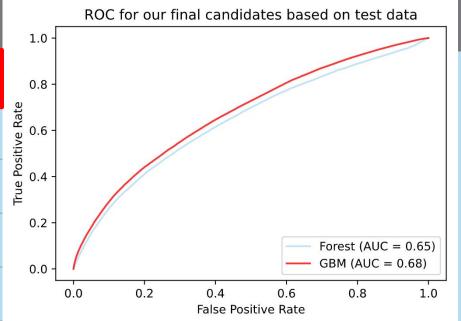
## XGBoost generally outperforms Random Forest

Scor	e R	andom Forest	XGBoost
AUC	:	.65	.68



## XGBoost generally outperforms Random Forest

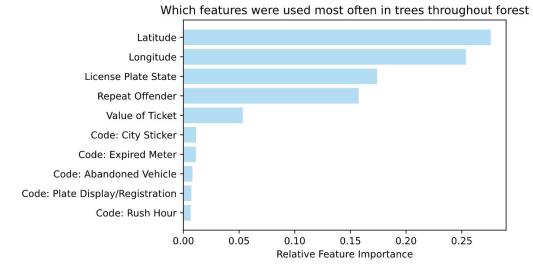
Score	Random Forest	XGBoost	
AUC	.65	.68	a
Accuracy	.64	.64	True Positive Rate
Recall	.53	.58	True Pos
Precision	.42	.43	
F1	.47	.49	

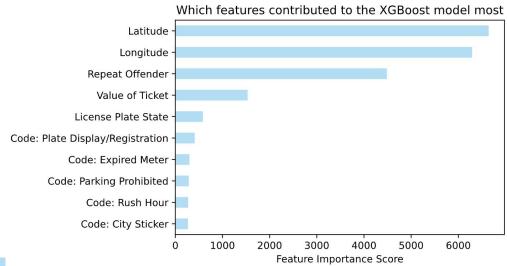


## **Feature Importance**

- General agreement across models
- Ticket location used most

 Many violations, importance spread disaggregated





Use cloud computing to handle full dataset

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Continue tuning hyperparameters to improve the model performance

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Rather than paid or not paid, dig deeper:

Given these features, predicting if ticket goes to court Given ticket goes to court court cases, predicting judgements Given these features, predicting car seizure

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Rather than paid or not paid, predict:

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Create additional model(s) for red light ticket data

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Create additional model(s) for red light ticket data

Create an applet to allow for ticket info to be entered and output a prediction

## **Potential Applications**

Predict whether a given parking ticket will be paid or not paid

A) Since tickets are only written if infractions are found, the city must decide how to allocate employees. To generate more revenue, identify areas and tickets more likely to yield payment.

B) Since tickets are intended to be consequences, the city should be looking to monitor its citizens fairly, so no change should occur to ticket writing. However, it would be useful to know if the city could flag a ticket as being more likely to be delinquent and need following up.

# Thank you!

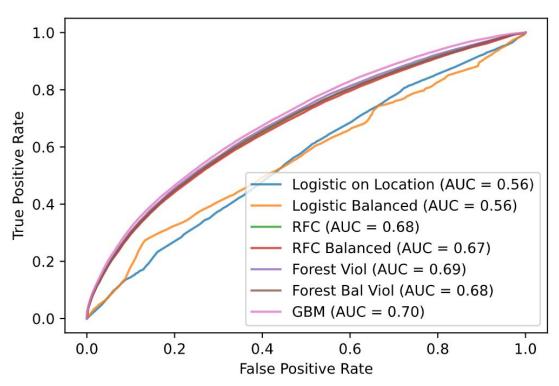
Questions?

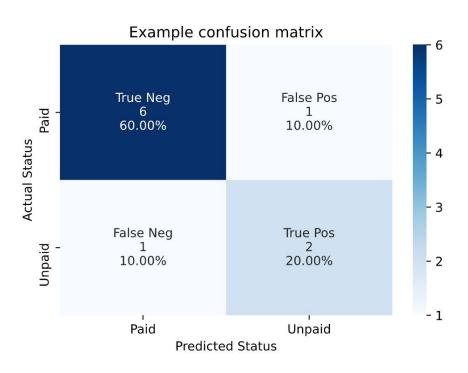
## **Appendix**

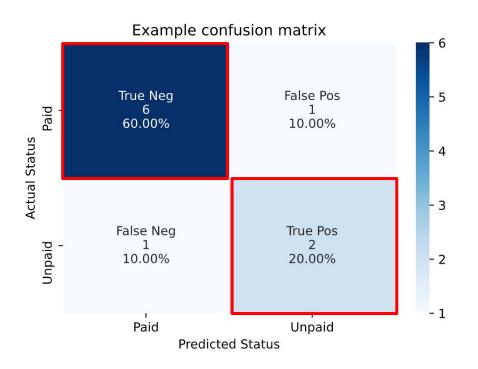
## **Potential Features**

Ticket Number	Issue Date	Norm Address
Violation Location	License Plate Code	Year
License Plate State	License Plate Type	Month
Zip code	Violation Code	Hour
Violation Description	Unit	Warm
Unit Description	Vehicle Make	Tract ID
Fine Level 1	Fine Level 2	Community Area #
Current Amount Due	Total Payments	Community Area Name
Ticket Queue (Status)	Ticket Queue Date	Geocoded Address
Notice Level	Notice Number	Geocode Latitude
Hearing Disposition	Officer	Geocode Longitude

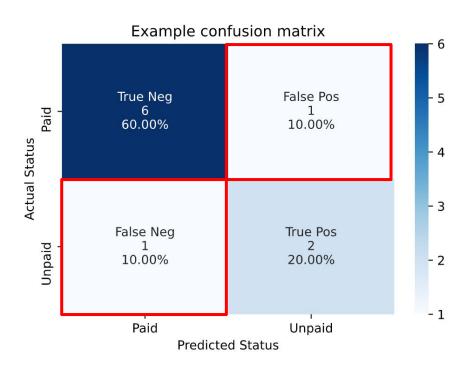
## **ROC Comparison (On Validation Data)**





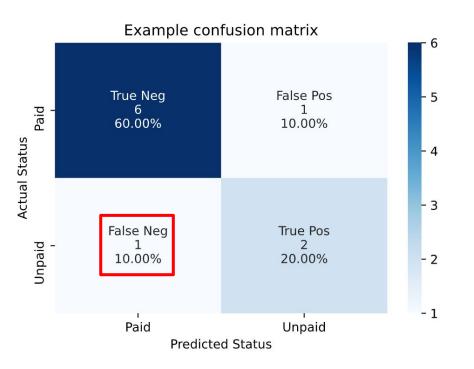


 Correct predictions on the main diagonal



 Correct predictions on the main diagonal

 False Positives and Negatives shown on the other diagonal



Correct predictions on the main diagonal

 False Positives and Negatives shown on the other diagonal

 Displays number classified and percentage of the total