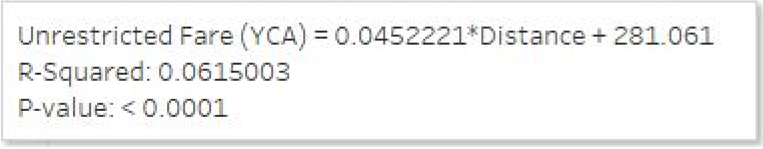
Linear Regression



Unrestricted Fare (YCA) = 0.0452221*Distance + 281.061
R-Squared: 0.0615003
P-value: < 0.0001

Formula

- Simply stated, when we don't travel any distance (i.e., X is 0) we pay $281.06 to the airline
- If we travel one mile:
  - $Unrestricted\ Fare\ (\$) = 0.0452221 * (1) + 281.061$
  - $Unrestricted\ Fare\ (\$) = 0.0452221 + 281.061$
  - $Unrestricted\ Fare\ (\$) = 281.11$
- If we travel 3000 miles:
  - $Unrestricted\ Fare\ (\$) = 0.0452221 * (3000) + 281.061$
  - $Unrestricted\ Fare\ (\$) = 135.663 + 281.061$
  - $Unrestricted\ Fare\ (\$) = 416.72$

<u>Note</u>: In the formula, typically, you'll see the dependent variable (what we're trying to predict) represented as $\hat{y}$ (or y-hat), this simply means that our results are an estimation of the value (i.e., the model is in no way 100% accurate for every value of X (or independent variable).

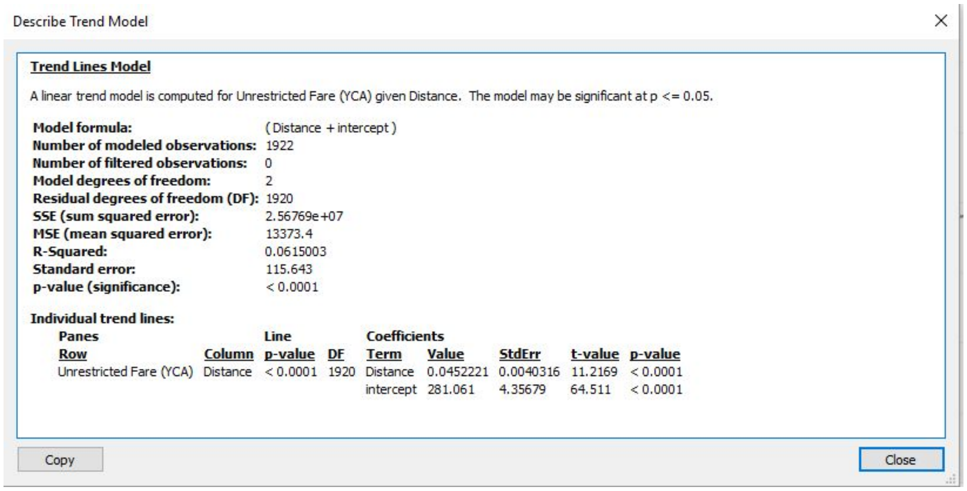
R^2

- Simply stated, the R^2 value tells us roughly how much of our data fell within the results of the line formed by the regression equation (closer to 1, we are achieving a perfect match, closer to 0, we have many data points that won't agree with the model formula)
- 0.0615003 or 6.15% (roughly 6.15% of our data points can be explained well with the formula)
  - Is this good or bad? Why?

p-value

- Simply stated, will a change in one variable (X) affect a change in the other (Y)
- If p-value > 0.05 then you can accept the null hypothesis (that there isn't a relationship)
- Conversely, a p-value ≤ 0.05 then we can reject the null hypothesis and conclude there is an affect
- p-value = < 0.0001

Go back to Tableau and click on the Trend Line, select Describe Model



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Trend Lines Model

A linear trend model is computed for Unrestricted Fare (YCA) given Distance.  The model may be significant at p <= 0.05.

Model formula:                      ( Distance + intercept )
Number of modeled observations:     1922
Number of filtered observations:    0
Model degrees of freedom:           2
Residual degrees of freedom (DF):   1920
SSE (sum squared error):            2.56769e+07
MSE (mean squared error):           13373.4
R-Squared:                          0.0615003
Standard error:                     115.643
p-value (significance):             < 0.0001

Individual trend lines:
     Panes                             Line               Coefficients
     Row                     Column    p-value    DF      Term       Value       StdErr      t-value   p-value
     Unrestricted Fare (YCA) Distance  < 0.0001   1920    Distance   0.0452221   0.0040316   11.2169   < 0.0001
                                                          intercept  281.061     4.35679     64.511    < 0.0001
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Sum of Squared Error (SSE)

- Simply stated, it's the actual values minus the predictive values, squared
- Squared because we want to make all values positive, and also emphasize large variations
- Our goal is for a low SSE which would indicate that actual and predicted values match up
- Our model SSE is 25,676,900

Standard Error

- Absolute difference to the trend line, on average
- Our goal is for a low Standard Error
- Our model Standard Error is 115.643, for this model we can expect that there is an additional $115.64 variation in the model formula that should be attributed to error

Question: What is the general theme can we conclude from this model?

Alternatives to Consider

- Weakness – Simple linear regression only accounts for a single independent variable
- Weakness – Data may not be linear (e.g., what if it's curvilinear), you may want to apply other type of model formulas to regression analysis
- In R or Python consider running multiple regression and review the affect of each coefficient's p-value

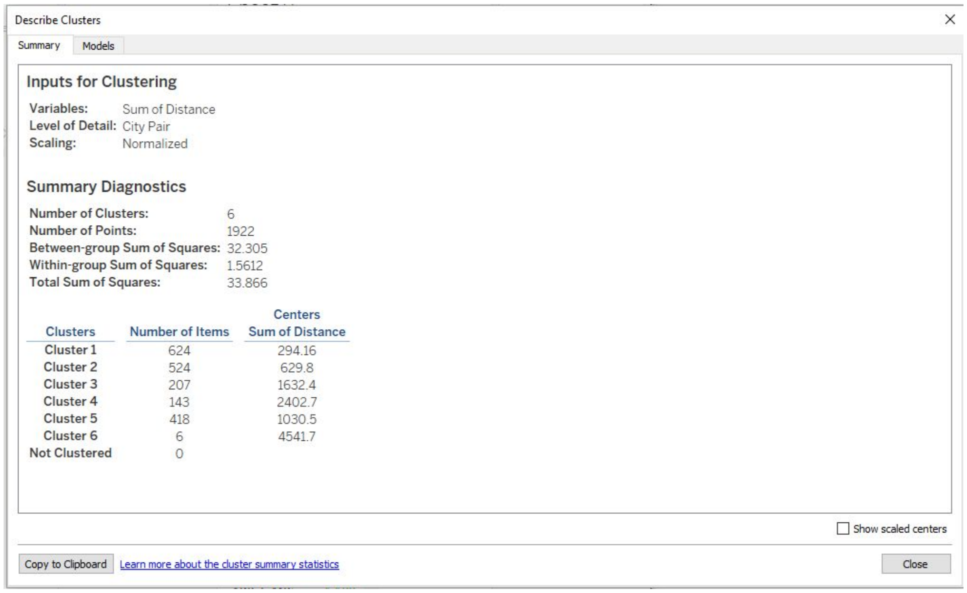
K-Means

Algorithm

The general steps for k-means are:

- Randomly select cluster centers (given required number of clusters)
- Assign each instance to the nearest center
- Recalculate the new cluster centers
- Reassign each instance to the new closest cluster center (I believe Tableau is using the Euclidean [straight line] distance)
- The process stops either when no instances are reassigned to a different cluster or when the specified number of maximum iterations is reached

- This is a good animated GIF regarding how the process works https://en.wikipedia.org/wiki/K-means_clustering#/media/File:K-means_convergence.gif



Inputs for Clustering

Variables: Sum of Distance
Level of Detail: City Pair
Scaling: Normalized

Summary Diagnostics

Number of Clusters: 6
Number of Points: 1922
Between-group Sum of Squares: 32.305
Within-group Sum of Squares: 1.5612
Total Sum of Squares: 33.866

Clusters	Number of Items	Centers Sum of Distance
Cluster 1	624	294.16
Cluster 2	524	629.8
Cluster 3	207	1632.4
Cluster 4	143	2402.7
Cluster 5	418	1030.5
Cluster 6	6	4541.7
Not Clustered	0	

Between-group sum of squares

- A metric quantifying the separation between clusters as a sum of squared distances between each cluster’s center (average value), weighted by the number of data points assigned to the cluster, and the center of the data set
- The larger the value, the better the separation between clusters (i.e., the cleaner the cluster are segmented, limited overlap)

Within-group sum of squares

- A metric quantifying the cohesion of clusters as a sum of squared distances between the center of each cluster and the individual marks in the cluster
- The smaller the value, the more cohesive the clusters (i.e., the tighter the cluster groups)

Total sum of squares

- Totals the between-group sum of squares and the within-group sum of squares.
- The ratio (between-group sum of squares)/(total sum of squares) gives the proportion of variance explained by the model.
- Values are between 0 and 1; larger values typically indicate a better model. However, you can increase this ratio just by increasing the number of clusters, so it could be misleading if you compare a five-cluster model with a three-cluster model using just this value.

Ideal K-clusters?

- Weakness -You must define how many clusters you want to include in your data
- In R or Python consider the Elbow Method, which plots the lift for each additional cluster in your dataset