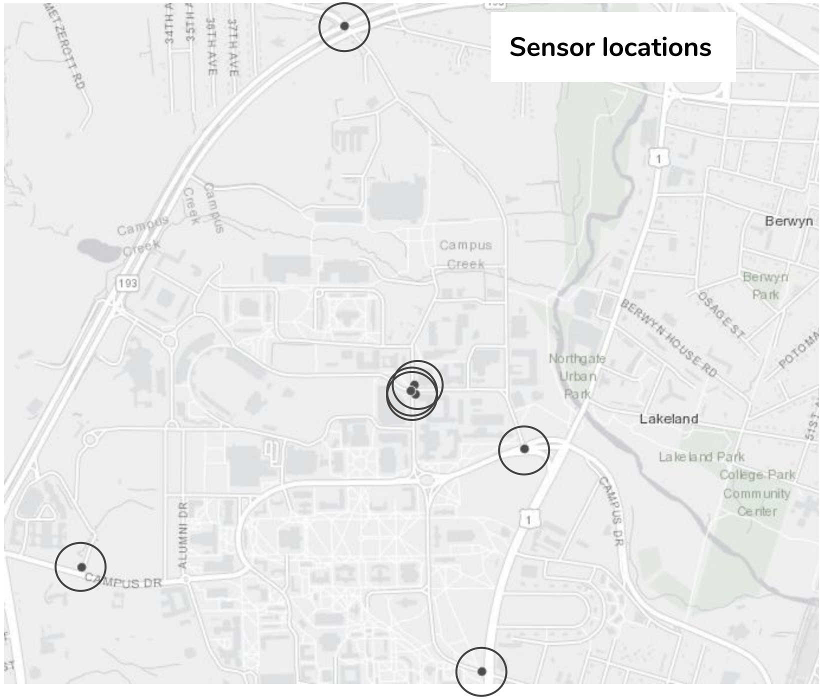
Dataset: UMD Traffic Count Sensor Data

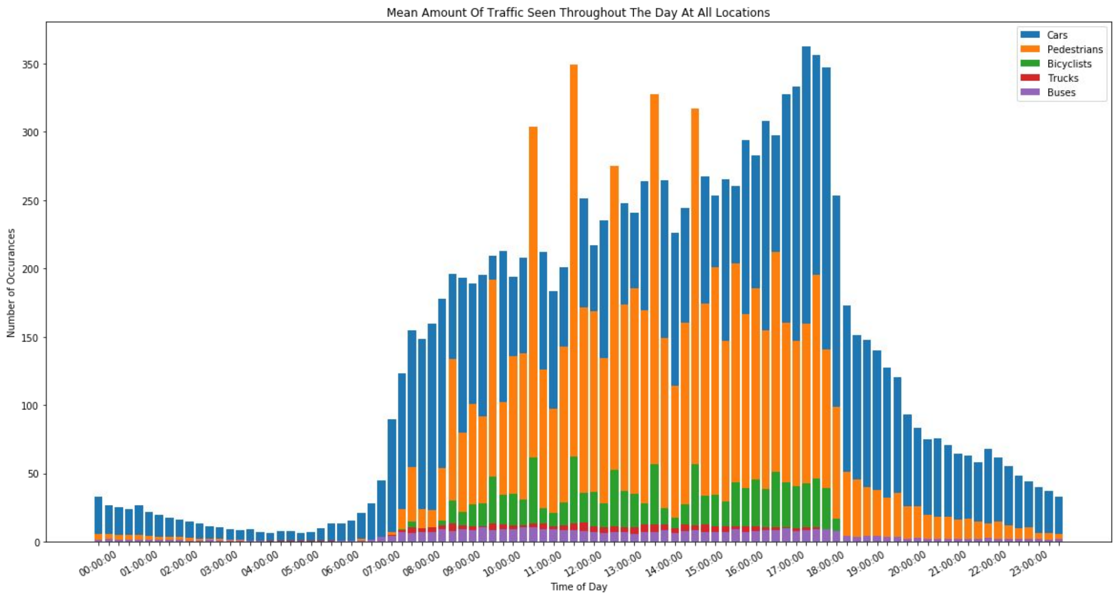
Team: DC20072

What Does The Data Look Like?



- Features:
  - Car count (Integer)
  - Truck count (Integer)
  - Bus count (Integer)
  - Bicyclist count (Integer)
  - Pedestrian count (Integer)
  - Timestamp (Date/Time)
  - Sensor location (String)

What preparation steps did we take?



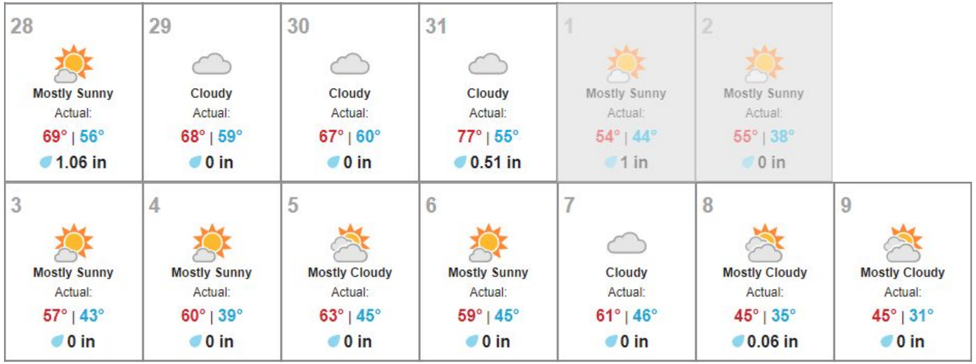
- Gathered weather data for the time that the data was gathered
- Gathered crime data for the areas and time period that matches with the provided dataset
- Created new dataset that divides the time periods into 4 chunks in the day rather than the 15 minute chunks given
- Applied latitude, longitude, and directionality to each sensor

Questions to answer

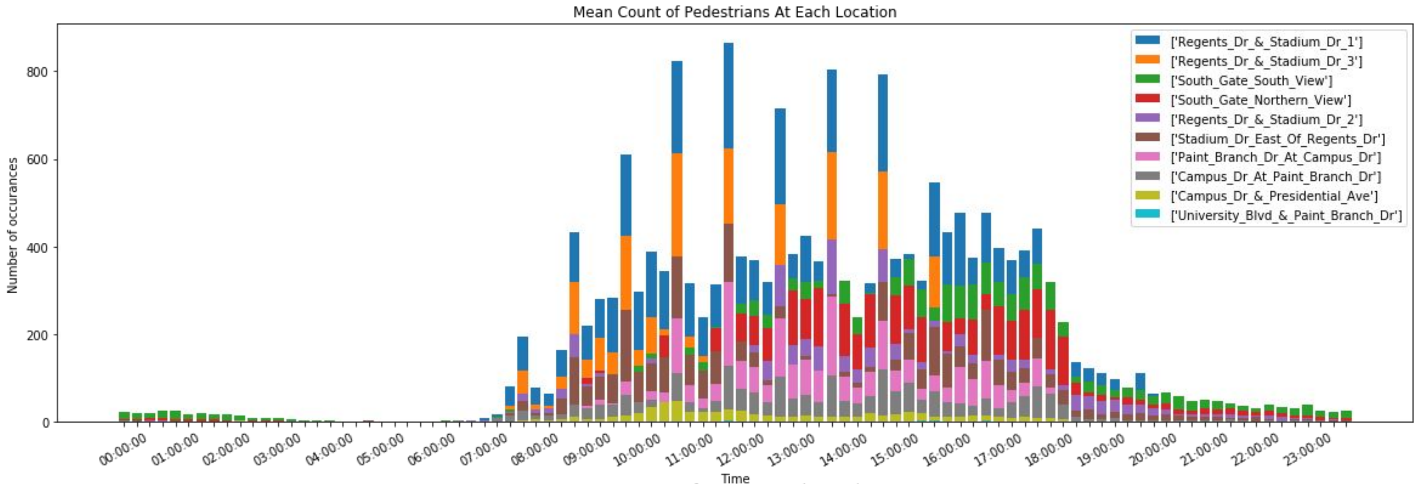
- What is the relationship between weather and traffic?
  - Does weather decrease one mode of transportation and increase another?
- What is the relationship between sensor location and favored mode of transportation?
  - What are the traffic patterns at each location?
- What time of day has the most traffic? Is this different when taking mode of transportation into account? How about for day of the week?
  - How do major events affect these numbers? Ex: Football games
- Are there any correlations between the modes of transportation?
  - Ex: As amount of cars goes down does that also decrease pedestrians?
- How does crime affect the traffic flow?
  - Which crimes typically occur when more people are around? Less people?
  - What time of day do specific crimes typically occur?
- Can we predict future traffic?
  - Can we create some kind of model to predict traffic in the future?

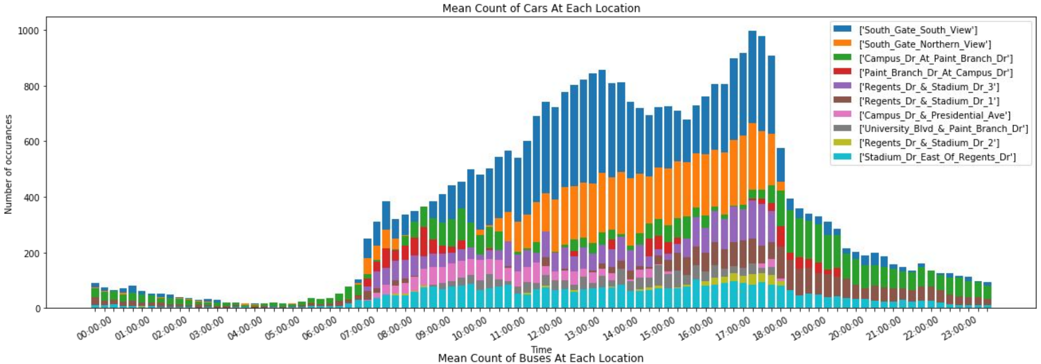
What is the relationship between weather and traffic?

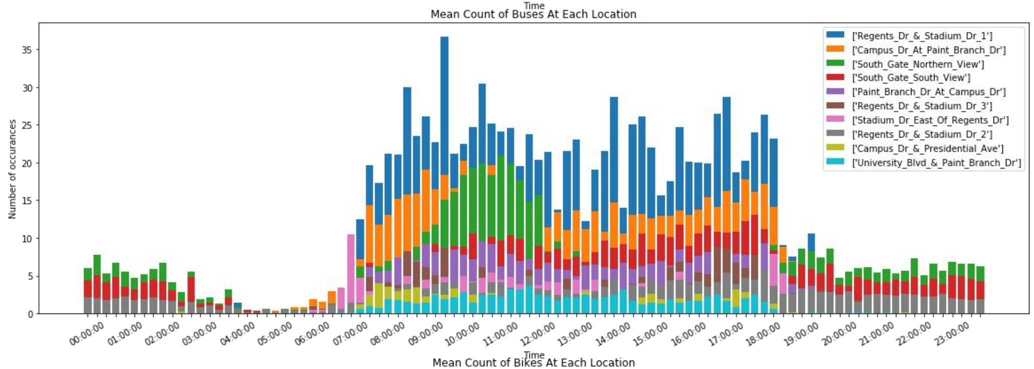
- Not enough variation in weather to see how rain or very cold temperatures affect changes in traffic

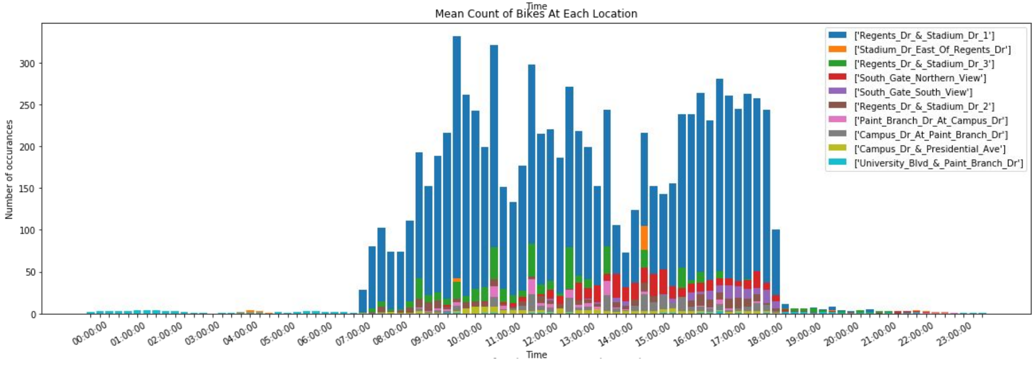


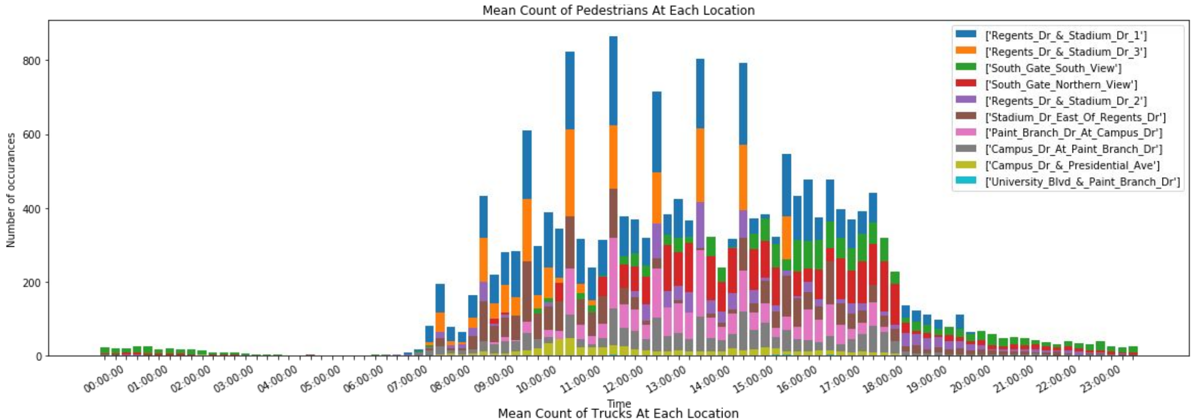
What is the relationship between location and mode of transportation?

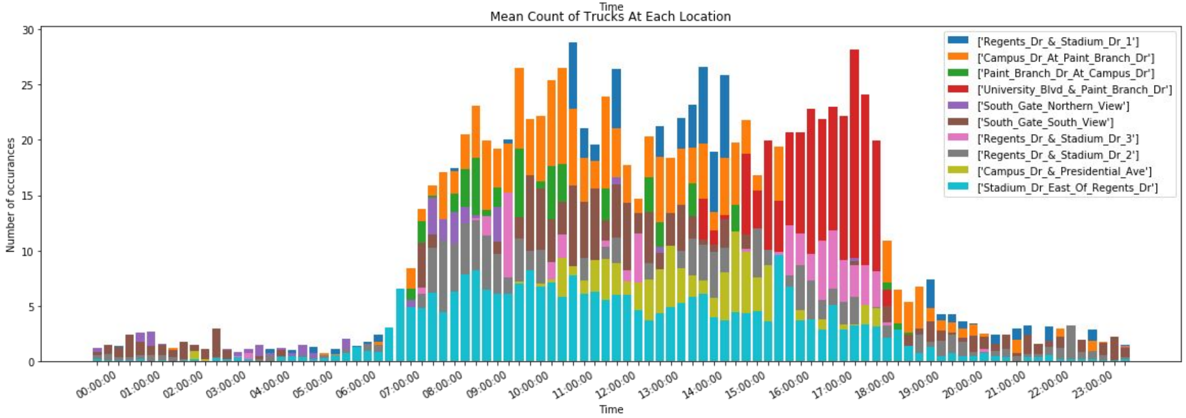



Mean Count of Cars At Each Location
Number of occurances
Time
['South_Gate_South_View']
['South_Gate_Northern_View']
['Campus_Dr_At_Paint_Branch_Dr']
['Paint_Branch_Dr_At_Campus_Dr']
['Regents_Dr_&_Stadium_Dr_3']
['Regents_Dr_&_Stadium_Dr_1']
['Campus_Dr_&_Presidential_Ave']
['University_Blvd_&_Paint_Branch_Dr']
['Regents_Dr_&_Stadium_Dr_2']
['Stadium_Dr_East_Of_Regents_Dr']

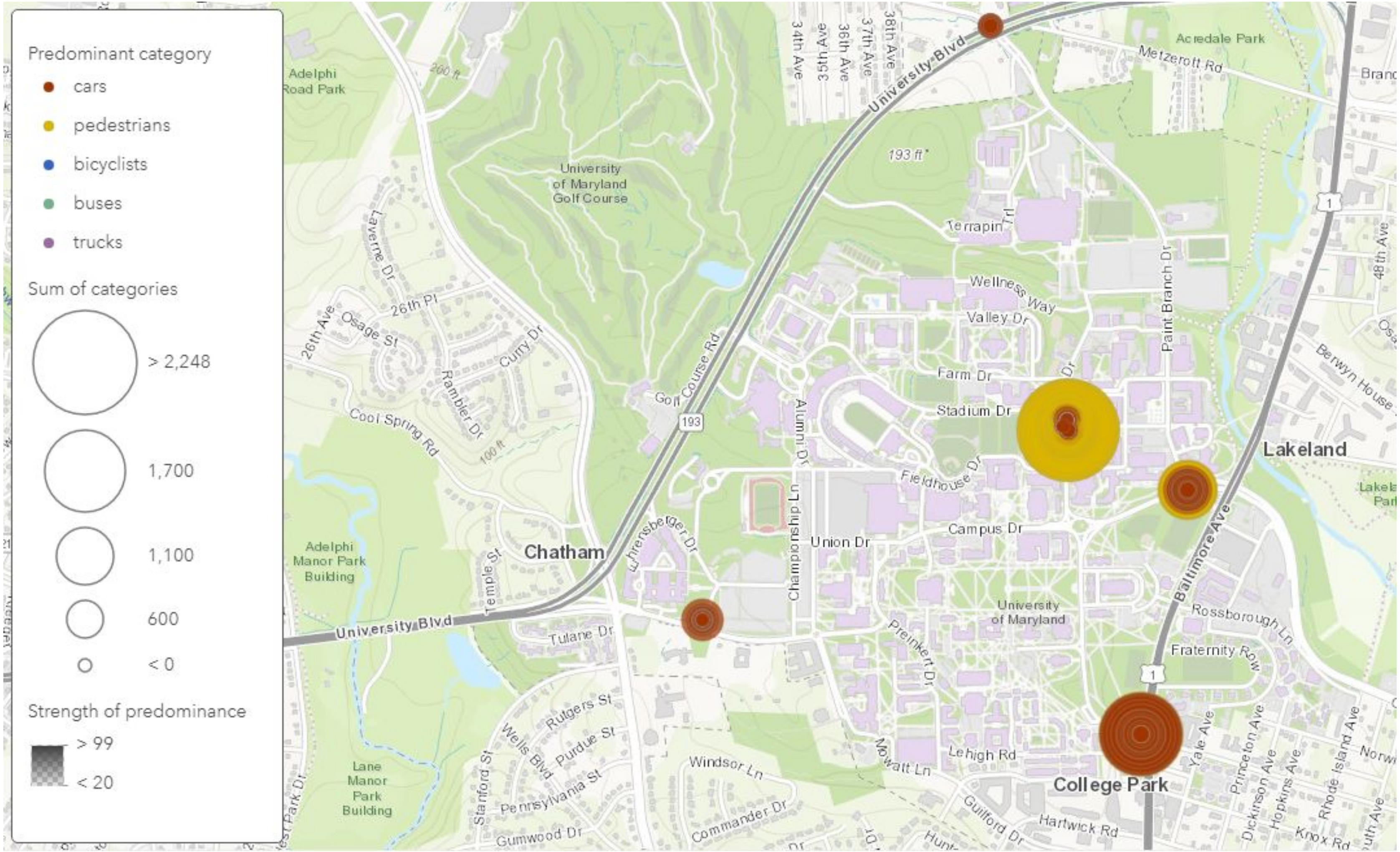

Mean Count of Buses At Each Location
Number of occurances
Time
['Regents_Dr_&_Stadium_Dr_1']
['Campus_Dr_At_Paint_Branch_Dr']
['South_Gate_Northern_View']
['South_Gate_South_View']
['Paint_Branch_Dr_At_Campus_Dr']
['Regents_Dr_&_Stadium_Dr_3']
['Stadium_Dr_East_Of_Regents_Dr']
['Regents_Dr_&_Stadium_Dr_2']
['Campus_Dr_&_Presidential_Ave']
['University_Blvd_&_Paint_Branch_Dr']


Mean Count of Bikes At Each Location
Number of occurances
Time
['Regents_Dr_&_Stadium_Dr_1']
['Stadium_Dr_East_Of_Regents_Dr']
['Regents_Dr_&_Stadium_Dr_3']
['South_Gate_Northern_View']
['South_Gate_South_View']
['Regents_Dr_&_Stadium_Dr_2']
['Paint_Branch_Dr_At_Campus_Dr']
['Campus_Dr_At_Paint_Branch_Dr']
['Campus_Dr_&_Presidential_Ave']
['University_Blvd_&_Paint_Branch_Dr']



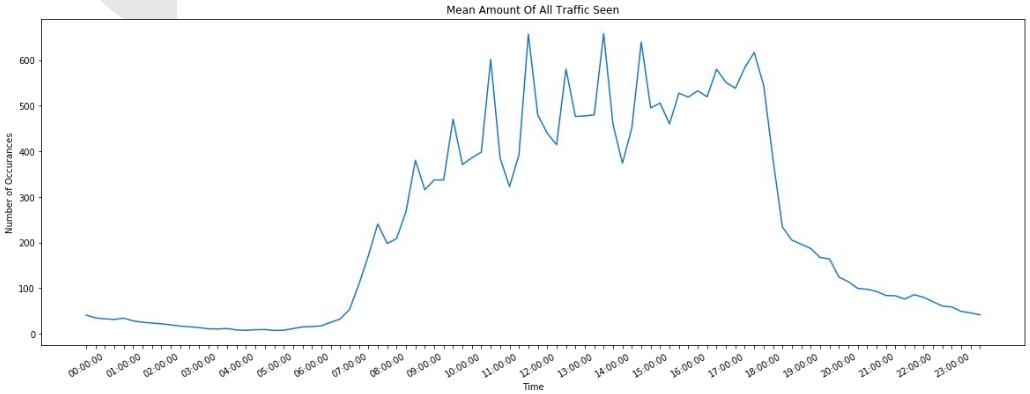


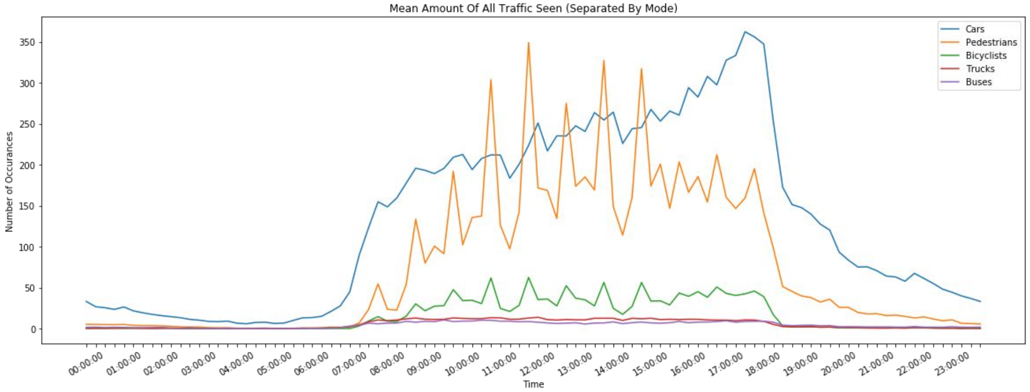
- University Blvd & Point Branch Dr seems to get the least amount of traffic aside from truck traffic
  - Truck traffic increases linearly throughout the week for this street
- South Gate has by far the most car traffic
  - Makes sense given that it is adjacent to a large road
  - Cars most likely aren't actually entering campus
- Regents Dr & Stadium Dr 1 sensor counted a huge amount of bikes compared to other sensors



Predominant category
cars
pedestrians
bicyclists
buses
trucks
Sum of categories
> 2,248
1,700
1,100
600
< 0
Strength of predominance
> 99
< 20
University Blvd
University of Maryland Golf Course
Adelphi Road Park
Acredale Park
Metzerott Rd
Terrapin Trl
Wellness Way
Valley Dr
Paint Branch Dr
Farm Dr
Stadium Dr
Fieldhouse Dr
Campus Dr
Union Dr
Championship Ln
Alumni Dr
Golf Course Rd
193
Lakeland
Baltimore Ave
Rossborough Ln
Fraternity Row
University of Maryland
College Park
Chatham
Adelphi Manor Park Building
Lane Manor Park Building
Tulane Dr
Rutgers St
Purdue St
Pennsylvania St
Windsor Ln
Commander Dr
Lehigh Rd
Mowatt Ln
Guilford Dr
Hartwick Rd
Preinkert Dr
Cool Spring Rd
Rambler Dr
Curry Dr
Osage St
26th Pl
26th Ave
Laverne Dr
Temple St
Berwyn House Rd
34th Ave
35th Ave
36th Ave
37th Ave
38th Ave
48th Ave
Yale Ave
Princeton Ave
Dickinson Ave
Hopkins Ave
Rhode Island Ave
Knox Rd
Gumwood Dr
Stanford St

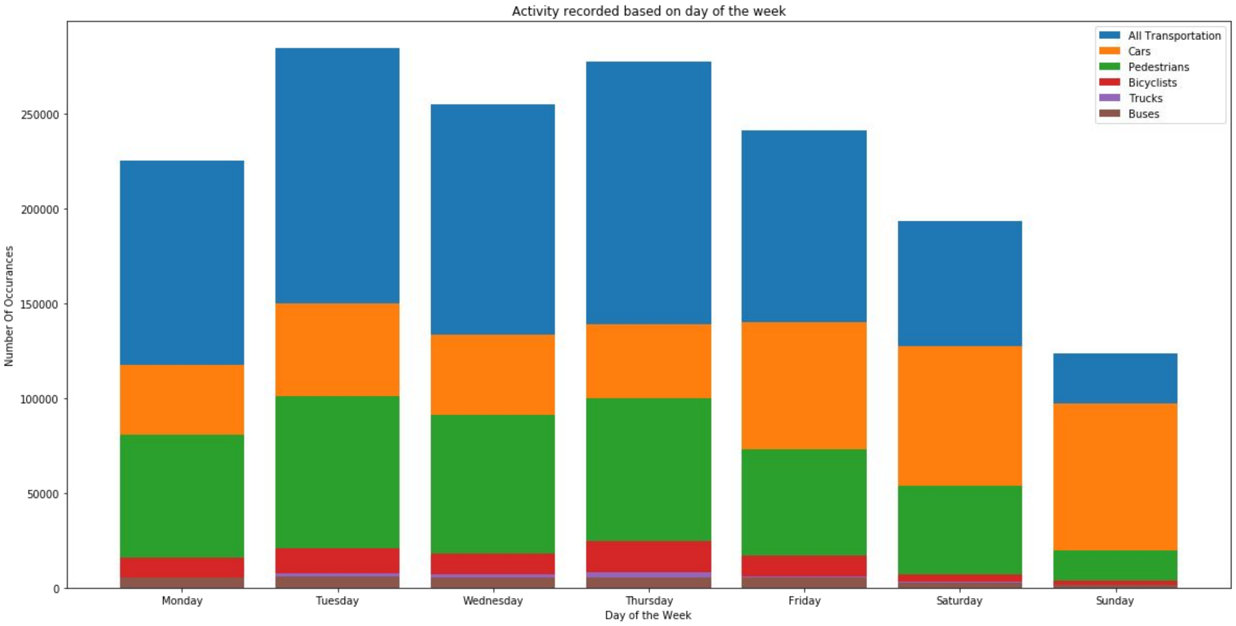
What time of day has the most traffic?





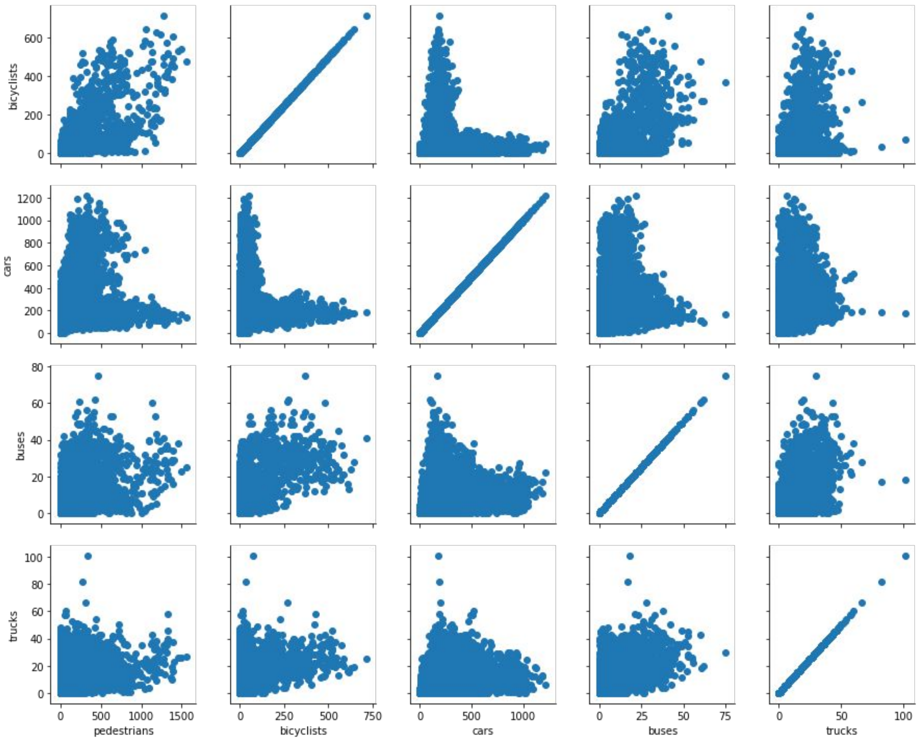
- Traffic doesn't usually spike up until around 0700
- At its heaviest around 1600-1800
- Interesting to see huge spikes in traffic every hour starting at 1000
  - Due to students getting to class
  - Modes of traffic that increase are pedestrian traffic and bicycles (almost certainly students)
- Spike at 1730
  - Likely due to faculty & staff returning home
  - Why is there no spike like this in the morning?

How about day of the week?



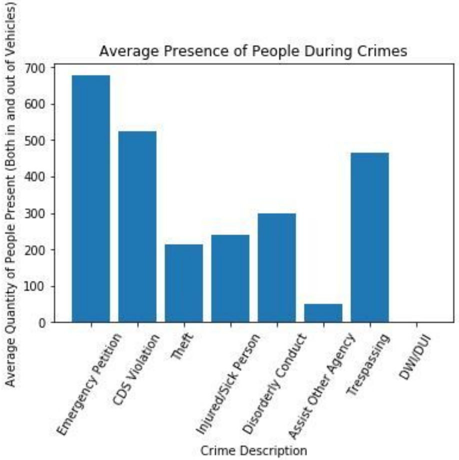
- Tuesday and Thursday seem to be days with most traffic overall
  - Likely to do with how class schedules line up
- Weekend has least amount of traffic

Correlations between modes of transportation?

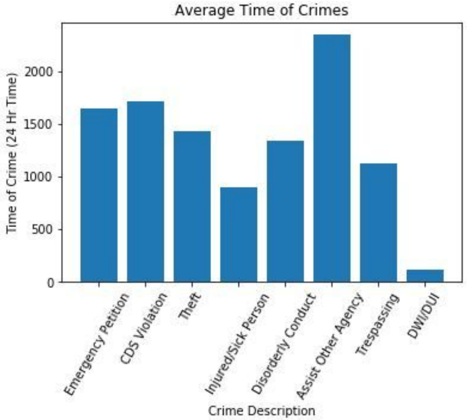


- Strong correlation in amount of cars by bicyclists
    - As the amount of cars on the road decrease, amount of bicyclists increase and other way around is true
- Some correlation in amount of cars by pedestrians
    - As more pedestrians travel, less cars do
- Some correlation in amount of bicyclists by pedestrians
    - The more bicyclists on the road, roughly translates to more pedestrians
    - Makes sense when you think about classes getting out (more pedestrians and bicyclists)

How does crime affect the traffic flow?



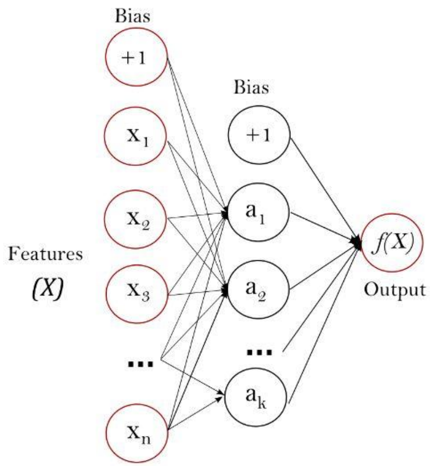
	event	avgTime	avgTraffic
0	Emergency Petition	1645	677
1	CDS Violation	1715	525
2	Theft	1430	215
3	Injured/Sick Person	0900	239
4	Disorderly Conduct	1345	298
5	Assist Other Agency	2345	49
6	Trespassing	1130	465
7	DWI/DUI	0115	1



- Interesting to see correlation between how many potential witnesses are present for specific crime types and how that relates to the time of day
- It makes sense that DUI’s typically occur late at night around 0115 when bars close and there are few people around for late night crimes like DUI’s and Assist Other Agency’s
- In the two week period we have data for, there aren’t that many crimes so some correlations are fairly loose. There was a higher volume of theft crimes so its results are more accurate:
    - According to ASECURELIFE, most burglaries occur between the hours of 1000-1500, and this data shows that most thefts occurred at 1430 on average

Building Predictive Models

- Linear Regression
  - Fits a linear model to minimize the sum of squares between observed targets in the dataset and the target values of the dataset.
- Multilayer Perceptron Regressor
  - An iteratively trained regressor than can be used to fit models using non-linear, hidden layers.



Building Predictive Models

- Both sets of models were trained on the same set of inputs and outputs.
- Input vector example:
  - `[pedestrians, bicyclists, buses, trucks, earlyMorning, midMorning, midAfternoon, lateEvening, CampusAndPresidential, CampusAndPaintBranch, RegentsAndStadium, SouthGate, UniversityAndPaintBranch]`
- Output example
  - `[cars]`
- We trained several models on both methods with varying input vectors and output values
- Loose correlations between some input values drove the need to include several modes of transportation as input.

Building Predictive Models

Method

- Dealing with time variance in the model
  - Break 24 hour day into 6-hr blocks (early morning, mid morning, late afternoon, and late evening) and store each 6-hr block as a feature for every datapoint
- Splitting training and testing data
  - Shuffling the dataset gave a good spread of locations and time periods for the training and testing sets respectively
- Dealing with sensors sharing an intersection
  - Group the sensors by intersection, integrate new features to the dataset representing the intersection that the datapoint was recorded at

Building Predictive Models

Root Mean Squared Error

$$RMSE(y,\hat{y}) = \sqrt{\frac{1}{n_{samples}} \sum_{i=0}^{n_{samples}-1} (y_i - \hat{y}_i)^2}$$

A risk metric corresponding to the expected value of the error or loss.[1]

Coefficient of Determination (R^2)

$$R^2(y,\hat{y}) = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$$

where $\bar{y} = \frac{1}{n} \sum_{i=1}^{n} y_i$

Represents the proportion of variance (of y) that has been explained by the independent variables. It provides an indication of goodness of fit.[1]

[1] *scikit-learn 3.3, Metrics and scoring: quantifying the quality of predictions*

Building Predictive Models

Results

Linear Regression	**Pedestrians**	**Bicyclists**	**Cars**	**Trucks**	**Buses**
RMSE	87.28	31.54	110.55	4.35	5.32
R^2	0.67	0.66	0.63	0.65	0.62

MLP Reg	**Pedestrians**	**Bicyclists**	**Cars**	**Trucks**	**Buses**
RMSE	75.08	26.65	93.48	4.17	5.11
R^2	0.76	0.76	0.73	0.67	0.65

Building Predictive Models

Analysis

- Both methods were good at predicting numbers of trucks and buses, probably because trucks and buses operate on a much more regular schedule with less variability than cars or pedestrians.

- Cars, pedestrians, and bicyclists were hard to predict because of this same fact. Their variability made training a model more difficult

- The MLP Regressor outperformed the Linear Regression model on all metrics, most likely due to this model’s ability to fit non-linear data.

Building Predictive Models

Application

- The MLP Regressor models are reasonably good at predicting snapshots.

- Given pedestrians, bicyclists, trucks, buses, time, and location, these models can predict with reasonable accuracy, the number of cars present.

- Models were created for each transportation method, so one can swap in pedestrians for the target value.