Advanced Data Analytics - D213 Task 1

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Part I: Research Question

A1. Can the ARIMA model effectively forecast 180 days of telecom revenue data with high accuracy?

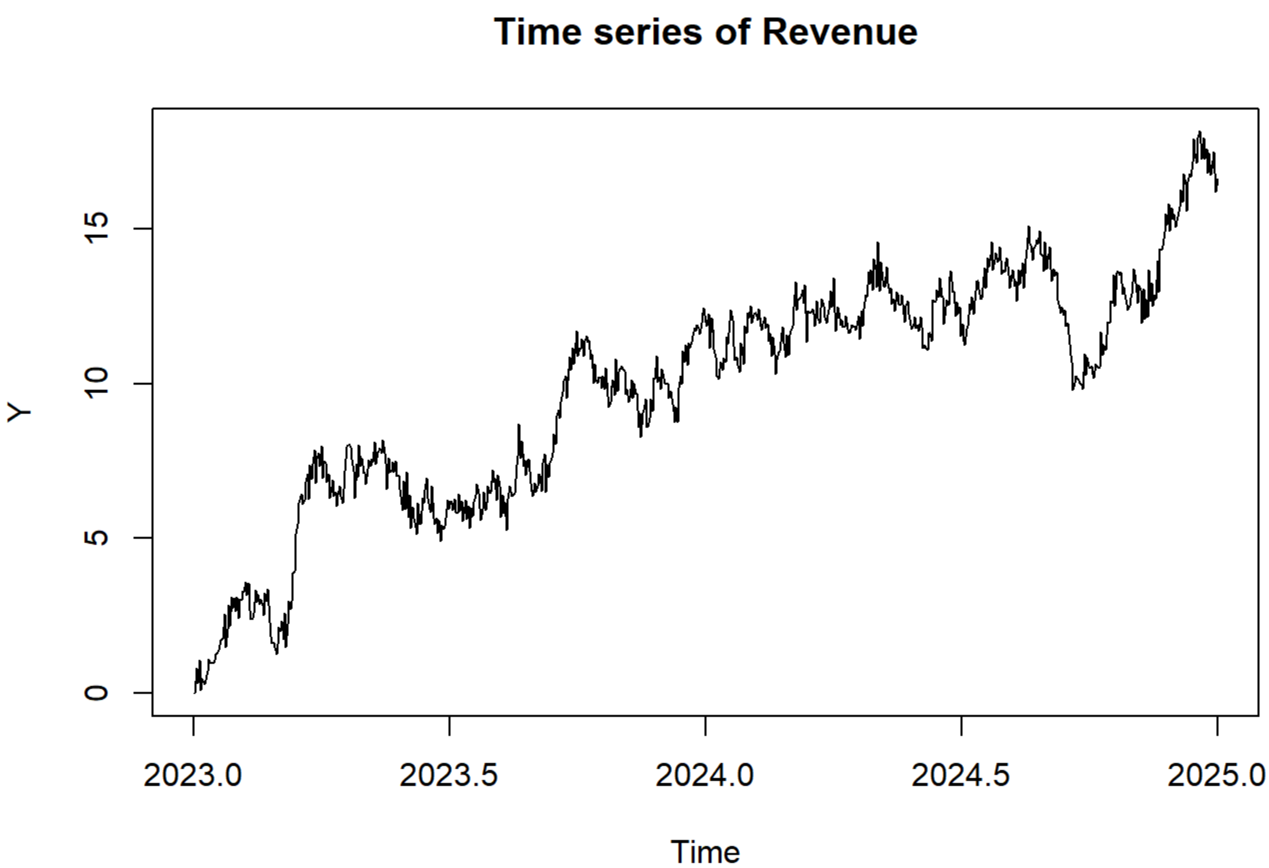
A2. The main purpose of this assessment is to evaluate the ARIMA model's ability to accurately forecast 180 days of revenue data. The objective is to assess the model's performance by comparing its forecasts to the actual observed revenue values from the test data.

Part II: Method Justification

B1. Time series models assume that the data is stationary (GeeksforGeeks, 2024), meaning that the mean and variance remain constant over time. Additionally, time series models typicaly rely on autocorrelation, where past values influence current ones. This is important because models like ARIMA leverage this correlation to identify patterns over time, enabling accurate forecast pred

Part III: Data Preparation

C1. The time series plot shows a clear upward trend over the years. There appears to be some variability along the way without any imediate signs of patters or seasonality. These will be investigated further later.



C2. The time step formatting required that the days be converted into a proper date format. In this time series model I chose to start the date on 2023-01-01 and ending on 2024-12-31 as shown in the code `range(data$Day)`.

```
[1] "2023-01-01" "2024-12-31"
```

This formatting uses daily intervals to ensure a regular time step without any gaps. However, to ensure that there were no gaps, I ran `any(is.na(data))` and `length(data$Day)`. Lastly the data is converted into a time series object with a yearly frequency of 365 observations per year.

```
There are 731 rows of data.
```

```
Missing values: FALSE
```

C3. I checked stationarity using the Augmented Dickey-Fuller (ADF) test. Initially the test returned a p-value of 0.02431 when ran on the original data. A p-value of this size suggests that the data is stationary (StatisticsHowTo, n.d.). However, there is a visible trend in the data.

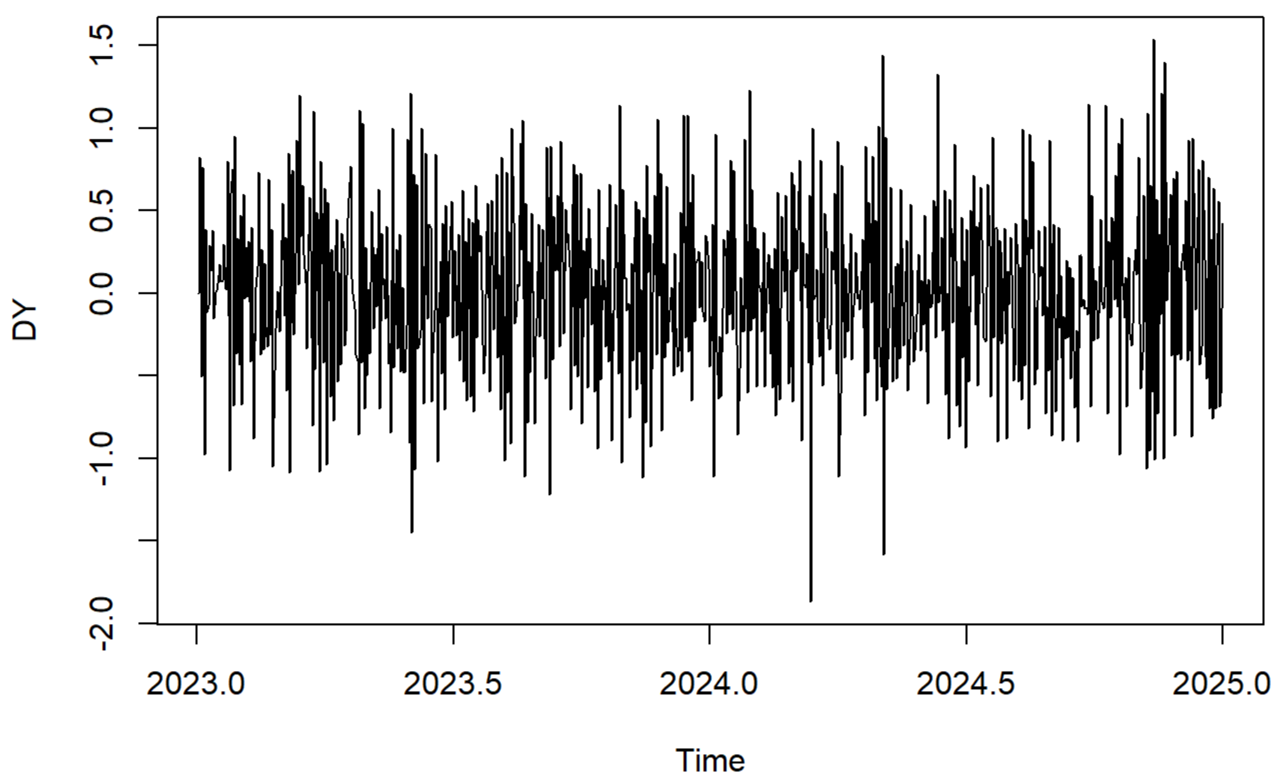
The `ndiffs()` function suggests that time series data needs differencing. I differenced the data and accounted for seasonality (`DY <- diff(Y, s = 1)`) and ran ADF on the differenced data. The new p-value shows improved stationarity and a more significant result at .01 as well as removal of the trend.

The seasonal differencecing accounts for the yearly seasonality that appears to occur once a year. I will explain more about this in the coming sections.

```
	Augmented Dickey-Fuller Test

data:  Y
Dickey-Fuller = -3.6938, Lag order = 9, p-value = 0.02431
alternative hypothesis: stationary

Recomended number of differencing: 1
```

After differencing the time series data (Y):

```
	Augmented Dickey-Fuller Test

data:  DY
Dickey-Fuller = -8.6354, Lag order = 8, p-value = 0.01
alternative hypothesis: stationary
```

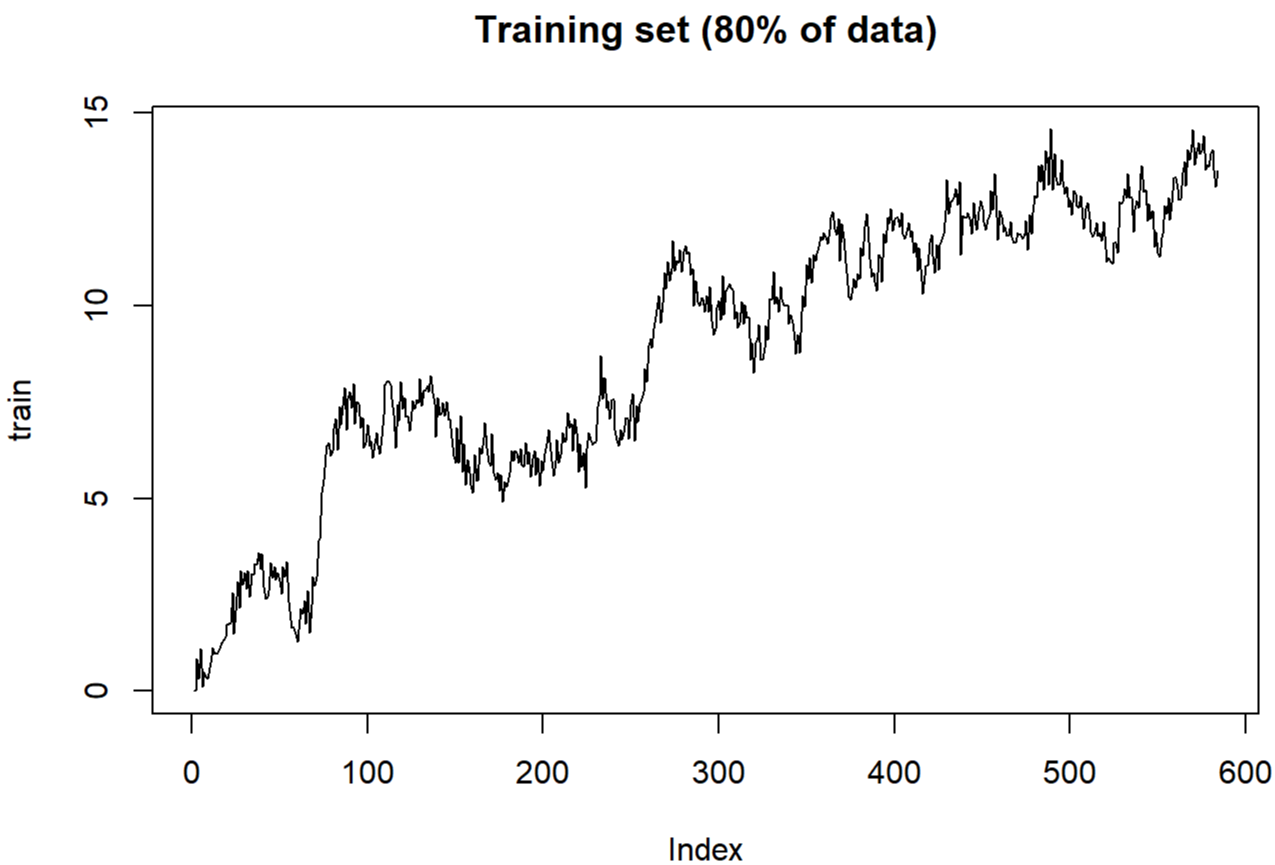


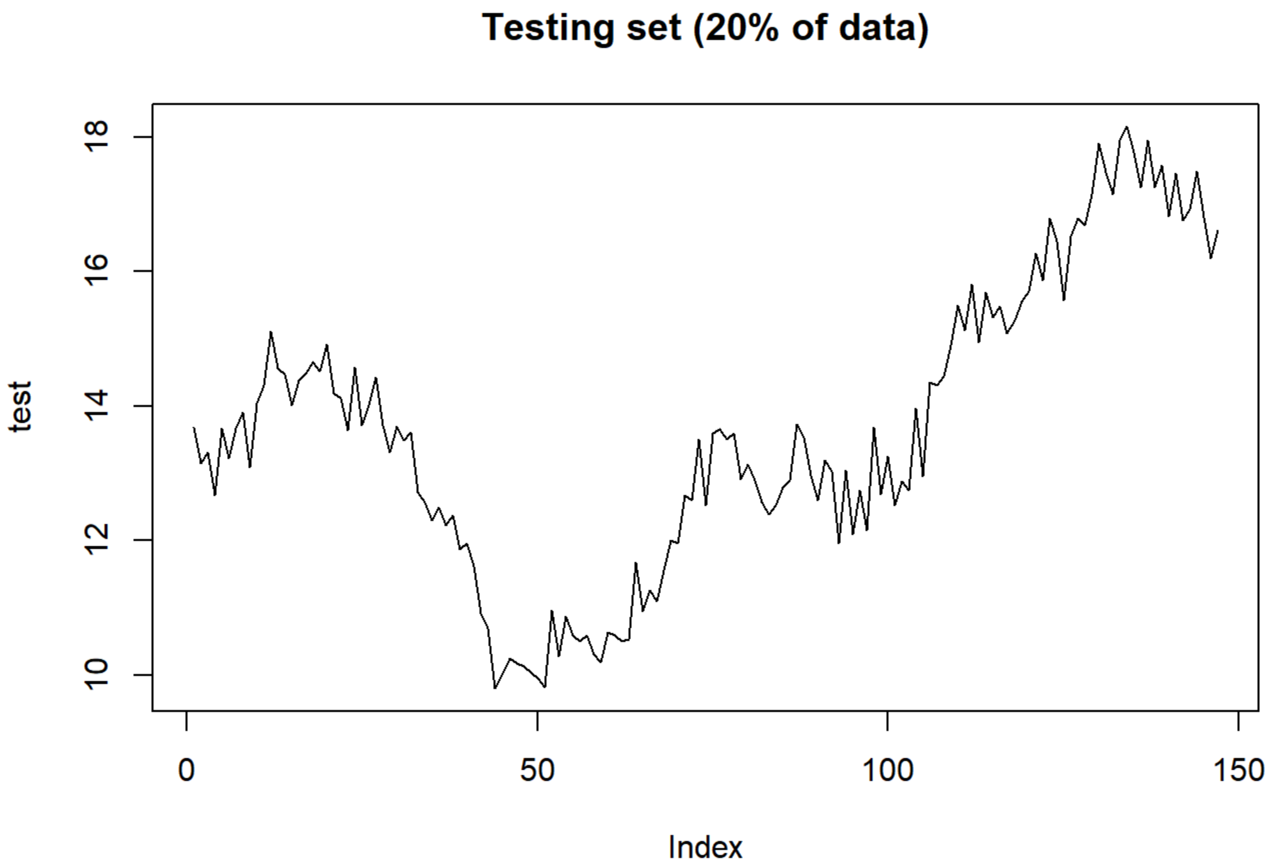
C4. In order to prepare the data, I started by loading the libraries (`tidyverse` , `forecast` , `tseries`) and then I converted the data into a time series format noting the daily nature of the data with `frequency=365`.

```
#converting to ts
Y <- ts(data$Revenue, start = c(2023, 1), frequency = 365)
```

I checked for missing values to ensure there were no gaps in the data, and then plotted the data to visualize trends and any fluctuations.

Before exporting the cleaned data, I split the data into a train and test set, 80/20 split. I allocated the first 80% of the data to the training set, and the remaining 20% to the test set.





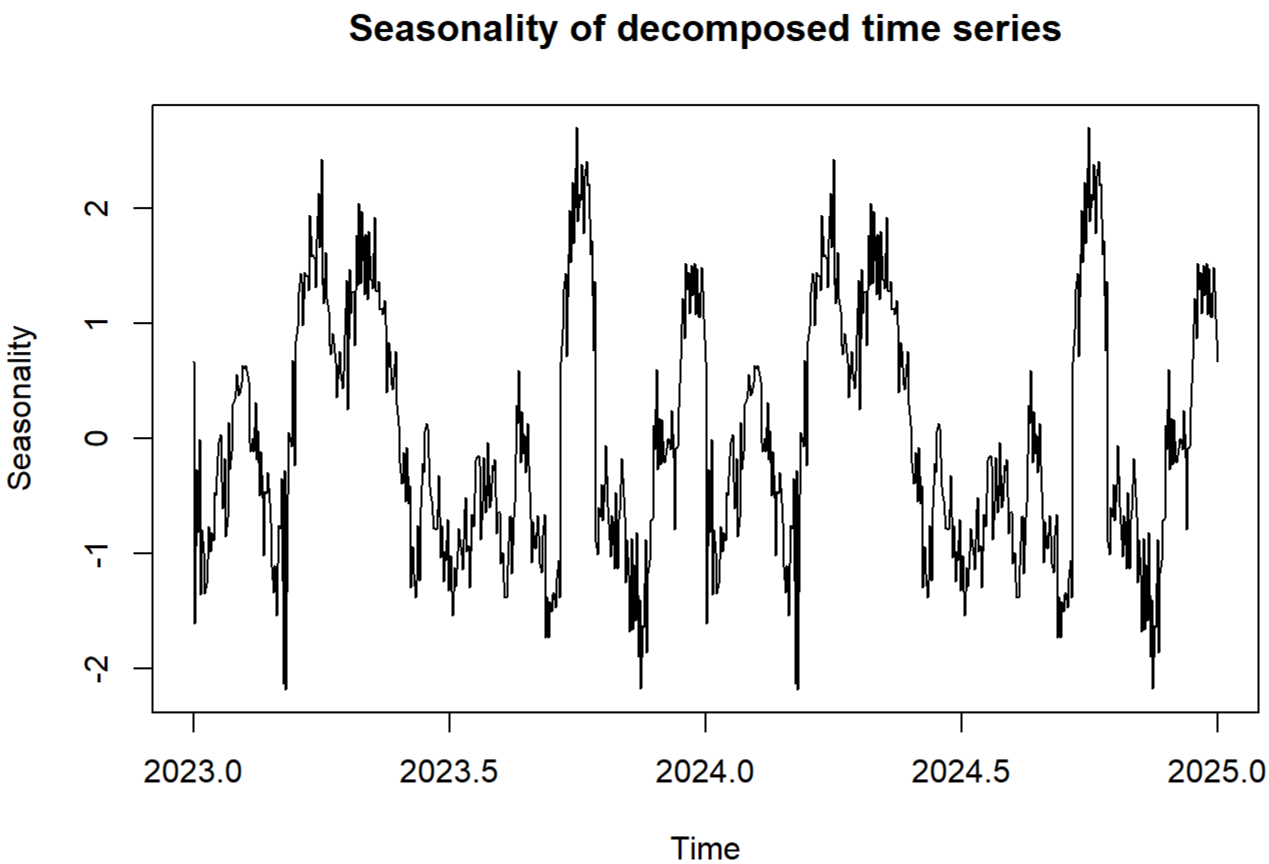
C5. A copy of the cleaned csv file will be included in the submission files. The cleaned csv file is named `cleaned_ts_data.csv`

Part IV: Model Identification and Analysis

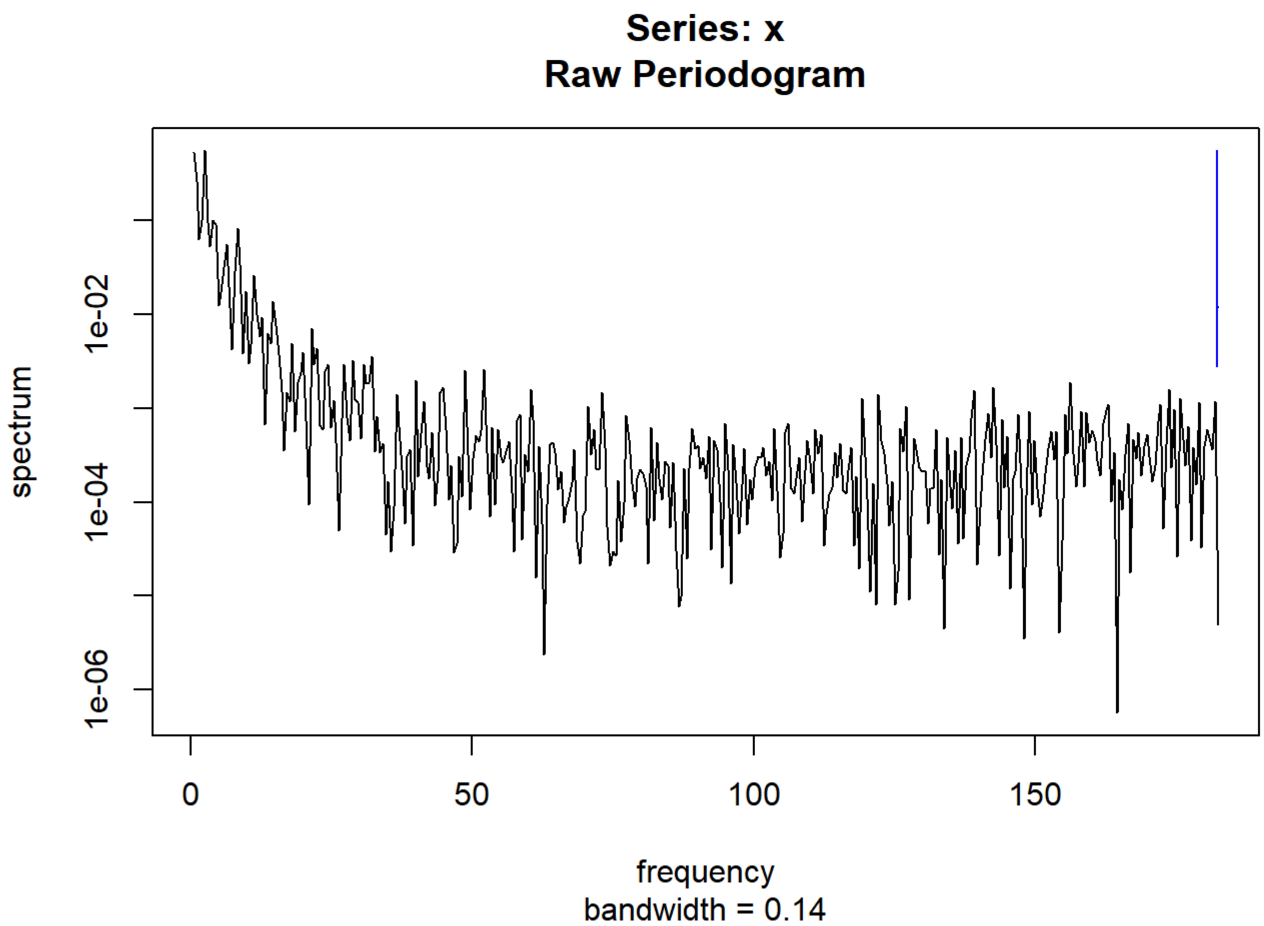
D1. The seasonality component shows and IQR accounting for 29.1% of the total IQR meaning that the seasonal fluctuations have an impact on the variability of the data. This seasonality can also be seen in the plot below.

```
Call:
stl(x = Y, s.window = "periodic", t.window = 365, robust = TRUE)

Time.series components:
   seasonal             trend              remainder
Min.   :-2.1803841   Min.   : 2.043455   Min.   :-6.723049
1st Qu.:-0.8099809   1st Qu.: 6.963760   1st Qu.:-0.661487
Median :-0.1907993   Median :10.690851   Median : 0.032188
Mean   : 0.0009227   Mean   : 9.953382   Mean   :-0.131404
3rd Qu.: 0.8467831   3rd Qu.:13.107337   3rd Qu.: 0.670740
Max.   : 2.7027377   Max.   :15.837858   Max.   : 3.898453
IQR:
    STL.seasonal STL.trend STL.remainder data
    1.657        6.144     1.332         5.694
```

```
  %  29.1        107.9      23.4         100.0

Weights:
  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
0.0000  0.8739  0.9452  0.8865  0.9871  1.0000

Other components: List of 5
$ win  : Named num [1:3] 7311 365 365
$ deg  : Named int [1:3] 0 1 1
$ jump : Named num [1:3] 732 37 37
$ inner: int 1
$ outer: int 15
```

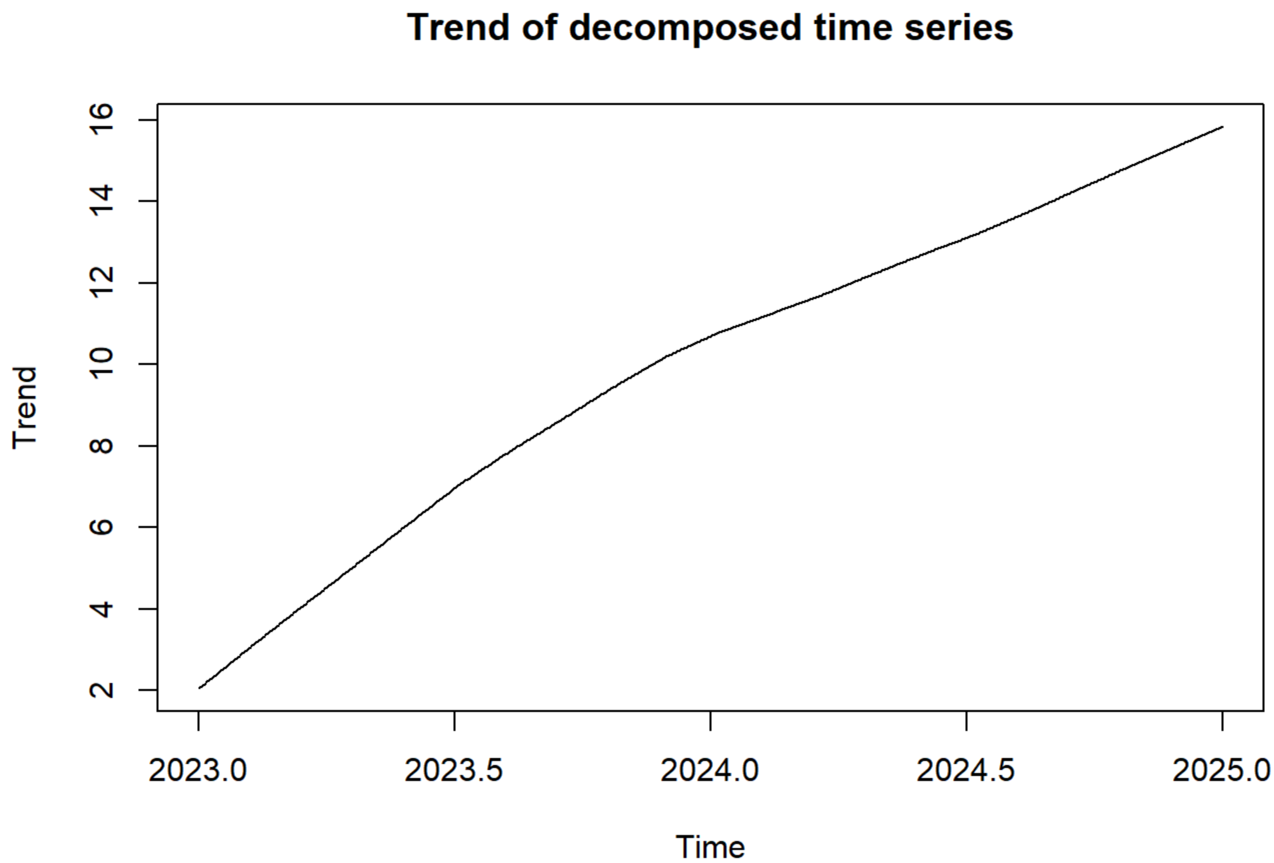


In addition, the spectral density plot shows that the highest spectral density happens at the lower end of the frequencies, suggesting a long term seasonality.



Trend

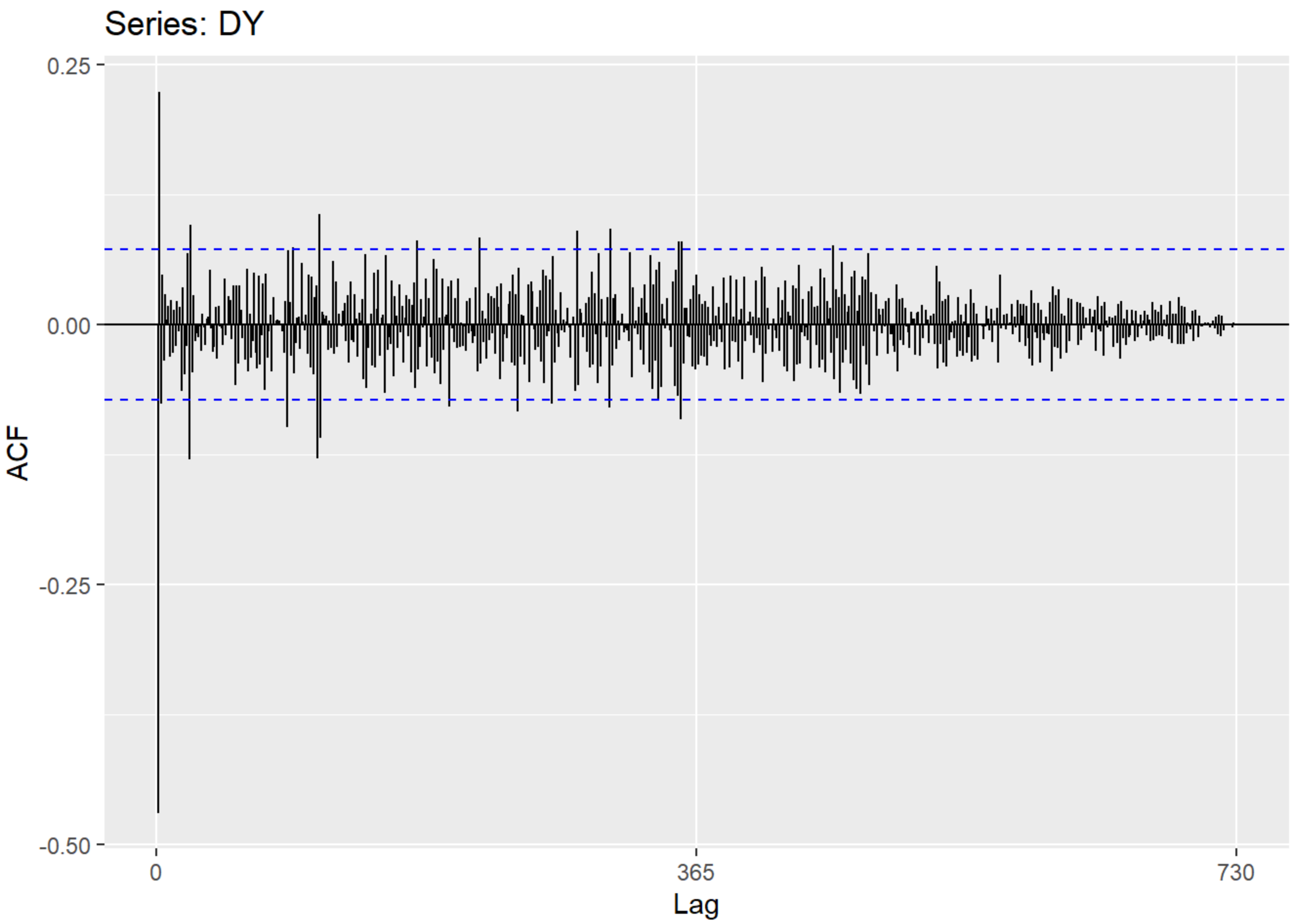
The decomposed time series plot shows a clean upward trend. The data begins in 2023 and gradually increases through 2025.




```
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  2.043   6.964  10.691   9.953  13.107  15.838 
```

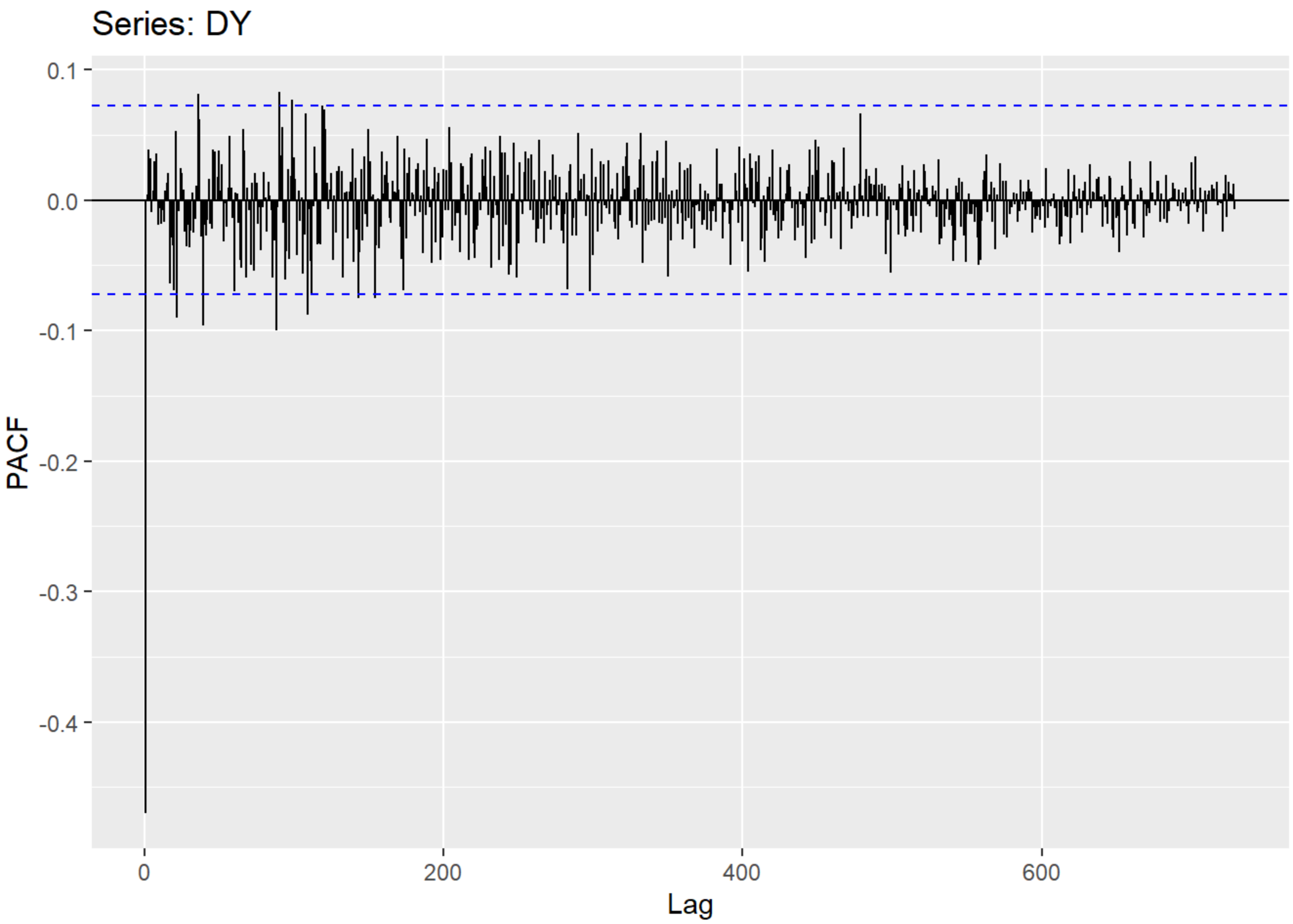
ACF

In the Autocorrelation (ACF) plot of the differenced data, it appears that most values fall within the confidence lines. However, there are several lines that do pass the confidence lines indicating that there may be seasonality, or at least a strong relationship witht the previous lag. Seasonality can be examined further in the decomposition plot using `stl()`. This plot also shows a significant correlation at lag 2 and then tappers off, indicating an `AR(2)`.



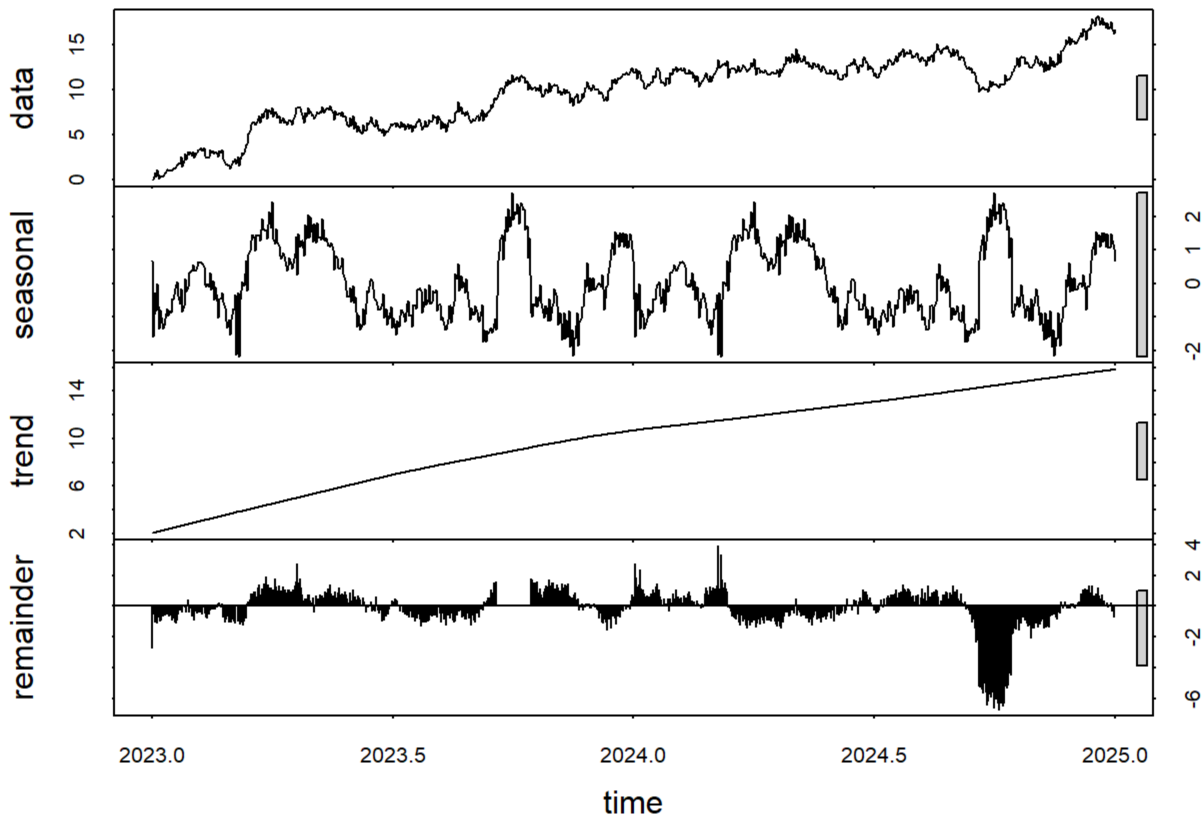
PACF

The Partial Autocorrelation (PACF) plot of the differenced data, looks very similar to the ACF plot where most of the values fall within the confidence interval lines. This would suggest that there is minimal partial autocorrelation at most lags. This plot shows a clear spike at lag 1 and then tappers off, indicating an `AR(1)`. Because PACF better isolates the relationship at each lag, I will be interested in an ARMIA model with an `AR(1)`.



The decomposed time series plot shows several of the components already spoken about in previous sections, in addition to the remainder component. In essence, decomposition is the break down of the data set into its key components. The remainder component being the only one not yet spoken about explicitly, explains the portion of the data that can not be explained by the seasonal or tend components. In otherwords, the elements within this remainder component are the ones that do not follow a consistent trend or cyclical pattern (seasonality).

In this plot we can see that the remainder fluctuates around 0 with minor ups and downs. However, near the end of 2024 we can see a significant dip in the remainder that would suggest that during this period, an external or random event happened that affected the data which is why it wouldn’t be captured by the trend or seasonality in the data.



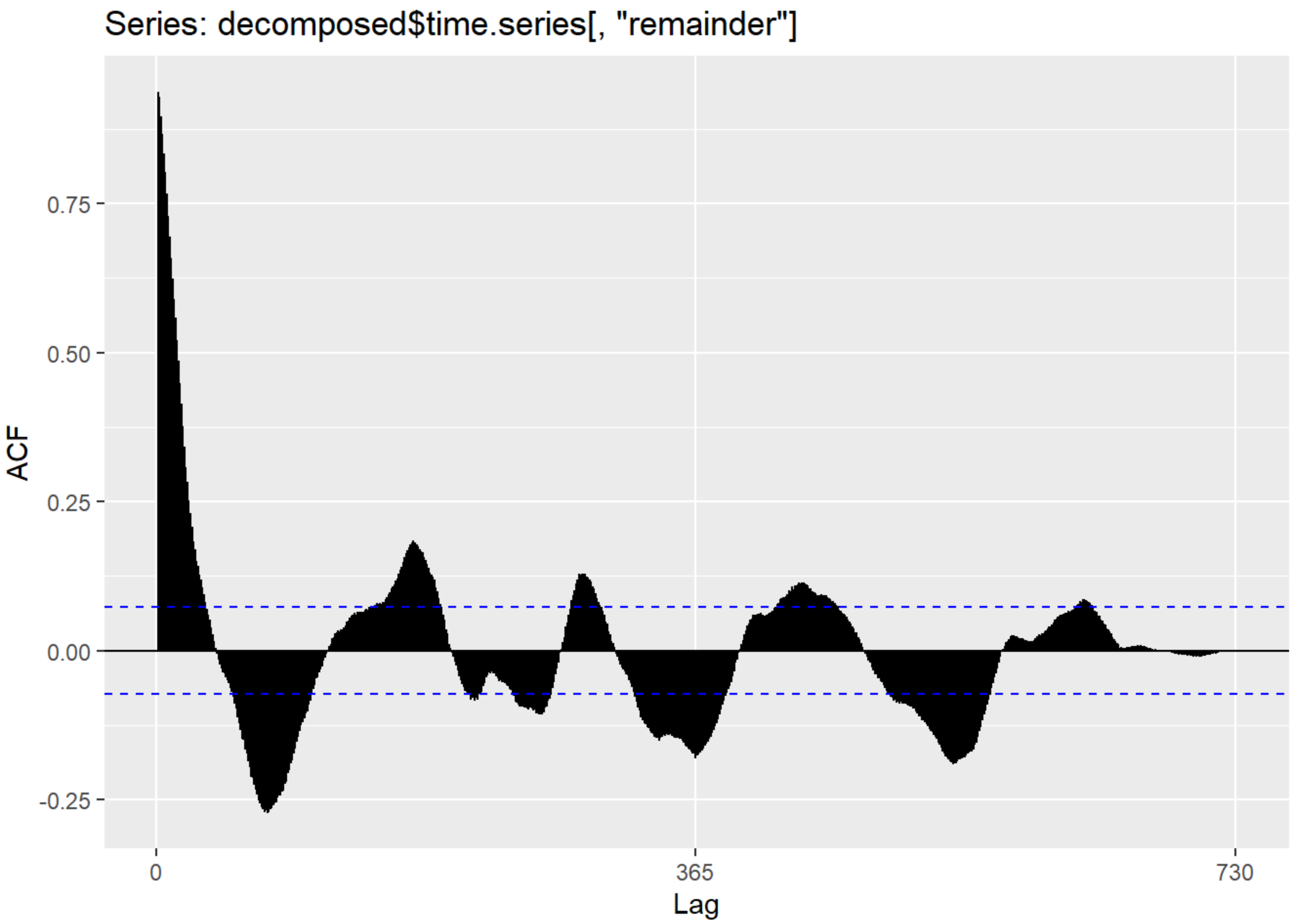
The **Ljung-box test**, tests the if the residuals show any autocorrelation. with a p-value far less than 0.05 (<2.2e-16) at lag 1, I can assume that there is some pattern or dependence that is not fully explained by the seasonality or trend mentioned earlier.

```
	Box-Ljung test

data:  decomposed$time.series[, "remainder"]
X-squared = 644.82, df = 1, p-value < 2.2e-16
```

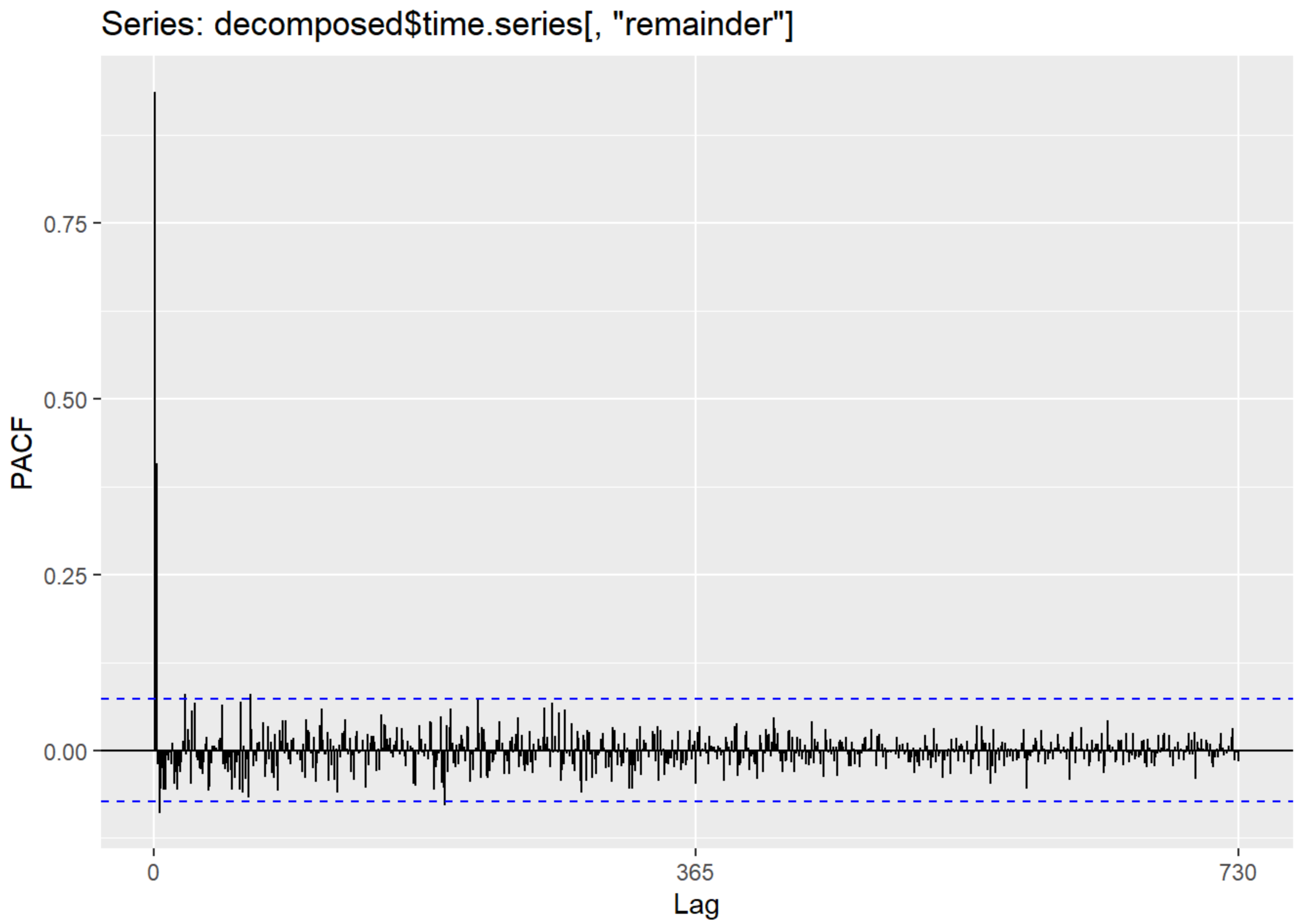
To confirm the residuals (remainder) do not have a trend, I computed the ADF once again but this time on the remainder component. We can see that the p-value (`p-value=0.01`) is less than the standard significance level of 0.05. While the data, statistically, appears to be stationary, the Ljung-box test would still indicate that there might still be some predictable relationship between the lags.

```
	Augmented Dickey-Fuller Test

data:  decomposed$time.series[, "remainder"]
Dickey-Fuller = -4.0837, Lag order = 9, p-value = 0.01
alternative hypothesis: stationary
```

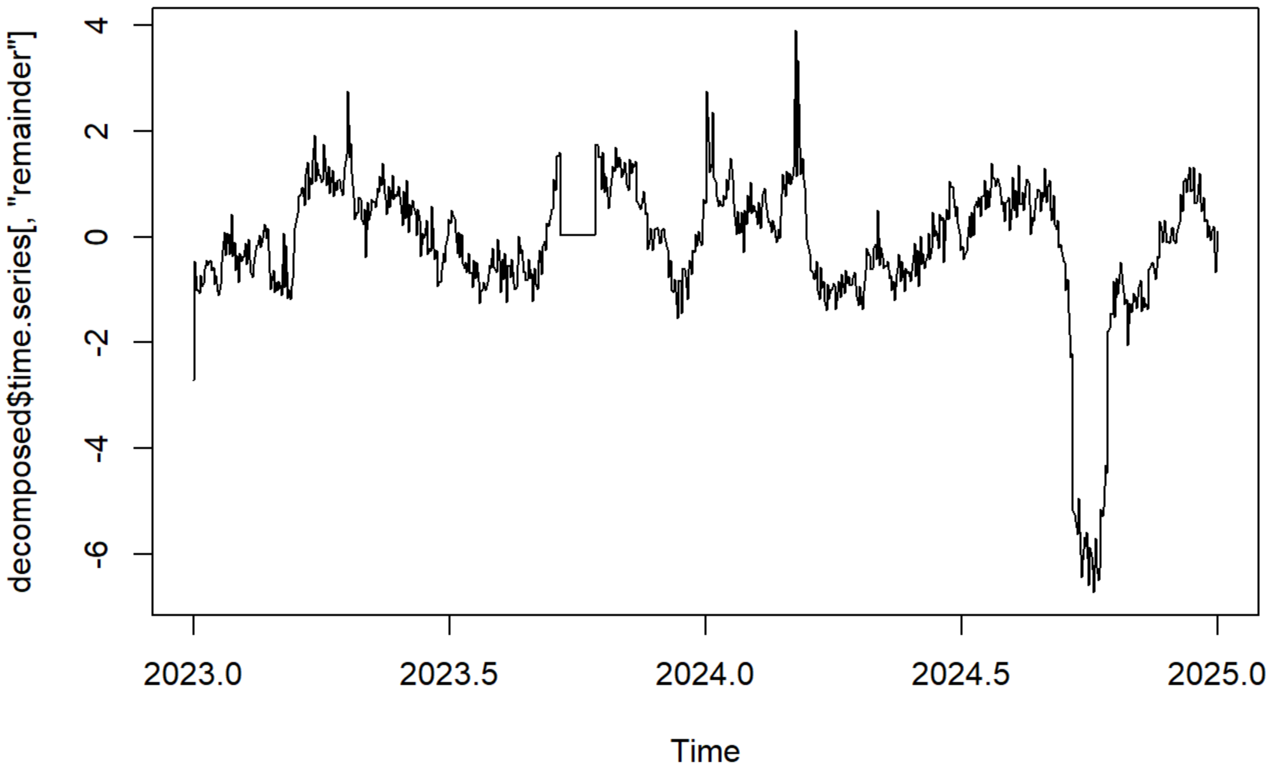
The ACF of the residuals plot shows that several peaks that are outside the confidence intervals. This means that the some patters or dependancy still exists in the data.



However, when looking at the PACF we can see that only lags 1 and 2 have a direct significant influence on the remainder component. After lag 2 all the spikes fall within the confidence interval and the spikes get smaller overtime. While the ACF plot suggests that there is autocorrelation at many different lags, the PACF plot clarifies that the patterns seen in the ACF are likely indirect relationships that stem from the first 2 lags.



Decomposed Time Series



D2. I used `auto.arima()` to find the best ARIMA model. `d=1` tells ARIMAto take the difference of the data before it fits the data. `D=1` accounts for seasonality. `Stepwise=FALSE` trys all models to get the most accurate results. And lastly, `approximation=FALSE` ensures that the `AIC` values are not approximated. Run time was not an issue here so I set approximation to false (RDocumentation, n.d.).

```
fit_arima <- auto.arima(train, d=1, D=1, stepwise = FALSE, approximation = FALSE, trace = TRUE)
```

```
 ARIMA(0,1,0)                    : 909.2825
 ARIMA(0,1,0) with drift         : 910.1682
 ARIMA(0,1,1)                    : 800.4773
 ARIMA(0,1,1) with drift         : 798.946
 ARIMA(0,1,2)                    : 776.4192
 ARIMA(0,1,2) with drift         : 776.048
 ARIMA(0,1,3)                    : 775.7495
 ARIMA(0,1,3) with drift         : 775.0052
 ARIMA(0,1,4)                    : 777.7842
 ARIMA(0,1,4) with drift         : 777.0359
 ARIMA(0,1,5)                    : 779.7498
 ARIMA(0,1,5) with drift         : 779.0592
 ARIMA(1,1,0)                    : 774.056
 ARIMA(1,1,0) with drift         : 773.0878
 ARIMA(1,1,1)                    : 776.0741
```

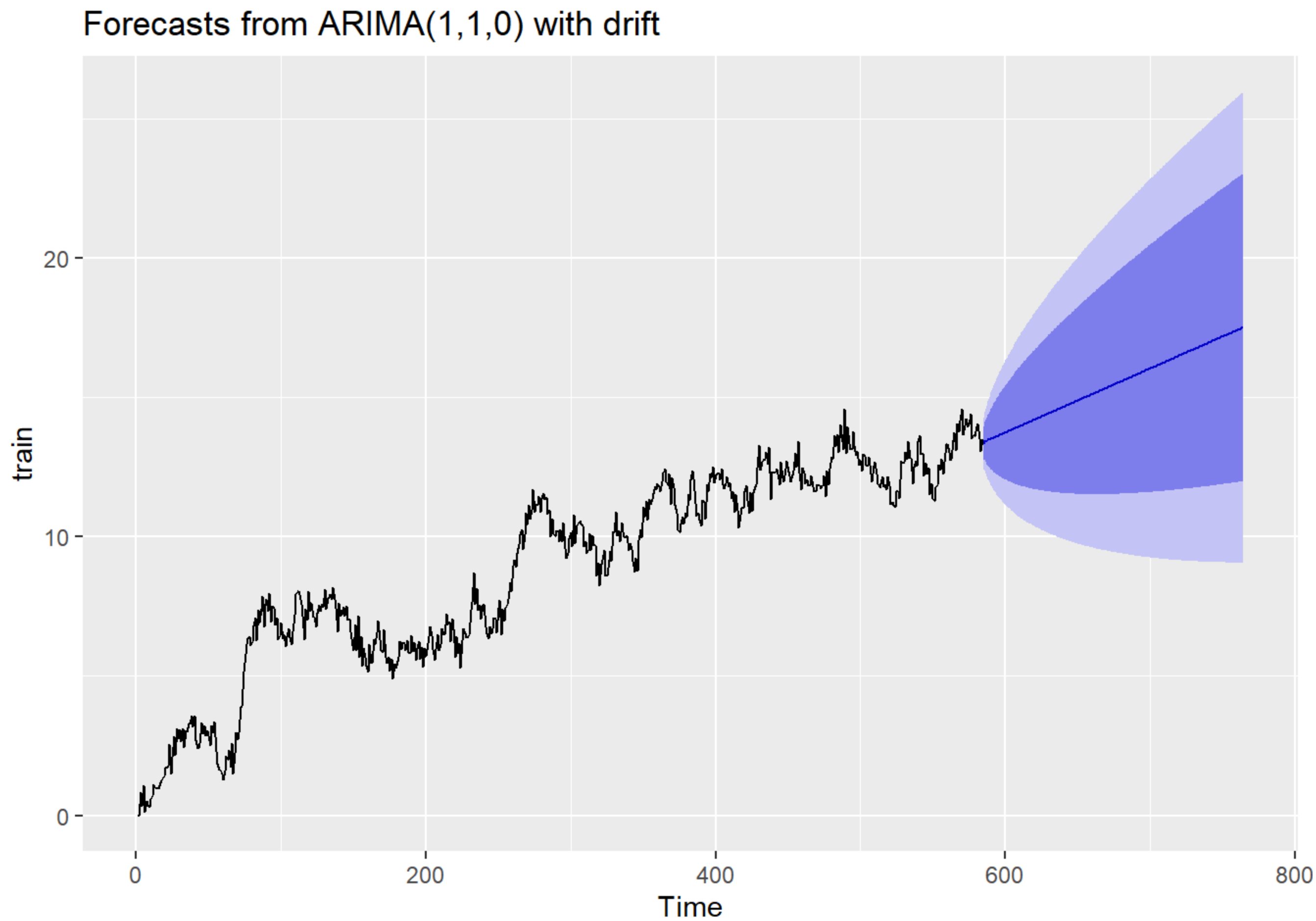
```
ARIMA(1,1,1) with drift         : 775.1125
ARIMA(1,1,2)                    : 776.0088
ARIMA(1,1,2) with drift         : 775.4037
ARIMA(1,1,3)                    : 777.7843
ARIMA(1,1,3) with drift         : 777.0377
ARIMA(1,1,4)                    : Inf
ARIMA(1,1,4) with drift         : 779.0796
ARIMA(2,1,0)                    : 776.0734
ARIMA(2,1,0) with drift         : 775.1118
ARIMA(2,1,1)                    : 777.6634
ARIMA(2,1,1) with drift         : 776.6363
ARIMA(2,1,2)                    : 777.7935
ARIMA(2,1,2) with drift         : 777.1338
ARIMA(2,1,3)                    : 779.86
ARIMA(2,1,3) with drift         : 779.1622
ARIMA(3,1,0)                    : 775.885
ARIMA(3,1,0) with drift         : 775.2674
ARIMA(3,1,1)                    : 777.8984
ARIMA(3,1,1) with drift         : 777.2592
ARIMA(3,1,2)                    : 779.8004
ARIMA(3,1,2) with drift         : 779.1123
ARIMA(4,1,0)                    : 777.8895
ARIMA(4,1,0) with drift         : 777.2283
ARIMA(4,1,1)                    : Inf
ARIMA(4,1,1) with drift         : Inf
ARIMA(5,1,0)                    : 779.846
ARIMA(5,1,0) with drift         : 779.1125



Best model: ARIMA(1,1,0) with drift
```

```
#accounting for trend with d=1. Tells arima that before it fits the data, take the difference of 

#accounting for seasonality with D=1. Gets rid of the seasonality by taking the first seasonal di

#stepwise=FALSE trying all models to get the most accurate results

#approximation=FALSE because time isnt an issue. If it were an issue thenapproximation could be s
```

We can see that the best model, according the auto.arima() is `ARIMA(1,1,0) with drift` (accounting for the trend).

The model summary shows that the `AR(1)` that was mentioned in the D1 as a result of the PACF test was accurate. 'l', shows that difference has been applied, and '0' indicates that there is no moving average in this model.

D3. The following plot shows the forecast with confidence intervals for 90 days in advance.



D4. In the following code output, you can see the daily values for 90 days as well as the upper and lower confidence values.

```
Forecast method: ARIMA(1,1,0) with drift

Model Information:
Series: train
ARIMA(1,1,0) with drift

Coefficients:
          ar1   drift
      -0.4605  0.0230
s.e.   0.0367  0.0133

sigma^2 = 0.2189:  log likelihood = -383.52
AIC=773.05   AICc=773.09   BIC=786.15

Error measures:
                        ME      RMSE       MAE  MPE MAPE      MASE         ACF1
Training set -1.354846e-05 0.4666594 0.3758019 -Inf  Inf 0.8756595 -0.001967013

Forecasts:
    Point Forecast    Lo 80    Hi 80     Lo 95    Hi 95
```

585	13.34397	12.74438	13.94356	12.426978	14.26097
586	13.45161	12.77033	14.13289	12.409682	14.49354
587	13.43558	12.61875	14.25240	12.186346	14.68481
588	13.47649	12.57044	14.38254	12.090810	14.86218
589	13.49118	12.49293	14.48944	11.964482	15.01789
590	13.51795	12.44006	14.59585	11.869456	15.16645
591	13.53916	12.38509	14.69323	11.774162	15.30416
592	13.56293	12.33829	14.78757	11.690008	15.43585
593	13.58552	12.29378	14.87726	11.609975	15.56106
594	13.60865	12.25330	14.96400	11.535816	15.68148
595	13.63153	12.21534	15.04772	11.465660	15.79740
596	13.65453	12.18005	15.12901	11.399505	15.90955
597	13.67747	12.14690	15.20804	11.336667	16.01828
598	13.70044	12.11577	15.28511	11.276898	16.12398
599	13.72340	12.08641	15.36038	11.219846	16.22695
600	13.74636	12.05868	15.43404	11.165280	16.32744
601	13.76932	12.03243	15.50621	11.112973	16.42567
602	13.79228	12.00753	15.57703	11.062742	16.52182
603	13.81524	11.98388	15.64660	11.014422	16.61606
604	13.83820	11.96139	15.71501	10.967873	16.70853
605	13.86116	11.93998	15.78235	10.922967	16.79936
606	13.88412	11.91957	15.84868	10.879593	16.88866
607	13.90708	11.90009	15.91408	10.837653	16.97652
608	13.93005	11.88149	15.97860	10.797057	17.06303
609	13.95301	11.86372	16.04229	10.757725	17.14829
610	13.97597	11.84673	16.10520	10.719585	17.23235
611	13.99893	11.83048	16.16738	10.682570	17.31529
612	14.02189	11.81492	16.22886	10.646620	17.39716
613	14.04485	11.80002	16.28968	10.611681	17.47802
614	14.06781	11.78575	16.34987	10.577703	17.55792
615	14.09077	11.77208	16.40946	10.544639	17.63690
616	14.11373	11.75898	16.46849	10.512446	17.71502
617	14.13669	11.74642	16.52696	10.481085	17.79230
618	14.15965	11.73438	16.58492	10.450520	17.86879
619	14.18261	11.72284	16.64239	10.420716	17.94451
620	14.20557	11.71178	16.69937	10.391642	18.01951
621	14.22853	11.70117	16.75590	10.363269	18.09380
622	14.25150	11.69101	16.81198	10.335568	18.16742
623	14.27446	11.68127	16.86765	10.308515	18.24040
624	14.29742	11.67193	16.92290	10.282084	18.31275
625	14.32038	11.66299	16.97777	10.256254	18.38450
626	14.34334	11.65443	17.03225	10.231003	18.45567
627	14.36630	11.64623	17.08637	10.206310	18.52629
628	14.38926	11.63838	17.14014	10.182157	18.59636
629	14.41222	11.63088	17.19356	10.158525	18.66592
630	14.43518	11.62370	17.24666	10.135399	18.73496
631	14.45814	11.61685	17.29943	10.112761	18.80352
632	14.48110	11.61031	17.35190	10.090597	18.87161
633	14.50406	11.60406	17.40407	10.068892	18.93923
634	14.52702	11.59811	17.45594	10.047633	19.00642
635	14.54998	11.59244	17.50753	10.026805	19.07316

636	14.57295	11.58704	17.55885	10.006398	19.13949
637	14.59591	11.58191	17.60990	9.986398	19.20541
638	14.61887	11.57704	17.66069	9.966796	19.27094
639	14.64183	11.57242	17.71123	9.947579	19.33608
640	14.66479	11.56805	17.76153	9.928738	19.40084
641	14.68775	11.56392	17.81158	9.910262	19.46524
642	14.71071	11.56002	17.86140	9.892143	19.52928
643	14.73367	11.55635	17.91100	9.874371	19.59297
644	14.75663	11.55289	17.96037	9.856938	19.65633
645	14.77959	11.54966	18.00953	9.839835	19.71935
646	14.80255	11.54663	18.05847	9.823054	19.78205
647	14.82551	11.54381	18.10721	9.806588	19.84444
648	14.84847	11.54120	18.15575	9.790429	19.90652
649	14.87143	11.53877	18.20410	9.774571	19.96830
650	14.89440	11.53654	18.25225	9.759006	20.02979
651	14.91736	11.53450	18.30021	9.743728	20.09098
652	14.94032	11.53264	18.34799	9.728730	20.15190
653	14.96328	11.53096	18.39559	9.714007	20.21255
654	14.98624	11.52946	18.44302	9.699552	20.27292
655	15.00920	11.52813	18.49027	9.685361	20.33304
656	15.03216	11.52696	18.53735	9.671427	20.39289
657	15.05512	11.52597	18.58427	9.657745	20.45250
658	15.07808	11.52513	18.63103	9.644310	20.51185
659	15.10104	11.52445	18.67763	9.631117	20.57097
660	15.12400	11.52393	18.72408	9.618162	20.62984
661	15.14696	11.52356	18.77037	9.605440	20.68849
662	15.16992	11.52333	18.81651	9.592946	20.74690
663	15.19288	11.52326	18.86251	9.580675	20.80509
664	15.21585	11.52333	18.90836	9.568625	20.86307
665	15.23881	11.52354	18.95408	9.556790	20.92082
666	15.26177	11.52388	18.99965	9.545167	20.97837
667	15.28473	11.52437	19.04509	9.533753	21.03570
668	15.30769	11.52498	19.09039	9.522542	21.09283
669	15.33065	11.52573	19.13557	9.511532	21.14977
670	15.35361	11.52661	19.18061	9.500719	21.20650
671	15.37657	11.52761	19.22553	9.490100	21.26304
672	15.39953	11.52874	19.27032	9.479671	21.31939
673	15.42249	11.52999	19.31499	9.469430	21.37555
674	15.44545	11.53137	19.35954	9.459373	21.43153
675	15.46841	11.53286	19.40397	9.449497	21.48733
676	15.49137	11.53446	19.44829	9.439799	21.54295
677	15.51433	11.53618	19.49249	9.430276	21.59839
678	15.53730	11.53802	19.53657	9.420926	21.65366
679	15.56026	11.53996	19.58055	9.411746	21.70877
680	15.58322	11.54202	19.62442	9.402733	21.76370
681	15.60618	11.54418	19.66818	9.393885	21.81847
682	15.62914	11.54645	19.71183	9.385198	21.87308
683	15.65210	11.54882	19.75538	9.376671	21.92753
684	15.67506	11.55129	19.79883	9.368301	21.98182
685	15.69802	11.55387	19.84217	9.360087	22.03595
686	15.72098	11.55654	19.88542	9.352024	22.08994

687	15.74394	11.55932	19.92857	9.344113	22.14377
688	15.76690	11.56219	19.97162	9.336349	22.19746
689	15.78986	11.56516	20.01457	9.328731	22.25100
690	15.81282	11.56822	20.05743	9.321258	22.30439
691	15.83578	11.57137	20.10020	9.313926	22.35764
692	15.85875	11.57462	20.14287	9.306735	22.41076
693	15.88171	11.57795	20.18546	9.299682	22.46373
694	15.90467	11.58138	20.22796	9.292765	22.51657
695	15.92763	11.58489	20.27037	9.285982	22.56927
696	15.95059	11.58849	20.31269	9.279332	22.62184
697	15.97355	11.59217	20.35493	9.272813	22.67429
698	15.99651	11.59594	20.39708	9.266423	22.72660
699	16.01947	11.59979	20.43915	9.260160	22.77878
700	16.04243	11.60373	20.48113	9.254023	22.83084
701	16.06539	11.60775	20.52304	9.248011	22.88277
702	16.08835	11.61184	20.56486	9.242121	22.93458
703	16.11131	11.61602	20.60661	9.236352	22.98628
704	16.13427	11.62027	20.64828	9.230702	23.03785
705	16.15723	11.62460	20.68987	9.225171	23.08930
706	16.18020	11.62901	20.73138	9.219756	23.14063
707	16.20316	11.63349	20.77282	9.214457	23.19186
708	16.22612	11.63805	20.81419	9.209271	23.24296
709	16.24908	11.64268	20.85548	9.204198	23.29396
710	16.27204	11.64738	20.89670	9.199236	23.34484
711	16.29500	11.65216	20.93784	9.194384	23.39561
712	16.31796	11.65700	20.97892	9.189640	23.44628
713	16.34092	11.66192	21.01992	9.185003	23.49684
714	16.36388	11.66690	21.06086	9.180473	23.54729
715	16.38684	11.67196	21.10173	9.176047	23.59764
716	16.40980	11.67708	21.14253	9.171725	23.64788
717	16.43276	11.68227	21.18326	9.167506	23.69802
718	16.45572	11.68752	21.22393	9.163387	23.74806
719	16.47868	11.69284	21.26453	9.159369	23.79800
720	16.50165	11.69823	21.30506	9.155450	23.84784
721	16.52461	11.70368	21.34554	9.151629	23.89758
722	16.54757	11.70919	21.38595	9.147905	23.94723
723	16.57053	11.71476	21.42629	9.144277	23.99678
724	16.59349	11.72040	21.46658	9.140744	24.04623
725	16.61645	11.72610	21.50680	9.137304	24.09559
726	16.63941	11.73186	21.54696	9.133957	24.14486
727	16.66237	11.73768	21.58706	9.130703	24.19404
728	16.68533	11.74356	21.62711	9.127539	24.24312
729	16.70829	11.74949	21.66709	9.124465	24.29212
730	16.73125	11.75549	21.70702	9.121480	24.34102
731	16.75421	11.76154	21.74688	9.118584	24.38984
732	16.77717	11.76765	21.78669	9.115774	24.43857
733	16.80013	11.77382	21.82645	9.113051	24.48722
734	16.82310	11.78004	21.86615	9.110414	24.53578
735	16.84606	11.78632	21.90579	9.107861	24.58425
736	16.86902	11.79266	21.94538	9.105392	24.63264
737	16.89198	11.79904	21.98491	9.103006	24.68095

```
738       16.91494 11.80548 22.02439  9.100703 24.72917
739       16.93790 11.81198 22.06382  9.098481 24.77732
740       16.96086 11.81853 22.10319  9.096339 24.82538
741       16.98382 11.82513 22.14252  9.094277 24.87336
742       17.00678 11.83178 22.18179  9.092295 24.92127
743       17.02974 11.83848 22.22100  9.090390 24.96909
744       17.05270 11.84523 22.26017  9.088564 25.01684
745       17.07566 11.85204 22.29929  9.086814 25.06451
746       17.09862 11.85889 22.33836  9.085141 25.11211
747       17.12158 11.86579 22.37738  9.083543 25.15963
748       17.14455 11.87274 22.41635  9.082019 25.20707
749       17.16751 11.87974 22.45527  9.080570 25.25444
750       17.19047 11.88679 22.49414  9.079195 25.30174
751       17.21343 11.89389 22.53297  9.077892 25.34896
752       17.23639 11.90103 22.57175  9.076661 25.39612
753       17.25935 11.90822 22.61048  9.075502 25.44320
754       17.28231 11.91545 22.64916  9.074414 25.49021
755       17.30527 11.92274 22.68780  9.073396 25.53715
756       17.32823 11.93006 22.72640  9.072447 25.58401
757       17.35119 11.93744 22.76495  9.071568 25.63082
758       17.37415 11.94485 22.80345  9.070757 25.67755
759       17.39711 11.95232 22.84191  9.070014 25.72421
760       17.42007 11.95982 22.88033  9.069338 25.77081
761       17.44303 11.96737 22.91870  9.068729 25.81734
762       17.46600 11.97496 22.95703  9.068186 25.86380
763       17.48896 11.98260 22.99531  9.067709 25.91020
764       17.51192 11.99028 23.03356  9.067297 25.95654
```

D5. The full code file will be included in the submission files. The code file will be named `D213_code.R`

Part V: Data Summary and Implications

E1. As mentioned in section D2 the ARIMA model with the best fit is `ARIMA(1,1,0) with drift`.

```
Series: train
ARIMA(1,1,0) with drift

Coefficients:
          ar1   drift
      -0.4605  0.0230
s.e.   0.0367  0.0133

sigma^2 = 0.2189:  log likelihood = -383.52
AIC=773.05   AICc=773.09   BIC=786.15

Training set error measures:
                        ME      RMSE       MAE  MPE MAPE      MASE         ACF1
Training set -1.354846e-05 0.4666594 0.3758019 -Inf  Inf 0.8756595 -0.001967013
```

The predictions intervals are 80% (Lo), and 95%(Hi) for each forecast point. For example, at point 585, the forecast is 13.34397, with an 80% interval of 12.74438 on the low end and 13.94356 on the high end. Likewise, 95% interval of 12.426978 on the low end and 14.26097 on the high end. In other wards, for point 585, I can say that there is an 80% chance that the value is between 13.34397 and 12.74438. However, there is a 95% chance that the value is between 12.426978 and 14.26097 . So the higher the confidence, the wider the range because it is reflecting the greater uncertainty in the prediction.

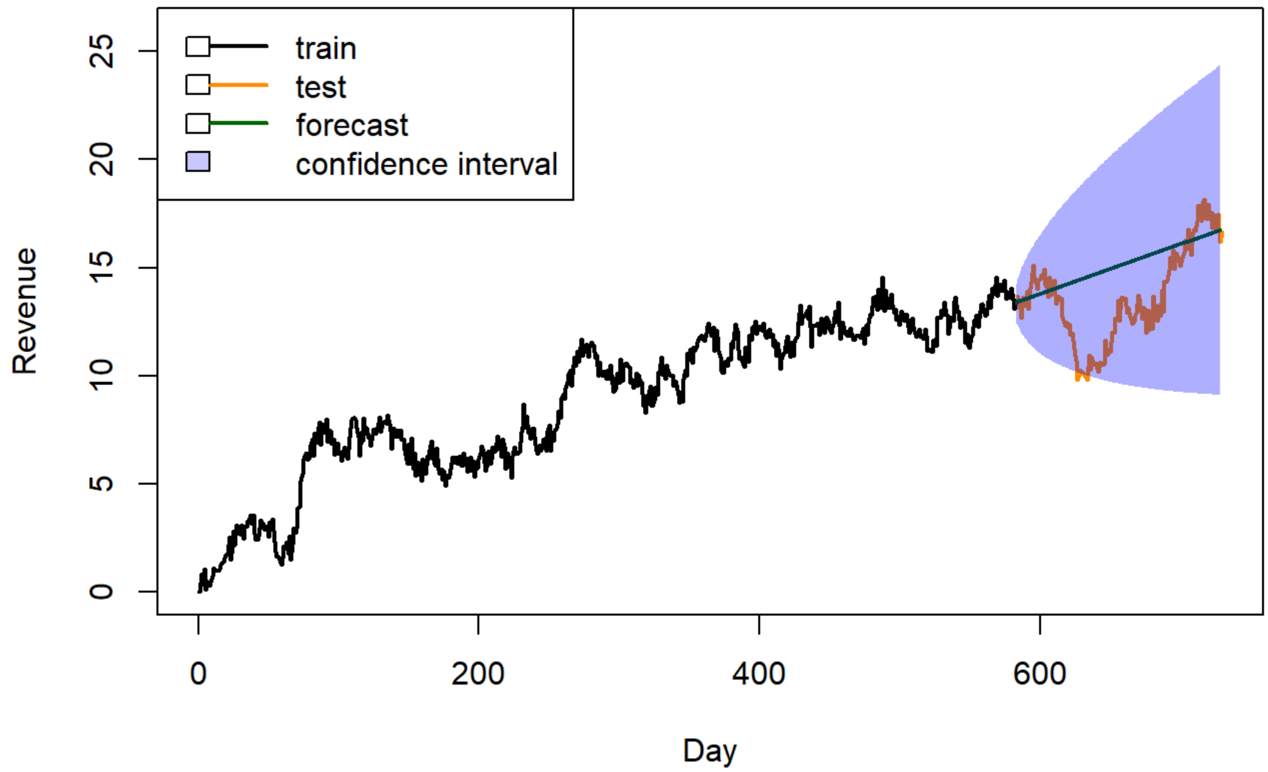
The forecast length is 180 days worth of data because the data contains enough information to identify season trends or patterns.

The error metrics that are provided in the summary function include RMSE and MAE as well as others. To test how well the data forecasts the trained data, I will be comparing the test set vs the training set.

```
                        ME      RMSE       MAE       MPE     MAPE      MASE
Training set -1.354846e-05 0.4666594 0.3758019      -Inf      Inf 0.8756595
Test set     -1.432728e+00 2.2949433 1.8155156 -12.74361 15.11012 4.2303496
                     ACF1
Training set -0.001967013
Test set               NA
```

This ARIMA model `(1,1,0)` appears to work well with the training data as indicated by the low `RMSE (0.4666594)`, `MASE (0.8756595)`, meaning that it first the historical data well. However, when tested on the unseen data, the model does not do as well. The errors `RMSE (2.2949433)`, and `MASE (4.2303496)` are much higher with the test data, and the model tends to underestimate the values as evidenced by the negative `ME (-1.432728e+00)`.

E2. Annotated visual of the forecast and test data: (Sewell, n.d., 7:20)



E3. This model performs well with the historical data in that it can identify patters and trends accurately but seems to struggle with future data as it tends to underestimate the actual values. Because of this I would recommend that the company take into account the model's tendency to under predict revenue and expect that the actual revenue will be someone higher. This could also imply that the demand is higher as well, and therefore the company should take this into account when allocating resources or esitimating inventory. Additionally I would recommend monittoring this model's performance on a regular schedule to compare the actual and foretasted numbers.

Part VI: Reporting

G-H. Acknowledge sources, using in-text citations and references, for content that is quoted, paraphrased, or summarized.

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weecology. (2020, September 21). *Introduction to making forecasts from time-series models in R* [Video]. YouTube. https://www.youtube.com/watch?v=kyPg3jV4pJ8