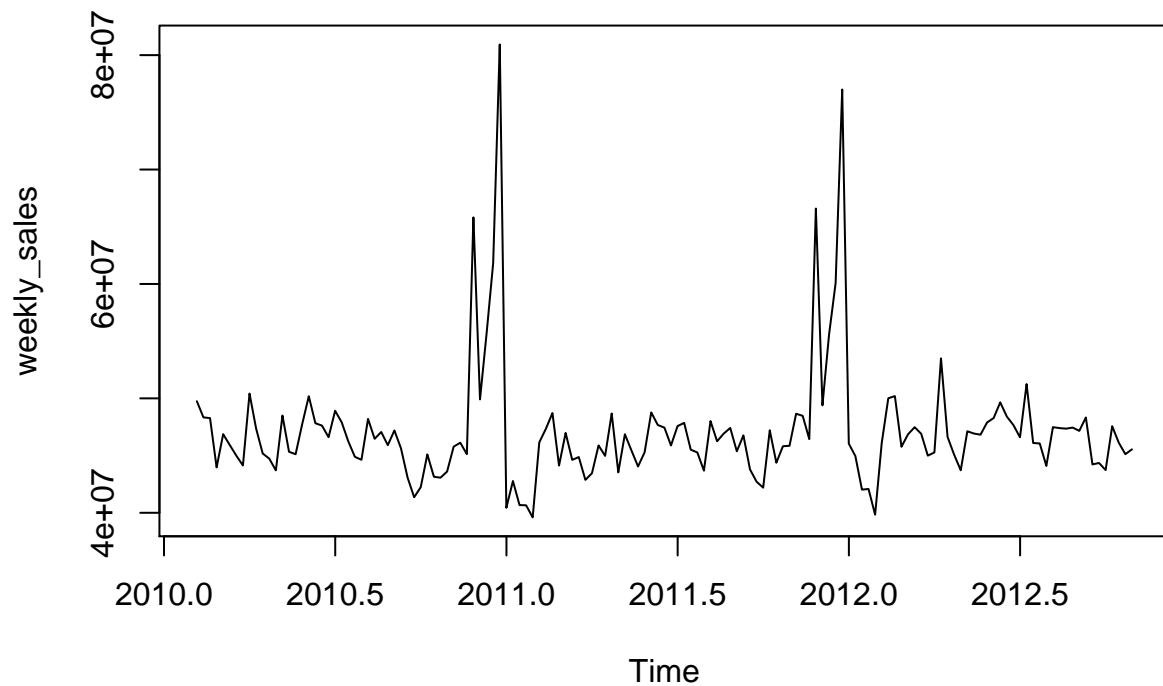


Sales

Oscar

2/6/2021

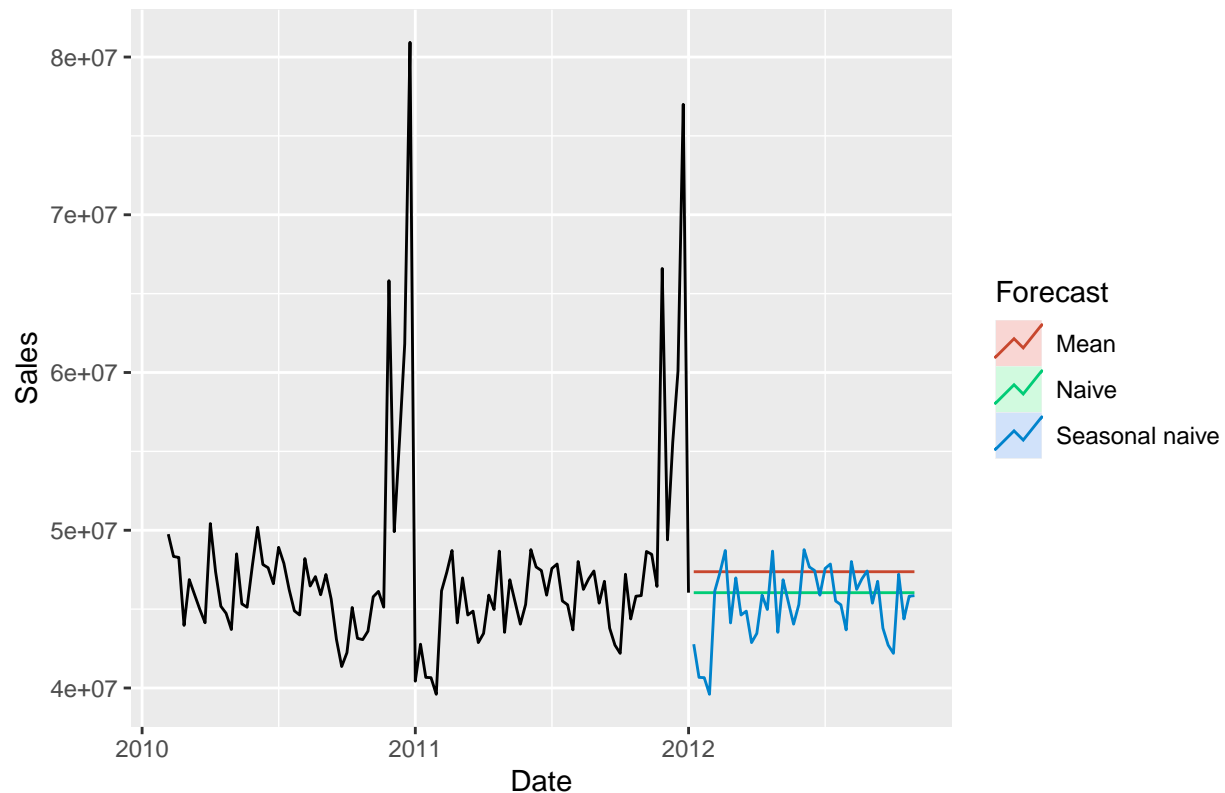
Time Series Analysis We will forecast our sales by using weekly data from the data set that we used in our python project. This will give us about 143 observations with which to forecast. First here is a plot of our weekly sales from 2010-02-05 to 2012-10-26.



As you can see our sales seem to spike around the end of the year, most likely because of the holiday sales boom that retail stores typically get.

Before we do any forecasting we need to decide on some baseline models to use as a benchmark. This will allow us to compare seemingly simpler forecasting models with more complicated models. We will use the mean, naive, and seasonal naive as our baseline models. Down below we plot them.

Forecasts for Sales Data



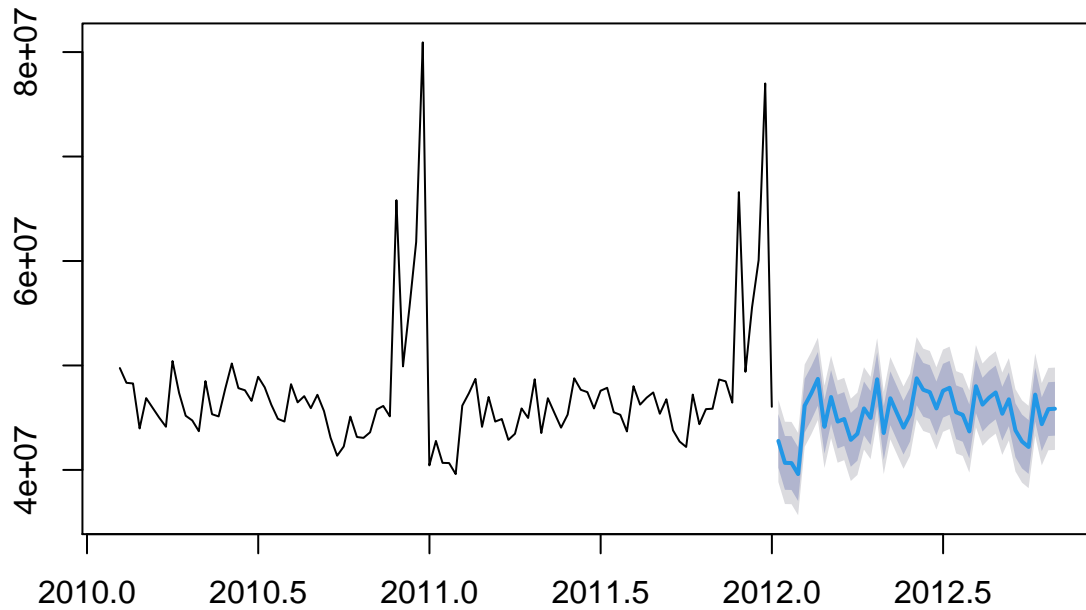
We first partition our data into train and test splits. The training data is what we use to train our model on. While the testing data is how we evaluate our models performance against data that it hasn't been trained on. Up above the *mean* forecast is merely the historical average of the data. The *naive* forecast is simply the value of the last observation. While the *seasonal naive* forecast is equal to the last observed value from the same period in the previous year.

Since our data is highly seasonal we are most concerned with the seasonal naive method. Below we show the accuracy metrics for the seasonal naive method.

```
##           ME    RMSE    MAE    MPE    MAPE    MASE    ACF1
## Training set -91460 2009836 1387984 -0.160249 2.917466 1.000000 0.19892562
## Test set    1166821 1985905 1483137  2.437898 3.129202 1.068555 0.03856437
##           Theil's U
## Training set      NA
## Test set         0.7047942
```

As you can see our mean absolute error (MAE) is 1,387,984 for the training set and 1,483,137 for the test set. This means that on average with our testing data we are off by about 1,483,137 from the true value. There's a couple of things to keep in mind when hearing this forecast. First, we only have about 2 years or 104 weeks of weekly data to forecast off of. Ideally we would want several years worth of data to give effective accurate forecasts. This is to ensure that we have enough data to capture and deal with periodic effects such as seasonality. Second, we are forecasting quite far out into the future (about 43 weeks). If we were forecasting not so far out say only a couple of weeks our forecasts and thus MAE would be more accurate.

Forecasts from Seasonal naive method



The forecast you see above shows the prediction intervals. The 95% prediction interval is shown in light gray while the 80% interval is shown in dark gray. Below I show our forecast numbers which include the date, point estimate, 80% and 95% prediction interval for all 43 weeks of our forecast.

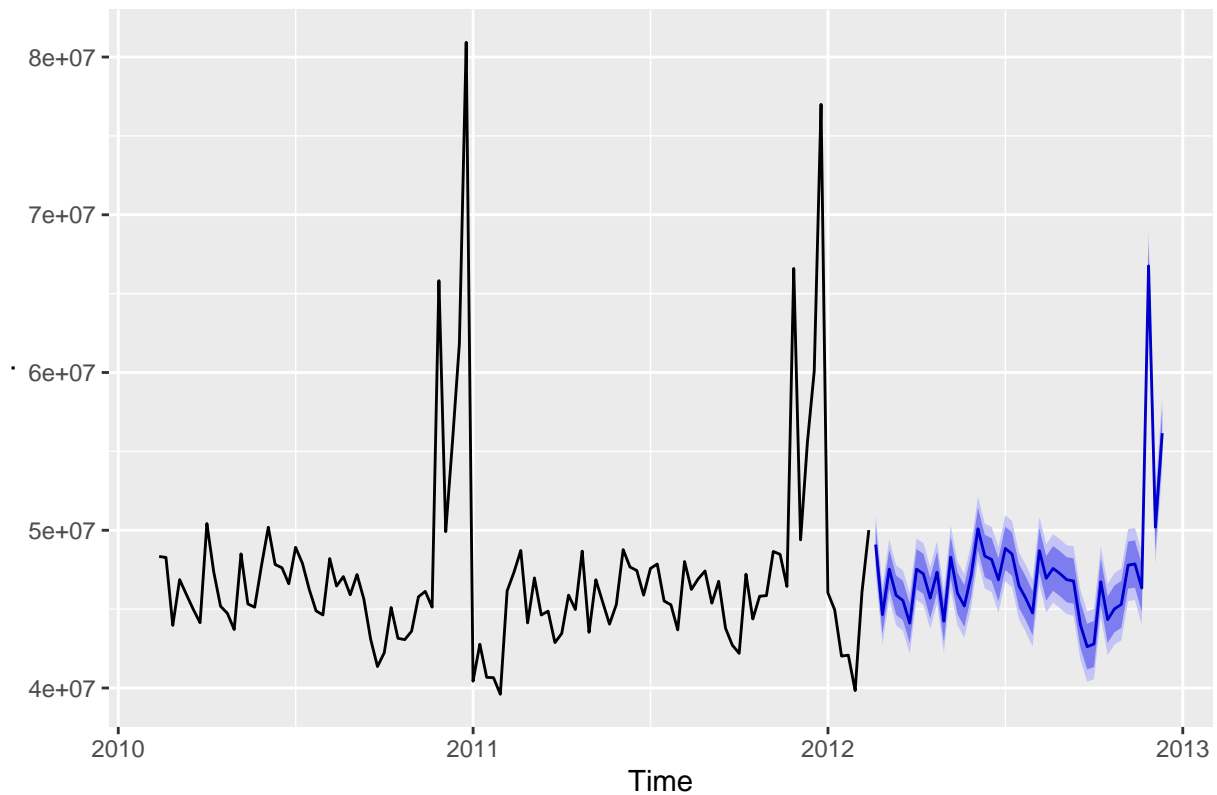
##	Date	Point	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
## 1	2012-01-07		42775788	40200079	45351497	38836581	46714995
## 2	2012-01-14		40673678	38097969	43249387	36734471	44612885
## 3	2012-01-21		40654648	38078939	43230357	36715441	44593855
## 4	2012-01-29		39599853	37024144	42175562	35660646	43539060
## 5	2012-02-05		46153111	43577402	48728820	42213904	50092318
## 6	2012-02-12		47336193	44760484	49911902	43396986	51275400
## 7	2012-02-19		48716164	46140455	51291873	44776957	52655371
## 8	2012-02-26		44125860	41550151	46701569	40186653	48065067
## 9	2012-03-04		46980604	44404895	49556313	43041397	50919811
## 10	2012-03-11		44627319	42051610	47203028	40688113	48566526
## 11	2012-03-18		44872326	42296617	47448035	40933119	48811533
## 12	2012-03-25		42876199	40300490	45451908	38936992	46815406
## 13	2012-04-01		43458991	40883282	46034700	39519784	47398198
## 14	2012-04-08		45887467	43311758	48463176	41948260	49826674
## 15	2012-04-15		44973328	42397619	47549037	41034121	48912535
## 16	2012-04-22		48676692	46100983	51252401	44737485	52615899
## 17	2012-04-29		43530033	40954324	46105742	39590826	47469240
## 18	2012-05-06		46861958	44286249	49437667	42922751	50801165
## 19	2012-05-13		45446145	42870436	48021854	41506938	49385352
## 20	2012-05-20		44046598	41470889	46622307	40107391	47985805
## 21	2012-05-27		45293457	42717748	47869166	41354250	49232664
## 22	2012-06-03		48771994	46196285	51347703	44832787	52711201

## 23	2012-06-10	47669735	45094026	50245444	43730528	51608941
## 24	2012-06-17	47447562	44871853	50023271	43508355	51386769
## 25	2012-06-25	45884095	43308386	48459803	41944888	49823301
## 26	2012-07-02	47578520	45002811	50154228	43639313	51517726
## 27	2012-07-08	47859264	45283555	50434973	43920057	51798471
## 28	2012-07-15	45515930	42940221	48091639	41576723	49455137
## 29	2012-07-22	45274411	42698702	47850120	41335205	49213618
## 30	2012-07-30	43683274	41107565	46258983	39744067	47622481
## 31	2012-08-06	48015467	45439758	50591176	44076260	51954674
## 32	2012-08-13	46249569	43673860	48825278	42310362	50188776
## 33	2012-08-20	46917348	44341639	49493057	42978141	50856554
## 34	2012-08-27	47416948	44841240	49992657	43477742	51356155
## 35	2012-09-03	45376623	42800914	47952332	41437416	49315830
## 36	2012-09-10	46763228	44187519	49338936	42824021	50702434
## 37	2012-09-17	43793960	41218251	46369669	39854753	47733167
## 38	2012-09-24	42718097	40142388	45293806	38778890	46657304
## 39	2012-10-01	42195831	39620122	44771540	38256624	46135038
## 40	2012-10-08	47211688	44635979	49787397	43272482	51150895
## 41	2012-10-15	44374820	41799111	46950529	40435613	48314027
## 42	2012-10-22	45818953	43243245	48394662	41879747	49758160
## 43	2012-10-29	45855821	43280112	48431530	41916614	49795028

STL Decomposition and Exponential Smoothing

Time series decomposition simply means to break up time series data into different components. One such method is called “Seasonal and Trend decomposition using Loess” or STL for short. We can then use this decomposition to help us forecast values by combining it with another forecasting method. We will now forecast our sales data using STL decomposition along with exponential smoothing (ETS).

Forecasts from STL + ETS(M,N,N)



```
##              ME      RMSE      MAE      MPE      MAPE      MASE
## Training set  6214.256  931633.6  653161.3 -0.02322703  1.369993  0.4878678
## Test set     459979.936 1606675.9 1185812.3  0.91312824  2.483784  0.8857225
##              ACF1 Theil's U
## Training set  0.1389597      NA
## Test set     -0.2374639  0.6196751
```

As you can see we improved upon our previous seasonal naive model. Our mean absolute error using STL and ETS for the test set is 1,185,812.3. We beat our previous error for the seasonal naive model by about 297,324.7. The MASE error on the far right also confirms this. A MASE below one means that the current model is better than the average naive model.

It appears that our Exponential Smoothing model beat out our previous baseline model. We can now use this model for forecasting any future sales. Below we list our forecasting for the future 43 weeks using our new model.

```
##      Date Point Forecast    Lo 80    Hi 80    Lo 95    Hi 95
## 1  2012-02-19   49092492 47872280 50312705 47226338 50958647
## 2  2012-02-26   44651828 43423466 45880190 42773211 46530445
## 3  2012-03-04   47532516 46296059 48768973 45641518 49423514
## 4  2012-03-11   45879974 44635474 47124474 43976675 47783272
## 5  2012-03-18   45540412 44287921 46792903 43624892 47455932
## 6  2012-03-25   44112905 42852473 45373336 42185241 46040569
## 7  2012-04-01   47531408 46263086 48799731 45591676 49471140
## 8  2012-04-08   47237506 45961341 48513671 45285780 49189231
## 9  2012-04-15   45696073 44412114 46980032 43732427 47659718
```

## 10	2012-04-22	47339126	46047420	48630832	45363632	49314620
## 11	2012-04-29	44238330	42938923	45537738	42251058	46225602
## 12	2012-05-06	48296739	46989676	49603802	46297758	50295719
## 13	2012-05-13	46006856	44692182	47321530	43996235	48017477
## 14	2012-05-20	45196446	43874204	46518688	43174252	47218641
## 15	2012-05-27	47132226	45802460	48461993	45098524	49165928
## 16	2012-06-03	50089153	48751905	51426402	48044008	52134298
## 17	2012-06-10	48359902	47015213	49704591	46303377	50416426
## 18	2012-06-17	48144996	46792907	49497085	46077155	50212838
## 19	2012-06-25	46852653	45493204	48212101	44773556	48931749
## 20	2012-07-02	48849763	47482995	50216531	46759471	50940054
## 21	2012-07-08	48483426	47109377	49857475	46381999	50584852
## 22	2012-07-15	46479299	45098008	47860591	44366796	48591802
## 23	2012-07-22	45682639	44294143	47071135	43559117	47806161
## 24	2012-07-30	44750938	43355275	46146602	42616455	46885422
## 25	2012-08-06	48704738	47301943	50107533	46559348	50850128
## 26	2012-08-13	46949159	45539269	48359049	44792919	49105400
## 27	2012-08-20	47579311	46162362	48996261	45412274	49746349
## 28	2012-08-27	47256614	45832640	48680588	45078833	49434395
## 29	2012-09-03	46864502	45433538	48295466	44676031	49052973
## 30	2012-09-10	46784927	45347006	48222847	44585817	48984036
## 31	2012-09-17	44018809	42573966	45463652	41809112	46228506
## 32	2012-09-24	42618819	41167086	44070552	40398585	44839053
## 33	2012-10-01	42790280	41331689	44248870	40559558	45021001
## 34	2012-10-08	46734047	45268632	48199463	44492888	48975207
## 35	2012-10-15	44332587	42860377	45804796	42081037	46584136
## 36	2012-10-22	45015363	43536392	46494335	42753471	47277255
## 37	2012-10-29	45297351	43811648	46783055	43025164	47569538
## 38	2012-11-05	47786159	46293755	49278564	45503724	50068595
## 39	2012-11-12	47861767	46362691	49360843	45569128	50154406
## 40	2012-11-19	46337613	44831895	47843331	44034816	48640410
## 41	2012-11-26	66757434	65245103	68269765	64444524	69070344
## 42	2012-12-03	50192111	48673196	51711025	47869131	52515090
## 43	2012-12-10	56154396	54628926	57679866	53821390	58487402