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Complete guide to create a Time Series Forecast (with Codes in Python)

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(http://admissions.bridgesom.com/pba-new/?utm_source=AV&utm_medium=BannerInline&utm_campaign=AVBanner20August)

Introduction

Time Series (referred as TS from now) is considered to be one of the less known skills in the analytics space (Even I had little clue about it a couple of days back). But as you know our inaugural **Mini Hackathon** (<http://datahack.analyticsvidhya.com/contest/mini-datahack>) is based on it, I set myself on a journey to learn the basic steps for solving a Time Series problem and here I am sharing the same with you. These will definitely help you get a decent model in our hackathon today.



(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/guide.jpg>)

Before going through this article, I highly recommend reading [A Complete Tutorial on Time Series Modeling in R](#) (<https://www.analyticsvidhya.com/blog/2015/12/complete-tutorial-time-series-modeling/>), which is like a prequel to this article. It focuses on fundamental concepts and is based on R and I will focus on using these concepts in solving a problem end-to-end along with codes in Python. Many resources exist for TS in R but very few are there for Python so I'll be using Python in this article.

Our journey would go through the following steps:

1. What makes Time Series Special?
2. Loading and Handling Time Series in Pandas
3. How to Check Stationarity of a Time Series?
4. How to make a Time Series Stationary?
5. Forecasting a Time Series



(<https://datahack.analyticsvidhya.com/contest/skilltest-r-for-data-science/>)

1. What makes Time Series Special?

As the name suggests, TS is a collection of data points collected at **constant time intervals**. These are analyzed to determine the long term trend so as to forecast the future or perform some other form of analysis. But what makes a TS different from say a regular regression problem? There are 2 things:

1. It is **time dependent**. So the basic assumption of a linear regression model that the observations are independent doesn't hold in this case.
2. Along with an increasing or decreasing trend, most TS have some form of **seasonality trends**, i.e. variations specific to a particular time frame. For example, if you see the sales of a woolen jacket over time, you will invariably find higher sales in winter seasons.

Because of the inherent properties of a TS, there are various steps involved in analyzing it. These are discussed in detail below. Lets start by loading a TS object in Python. We'll be using the popular AirPassengers data set which can be downloaded here (<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/AirPassengers.csv>).

Please note that the aim of this article is to familiarize you with the various techniques used for TS in general. The example considered here is just for illustration and I will focus on coverage a breadth of topics and not making a very accurate forecast.

2. Loading and Handling Time Series in Pandas

Pandas has dedicated libraries for handling TS objects, particularly the **datetime64[ns]** class which stores time information and allows us to perform some operations really fast. Lets start by firing up the required libraries:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
from matplotlib.pyplot import rcParams
rcParams['figure.figsize'] = 15, 6
```

Now, we can load the data set and look at some initial rows and data types of the columns:

```
data = pd.read_csv('AirPassengers.csv')
print data.head()
print '\n Data Types:'
print data.dtypes
```

	Month	#Passenger
0	1949-01	112
1	1949-02	118
2	1949-03	132
3	1949-04	129
4	1949-05	121

Data Types:	
Month	object
#Passenger	int64
dtype:	object

(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/1.-dataload-1.png>)

The data contains a particular month and number of passengers travelling in that month. But this is still not read as a TS object as the data types are 'object' and 'int'. In order to read the data as a time series, we have to pass special arguments to the read_csv command:

```
dateparse = lambda dates: pd.datetime.strptime(dates, '%Y-%m')

data = pd.read_csv('AirPassengers.csv', parse_dates='Month', index_col='Month', date_parser=dateparse)

print data.head()
```

	#Passenger
Month	
1949-01-01	112
1949-02-01	118
1949-03-01	132
1949-04-01	129
1949-05-01	121

(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/2.-dataload-2.png>)

Let's understand the arguments one by one:

1. **parse_dates**: This specifies the column which contains the date-time information. As we say above, the column name is 'Month'.
2. **index_col**: A key idea behind using Pandas for TS data is that the index has to be the variable depicting date-time information. So this argument tells pandas to use the 'Month' column as index.
3. **date_parser**: This specifies a function which converts an input string into datetime variable. By default Pandas reads data in format 'YYYY-MM-DD HH:MM:SS'. If the data is not in this format, the format has to be manually defined. Something similar to the dataparse function defined here can be used for this purpose.

Now we can see that the data has time object as index and #Passengers as the column. We can cross-check the datatype of the index with the following command:

```
data.index
```

```
DatetimeIndex(['1949-01-01', '1949-02-01', '1949-03-01', '1949-04-01',
                '1949-05-01', '1949-06-01', '1949-07-01', '1949-08-01',
                '1949-09-01', '1949-10-01',
                ...
                '1960-03-01', '1960-04-01', '1960-05-01', '1960-06-01',
                '1960-07-01', '1960-08-01', '1960-09-01', '1960-10-01',
                '1960-11-01', '1960-12-01'],
               dtype='datetime64[ns]', name=u'Month', length=144, freq=None)
```

(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/3.-index-type.png>)

Notice the **dtype='datetime[ns]'** which confirms that it is a datetime object. As a personal preference, I would convert the column into a Series object to prevent referring to columns names every time I use the TS. Please feel free to use as a dataframe if that works better for you.

```
ts = data['#Passengers'].head(10)
```

Month	
1949-01-01	112
1949-02-01	118
1949-03-01	132
1949-04-01	129
1949-05-01	121
1949-06-01	135
1949-07-01	148
1949-08-01	148
1949-09-01	136
1949-10-01	119

Name: #Passengers, dtype: int64

(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/4.-series.png>)

Before going further, I'll discuss some indexing techniques for TS data. Let's start by selecting a particular value in the Series object. This can be done in following 2 ways:

#1. Specify the index as a string constant:

```
ts['1949-01-01']
```

#2. Import the datetime library and use 'datetime' function:

```
from datetime import datetime
ts[datetime(1949,1,1)]
```

Both would return the value '112' which can also be confirmed from previous output. Suppose we want all the data upto May 1949. This can be done in 2 ways:

```
#1. Specify the entire range:
```

```
ts['1949-01-01':'1949-05-01']
```

```
#2. Use ':' if one of the indices is at ends:
```

```
ts[:'1949-05-01']
```

Both would yield following output:

Month	
1949-01-01	112
1949-02-01	118
1949-03-01	132
1949-04-01	129
1949-05-01	121

Name: #Passengers, dtype: int64

(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/5.-index-range.png>)

There are 2 things to note here:

1. Unlike numeric indexing, the **end index is included here**. For instance, if we index a list as a[5:] then it would return the values at indices – [0,1,2,3,4]. But here the index '1949-05-01' was included in the output.
2. The **indices have to be sorted** for ranges to work. If you randomly shuffle the index, this won't work.

Consider another instance where you need all the values of the year 1949. This can be done as:

```
ts['1949']
```

```

Month
1949-01-01    112
1949-02-01    118
1949-03-01    132
1949-04-01    129
1949-05-01    121
1949-06-01    135
1949-07-01    148
1949-08-01    148
1949-09-01    136
1949-10-01    119
1949-11-01    104
1949-12-01    118
Name: #Passengers, dtype: int64

```

(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/6.-index-year.png>)

The month part was omitted. Similarly if you all days of a particular month, the day part can be omitted.

Now, lets move onto the analyzing the TS.

3. How to Check Stationarity of a Time Series?

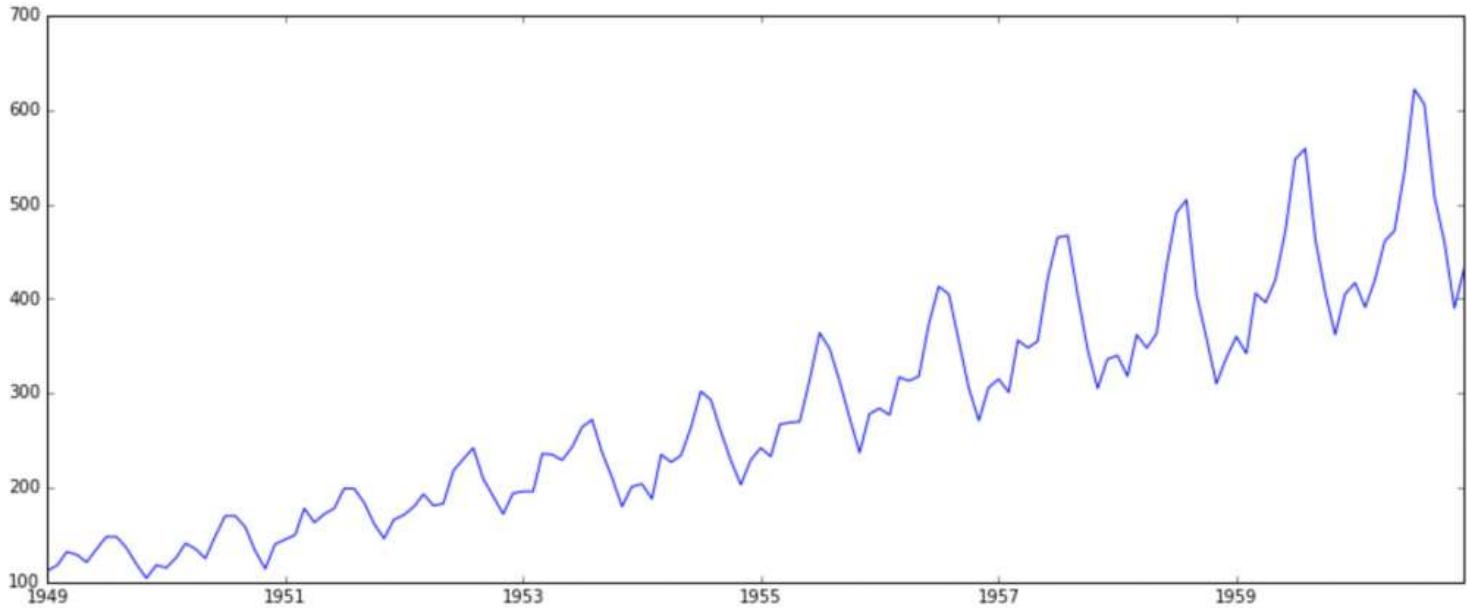
A TS is said to be stationary if its **statistical properties** such as mean, variance remain **constant over time**. But why is it important? Most of the TS models work on the assumption that the TS is stationary. Intuitively, we can say that if a TS has a particular behaviour over time, there is a very high probability that it will follow the same in the future. Also, the theories related to stationary series are more mature and easier to implement as compared to non-stationary series.

Stationarity is defined using very strict criterion. However, for practical purposes we can assume the series to be stationary if it has constant statistical properties over time, ie. the following:

1. constant mean
2. constant variance
3. an autocovariance that does not depend on time.

I'll skip the details as it is very clearly defined in this article (<https://www.analyticsvidhya.com/blog/2015/12/complete-tutorial-time-series-modeling/>). Lets move onto the ways of testing stationarity. First and foremost is to simple plot the data and analyze visually. The data can be plotted using following command:

```
plt.plot(ts)
```



(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/7-ts.png>)

It is clearly evident that there is an **overall increasing trend** in the data along with some seasonal variations. However, it might not always be possible to make such visual inferences (we'll see such cases later). So, more formally, we can check stationarity using the following:

1. **Plotting Rolling Statistics:** We can plot the moving average or moving variance and see if it varies with time. By moving average/variance I mean that at any instant 't', we'll take the average/variance of the last year, i.e. last 12 months. But again this is more of a visual technique.
2. **Dickey-Fuller Test:** This is one of the statistical tests for checking stationarity. Here the null hypothesis is that the TS is non-stationary. The test results comprise of a **Test Statistic** and some **Critical Values** for difference confidence levels. If the 'Test Statistic' is less than the 'Critical Value', we can reject the null hypothesis and say that the series is stationary. Refer this article (<https://www.analyticsvidhya.com/blog/2015/12/complete-tutorial-time-series-modeling/>) for details.

These concepts might not sound very intuitive at this point. I recommend going through the prequel article. If you're interested in some theoretical statistics, you can refer **Introduction to Time Series and Forecasting** by **Brockwell and Davis**. The book is a bit stats-heavy, but if you have the skill to read-between-lines, you can understand the concepts and tangentially touch the statistics.

Back to checking stationarity, we'll be using the rolling statistics plots along with Dickey-Fuller test results a lot so I have defined a function which takes a TS as input and generated them for us. Please note that I've plotted standard deviation instead of variance to keep the unit similar to mean.

```
from statsmodels.tsa.stattools import adfuller

def test_stationarity(timeseries):

    #Determining rolling statistics
    rolmean = pd.rolling_mean(timeseries, window=12)
    rolstd = pd.rolling_std(timeseries, window=12)

    #Plot rolling statistics:
    orig = plt.plot(timeseries, color='blue',label='Original')
    mean = plt.plot(rolmean, color='red', label='Rolling Mean')
    std = plt.plot(rolstd, color='black', label = 'Rolling Std')
    plt.legend(loc='best')
    plt.title('Rolling Mean & Standard Deviation')
    plt.show(block=False)

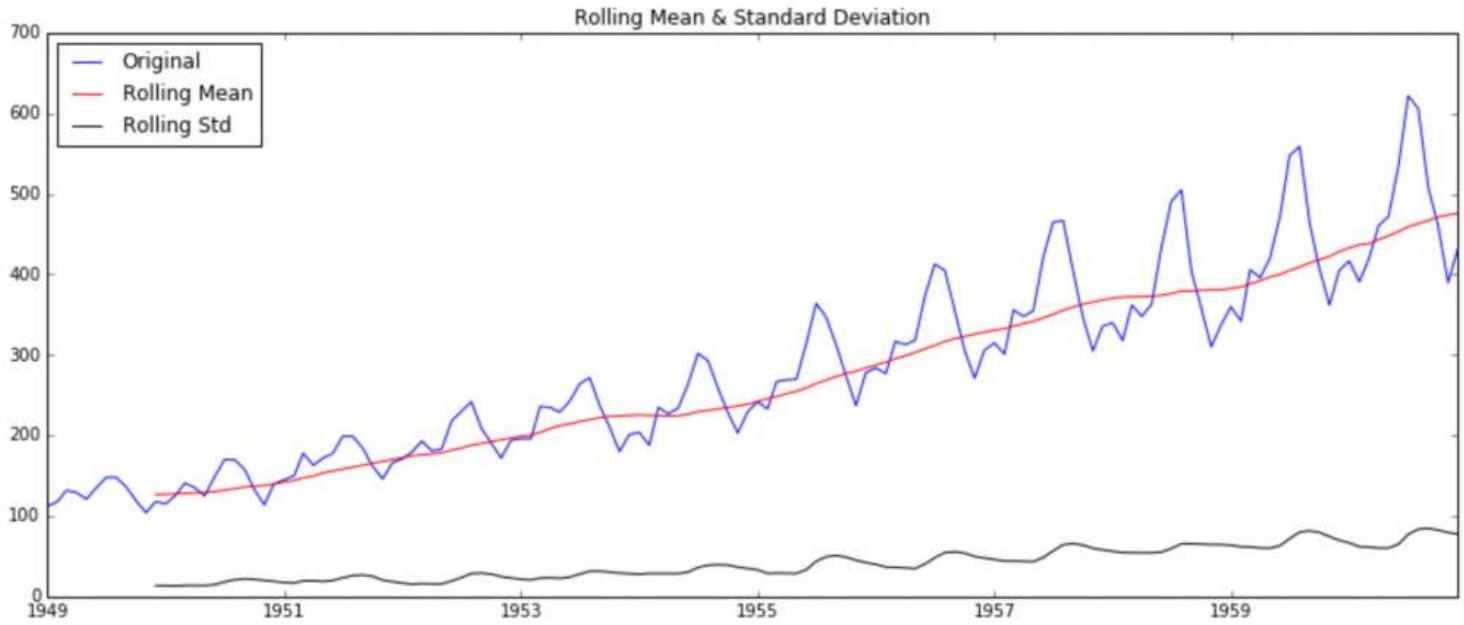
    #Perform Dickey-Fuller test:
    print 'Results of Dickey-Fuller Test:'
    dftest = adfuller(timeseries, autolag='AIC')
    dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#Lags Used','Number of Observations Used'])

    for key,value in dftest[4].items():
        dfoutput['Critical Value (%s)'%key] = value
    print dfoutput
```

The code is pretty straight forward. Please feel free to discuss the code in comments if you face challenges in grasping it.

Let's run it for our input series:

```
test_stationarity(ts)
```



Results of Dickey-Fuller Test:

Test Statistic	0.815369
p-value	0.991880
#Lags Used	13.000000
Number of Observations Used	130.000000
Critical Value (5%)	-2.884042
Critical Value (1%)	-3.481682
Critical Value (10%)	-2.578770
dtype: float64	

(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/1.-dfuller-ts.png>)

Though the variation in standard deviation is small, mean is clearly increasing with time and this is not a stationary series. Also, the test statistic is way more than the critical values. Note that the **signed values should be compared** and not the absolute values.

Next, we'll discuss the techniques that can be used to take this TS towards stationarity.

4. How to make a Time Series Stationary?

Though stationarity assumption is taken in many TS models, almost none of practical time series are stationary. So statisticians have figured out ways to make series stationary, which we'll discuss now. Actually, it's almost impossible to make a series perfectly stationary, but we try to take it as close as possible.

Lets understand what is making a TS non-stationary. There are 2 major reasons behind non-stationarity of a TS:

1. **Trend** – varying mean over time. For eg, in this case we saw that on average, the number of passengers was growing over time.
2. **Seasonality** – variations at specific time-frames. eg people might have a tendency to buy cars in a particular month because of pay increment or festivals.

The underlying principle is to model or estimate the trend and seasonality in the series and remove those from the series to get a stationary series. Then statistical forecasting techniques can be implemented on this series. The final step would be to convert the forecasted values into the original scale by applying trend and seasonality constraints back.

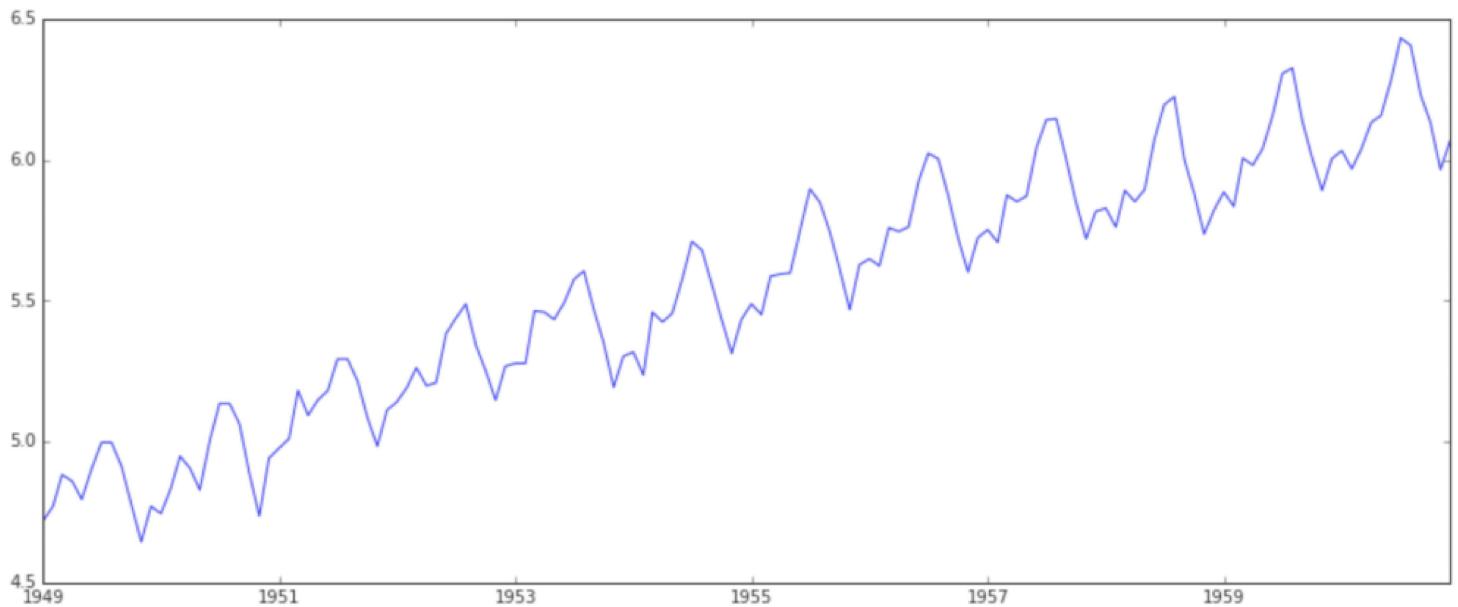
Note: I'll be discussing a number of methods. Some might work well in this case and others might not. But the idea is to get a hang of all the methods and not focus on just the problem at hand.

Let's start by working on the trend part.

Estimating & Eliminating Trend

One of the first tricks to reduce trend can be **transformation**. For example, in this case we can clearly see that there is a significant positive trend. So we can apply transformation which penalize higher values more than smaller values. These can be taking a log, square root, cube root, etc. Lets take a **log transform** here for simplicity:

```
ts_log = np.log(ts)
plt.plot(ts_log)
```



(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/9.-ts-log.png>)

In this simpler case, it is easy to see a forward trend in the data. But its not very intuitive in presence of noise. So we can use some techniques to estimate or model this trend and then remove it from the series. There can be many ways of doing it and some of most commonly used are:

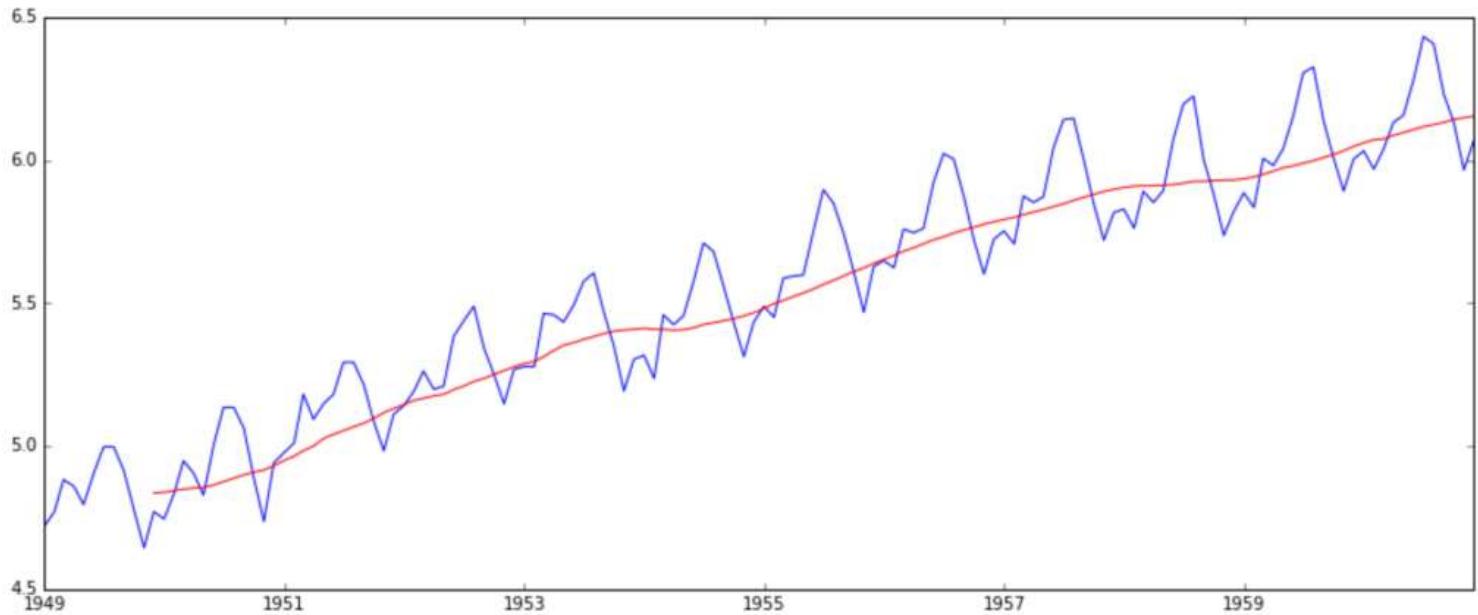
1. **Aggregation** – taking average for a time period like monthly/weekly averages
2. **Smoothing** – taking rolling averages
3. **Polynomial Fitting** – fit a regression model

I will discuss smoothing here and you should try other techniques as well which might work out for other problems. Smoothing refers to taking rolling estimates, i.e. considering the past few instances. There are can be various ways but I will discuss two of those here.

Moving average

In this approach, we take average of 'k' consecutive values depending on the frequency of time series. Here we can take the average over the past 1 year, i.e. last 12 values. Pandas has specific functions defined for determining rolling statistics.

```
moving_avg = pd.rolling_mean(ts_log,12)
plt.plot(ts_log)
plt.plot(moving_avg, color='red')
```



(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/10.-smooth-1.png>)

The red line shows the rolling mean. Lets subtract this from the original series. Note that since we are taking average of last 12 values, rolling mean is not defined for first 11 values. This can be observed as:

```
ts_log_moving_avg_diff = ts_log - moving_avg
ts_log_moving_avg_diff.head(12)
```

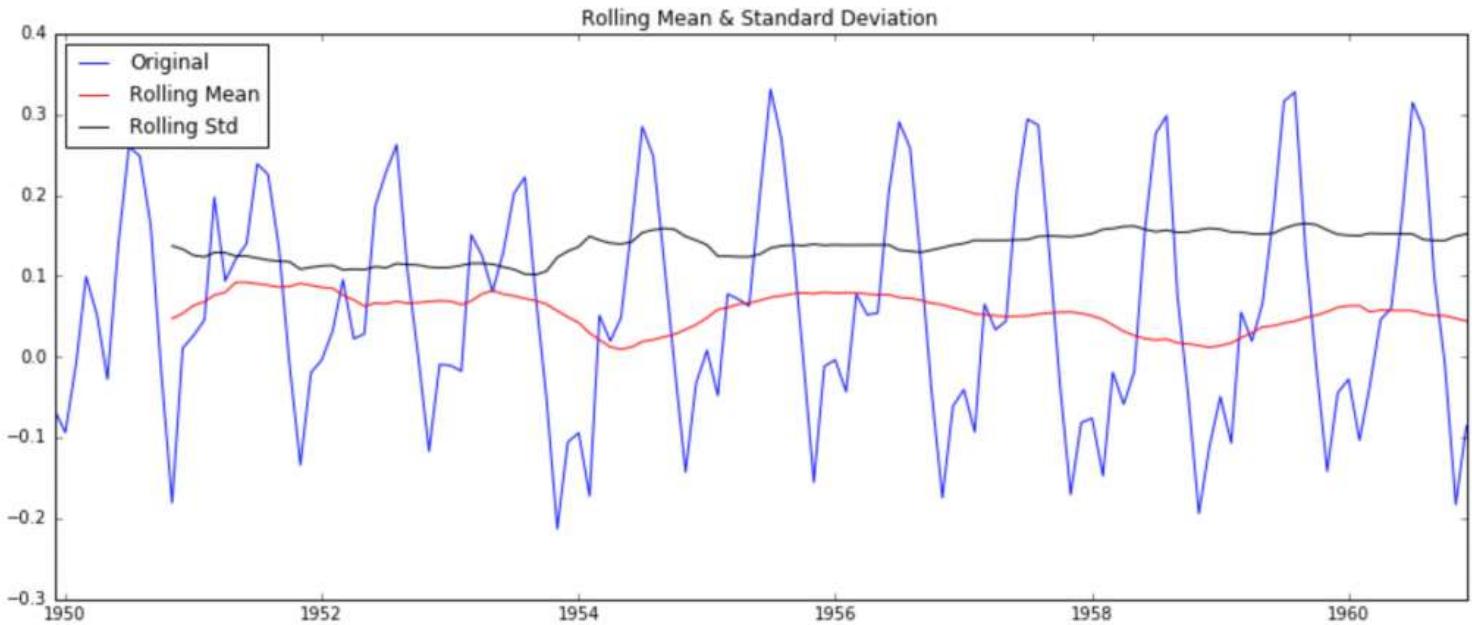
```
Month
1949-01-01      NaN
1949-02-01      NaN
1949-03-01      NaN
1949-04-01      NaN
1949-05-01      NaN
1949-06-01      NaN
1949-07-01      NaN
1949-08-01      NaN
1949-09-01      NaN
1949-10-01      NaN
1949-11-01      NaN
1949-12-01    -0.065494
Name: #Passengers, dtype: float64
```

(<https://www.analyticsvidhya.com/wp->

content/uploads/2016/02/10.5-missing-rolling.png)

Notice the first 11 being Nan. Lets drop these NaN values and check the plots to test stationarity.

```
ts_log_moving_avg_diff.dropna(inplace=True)
test_stationarity(ts_log_moving_avg_diff)
```



```
Results of Dickey-Fuller Test:
Test Statistic           -3.162908
p-value                  0.022235
#Lags Used              13.000000
Number of Observations Used 119.000000
Critical Value (5%)      -2.886151
Critical Value (1%)       -3.486535
Critical Value (10%)      -2.579896
dtype: float64
```

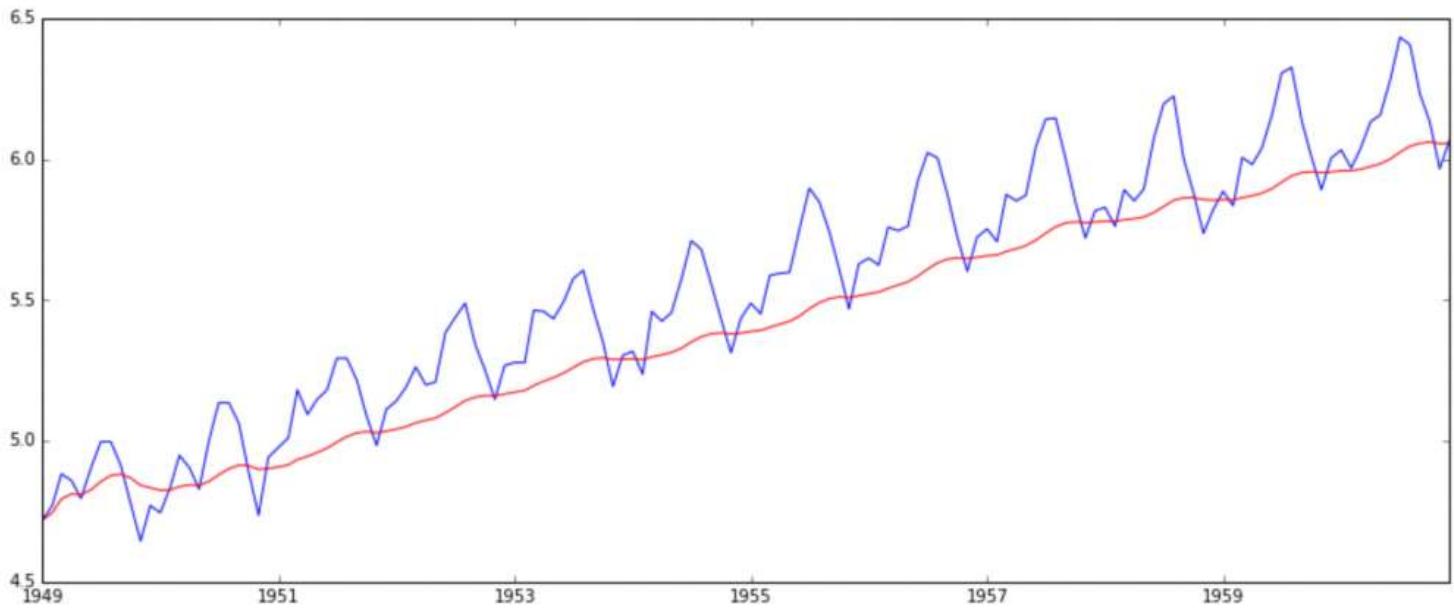
(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/2.-dfuller-smooth-1.png>)

This looks like a much better series. The rolling values appear to be varying slightly but there is no specific trend. Also, the test statistic is **smaller than the 5% critical values** so we can say with 95% confidence that this is a stationary series.

However, a drawback in this particular approach is that the time-period has to be strictly defined. In this case we can take yearly averages but in complex situations like forecasting a stock price, its difficult to come up with a number. So we take a 'weighted moving average' where more recent values are given a higher weight. There can be many technique for assigning weights. A popular one is **exponentially weighted moving average** where weights are assigned to all the previous values

with a decay factor. Find details here (<http://pandas.pydata.org/pandas-docs/stable/computation.html#exponentially-weighted-moment-functions>). This can be implemented in Pandas as:

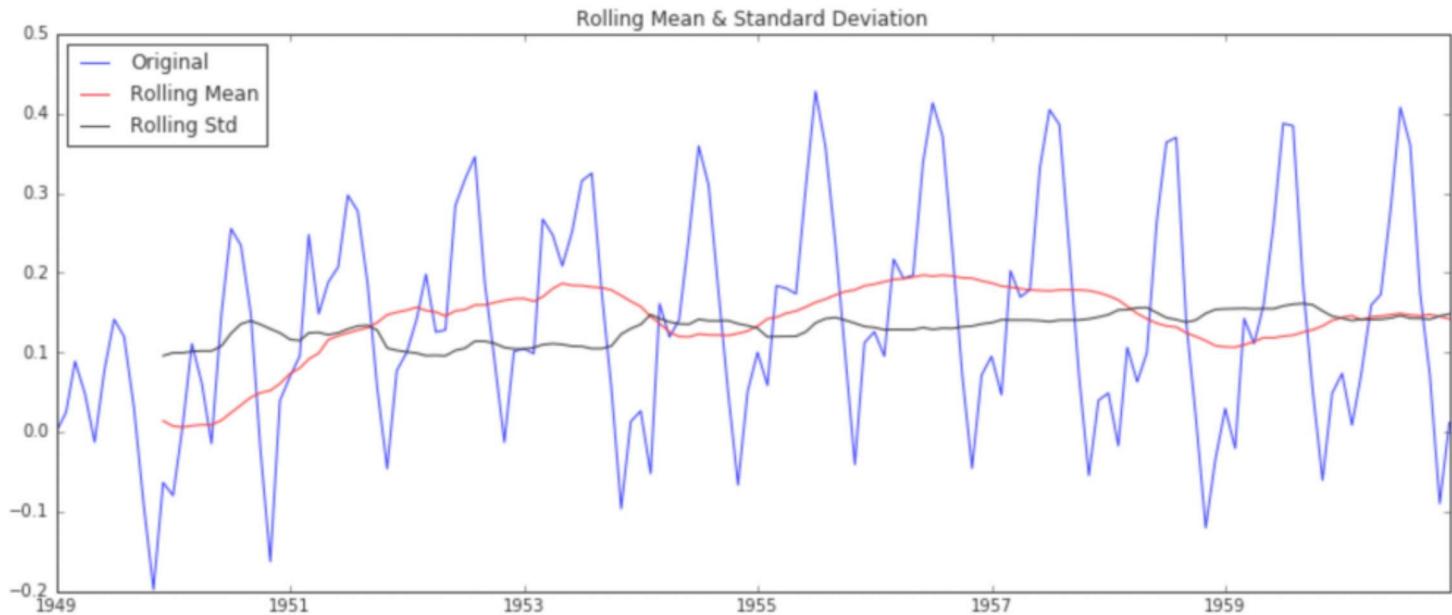
```
expweighted_avg = pd.ewma(ts_log, halflife=12)
plt.plot(ts_log)
plt.plot(expweighted_avg, color='red')
```



(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/12.-smooth-2.png>)

Note that here the parameter 'halflife' is used to define the amount of exponential decay. This is just an assumption here and would depend largely on the business domain. Other parameters like span and center of mass can also be used to define decay which are discussed in the link shared above. Now, let's remove this from series and check stationarity:

```
ts_log_ewma_diff = ts_log - expweighted_avg
test_stationarity(ts_log_ewma_diff)
```



```
Results of Dickey-Fuller Test:
```

Test Statistic	-3.601262
p-value	0.005737
#Lags Used	13.000000
Number of Observations Used	130.000000
Critical Value (5%)	-2.884042
Critical Value (1%)	-3.481682
Critical Value (10%)	-2.578770
dtype:	float64

(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/3.-dfuller-smooth-2.png>)

This TS has even lesser variations in mean and standard deviation in magnitude. Also, the test statistic is **smaller than the 1% critical value**, which is better than the previous case. Note that in this case there will be no missing values as all values from starting are given weights. So it'll work even with no previous values.

Eliminating Trend and Seasonality

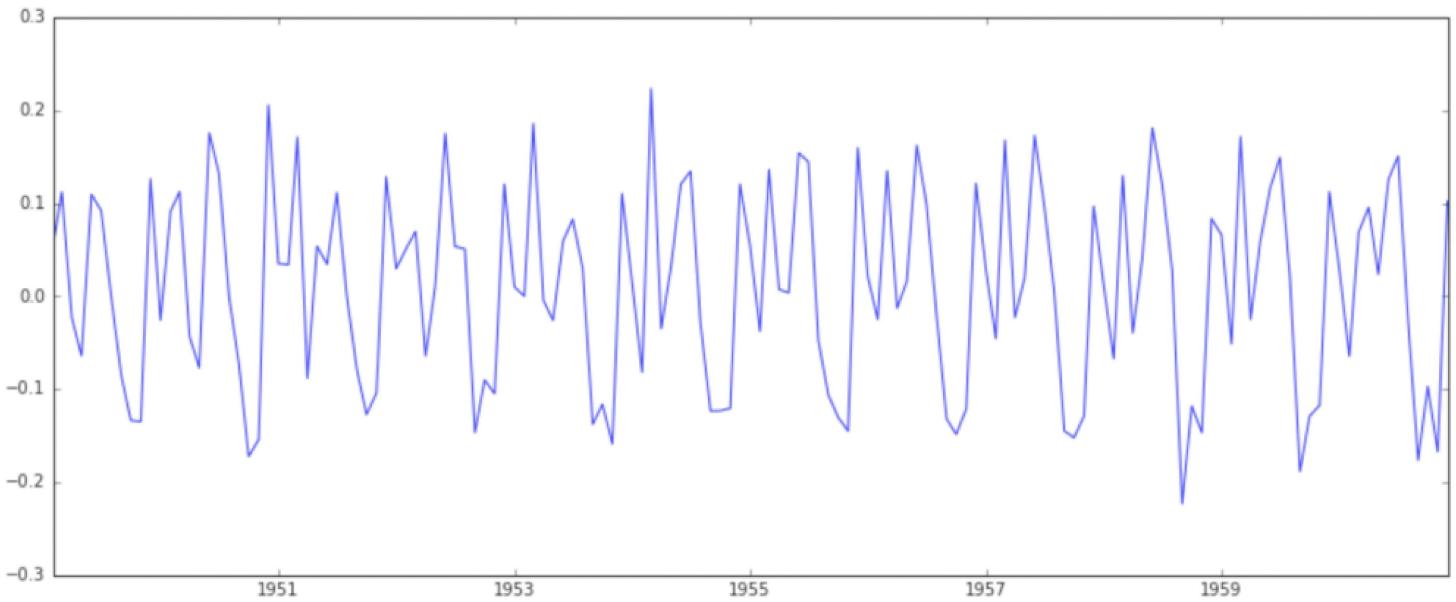
The simple trend reduction techniques discussed before don't work in all cases, particularly the ones with high seasonality. Lets discuss two ways of removing trend and seasonality:

1. **Differencing** – taking the difference with a particular time lag
2. **Decomposition** – modeling both trend and seasonality and removing them from the model.

Differencing

One of the most common methods of dealing with both trend and seasonality is differencing. In this technique, we take the difference of the observation at a particular instant with that at the previous instant. This mostly works well in improving stationarity. First order differencing can be done in Pandas as:

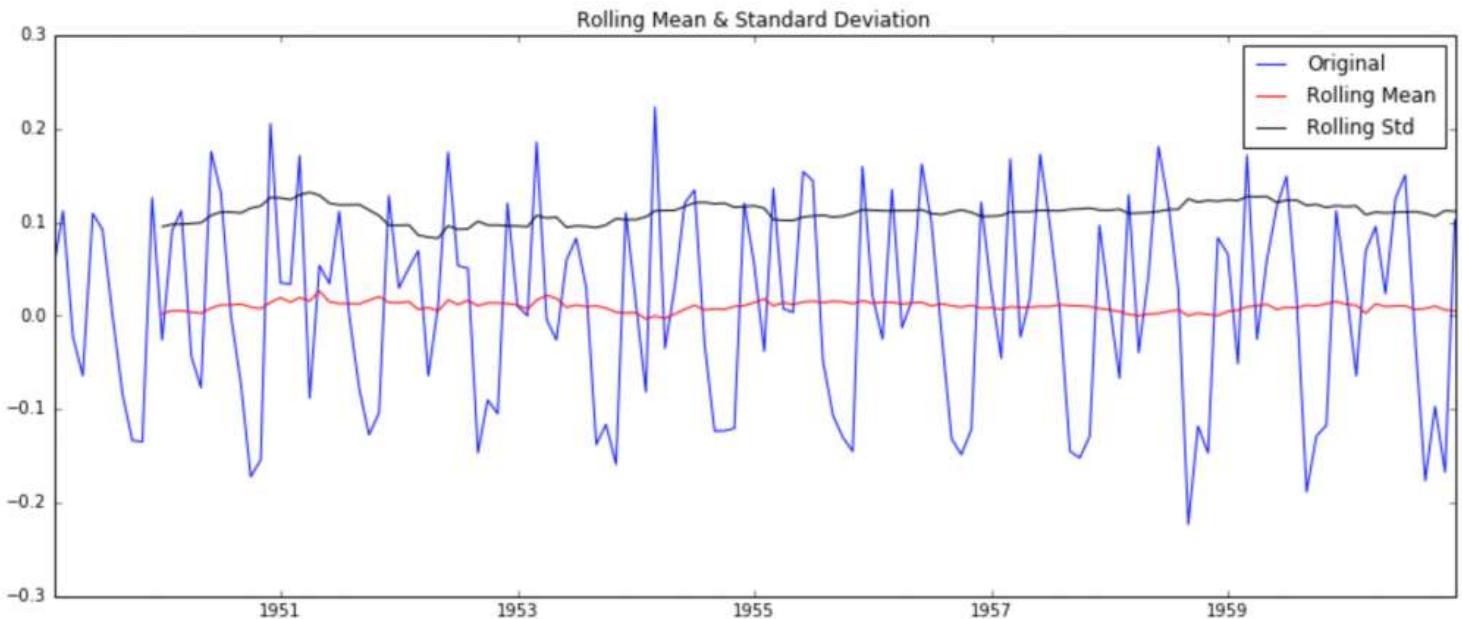
```
ts_log_diff = ts_log - ts_log.shift()
plt.plot(ts_log_diff)
```



(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/14.-ts-diff.png>)

This appears to have reduced trend considerably. Lets verify using our plots:

```
ts_log_diff.dropna(inplace=True)
test_stationarity(ts_log_diff)
```



```
Results of Dickey-Fuller Test:
Test Statistic           -2.717131
p-value                  0.071121
#Lags Used              14.000000
Number of Observations Used 128.000000
Critical Value (5%)      -2.884398
Critical Value (1%)       -3.482501
Critical Value (10%)      -2.578960
dtype: float64
```

(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/4.-dfuller-diff.png>)

We can see that the mean and std variations have small variations with time. Also, the Dickey-Fuller test statistic is **less than the 10% critical value**, thus the TS is stationary with 90% confidence. We can also take second or third order differences which might get even better results in certain applications. I leave it to you to try them out.

Decomposing

In this approach, both trend and seasonality are modeled separately and the remaining part of the series is returned. I'll skip the statistics and come to the results:

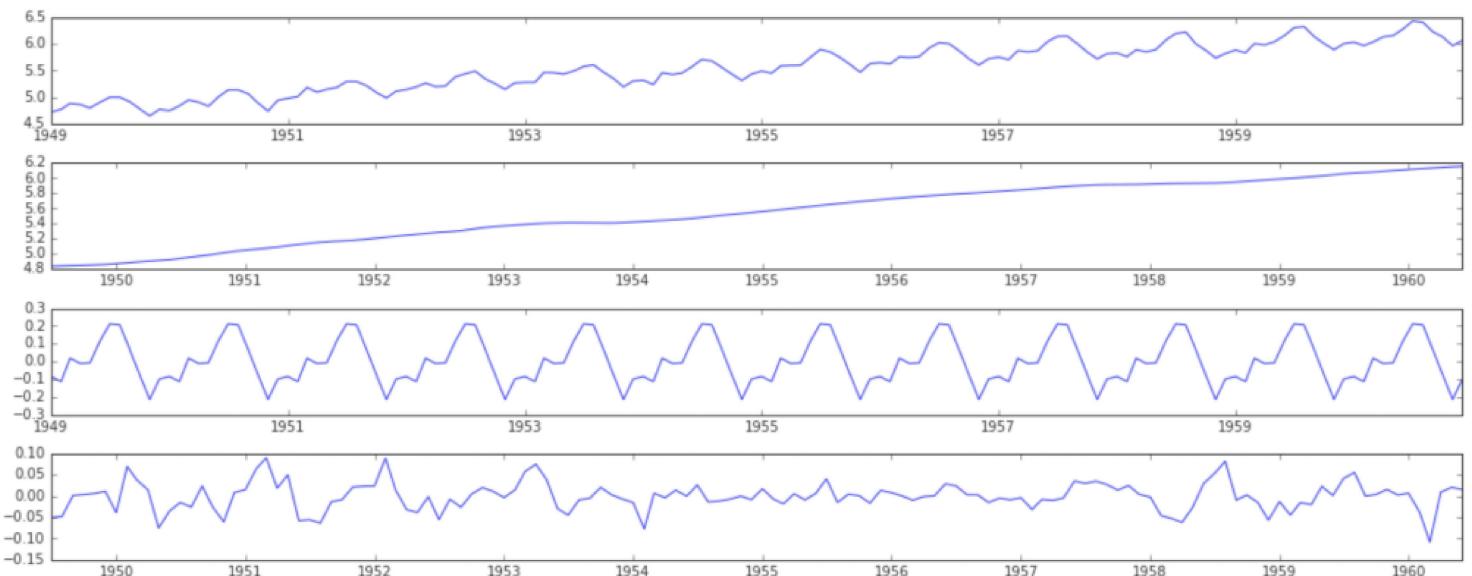
```

from statsmodels.tsa.seasonal import seasonal_decompose
decomposition = seasonal_decompose(ts_log)

trend = decomposition.trend
seasonal = decomposition.seasonal
residual = decomposition.resid

plt.subplot(411)
plt.plot(ts_log, label='Original')
plt.legend(loc='best')
plt.subplot(412)
plt.plot(trend, label='Trend')
plt.legend(loc='best')
plt.subplot(413)
plt.plot(seasonal,label='Seasonality')
plt.legend(loc='best')
plt.subplot(414)
plt.plot(residual, label='Residuals')
plt.legend(loc='best')
plt.tight_layout()

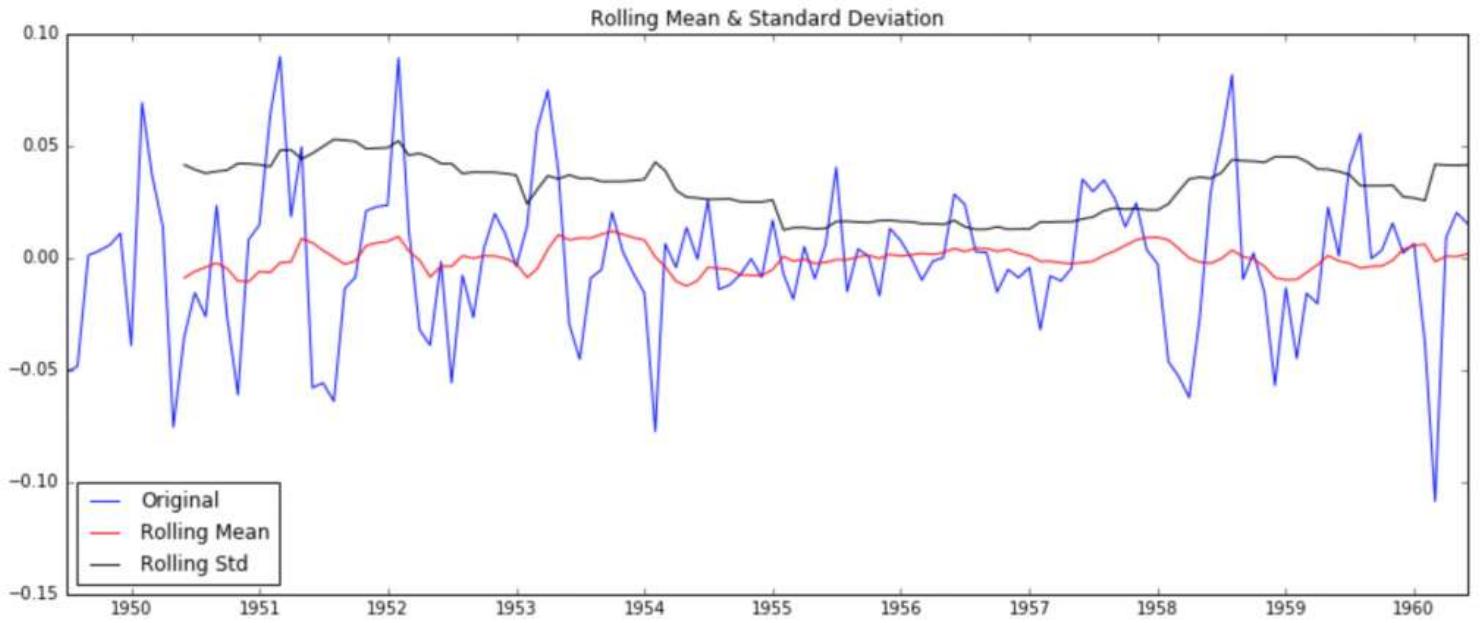
```



(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/16.-decompose.png>)

Here we can see that the trend, seasonality are separated out from data and we can model the residuals. Lets check stationarity of residuals:

```
ts_log_decompose = residual
ts_log_decompose.dropna(inplace=True)
test_stationarity(ts_log_decompose)
```



```
Results of Dickey-Fuller Test:
Test Statistic           -6.332387e+00
p-value                  2.885059e-08
#Lags Used              9.000000e+00
Number of Observations Used 1.220000e+02
Critical Value (5%)      -2.885538e+00
Critical Value (1%)       -3.485122e+00
Critical Value (10%)      -2.579569e+00
dtype: float64
```

(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/5.-dfuller-decompose.png>)

The Dickey-Fuller test statistic is significantly **lower than the 1% critical value**. So this TS is very close to stationary. You can try advanced decomposition techniques as well which can generate better results. Also, you should note that converting the residuals into original values for future data is not very intuitive in this case.

5. Forecasting a Time Series

We saw different techniques and all of them worked reasonably well for making the TS stationary. Lets make model on the TS after differencing as it is a very popular technique. Also, its relatively easier to add noise and seasonality back into predicted residuals in this case. Having performed the trend and seasonality estimation techniques, there can be two situations:

1. A **strictly stationary series** with no dependence among the values. This is the easy case wherein we can model the residuals as white noise. But this is very rare.
2. A series with significant **dependence among values**. In this case we need to use some statistical models like ARIMA to forecast the data.

Let me give you a brief introduction to **ARIMA**. I won't go into the technical details but you should understand these concepts in detail if you wish to apply them more effectively. ARIMA stands for **Auto-Regressive Integrated Moving Averages**. The ARIMA forecasting for a stationary time series is nothing but a linear (like a linear regression) equation. The predictors depend on the parameters (p,d,q) of the ARIMA model:

1. **Number of AR (Auto-Regressive) terms (p):** AR terms are just lags of dependent variable. For instance if p is 5, the predictors for $x(t)$ will be $x(t-1), \dots, x(t-5)$.
2. **Number of MA (Moving Average) terms (q):** MA terms are lagged forecast errors in prediction equation. For instance if q is 5, the predictors for $x(t)$ will be $e(t-1), \dots, e(t-5)$ where $e(i)$ is the difference between the moving average at i^{th} instant and actual value.
3. **Number of Differences (d):** These are the number of nonseasonal differences, i.e. in this case we took the first order difference. So either we can pass that variable and put $d=0$ or pass the original variable and put $d=1$. Both will generate same results.

An importance concern here is how to determine the value of 'p' and 'q'. We use two plots to determine these numbers. Lets discuss them first.

1. **Autocorrelation Function (ACF):** It is a measure of the correlation between the TS with a lagged version of itself. For instance at lag 5, ACF would compare series at time instant 't1'.. 't2' with series at instant 't1-5'.. 't2-5' (t1-5 and t2 being end points).
2. **Partial Autocorrelation Function (PACF):** This measures the correlation between the TS with a lagged version of itself but after eliminating the variations already explained by the intervening comparisons. Eg at lag 5, it will check the correlation but remove the effects already explained by lags 1 to 4.

The ACF and PACF plots for the TS after differencing can be plotted as:

```
#ACF and PACF plots:
```

```
from statsmodels.tsa.stattools import acf, pacf
```

```
lag_acf = acf(ts_log_diff, nlags=20)
```

```
lag_pacf = pacf(ts_log_diff, nlags=20, method='ols')
```

```
#Plot ACF:
```

```
plt.subplot(121)
```

```
plt.plot(lag_acf)
```

```
plt.axhline(y=0,linestyle='--',color='gray')
```

```
plt.axhline(y=-1.96/np.sqrt(len(ts_log_diff)),linestyle='--',color='gray')
```

```
plt.axhline(y=1.96/np.sqrt(len(ts_log_diff)),linestyle='--',color='gray')
```

```
plt.title('Autocorrelation Function')
```

```
#Plot PACF:
```

```
plt.subplot(122)
```

```
plt.plot(lag_pacf)
```

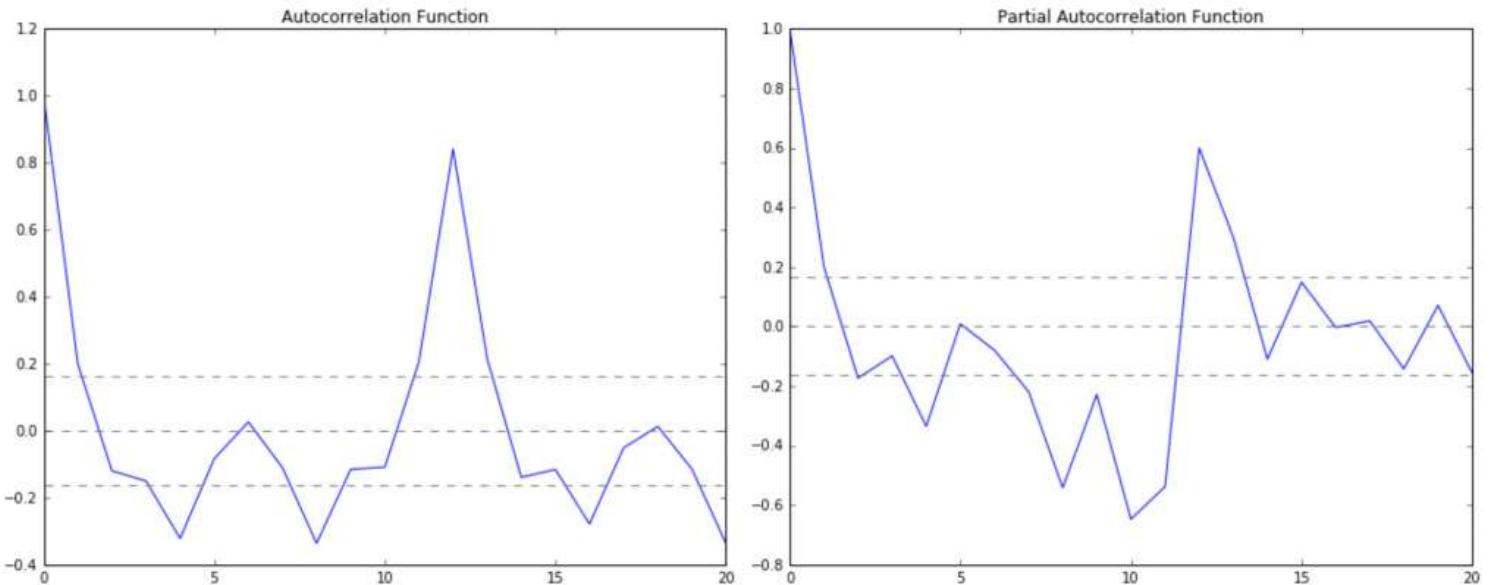
```
plt.axhline(y=0,linestyle='--',color='gray')
```

```
plt.axhline(y=-1.96/np.sqrt(len(ts_log_diff)),linestyle='--',color='gray')
```

```
plt.axhline(y=1.96/np.sqrt(len(ts_log_diff)),linestyle='--',color='gray')
```

```
plt.title('Partial Autocorrelation Function')
```

```
plt.tight_layout()
```



(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/6.-acf-pcf-final.png>)

In this plot, the two dotted lines on either sides of 0 are the confidence intervals. These can be used to determine the 'p' and 'q' values as:

1. **p** – The lag value where the **PACF** chart crosses the upper confidence interval for the first time. If you notice closely, in this case $p=2$.
2. **q** – The lag value where the **ACF** chart crosses the upper confidence interval for the first time. If you notice closely, in this case $q=2$.

Now, let's make 3 different ARIMA models considering individual as well as combined effects. I will also print the RSS for each. Please note that here RSS is for the values of residuals and not actual series.

We need to load the ARIMA model first:

```
from statsmodels.tsa.arima_model import ARIMA
```

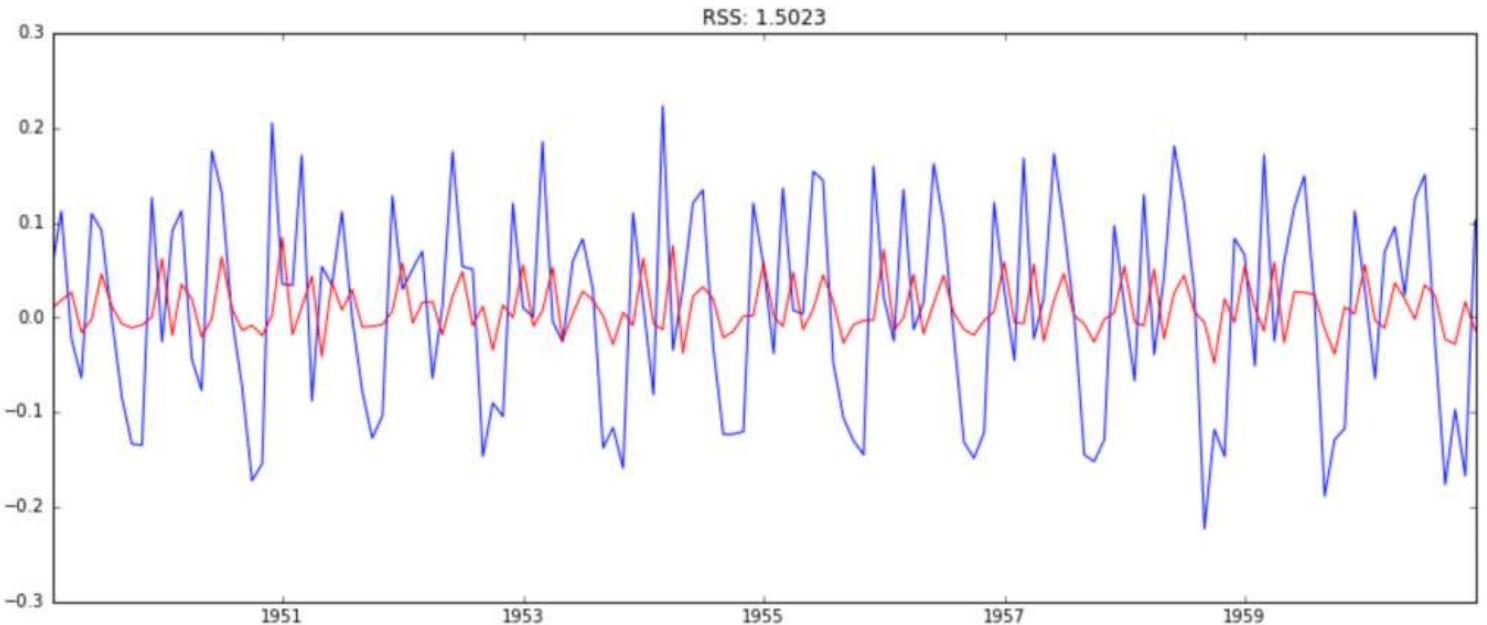
The p,d,q values can be specified using the order argument of ARIMA which take a tuple (p,d,q). Let's model the 3 cases:

AR Model

```

model = ARIMA(ts_log, order=(2, 1, 0))
results_AR = model.fit(disp=-1)
plt.plot(ts_log_diff)
plt.plot(results_AR.fittedvalues, color='red')
plt.title('RSS: %.4f' % sum((results_AR.fittedvalues-ts_log_diff)**2))

```



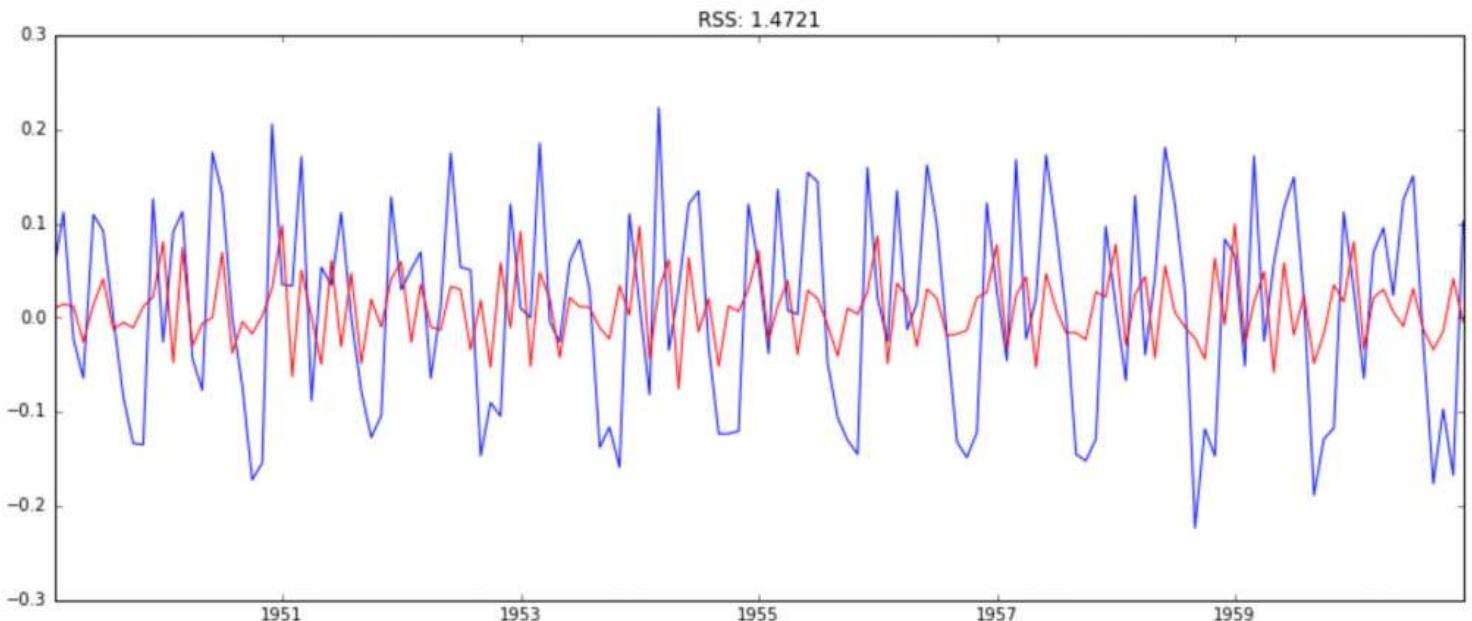
(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/18.-model-AR.png>)

MA Model

```

model = ARIMA(ts_log, order=(0, 1, 2))
results_MA = model.fit(disp=-1)
plt.plot(ts_log_diff)
plt.plot(results_MA.fittedvalues, color='red')
plt.title('RSS: %.4f' % sum((results_MA.fittedvalues-ts_log_diff)**2))

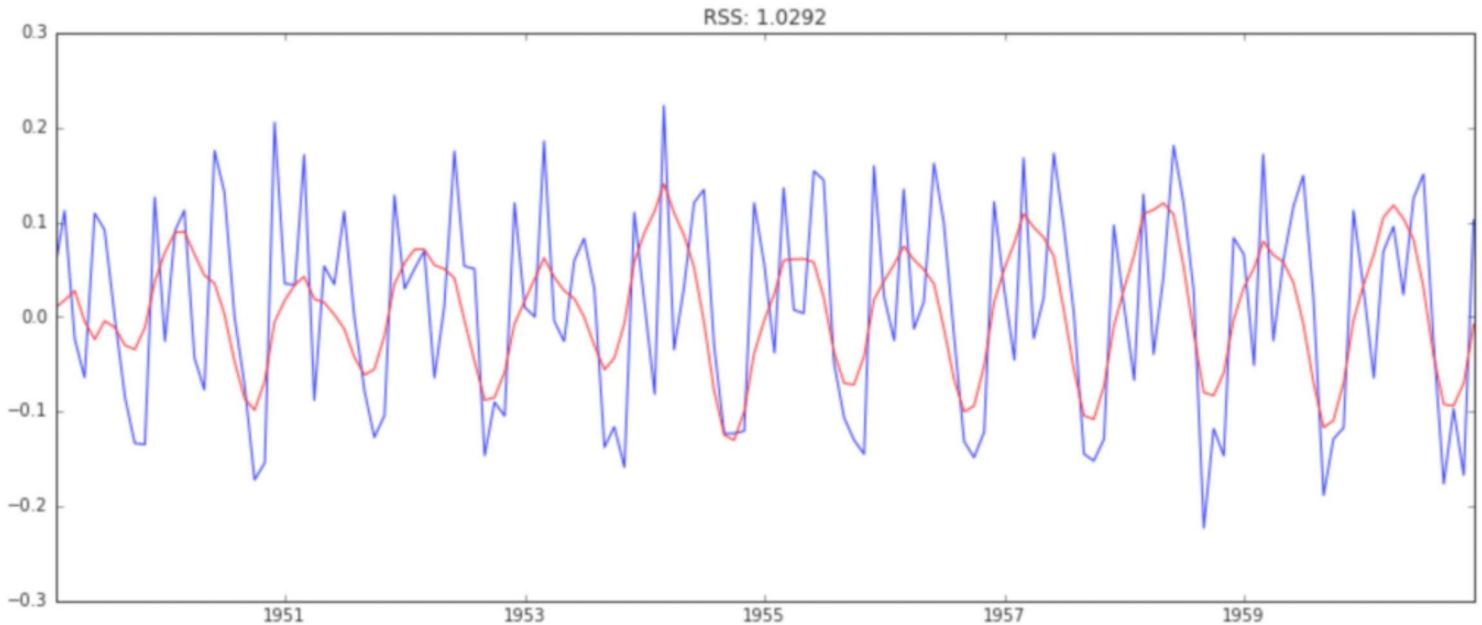
```



(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/19.-model-MA.png>)

Combined Model

```
model = ARIMA(ts_log, order=(2, 1, 2))
results_ARIMA = model.fit(disp=-1)
plt.plot(ts_log_diff)
plt.plot(results_ARIMA.fittedvalues, color='red')
plt.title('RSS: %.4f'% sum((results_ARIMA.fittedvalues-ts_log_diff)**2))
```



(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/20.-model-both.png>)

Here we can see that the AR and MA models have almost the same RSS but combined is significantly better. Now, we are left with 1 last step, i.e. taking these values back to the original scale.

Taking it back to original scale

Since the combined model gave best result, lets scale it back to the original values and see how well it performs there. First step would be to store the predicted results as a separate series and observe it.

```
predictions_ARIMA_diff = pd.Series(results_ARIMA.fittedvalues, copy=True)
print predictions_ARIMA_diff.head()
```

Month	
1949-02-01	0.009580
1949-03-01	0.017491
1949-04-01	0.027670
1949-05-01	-0.004521
1949-06-01	-0.023889
dtype:	float64

(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/21.-check-output.png>)

Notice that these start from '1949-02-01' and not the first month. Why? This is because we took a lag by 1 and first element doesn't have anything before it to subtract from. The way to convert the differencing to log scale is to add these differences consecutively to the base number. An easy way to do it is to first determine the cumulative sum at index and then add it to the base number. The cumulative sum can be found as:

```
predictions_ARIMA_diff_cumsum = predictions_ARIMA_diff.cumsum()
print predictions_ARIMA_diff_cumsum.head()
```

Month	
1949-02-01	0.009580
1949-03-01	0.027071
1949-04-01	0.054742
1949-05-01	0.050221
1949-06-01	0.026331
dtype:	float64

(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/22.-cumsum.png>)

You can quickly do some back of mind calculations using previous output to check if these are correct. Next we've to add them to base number. For this lets create a series with all values as base number and add the differences to it. This can be done as:

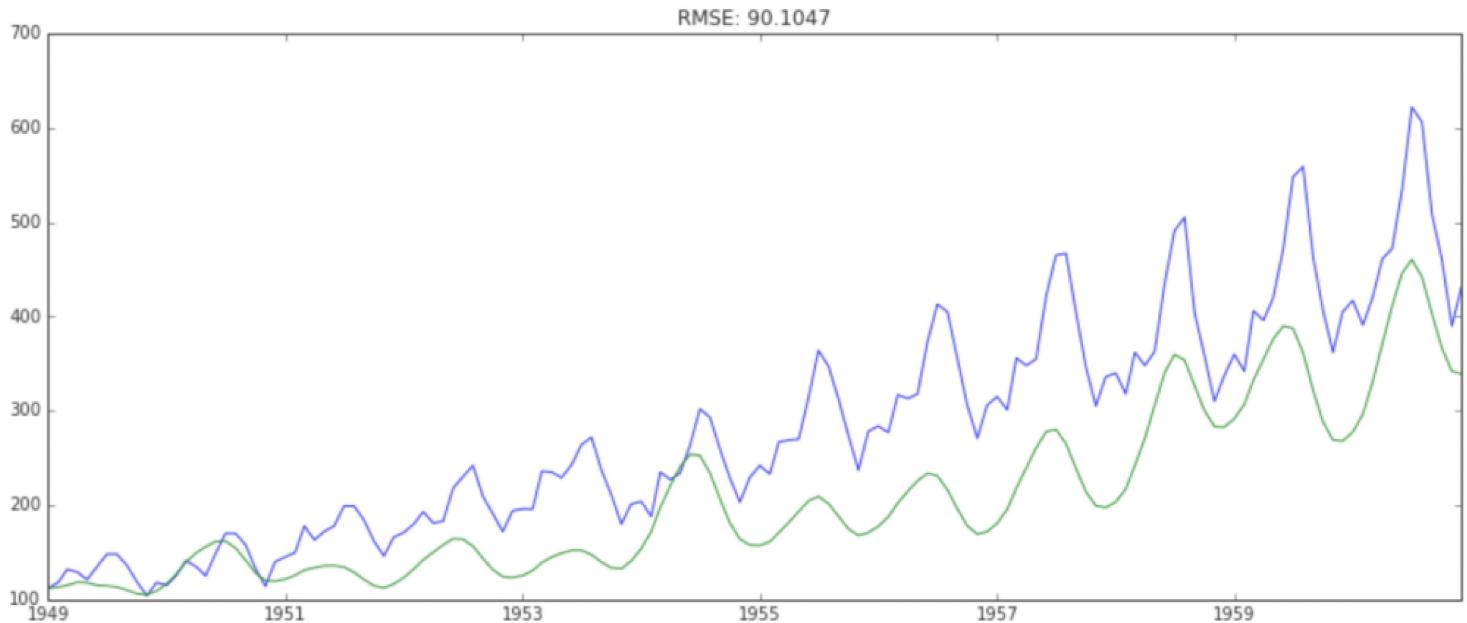
```
predictions_ARIMA_log = pd.Series(ts_log.ix[0], index=ts_log.index)
predictions_ARIMA_log = predictions_ARIMA_log.add(predictions_ARIMA_diff_cumsum, fill_value=0)
predictions_ARIMA_log.head()
```

```
Month
1949-01-01    4.718499
1949-02-01    4.728079
1949-03-01    4.745570
1949-04-01    4.773241
1949-05-01    4.768720
dtype: float64
```

(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/23.-add-cumsum.png>)

Here the first element is base number itself and from thereon the values cumulatively added. Last step is to take the exponent and compare with the original series.

```
predictions_ARIMA = np.exp(predictions_ARIMA_log)
plt.plot(ts)
plt.plot(predictions_ARIMA)
plt.title('RMSE: %.4f' % np.sqrt(sum((predictions_ARIMA-ts)**2)/len(ts)))
```



(<https://www.analyticsvidhya.com/wp-content/uploads/2016/02/24.-final-plot.png>)

Finally we have a forecast at the original scale. Not a very good forecast I would say but you got the idea right? Now, I leave it upto you to refine the methodology further and make a better solution.

End Notes

Through this article I have tried to give you a standard approach for solving time series problem. This couldn't have come at a better time as today is our Mini DataHack (<http://datahack.analyticsvidhya.com/contest/mini-datahack>) which will challenge you to solve a similar problem. We've covered concepts of stationarity, how to take a time series closer to stationarity and finally forecasting the residuals. It was a long journey and I skipped some statistical details which I encourage you to refer using the suggested material. If you don't want to copy-paste, you can download the iPython notebook with all the codes from my GitHub (https://github.com/aarshayj/Analytics_Vidhya/tree/master/Articles) repository.

I hope this article will help you achieve a good first solution today. All the best guys!

Did you like the article? How helpful was it in the hackathon today? Somethings bothering you which you wish to discuss further? Please feel free to post a comment and I'll be more than happy to discuss.

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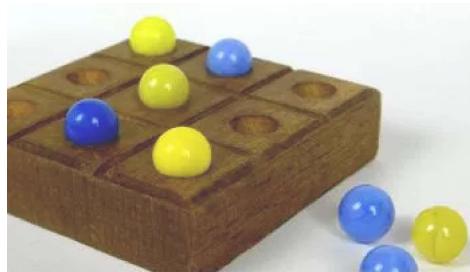
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Author

Aarshay Jain (<https://www.analyticsvidhya.com/blog/author/aarshay/>)

Aarshay is a ML enthusiast, pursuing MS in Data Science at Columbia University, graduating in Dec 2017. He is currently exploring the various ML techniques and writes articles for AV to share his knowledge with the community.

✉ (<mailto:aarshayjain@gmail.com>) **in** (<https://in.linkedin.com/in/aarshayjain>)

 (<https://github.com/aarshayj>)  (aarshay)

38 COMMENTS



Dr.D.K.Samuel says:

REPLY | <https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/?replytocom=105271#respond>

FEBRUARY 6, 2016 AT 10:02 AM ([HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/#COMMENT-105271](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/#comment-105271))

Real thanks for a post which met my need



Aarshay Jain says:

REPLY ([HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/?REPLYTOCOM=105272#RESPOND](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/?replytocom=105272#respond))
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I'm glad you liked it 😊



satish says:

REPLY ([HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/?REPLYTOCOM=105327#RESPOND](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/?replytocom=105327#respond))
FEBRUARY 7, 2016 AT 3:17 PM ([HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/#COMMENT-105327](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/#comment-105327))

Thanks for great explanation related to timeseries. What is difference between holtwinters and arima forcast?



shan says:

REPLY ([HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/?REPLYTOCOM=105357#RESPOND](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/?replytocom=105357#respond))
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Holtwinters is double exponential smoothening method. ARIMA, forecasts by identifying p,d,q component of a series. Hope it helps.



Aarshay Jain says:

REPLY ([HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/?REPLYTOCOM=105358#RESPOND](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/?replytocom=105358#respond))
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To add to Shan, Holtwinters uses a weighted average of past values while ARIMA uses both past values and past errors. You can find more details here:

https://www.google.co.in/url?sa=t&rct=j&q=&esrc=s&source=web&cd=2&ved=oahUKEwiUgKXCxfKAhXIc44KHTTpDyUQFggjMAE&url=http%3A%2F%2Fwww.ons.gov.uk%2Fons%2Fguide-method%2Fukcemga%2Fukcemga-publications%2Fpublications%2Farchive%2Ffrom-holt-winters-to-arima-modelling-measuring-the-impact-on-forecasting-errors-for-components-of-quarterly-estimates-of-public-service-output.pdf&usg=AFQjCNGmYzfVB-gdss4LKTGw4VVZgBC_w&sig2=9pnseABiC_4oxC2KnWmHNw&cad=rja

(https://www.google.co.in/url?sa=t&rct=j&q=&esrc=s&source=web&cd=2&ved=oahUKEwiUgKXCx-fKAhXlc44KHTTpDyUQFggjMAE&url=http%3A%2Fwww.ons.gov.uk%2Fons%2Fguide-method%2Fukcemga%2Fukcemga-publications%2Fpublications%2Farchive%2Ffrom-holt-winters-to-arima-modelling--measuring-the-impact-on-forecasting-errors-for-components-of-quarterly-estimates-of-public-service-output.pdf&usg=AFQjCNGmYzfVB-gdss4LKTGw4VVZgBC_w&sig2=9pnseABiC_4oxC2KnWmHNw&cad=rja)



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Holt winters (at least the additive model) is a special case of arima model (a seasonal arima model). That would be an arima(p,d,q)(P,D,Q) where the second parentheses contains the seasonal effects. I would additionally recommend checking out any of Rob Hyndman's work on arima modeling, I find it to be very accessible.



shan says: REPLY ([HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/?REPLYTOCOM=105332#RESPOND](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/?replytocom=105332#respond))
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Hi..

Thanks. for an informative article.

I am eager to know on followings :

a) how can we identify what should be nlags value to test with

lag_acf = acf(ts_log_diff, nlags=20)

lag_pacf = pacf(ts_log_diff, nlags=20, method='ols')

b) How can we forecast for future time points (say 12 time points ahead).

Can we use followings still ?

predictions_ARIMA_log = pd.Series(ts_log.ix[0], index=ts_log.index)

predictions_ARIMA_log =

predictions_ARIMA_log.add(predictions_ARIMA_diff_cumsum, fill_value=0)

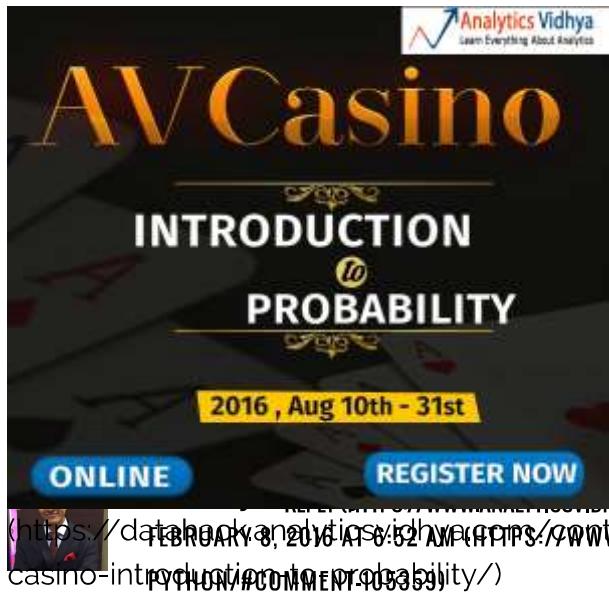
ts_log is not available for future points.

c) In one of the article (A Complete Tutorial on Time Series Modeling in R,) referred by you ,

while performing adf says

```
adf.test(diff(log(AirPassengers)), alternative= "stationary", k=0)
```

What is k , and how can we identify the value of k while performing the test..



(https://datahack.analyticsvidhya.com/forums/thread/105359/replytothread/REPLYTOCOM-105359#RESPOND)
 (https://datahack.analyticsvidhya.com/forums/thread/105359/replytothread/REPLYTOCOM-105359#RESPOND)
 (https://datahack.analyticsvidhya.com/forums/thread/105359/replytothread/REPLYTOCOM-105359#RESPOND)

Hi Shan,

Thanks for reaching out. Please find my responses below:

- So the 'nlags' doesn't affect the output values. I just specifies how many values to display. So you can start with a small number and if you don't find the crossing point within that, you can increase maximum upto the number of observations in data.
- ARIMA has a specific function for forecasting values. The 'results_ARIMA' variable here is of the type 'ARIMAResults' which has a 'predict' function. You can check the details as –
http://statsmodels.sourceforge.net/devel/generated/statsmodels.tsa.arima_model.ARMAResults.html
 Please feel free to get back to me in case you face challenges in implementing this. You can also start a thread in the discussion forum which will allow more freedom of expression while discussing 😊
- I'm not much experienced with R so let me read the code syntax. I'll get back to you on this.

Cheers!



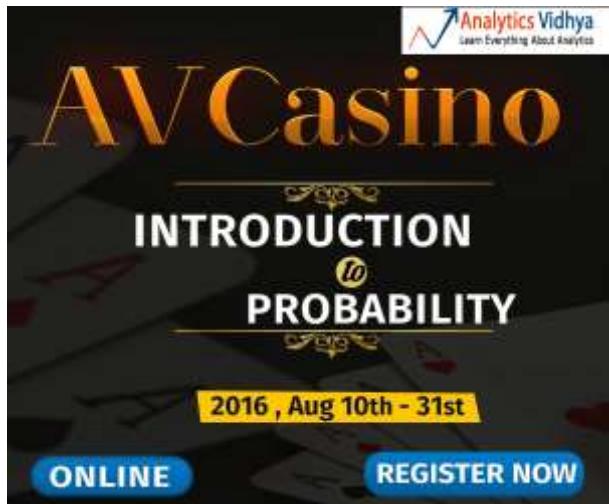
Aarshay Jain says:

(https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/?REPLYTOCOM-105373#RESPOND)



FEBRUARY 8, 2016 AT 12:32 PM ([HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/#COMMENT-105373](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/#comment-105373))

Hi Shan,



te discussion thread for your query 'c'. Lets continue the same reading this and interested in exploring further, please check

<https://www.analyticsvidhya.com/blog/2016/02/time-series-parameter-in-arima-and-adf-test/7385/1>

<https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/#comment-105585>

<https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/#comment-105585>

[...] Complete guide to create a Time Series Forecast (with Codes in Python) Time Series (referred as TS from now) is considered to be one of the less known skills in the analytics space (Even I had little clue about it a couple of days back). But as you know our inaugural Mini Hackathon is based on it, I set myself on a journey to learn the basic steps for solving a Time Series problem and here I am sharing the same with you. These will definitely help you get a decent model in our hackathon today. [...]

What I learnt about Time Series Analysis in 3 hour Mini DataHack?

(<http://www.analyticsvidhya.com/blog/2016/02/hand-learn-time-series-3-hours-mini-datahack/>) says:

FEBRUARY 8, 2016 AT 8:00 PM ([HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/#COMMENT-105386](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/#comment-105386))

[...] Since it was already decided that the problem would be about Time Series – I made sure I was well equipped with knowledge and packages about Time Series. Infact, I even wrote a guide to Time Series in Python, [...]

Complete guide to create a Time Series Forecast (<http://big-data-fr.com/complete-guide-to-create-a-time-series-forecast-with-codes-in-python/>) says:

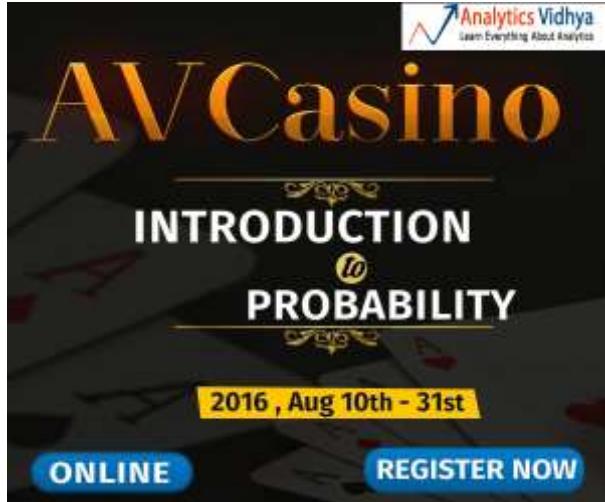
FEBRUARY 13, 2016 AT 1:14 AM ([HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/#COMMENT-105598](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/#comment-105598))

[...] Read tutorial By Aarshay Jain Source: analyticsvidhya.com [...]



amitsethia says: REPLY ([HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/?REPLYTOCOM=105619#RESPOND](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/?replytocom=105619#respon))
FEBRUARY 13, 2016 AT 12:23 PM ([HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/#COMMENT-105619](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/#comment-105619))

Thanks Aarshay for this write up. It is also recommended to not to go for combined models as p & q used together will nullify their impact on the model, hence, it is either a moving average or auto correlation along with differences, but here combined model has given the best results. Can you please correct my understanding around combined models.



(<https://datahack.analyticsvidhya.com/contest/avcasino-introduction-to-probability/>)
Ayush Kumar Singh says: ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/?REPLYTOCOM-106400#RESPOND
 FEBRUARY 29, 2016 AT 10:58 PM ([HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/#COMMENT-106400](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/#comment-106400))

Hi!

The article is the best available on Time Series with Python with great external links too for those who want to understand the stat behind also.

I would like to request to please extend this article to predict out-of-sample data range also with different models to depict the better ones as you did for eliminating trend (taking rolling average and ewma).

That will make it all fully fledged time-series article.

Thanks in advance.



Aarshay Jain says: ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/?REPLYTOCOM-106425#RESPOND
 MARCH 1, 2016 AT 8:46 AM ([HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/#COMMENT-106425](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/#comment-106425))

Hi Ayush!

Thanks for your valuable feedback. Yes I think that component is necessary. But instead of extending this article, I'll probably write a separate post taking another case study. I'm a bit crunched for bandwidth but you can expect it sometime in this month. Stay tuned!



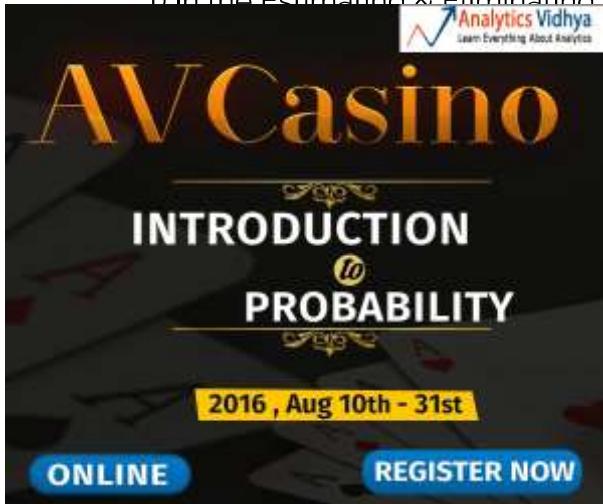
Michael says:



MARCH 13, 2016 (HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/?REPLYTOCOM-107267#RESPOND)
PYTHON/#COMMENT-107267)

Thanks for the excellent article. I have 2 clarifications

- 1) In the Estimating & Eliminating Trend step, I have negative numbers. Could you please tell me why Log and Sqrt returns NAN?
- 2) When I use seasonal_decompose(nlags=10) while executing specifies nlags not defined.



(<https://datahack.analyticsvidhya.com/contest/av-casino-introduction-to-probability/>) Regarding your queries:

1. You can try scaling up your values and then applying transformations. Also, you might want to check if log transformation is actually required in your case. You can try a cube root as well.
2. Please remove the nlags argument and then run the code. I've updated the code above as well.



will welch says: MARCH 14, 2016 AT 1:34 AM (<https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/?replaytocom-107299#respond>) PYTHON/#COMMENT-107299)

Nice article, you rarely see this range of models discussed in one place and in such a hands-on way.

For anyone doing seasonal decomposition in Python, I'd like to shamelessly plug my `seasonal` package (PyPI or <https://github.com/welch/seasonal> (<https://github.com/welch/seasonal>)) in addition to statsmodels seasonal_decompose. `seasonal` offers some richer and more robust detrending possibilities, and will also estimate your model's periodicity for you (convenient in a dev-ops setting with thousands of streams at hand). It also includes a robust periodogram for visualizing the periodicities in your data.





Aarshay Jain says:

REPLY (HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/?REPLYTOCOM=107313#RESPOND)
MARCH 14, 2016 AT 5:58 AM (HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/#COMMENT-107313)

Thanks Will for sharing your library. It'll be helpful for everyone.



36 大数据 (http://www.36dsj.com/archives/44065) says:

HYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/#COMMENT-

Series Forecast (with Codes in Python) [...]

HYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/?REPLYTOCOM=108176#RESPOND)
ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-

the dftest[0:4]?

(https://datahack.analyticsvidhya.com/contest/av-casino-introduction-to-probability/)



Aarshay Jain says:

REPLY (HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/?REPLYTOCOM=108224#RESPOND)
MARCH 25, 2016 AT 6:26 AM (HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/#COMMENT-108224)

the adfuller function returns a list with many values. I'm picking the first 4 using [0:4]. I've used the 5th value separately. You might want to print the dftest variable and you'll know.



Libert says:

REPLY (HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/?REPLYTOCOM=109243#RESPOND)
APRIL 10, 2016 AT 5:53 AM (HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/#COMMENT-109243)

Can we use this method for decimal data? Why the program gave me an error of "ValueError: You must specify a freq or x must be a pandas object with a timeseries index"?



Aarshay Jain says:

REPLY (HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/?REPLYTOCOM=109280#RESPOND)
APRIL 11, 2016 AT 6:59 AM (HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/#COMMENT-109280)

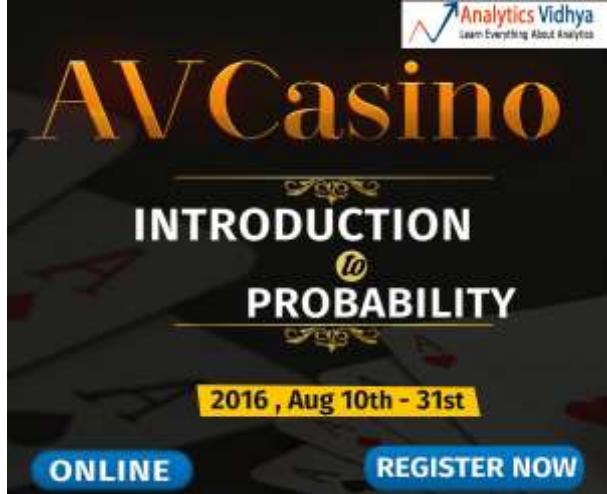
I don't think it is a decimal error. Please check whether your index is a timeseries object.



Cloga (<https://www.cloga.info/>) says:

APRIL 14, 2016 AT 9:54 AM ([HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/?REPLYTOCOM=109445#RESPOND](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/?replytocom=109445#respond))
[PYTHON/#COMMENT-109445](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/#comment-109445))

Hi Aarshay Jain,



og as sampel, ie. model = ARIMA(ts_log, order=(2, 1, 2)) , but when
as diff value : predictions_ARIMA_diff =
yes, copy=True), is results_ARIMA.fittedvalues return log value or



Aarshay Jain says: ([https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/?REPLYTOCOM=109454#RESPOND](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/?replytocom=109454#respond))

APRIL 14, 2016 AT 10:53 AM ([HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-CASINO-INTRODUCTION-TO-PROBABILITY/](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-casino-introduction-to-probability/))
[PYTHON/#COMMENT-109454](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-casino-introduction-to-probability/#comment-109454))

actually while calling ARIMA I have set order = (2,1,2). Here the middle argument 1 means that ARIMA will automatically take a difference of 1 while making predictions.



Cloga (<https://www.cloga.info/>) says:

APRIL 15, 2016 AT 2:31 AM ([HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/?REPLYTOCOM=109489#RESPOND](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/?replytocom=109489#respond))
[PYTHON/#COMMENT-109489](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/#comment-109489))

Got it thank you!



Ayodeji Olufemi Ayotunde says:

APRIL 19, 2016 AT 12:44 AM ([HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/?REPLYTOCOM=109660#RESPOND](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/?replytocom=109660#respond))
[PYTHON/#COMMENT-109660](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/#comment-109660))

What an excellent article on Time Series, more grease to your elbow. But the question is, is this method a package of analyzing Time Series related data or what? And can't we do the same on SPSS and have the same simple method as this? However, I have to commend you a lot for this wonderful presentation. God will continue to increase your knowledge.

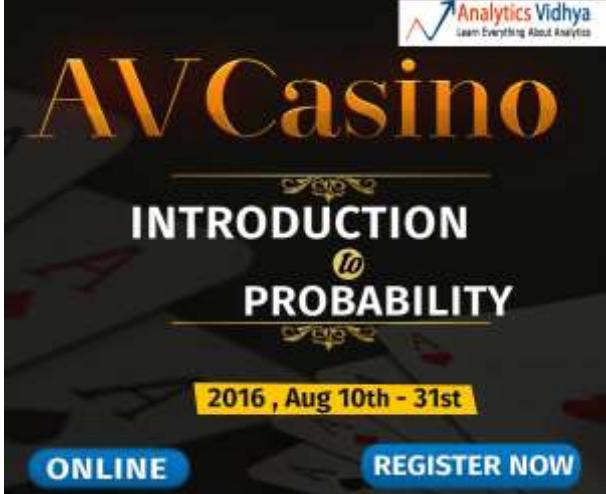




Aarshay Jain says:

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APRIL 19, 2016 AT 5:09 AM (HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/#COMMENT-109664)

Thanks Avodevil,



I didn't get your questions – what do you mean "is this method related to time series related data"? Please elaborate.

(HYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/?REPLYTOCOM=109830#RESPOND)
ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-

de with different dataset and then an error shown up like this:
(https://datahack.analyticsvidhya.com/contest/avcasino-introduction-to-probability/values to unpack

please give an advice

thank you



Aarshay Jain says:

REPLY (HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/?REPLYTOCOM=110007#RESPOND)
APRIL 25, 2016 AT 5:50 PM (HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/#COMMENT-110007)

please share the code..



Dennis says:

REPLY (HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/?REPLYTOCOM=111506#RESPOND)
MAY 27, 2016 AT 1:41 AM (HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/#COMMENT-111506)

Andrew, you are probably passing in a dataframe instead of a series, in the code Aarshay wrote up for the dftest.

Specifically here: dftest = adfuller(timeseries.unstack(), autolag='AIC')

note the .unstack() that I added — transforming the df into a series — when I also encountered the same error.



bawasir ki dawa (http://rajherbals.com/arshoher_bawasir_ki_dawa.html) says:

MAY 6, 2016 AT 12:47 PM ([HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-pyton/))

Great blog post, thanks for sharing this post.

The image features the Analytics Vidhya logo at the top right, which includes a blue checkmark icon and the text "Analytics Vidhya" with "Learn Everything About Analytics" underneath. The main title "VCasino" is in large, gold-colored serif letters. Below it, the word "INTRODUCTION" is centered, followed by a decorative flourish. Underneath "INTRODUCTION" is the word "TO" in a smaller circle, and then "PROBABILITY" in large, bold, gold-colored letters. Another decorative flourish is positioned below "PROBABILITY". At the bottom left, there is a yellow rectangular box containing the text "2016 , Aug 10th - 31st". At the bottom right, there is another yellow rectangular box with the text "REGISTER NOW".

HYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/?REPLYTOCOM=110533#RESPOND)
LYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-

(https://datacamp.com/replyto/111435#comment-111435) prakhar.shrivastava says: casino-introduction-to-probability PYTHON/#COMMENT-111435

In Dickey-Fuller test my came Results of Dickey-Fuller Test:

Test Statistic -2.287864

p-value 0.175912

#Lags Used 11.000000

Number of Observations Used 215.00000

Critical Value (1%) -3.461136

Critical Value (10%) -2.573986

Critical Value (5%) -2.875079

dtype: float64

My p value is



Jie says: REPLY ([HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/?REPLYTOCOM=112372#RESPOND](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/?replytocom=112372#respond))
JUNE 19, 2016 AT 3:59 AM ([HTTPS://WWW.ANALYTICSVIDHYA.COM/BLOG/2016/02/TIME-SERIES-FORECASTING-CODES-PYTHON/#COMMENT-112372](https://www.analyticsvidhya.com/blog/2016/02/time-series-forecasting-codes-python/#comment-112372))

really liked this post. Thank you very much for sharing.

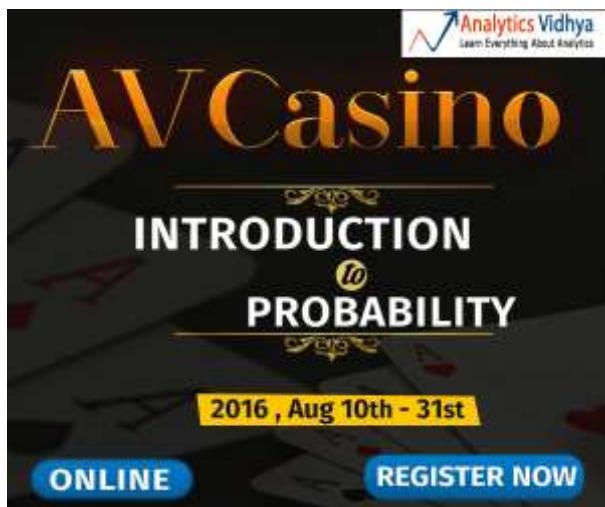
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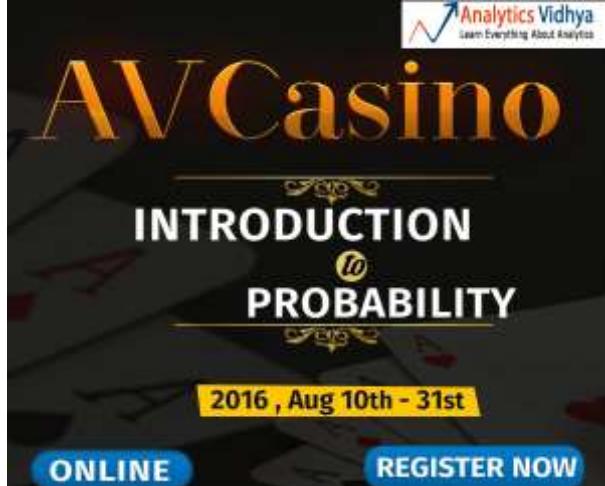
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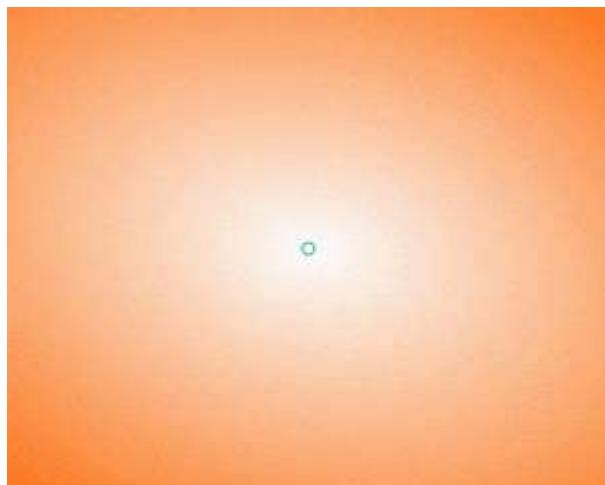
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KUNAL JAIN , AUGUST 27, 2016



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SWATI KASHYAP , AUGUST 26, 2016

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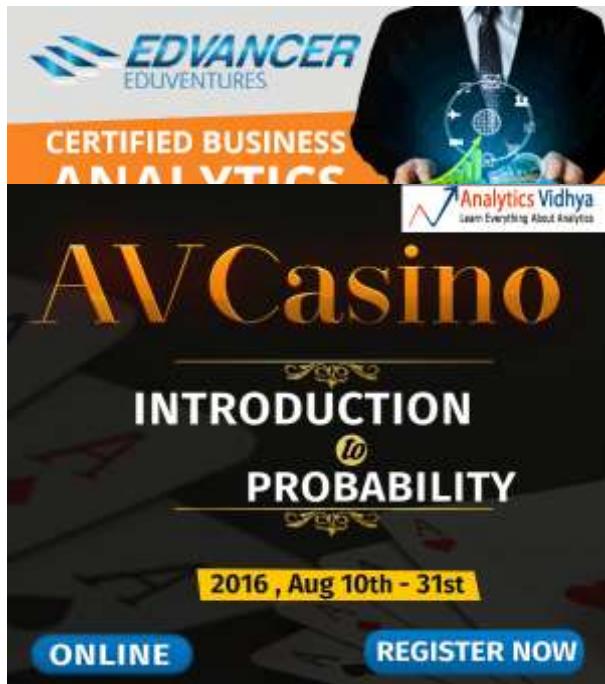
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(<https://www.analyticsvidhya.com/blog/2016/08/full-solution-skill-test-on-r-for-data-science/>)





([http://www.edvancer.in/course/cbap?](http://www.edvancer.in/course/cbap?utm_source=AVadsnonfc&utm_medium=campaign&utm_campaign=AVadsnonfc&utm_content=cbapavad)

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science/)

Full Solution - Skilltest on R for Data Science (<https://www.analyticsvidhya.com/blog/2016/08/full-solution-skill-test-on-r-for-data-science/>)

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