SARIMA_v002

November 20, 2019

1 Erstellen einer Umsatzprognose

© Thomas Robert Holy 2019 Version 0.0.2 Visit me on GitHub: https://github.com/trh0ly

1.1 Import Packages

[1]:
```
#----------------
# Web Scrap
from urllib.request import urlopen
from bs4 import BeautifulSoup
import requests
import re
import string

#----------------
# Forecast
from statsmodels.tsa.seasonal import seasonal_decompose
from pmdarima.arima import auto_arima
import statsmodels.api as sm

#----------------
# Verschiedenes
from plotly.offline import download_plotlyjs, init_notebook_mode, plot, iplot
init_notebook_mode(connected=True)
import chart_studio.plotly as py
import plotly.graph_objs as go
import matplotlib.pyplot as plt
%matplotlib inline
import matplotlib.patches as mpatches
import numpy as np
import pandas as pd
import datetime
```

1.2 Optikeinstellungen

[2]:
```
%%javascript
IPython.OutputArea.auto_scroll_threshold = 9999;
```

```
<IPython.core.display.Javascript object>
```

[3]:
```
from IPython.core.display import display, HTML
display(HTML("<style>.container { width:100% !important; }</style>"))
pd.set_option('display.width', 350)
plt.rcParams['figure.figsize'] = (24, 12) # macht die Plots größer
```

```
<IPython.core.display.HTML object>
```

1.3 Datenbeschaffung und Manipulation

1.3.1 Web Scrap historischer Daten von Statista

[4]:
```
"""
#url = 'https://www.statista.com/statistics/273963/quarterly-revenue-of-amazoncom/' # Amazon
#url = 'https://www.statista.com/statistics/263427/apples-net-income-since-first-quarter-2005/' # Apple
url = 'https://www.statista.com/statistics/323046/alibaba-quarterly-group-revenue/' # Alibaba

html = requests.get(url)
soup = BeautifulSoup(html.text, 'lxml')

chart = soup.find("tbody")
children = chart.find_all("tr")

data = []
for tag in children:
    data_tuple = (tag.text[:6],tag.text[6:])
    data.append(data_tuple)

quartals, revenues = [], []
for i in range(0, len(data)):
    x = data[i][0]
    y = data[i][1]
    quartal = x.replace(' ', '')
    y = y.replace(',', '.')
    revenue = float(y)
    quartals.append(quartal)
    revenues.append(revenue)

quartals = quartals[::-1]
revenues = revenues[::-1]
print(quartals)
print(revenues)
"""
```

[4]:
```
'\n#url = \'https://www.statista.com/statistics/273963/quarterly-revenue-of-
amazoncom/\' # Amazon\n#url =
\'https://www.statista.com/statistics/263427/apples-net-income-since-first-
quarter-2005/\' # Apple\nurl =
\'https://www.statista.com/statistics/323046/alibaba-quarterly-group-revenue/\'
# Alibaba\n\nhtml = requests.get(url)\nsoup = BeautifulSoup(html.text,
\'lxml\')\n\nchart = soup.find("tbody")\nchildren = chart.find_all("tr")\n\ndata
= []\nfor tag in children:\n    data_tuple = (tag.text[:6],tag.text[6:])\n
data.append(data_tuple)\n\nquartals, revenues = [], []\nfor i in range(0,
len(data)):\n    x = data[i][0]\n    y = data[i][1]\n    quartal = x.replace(\'
\', \'\')\n    y = y.replace(\',\', \'.\')\n    revenue = float(y)\n
quartals.append(quartal)\n    revenues.append(revenue)\n\nquartals =
quartals[::-1]\nrevenues = revenues[::-1]\nprint(quartals)\nprint(revenues)\n'
```

1.3.2 DataFrame mit den Daten erzeugen und Überprüfen

[5]:
```
#----------------------------------------
# Daten als Array manuell gespeichert

#-----------------------
# Apple

quartals = ["Q1'05", "Q2'05", "Q3'05", "Q4'05", "Q1'06", "Q2'06", "Q3'06", "Q4'06", "Q1'07", "Q2'07", "Q3'07",
            "Q4'07", "Q1'08", "Q2'08", "Q3'08", "Q4'08", "Q1'09", "Q2'09", "Q3'09", "Q4'09", "Q1'10", "Q2'10",
            "Q3'10", "Q4'10", "Q1'11", "Q2'11", "Q3'11", "Q4'11", "Q1'12", "Q2'12", "Q3'12", "Q4'12", "Q1'13",
            "Q2'13", "Q3'13", "Q4'13", "Q1'14", "Q2'14", "Q3'14", "Q4'14", "Q1'15", "Q2'15", "Q3'15", "Q4'15",
            "Q1'16", "Q2'16", "Q3'16", "Q4'16", "Q1'17", "Q2'17", "Q3'17", "Q4'17", "Q1'18", "Q2'18", "Q3'18",
            "Q4'18", "Q1'19", "Q2'19", "Q3'19", "Q4'19"]

revenues = [0.3, 0.29, 0.32, 0.43, 0.57, 0.41, 0.47, 0.55, 1.01, 0.77, 0.84, 0.87, 1.64, 1.1, 1.13, 2.25, 2.26,
            1.62, 1.82, 2.53, 3.38, 3.07, 3.25, 4.31, 6.0, 5.99, 7.31, 6.62, 13.06, 11.62, 8.82, 8.22, 13.1, 9.55,
            6.9, 7.5, 13.07, 10.22, 7.75, 8.47, 18.02, 13.57, 10.68, 11.12, 18.36, 10.52, 7.8, 9.01, 17.89, 11.03,
            8.72, 10.71, 20.07, 13.82, 11.52, 14.13, 19.97, 11.56, 10.04, 13.69]

print(len(quartals))
print(len(revenues))

#----------------------------------------
# Logarithmus anwenden
revenues = np.log(revenues)

#----------------------------------------
# Quartale umbenennen
quartals_new = []
for i in quartals:
    x = '20' + str(i[3:])
    y = i[:2]
    z = str(x) + '-' + str(y)
    quartals_new.append(z)

#----------------------------------------
# DataFrame mit bereinigten Daten erzeugen
original_data = pd.DataFrame({'Periode':quartals_new, 'Umsatz':revenues})
original_data['Periode'] = pd.to_datetime(original_data['Periode'].str.replace(r'(Q\d) (\d+)', r'\2-\1'), errors='coerce')
original_data.isnull().sum()
```

```
60
60
```

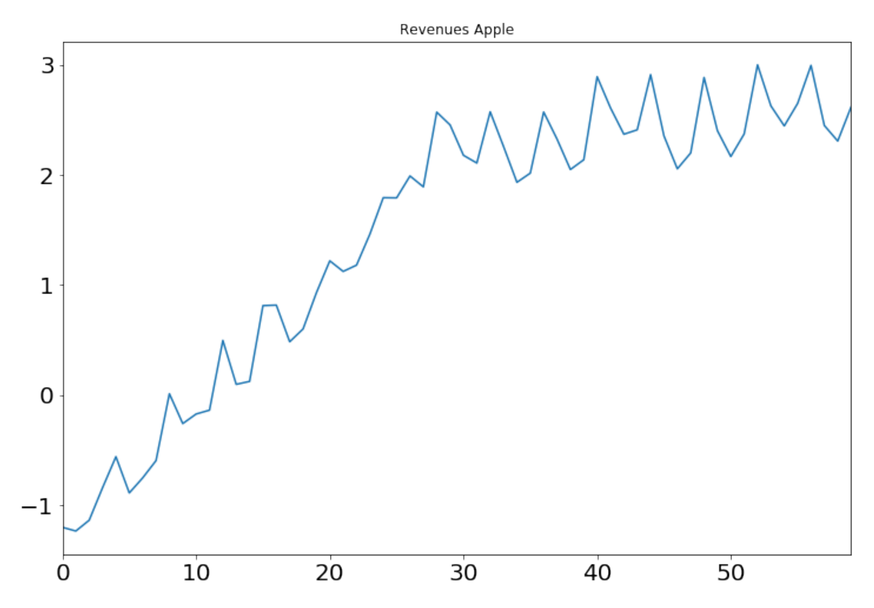
[5]:
```
Periode    0
Umsatz     0
dtype: int64
```

1.4 Visualisierung des DataFrames

[6]:
```
original_data.Umsatz.plot(figsize=(12,8), title= 'Revenues Apple', fontsize=20)
original_data.tail(8)
```

[6]:

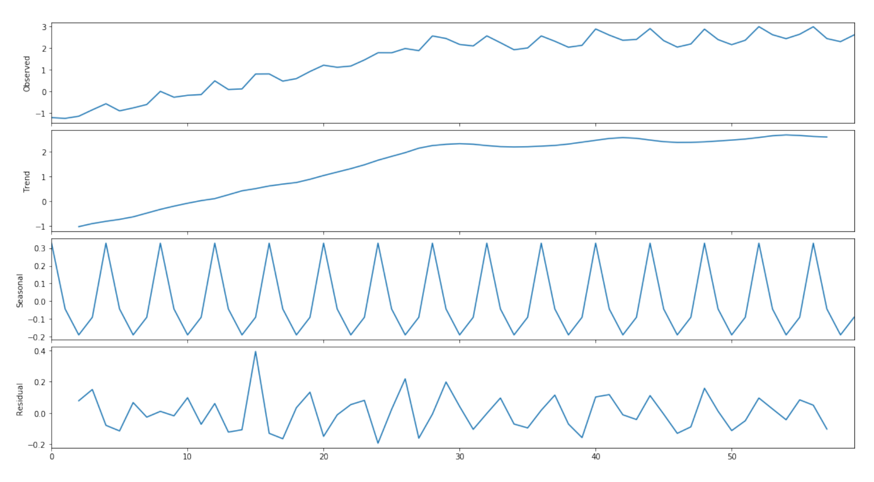
	Periode	Umsatz
52	2018-01-01	2.999226
53	2018-04-01	2.626117
54	2018-07-01	2.444085
55	2018-10-01	2.648300
56	2019-01-01	2.994231
57	2019-04-01	2.447551
58	2019-07-01	2.306577
59	2019-10-01	2.616666



1.5 Zerlegung der Zeitreihe in einzelne Komponenten

[7]:
```
decomposition = seasonal_decompose(original_data.Umsatz, freq=4)
fig = plt.figure()
fig = decomposition.plot()
fig.set_size_inches(15, 8)
```

```
<Figure size 1728x864 with 0 Axes>
```



1.6 Test- und Trainingsdatensatz erstellen

[8]:
```
#----------------------------------------
# Test-Datensatz
test_df = original_data.tail(6)
test_df = test_df.drop('Umsatz', axis=1)
test_df.head(6)
```

[8]:

	Periode
54	2018-07-01
55	2018-10-01
56	2019-01-01
57	2019-04-01
58	2019-07-01
59	2019-10-01

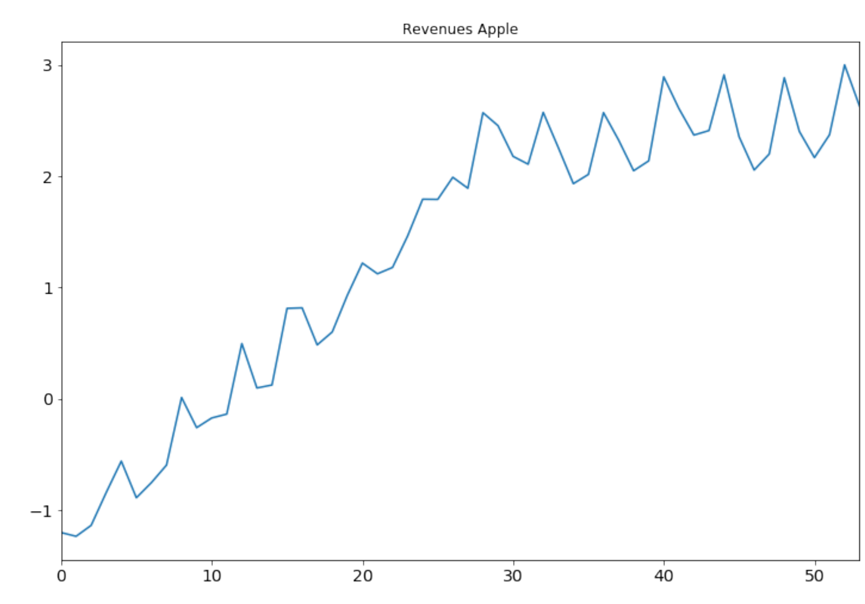
[9]:
```
#----------------------------------------
# Trainings-Datensatz
train_df = original_data.copy(deep=True)
train_df.drop(train_df.tail(6).index,inplace=True)
train_df.tail(6)
```

[9]:

	Periode	Umsatz
48	2017-01-01	2.884242
49	2017-04-01	2.400619
50	2017-07-01	2.165619
51	2017-10-01	2.371178
52	2018-01-01	2.999226
53	2018-04-01	2.626117

[10]:
```
train_df.Umsatz.plot(figsize=(12,8), title= 'Revenues Apple', fontsize=14)
```

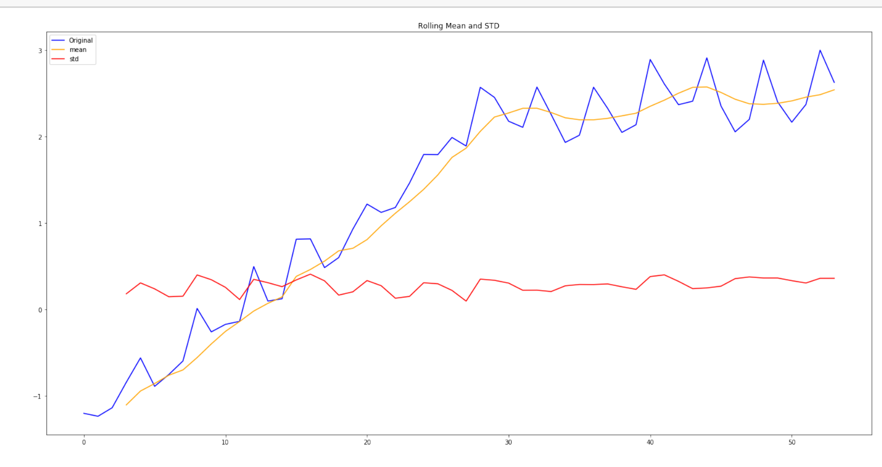
[10]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1e291d76948>
```



1.7 Visuelle Überprüfung der Zeitreihe auf Stationarität

[11]:
```
rolmean = train_df.rolling(window=4).mean()
rolstd = train_df.rolling(window=4).std()

orig = plt.plot(train_df.Umsatz, color='blue', label='Original')
mean = plt.plot(rolmean, color='orange', label='mean')
std = plt.plot(rolstd, color='red', label='std')
plt.legend(loc='best')
plt.title('Rolling Mean and STD')
plt.show()
```



1.8 Automatisierte Suche nach bestem Modell (SARIMA)

[12]:
```
decomposition = auto_arima(train_df.Umsatz, start_p=1, start_q=1,
                           max_p=3, max_q=3, m=4,
                           start_P=0, seasonal=True,
                           d=1, D=1, trace=True,
                           error_action='ignore',
                           suppress_warnings=True,
                           stepwise=True)
```

```
Fit ARIMA: order=(1, 1, 1) seasonal_order=(0, 1, 1, 4); AIC=-14.871, BIC=-5.412,
Fit time=0.097 seconds
Fit ARIMA: order=(0, 1, 0) seasonal_order=(0, 1, 0, 4); AIC=-7.141, BIC=-3.358,
Fit time=0.014 seconds
Fit ARIMA: order=(1, 1, 0) seasonal_order=(1, 1, 0, 4); AIC=-10.932, BIC=-3.365,
Fit time=0.078 seconds
Fit ARIMA: order=(0, 1, 1) seasonal_order=(0, 1, 1, 4); AIC=-16.627, BIC=-9.060,
Fit time=0.061 seconds
Fit ARIMA: order=(0, 1, 1) seasonal_order=(1, 1, 1, 4); AIC=-16.091, BIC=-6.632,
Fit time=0.111 seconds
Fit ARIMA: order=(0, 1, 1) seasonal_order=(0, 1, 0, 4); AIC=-9.253, BIC=-3.577,
Fit time=0.026 seconds
Fit ARIMA: order=(0, 1, 1) seasonal_order=(0, 1, 2, 4); AIC=-16.423, BIC=-6.964,
Fit time=0.104 seconds
Fit ARIMA: order=(0, 1, 1) seasonal_order=(1, 1, 2, 4); AIC=-14.567, BIC=-3.216,
Fit time=0.203 seconds
Fit ARIMA: order=(0, 1, 0) seasonal_order=(0, 1, 1, 4); AIC=-14.361, BIC=-8.686,
Fit time=0.071 seconds
Fit ARIMA: order=(0, 1, 2) seasonal_order=(0, 1, 1, 4); AIC=-15.434, BIC=-5.975,
Fit time=0.131 seconds
Fit ARIMA: order=(1, 1, 2) seasonal_order=(0, 1, 1, 4); AIC=-15.497, BIC=-4.146,
Fit time=0.215 seconds
Total fit time: 1.111 seconds
```

[13]:
```
decomposition.aic()
```

[13]:
```
-16.62738746889217
```

1.9 Fitten des Modells auf den Trainingsdatensatz

[14]:
```
mod = sm.tsa.statespace.SARIMAX(train_df.Umsatz,
                                order=(0, 1, 1),
                                seasonal_order=(0, 1, 1, 4),
                                enforce_stationarity=False,
                                enforce_invertibility=False)
decomposition = mod.fit()
#print(decomposition.summary())
```

[15]:
```
#decomposition.plot_diagnostics(figsize=(15, 12))
#plt.show()
```

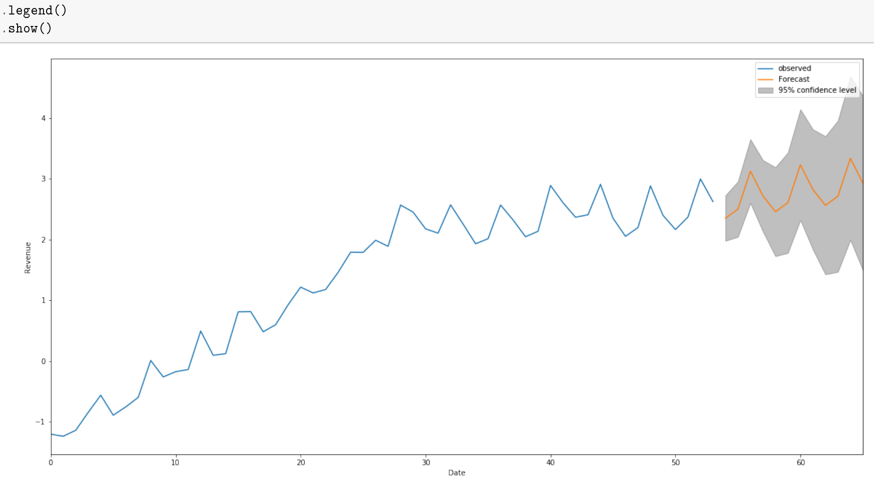
1.10 Forcast und Visualisierung

[16]:
```
# Get forecast ahead in future
pred_uc = decomposition.get_forecast(steps=12)

# Get confidence intervals of forecasts
pred_ci = pred_uc.conf_int()
```

[17]:
```
ax = train_df['Umsatz'].plot(label='observed', figsize=(20, 10))
pred_uc.predicted_mean.plot(ax=ax, label='Forecast')
ax.fill_between(pred_ci.index,
                pred_ci.iloc[:, 0],
                pred_ci.iloc[:, 1], color='k',
                label='95% confidence level', alpha=.25)
ax.set_xlabel('Date')
ax.set_ylabel('Revenue')

plt.legend()
plt.show()
```



[18]:
```
pred_ci.head(6)
```

[18]:

	lower Umsatz	upper Umsatz
54	1.979160	2.727292
55	2.044845	2.958215
56	2.600410	3.653400
57	2.131835	3.307987
58	1.726319	3.191707
59	1.779821	3.434813

[19]:
```
forecast = decomposition.forecast(6)
forecast.head(6)
```

[19]:
```
54    2.353226
55    2.501530
56    3.126905
57    2.719911
58    2.459013
59    2.607317
dtype: float64
```

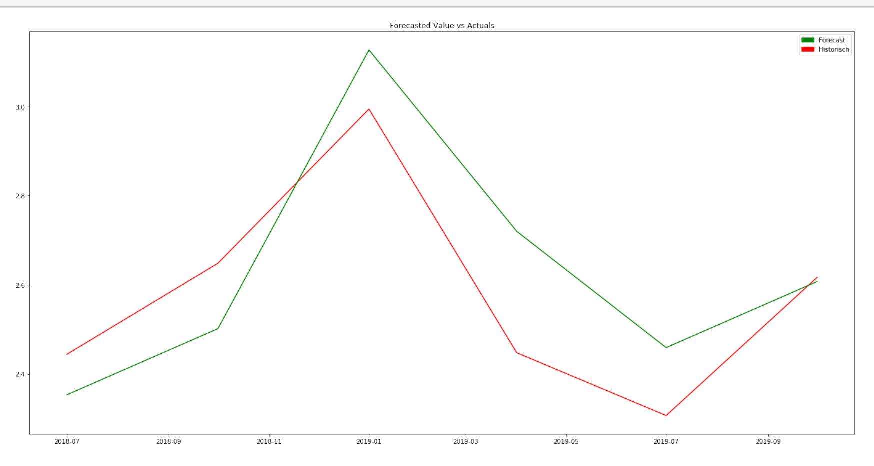
1.11 Forecast vs. historische Daten im Testdatensatz

[20]:
```
#----------------------------------------
# Forecast DataFrame und Original-DataFrame

yActual = original_data.tail(6)['Umsatz'].values.tolist()
yPredicted = forecast.head(6).values.tolist()
periode = original_data.Periode.tail(6)

#----------------------------------------
# Plot Prognose vs. Original

plt.plot(periode,yActual, color='red') # Rot
plt.plot(periode,yPredicted, color='green') # Grün
green_patch = mpatches.Patch(color='green', label='Forecast')
red_patch = mpatches.Patch(color='red', label='Historisch')
plt.legend(handles=[green_patch, red_patch])
plt.title("Forecasted Value vs Actuals")
plt.show()
```



[21]:
```
compare_df = pd.DataFrame()
compare_df['Period'] = original_data.Periode.tail(6)
compare_df['Umsatz_original'] = np.exp(yActual)
compare_df['Umsatz_Forecast'] = np.exp(yPredicted)
compare_df['PctChg'] = round(((compare_df.Umsatz_original - compare_df.Umsatz_Forecast) / compare_df.Umsatz_original *
 ↪100), 2)
compare_df
```

[21]:

	Period	Umsatz_original	Umsatz_Forecast	PctChg
54	2018-07-01	11.52	10.519450	8.69
55	2018-10-01	14.13	12.201145	13.65
56	2019-01-01	19.97	22.803294	-14.19
57	2019-04-01	11.56	15.178966	-31.31
58	2019-07-01	10.04	11.693267	-16.47
59	2019-10-01	13.69	13.562614	0.93

[22]:
```
compare_df.PctChg.mean()
```

[22]:
```
-6.449999999999999
```

1.12 Prognose für die nächsten 6 Quartale

[23]:
```
periods_forcast = range(0,6)
x = forecast = decomposition.forecast(12)

forecast = pd.DataFrame({'Periode':periods_forcast, 'OOS-Forecast': np.exp(x[6:])})
forecast.head(6)
```

[23]:

	Periode	OOS-Forecast
60	0	25.347809
61	1	16.872717
62	2	12.998065
63	3	15.076004
64	4	28.176254
65	5	18.755466

[24]:
```
forecast['OOS-Forecast'].plot()
```

[24]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1e292dbbc08>
```