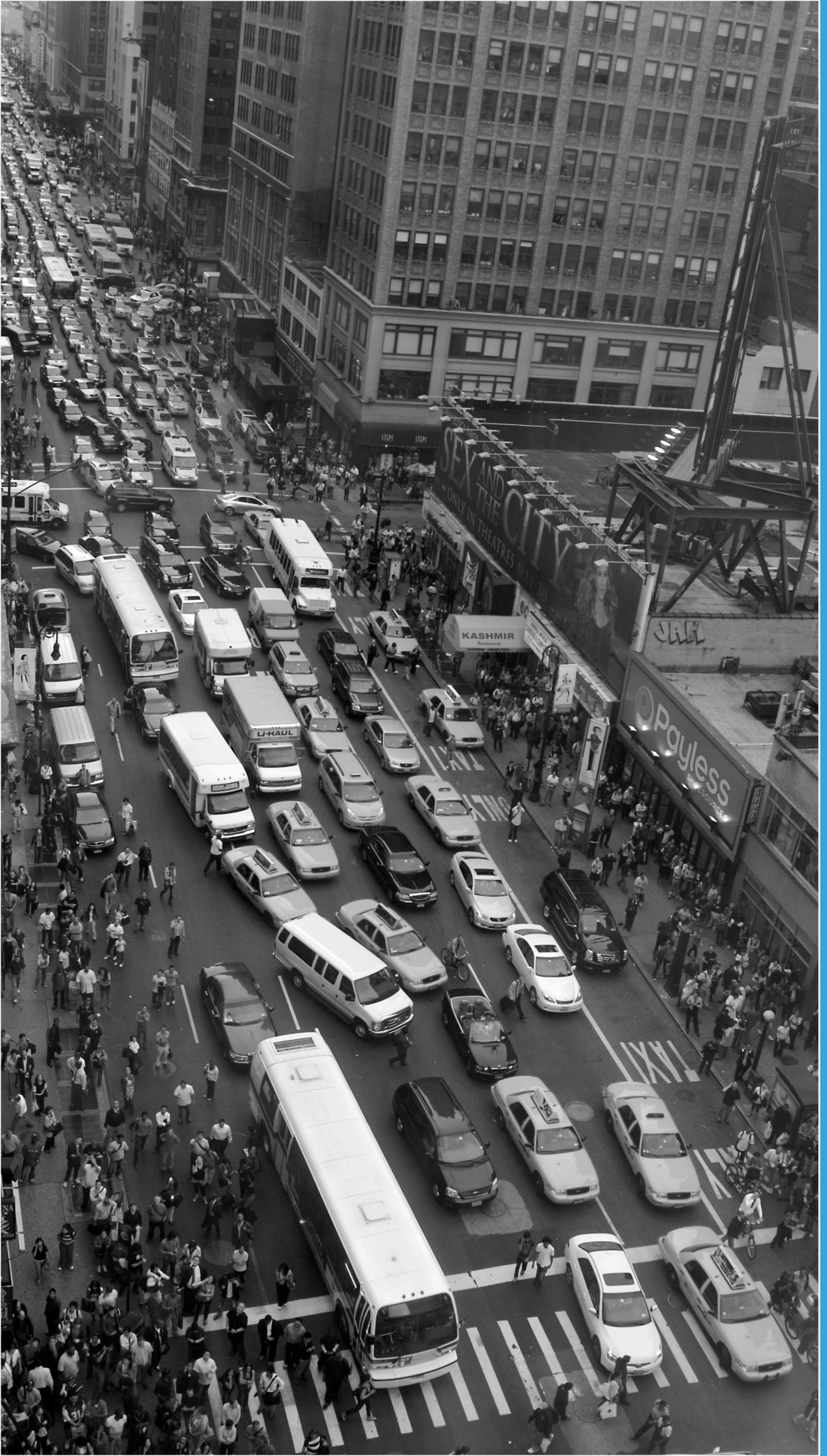
NEW YORK CITY CAB FARE

THE ADVANTAGE OF DEEP LEARNING

COREY WADE, SEPTEMBER, 2018



I LOVE TRAFFIC. IT'S FANTASTIC. NEW YORK TRAFFIC IS SO RELAXING.

Chris Kattan

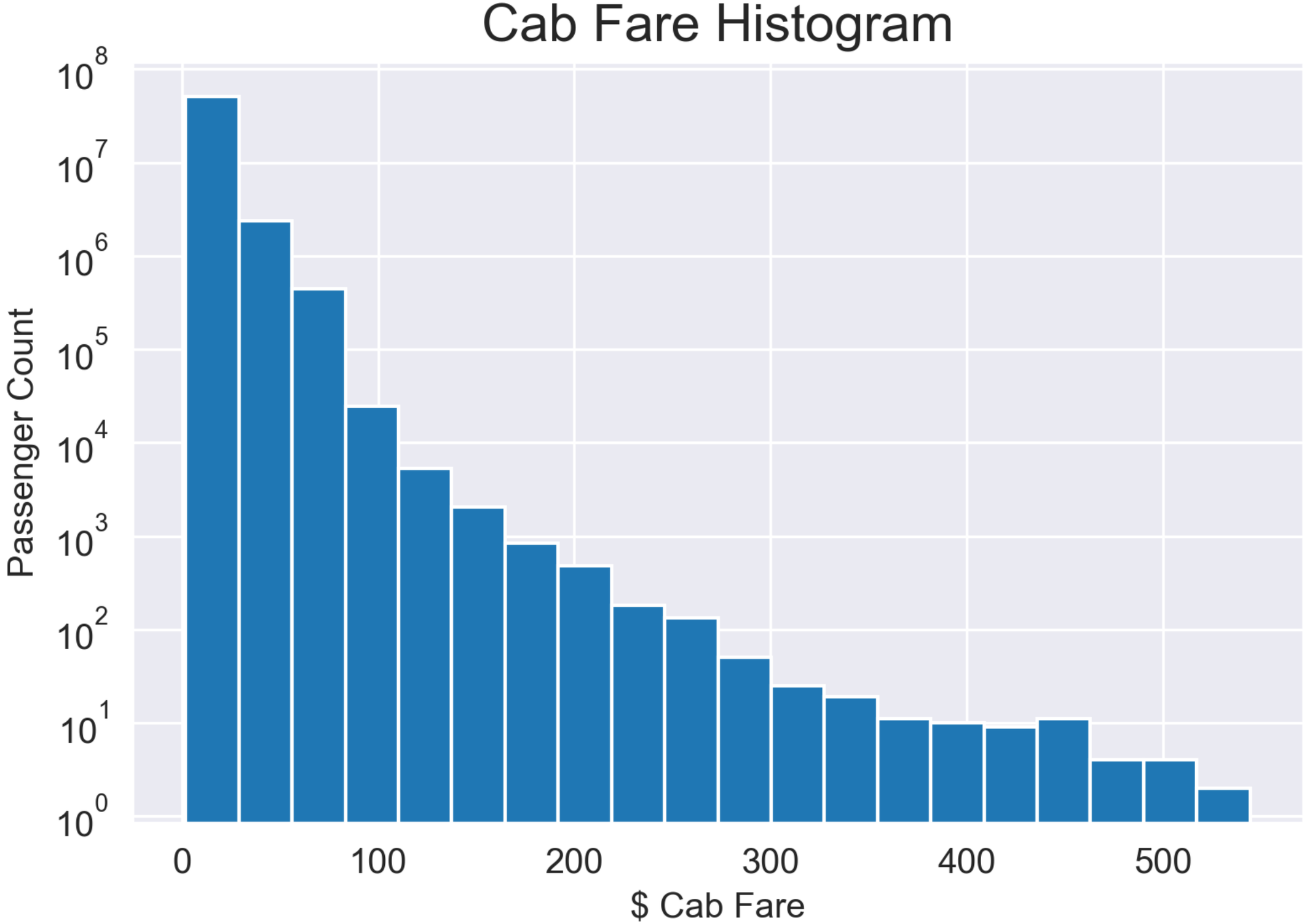
Alain Robert ascend of New York Times Building – 12 – 8th Avenue, gridlocked from 40th to 34th.png,, Wikimedia

NEW YORK CITY CAB FARE DATASET

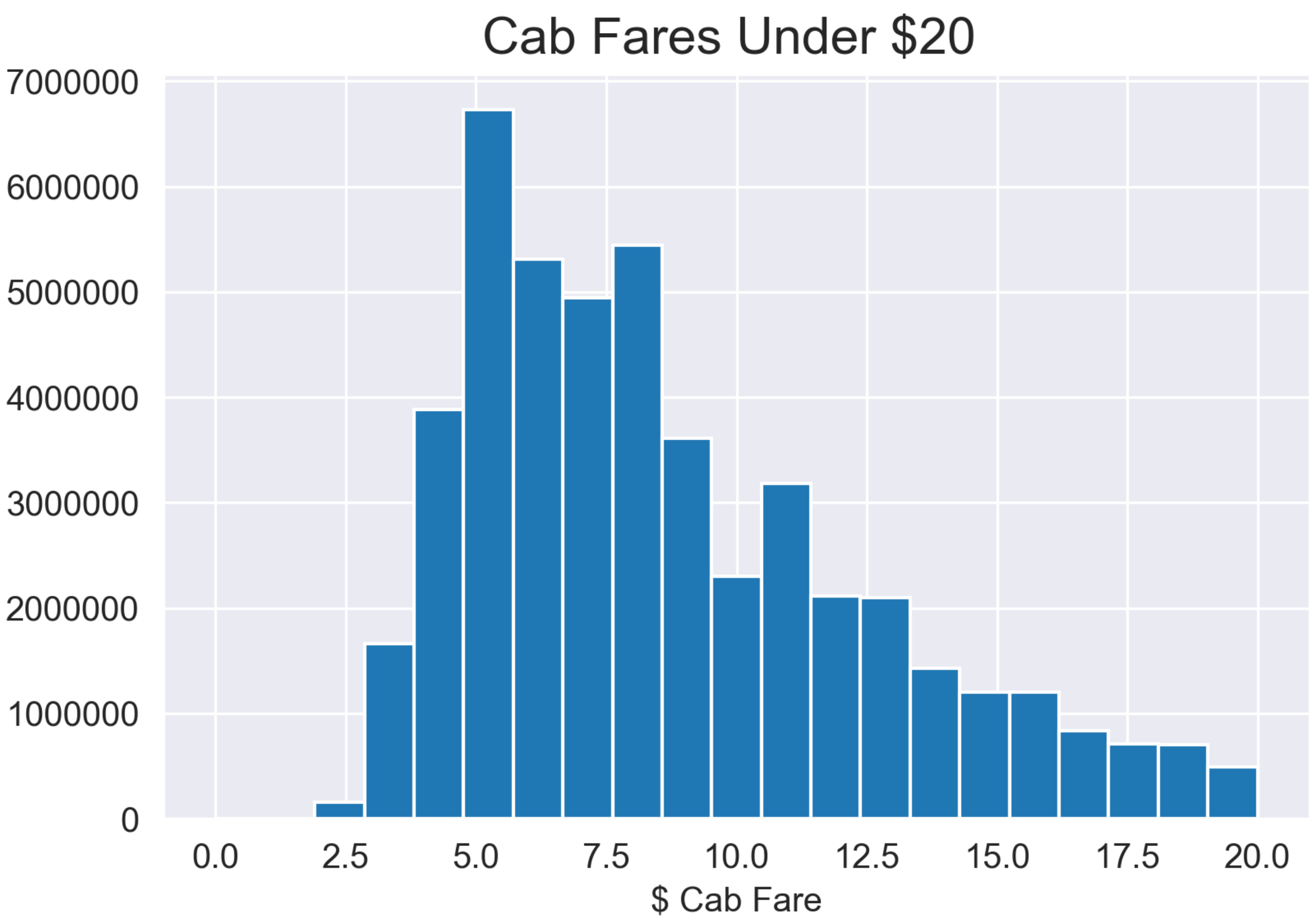
- Kaggle Competition sponsored by Google/Coursera.
- 55+ million rows.
- Years include 2009-2015.
- Goal: predict cab fare.
- Given: latitude/longitude of pickup/drop-off, timestamp of pickup, and passenger_count.
- That's all.

CAB FARE FACTS & FABRICATIONS

- Mean fare: $11.35.
- Median fare: $8.50.
- Max fare: $93,963.36.
- Min fare: -$300.00.
- According to city data, current min cab fare is $2.50.
- Errors/Outliers need work.



Note that the graph is a log scale. Cab fares are very right skewed.



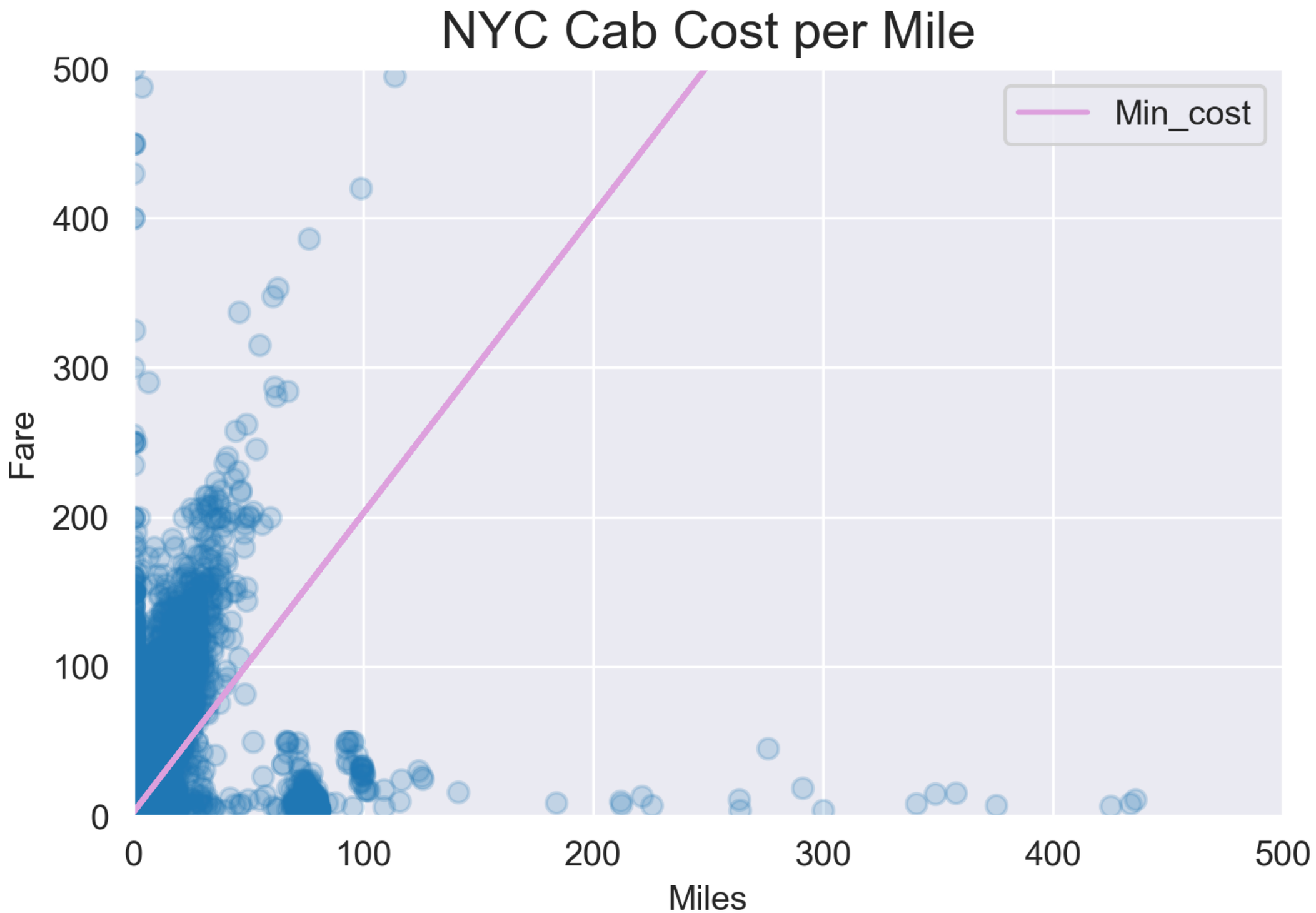
It looks like the majority of fares are between 4 and 10 dollars.

ELIMINATING ERRORS & OUTLIERS

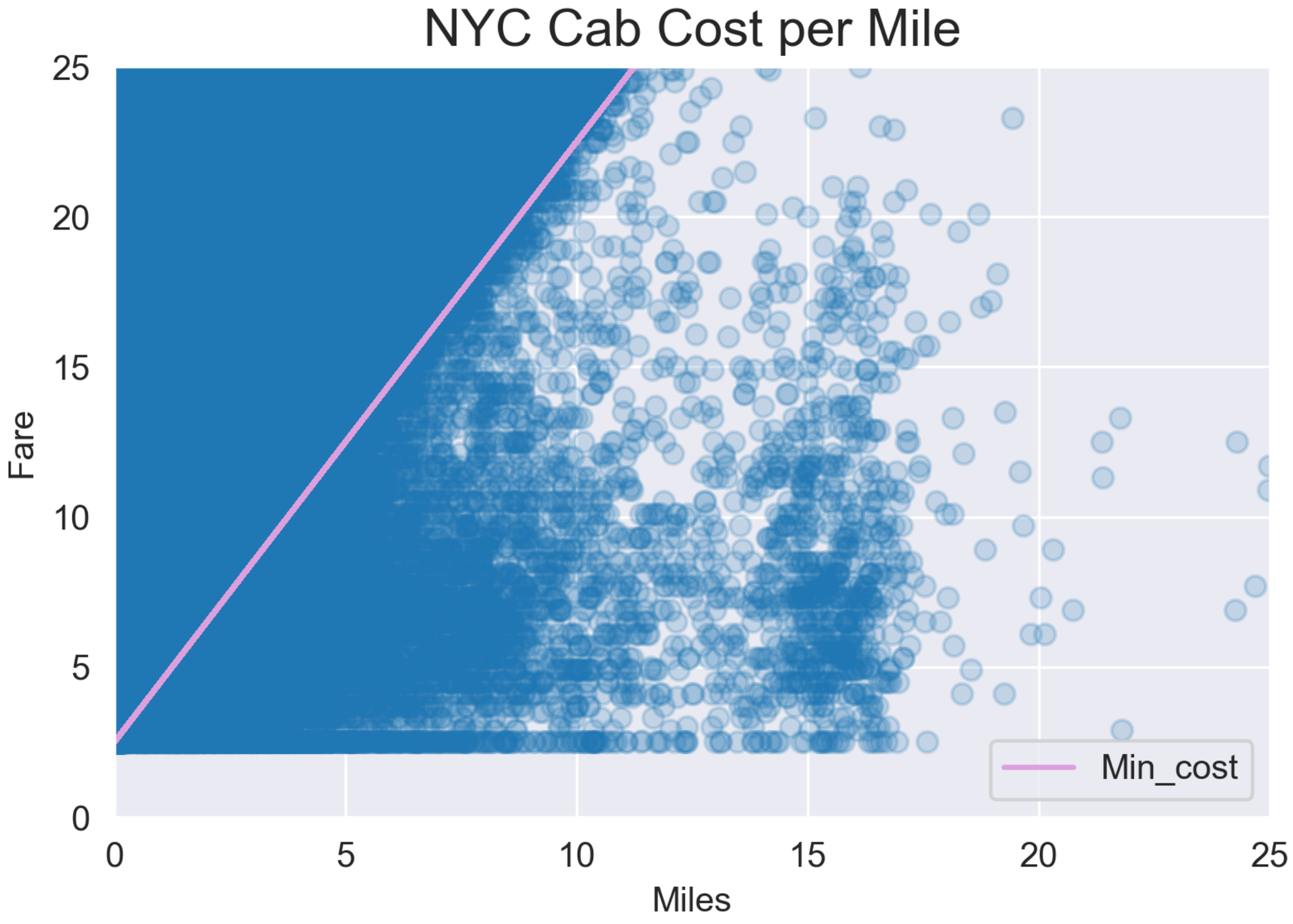
- Eliminate all NaN values.
  - With 55,000,000 rows, this is safe.
- Eliminate cab fares under $2.50.
  - This min is revealed by the histogram and confirmed by city data.
- Eliminate cab fares that do not start or end in NYC.
  - Need to find NYC latitude & longitudes.
- Convert latitude & longitude pickup & drop-off to distance.
  - Can be used to find unrealistic outliers.

DISTANCE METRICS

- Euclidean Distance measures the distance squared (Pythagorean) between 2 points. Ideal for flat surfaces.
- Taxicab Distance (Manhattan) measures the absolute value distance between 2 points. Realistic measure for city blocks.
- Spherical Distance measures the geometric distance between 2 points on a spherical surface. Sensible for surface distance.
- Vincenty Distance makes adjustments to spherical distance to account for actual curvature of the Earth. Most sensible option.
- Euclidean Distance, perhaps not the most accurate, gave the best initial results. (Possibly due to Euclidean Functions used elsewhere.)



1) The min cost is a base-fare of $2.50 plus $2.00 per additional mile. All points under this line can be eliminated. 2) The most expensive fares traveled very few miles, and the fares that traveled very far were inexpensive.



Zooming in, we can see a striking difference above and below the Min_cost line.

FEATURE ENGINEERING

- Create Manhattan column by circumscribing Manhattan with quadrilateral using lat/lon coordinates.
- Create Newark, JFK columns with same approach.
- Create standard time columns using minutes, hours, day_of_week, month, and total seconds.
- Create additional time columns for morning rush, weekday surcharge, night surcharge, 15-minute intervals.
- Eliminate unrealistic max fares.

A DEEP LEARNING SYSTEM DOESN'T HAVE ANY EXPLANATORY POWER.

Geoffery Hinton

MACHINE LEARNING MODELS

- Linear Regression
- Ridge Regression
- Decision Trees
- Random Forests
- Light GBM
- Deep Learning Sequential
- Top Performers in Blue

DEEP LEARNING INTRODUCTION

- Keras is a high-level deep learning introduction to Tensor Flow.
- Standard inputs: X, y, nodes, batch_size, activation, optimizer, loss.
- The nodes are the number of hidden layers in an array. For example, [100,100,50], or [64, 32]. Any length and number is possible.
- Batch-size is the number of training examples used in each iteration, in my case, 32.
- Epochs are the number of iterations, often ranging from a half-dozen to thousands.
- Activation is the function used to start the run. 'Relu,' which converts negative values to 0, and accepts positive values as they are, is a popular option.
- The optimizer updates the model in response to the loss. Gradient Descent and Adam are two popular options.
- The loss for this particular example is the 'mean_squared_error'.

```
DEF DEEP_LEARNING(X_TRAIN, Y_TRAIN, NODES=[100,50,50], BATCH_SIZE=32,
ACTIVATION='RELU', OPTIMIZER='ADAM', LOSS='MEAN_SQUARED_ERROR'):
X, X_val, y, y_val = train_test_split(X_train, y_train, test_size=0.05)

n_cols = X.shape[1]

model = Sequential()

model.add(Dense(nodes[0], activation=activation, input_shape=(n_cols,)))    # First layer

for i in range(len(nodes)-1):     # Additional layers

        model.add(Dense(nodes[i+1], activation=activation, kernel_constraint=maxnorm(3)))

        model.add(Dropout(0.2))     # Regularization

model.add(Dense(1))      # Output layer

model.compile(optimizer=optimizer, loss=loss)

early_stopping_monitor = EarlyStopping(patience=3)

model.fit(X, y, validation_split=0.05, epochs=1000, batch_size=batch_size,
callbacks=[early_stopping_monitor])

score = model.evaluate(X_val, y_val)

rmse = np.sqrt(score)     # Root mean squared error
```

DEEP LEARNING RESULTS

```
Train on 2429118 samples, validate on 127849 samples
Epoch 1/1000
2429118/2429118 [==============================] - 107s 44us/step - loss: 12.4999 - val_loss: 9.7576
Epoch 2/1000
2429118/2429118 [==============================] - 108s 45us/step - loss: 10.7824 - val_loss: 9.6408
Epoch 3/1000
2429118/2429118 [==============================] - 111s 46us/step - loss: 10.5082 - val_loss: 9.3295
Epoch 4/1000
2429118/2429118 [==============================] - 100s 41us/step - loss: 10.3397 - val_loss: 9.0330
Epoch 5/1000
2429118/2429118 [==============================] - 96s 40us/step - loss: 10.2256 - val_loss: 9.4364
Epoch 6/1000
2429118/2429118 [==============================] - 96s 40us/step - loss: 10.1093 - val_loss: 8.9241
Epoch 7/1000
2429118/2429118 [==============================] - 97s 40us/step - loss: 9.9892 - val_loss: 8.9832
Epoch 8/1000
2429118/2429118 [==============================] - 97s 40us/step - loss: 9.9665 - val_loss: 12.1911
Epoch 9/1000
2429118/2429118 [==============================] - 97s 40us/step - loss: 9.9324 - val_loss: 9.0024
134578/134578 [==============================] - 2s 12us/step
3.060327543786993 7
Saved deep learning model as 'dl_model.json'
```

DEEP LEARNING HIGHLIGHTS

- Nodes are fun to experiment with. They can be long and low, [8, 8, 8, 8, 8, 8, 8, 8] or short and high, [32000]. It's worth trying a wide range of options.
- "Early Stopping" is a great option to stop epochs early when no improvement is shown over several rounds.
- "Dropout" is a standard regularization method to prevent overfitting. It selects a percentage of neurons to randomly remove after each round.
- Input and output layers are distinct from hidden middle layers.
- 'Loss' shows rmse for training data, 'val_loss' for validation set.
- Trained models can be saved for future use.

DEEP LEARNING ADVANTAGE

- I used 10% of the data due to the size. Deep Learning will perform better with more data.
- I achieved a top min RMSE of about 2.8 with Deep Learning, very close to optimized Random Forests and LightGBM.
- Deep Learning consistently outperformed Linear Regression and Decision Trees.
- Deep Learning has more layers of experimentation.
- Since more data gives better results, deep learning has the edge in the long run.

AND WHAT ABOUT KAGGLE?

. . . Top Third Finish!

REFERENCES

- Github Repository: https://github.com/coreyjwade/NYC_Cab_Fare.
- Kaggle Competition Link: https://www.kaggle.com/c/new-york-city-taxi-fare-prediction.
- Additional Photo Credits: https://www.flickr.com/photos/ugod/5329854658, https://creativecommons.org/licenses/by/2.0/, https://commons.wikimedia.org/wiki/File:52nd_Street,_New_York_City,_NY_0001_original.jpg, William P. Gottlieb.