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MISK ACADEMY

UDACITY

TECH LAB

Predictive Analytics for Business

Project #6 Combining Predictive Techniques

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INTRODUCTION

Time Series Forecasting Summary

ETS Models

ETS models are designed to forecast time series data by observing the trend and seasonality patterns in a time series, and projecting those trends into the future.

STEP 1: TIME SERIES DECOMPOSITION PLOT

A time series decomposition plot allows you to observe the seasonality, trend, and error/remainder terms of a time series.

Useful Alteryx Tool: TS Plot

STEP 2: DETERMINE ERROR, TREND, AND SEASONALITY

An ETS model has three main components: error, trend, and seasonality. Each can be applied either additively, multiplicatively, or not at all.

Trend - If the trend plot is linear then we apply it additively (A). If the trend line grows or shrinks exponentially, we apply it multiplicatively (M). If there is no clear trend, no trend component is included (N).

Seasonal - If the peaks and valleys for seasonality are constant over time, we apply it additively (A). If the size of the seasonal fluctuations tends to increase or decrease with the level of time series, we apply it multiplicatively (M). If there is no seasonality, it is not applied (N).

Error - If the error plot has constant variance over time (peaks and valleys are about the same size), we apply it additively (A). If the error plot is fluctuating between large and small errors over time, we apply it multiplicatively (M).

Useful Alteryx Tool: TS Plot

STEP 3: BUILD AND VALIDATE THE ETS MODEL

Build the ETS model using the components determined in step 2. You can use internal and external validation to validate the quality of the model.

Internal validation: Look at in-sample error measures, particularly RMSE (Root-Mean-Square Error) and MASE (Mean Absolute Scaled Error).

External validation: Determine the accuracy measures by comparing the forecasted values with the holdout sample. This is especially important for comparing ETS models to other types of models, such as ARIMA.

Pick the ETS model with lowest AIC value. If the AIC values are comparable, use calculated errors to pick one that minimizes error the most. Many software tools will automate the selection of the model by minimizing AIC.

Useful Alteryx Tools: ETS, TS Compare

STEP 4: FORECAST!

Use the best ETS model to forecast for the desired time period. Make sure to add the holdout sample back into the model. Plot the results along with 80% and 95% confidence intervals.

Useful Alteryx Tool: TS Forecast

ARIMA Models

Summary: ARIMA which stands for Autoregressive Integrated Moving Average helps you forecast data for seasonal and nonseasonal data

STEP 1: TIME SERIES DECOMPOSITION PLOT

A time series decomposition plot allows you to observe the seasonality, trend, and error/remainder terms of a time series.

Useful Alteryx tool: TS Plot

STEP 2: DETERMINE THE ARIMA TERMS

Nonseasonal ARIMA models are displayed in the terms (p,d,q) which stand for p - periods to lag for, d - number of transformations used to make the data stationary, q - lags of the error component

Stationary - mean and variance are constant over time vs Non-Stationary - mean and variance change over time

Differencing - take the value in the current period and subtract it by the value from the previous period. You might have to do this several times to make the data stationary. This is the Integrated component which is d in the model terms.

Autocorrelation - How correlated a time series is with its past values, if positive at Lag-1 then AR if negative then MA

Partial Autocorrelation - The correlation between 2 variables controlling for the values of another set of variables. If the partial autocorrelation drops of quickly then AR terms, if it slowly decays then MA

Seasonal ARIMA models are denoted (p,d,q)(P,D,Q)m

These models may require seasonal differencing in addition to non-seasonal differencing. Seasonal differencing is when you subtract the value from a year previous of the current value.

Useful Alteryx tool: TS Plot

STEP 3: BUILD AND VALIDATE THE ARIMA MODEL

Build the ARIMA model using the terms determined in step 2. You can use internal and external validation to validate the quality of the model.

Internal validation: Look at in-sample error measures, particularly RMSE (Root-Mean-Square Error) and MASE (Mean Absolute Scaled Error).

External validation: Determine the accuracy measures by comparing the forecasted values with the holdout sample. This is especially important for comparing ARIMA models to other types of models, such as ETS.

Pick the ARIMA model with lowest AIC value. If the AIC values are comparable, use calculated errors to pick one that minimizes error the most. Many software tools will automate the selection of the model by minimizing AIC.

Useful Alteryx tools: ARIMA, TS Compare

STEP 4: FORECAST!

Use the best ARIMA model to forecast for the desired time period. Make sure to add the holdout sample back into the model. Plot the results along with 80% and 95% confidence intervals.

Useful Alteryx tool: TS Forecast

Segmentation and Clustering

K-Centroid Clustering

Summary: Cluster analysis identifies cohesive subgroups of observations within a dataset. It allows us to reduce a large number of observations into a smaller number of clusters.

STEP 1: SELECT APPROPRIATE VARIABLES

The first step is to understand the objectives for segmentation. Then, choose the appropriate variables that provide the information needed for clustering. A sophisticated cluster analysis cannot compensate for the poor choice of attributes.

STEP 2: DATA PREPARATION

Numeric data: Cluster analyses requires numeric data. Many non-numeric variables can be converted to numeric ones. Make sure to remove outliers as clustering algorithms are highly sensitive to outliers.

Variable reduction: This step often requires variable reduction techniques to combine variables that revolve around a particular theme. A common method is Principal Component Analysis (PCA), which reduces a set of related variables into few principal components (PCs) that explain most of the variances in the data. Rule of thumb is to use PCs that account for ~80% variance.

Scaling the data: Standardizing each variable using the z-score ensures that the results are not overly sensitive to variables with higher values.

Useful Alteryx Tool: Principal Components

STEP 3: DETERMINE THE NUMBER OF CLUSTERS

Use the AR and CH indices to determine the optimal method and number of clusters. Use a box and whisker plot. The higher the median and smaller the variation the better. Remember, clustering is an iterative process and may require comparing several models to arrive at a good solution.

Useful Alteryx Tool: K-Centroid Cluster Diagnostics

STEP 4: CREATE THE CLUSTERING MODEL

Select the variables, standardization process, clustering method, and number of clusters that gave the best solution. Create the cluster model and append the clusters to the dataset.

Useful Alteryx Tool: K-Centroid Cluster Analysis

STEP 5: VISUALIZE AND VALIDATE RESULTS

Visualization helps us determine the meaning and usefulness of the clustering solution. Use summary statistics to understand difference among clusters.

Validate the results: You can use internal validation and/or external validation. Plot the distribution of the validation variable for each cluster using box and whisker plot to visualize the differences.

Useful Alteryx Tool: Append Clusters

Data Visualizations in Tableau

I. Connecting to Data

In this section, you will get started with importing data into Tableau. Tableau public has fewer options, but paid versions of Tableau are quite extensive connecting directly to databases and cloud based data storage systems.

II. Combining Data

In this section, you will learn how to connect data from multiple sources for use in your visuals. If you are comfortable with SQL joins, this section should be second nature.

III. Worksheets

The visuals you create will be stored in worksheets. This is the template we will be working in for this course.

IV. Aggregations

Tableau performs aggregations of our data by default. In this section, you will learn more about how to work with different aggregations, as well as how to break your aggregations into a more granular level of the data.

V. Hierarchies

Hierarchies allow you to 'drill' into your data and questions at different levels. One of the easiest ways to think of hierarchies is in relation to time. You could look at your data at a year, month, day, hour, or another level. Moving across these levels is considered working with hierarchies.

You can also perform hierarchical calculations in other ways. Imagine you have a different company, with different departments, and teams within those departments. This creates a hierarchy that you might want to analyze at different levels.

VI. Marks & Filters

Filtering is one of the most powerful techniques in creating dashboards. This relates to the marks portion of a dashboard, which controls the colors, shapes and other attributes of our data. You can think of this like a WHERE statement in SQL used to filter your data to only the parts you are interested in for a specific question.

VII. Show Me

The Show Me portion of Tableau controls what your ending visual looks like. There are a lot of options here. In most cases, Tableau will guess what visual you want to create, but sometimes you might have your own ideas for implementation.

VIII. Small Multiples & Dual Axis

Small multiples & dual charts are a way to visualize data that needs to share an axis for comparison purposes. This and this are great articles for explaining how these two parts of Tableau work and why you might use them.

IX. Groups & Sets

Groups and sets are two ways to categorize our data within a visualization. The difference between these two can be confusing, but we will see when and why you would use each.

X. Calculated Fields

Often you might add these fields to your dataset before adding your data to Tableau, but sometimes you want to add them to a visualization on the fly. Many of these calculated fields are things you have probably done in a spreadsheets application like finding a total or a cost per item.

XI. Table Calculations

Table calculations are often used to perform comparisons of our data over time or between groups. A great article on table calculations is available here.

Capstone Project Overview

The capstone project has three main tasks, each of which requires you to use skills you developed during the Nanodegree program. Once you complete all three tasks, please submit the project as a PDF.

Tips

Split up your Alteryx workflows: You will be using multiple data sources and complex tools, which can slow down the workflow runtime. Splitting up the workflows makes the process more manageable.
Map out your work: Before you dive into your analysis, think about the steps and plan ahead. This will reduce the amount of unnecessary work.
Use visualizations: Include visualizations to help explain your decisions and communicate your findings. Remember what you learned about making them look great!
Ask for help: Mentors and your fellow students can help you if you get stuck on something. When posting a question, make sure you include enough specificity so others can help.

Task 1: Store Format for Existing Stores
Your company currently has 85 grocery stores and is planning to open 10 new stores at the beginning of the year. Currently, all stores use the same store format for selling their products. Up until now, the company has treated all stores similarly, shipping the same amount of product to each store. This is beginning to cause problems as stores are suffering from product surpluses in some product categories and shortages in others. You've been asked to provide analytical support to make decisions about store formats and inventory planning.

Task 1: Determining Store Format
To remedy the product surplus and shortages, the company wants to introduce different store formats. Each store format will have a different product selection in order to better match local demand. The actual building sizes will not change, just the product selection and internal layouts.
The terms "formats" and "segments" will be used interchangeably throughout this project. You've been asked to:

- Determine the optimal number of store formats based on sales data.
    - Sum sales data by StoreID and Year

    - Use percentage sales per category per store for clustering (category sales as a percentage of total store sales).
    - Use only 2015 sales data.
    - Use a K-means clustering model.
- Segment the 85 current stores into the different store formats.
- Use the StoreSalesData.csv and StoreInformation.csv files.

Note:

PCA is not used in this project.

Task 1 Submission

1. What is the optimal number of store formats? How did you arrive at that number?
2. How many stores fall into each store format?
3. Based on the results of the clustering model, what is one way that the clusters differ from one another?
4. Please provide a map created in Tableau that shows the location of the existing stores, uses color to show cluster, and size to show total sales. Make sure to include a legend! Feel free to simply copy and paste the map into the submission template.

Task 2: Store Format for New Stores

The grocery store chain has 10 new stores opening up at the beginning of the year. The company wants to determine which store format each of the new stores should have. However, we don't have sales data for these new stores yet, so we'll have to determine the format using each of the new store's demographic data.

Project: Predictive Analytics Capstone

Business Problem #1: Store Format for Existing Stores

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Determining Store Format

To remedy the product surplus and shortages, the company wants to introduce different store formats. Each store format will have a different product selection in order to better match local demand. The actual building sizes will not change, just the product selection and internal layouts. The terms "formats" and "segments" will be used interchangeably throughout this project. You've been asked to:

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- Use only 2015 sales data.
- Use a K-means clustering model.
- Segment the 85 current stores into the different store formats.
- Use the StoreSalesData.csv and StoreInformation.csv files.

Task 1: Determine Store Formats for Existing Stores

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

A K-centroids analysis was conducted using K-means method to determine the number of clusters. According to our K-means assessment, Adjusted Rand Indices, and Calinski-Harabasz Indices, the optimal number of store formats is three as both the indices projected the highest median value at such and has smaller variation in its spread. see the report and plot

K-Means Cluster Assessment Report

Summary Statistics

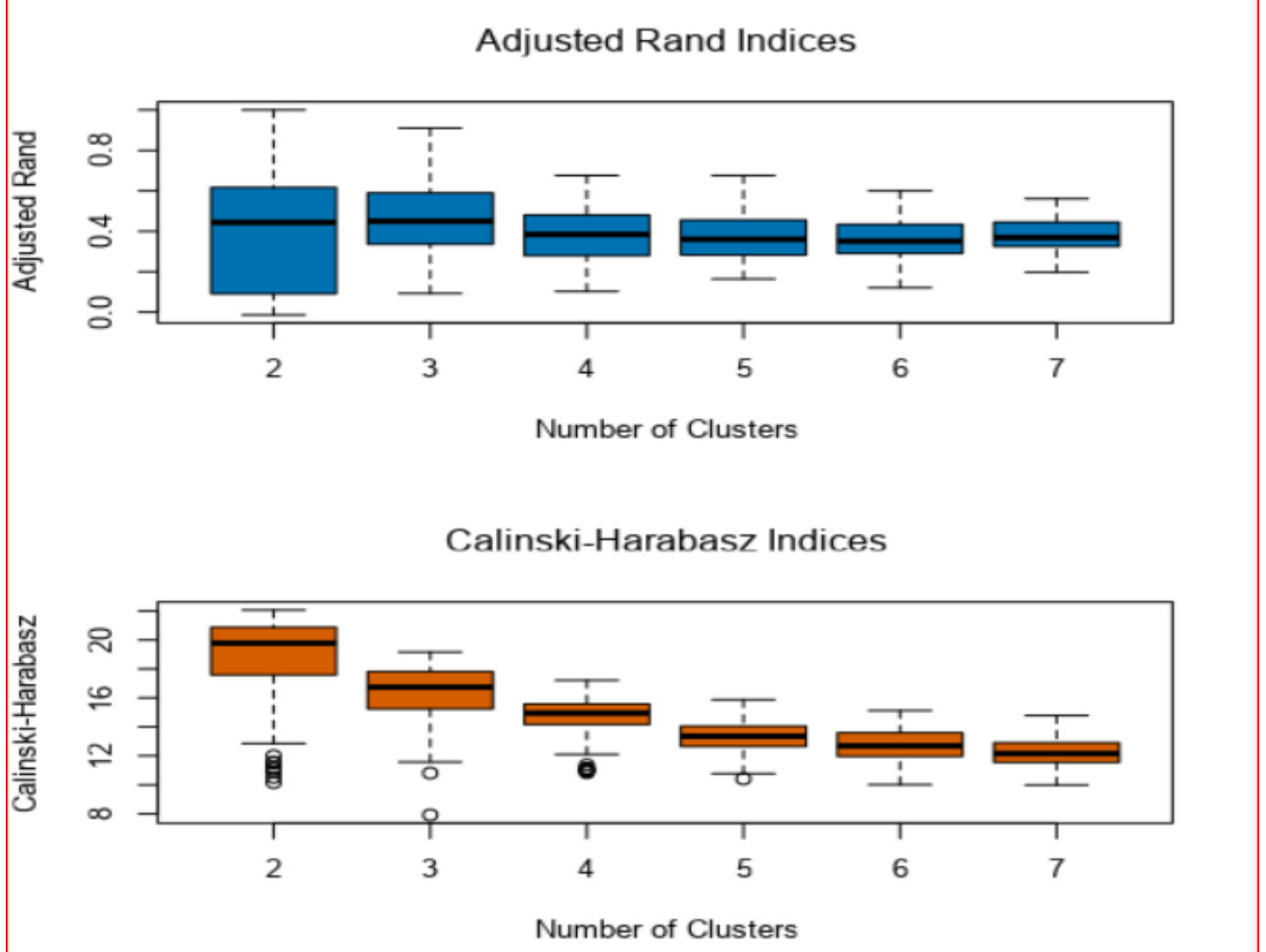
Adjusted Rand Indices:

	2	3	4	5	6	7
Minimum	-0.013227	0.092925	0.102617	0.164598	0.121081	0.196904
1st Quartile	0.103444	0.337693	0.28301	0.283134	0.293466	0.325085
Median	0.444014	0.449691	0.384307	0.36035	0.351008	0.368995
Mean	0.397174	0.464134	0.379543	0.373194	0.363684	0.378304
3rd Quartile	0.607698	0.587856	0.479755	0.455239	0.429452	0.442043
Maximum	1	0.910092	0.675798	0.6755	0.600053	0.561372

Calinski-Harabasz Indices:

	2	3	4	5	6	7
Minimum	10.15096	7.915219	10.83669	10.41103	10.00938	9.984881
1st Quartile	17.64958	15.261997	14.17336	12.64449	11.9686	11.551715
Median	19.77924	16.740045	14.94726	13.35011	12.6784	12.146197
Mean	18.57733	16.294384	14.65503	13.36064	12.72915	12.16866
3rd Quartile	20.87477	17.810829	15.57201	14.04538	13.59589	12.894823
Maximum	22.06169	19.164117	17.21682	15.8766	15.12815	14.780739

Plots



AR The higher the index, the better the stability of the block.
CH The higher the index, the better the differentiation and grouping.
According to the K-Means analysis, both Adjusted Rand Indices and Calinski-Harabasz Indices shows highest median value at 2,3, indicating that the optimal number of store formats is 3.

: Awesome: Great job! Yes, the RAND and CH indices indicate that 3 clusters is optimal, so we chose 3 for the number of formats.

Note: Older versions of Alteryx clearly showed that 3 is the optimal number because AR and CH indices both had the highest median for 3 clusters. But newer versions of Alteryx seems to favor 2 clusters too. But still, 3 is the optimal number because for 3 clusters CH and AR indices have high median value and are compact.

2. How many stores fall into each store format?
   According to the Cluster Information, Cluster 1 has 23 stores, cluster 2 has 29 stores and cluster 3 has 33 stores

Report

Summary Report of the K-Means Clustering Solution Cluster

Solution Summary

Call:
stepFlexclust(scale(model.matrix(~-1 + Percent_Dry_Grocery + Percent_Dairy + Percent_Frozen_Food + Percent_Meat + Percent_Produce + Percent_Floral + Percent_Deli + Percent_Bakery + Percent_General_Merchandise, the.data)), k = 3, nrep = 10, FUN = kcca, family = kccaFamily("kmeans"))

Cluster Information:

Cluster	Size	Ave Distance	Max Distance	Separation
1	23	2.320539	3.55145	1.874243
2	29	2.540086	4.475132	2.118708
3	33	2.115045	4.9262	1.702843

Convergence after 12 iterations.
Sum of within cluster distances: 196.83135.

	Percent_Dry_Grocery	Percent_Dairy	Percent_Frozen_Food	Percent_Meat	Percent_Produce	Percent_Floral	Percent_Deli
1	0.327833	-0.761016	-0.389209	-0.086176	-0.509185	-0.301524	-0.23259
2	-0.730732	0.702609	0.345898	-0.485804	1.014507	0.851718	-0.554641
3	0.413669	-0.087039	-0.032704	0.48698	-0.53665	-0.538327	0.64952

	Percent_Bakery	Percent_General_Merchandise
1	-0.894261	1.208516
2	0.396923	-0.304862
3	0.274462	-0.574389

: Awesome: The number of stores in each format is correct - great job!

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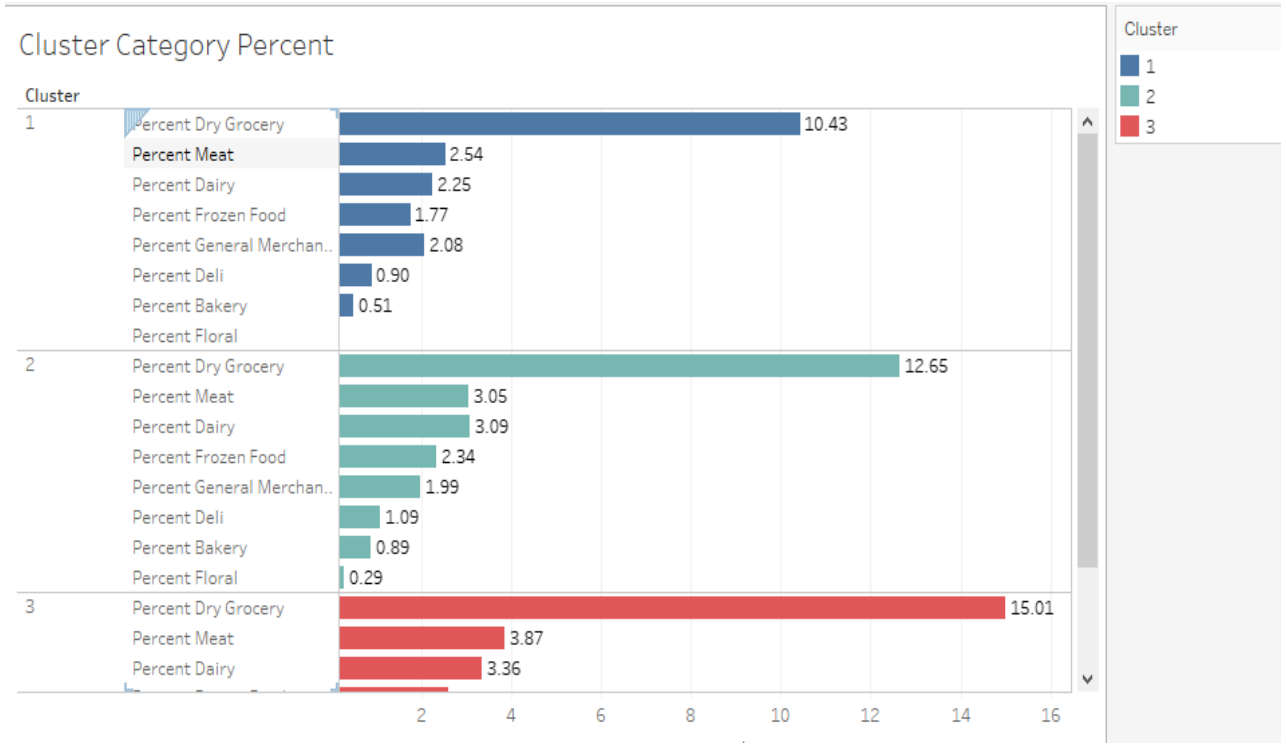
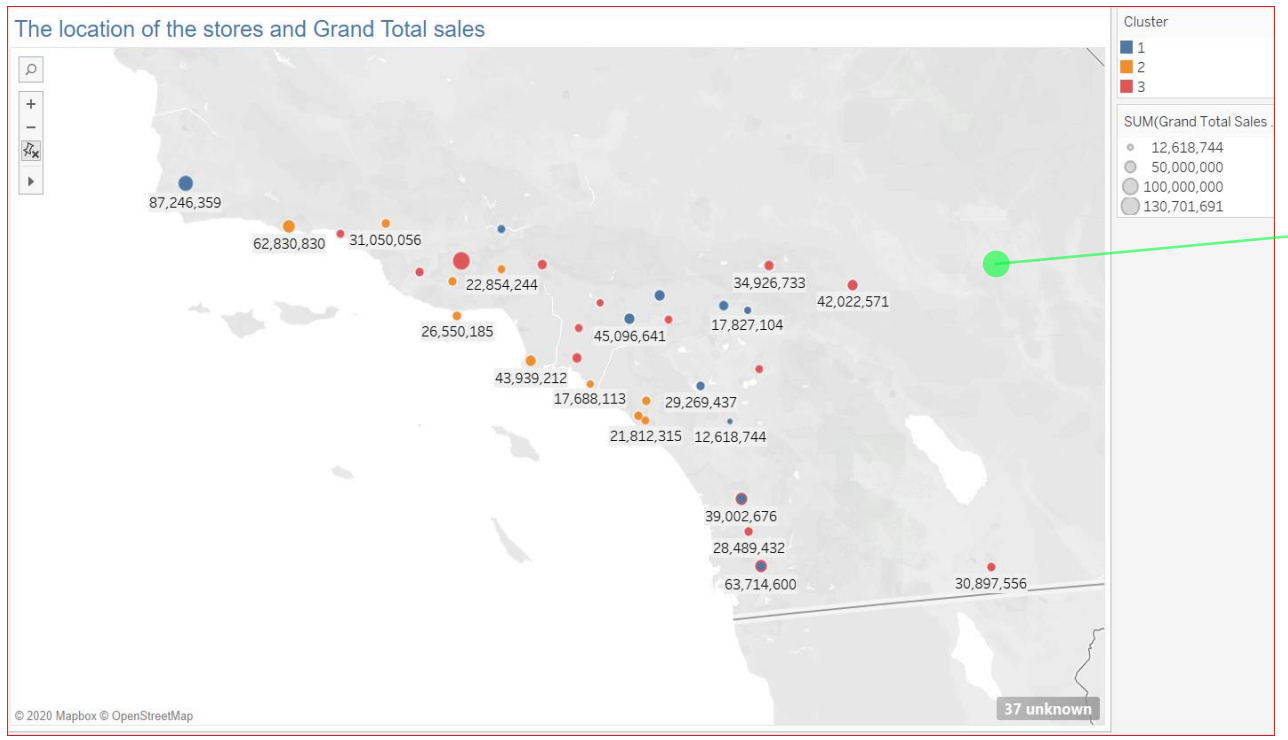
3. Based on the results of the clustering model, what is one way that the clusters differ from one another?
   Based on the Category Share by cluster and category total sales by cluster plots, Cluster 3 has the widest range of the sales and its sales are largest for most categories Percentage of total sales highest on Percent Dry Grocery cluster 2 ,3 see the plot

: Awesome: Excellent work providing observations about the difference among the clusters in terms of Dry Groceries sales and total sales.

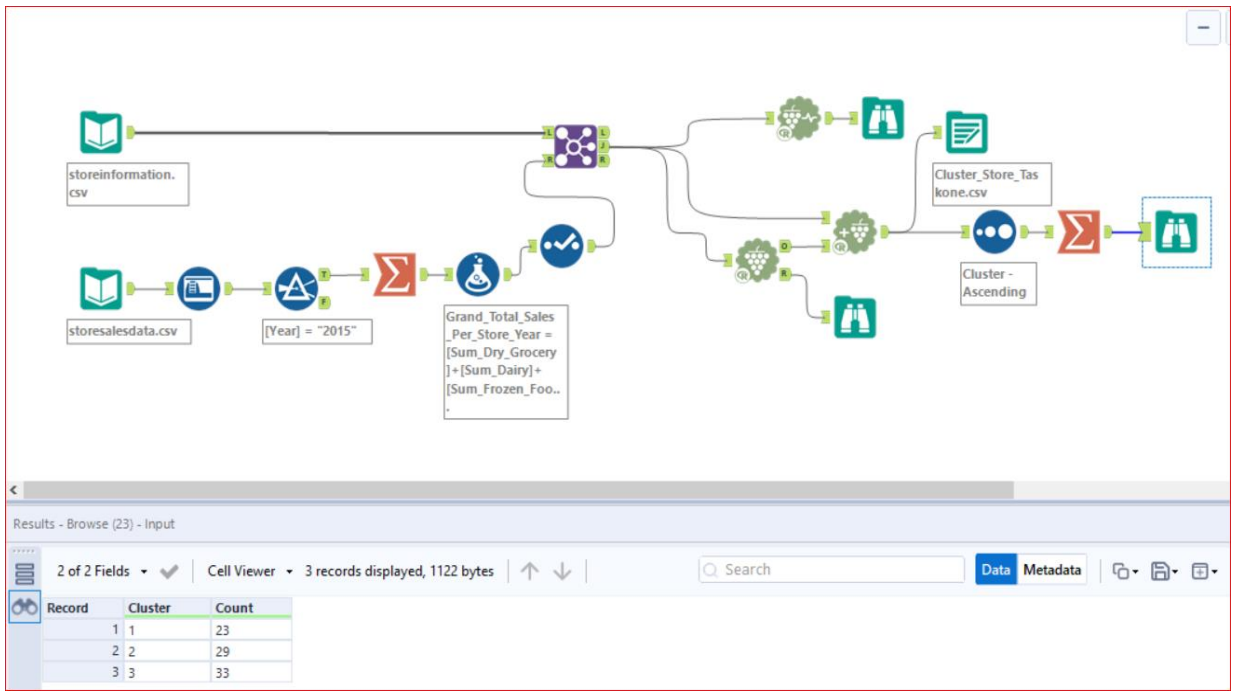


1. Please provide a Tableau visualization (saved as a Tableau Public file) that shows the location of the stores, uses color to show cluster, and size to show total sales.



: Awesome: The map looks great. Color is used to show the clusters and size is used to show total sales.

Workflow Task1



Task 2: Determine the Store Format for New Stores

You've been asked to:

- Develop a model that predicts which segment a store falls into based on the demographic and socioeconomic characteristics of the population that resides in the area around each new store.
- Use a 20% validation sample with *Random Seed* = 3 when creating samples with which to compare the accuracy of the models. Make sure to compare a decision tree, forest, and boosted model.
- Use the model to predict the best store format for each of the 10 new stores.
- Use the StoreDemographicData.csv file, which contains the information for the area around each store.
- **Note:** In a real world scenario, you could use PCA to reduce the number of predictor variables. However, there is no need to do so in this project. You can leave all predictor variables in the model.

Task 2 Submission

- What methodology did you use to predict the best store format for the new stores? Why did you choose that methodology?
- What are the three most important variables that help explain the relationship between demographic indicators and store formats? Please include a visualization.
- What format do each of the 10 new stores fall into? Please provide a data table.

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.)

In any classification problem you will need to set an estimation sample 80 and a validation sample 20 of your data. This helps us compare different classification models to see which better fit the data. The comparison result made me choose boosted model have the best results in Accuracy = 0.8235, F1= 0.8543 and Accuracy_1= 0.8000

: Awesome: Great job! Yes, the Boosted model should be used since it has high accuracy and higher F1 score. F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account.

Model Comparison Report

Fit and error measures

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

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 Random_Forest

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

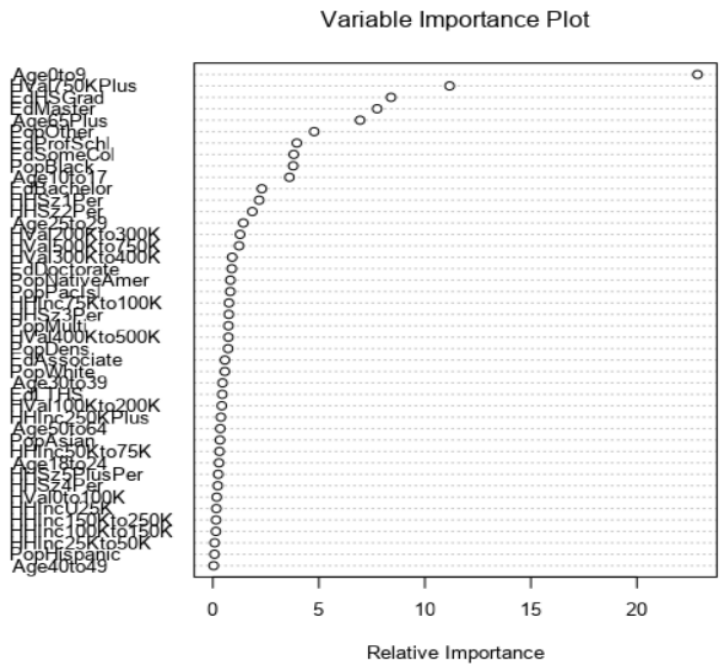
Model Comparison Report, Boosted Model is appropriate to use for lassifying format of the new stores

Report for Boosted Model Boosted_Model

Basic Summary:

Loss function distribution: Multinomial
Total number of trees used: 4000
Best number of trees based on 5-fold cross validation: 1612

Plots:



The Variable Importance Plot provides information about the relative importance of each predictor field. The measures are normalized to sum to 100, and the value for each field gives the relative percentage importance of that field to the overall model.

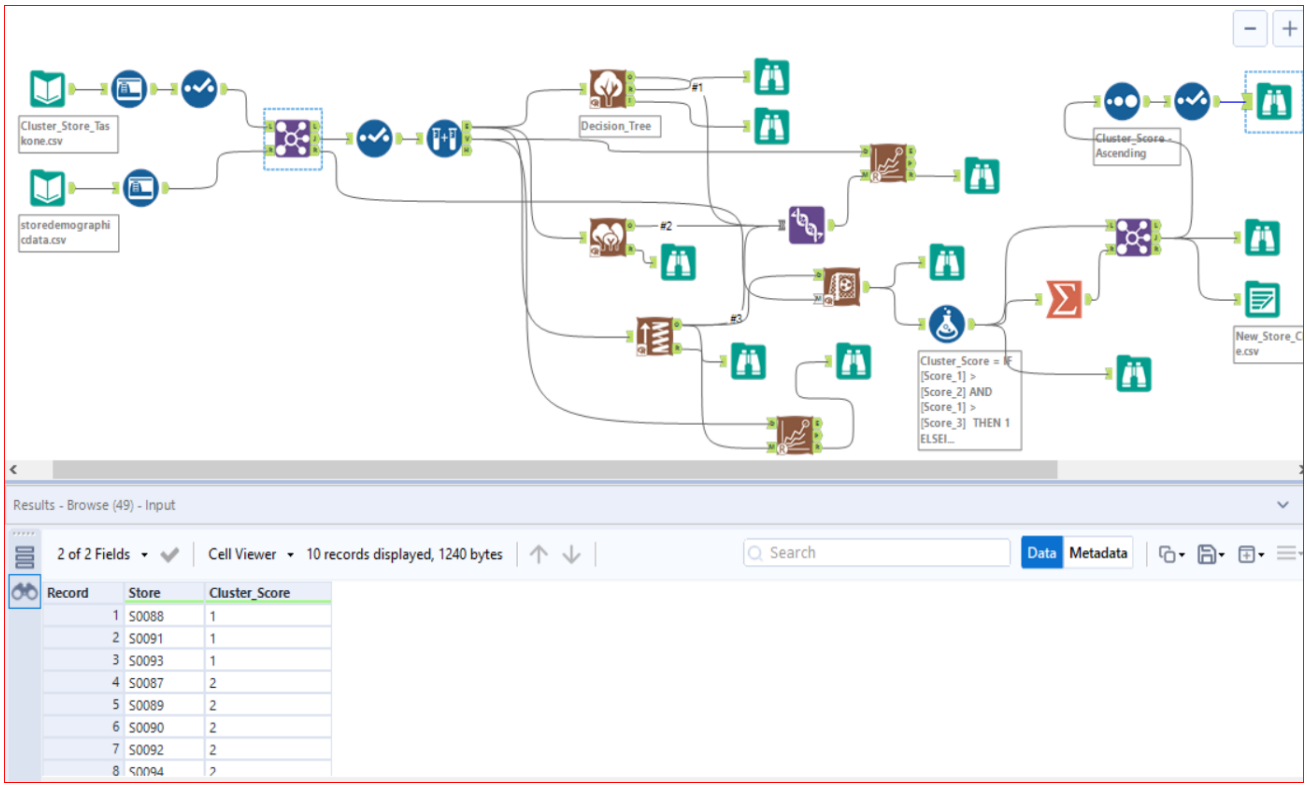
Ave0to9 , *HVal750KPlus* and *EdHSGrad* are the three most important variables.

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

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

: Awesome: The stores are correctly segmented - great job!

Workflow Task 2:



Record	Store	Cluster_Score
1	S0088	1
2	S0091	1
3	S0093	1
4	S0087	2
5	S0089	2
6	S0090	2
7	S0092	2
8	S0094	2

Task 3: Forecasting

Fresh produce has a short life span, and due to increasing costs, the company wants to have an accurate monthly sales forecast.

Task 3: Forecasting Produce Sales

You've been asked to prepare a monthly forecast for produce sales for the full year of 2016 for both existing and new stores. To do so, follow the steps below.

Note: Use a 6 month holdout sample for the TS Compare tool (this is because we do not have that much data so using a 12 month holdout would remove too much of the data)

Step 1: To forecast produce sales for existing stores you should aggregate produce sales across all stores by month and create a forecast.

Step 2: To forecast produce sales for new stores:

- Forecast **produce sales (not total sales)** for the average store (rather than the aggregate) for each segment.
- Multiply the average store produce sales forecast by the number of new stores in that segment.
- For example, if the forecasted average store produce sales for segment 1 for March is 10,000, and there are 4 new stores in segment 1, the forecast for the new stores in segment 1 would be 40,000.
- Sum the new stores produce sales forecasts for each of the segments to get the forecast for all new stores.

Step 3: Sum the forecasts of the existing and new stores together for the total produce sales forecast.

Task 3: Predicting Produce Sales

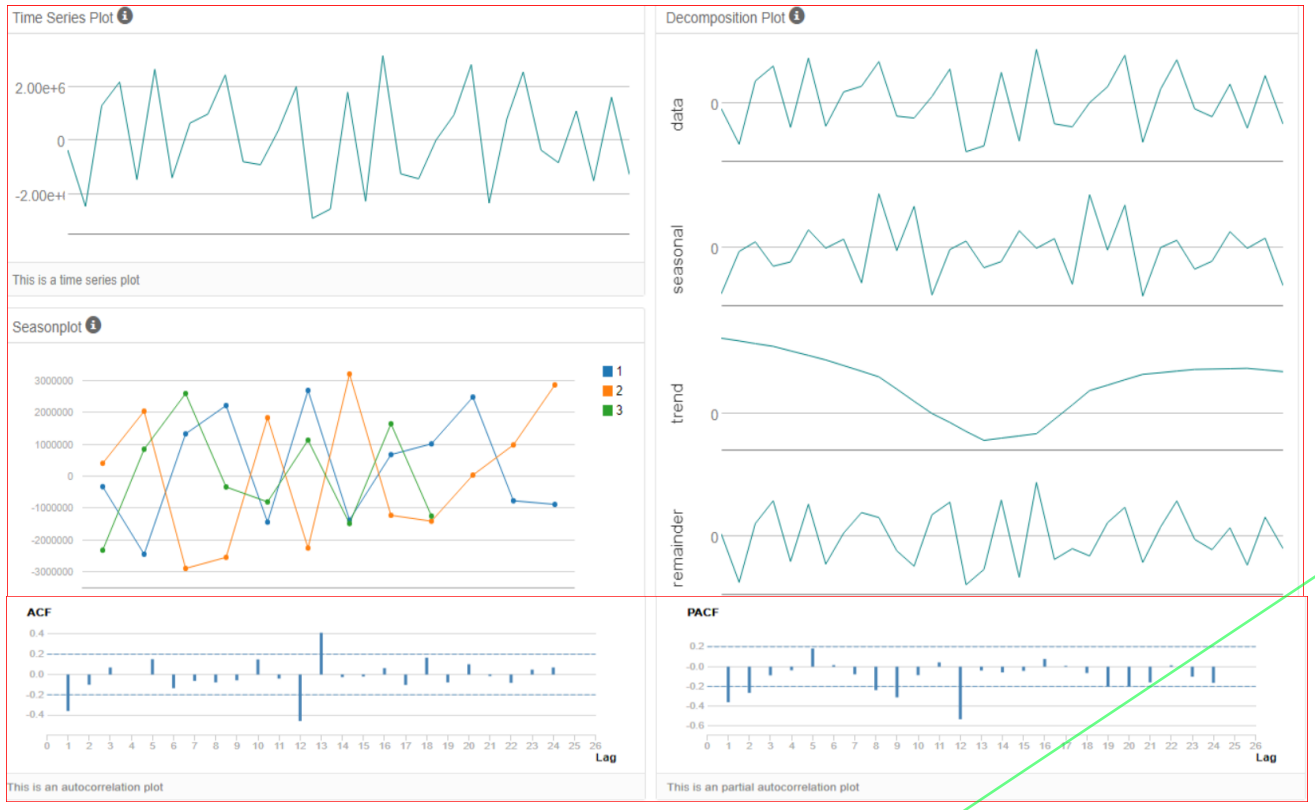
2. What type of ETS or ARIMA model did you use for each forecast? Use ETS(a,m,n) or ARIMA(ar, i, ma) notation. How did you come to that decision?

The decision to use ETS or ARIMA model can be clarified with Time Series model with a holdout sample of 12 months.
Based on the decomposition plot, our ETS(M,N,M) models shows the following:
(1) The seasonality has an increasing trend and multiplicative as the peaks change over time.
(2) The trend is zero as the trend seems inconsistent.
(3) The error is irregular and multiplicative since the errors are abruptly growing and shrinking over time.
ETS(M,N,M) with no dampening is used for ETS model.

: Awesome: Great job! Yes, we should use ETS(MNM) as the type of ETS model. By looking at the decomposition plot we can see that there is quite a bit of seasonality. From plot, we can also see that the trend turns up at the end, so trend should not be applied, and it appears that the remainder changes in magnitude, so we should apply it multiplicatively.

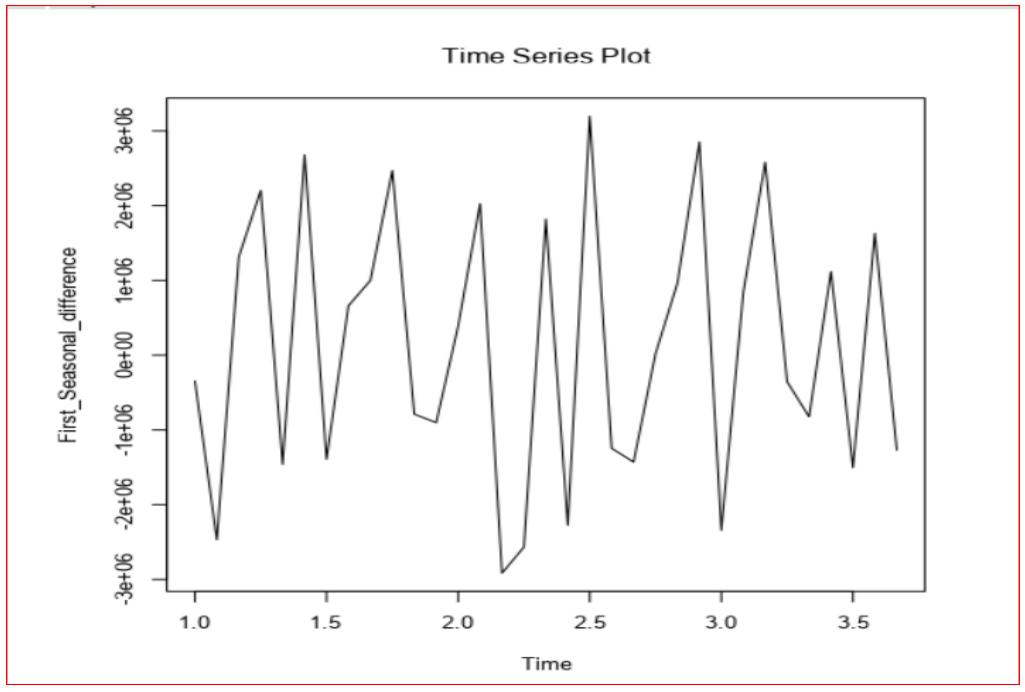
Autocorrelation plots after adding the AR term in the seasonal part of the model.

Determine Trend, Seasonal, and Error components:



Autocorrelation plots after applying the ARIMA(1,0,0)(1,1,0)[12] model.

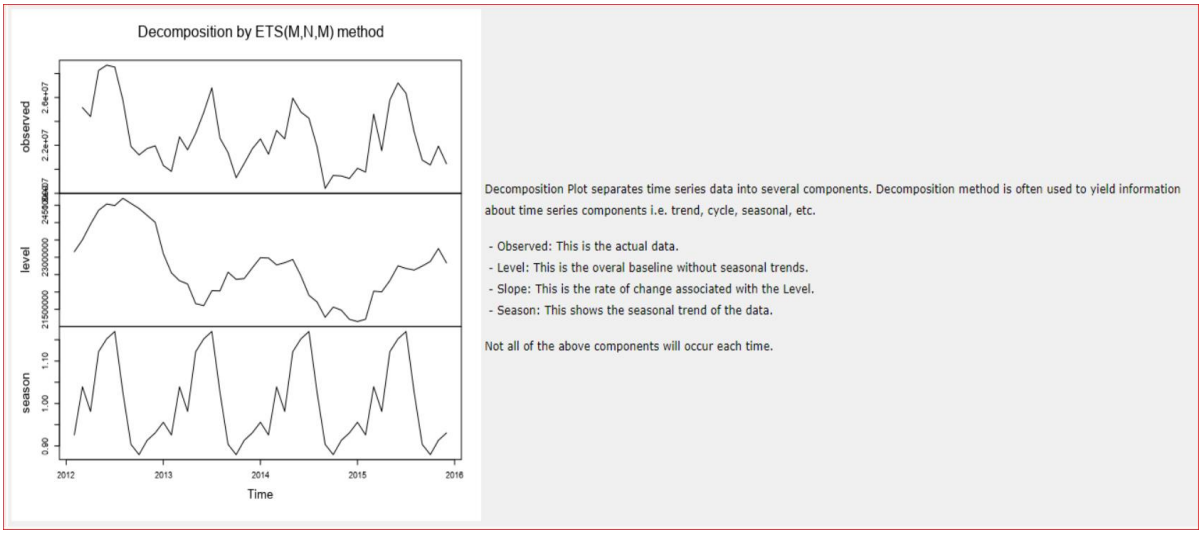
The decomposition plot shows our time series broken down into its three components: trend seasonal and the error. Each of these components makes up our time series and helps us confirm what we saw in our initial time series plot



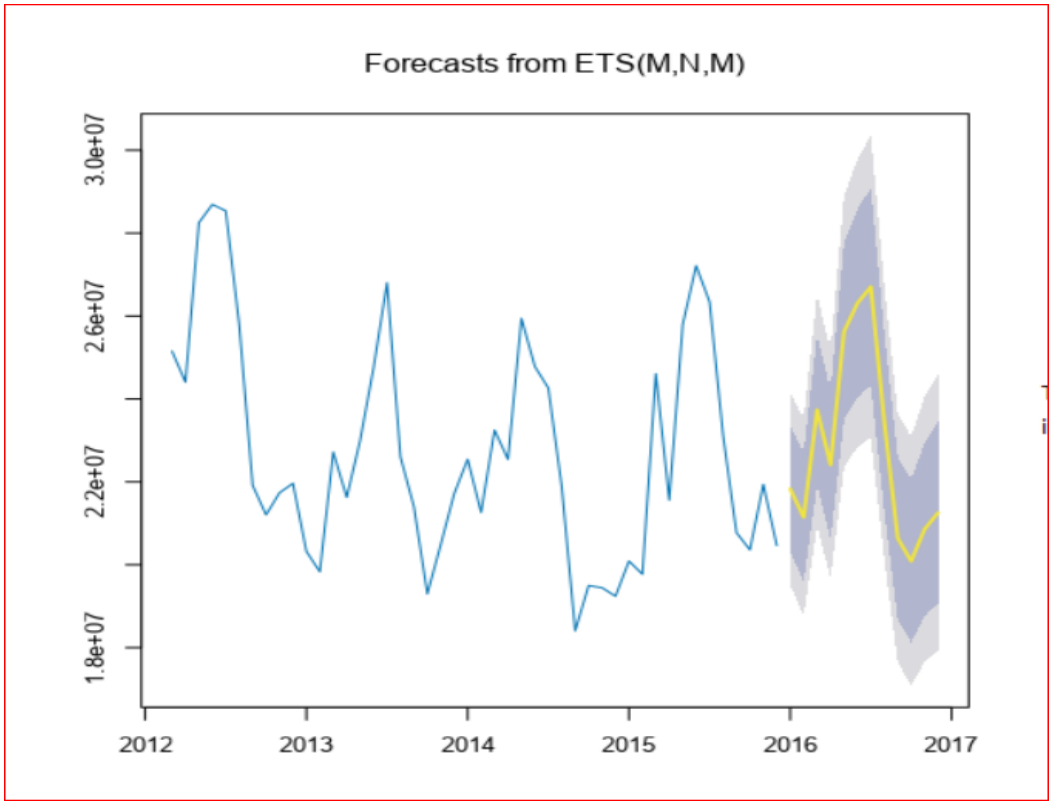
: Awesome: For ARIMA well done selecting ARIMA(1,0,0)(1,1,0)[12] where seasonal differencing is applied just. And then AR terms are selected. No regular differencing is applied because in some cases AR terms can be used in the role of a non-seasonal differencing. In that case, the series go into category ”underdifferenced”. Please check the project review section for a link to rule 6 where that is stated in more details: “Rule 6: If the PACF of the differenced series displays a sharp cutoff and/or the lag-1 autocorrelation is positive--i.e., if the series appears slightly “underdifferenced”--then consider adding an AR term to the model.The lag at which the PACF cuts off is the indicated number of AR terms.” Also, we do not have a trend in the series so that is why we should not apply non-seasonal differencing since it used to remove the trend. Since we don’t have trend there is no point of adding a non-seasonal differencing.

Plots of Time Series Exponential Smoothing Model ETS1

In statistics, a time series is a sequence of data points measured at successive points in time spaced at uniform intervals. Examples of time series are the daily closing value of a stock market index or the annual flow volume of a river. Time series analysis comprises methods for analyzing time series data in order to extract meaningful statistics and other characteristics of the data.



The Forecast Plot shows the historic data in black and the expected value in blue. The orange in the plot shows the 90% confidence interval, and the yellow shows the 95% confidence interval.



Summary of Time Series Exponential Smoothing Model ETS1

Method:
ETS(M,N,M)

In-sample error measures:

ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
-14783.6612202	1044018.8940828	809742.8924252	-0.2664397	3.5527937	0.4555978	0.3283229

Information criteria:

AIC	AICc	BIC
1479.4048	1495.4048	1506.8344

Smoothing parameters:

Parameter	Value
alpha	0.327727
gamma	0.001656

Initial states:

State	Value
l	23159664.744847
s0	0.926093
s1	0.956024
s2	0.930877
s3	0.91335
s4	0.879554
s5	0.903808
s6	1.02648
s7	1.169472
s8	1.151996
s9	1.121918
s10	0.981225

When fitting a forecasting model we can use a series of identifiers that help us choose the best model

Comparison ARIMA/ETS

Report

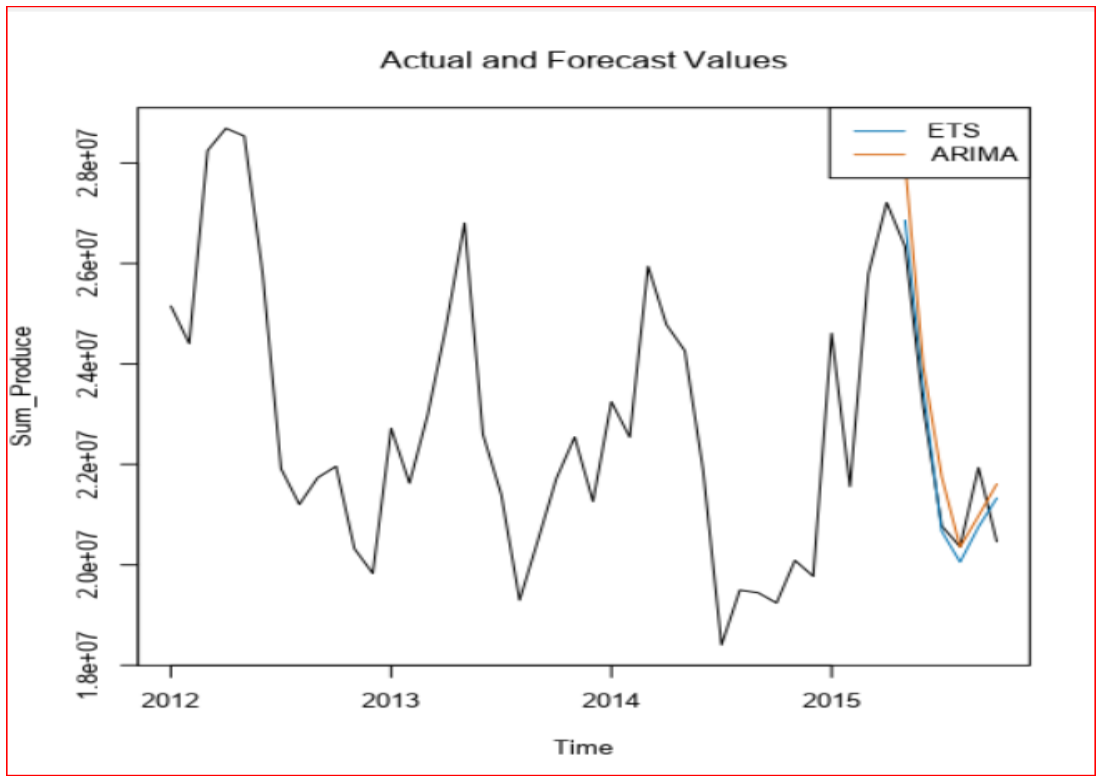
Comparison of Time Series Models

Actual and Forecast Values:

Actual	ETS	ARIMA
26338477.15	26860639.57444	27997835.63764
23130626.6	23468254.49595	23946058.0173
20774415.93	20668464.64495	21751347.87069
20359980.58	20054544.07631	20352513.09377
21936906.81	20752503.51996	20971835.10573
20462899.3	21328386.80965	21609110.41054

Accuracy Measures:

Model	ME	RMSE	MAE	MPE	MAPE	MASE
ETS	-21581.13	663707.2	553511.5	-0.0437	2.5135	0.3257
ARIMA	-604232.29	1050239.2	928412	-2.6156	4.0942	0.5463



The model for each forecast was ETS(M,N,M), which compared to ARIMA(1,0,0)(1,1,0)[12] in terms of forecast error measurements against the holdout sample obtained from the TS Compare tool, the results were better (especially lower RMSE and MASE as indicated in Tables 4 for ETS model and 5 for ARIMA model). Root Mean Squared Error (RMSE) represents the sample standard deviation of the differences between predicted values and observed values. Mean Absolute Scaled Error (MASE) is defined as the mean absolute error of the model divided by the mean absolute value of the first difference of the series.

: Awesome: Great work presenting the forecast accuracy measures against the holdout sample as a justification for selecting ETS. Yes, from the values in the table we can see that ETS has
lower errors so it has better predictive qualities.

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.

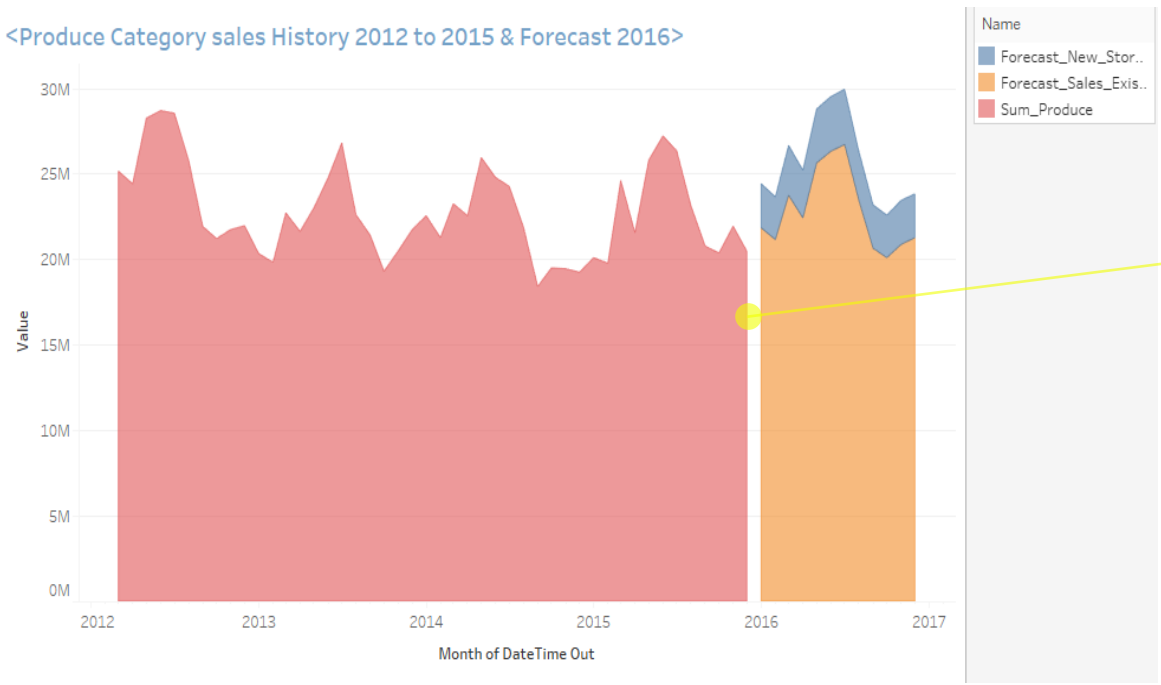
The forecasted values for produce, monthly in 2016 for new and existing stores, table down shows the historical data together with these forecasts.

Record	Year	Month	Forecast_Sales_Existing_Stores	Forecast_New_Store_Sales	Forecast_Total_Salse
1	2016	1	21829060.031666	2588356.558187	24417416.5898529
2	2016	10	20086270.462075	2485732.284852	22572002.7469266
3	2016	11	20858119.957540	2583447.593735	23441567.5512745
4	2016	12	21255190.244976	2562181.69998	23817371.944956
5	2016	2	21146329.631982	2498567.174382	23644896.8063643
6	2016	3	23735686.938790	2919067.024801	26654753.9635906
7	2016	4	22409515.284474	2797280.082984	25206795.3674585
8	2016	5	25621828.725097	3163764.859191	28785593.5842883
9	2016	6	26307858.040046	3202813.288678	29510671.3287239
10	2016	7	26705092.556349	3228212.242266	29933304.7986153
11	2016	8	23440761.329527	2868914.812082	26309676.1416093
12	2016	9	20640047.319971	2538372.266534	23178419.5865047

: Awesome: The forecasts for the existing and new stores are within the expected range - great job! Great job plotting the results!

Forecast results using 95% and 80% confidence intervals:

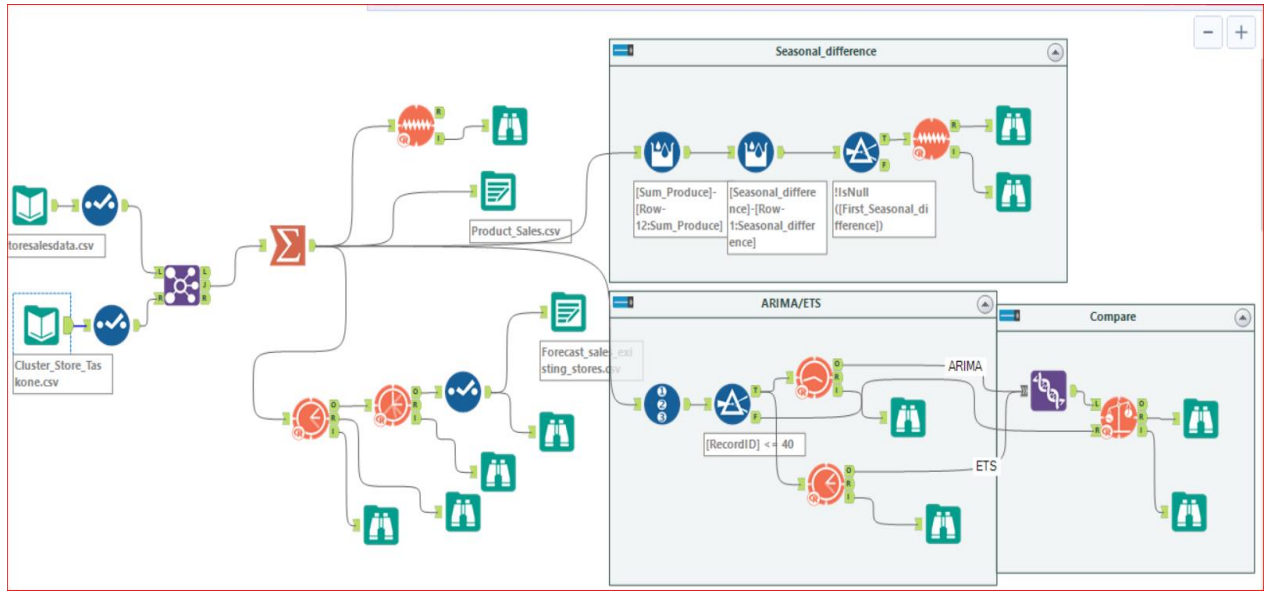
	Period	Sub_Period	Sum_forecast	Sum_forecast_high_95	Sum_forecast_high_80	Sum_forecast_low_80	Sum_forecast_low_95
1	2016	1	2588356.558187	823200.179674	795596.513973	691307.382453	663703.716752
2	2016	2	2498567.174382	809662.007302	778975.411669	663038.693604	632352.097969
3	2016	3	2919067.024801	960914.020109	920983.415370	770121.999560	730191.394820
4	2016	4	2797280.082985	921132.106348	879943.371721	724328.628046	683139.893419
5	2016	5	3163764.859191	1058929.986734	1008579.875507	818352.627122	768002.515895
6	2016	6	3202813.288678	1078867.364553	1024796.766511	820513.184337	766442.586294
7	2016	7	3228212.242266	1098259.544599	1040630.447191	822902.534387	765273.436978
8	2016	8	2868914.812083	976664.219244	923239.845336	721397.756063	667973.382155
9	2016	9	2538372.266534	868817.404707	819446.038665	632916.577611	583545.211570
10	2016	10	2485732.284852	856074.334593	805749.728497	615618.840788	565294.234693
11	2016	11	2583447.593735	899437.316669	844869.610057	638707.906999	584140.200388
12	2016	12	2562181.699980	907730.742211	851074.472700	637021.991180	580365.721669

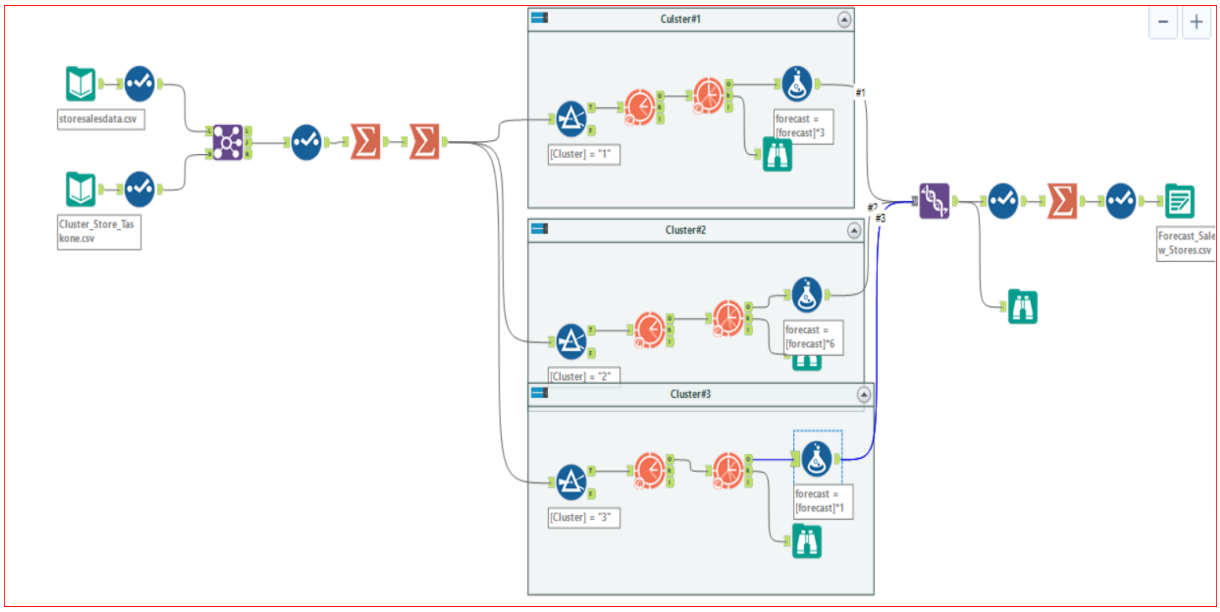


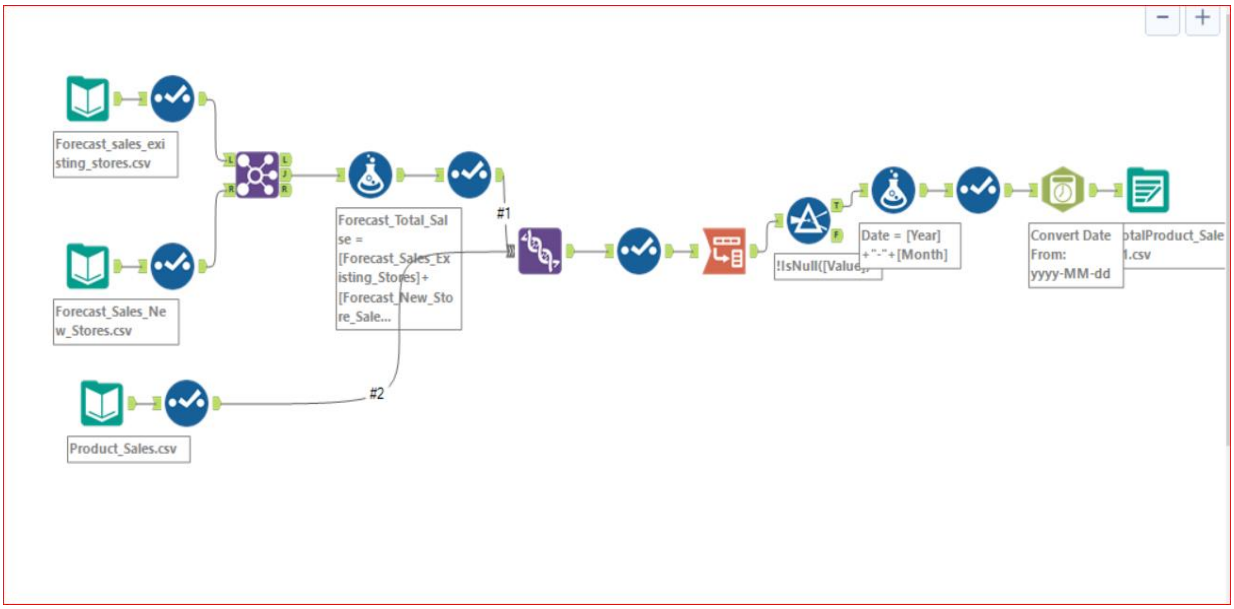
: Suggestion: Great job with the plot! By the way, if you are interested in how to close the gap in the plot between the actual sales and the forecasted ones you can check the example in the project review section.

Produce values for existing stores from 2012 to 2015 and forecasted produce values for existing and new stores monthly in 2016.

Workflow Task3




storesalesdata.csv
Cluster_Store_Taskone.csv
Culster#1
[Cluster] = "1"
forecast = [forecast]*3
Cluster#2
[Cluster] = "2"
forecast = [forecast]*6
Cluster#3
[Cluster] = "3"
forecast = [forecast]*1
#1
#2
#3
Forecast_Sales_Stores.csv


Forecast_sales_existing_stores.csv
Forecast_Sales_New_Stores.csv
Product_Sales.csv
Forecast_Total_Sale = [Forecast_Sales_Existing_Stores]+[Forecast_New_Store_Sale...
#1
#2
!IsNull([Value
Date = [Year]+"-"+[Month]
Convert Date From: yyyy-MM-dd

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.

I hope to be home to the project requirements despite the valuable information that we learned from the lessons and also the project, but we do not know the exact correct result

Help resources Forums :https://knowledge.udacity.com

I wish success to all.

M*arwan Saeed Alsharabbi*