1) Describe your data set, why you chose it, and what you are trying to predict with it

Before choosing my dataset, I had the idea of predicting cryptocurrency prices, but it was advised that times series prediction was out of the scope of this course. Then, I looked into predicting Inspection Scores from Restaurants in Manhattan, and again, it was not a good choice because the dataset did not have enough features to come up with a good analysis. Finally, I took the professor's recommendation to work with the dataset from StreetEasy about Rental Prediction in Manhattan. This one was a good choice because it has enough features, and it is large enough to run the ML models introduced in the class. Also, I decided to work with it because I was curious about the fluctuations in the rent prices in Manhattan. The dataset is composed of 3,539 rows and 18 columns, and my target variable is predicting the rent prices in Manhattan.

```
manhattan = pd.read_csv('manhattan.csv')
manhattan.shape
#below we can see our dataset has 3539 rows and 18 columns
```

```
(3539, 18)
```

2) Detail what you did to clean your data and any changes in the data representation that you applied. Discuss any challenges that arose during this process.

Before proceeding with the data cleaning, I split the dataset into the training and test set as indicated in the assignment instructions. I set the training dataset to have 66% of the data, and the test dataset to have 33%. My "y" variable as I mentioned before was the "rent", and my "X" was the everything, but "rent" since this variable was dropped because it is the target variable.

Then, I used pandas.isnull().sum() to find the null values. Luckily, this dataset did not have any nulls values, and I did not have to use IMPUTER in scikilearn to value replacement. In the pictures below, we can see the features of the dataset without any null values.

```
X_train_cleaned.isnull().sum() # not missing values
```

```
rental_id           0
bedrooms            0
bathrooms           0
size_sqft           0
min_to_subway       0
floor               0
building_age_yrs    0
no_fee              0
has_roofdeck        0
has_washer_dryer    0
has_doorman         0
has_elevator        0
has_dishwasher      0
has_patio           0
has_gym             0
neighborhood        0
borough             0
dtype: int64
```

```
X_train.info() #using info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2123 entries, 1491 to 2732
Data columns (total 17 columns):
rental_id           2123 non-null int64
bedrooms            2123 non-null float64
bathrooms           2123 non-null int64
size_sqft           2123 non-null int64
min_to_subway       2123 non-null int64
floor               2123 non-null float64
building_age_yrs    2123 non-null int64
no_fee              2123 non-null int64
has_roofdeck        2123 non-null int64
has_washer_dryer    2123 non-null int64
has_doorman         2123 non-null int64
has_elevator        2123 non-null int64
has_dishwasher      2123 non-null int64
has_patio           2123 non-null int64
has_gym             2123 non-null int64
neighborhood        2123 non-null object
borough             2123 non-null object
dtypes: float64(2), int64(13), object(2)
```

After looking at the shape of the data, I decided to drop the "borough" feature since the entire dataset is about Manhattan. I dropped this column from both my training and test sets. Another important step in the data exploration was using pandas.describe() to get the summary statistics of the data. It was another way to confirm that all my columns had the same number of count values. Then, I looked into the mean values of important features such as "bedrooms", "bathrooms", "has_elevator", "has_gym", and others since by intuition I thought the might critical features influencing the target variable in the dataset.

```
X_train.describe() #using describe()
```

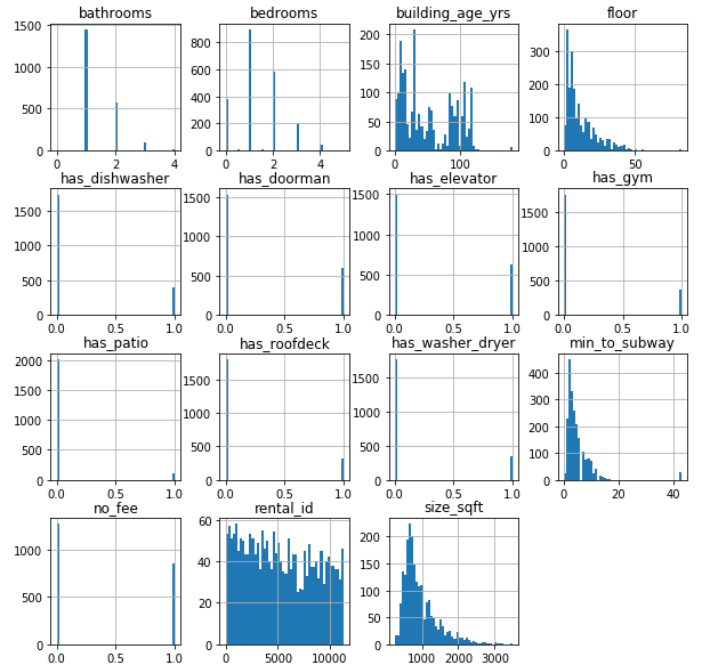
	rental_id	bedrooms	bathrooms	size_sqft	min_to_subway	floor	t
count	2123.000000	2123.000000	2123.000000	2123.000000	2123.000000	2123.000000	
mean	5280.276967	1.357984	1.375412	944.876119	4.879416	11.898022	
std	3316.279919	0.966555	0.603866	472.785072	5.285583	11.069380	

To my surprise, the mean number of bedrooms and bathrooms was very similar with 1.35 for bedrooms and 1.37 for bathrooms. With this information we can assume most apartments in Manhattan have 1 and 2 bedrooms and bathrooms. Also, it was interesting to see that the mean number for "min_to_subway" was 4.87. This means most apartments in Manhattan are relatively close to subway stations.

3) Discuss what you learned by visualizing your data

In the picture below we can see how the data looks when using pandas.hist():

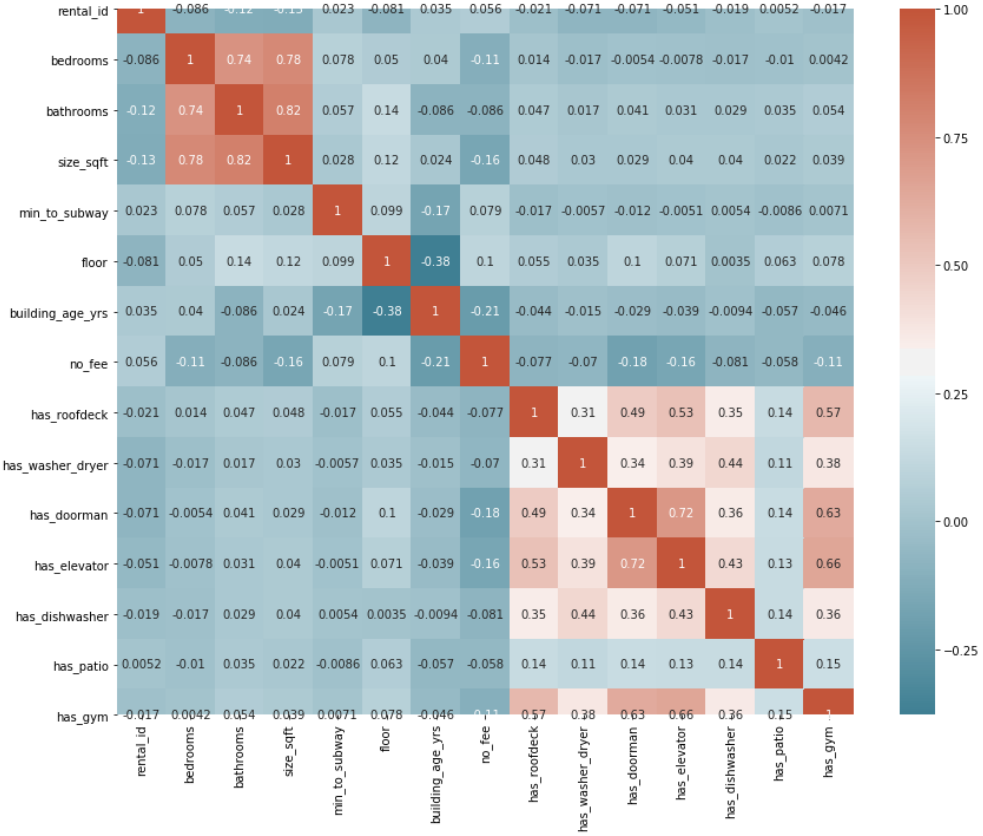
```
X_train_cleaned.hist(bins=50, figsize=(10, 10))
plt.show() #histograms
```



Here I can confirm my assumptions regarding the number of bedrooms and bathrooms in the dataset. According to the graph, most apartments have 1 and 2 bedrooms, as the same with the number of bathrooms. Looking at the "size_sqft" histogram we can see the data is positive skew to the right, and most apartments are around 1000 sqft with a mean value of 944. Also, it is surprising to see that the frequency of "building_age_yrs" is very high close to 100. We have around 25% of the dataset with buildings going over 100 years old where the mean value for this feature is 51. Another important fact to note is that very few apartments have gyms, elevators, doormen, patios, or dishwashers. Which makes sense because most of the apartments are relatively old. Years ago,

having this type of luxury was not a priority since it can be a factor in reducing the usable living space for the apartments.

I printed a correlation matrix to explore the significant levels among the features and the result was very intuitive. "Bedrooms", "bathrooms", and "size_sqft" were highly correlated among each other, which makes sense because the size will influence in the number of bedrooms and bathrooms in the apartments. Also, surprisingly "has_doorman" and "has_elevator" had a high correlation together with "has_gym" and "has_elevator".



Beside using the correlation matrix and the histogram, I also used the scatter_matrix from pandas, and the result was similar to the conclusions already mentioned above.

4) Describe your experiments with the two supervised learning algorithms you chose. This should include a brief description, in your own words, of what the algorithms do and the parameters that you adjusted. You should also report the relative performance of the algorithms on predicting your target attribute, reflecting on the reasons for any differences in performance between models and parameter settings.

The 2 supervised machine learning models I chose are the ***decision tree regressor*** and the ***lasso regression***. I will start by defining how the ***decision tree regressor*** works. Decision trees can either by used for classification and regression problems. The methodology behind it works similar to an if/else statement where the "decision nodes" are the questions and the "leaves" are the answers. Then, the data is classified in groups and the algorithm learns from these decisions and makes the group classifications. I decided to use the decision tree regressor is because of its main advantages. It is very easy to understand by non-experts analyst like myself, and by just picking one of the parameters such as max_depth, max_leaf_nodes, or min_samples_leaf it is sufficient to prevent overfitting. It is worth to mention that one of the disadvantages of this model is that it can result in poor generalizing performance even when using "pre-pruning" or choosing parameters.

To find the best parameter , in this case I picked the max_depth, I used the grid search from the sklearn library with my training set. The result was the best max_depth parameter was 4 and the best R2 was 0.75. The R2 is the metric that indicates the variance of the target variable in your model, if R2 the is close to 1, that means this is a good model to explain the variance of your data. When using the best parameter in my test set, in this case 4, I got and R2 score of 0.77. To test the differences, I ran the model again with a max_depth of 3 and the R2 was 0.75, lower than in the previous model, this way confirming the accuracy of the grid search result.

Overall, this model was not too bad in predicting the variance of my target variable with a 77% of accuracy.

As I mentioned previously, the other supervised machine learning model I used was the ***lasso regression***. I chose ***lasso*** because amount the others, linear and ridge regression, I thought it was the best fit for this experiment. Linear regression is known as not a very good fit because there are high chances of overfitting the model. It is recommended to use either ridge or lasso regression instead. The difference between ridge and lasso is the type of regularization. Ridge regression uses L2 regularization, which means the coefficients gets as small as possible close to zero, but not exactly zero. In the other hand, lasso regression uses regularization L1, which mean it can reduce the coefficients to be exactly zero looking for the optimal or more important features in the model omitting the features that might consider to be useless or irrelevant to improve performance of the model. In terms of parameter, when using regression look for the optimal alpha. The optimal alpha will vary depending on the type of dataset you are working on. As I did with the previous model, I used the grid search to find the optimal alpha. I used an array with values from 0 to 5 and, and the best alpha resulted to be 1 and best score of 0.81. Another important parameter is adjusting the max_iter value. When increasing the alpha, the max_iter should be reduced, and when decreasing the alpha it should be increased. When running the model with an alpha of 1, my score value R2 value was 0.82 for both training and testing sets. Surprisingly, I ran the model with other different alphas and max_iter, the R2 score was again 0.82 for both sets which I found to be very strange. Overall, the R2 indicates to be a relatively good model to predict the variance of my data with 82% of accuracy.

5) Describe your experiments using PCA for feature selection, discussing whether it improved any of your results with your best performing supervised learning algorithm.