Project: Predictive Analytics Capstone

Complete each section. When you are ready, save your file as a PDF document and submit it here:

https://coco.udacity.com/nanodegrees/nd008/locale/en-us/versions/1.0.0/parts/7271/project

Task 1: Determine Store Formats for Existing Stores

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

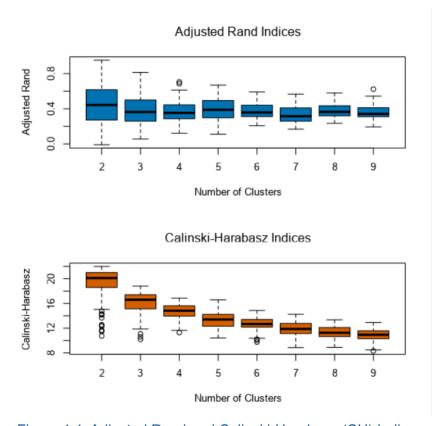


Figure 1.1: Adjusted Rand and Calinski-Harabasz (CH) Indices

The optimal number of store formats is 3.

In Figure 1.1, the Adjusted Rand Index has similar median values, and the cluster solutions with higher median values appear to have higher interquartile range values. In this case, the Adjusted Rand Index does not produce a conclusive result.

On the other hand, the Calinski-Harabasz (CH) Index shows that the 2-cluster solution produces the highest median value. However, this cluster solution has the largest range

and a considerable number of outliers. The 3-cluster solution is the best option as it has the second highest median and few outliers. Its range is much smaller than that of the 2-cluster solution, and its interquartile range is not much larger than those of the others.

2. How many stores fall into each store format?

Cluster Information:				
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

Figure 1.2: Cluster Information of the K-Means Clustering Solution

Cluster 1 and 3 have 25 stores each, while cluster 2 has 35 stores.

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

	Pct_Dry_Grocery	Pct_Dairy	Pct_Frozen_Food	Pct_Meat	Pct_Produce	Pct_Floral	Pct_Deli
1	0.528249	-0.215879	-0.261597	0.614147	-0.655027	-0.663872	0.824834
2	-0.594802	0.655893	0.435129	-0.384631	0.812883	0.71741	-0.46168
3	0.304474	-0.702372	-0.347583	-0.075664	-0.483009	-0.340502	-0.178481
	Pct_Bakery	Pct_General_Merchandise					
1	0.428226	-0.674769					
2	0.312878	-0.329045					
3	-0.866255	1.135432					

Figure 1.3: Variable Comparisons

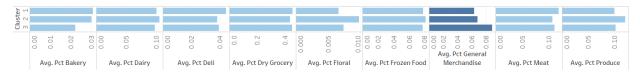


Figure 1.4: Average Percentage Sales for All Categories

Figure 1.3 shows that in Pct_General_Merchandise cluster 3 has the largest positive value, and cluster 1 has the largest negative value. Looking at Figure 1.4, we can see that on average stores in cluster 3 sell more general merchandise products.

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.



Figure 1.5: Map Showing the Locations of Existing Stores

Figure 1.5 visualises Cluster 1, 2 and 3 in blue, pink and green respectively. The sizes of the circles represent total sales, while the labels represent zip codes.

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.)

As this is a non-binary classification problem, three decision models are used: a decision tree, a forest model and a boosted model. These three models are then compared to find out which one fits the data best.

Layout								
	Model Comparison Report							
Fit a	Fit and error measures							
Mode	I A	ccuracy	F1	Accuracy_1	Accuracy_2	Accuracy_3		
DT_Ne	wStore	0.6471	0.6667	0.5000	1.0000	0.5000		
_	wStore	0.7059	0.7500	0.5000	1.0000	0.7500		
BM_Ne	wStore	0.7059	0.7500	0.5000	1.0000	0.7500		
Mode	l: model names in	the curre	nt compariso	n.				
Accur	acy: overall accura	cy, numb	er of correct p	predictions of al	l classes divided by	total sample		
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Figure 2.1: Model Comparison Report for Decision Tree Model (DT_NewStore), Forest

Model (FM_NewStore) and Boosted Model (BM_NewStore)

As we can see in Figure 2.1, accuracy of segments 1 and 2 are the same for all the models (Decision Tree, Forest Model and Boosted Model). Forest Model and Boosted Model have the highest overall accuracy, F1 score and accuracy of segment 3. Therefore, either Forest Model or Boosted Model can be used to predict the best store format for the new stores. I decided to choose the Boosted Model.

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	3
S0089	2
S0090	2
S0091	3
S0092	2
S0093	3
S0094	2
S0095	2

Segment 1 has 1 new store, Segment 2 has 6 new stores, and Segment 3 has 3 new stores.

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(M,N,M) is used for each forecast.

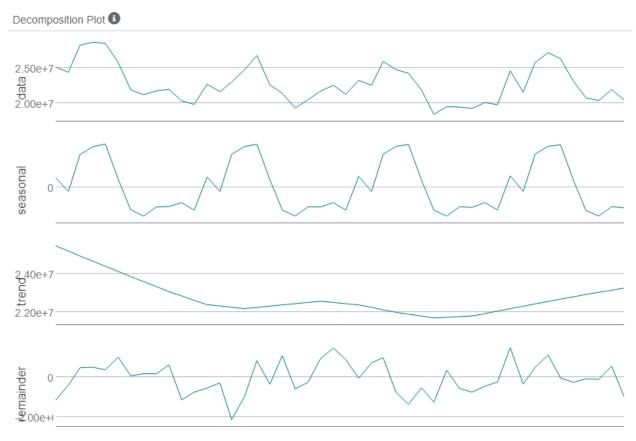


Figure 3.1: Decomposition Plot

Figure 3.1 shows a time series broken down into its three components: seasonality, trend and error. As the seasonality plot changes in magnitude (i.e. the peaks are decreasing), the seasonality is applied multiplicatively (M). On the other hand, the time series does not have a trend (N) as the line is decreasing significantly, increasing a little, decreasing a little and then increasing considerably. Additionally, as the error plot fluctuates between larger and smaller errors and therefore does not have a constant variance, the error is applied multiplicatively (M).

ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
3502.9443415	969051.6076376	787577.7006835	-0.1381187	3.4677635	0.4396486	0.0077488

Figure 3.2: In-sample error measures of ETS(M,N,M)

ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
-102530.8325034	1042209.8528363	738087.5530941	-0.5465069	3.3006311	0.4120218	-0.1854462

Figure 3.3: In-sample error measures of ARIMA(1,0,0)(1,1,0)[12]

(As for the ARIMA model, the non-seasonal component has an autoregressive term of 1,

a differencing term of 0 and a moving average term of 0. In addition, its seasonal component has 12 periods in each season, an autoregressive term of 1, a differencing term of 1 and a moving average term of 0.)

When comparing the in-sample error measures in Figure 3.2 and 3.3, we focus on RMSE (Root Mean Squared Error) and MASE (Mean Absolute Scaled Error). RMSE shows how many standard deviations from the mean the forecasted values fall, whereas MASE measures the relative reduction in error compared to a naive model. The ETS model has a lower RMSE and a slightly higher MASE.

Model	ME	RMSE	MAE	MPE	MAPE	MASE
	-21581.13					
ARIMA	-604232.29	1050239.2	928412	-2.6156	4.0942	0.5463

Figure 3.4: Accuracy Measures of ETS(M,N,M) and ARIMA(1,0,0)(1,1,0)[12]

Looking at the models' ability to predict the holdout sample (in Figure 3.4), we see that the ETS model has better predictive qualities. The ME (Mean Error), RMSE, MAE (Mean Absolute Error), MPE (Mean Percentage Error), MAPE (Mean Absolute Percentage Error) and MASE of the ETS model are closer to 0.

In-sample errors are training errors. The training data is used to estimate any parameters of a forecasting method, while the test data is used to evaluate its accuracy.

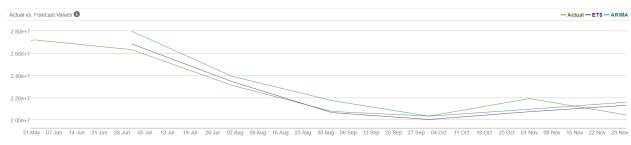


Figure 3.5: Actual vs Forecast Values

Figure 3.5 compares the forecasts provided by the ETS and ARIMA models by plotting them along with the actual values. It shows that the ETS forecasts on average are closer to the actual produce sales.

2. 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.

Month	New Stores	Existing Stores
month	11011 010100	=xioting otoroo

2,563,357.91	21,136,641.78
2,483,924.73	20,507,039.12
2,910,944.15	23,506,565.98
2,764,881.87	22,208,405.76
3,141,305.87	25,380,147.77
3,195,054.20	25,966,799.47
3,212,390.95	26,113,792.57
2,852,385.77	22,899,285.77
2,521,697.19	20,499,583.91
2,466,750.89	19,971,242.82
2,557,744.59	20,602,665.92
2,530,510.81	21,073,222.08
	2,483,924.73 2,910,944.15 2,764,881.87 3,141,305.87 3,195,054.20 3,212,390.95 2,852,385.77 2,521,697.19 2,466,750.89 2,557,744.59

The table above shows our produce forecasts for existing and new stores.

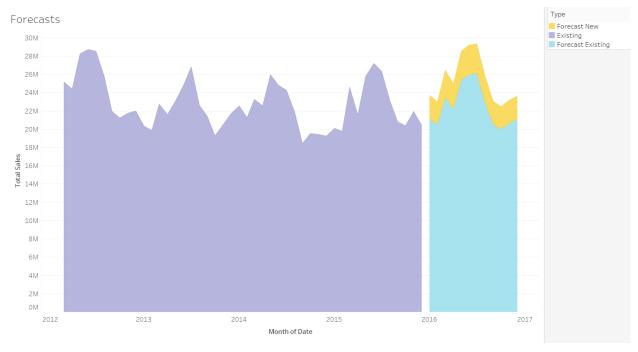


Figure 3.6: Visualisation of Forecasts

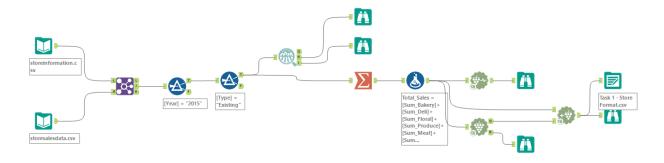
Figure 3.6 shows historical data, existing stores forecasts and new stores forecasts.

Before you submit

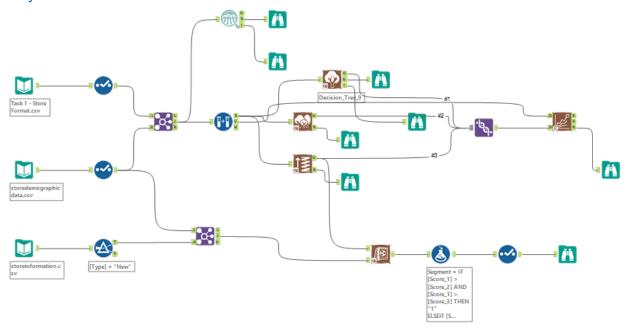
Please check your answers against the requirements of the project dictated by the rubric. Reviewers will use this rubric to grade your project.

Appendix

Alteryx workflow of Task 1:



Alteryx workflow of Task 2:



Alteryx workflow of Task 3:

