Insurance

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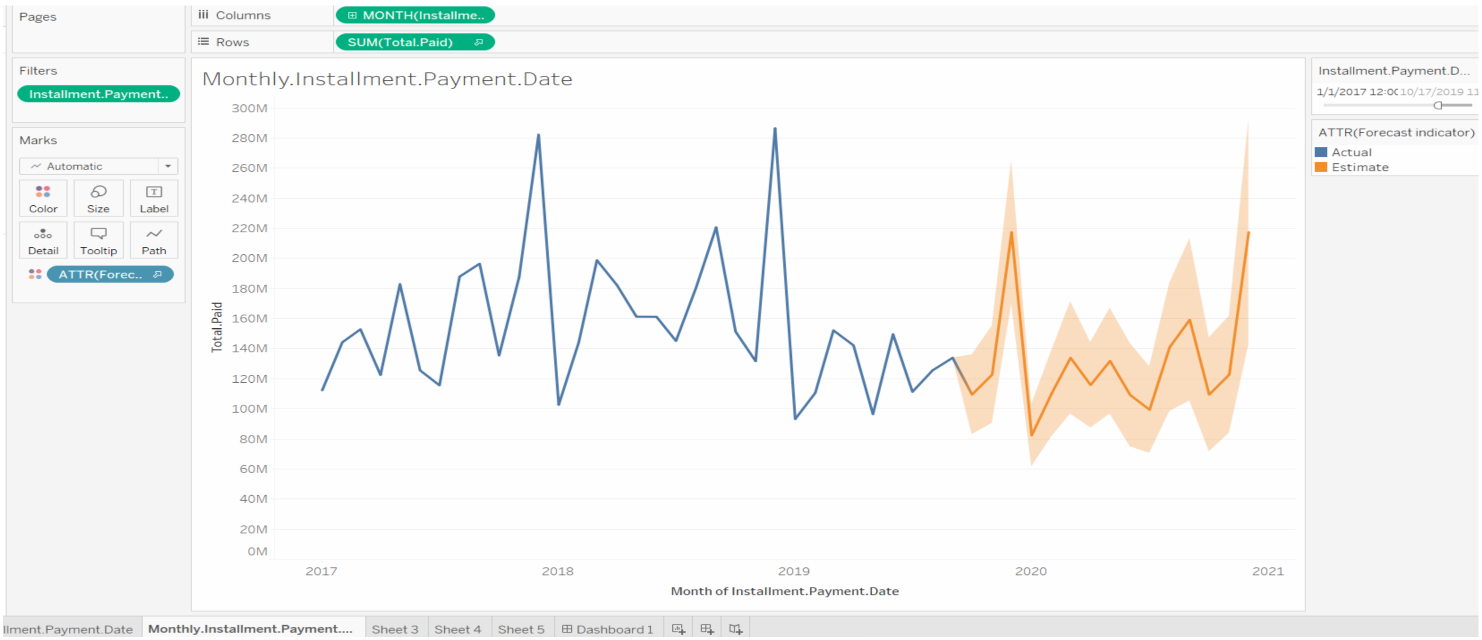
Forecast:



Options Used to Create Forecasts

Time series: Month of Installment.Payment.Date
Measures: Sum of Total.Paid
Forecast forward: 15 months (October 2019 – December 2020)
Forecast based on: January 2017 – September 2019
Ignore last: 1 month (October 2019)
Seasonal pattern: 12 month cycle

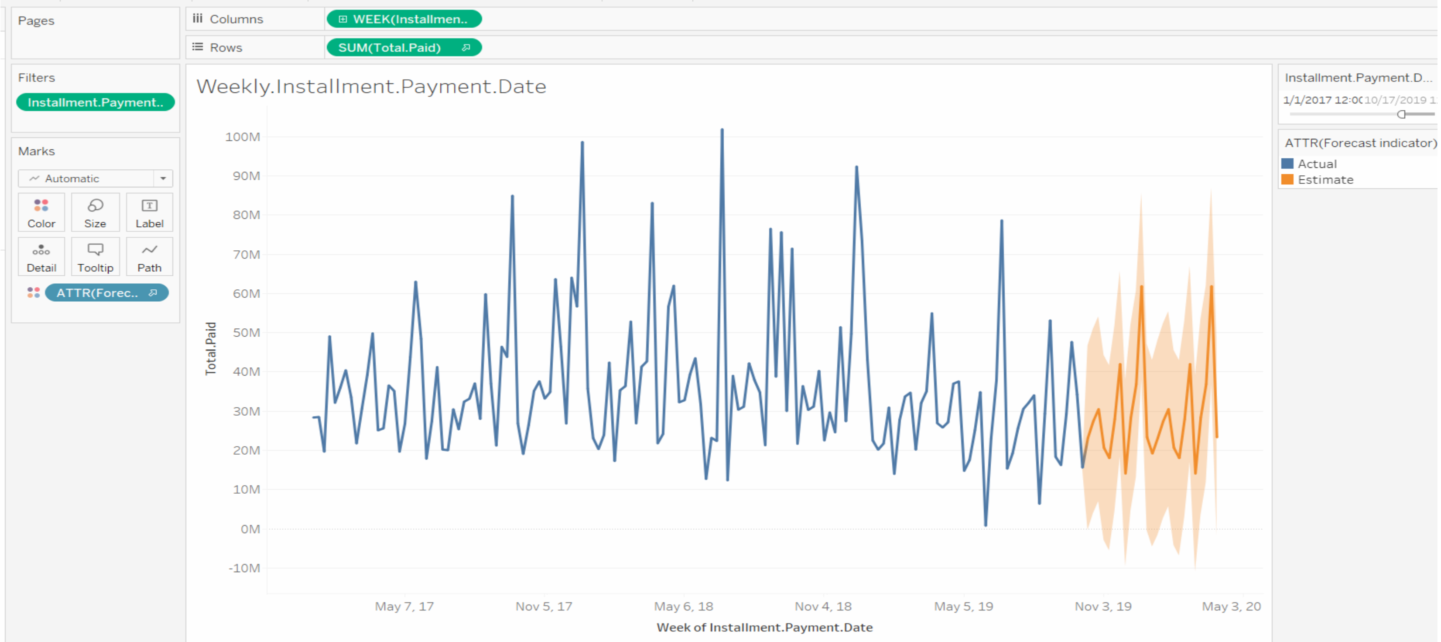
Sum of Total.Paid

Initial	Change From Initial	Seasonal Effect				Contribution		Quality
October 2019	October 2019 – December 2020	High		Low		Trend	Season	
109,456,102 ± 26,439,459	107,972,733	December 2020	2	January 2020	1	0.0%	100.0%	Ok

All forecasts were computed using exponential smoothing.

Sum of Total.Paid

Model			Quality Metrics					Smoothing Coefficients		
Level	Trend	Season	RMSE	MAE	MASE	MAPE	AIC	Alpha	Beta	Gamma
Multiplicative	None	Multiplicative	21,790,264	16,472,100	0.50	11.9%	1,145	0.292	0.000	0.000



Options Used to Create Forecasts

Time series: Week of Installment.Payment.Date
Measures: Sum of Total.Paid
Forecast forward: 25 weeks (October 13, 2019 – March 29, 2020)
Forecast based on: January 8, 2017 – October 6, 2019
Ignore last: 1 week (October 13, 2019)
Seasonal pattern: 13 week cycle

Sum of Total.Paid

Initial	Change From Initial	Seasonal Effect				Contribution		
October 13, 2019	October 13, 2019 – March 29, 2020	High		Low		Trend	Season	Quality
23,139,097 ± 23,504,834	204,358	March 22, 2020	31,707,782	March 1, 2020	-16,093,054	0.0%	100.0%	Ok

Show values as percentages

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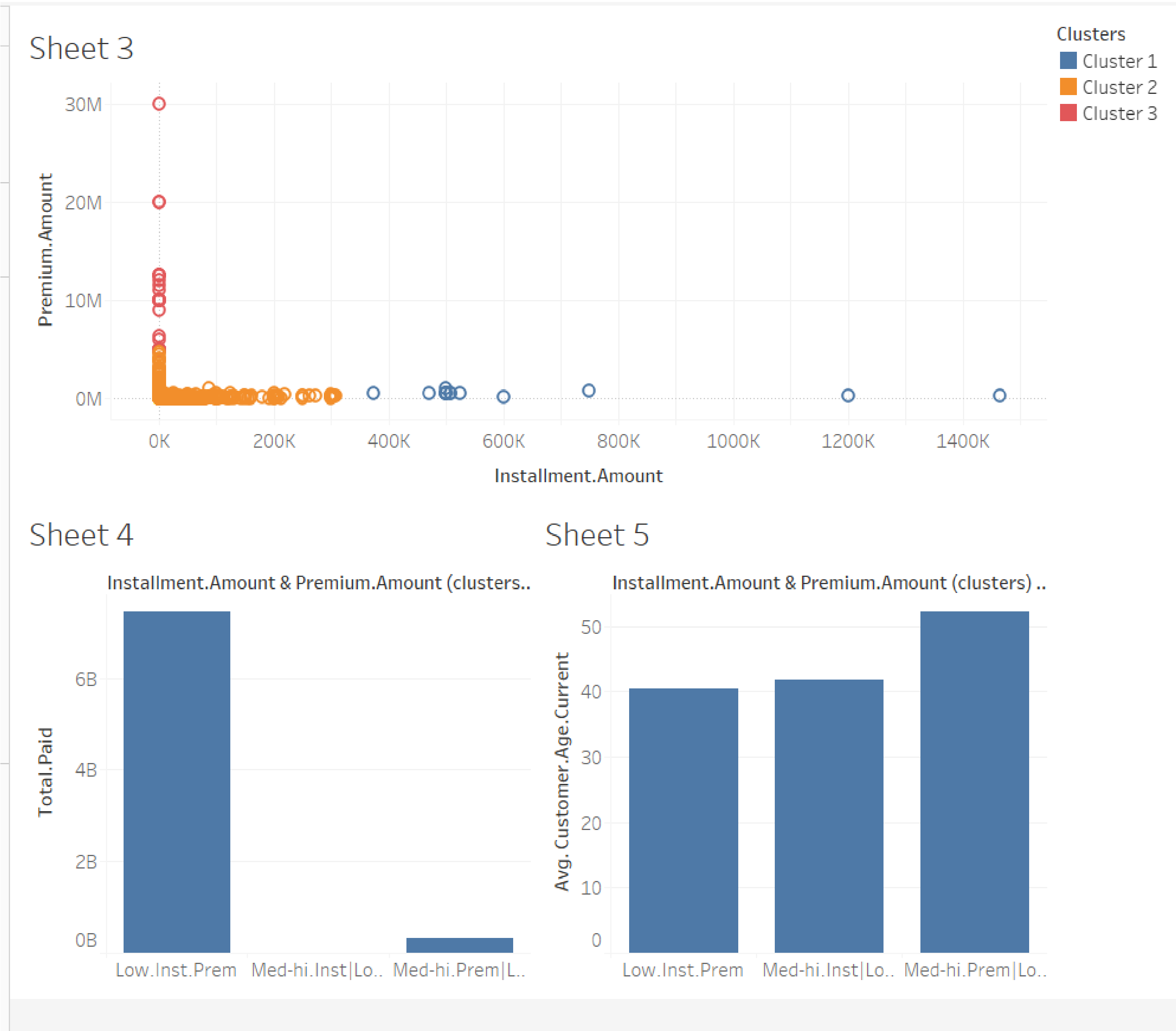
All forecasts were computed using exponential smoothing.

Sum of Total.Paid

Model			Quality Metrics					Smoothing Coefficients		
Level	Trend	Season	RMSE	MAE	MASE	MAPE	AIC	Alpha	Beta	Gamma
Additive	None	Additive	14,289,924	10,404,191	0.80	50.9%	4,777	0.046	0.000	0.265

Interpretation: I made two forecasts, one for the monthly and other for the weekly trend. I used installment payment date as my date variable. Next, I added a filter to it, since I had seen some outlier in the total paid amount, so I used this filter to remove it and through filter I tried to increase the quality of forecast by picking up data that was more useful for the modal, which better showed the trends of total paid amounts. So as a result, I set the filter to get data starting 2017. Both of my models were said to be 'OK' by tableau. It is also visible from the line chart that the forecast somewhat captures the trend of total paid amount since the line follows a similar pattern. One thing that is visible from the outputs of the modals is that in both, Trend is not present from a time series point of view, but the Seasonality is present which is also evident from the line graph. Next the weekly forecast uses an additive approach for season and level, while monthly forecast uses a multiplicative approach for these. Finally, the RMSE and AIC both are towards the high side for both the forecasts which is not very good.

Clustering:



Inputs for Clustering

Variables:	Sum of Installment.Amount Sum of Premium.Amount
Level of Detail:	Not Aggregated
Scaling:	Normalized

Summary Diagnostics

Number of Clusters:	3
Number of Points:	57019
Between-group Sum of Squares:	6.0564
Within-group Sum of Squares:	4.6701
Total Sum of Squares:	10.727

Clusters	Number of Items	Centers: Sum of Installment.Amount	Centers: Sum of Premium.Amount
Cluster 1	14	6.358e+05	5.07e+05
Cluster 2	56970	606.14	73896.0
Cluster 3	35	0.0	9.4486e+06
Not Clustered	0		

Analysis of Variance:

Variable	F-statistic	p-value	Model Sum of Squares	Model DF	Error Sum of Squares	Error DF
Sum of Premium.Amount	1.666e+04	0.0	3.418	2	5.851	57016
Sum of Installment.Amount	1.543e+04	0.0	2.638	2	4.875	57016

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Interpretation: So, I used premium amount paid versus installment as the two KPIs which made the most sense for me for making clusters of customer payment pattern. Three clusters were made and showed three type of people as can be seen in the screen shot:

The ones in red had medium to high premium amounts but zero installment amounts, second in yellow had both the amount in the low category and third in blue had medium to high installment amounts but zero premium amounts.

I tried to make a story out of this to show the use of the clustering, the first chart on the left bottom shows that the cluster which had the low amount for both premium and installment in fact were the people who paid the highest in total, so this tells that these people are very important. We can further drill our analysis from the chart at the bottom right that then these are the people whose average age is somewhere around 40 which further helps to build a customer profile to target.

Lastly coming on to description of model, we see that Anova is used for the clustering and both the variables are significant which is good.