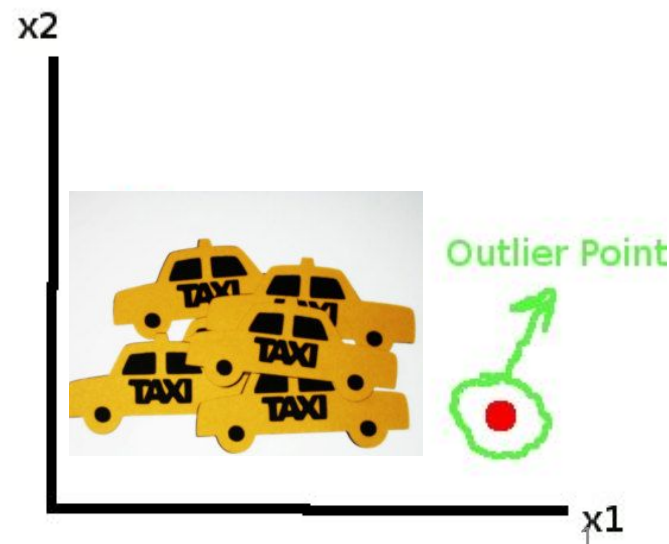


# Anomaly Detection in NYC Taxi Data

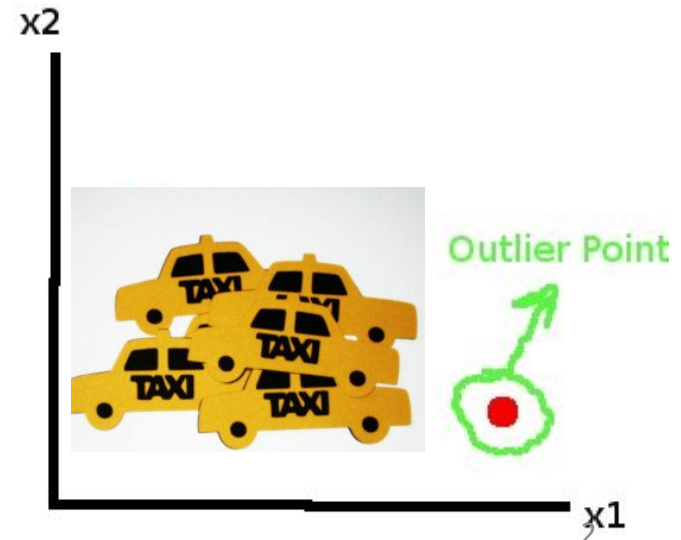
Harish Pullagurla  
Hari Krishna Majety  
Kenneth Tran



What are Anomalies ??

# Anomaly Detection in NYC Taxi Data

Harish Pullagurla  
Hari Krishna Majety  
Kenneth Tran

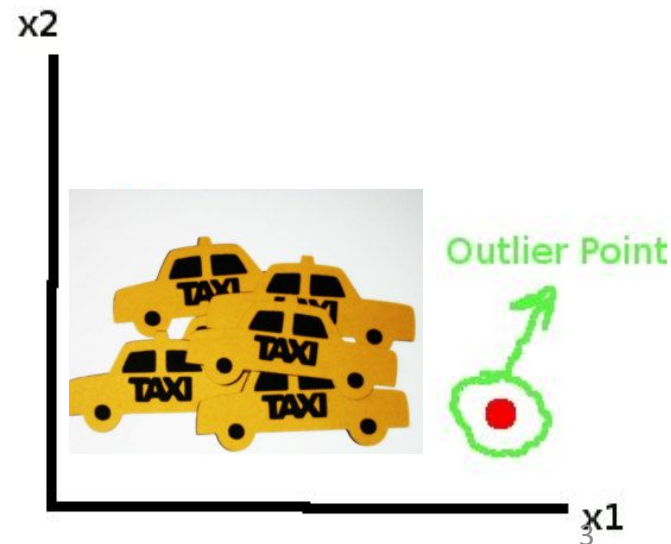


What are Anomalies ??

What is this Data Set about ??

# Anomaly Detection in NYC Taxi Data

Harish Pullagurla  
Hari Krishna Majety  
Kenneth Tran



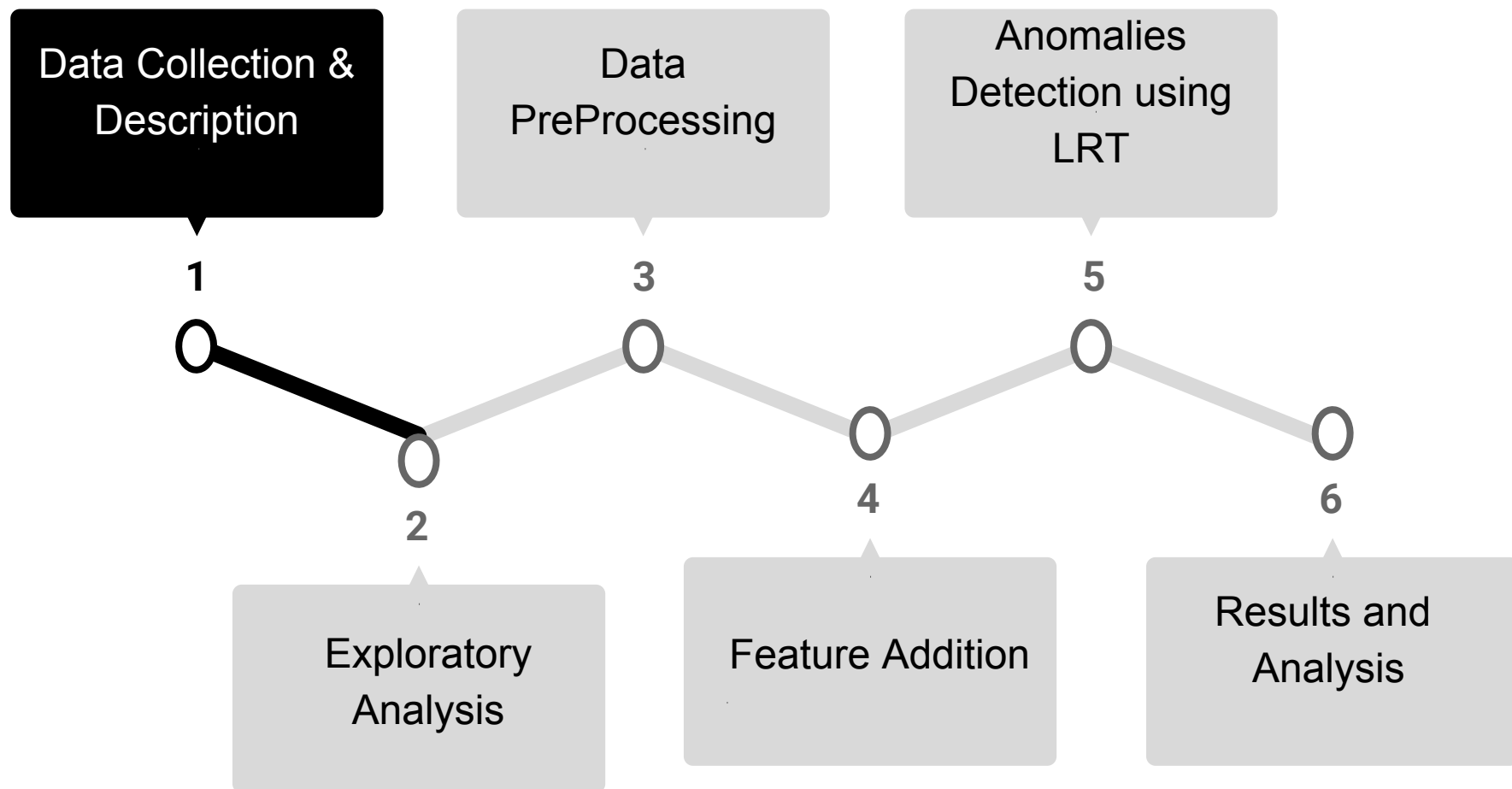
# What are Anomalies ?

- The set of data points that are considerably different than the remainder of the data
- Anomaly is a pattern in the data that does not conform to the expected behaviour
- “An outlier is an observation which deviates so much from the other observations as to arouse suspicions that it was generated by a different mechanism”, (Hawkins 1980)

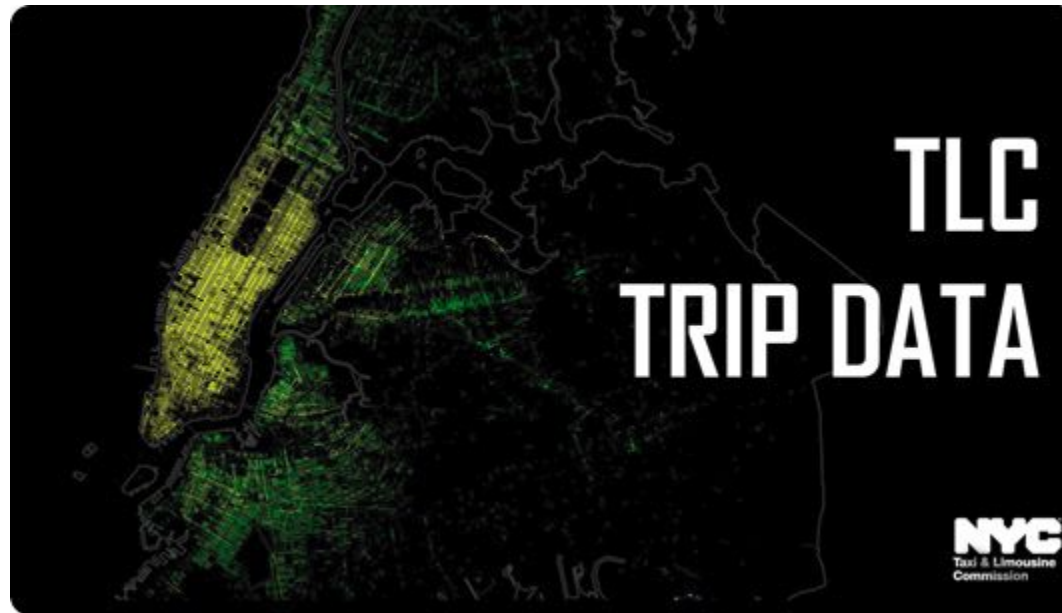
# Related Work

- *Wu, Mingxi, et al. A LRT Framework for Fast Spatial Anomaly Detection. Research Gate, Proceedings of the 15th ACM SIGKDD, Jan. 2009.*
  - Applying LRT to Anomaly Detection
  - Region pruning methods to reduce computation
- *Pang, Linsey Xiaolin, et al. On Detection of Emerging Anomalous Traffic Patterns Using GPS Data. Data Knowledge Engineering, North-Holland, 18 May 2013.*
  - Applying Anomaly Detection LRT to specific data sets
  - Includes case study on Beijing taxi data

# Pipeline



## Data Set



# Data Set Description

**1.5 Million Trip Records  
From Jan - July 2016**





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**Temporal Attributes - 3 dim**  
Pick up & drop off Time,  
Trip Duration



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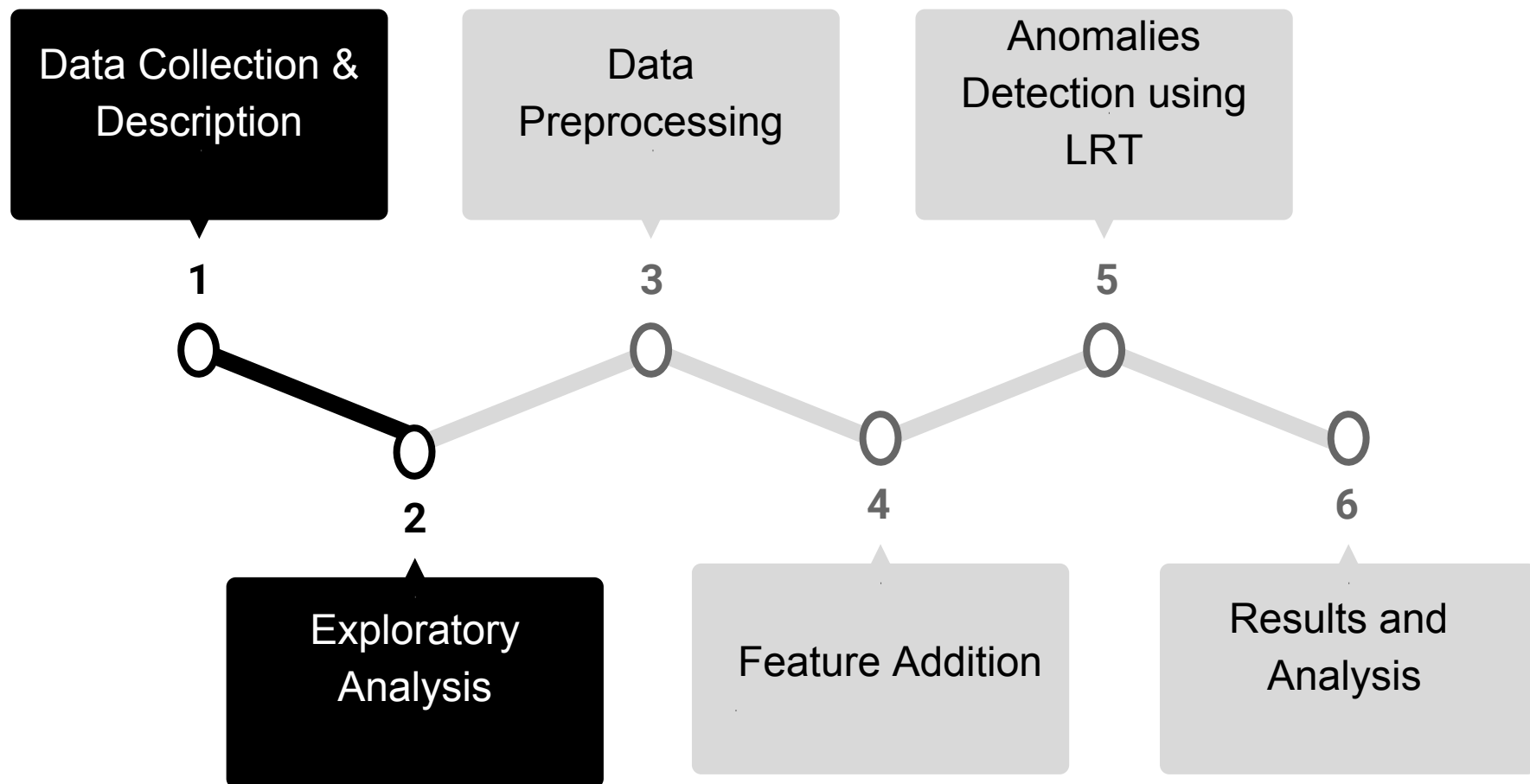
**Temporal Attributes - 3 dim**  
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Trip Duration



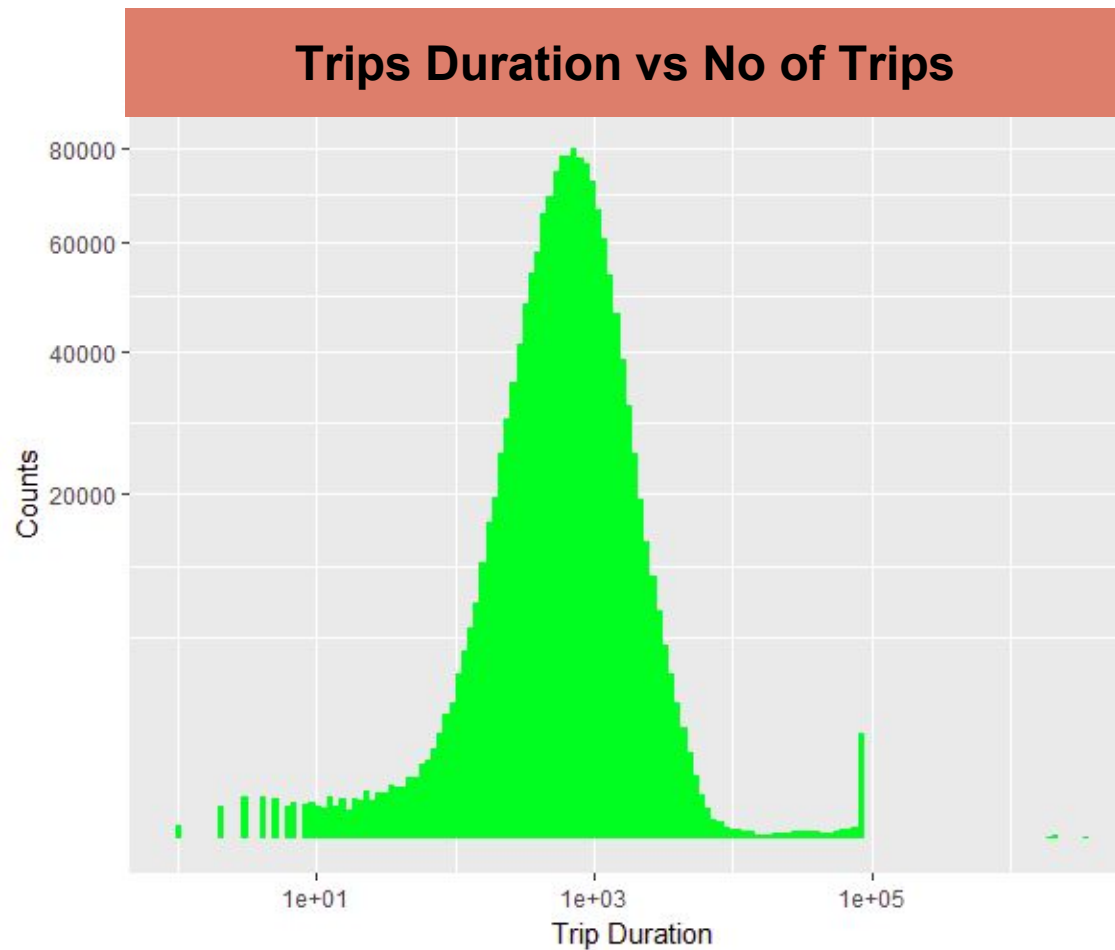
**General Attributes - 4 dim**  
Passenger Count, Vendor Id  
Transmission Type

**Spatial Attributes - 4 dim**  
Latitude , Longitude  
Pick up & Drop

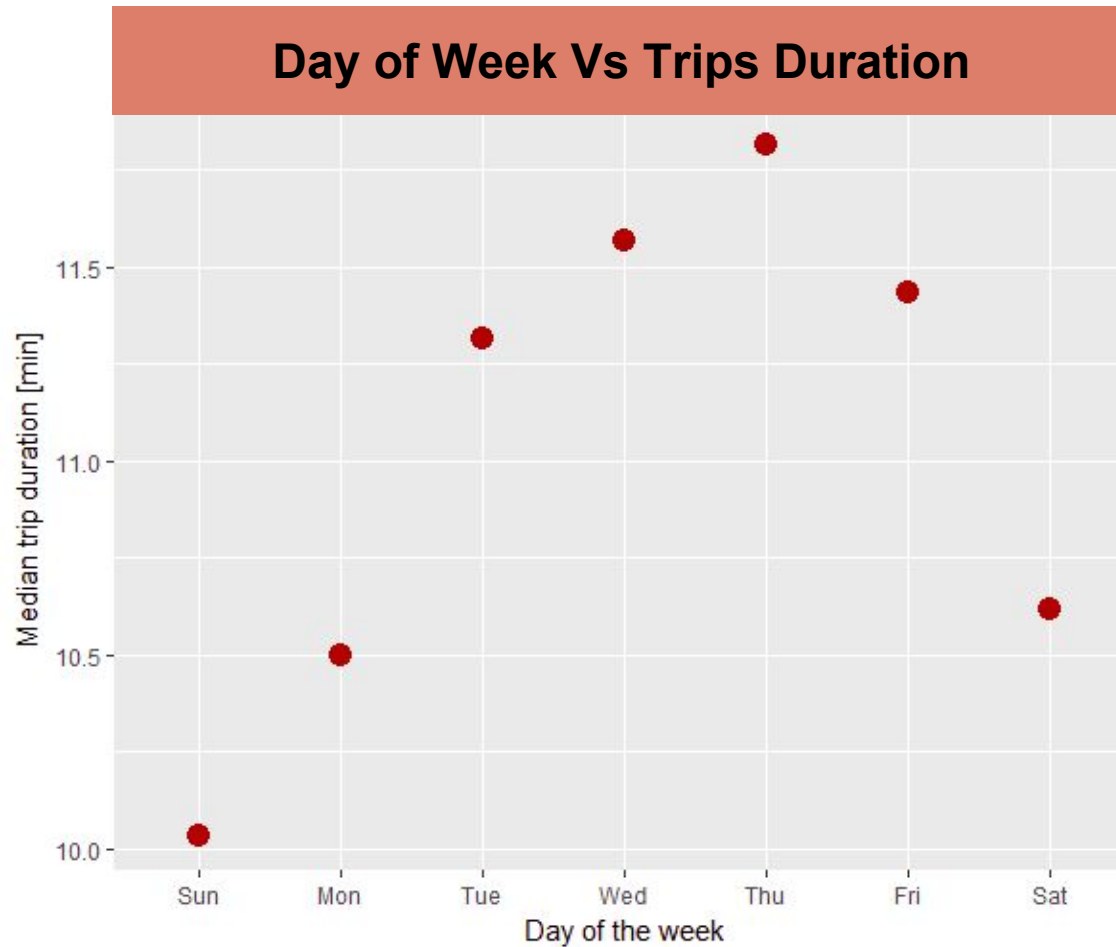
# Pipeline



# Exploratory Analysis

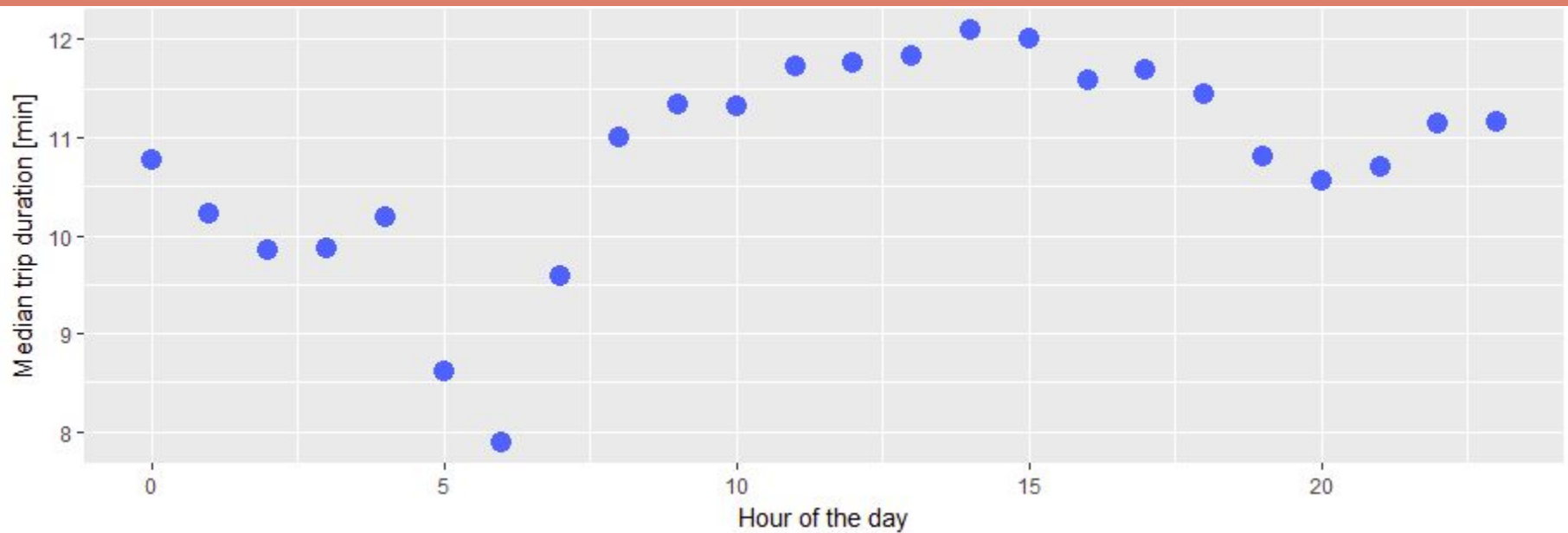


# Exploratory Analysis

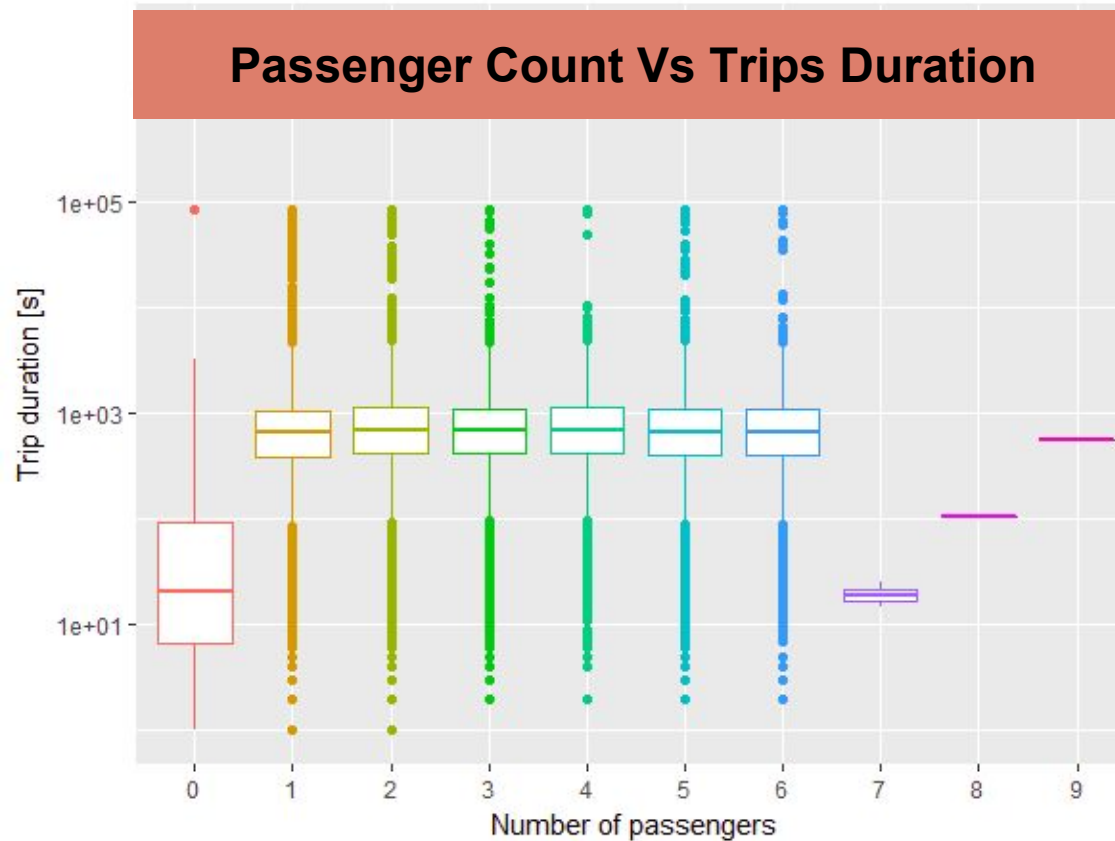


# Exploratory Analysis

## Hour of Day Vs Trips Duration

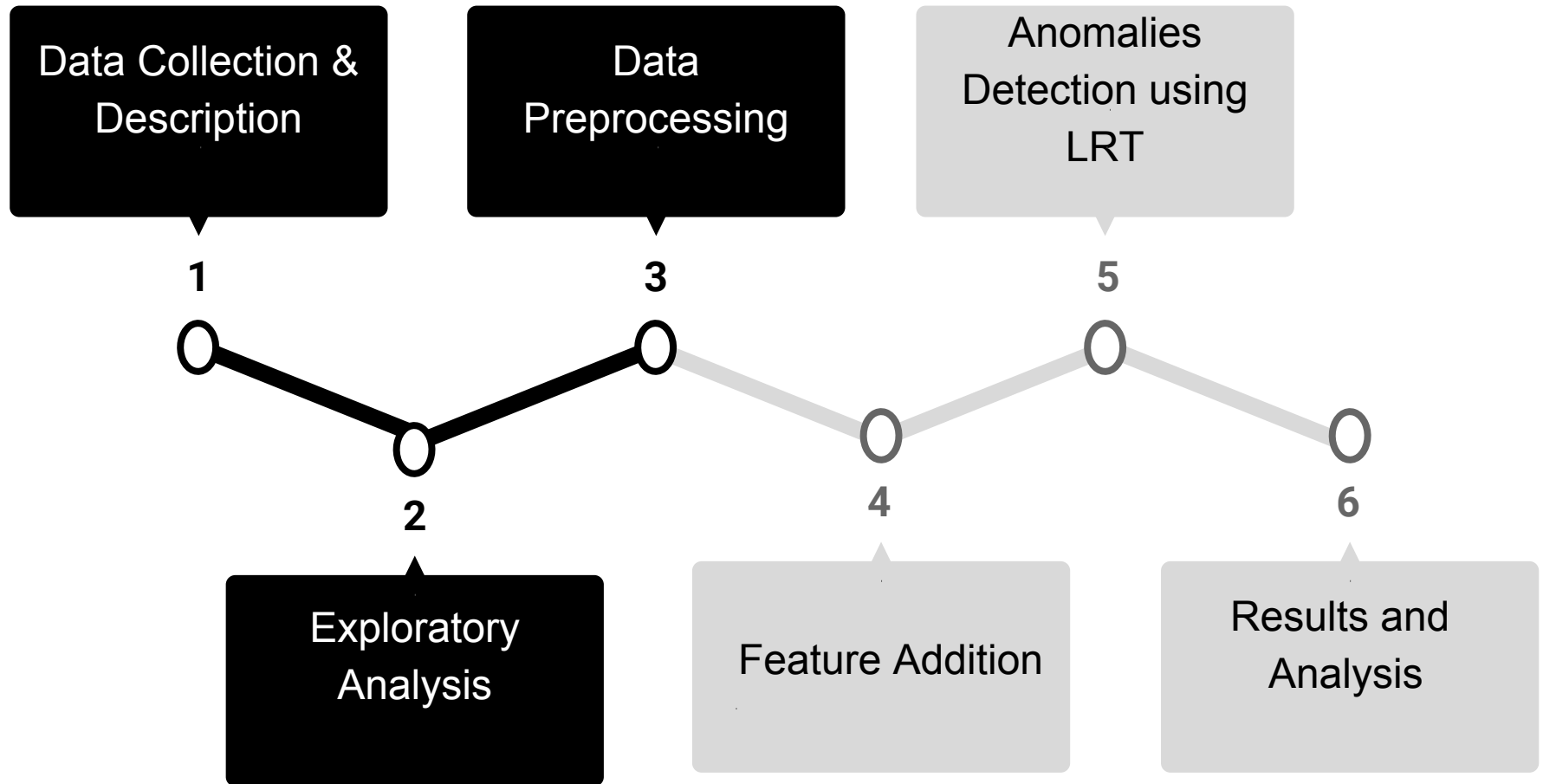


# Exploratory Analysis





# Pipeline

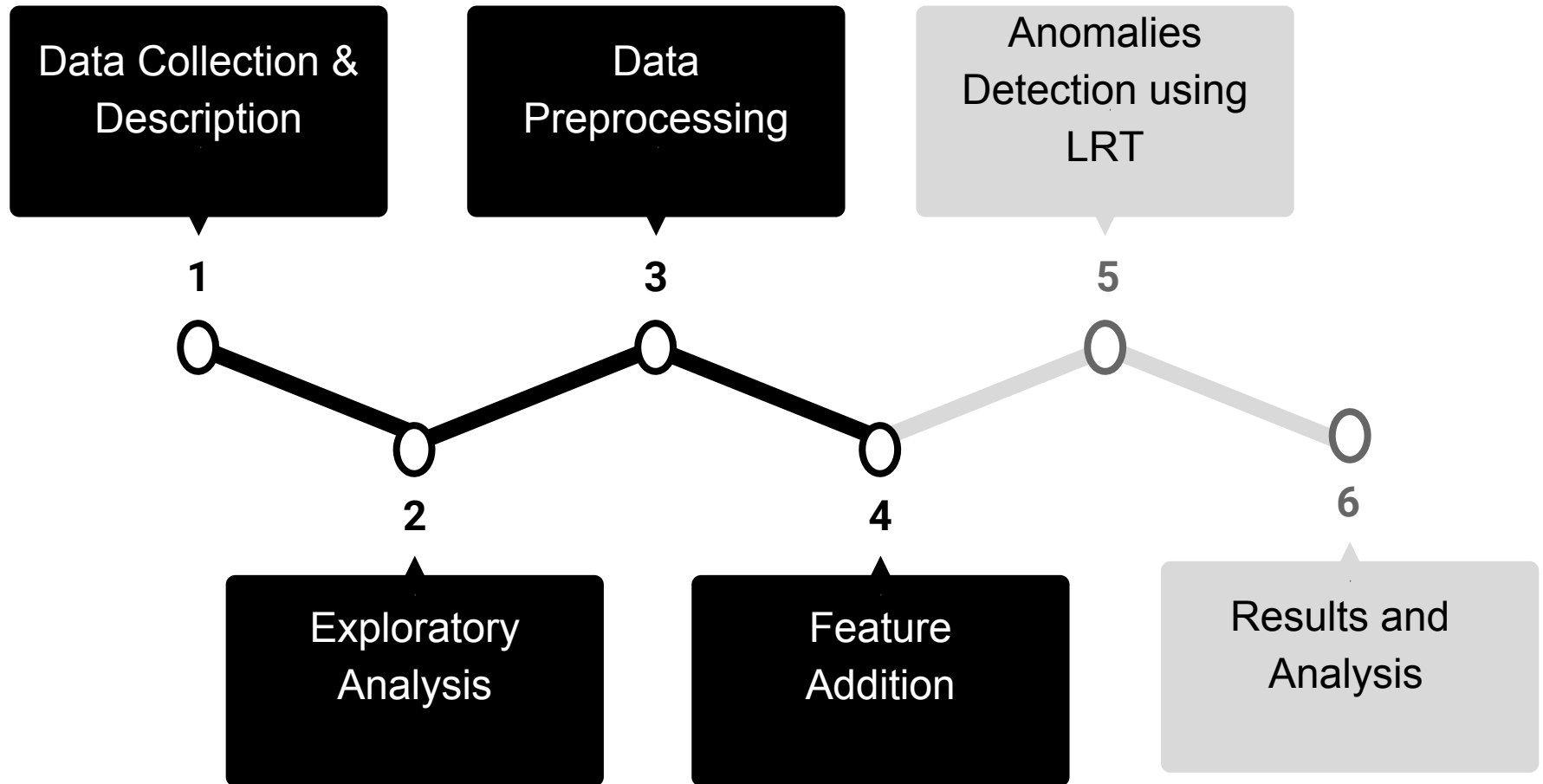


# Data PreProcessing

- *Following data points were eliminated:*
  - Data points with missing attribute values
  - Duplicates
  - Pick up and drop locations which are not within the New York city limits
  - Data points with passenger counts like 0,7,8,9
  - Trip Durations which are more than 5 standard deviations away from the mean.
- *This reduced the total number of data points from 1.45 million to 1.438 million samples.*



# Pipeline



# Feature Addition

## Existing Features

### **Spatial Attributes - 4 dim**

Latitude , Longitude  
Pick up & Drop

### **Temporal Attributes - 3 dim**

Pick up & drop off Time,  
Trip Duration

### **General Attributes - 4 dim**

Passenger Count, Vendor Id  
Transmission Type

## New Features

### **OSRM Data -**

Gives real world travel info  
like Google Maps



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### **Haversine Distance**



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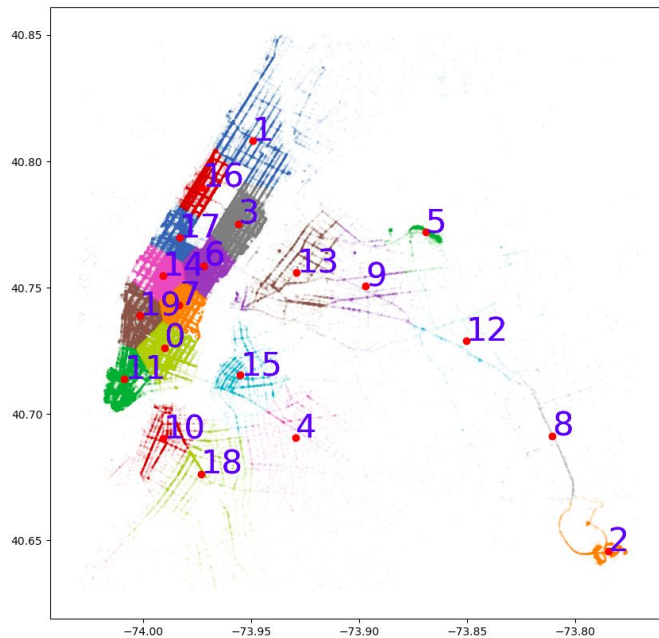
Extract Features such as Day  
of Year, week etc

### **Haversine Distance**

### **Region Clustering**



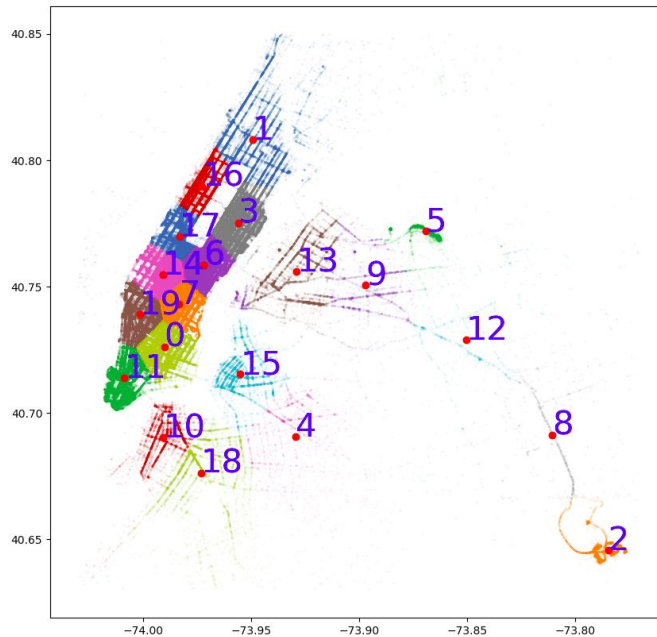
# Region Labeling



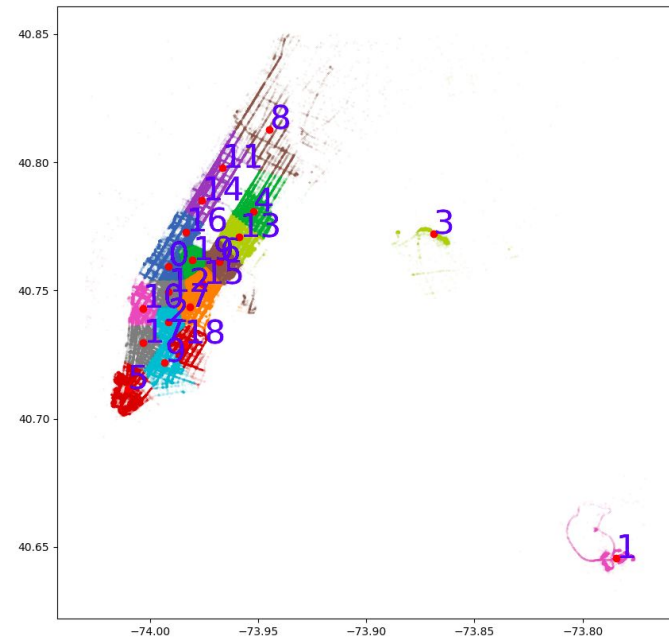
**K means Cluster Label Map  
with Full Data**



# Region Labeling

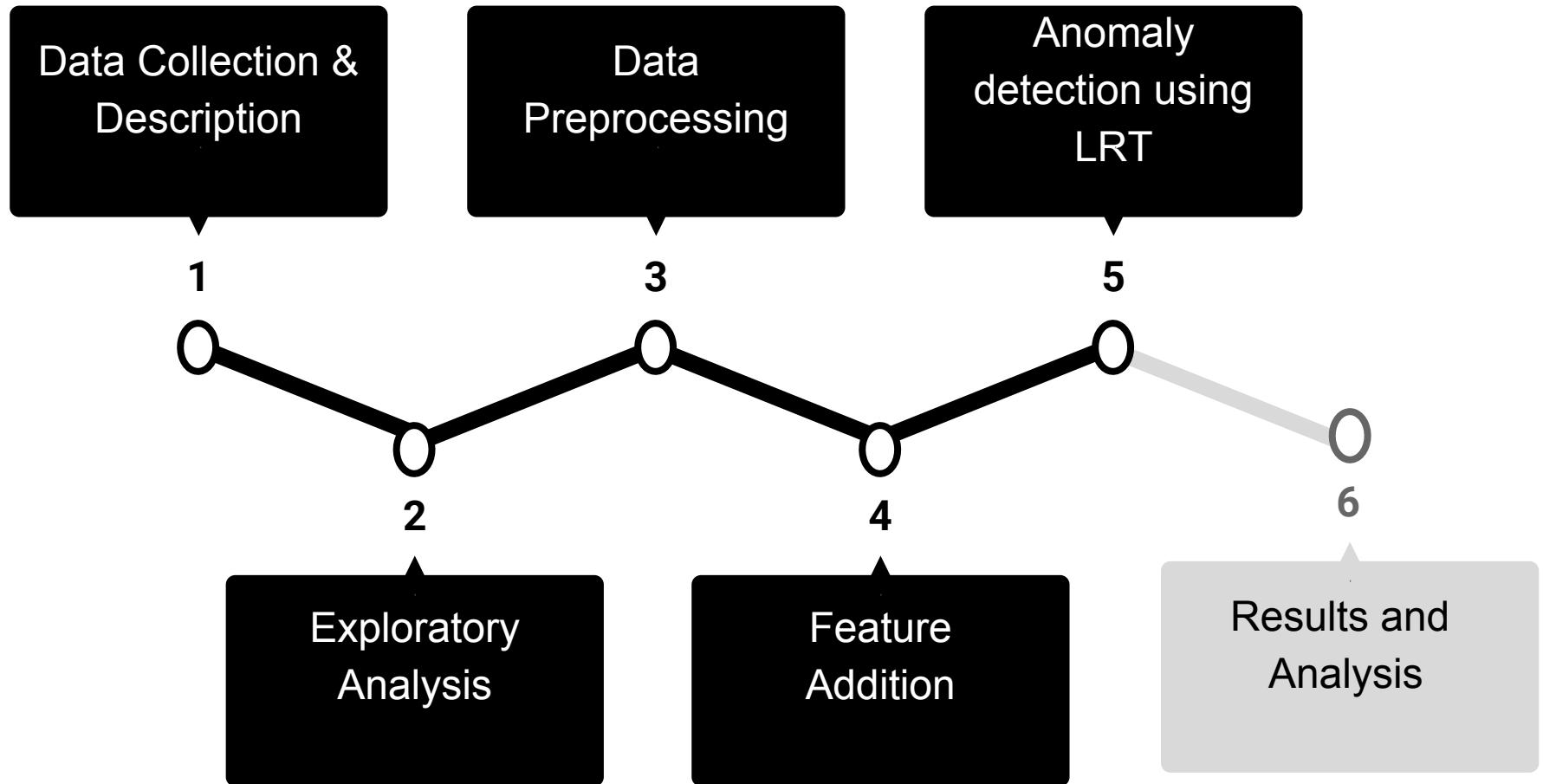


**K means Cluster Label Map  
with Full Data**



**Cluster Label map after  
removing small clusters**

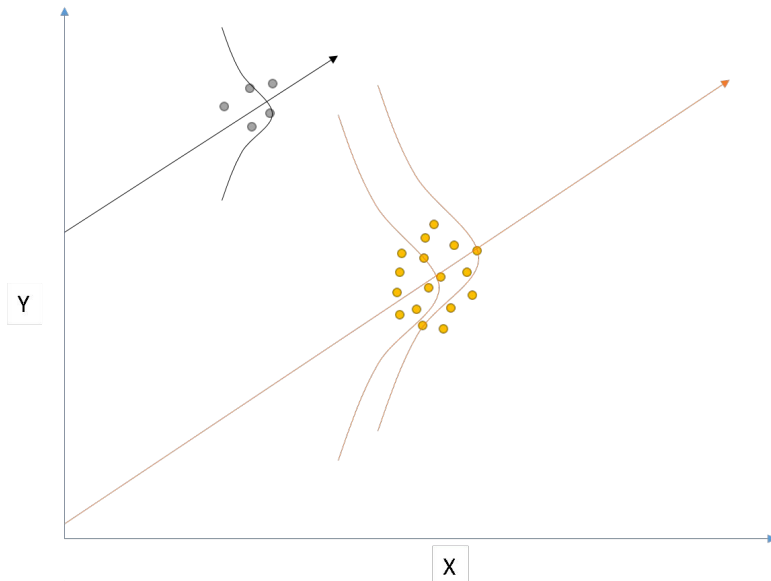
# Pipeline



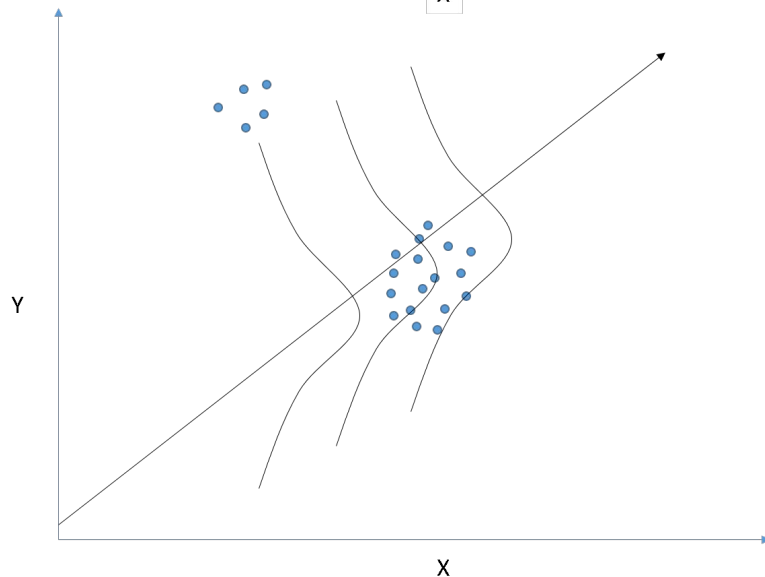
# What is the Likelihood Ratio Test ?



# Likelihood Ratio Test



$$\lambda = \frac{L(\theta_s | X_s) L(\theta_{\bar{s}} | X_{\bar{s}})}{L(\theta | X)}$$



Ratio of likelihoods between:

- Product of anomaly specific model and non-anomaly model
- Global model

# How do we Model the Data for LRT ?



# Generalized Linear Model (GLM)

The model that encompasses a group of regressions including linear regression and logistic regression.

Consists of three parts:

1. Exponential family that predicted value follows
2. Linear predictors (i.e.  $b_1x_1 + b_2x_2$ )
3. Link function that maps linear predictors to predicted variables

Examples:

Linear Regression: Predicted follows normal with an identity link

Logistic Regression: Predicted follows Bernoulli with a logit (or inverse sigmoid) link

# Data Subsampling

Assumption : Data is homogeneous, it models similarly for all subsets

Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday

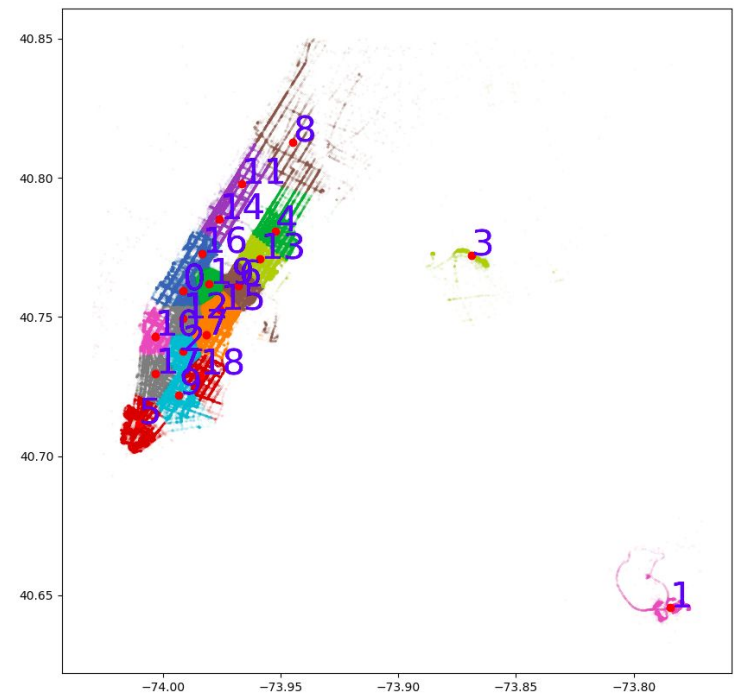
**Day Sample**



**Hour Sample - 8 am - 12 am**

# Model 1 - Spatial Anomalies

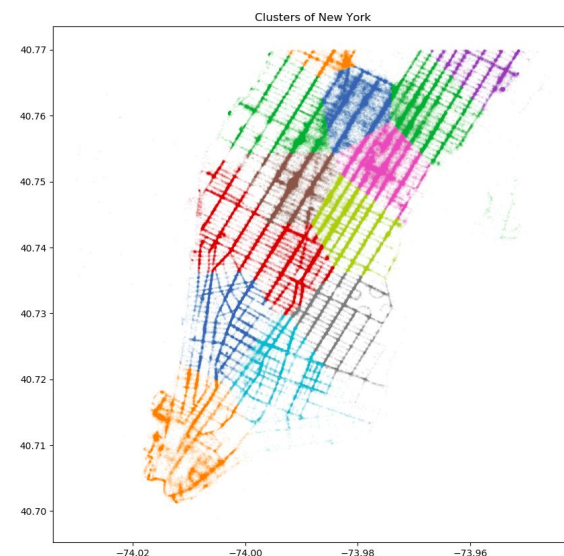
- Subset data by spatial information
  - Use the K-Means clusters performed in pre-processing
- Model all data using generalized linear model (GLM)
- For each different region, model data within the region and outside of the region, using same GLM configurations
- Compute the likelihood ratio for each region



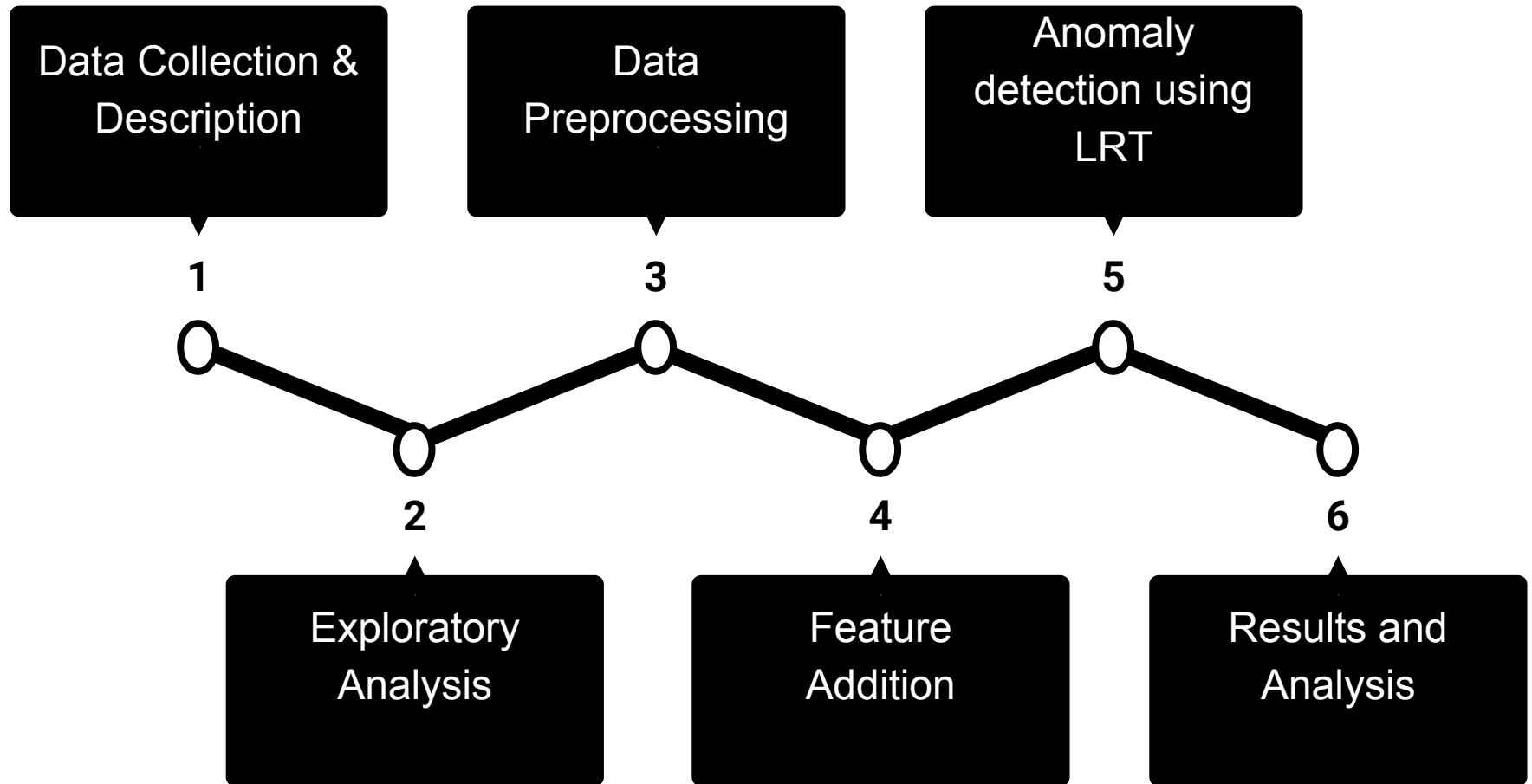


## Model 2 - Temporal Anomalies

- Subset data by Temporal information
  - Consider only Lower Manhattan Region
  - Use variable day of year
- Model all data using generalized linear model (GLM)
- For each different time segment, model data within the time segment and outside of the time segment, using same GLM configurations
- Compute the likelihood ratio for each time segment



# Pipeline



# Demo

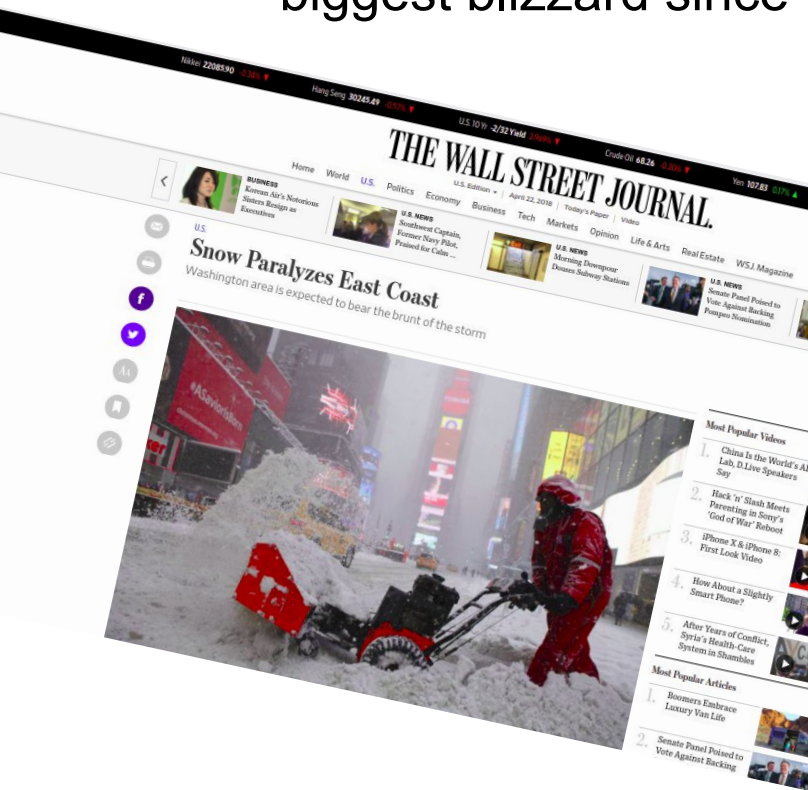
# Results and Conclusion

- *Spatial Analysis*
  - Top two anomalous regions were the JFK and La Guardia Airports in the city



# Results and Conclusion

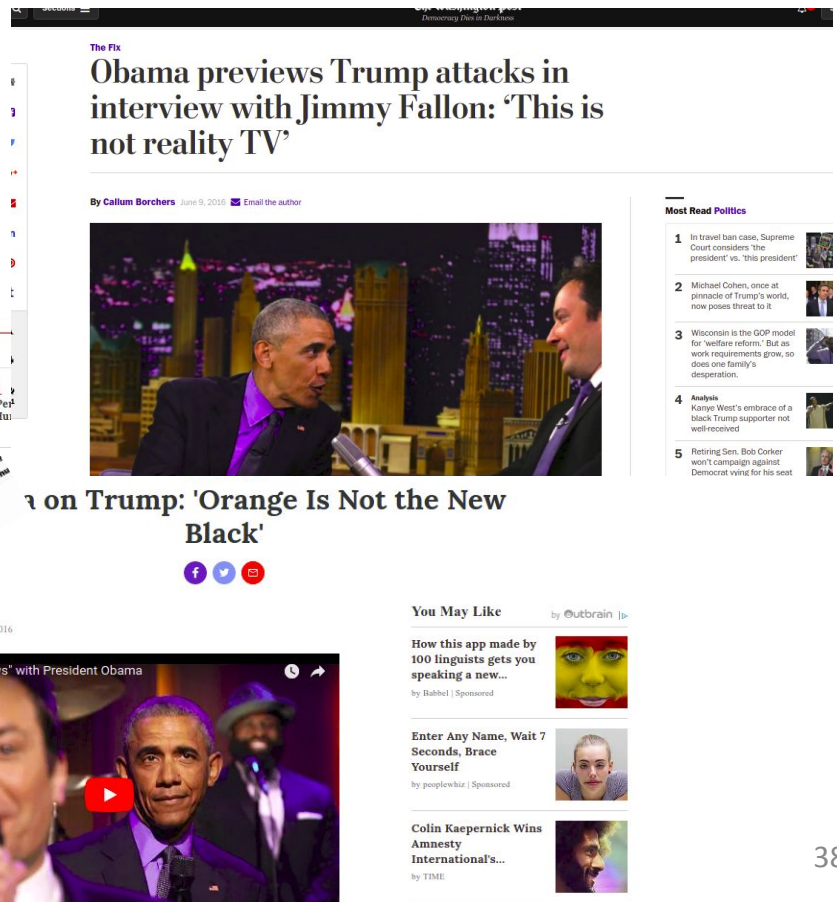
- *Temporal Analysis*
  - Most anomalous - January 26th - After New York was hit by biggest blizzard since 1869.



<https://www.nytimes.com/video/nyregion/100000003473176/christie-on-new-jerseys-preparations.html>

# Results and Conclusion

- *Temporal Analysis*
  - Followed by June 8th - President Obama tapes a show with Jimmy Fallon in Time Square





- Followed by May 16 - Fire under Metro North track in Manhattan blocking the services in and out of Grand Central



## Future Work

- Spatio-temporal analysis(Computationally intensive)
- Considering seasonality during temporal analysis
- Addressing positive correlation between data points and their likelihood values.

## Project Learnings

- Different Modeling Strategies - MLE , GLM
- Likelihood Ratio Test and ways to incorporate it with NY Taxi cab data