Netflix Subscribers Forecasting



Introduction

- Netflix had just 21.4 million paid subscribers in 2011. In 7 years, that number is more than 7x as high. The data tells us a story of how streaming platforms came to popularity over time.
- Now, at approximately **158.33 million paid subscribers worldwide**, Netflix faces rivals such as Hulu, Disney+, Amazon and other streaming platforms that are growing at a rapid rate.
- Even with growing rivals, Netflix continues to see an increase in subscribers over time. This shows how popular streaming platforms as a whole are becoming, and how Netflix's strategies for growth continue to be successful.

Objectives

- With the rise of rivals, Netflix must be able analyze its growth thus far, and be able to forecast future performance.
- Using historical data of additional paid subscribers per quarter, we used time series techniques to forecast Netflix's growth.
- Factors such as **price hikes**, **rival growth** and **popular show releases** have affected Netflix's overall performance.
- Allowing past trends to predict future growth will allow for consistent subscriber growth.

Data Description

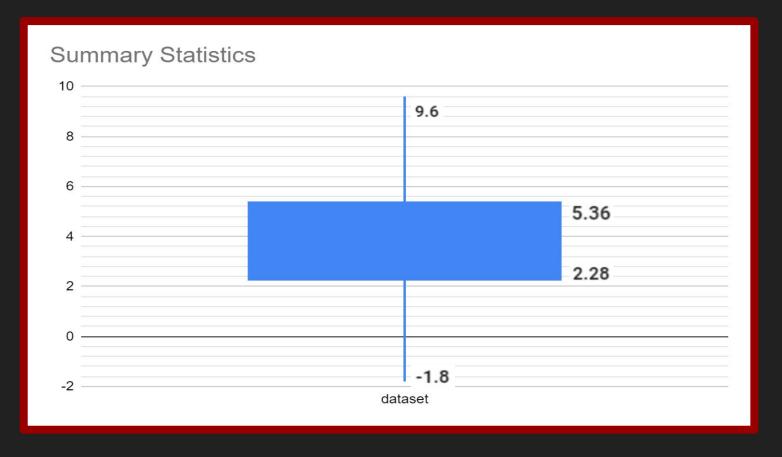
- There are **35** total data points in our dataset
 - For the purpose of forecasting, our **training data** comprised of **additional paid subscribers** from Q1 2011 Q4 2017.
 - Our testing dataset comprised of additional paid subscribers from Q1 2018 Q3 2019
- Each fiscal year is separated in 4 quarters.
 - o Ranges from Q1 2011 to Q3 2019

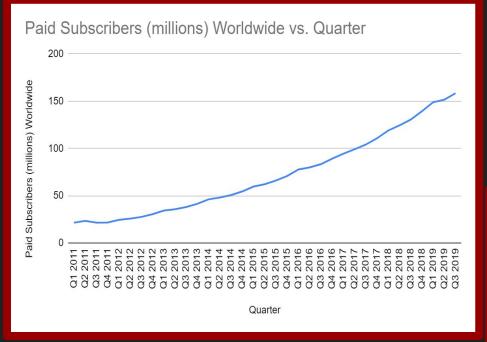
MEAN	1 1	MEDIAN	STD. D	DEV.	VARIANCE
	3.952	3.83	2.4836	653381	6.168534118
> summar	y(subscr	ibers)			
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-1.800	2.280	3.830	3.952	5.360	9.600

Netflix Additional Paid Subscribers (2011 - 2019)

Data Set	Quarter 1	Quarter 2	Quarter 3	Quarter 4
2011	1.39	1.9	-1.8	0.1
2012	2.83	1.28	1.78	2.87
2013	3.88	1.4	2.37	3.42
2014	4.7	1.86	2.66	3.83
2015	5.14	2.46	3.94	4.82
2016	6.87	2.19	3.38	5.81
2017	5.27	4.68	4.98	6.62
2018	8.26	5.45	6.07	8.84
2019	9.6	2.7	6.77	

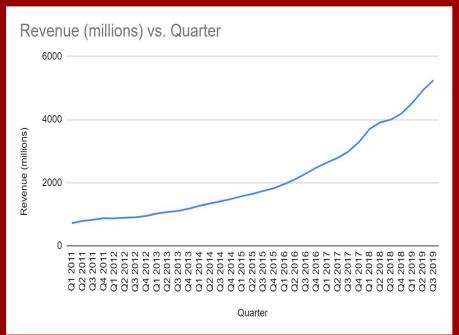
Boxplot of Change in Subscribers

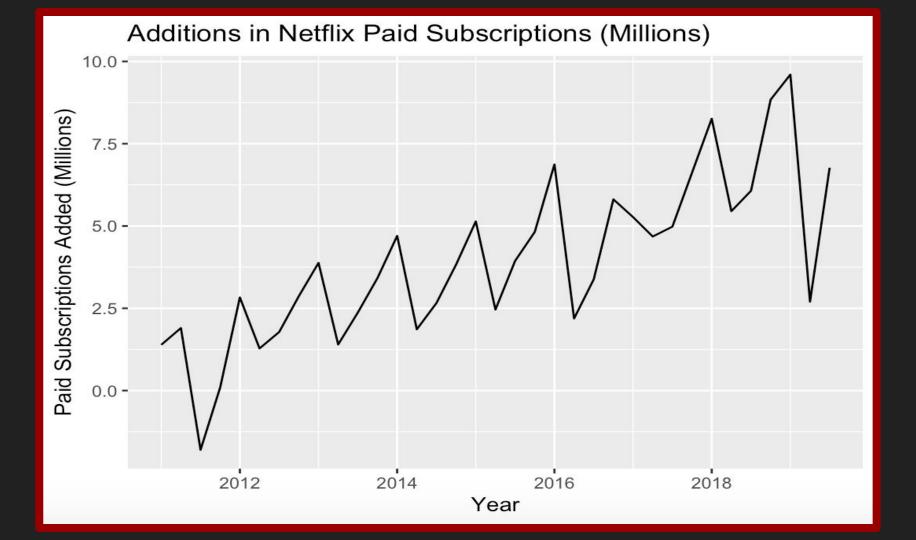




...so does Netflix's revenue per quarter

As subscribers increase over time...

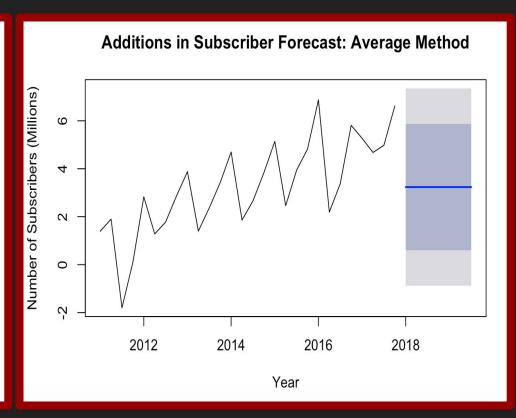




Time Series Techniques

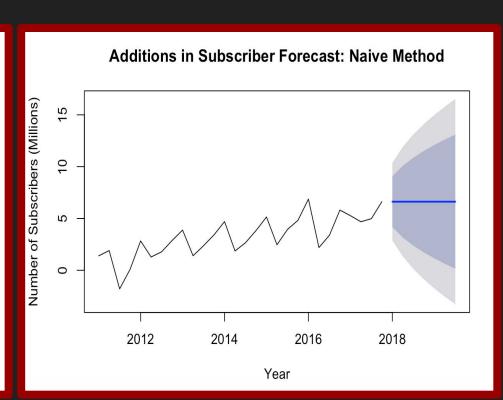
Forecasting: Average Method

```
> #SIMPLE AVG
> simpleaverage = meanf(subscribers,7)
> simpleaverage
        Point Forecast
                        Lo 80
                                  Hi 80
                                              Lo 95
              3.236786 0.6025661 5.871005 -0.8775175 7.351089
2018 Q1
2018 02
             3.236786 0.6025661 5.871005 -0.8775175 7.351089
2018 Q3
             3.236786 0.6025661 5.871005 -0.8775175 7.351089
2018 Q4
              3.236786 0.6025661 5.871005 -0.8775175 7.351089
2019 Q1
              3.236786 0.6025661 5.871005 -0.8775175 7.351089
2019 Q2
              3.236786 0.6025661 5.871005 -0.8775175 7.351089
2019 Q3
              3.236786 0.6025661 5.871005 -0.8775175 7.351089
```



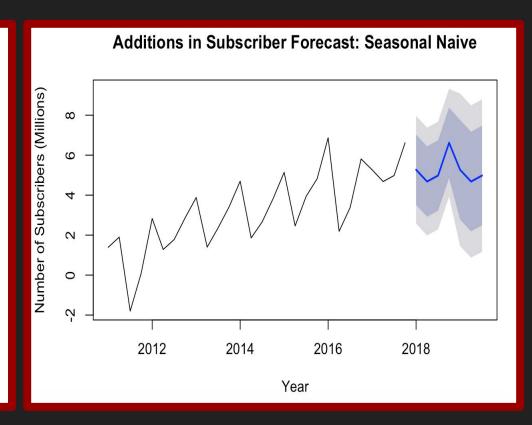
Forecasting: Naive Method

```
> #NAIVE
> naivemethod = naive(subscribers,7)
> naivemethod
                          Lo 80
        Point Forecast
                                  Hi 80
                                               Lo 95
                                                        Hi 95
2018 Q1
                  6.62 4.1723583 9.067642 2.8766550 10.36334
2018 Q2
                 6.62 3.1585119 10.081488
                                           1.3261108 11.91389
2018 Q3
                  6.62 2.3805602 10.859440 0.1363363 13.10366
2018 Q4
                 6.62 1.7247166 11.515283 -0.8666900 14.10669
2019 Q1
                  6.62 1.1469067 12.093093 -1.7503738 14.99037
2019 Q2
                  6.62 0.6245267 12.615473 -2.5492851 15.78929
2019 Q3
                  6.62 0.1441487 13.095851 -3.2839599 16.52396
```



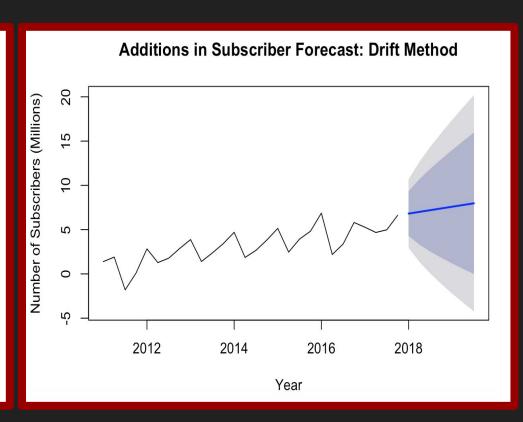
Forecasting: Seasonal Naive Method

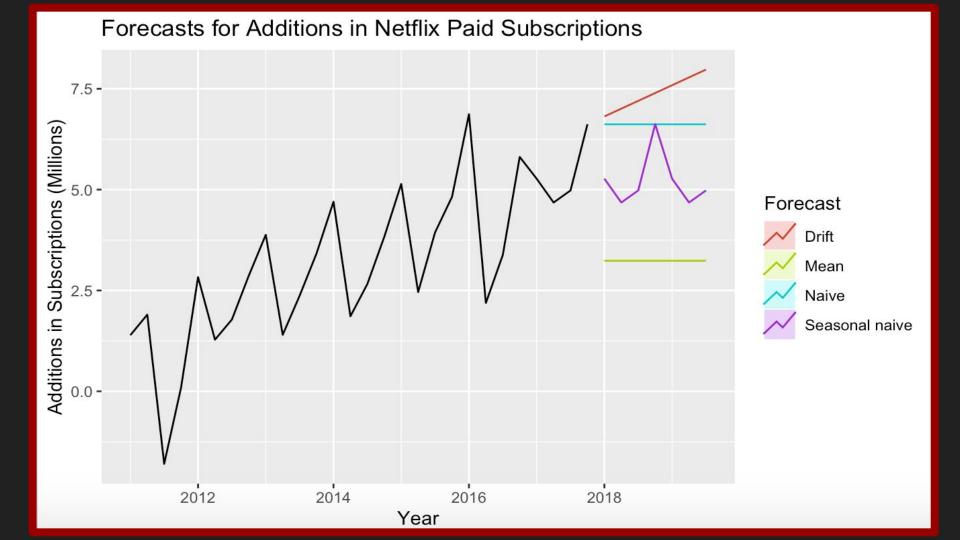
```
#SEASONAL NAIVE
  seasonalnaivemethod = snaive(subscribers, 7, freq=4)
  seasonalnaivemethod
        Point Forecast
                                   Hi 80
                          Lo 80
                                            Lo 95
                                                      Hi 95
2018 Q1
                  5.27 3.508181 7.031819 2.5755306 7.964469
2018 Q2
                  4.68 2.918181 6.441819 1.9855306 7.374469
2018 Q3
                  4.98 3.218181 6.741819 2.2855306 7.674469
2018 Q4
                  6.62 4.858181 8.381819 3.9255306 9.314469
2019 Q1
                  5.27 2.778412 7.761588 1.4594449 9.080555
2019 Q2
                  4.68 2.188412 7.171588 0.8694449 8.490555
2019 Q3
                  4.98 2.488412 7.471588 1.1694449 8.790555
```



Forecasting: Drift Method

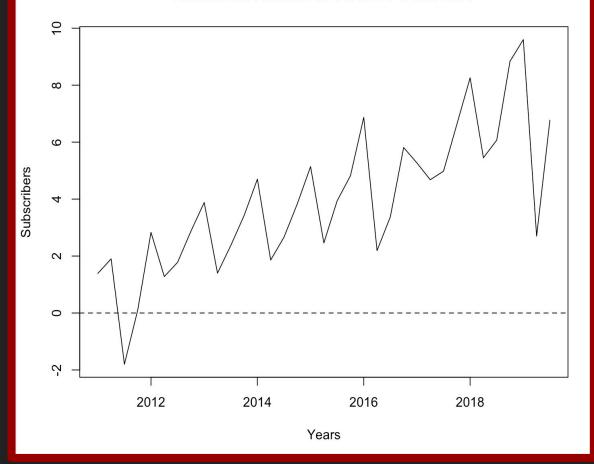
```
> #DRIFT
> driftmethod = rwf(subscribers, 7, drift = TRUE)
> driftmethod
        Point Forecast
                            Lo 80
                                      Hi 80
                                                  Lo 95
                                                           Hi 95
                       4.28676321 9.340644
2018 Q1
             6.813704
                                            2.94908171 10.67833
2018 Q2
                       3.30834529 10.706470
                                            1.35018008 12.66463
              7.007407
2018 Q3
                       2.52212651 11.880096 0.04522168 14.35700
                       1.82570920 12.963920 -1.12239722 15.91203
2018 Q4
2019 Q1
                       1.18155499 13.995482 -2.21008664 17.38712
2019 Q2
                       0.57142267 14.993022 -3.24574403 18.81019
2019 Q3
              7.975926 -0.01496155 15.966813 -4.24508186 20.19693
```





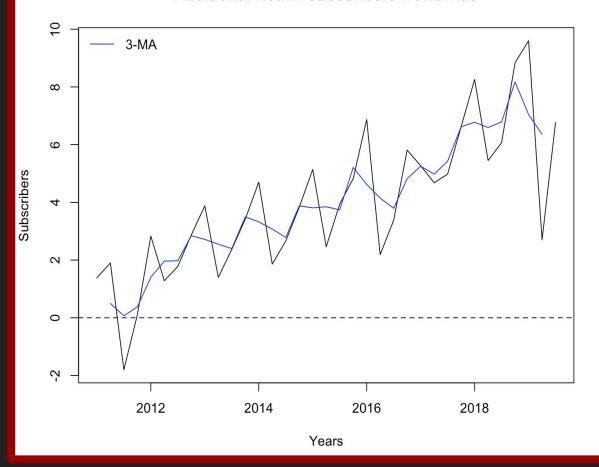
Purpose:

- See trend over time
- Smooths out short-term fluctuations



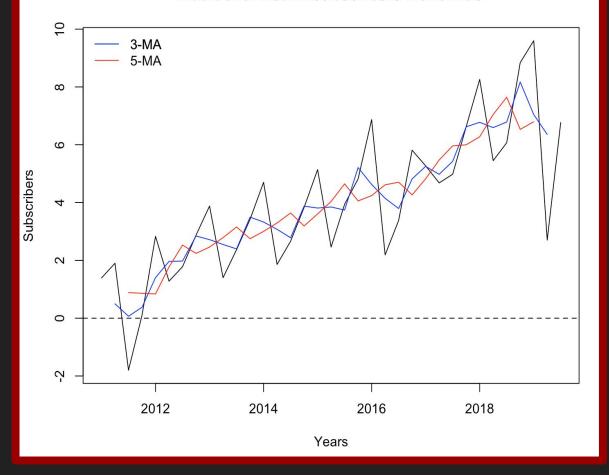
Purpose:

- See trend over time
- Smooths out short-term fluctuations



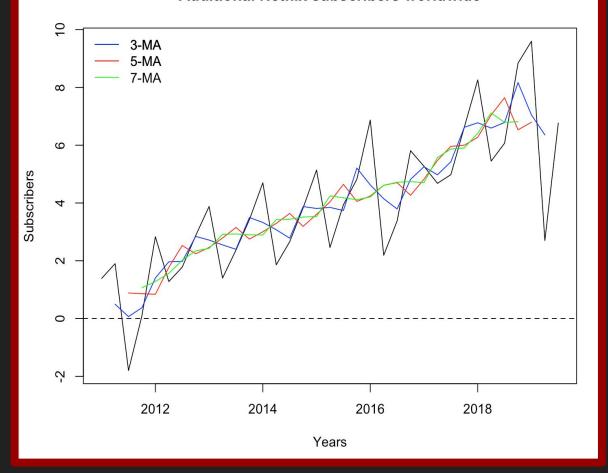
Purpose:

- See trend over time
- Smooths out short-term fluctuations



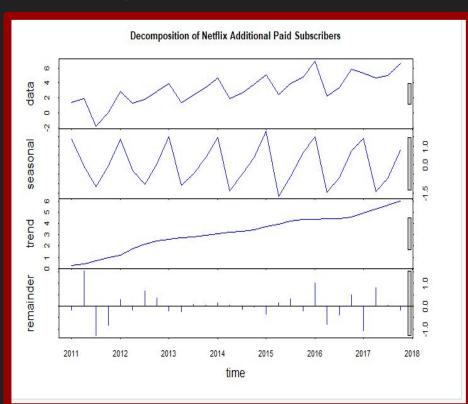
Over time:

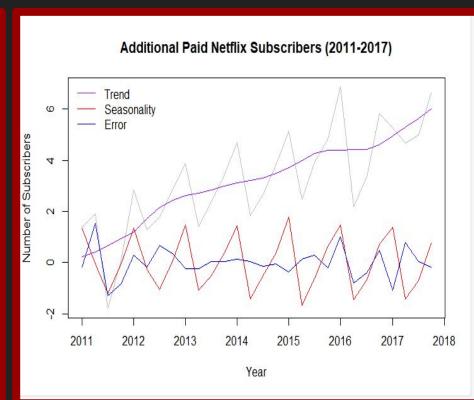
- Increasing trend
- Higher MA = smoother function



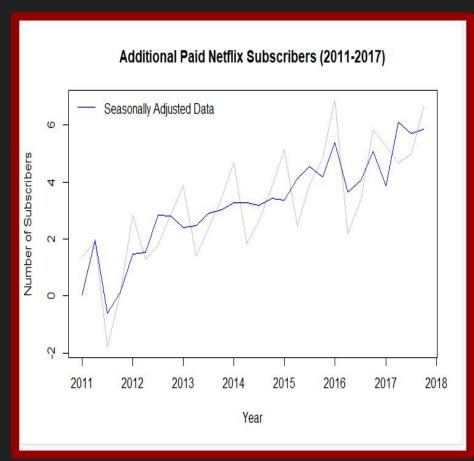
Additive Decomposition Using STL

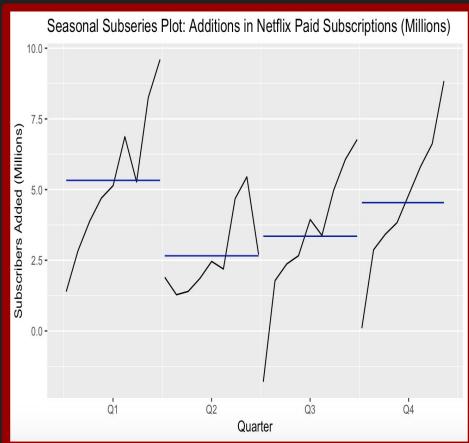
Analyzing Trend and Seasonality

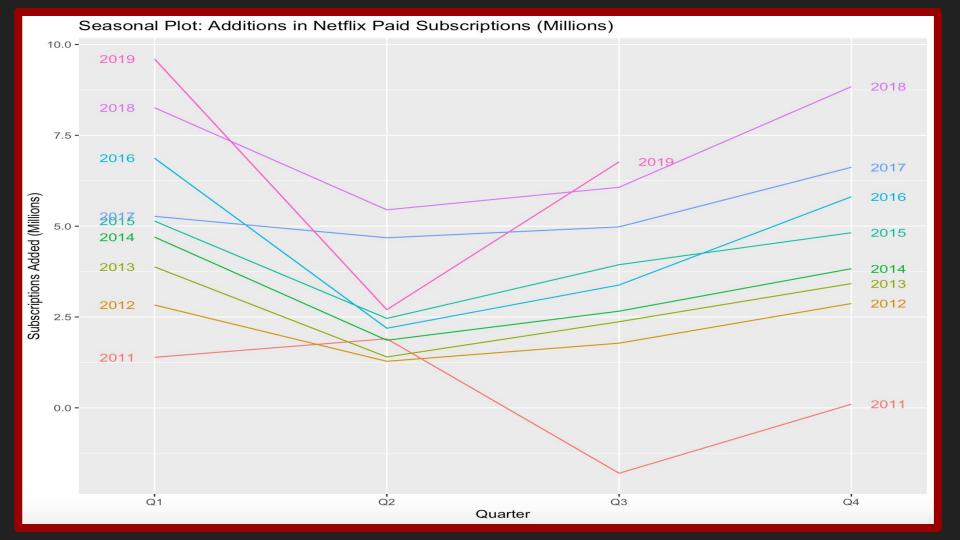




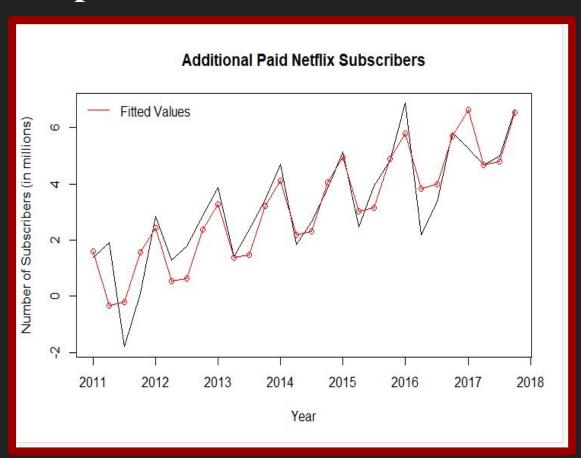
Seasonally Adjusted Data + Subseries Seasonal





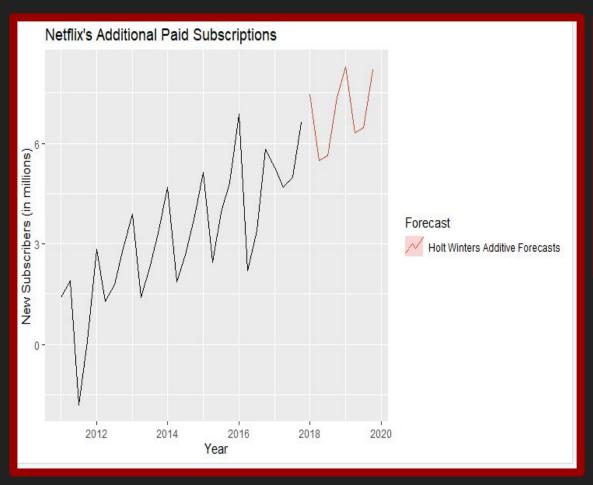


Implementation of Holt-Winters Seasonal Method



	Qtr1	Qtr2	Qtr3	Qtr4	
2011	1.6117650	-0.3262735	-0.1893177	1.5659876	
2012	2.4389559	0.5280641	0.6221529	2.3794307	
2013	3.2734598	1.3668904	1.4656322	3.2156925	
2014	4.1111521	2.1983991	2.3068939	4.0492200	
2015	4.9489359	3.0258647	3.1419753	4.8780250	
2016	5.7823409	3.8510999	3.9822290	5.7085242	
2017	6.6254457	4.6631389	4.8059917	6.5400591	
3.1					

Holt-Winters Seasonal Method Additive Forecasts



		Point	Forecast	Lo 80	Hi 80	Lo 95	Hi 95	_
2018	Q1		7.440724	6.124482	8.756966	5.427705	9.453743	
2018	Q2		5.493792	4.177550	6.810035	3.480773	7.506811	
2018	Q3		5.638410	4.322168	6.954653	3.625391	7.651429	
2018	Q4		7.371425	6.055183	8.687668	5.358406	9.384444	
2019	Q1		8.271196	6.954865	9.587527	6.258042	10.284350	
2019	Q2		6.324264	5.007933	7.640595	4.311110	8.337419	
2019	Q3		6.468882	5.152551	7.785214	4.455727	8.482037	
2019	Q4		8.201897	6.885565	9.518229	6.188742	10.215053	

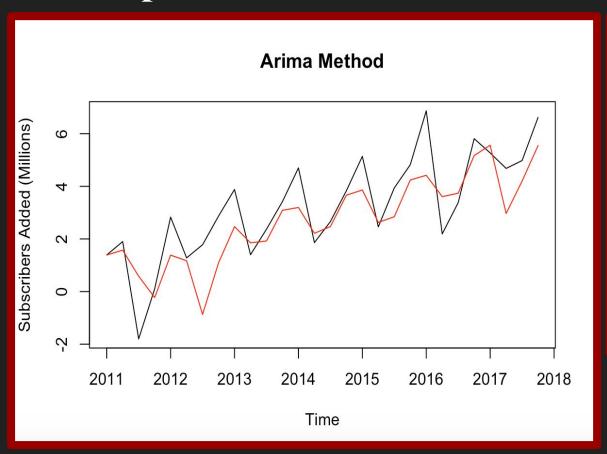
ARIMA

• The best ARIMA model is ARIMA(3,1,0): 3 previous observations, first differencing, and 0 previous errors

```
• ARIMA model with seasonality:
ARIMA(0,0,0) (1,1,0)[4] with drift
```

$$Y_{t}' = c - 0.8094Y_{t-1}' - 0.8430Y_{t-2}' - 0.5815Y_{t-3}'$$

Implementation of ARIMA: ARIMA (3,1,0)



```
> fc=forecast(fit, h=7)
> fc
        Point Forecast
                          Lo 80
                                   Hi 80
                                            Lo 95
              5.382735 3.734809 7.030661 2.862450 7.903021
2018 Q1
              4.827262 3.149682 6.504842 2.261625 7.392899
2018 02
2018 Q3
              5.366145 3.688559 7.043731 2.800498 7.931791
2018 04
              6.117738 4.388092 7.847384 3.472472 8.763004
2019 01
              5.378131 3.317229 7.439033 2.226254 8.530008
2019 02
              5.029828 2.933600 7.126055 1.823924 8.235731
2019 Q3
              5.498151 3.396691 7.599610 2.284246 8.712056
```



Results

Training Method	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Mean	-9.4992E-17	1.9348E+00	1.5732E+00	-1.1613E+02	1.6563E+02	1.4489E+00	4.5932E-01
Naive	1.9370E-01	1.9099E+00	1.6056E+00	7.0482E+01	1.2948E+02	1.4786E+00	-3.1836E-01
Seasonal Naive	8.3167E-01	1.3748E+00	1.0858E+00	2.5291E+01	3.4266E+01	1.0000E+00	-3.7275E-02
Drift	8.2078E-18	1.9001E+00	1.5266E+00	5.7585E+01	1.2131E+02	1.4060E+00	-3.1836E-01
Holts Winter	7.3509E-02	8.6803E-01	6.5199E-01	-4.1198E+01	7.6620E+01	4.0608E-01	-1.0463E-01
Arima	5.3143E-01	1.1905E+00	9.1903E-01	3.2028E+01	4.1966E+01	5.7240E-01	-5.1521E-02
Arima (Seasonal)	5.4783E-02	9.3259E-01	6.9481E-01	-1.0832E+00	2.7372E+01	6.3988E-01	-7.5373E-02

Testing Method	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Mean	3.5761E+00	4.1887E+00	3.7294E+00	4.4296E+01	4.9977E+01	3.4346E+00	-2.4333E-01
Naive	1.9286E-01	2.1895E+00	1.8043E+00	-1.3927E+01	3.6277E+01	1.6617E+00	-2.4333E-01
Seasonal Naive	1.6014E+00	2.4355E+00	2.1671E+00	1.3087E+01	3.4039E+01	1.9958E+00	-4.1599E-01
Drift	-5.8196E-01	2.3669E+00	1.9828E+00	-2.8349E+01	4.4009E+01	1.8261E+00	-1.6724E-01
Holts Winter	9.7329E-02	1.6039E+00	1.1453E+00	-1.1872E+01	2.6710E+01	7.1336E-01	NA
Arima	1.4414E+00	2.4332E+00	2.1071E+00	9.3036E+00	3.3958E+01	1.3124E+00	NA
Arima (Seasonal)	5.2419E-01	1.6518E+00	1.4073E+00	-3.9144E+00	2.8794E+01	1.2961E+00	-2.1838E-01

Results

Average Error	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Mean	1.8849E+00	3.0618E+00	2.6513E+00	-3.5918E+01	1.0781E+02	2.4417E+00	1.0799E-01
Naive	1.9328E-01	2.0497E+00	1.7049E+00	2.8277E+01	8.2876E+01	1.5701E+00	-2.8085E-01
Seasonal Naive	1.2165E+00	1.9051E+00	1.6265E+00	1.9189E+01	3.4153E+01	1.4979E+00	-2.2663E-01
Drift	-2.9098E-01	2.1335E+00	1.7547E+00	1.4618E+01	8.2661E+01	1.6160E+00	-2.4280E-01
Holts Winter	8.5419E-02	1.2360E+00	8.9867E-01	-2.6535E+01	5.1665E+01	5.5972E-01	NA
Arima	9.8643E-01	1.8118E+00	1.5131E+00	2.0666E+01	3.7962E+01	9.4239E-01	NA
Arima (Seasonal)	2.8949E-01	1.2922E+00	1.0511E+00	-2.4988E+00	2.8083E+01	9.6798E-01	-1.4688E-01

- Holt Winters Seasonal Method has the greatest number of minimum errors
- The Mean, Naive, Seasonal Naive, Drift, and Arima models have the greatest errors

Conclusion

Conclusions

- Overall, the best forecasting method is the **Holt's Winter Seasonal Method**.
- Takes seasonality and trend into account.
 - Netflix has certain seasons of growth, but also an overall increasing trend.
- Can be used to predict future number of paid subscribers added each quarter.
- This is evidenced by the fact that Holt's Winter Seasonal Method has the lowest values (closest to 0), for:
 - \circ ME
 - o RMSE
 - o MAE
 - o MASE
- This indicates that the model has the lowest errors, which are closest to 0, indicating the closest fit.

References

https://www.statista.com/statistics/250934/quarterly-number-of-netflix-streaming-subscribers-worldwide/ (Data Source)

https://www.statista.com/chart/16684/netflix-subscription-prices-in-the-united-states/

https://otexts.com/fpp2/moving-averages.html

https://www.statista.com/chart/16684/netflix-subscription-prices-in-the-united-states/

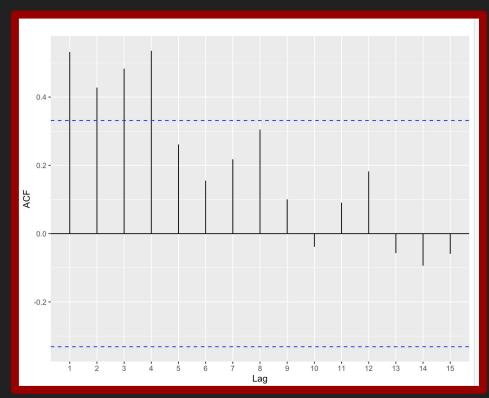
https://www.vox.com/2019/1/16/18185174/netflix-price-increase-subscription-chart-original-content-streaming

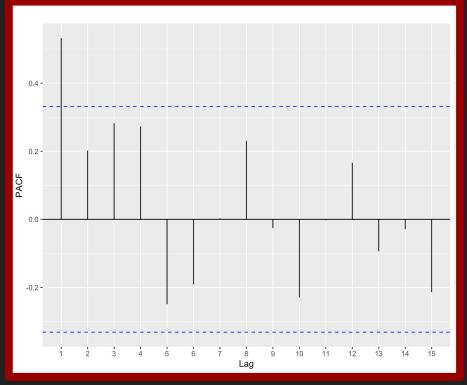
https://rcompanion.org/handbook/G_14.html

https://www.forbes.com/sites/theyec/2011/12/28/5-business-lessons-from-the-netflix-pricing-debacle/#4c18ff64d2a7

Appendix

ACF vs. PACF





Challenges

- Somewhat small dataset
 - Q1 2011 Q3 2019 (35 different data points total)
 - Difficult to attain data before 2011 because of changes in reporting