

Candidate Case Study

Brian Kao

5/31/19



- 1)What day of week had the most average daily calls for service in July 2018?
- 2) What was the most common time of day for a DRUG/NARCOTIC incident to occur in 2017?
- 3)Analyze and describe the relationship between the time of day and volume and type of incidents
- 4)Create a model which predicts the weekly volume of incidents in 2018 by crime category type

Introduction

Case Study Instructions

Please complete the following dataset challenge over the next week and prepare for a 30-minute presentation with 15 minutes of Q&A.

Create a short presentation derived from analyzing the dataset:

- In developing your slides, assume the intended audience is the Mayor of San Francisco
- · The presentation should tackle the following areas to the best of your ability:

Profile the provided data sets (e.g. datatypes, data distribution, missing values etc.)

- What day of week had the most average daily calls for service in July 2018?
- What was the most common time of day for a DRUG/NARCOTIC incident to occur in 2017?
- · Analyze and describe the relationship between the time of day and volume and type of incidents

Create a model which predicts the weekly volume of incidents in 2018 by crime category type

- Be prepared to explain your methodology
- Feel free to use any means to obtain the answers (Python, R, etc.) and be prepared to share your work You do not need to limit your presentation to the answers to the questions above

Methodology:

Tools: Jupyter Notebook, R Studio, MS Excel

- Data Wrangling/Mining: Python(numpy, Pandas, sklearn, matplotlib, seaborn), MS Excel
- Data Science: R(forecast(arima, tbats, nnetar), ggplot)
- Data Source: https://www.kaggle.com/san-francisco/sf-police-calls-for-service-and-incidents
 police-department-calls-for-service.csv (*data does not join to incidents.csv, did not find any accurate keys to join on).
 police-department-incidents.csv
- Code: Link to .ipynb and .R file used for analysis: https://github.com/kbyuan/apple/

Assumptions:

- Context (Based on Data Samples and Case Study Questions):
- 1. It is August 1st 2018, and the Mayor wants to review the latest July 2018 Call Volumes and Weekly Trends.
- The Major wants to Forecast 2018 Incidents for the year. Incidents data lags behind Call Volume data due to the amount of time it takes to
 record the event. Therefore the latest available data for Incidents is May 2018. *Furthermore, since the 2018 Incidents data shows a large
 YoY decline from Jan to May 2018, I am not using this in forecasting, as I am assuming it is still being gathered.
- 3. Not all slides presented today would be intended for the Mayor in this situation (i.e. in-depth forecast model slides).



1)What day of week had the most average daily calls for service in July 2018?

July 2018 Call Volumes



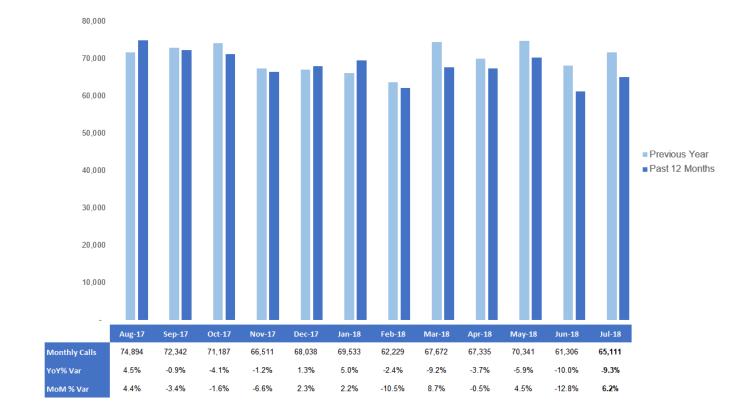
Monthly Call Volume:

Overall Monthly Calls were down -9.3% YOY in July 2018.

Monthly Call Volumes have dropped YoY for 5 straight months.

Monthly Call Volumes do seem to have a seasonal trend, as class in certain months seem tobe consistent! higher/lower than others. (i.e. October typically has a higher number of incidents than November)

Monthly Call Volume – Past 12 Months





Call Volume by Category:

Traffic Stops were up +15% YoY, and was the top Call type In July.

Passing Calls dropped -8%, a trend that has continued over the past 5 months.

Homeless, Muni Inspection, and ParkingCalls also saw large YoY declines, falling - 36%, -48%, and -57% YOY, respectively. A trend that began in April 2018.

*Note: it looks like some agencies may have changed Call Category Codes over the past 5 months. Therefore, we have cleaned the data (i.e. prefix: traf = Traffic Stop, Homeless combined with Trespassing).

Monthly Call Volume - July 2018

July 2018 Calls: By Top 2 Categories

	July 2018 Calls	% to Total Calls	YoY % Var
Traffic Stop	9,090	14.0%	15%
Passing Call	8,813	13.5%	-8%
Homeless /Trespasser Complaint	3,514	5.4%	-3 <mark>1%</mark>
Suspicious Person	3,373	5.2%	6%
Muni Inspection	2,242	3.4%	-3 <mark>3%</mark>
Audible Alarm	2,106	3.2%	-5%
Suspicious Vehicle	1,751	2.7%	14%
Well Being Check	1,695	2.6%	3%
Noise Nuisance	1,505	2.3%	3%
22500e (Parking)	1,484	2.3%	-54%
Fight No Weapon	1,442	2.2%	0%
Auto Boost / Strip	1,281	2.0%	-11 <mark>%</mark>
Poss	1,033	1.6%	1%
Mentally Disturbed	1,007	1.5%	5%
Assault / Battery	890	1.4%	-9%
Petty Theft	850	1.3%	9%
Meet W/citizen	788	1.2%	-14 <mark>%</mark>
Drugs	779	1.2%	39%
Total Calls - Top 20 Categories	43.643	67.0%	

YoY% Call Volume Trend: Top 20 Categories

	Mar-18	Apr-18	May-18	Jun-18	Jul-18
Traffic Stop	-30%	-8%	1%	-3%	14%
Passing Call	-15%	-11%	-12%	-11%	-9%
Homeless /Trespasser Complaint	15%	19%	-2%	-21%	-36%
Suspicious Person	-11%	-7%	-2%	4%	7%
Muni Inspection	28%	3%	-19%	-19%	-48%
Audible Alarm	-3%	-11%	-7%	1%	-5%
Suspicious Vehicle	0%	13%	8%	14%	16%
Well Being Check	6%	7%	15%	13%	3%
Noise Nuisance	7%	6%	7%	10%	4%
22500e (Parking)	7%	-10%	-21%	-45%	-57%
Fight No Weapon	5%	2%	0%	3%	0%
Auto Boost / Strip	-25%	-23%	-32%	-34%	-11%
Poss	13%	17%	19%	16%	1%
Mentally Disturbed	21%	15%	25%	24%	5%
Assault / Battery	0%	-5%	-2%	9%	-10%
Petty Theft	-13%	17%	9%	18%	10%
Meet W/citizen	-12%	-11%	-18%	-17%	-13%
Drugs	18%	15%	66%	86%	51%



Call Volume by Day of Week:

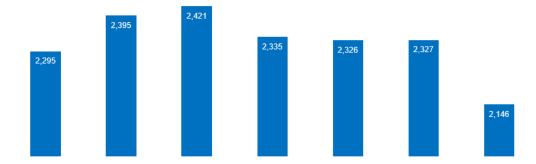
Wednesday had the most average calls in July 2018, of 2.421.

Typically Tuesday's to Friday have the highest overall Avg Calls.

Sunday's typically have the least, with ~10% less than the top day of the week.

*Heatmap is based on benchmarking each day based on the highest day of the week. (i.e. the highest day is 100%, and the next highest day will be a percentage of the highest days value).

Avg Calls Per Week



	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Jul-18	94%	98%	Top Day (100%)	94%	94%	93%	87%
Jun-18	96%	99.6%	99.6%	Top Day (100%)	97%	98%	88%
May-18	95%	95%	97%	96%	Top Day (100%)	99%	88%
Apr-18	99%	Top Day (100%)	99%	99%	97%	96%	88%
Mar-18	99%	94%	95%	97%	Top Day (100%)	97%	90%
Feb-18	92%	96%	98%	Top Day (100%)	99%	92%	87%
Jan-18	92%	99%	Top Day (100%)	99%	99%	94%	86%
Dec-17	87%	92%	Top Day (100%)	99%	95%	93%	83%
Nov-17	95%	Top Day (100%)	97%	90%	94%	93%	87%
Oct-17	95%	Top Day (100%)	96%	94%	100%	98%	92%
Sep-17	99%	97%	Top Day (100%)	98%	98%	92%	89%
Aug-17	91%	97%	97%	Top Day (100%)	98%	89%	87%



4)Create a model which predicts the weekly volume of incidents in 2018 by crime category type

2017 Incidents Trends



2017 Incidents

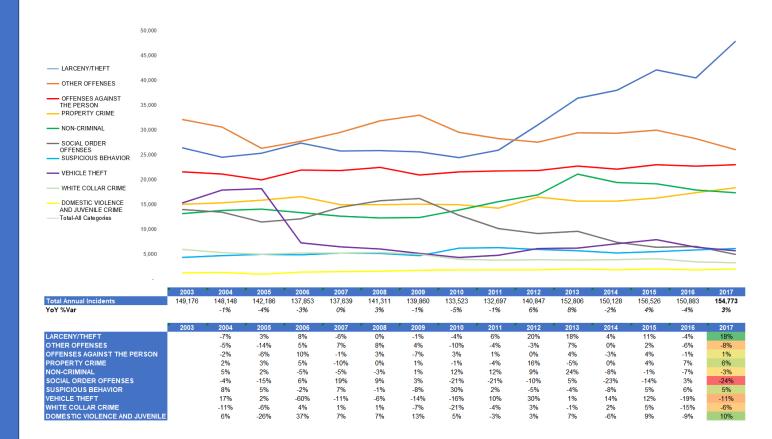
We had 154,773 Incidents in 2017, which was +3% YoY.

Larceny continues to be the Top Incident, and has grown +18% YoY.

Social Order Offenses are down significantly, a trend that began ~2010. July 2018 incidents were down -24% YoY. Most of this is due to a drop in Narcotic and Drug related incidents.

*Note: Incident Types were Categorized into 10 Groups for analysis and modeling purposes.

Annual Incidents - 2017





2017 Incidents by Category & Districts

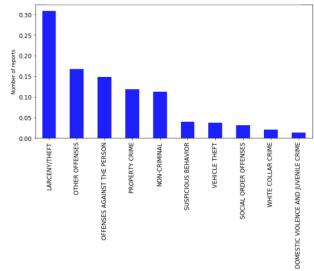
Larceny was the largest category in 2017, representing 31% of all incidents, and growing +18% YoY. Social Order Offenses dropped -24%, largely due to a drop in Narcotic/Drug related incidents.

When comparing incidents by District, we can see that 'High Incident' Districts can have significantly different growth rates compared to 'Low Incident' Districts.

* High Incident Districts: Central, Mission, Northern, Southern

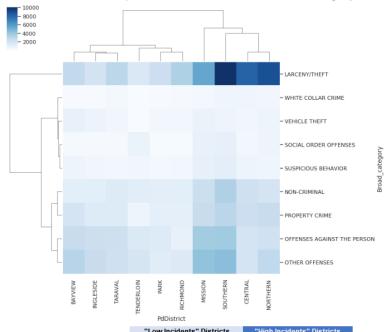
2017 Incidents by Category & District





	2017 incidents	YoY% Var	% To Total
LARCENY/THEFT	47,826	18.2%	30.9%
OTHER OFFENSES	26,036	- 7.8 %	16.8%
OFFENSES AGAINST THE PERSON	23,007	1.4%	14.9%
PROPERTY CRIME	18,382	5.7%	11.9%
NON-CRIMINAL	17,368	-3. <mark>11</mark> %	11.2%
SUSPICIOUS BEHAVIOR	6,152	5.2%	4.0%
VEHICLE THEFT	5,732	-10.7%	3.7%
SOCIAL ORDER OFFENSES	4,969	-24.4%	3.2%
DOMESTIC VIOLENCE & JUVEN	2,039	10.2%	1.3%
WHITE COLLAR CRIME	3,262	-6. 4 %	
TOTAL INCIDENTS	154,773	3%	

Cluster Map 2017 Incidents – District vs. Category



LARCENY/THEFT 15,246 9.4% 32,580 22,5% OTHER OFFENSES 12,603 -4.2% 13,433 -11,0% OFFENSES AGAINST THE PERSON 11,189 1.8% 11,818 0.9% PROPERTY CRIME 7,677 2.9% 10,705 7.4% NON-CRIMINAL 7,413 -5.2% 9,955 -1.0% SUSPICIOUS BEHAVIOR 2,814 3.6% 3,338 6.6% SOCIAL ORDER OFFENSES 2,020 -26.2% 2,949 -22.1% VEHICLE THEFT 3,073 -15.3% 2,659 -1.5% WHITE COLLAR CRIME 1,249 -10.2% 2,013 -1.4% DOME STIC VIOLENCE & JUVEN 1,209 16.8% 830 1.8%		LOW IIICIU	ciita Diatricta	riigii iiiciuc	iita Diatricta
OTHER OFFENSES 12,603 -4.25 13,433 -17.0% OFFENSES AGAINST THE PERSON 11,189 1.8% 11,818 0.9% PROPERTY CRIME 7,677 2.9% 10,705 7.3% NON-CRIMINAL 7,413 -5.75 9,955 -1.0% SUSPICIOUS BEHAVIOR 2,814 3.6% 3,338 6.5% SOCIAL ORDER OFFENSES 2,020 -26.2% 2,949 -23.1% VEHICLE THEFT 3,073 -15.2% 2,659 -19% WHITE COLLAR CRIME 1,249 -10.3% 2,013 -1.5% DOMESTIC VIOLENCE & JUVEN 1,209 16.8% 830 1.9%		2017	YoY% Var	2017	YoY% Var
OFFENSES AGAINST THE PERSON 11,189 1.8% 11,818 0.9% PROPERTY CRIME 7,677 2.9% 10,705 7.43% NON-CRIMINAL 7,413 -5.7% 9,955 -1.0% SUSPICIOUS BEHAVIOR 2,814 3.6% 3,338 6.4% SOCIAL ORDER OFFENSES 2,020 -26.2% 2,949 -22.1% VEHICLE THEFT 3,073 -15.9% 2,659 -3.9% WHITE COLLAR CRIME 1,249 -10.8% 2,013 -3.8% DOME STIC VIOLENCE & JUVEN 1,209 16.8% 830 1.8%	LARCENY/THEFT	15,246	9.4%	32,580	22.9%
PROPERTY CRIME 7,677 2.9% 10,705 7.8% NON-CRIMINAL 7,413 -5.7% 9,955 -1.0% SUSPICIOUS BEHAVIOR 2,814 3.6% 3,338 6.6% SOCIAL ORDER OFFENSES 2,020 -26.2% 2,949 -22.1% VEHICLE THEFT 3,073 -15.9% 2,659 -1.9% WHITE COLLAR CRIME 1,249 -10.2% 2,013 -1.4% DOME STIC VIOLENCE & JUVEN 1,209 16.8% 830 1.8%	OTHER OFFENSES	12,603	-4.2%	13,433	-11 0%
NON-CRIMINAL 7,413 -5 (25) 9,955 -1,0% SUSPICIOUS BEHAVIOR 2,814 3,6% 3,338 6,6% SOCIAL ORDER OFFENSES 2,020 -26.2% 2,949 -221 (%) VEHICLE THEFT 3,073 -15.0% 2,013 -3.1% WHITE COLLAR CRIME 1,249 -10.8% 2,013 -3.1% DOMESTIC VIOLENCE & JUVEN 1,209 16.8% 830 1.4%	OFFENSES AGAINST THE PERSON	11,189	1.8%	11,818	0.9%
SUSPICIOUS BEHAVIOR 2,814 3.6% 3,338 6.8% SOCIAL ORDER OFFENSES 2,020 -26.2% 2,949 -23.1% VEHICLE THEFT 3,073 -15.2% 2,059 -1.9% WHITE COLLAR CRIME 1,249 -10.3% 2,013 -3.1% DOMESTIC VIOLENCE & JUVEN 1,209 16.8% 830 1.8%	PROPERTY CRIME	7,677	2.9%	10,705	7.8%
SOCIAL ORDER OFFENSES 2,020 -26.2% 2,949 -22.1% VEHICLE THEFT 3,073 -15.2% 2,659 -3.9% WHITE COLLAR CRIME 1,249 -60.2% 2,013 -3.4% DOMESTIC VIOLENCE & JUVEN 1,209 16.8% 830 1.4%	NON-CRIMINAL	7,413	-5. <mark>79</mark> %	9,955	-1.0%
VEHICLE THEFT 3,073 15.0% 2,659 -3.0% WHITE COLLAR CRIME 1,249 -10.0% 2,013 -3.4% DOME STIC VIOLENCE & JUVEN 1,209 16.8% 830 1.4%	SUSPICIOUS BEHAVIOR	2,814	3.6%	3,338	6.6%
WHITE COLLAR CRIME 1,249 -1006 2,013 -14% DOMESTIC VIOLENCE & JUVEN 1,209 16.8% 830 1.4%	SOCIAL ORDER OFFENSES	2,020	-26.2 <mark>%</mark>	2,949	-23 1%
DOMESTIC VIOLENCE & JUVEN 1,209 16.8% 830 1.4%	VEHICLE THEFT	3,073	-15.9 <mark>%</mark>	2,659	-319%
, , , , , , , , , , , , , , , , , , ,	WHITE COLLAR CRIME	1,249	- <mark>10.8</mark> %	2,013	-314%
TOTAL INCIDENTS 64.403 400 00.000 F00	DOMESTIC VIOLENCE & JUVEN	1,209	16.8%	830	1.8%
TOTAL INCIDENTS 64,493 -1% 90,280 5%	TOTAL INCIDENTS	64,493	-1%	90,280	5%



2017 Incidents by Hour & Day

When looking at all incidents in 2017, 12pm and 6pm seem to have the most volume.

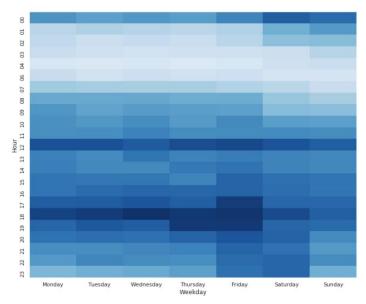
However, when we look at the incidents by Incident Category, we see that the Hour with the most volume can vary.

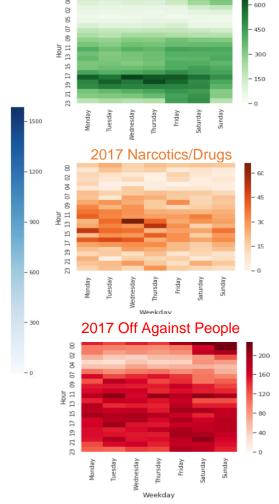
The Narcotics/Drug Category had the most incidents occur at 1PM, with 249 occurrences in 2017. 5PM is the next highest Hour at 246 incidents in 2017.

Offenses Against Other People incidents are distributed more evenly across the hours, with volume spread through Noon to around Midnight.

Incidents by Hour and Day

2017 All Incidents





2017 Larceny



4)Create a model which predicts the weekly volume of incidents in 2018 by crime category type

2018 Incidents Forecasts



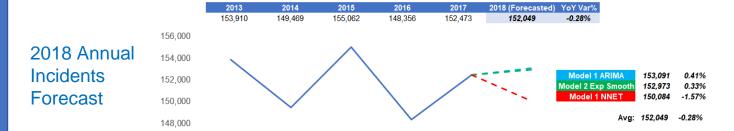
2018 Incidents Forecast

Our models forecast a slight YoY drop in incidents, falling -0.28% to 152K.

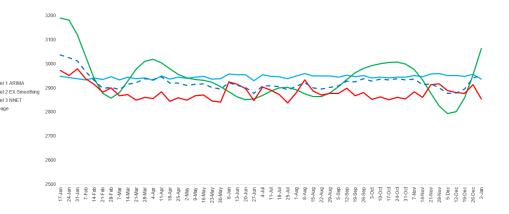
*The forecast is based on taking Weekly Incidents and forecasting through three separate time-series models.

*We used a date range starting Jan 2015 after observing less variance in data from recent years. I am making some assumptions that data from earlier years may have been impacted by suboptimal data collection methods.

2018 Forecasted Incidents By Week









Time Series Models

This slide compares 3 time series models from the Rforecast package: arima, tbats, nnetar.

For each model, we use Weekly data beginning from Jan 2015 to Dec 2017. *Although we have weekly data going back to 2003, we choose to use only a subset of data due to observed trends and stationarity in more recent years.

The Test set is the latest 12 weeks for each data set.

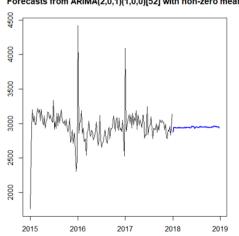
The Training set is the entire data set after removing the latest 12 weeks.

2018 Forecasted Incidents – By Week

Model 1

Weekly Avg. Yearly Total YoY% Forecast 2,944 153,091 0.41%

Forecasts from ARIMA(2,0,1)(1,0,0)[52] with non-zero mean



arima	MAPE	MPE
Train	4.78	-0.58
Test	3.09	-0.82

*MAPE: Mean Absolute Percentage Error

**MPE: Mean Percentage Error

Model 2

Weekly Avg. Yearly Total YoY% Forecast 152.973 0.33% 2,942

Forecasts from TBATS(1, {0.0}, 0.891, {<52.6>})

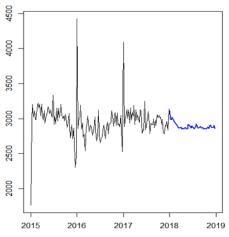
	Forecasi	S Irom 16	A 15(1, {0,0	}, 0.891, {<5/	2,0>})
4500		1			
4000					
3500					
3000	MAM	y.Mwl.	many	hah V	\sim
2500		77 "	'		
2000					
:	2015	2016	2017	2018	2019

tbats	MAPE	MPE
Train	4.83	-0.38
Test	3.06	-0.99

Model 3

Weekly Avg. Yearly Total YoY% Forecast 2.886 150.084 -1.57%

Forecasts from NNAR(4,1,3)[52]



nnetar	MAPE	MPE
Train	2.60	0.17
Test	3.17	-0.86



Time Series Models: Larceny

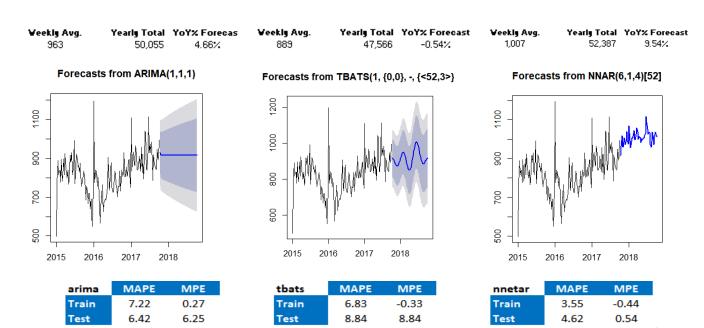
This slide compares Larceny incidents forecast based on 3 time series models from the R-forecast package: arima, tbats, nnetar.

Model 3(nnetar) seems to find a relatively strong trend compared to the other models. Nnetar also has the lowest test error of all models.

It is notable that there are material differences in the final forecasts of each model in terms of YoY % growth for 2018. (i.e. Model 3 predicts a 10% increase in Larceny, while Model 2 forecast a small - 0.54% drop for 2018).

Larceny Forecast 2018 – All Districts

Model 1 Model 2 Model 3





Time Series Models: Larceny by District Type

When breaking out 'High Incident' and 'Low Incident' Districts, we can we see that the forecast for YoY% incidents growth can differ significantly.

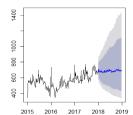
It is also notable that model performance can vary depending on the training data(i.e. Model 2 Test Errors on the High Incidents group are much higher than Test Errors for Low Incidents group.)

Larceny Forecast-2018

Model 1

Weekly Avg. Yearly Total YoY% Forecast 677 35,581 9.21%

Forecasts from ARIMA(3,1,0)(1,0,0)[52]



arima	MAPE	MPE
Train	7.74	0.13
Test	9.06	9.06

"Low Incident" Districts

"High

Incident"

Districts

Forecasts from ARIMA(3,0,0) with non-zero mean

Weekly Avg. Yearly Total YoY% Forecast

14,483

-5.01%

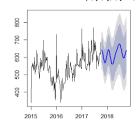
arima	MAPE	MPE
Train	4.78	-0.58
Test	3.09	-0.82

2016 2017

Model 2

Weekly Avg. Yearly Total YoY% Forecast 616 32,041 -1.65%

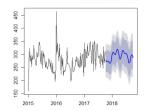
Forecasts from TBATS(1, {0,0}, -, {<52,4>}



tbats	MAPE	MPE
Train	7.65	-0.43
Test	13.28	13.28

Weekly Avg. Yearly Total YoY% Forecast 292 15,199 -0.31%

Forecasts from TBATS(1, {0,0}, -, {<52,6>})

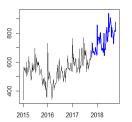


tbats	MAPE	MPE
Train	4.83	-0.38
Test	3.06	-0.99

Model 3

Weekly Avg. Yearly Total YoY% Forecast 755 39,265 20.52%

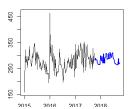
Forecasts from NNAR(4,1,3)[52]



nnetar	MAPE	MPE
Train	5.17	-0.69
Test	7.41	6.03

Weekly Avg. Yearly Total YoY% Forecast 283 14,695 -3.61%

Forecasts from NNAR(3,1,2)[52]



nnetar	MAPE	MPE
Train	2.60	0.17
Test	3.17	-0.86



Forecast Model Findings:

Model 1: arima

This model does not seem to find a strong trend in the data we tested. The forecasted weekly incident data has less weekly variance.

Model 2: tbats

This method allows for multiple seasonality, which seems appropriate for our use case. The model does find some trends, however the test error was the highest across all models.

Model 3: nnetar (best model)

This model seemed to do the best in finding trends, without over-fitting too much. This method works well with nonlinear trends and large amounts of data. The next step would be to add other variables and increase the time range.

Incidents Forecast Model: Next Steps & Considerations

Model Refinements:

Data Governance:

- Standardize data collection and timestamp logging
- Revisit and define Incident Categories
- Clean data to remove/smooth outliers

Add Data Attributes:

- Incorporate more Data attributes into the model: Holidays, Weather, Economics, etc.
- · Create Key to join to Call Data

Model Optimization:

- Create and engineer features that may help improve model accuracy (i.e. smoothing or weighting data based on off-line data).
- Continue to test different models to improve accuracy.

