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?
   The optimal number of store formats is 3. This was arrived using the K-Centroid Diagnostics tool in Alteryx. AR and CH value for each of the cluster is compared, in which Median of 3 cluster is high. AR value 0.6936 and CH Value 30.7.

EA: Awesome: Good job using the CH and AR indices to find the optimal number of clusters.

K-Means Cluster Assessment Report

Summary Statistics

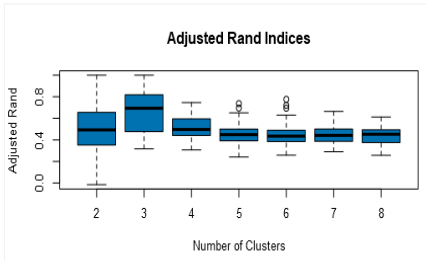
Adjusted Rand Indices:

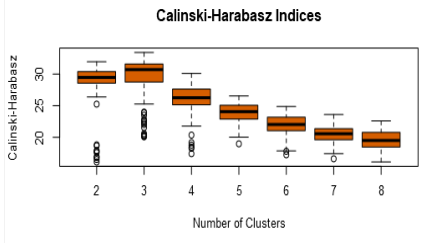
	2	3	4	5	6	7	8
Minimum	-0.0152	0.3171	0.3072	0.2412	0.2586	0.2903	0.2568
1st Quartile	0.352	0.4819	0.4431	0.3943	0.3896	0.3877	0.377
Median	0.4926	0.6936	0.4964	0.4487	0.4348	0.4417	0.4526
Mean	0.484	0.6575	0.5125	0.4623	0.4532	0.4498	0.4411
3rd Quartile	0.655	0.816	0.5913	0.4982	0.489	0.4997	0.491
Maximum	1	1	0.7458	0.7366	0.7762	0.6637	0.6118

Calinski-Harabasz Indices:

	2	3	4	5	6	7	8
Minimum	16.1	20.09	17.41	18.98	17.24	16.61	16.11
1st Quartile	28.61	28.76	25.16	22.91	21.05	19.61	18.46
Median	29.47	30.7	26.25	24.05	22.02	20.56	19.5
Mean	28.41	29.47	25.99	23.88	21.96	20.48	19.62
3rd Quartile	30.39	31.58	27.62	25.06	23.14	21.35	20.77
Maximum	31.95	33.41	30.09	26.53	24.87	23.6	22.59

Plots





2. How many stores fall into each store format?

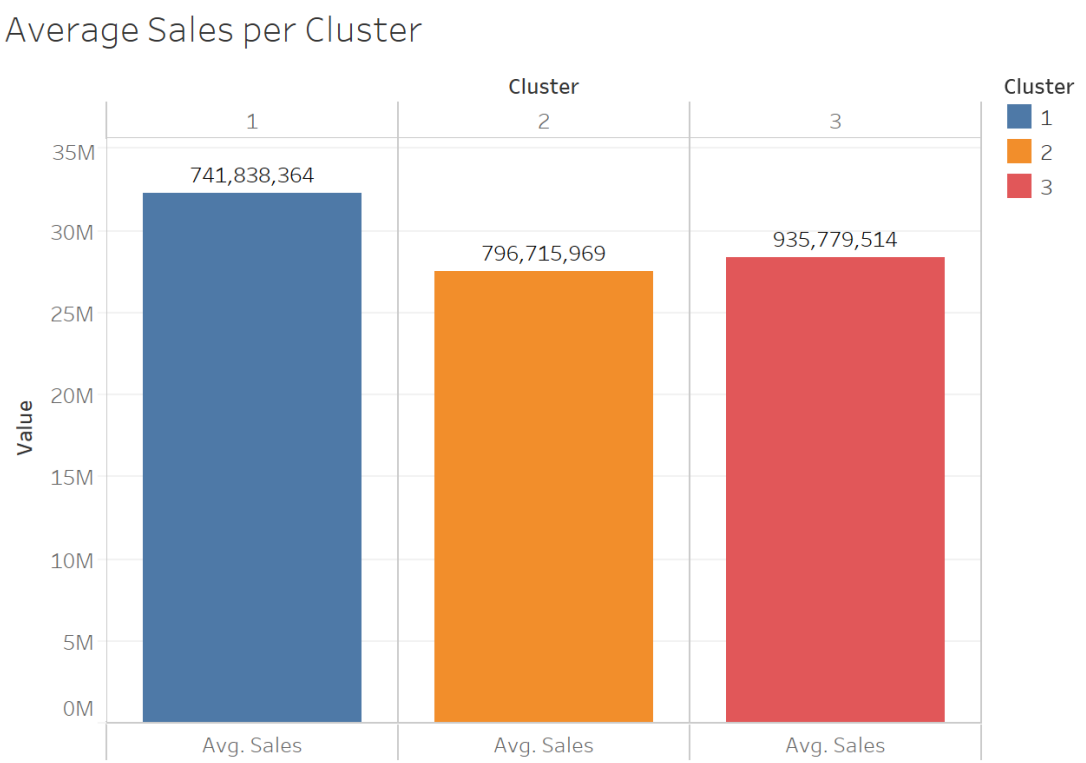
   Using K-Means, cluster analysis is performed and the distribution is as shown below.

Cluster Information:

Cluster	Size
1	23
2	29
3	33

EA: Awesome: The clustering model works well!

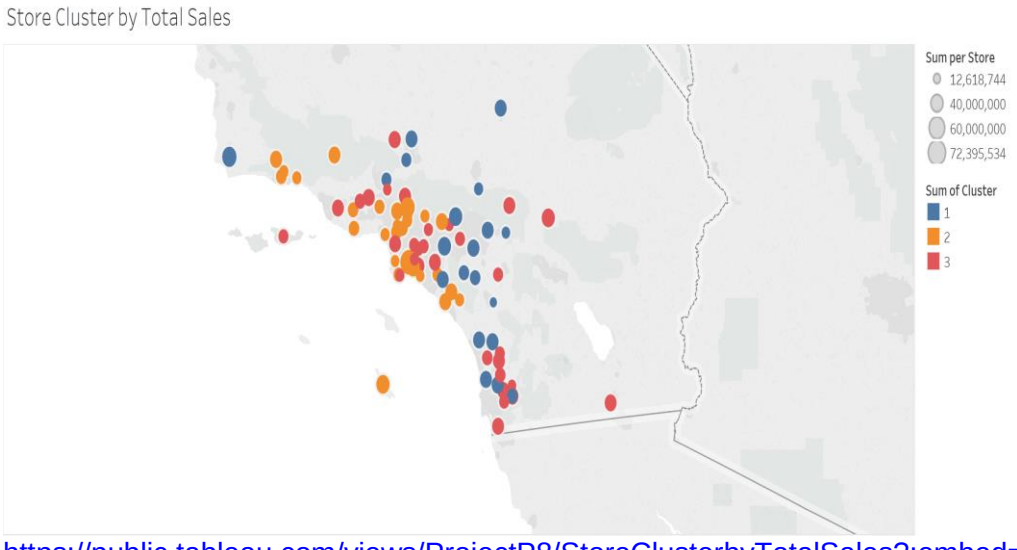
3. Based on the results of the clustering model, what is one way that the clusters differ from one another?



With the above results, we can notice that Stores in Cluster 1 sell more on an average when compared to the stores in the other two clusters.

EA: Awesome: Well done visualizing the difference!

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.



https://public.tableau.com/views/ProjectP8/StoreClusterbyTotalSales?:embed=y&:display_count=yes

EA: Suggestion: Good visualization, but the labels can be improved. For size, we should make clear that it is indicating sales. It's not so obvious what sum of stores mean.

Same for cluster. What do we mean with sum of cluster? Doesn't color just indicate which cluster a store belongs to?

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.)

   Constructed and compared the three models Decision Tree, Boosted Model and Forest Model and the Model comparison report is shown below.

Model Comparison Report

Fit and error measures

Model	Accuracy	F1	Accuracy_1	Accuracy_2	Accuracy_3
Decision_Tree	0.7059	0.7327	0.6000	0.6667	0.8333
Boosted_Model	0.8235	0.8543	0.8000	0.6667	1.0000
Forest_Model	0.8235	0.8251	0.7500	0.8000	0.8750

Model: model names in the current comparison.
Accuracy: overall accuracy, number of correct predictions of all classes divided by total sample number.
Accuracy_[class name]: accuracy of Class [class name], number of samples that are **correctly** predicted to be Class [class name] divided by number of samples predited to be Class [class name]
AUC: area under the ROC curve, only available for two-class classification.
F1: F1 score, precision * recall / (precision + recall)

Confusion matrix of Boosted_Model

	Actual_1	Actual_2	Actual_3
Predicted_1	4	0	1
Predicted_2	0	4	2
Predicted_3	0	0	6

Confusion matrix of Decision_Tree

	Actual_1	Actual_2	Actual_3
Predicted_1	3	0	2
Predicted_2	0	4	2
Predicted_3	1	0	5

Confusion matrix of Forest_Model

	Actual_1	Actual_2	Actual_3
Predicted_1	3	0	1
Predicted_2	0	4	1
Predicted_3	1	0	7

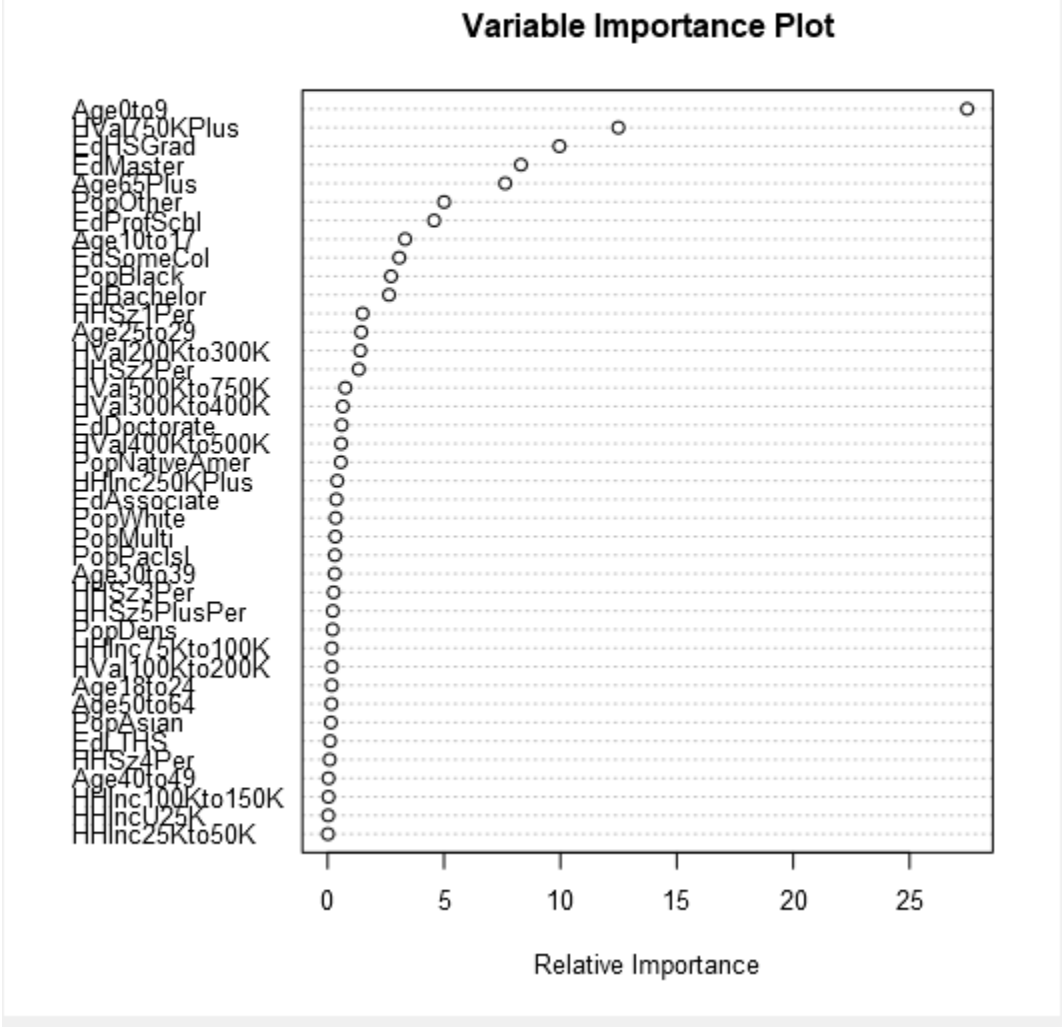
From the above report, we can observe that the overall accuracy of two of the models (Boosted Model and Forest Model) are the same. This is not uncommon when the datasets are small as in this case. Therefore, to pick the best model, I chose the F1 score. Based on the F1 score, I decided to use Boosted Model. To summarize the Boosted Model Overall accuracy – 82.35%, F1 score: 85.43%

EA: Awesome: Good analysis! Boosted model is the best choice.

2. What are the three most important variables that help explain the relationship between demographic indicators and store formats? Please include a visualization.

   Below is the variable importance plot for the Boosted model.

Plots:



Based on the above plot, the 3 most important variables for the Boosted model are:

Variable
Age0to9
HVal750KPlus
EdHSGrad

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

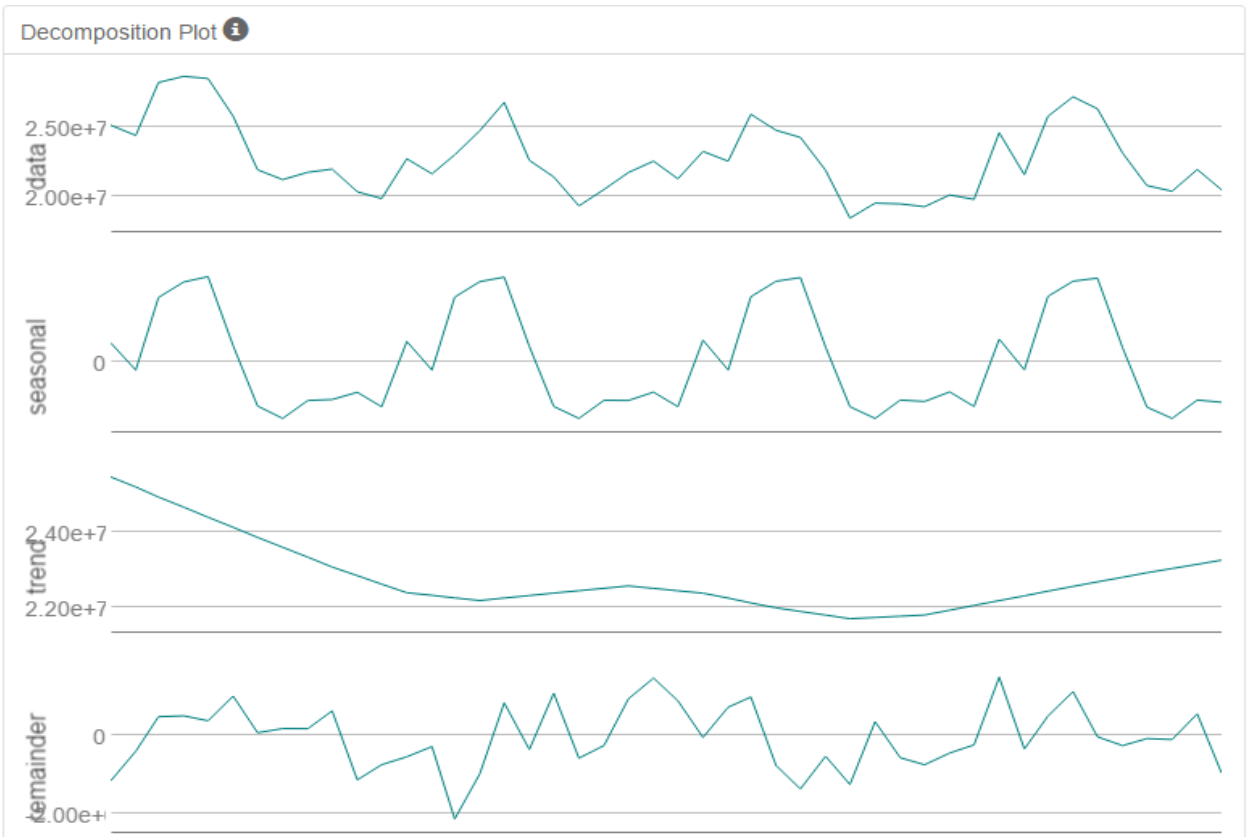
Record #	Store	Cluster
1	S0086	1
2	S0087	2
3	S0088	3
4	S0089	2
5	S0090	2
6	S0091	1
7	S0092	2
8	S0093	1
9	S0094	2
10	S0095	2

EA: Awesome: All stores are correctly classified!

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?

   To forecast sales for existing stores, Decomposition plot with the Produce data was generated with the TS-Plot tool.



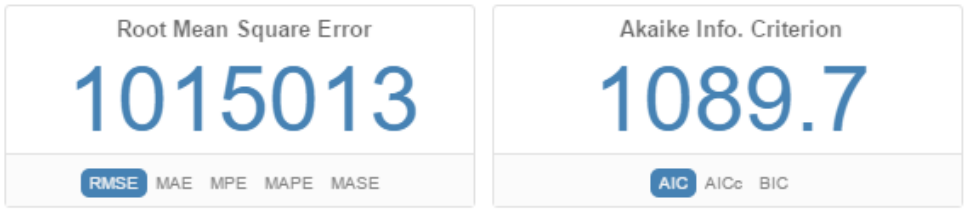
ETS:

From the above Decomposition plot, we can derive the ETS Model.
Error: The Remainder/Error is increasing in variance and hence it would be Multiplicative.
Trend: There is no clear trend, hence it would be None.
Seasonality: The sales fluctuate in similar intervals, thereby indicating the presence of Seasonality. It can also be observed that the Sales is also growing, hence it would be Multiplicative.

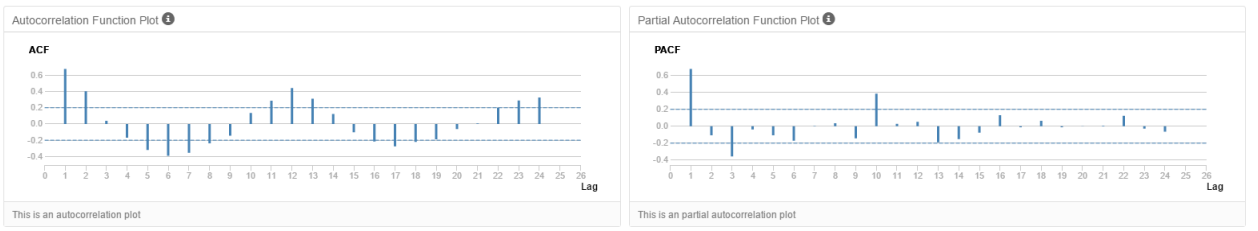
EA: Awesome:

Good job justifying the choice of ETS type, by referring to the decomposition plot.

So, based on the above observations, the ETS Model would be ETS(M,N,M).

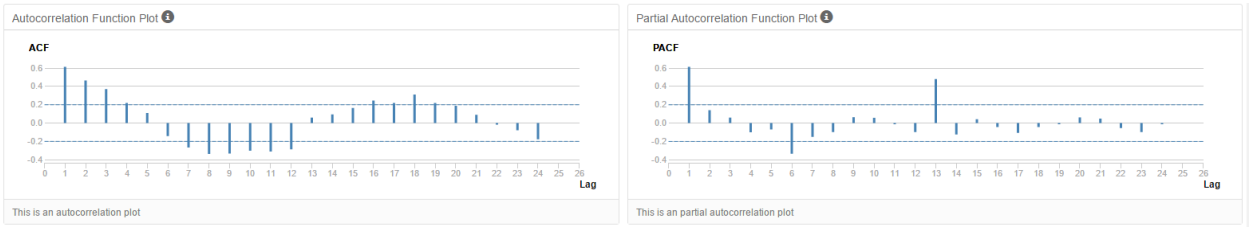


ARIMA:



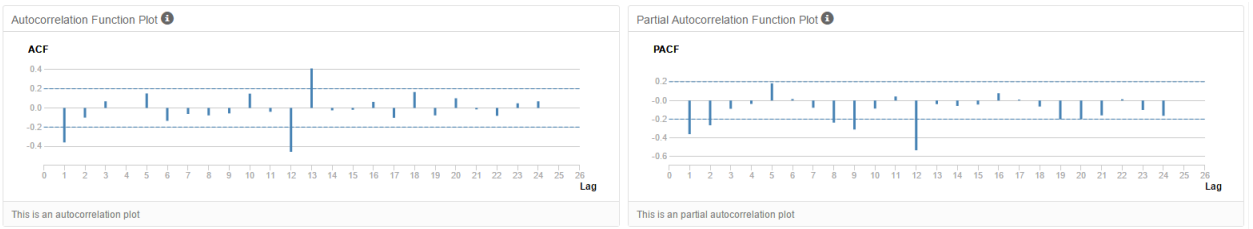
The ACF graph shows a gradual decline to zero with seasonal lag but there is high serial correlation, therefore it is required to be seasonally differenced. The PACF graph also shows high serial correlation after lag1, confirming the need to difference the dataset.

Seasonal Difference ACF & PACF:



The ACF graph shows positive co-relation at lag 1 and slow decay towards 0 with seasonal lags. However, the serial correlation of is still high. Therefore, we will need to seasonally difference it, to stationarize the time-series

First Seasonal Difference:



We can observe from the above chart the serial correlation has now subsidized and the time series is now stationary.

- Non-seasonal component: p=0 and q=1 as ACF negative and cuts off sharply, d=1 as mentioned above
- Seasonal component: P=0 and Q=1 as ACF negative at lags 1, 12 and D=1 as mentioned above.
- m=12, because holdout sample = 12

So, we have an ARIMA (0,1,1) (0,1,1)12 model.

Now, comparing the two Model with the below RMSE, MAE, MPE and MASE values, we can observe that ETS performs better than ARIMA. Also, the AIC value of ETS model is higher than the ARIMA Model. So, we will be using ETS model for further forecasting.

EA: Suggestion:

We are looking for low AIC values, but ETS is still the better model.

Record #	Model	ME	RMSE	MAE	MPE	MAPE	MASE	NA
1	ETS	1983592.6926	2226512.5538	1983592.6926	8.4729	8.4729	1.2691	[Null]
2	ARIMA	2878344.1382	3061362.1418	2878344.1382	12.5815	12.5815	1.8416	[Null]

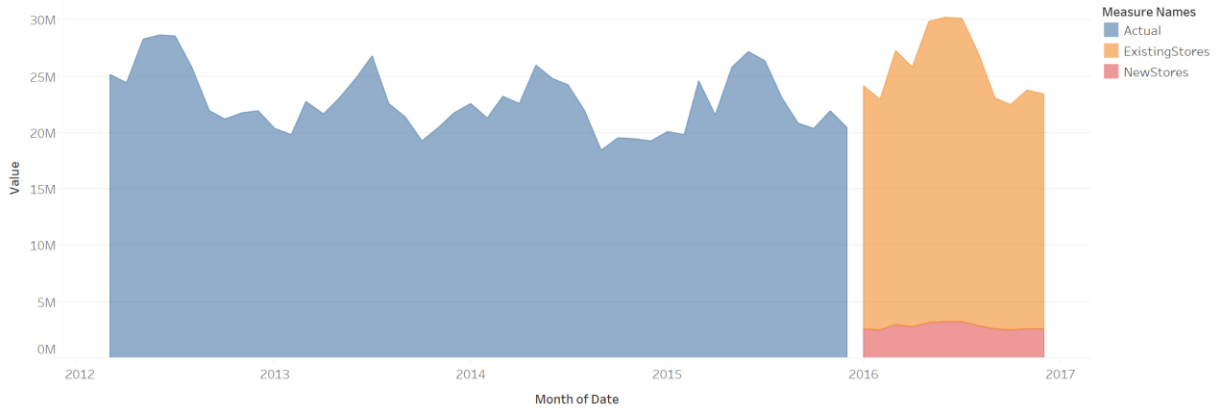
2. Please provide a Tableau Dashboard (saved as a Tableau Public file) that includes a table and a plot of the three-monthly forecasts; one for existing, one for new, and one for all stores. Please name the tab in the Tableau file "Task 3".

Record #	Period	Sub_Period	Forecast_for_NewStores	Forecast_for_ExistingStores	Total_Forecast
1	2016	1	2587450.851495	21539936.007498	24127386.858993
2	2016	2	2477352.892393	20413770.601348	22891123.493741
3	2016	3	2913185.23625	24325953.097608	27239138.333858
4	2016	4	2775745.609767	22993466.348591	25769211.958358
5	2016	5	3150866.835326	26691951.419141	29842818.254466
6	2016	6	3188922.00336	26989964.010544	30178886.013904
7	2016	7	3214745.646251	26948630.764769	30163376.41102
8	2016	8	2866348.663392	24091579.349105	26957928.012497
9	2016	9	2538726.84886	20523492.408639	23062219.257499
10	2016	10	2488148.287462	20011748.668594	22499896.956055
11	2016	11	2595270.386448	21177435.485843	23772705.872291
12	2016	12	2573396.62905	20855799.109612	23429195.738661

Forecast for Produce

Month of Date	ExistingStores	NewStores
January 2016	21,539,936	2,587,451
February 2016	20,413,771	2,477,353
March 2016	24,325,953	2,913,185
April 2016	22,993,466	2,775,746
May 2016	26,691,951	3,150,867
June 2016	26,989,964	3,188,922
July 2016	26,948,631	3,214,746
August 2016	24,091,579	2,866,349
September 2016	20,523,492	2,538,727
October 2016	20,011,749	2,488,148
November 2016	21,177,435	2,595,270
December 2016	20,855,799	2,573,397

Actual and Forecast over Time



https://public.tableau.com/views/CapstoneProject_14/ForecastTable?:embed=y&:display_count=yes

EA: Awesome:

Both the existing stores forecast and the new stores forecast are accurate!
Nice job with the visualization.