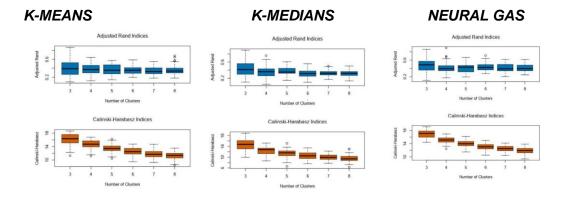
### **Project: Predictive Analytics Capstone**

# Task 1: Determine Store Formats for Existing Stores

1. What is the optimal number of store formats? How did you arrive at that number?

I have run k-centroids diagnostics tool for all three clustering methods for an internal validation. Below are the indices for each:



\*\*Clearly **3 clusters** have the highest mean-median in all methods with a fairly small range of 1<sup>st</sup> to 3<sup>rd</sup> quartiles.

2. How many stores fall into each store format?

Below is the clustering solution of K-Means (with z standardization applied, 3 clusters and 10 starting seeds)

Cluster	Size	Ave Distance	Max Distance	Separation
1	25	2.099985	4.823871	2.191566
2	35	2.475018	4.412367	1.947298
3	25	2.289004	3.585931	1.72574

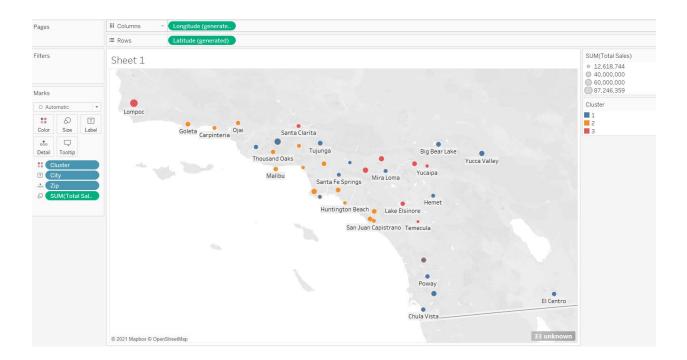
3. Based on the results of the clustering model, what is one way that the clusters differ from one another?

Comparing the percentage sales, cluster 1 has higher percent of General Merchandise sold, whereas Cluster 3 has a higher for Produce Sales.



4. Please provide a Tableau visualization (saved as a Tableau Public file) that shows the location of the stores, uses color to show cluster, and size to show total sales.

Below is the final map of stores, clusters are displayed with color&label, sales is shown with size. 33 cities remain unknown, could not resolve that issue with Tableau.



### Task 2: Formats for New Stores

1. What methodology did you use to predict the best store format for the new stores? Why did you choose that methodology? (Remember to Use a 20% validation sample with Random Seed = 3 to test differences in models.)

After data preprocessing and sampling, I applied Decision Tree, Forest Model and Boosted Model. Then compared all models with the Model Comparison tool using the validation data.

Boosted Model had the highest accuracy and F1 score in predictions.

# **Model Comparison Report**

Fit and error measures					
Model Decision_Tree RF_Model	Accuracy	F1	Accuracy_1	Accuracy_2	Accuracy_3
Decision_Tree	0.6471	0.6667	0.5000	1.0000	0.5000
RF_Model	0.7059	0.7500	0.5000	1.0000	0.7500
Boosted_Model	0.7647	0.8333	0.5000	1.0000	1.0000

2. What format do each of the 10 new stores fall into? Please fill in the table below.

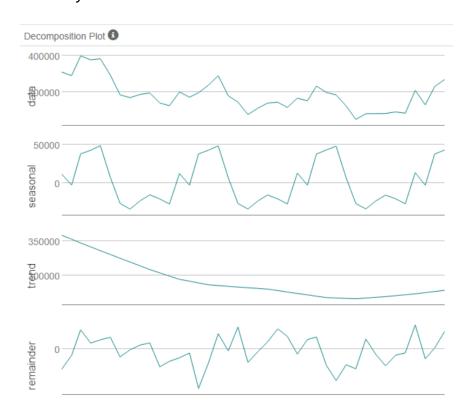
Store Number	Segment
S0086	1
S0087	2
S0088	1
S0089	2
S0090	2
S0091	3
S0092	2
S0093	3
S0094	2
S0095	2

## Task 3: Predicting Produce Sales

1. What type of ETS or ARIMA model did you use for each forecast? Use ETS(a,m,n) or ARIMA(ar, i, ma) notation. How did you come to that decision?

#### **ETS MODEL**

Applying Ts Plot to our monthy produce data, I observed yearly seasonality, with peaks decreasing every year. Seasonality component can be used multiplicatively. Variance of errors is changing. I decided to apply error component multiplicatively. Therefore my ETS Model is M-N-M



#### **ARIMA MODEL**

With the help of Ts Plot tool, I ended up with a stationary series after 1 seasonal differencing + 1 monthly differencing. Same with all 3 clusters.

With the use of ACF & PACF plots, I decided to use Method: ARIMA(0,1,2)(1,1,0)[12] for all clusters.

Using the TS Compare tool and the holdout set, below are the performances of both models.

#### **ETS Model**

Model	ME	RMSE	MAE	MPE	MAPE	MASE
MNM1	-932.0971					

### **Arima Model**

Model	ME	RMSE	MAE	MPE	MAPE	MASE
arima_1	-8384.712	11767.5	9513.072	-3.6775	4.1833	0.4568

Since RMSE is smaller with ETS Model, forecasted values are closer to predictions in this model. Besides, MASE is smaller compared to Arima model, which means ETS model is better at reducing error.

3. Please provide a table of your forecasts for existing and new stores. Also, provide visualization of your forecasts that includes historical data, existing stores forecasts, and new stores forecasts.

	New	Existing	
Month	Stores	Stores	
16-Jan	2,527,339	21,057,161	
16-Feb	2,446,155	20,415,892	
16-Mar	2,872,051	24,078,058	
16-Apr	2,722,158	22,670,736	
16-May	3,098,096	25,858,188	
16-Jun	3,150,603	26,288,437	
16-Jul	3,172,545	26,501,401	
16-Aug	2,814,270	23,303,548	
16-Sep	2,486,632	20,583,812	
16-Oct	2,434,261	20,160,032	
16-Nov	2,517,523	20,888,455	
16-Dec	2,491,340	20,891,395	

