Untitled

November 23, 2019

1 Erstellen einer Umsatzprognose

 Version 0.0.1 Visit me on GitHub: https://github.com/trh0ly

1.1 Grundlegende Einstellungen

1.1.1 Package Import

[1]:
```
import matplotlib.pyplot as plt
%matplotlib inline
import matplotlib.patches as mpatches
import numpy as np
import pandas as pd
import math
```

1.1.2 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'] = (12, 6) # macht die Plots größer
```

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

1.2 Datensatz und Datensatzmanipulation

[4]:
```
#-----------------------
# Amazon

quartals = ["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"]

revenues = [3.02, 2.89, 3.26, 5.67, 4.14, 4.06, 4.26, 6.7, 4.89, 4.65, 5.45, 9.
↪52, 7.13, 6.57, 7.56,
            12.95, 9.86, 9.91, 10.88, 17.43, 13.19, 12.83, 13.81, 21.27, 16.07,␣
↪15.7, 17.09, 25.59,
            19.74, 19.34, 20.58, 29.33, 22.72, 23.19, 25.36, 35.75, 29.13, 30.
↪4, 32.71, 43.74, 35.71,
            37.96, 43.74, 60.5, 51.04, 52.89, 56.58, 72.38, 59.7, 63.4]

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

#-----------------------
# DataFrame erstellen

rev_DF = pd.DataFrame({'Revs':revenues, 'Quart':range(1,len(revenues) + 1)})
rev_DF.head()
```

```
50
50
```

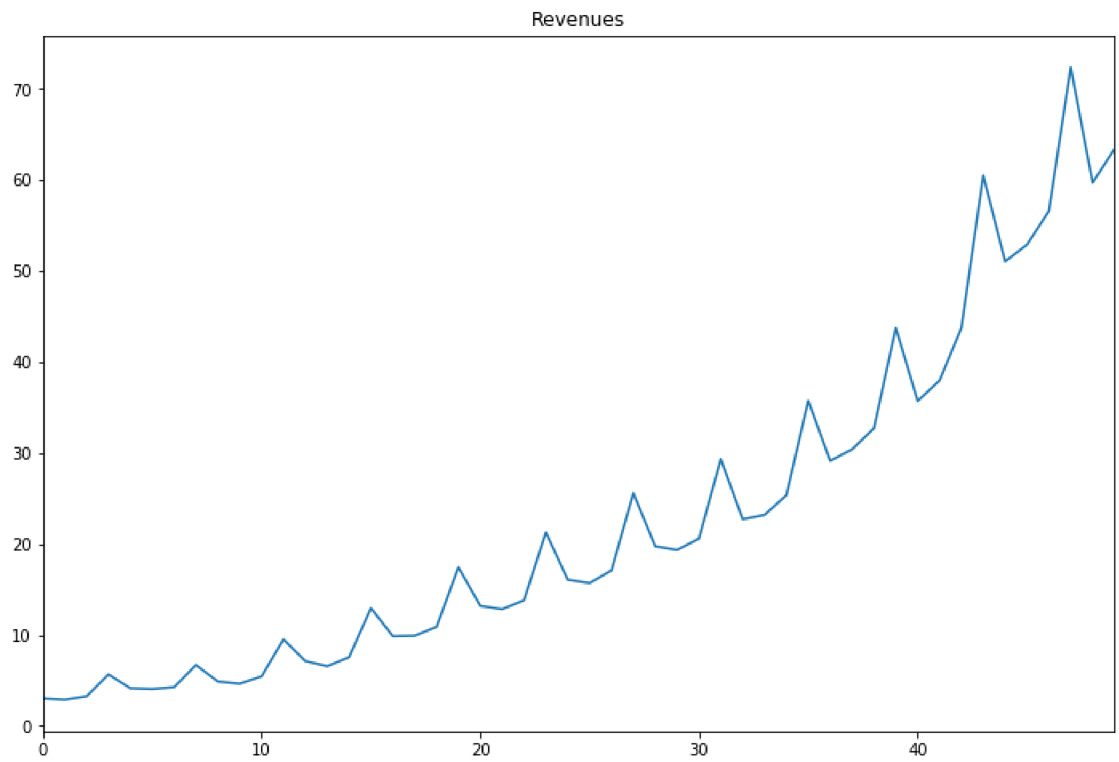
[4]:

	Revs	Quart
0	3.02	1
1	2.89	2
2	3.26	3
3	5.67	4
4	4.14	5

1.2.1 DataFrame plotten

[5]:
```
rev_DF.Revs.plot(figsize=(12,8), title= 'Revenues', fontsize=10)
```

[5]: <matplotlib.axes._subplots.AxesSubplot at 0x199d7e5d8c8>



1.3 Definition einige Hilfsfunktionen

1.3.1 Moving-Average

[6]:
```
def moving_average(k, array, weights=None):

    if weights == None:
        z_liste = []
        for i in range(k, len(array) - k):
            x = (i - k)
            y = (i + k + 1)
            z = np.mean(array[x:y])
            z_liste.append(z)

    if weights != None:
        z_liste, temp_liste = [], []
        for i in range(k, len(array) - k):
            x = (i - k)
            y = (i + k + 1)
            temp = array[x:y]
            temp_liste.append(temp)

        for i in temp_liste:
```

```
            for j in range(0, len(i)):
                i[j] = i[j] * weights[j]

        for i in temp_liste:
            i = np.mean(i)
            z_liste.append(i)

    return z_liste
```

1.3.2 $\Delta t, \Delta z$ und $\Delta t \Delta z$

[7]:
```
#-----------------------
# Delta t

def delta_t(t_array):
    mean_t = np.mean(t_array)

    delta_t_list = []
    for i in range(0, len(t_array)):
        delta_t = t_array[i] - mean_t
        delta_t_list.append(delta_t)

    delta_t_power_liste = []
    for i in delta_t_list:
        delta_t_power = np.power(i,2)
        delta_t_power_liste.append(delta_t_power)

    sum_delta_t_power_liste = np.sum(delta_t_power_liste)

    return delta_t_list, delta_t_power_liste, sum_delta_t_power_liste

#-----------------------
# Delta z

def delta_z(z_array, exp=False):
    mean_z = np.mean(z_array)

    if exp == False:
        delta_z_list = []
        for i in range(0, len(z_array)):
            delta_z = z_array[i] - mean_z
            delta_z_list.append(delta_z)

    if exp == True:
        delta_z_list = []
        for i in range(0, len(z_array)):
            delta_z = np.log(z_array[i]) - np.log(mean_z)
```

```
            delta_z_list.append(delta_z)

    return delta_z_list

#-----------------------
# Delta t Delta z

def delta_z__delta_t(delta_t_list, delta_z_list):

    delta_zt_liste = []
    for i in range(0, len(delta_t_list)):
        delta_zt = delta_t_list[i] * delta_z_list[i]
        delta_zt_liste.append(delta_zt)

    sum_delta_zt_liste = np.sum(delta_zt_liste)

    return delta_zt_liste, sum_delta_zt_liste
```

1.3.3 Berechnung a und b

[8]:
```
def calc_ab(z_array, t_array, delta_zt_liste, sum_delta_t_power_liste):

    mean_z = np.mean(z_array)
    mean_t = np.mean(t_array)

    b = sum_delta_zt_liste / sum_delta_t_power_liste
    a = mean_z - b * mean_t

    return a, b
```

1.3.4 Prognose

[9]:
```
def predict(a, b, array, exp=False):

    if exp == False:
        prediction_list = []
        for i in range(0, len(array)):
            prediction = a + b * array[i]
            prediction_list.append(prediction)

    if exp == True:
        prediction_list = []
        for i in range(0, len(array)):
            prediction = np.exp(a) * math.exp((b * array[i]))
            prediction_list.append(prediction)

```

```
    return prediction_list
```

1.3.5 Bestimmtheitsmaß

[10]:
```
def r_power(z_array, prediction_list):

    mean_z = np.mean(z_array)

    a_list, b_list = [], []
    for i in range(0, len(z_array)):
        a = np.power((prediction_list[i] - mean_z), 2)
        a_list.append(a)

        b = np.power((z_array[i] - mean_z), 2)
        b_list.append(b)

    sum_a_list = np.sum(a_list)
    sum_b_list = np.sum(b_list)

    r_power = sum_a_list / sum_b_list

    return r_power
```

1.4 Schrittweise Berechnung - Einfache lineare Regression

1.4.1 Δt und Summe Δt

[11]:
```
t_array = rev_DF.Quart.values.tolist()

delta_t_list, delta_t_power_liste, sum_delta_t_power_liste = delta_t(t_array)
#print(delta_t_list, delta_t_power_liste, sum_delta_t_power_liste)
```

1.4.2 Δz und Summe Δz

[12]:
```
z_array = rev_DF.Revs.values.tolist()

delta_z_list = delta_z(z_array)
#delta_z_list
```

1.4.3 $\Delta t \Delta z$ und Summe $\Delta t \Delta z$

[13]:
```
delta_zt_liste, sum_delta_zt_liste = delta_z__delta_t(delta_t_list,␣
↪delta_z_list)
#print(delta_zt_liste, sum_delta_zt_liste)
```

1.4.4 Parameter a und b

[14]:
```
a, b = calc_ab(z_array, t_array, delta_zt_liste, sum_delta_t_power_liste)
print(b, a)
```

```
1.186005282112845 -7.398334693877551
```

1.4.5 Prognosewerte für die 1. bis letzte Periode

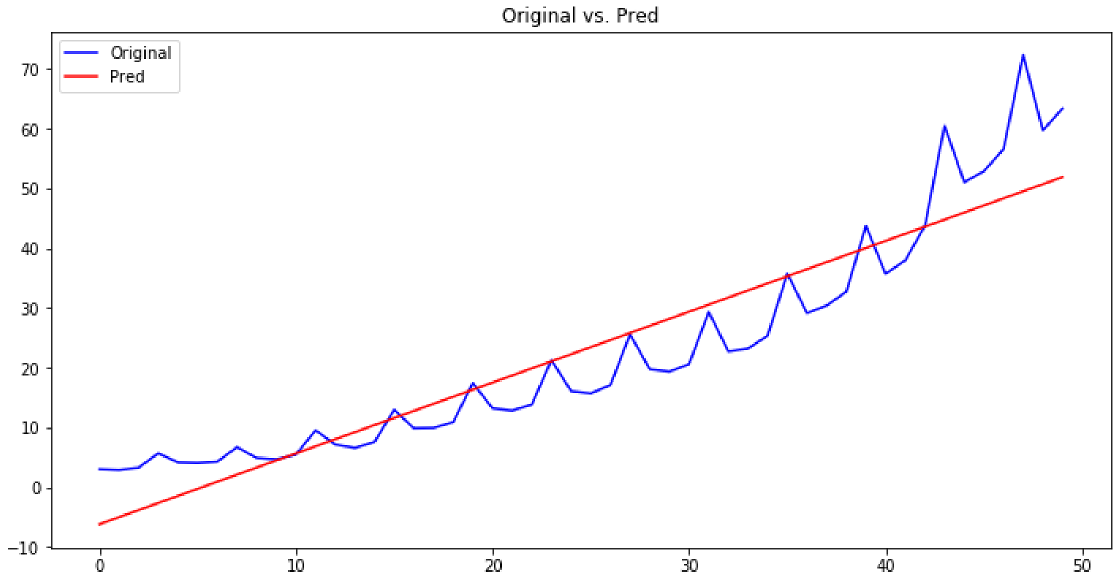
[15]:
```
#prediction_for_list = range(1,13)
prediction_for_list = range(1,len(revenues) + 1)

prediction_list = predict(a, b, prediction_for_list)
#prediction_list
```

1.4.6 DataFrame-Erweiterung und plotten der Prognosewerte

[16]:
```
rev_DF['Pred'] = prediction_list
```

[17]:
```
orig = plt.plot(rev_DF.Revs, color='blue', label='Original')
pred = plt.plot(rev_DF.Pred, color='red', label='Pred')
plt.legend(loc='best')
plt.title('Original vs. Pred')
plt.show()
```



1.4.7 Bestimmtheitsmaß berechnen

[18]:
```
r = r_power(z_array, prediction_list)
r
```

[18]: 0.8568745095957687

1.5 Schrittweise Berechnung unter Berücksichtigung nicht-linearer Zusammenhänge

1.5.1 Δt und Summe Δt

[19]:
```
t_array = rev_DF.Quart.values.tolist()

delta_t_list, delta_t_power_liste, sum_delta_t_power_liste = delta_t(t_array)
#print(delta_t_list, delta_t_power_liste, sum_delta_t_power_liste)
```

1.5.2 Δz und Summe Δz

[20]:
```
z_array = rev_DF.Revs.values.tolist()
#z_array = np.log(z_array)

delta_z_list = delta_z(z_array, exp=True)
#delta_z_list
```

1.5.3 $\Delta t\Delta z$ und Summe $\Delta t\Delta z$

[21]:
```
delta_zt_liste, sum_delta_zt_liste = delta_z__delta_t(delta_t_list,␣
 ↪delta_z_list)
#print(delta_zt_liste, sum_delta_zt_liste)
```

1.5.4 Parameter a und b

[22]:
```
a, b = calc_ab(np.log(z_array), t_array, delta_zt_liste,␣
 ↪sum_delta_t_power_liste)
print(b, a)
```

0.06184618332291243 1.1837146521242945

1.5.5 Prognosewerte für die 1. bis letze Periode

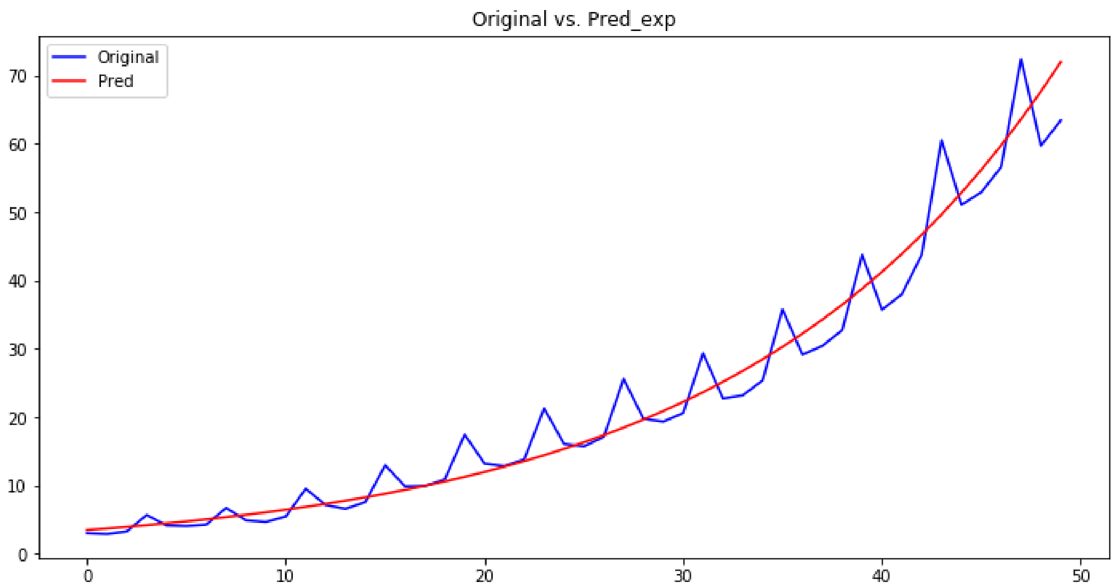
[23]:
```
#prediction_for_list = range(1,13)
prediction_for_list = range(1,len(revenues) + 1)
z_array = z_array

prediction_list_exp = predict(a, b, prediction_for_list, exp=True)
#prediction_list_exp
```

1.5.6 DataFrame-Erweiterung und plotten der Prognosewerte

[24]:
```
rev_DF['Pred_exp'] = prediction_list_exp
```

[25]:
```
orig = plt.plot(rev_DF.Revs, color='blue', label='Original')
pred = plt.plot(rev_DF.Pred_exp, color='red', label='Pred')
plt.legend(loc='best')
plt.title('Original vs. Pred_exp')
plt.show()
```



1.5.7 Bestimmtheitsmaß berechnen

[26]:
```
r = r_power(z_array, prediction_list_exp)
r
```

[26]: 1.0631618997382584

1.6 Weitere Verbesserungen

1.6.1 Definition weiterer Hilfsfunktionen

Berechnung des Residuums zwischen Moving-Average und Beobachtung

[27]:
```
def calc_residual(rev, moving_average_list):

    cut_len = len(rev) - len(moving_average_list)
    start = int(cut_len / 2)
    end = int(len(rev) - cut_len / 2)
    rev = rev[start:end]
```

```
    residual_list = []
    for i in range(0, len(rev)):
        residuum = rev[i] - moving_average_list[i]
        residual_list.append(residuum)

    return residual_list
```

Berechnung mittlere quartalsweise Sainsonkopmponente

```
[28]: def get_seasonal_components(residual_list):

    quartal_1_list = []
    for i in range(0, len(residual_list), 4):
        quartal_1_list.append(residual_list[i])

    quartal_2_list = []
    for i in range(1, len(residual_list), 4):
        quartal_2_list.append(residual_list[i])

    quartal_3_list = []
    for i in range(2, len(residual_list), 4):
        quartal_3_list.append(residual_list[i])

    quartal_4_list = []
    for i in range(3, len(residual_list), 4):
        quartal_4_list.append(residual_list[i])

    seasonal_component_quartal_1 = np.mean(quartal_1_list)
    seasonal_component_quartal_2 = np.mean(quartal_2_list)
    seasonal_component_quartal_3 = np.mean(quartal_3_list)
    seasonal_component_quartal_4 = np.mean(quartal_4_list)

    seasonal_components_list = [seasonal_component_quartal_1,␣
↪seasonal_component_quartal_2,
                                seasonal_component_quartal_3,␣
↪seasonal_component_quartal_4] * int(len(residual_list) / 4)

    return seasonal_components_list
```

Verbindung Saisonkomponente und MA-Komponente

```
[29]: def add_saison(prediction_list_MA, seasonal_components):

    ma_saison_list = []
    for i in range(0, len(prediction_list_MA)):
        x = prediction_list_MA[i] + seasonal_components[i]
```

```
        ma_saison_list.append(x)

    return ma_saison_list
```

1.6.2 Moving-Average als Trend

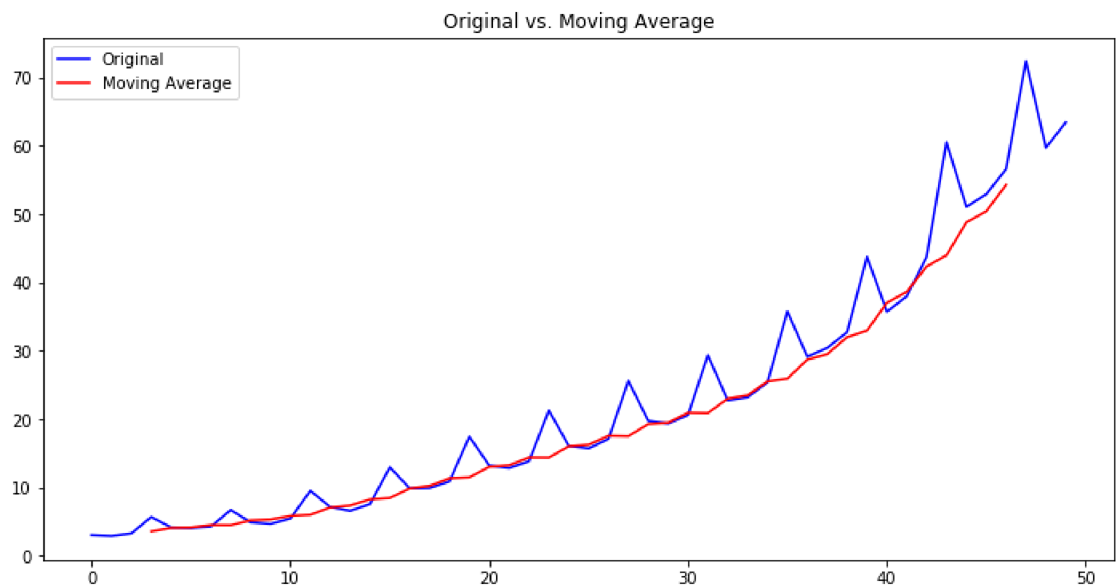
[30]:
```
k = 3

moving_average_list = moving_average(k, revenues, weights=[1,0.75,1,1,1,0.6,1])
#moving_average_list
```

DataFrame-Erweiterung und plotten der Prognosewerte auf Basis des MA

[31]:
```
test_DF = pd.DataFrame({'Quartal':range(k,len(moving_average_list) + k ),␣
 ↪'Revs':moving_average_list})
#test_DF.head()
```

[32]:
```
orig = plt.plot(rev_DF.Revs, color='blue', label='Original')
pred = plt.plot(test_DF.Quartal, test_DF.Revs, color='red', label='Moving␣
 ↪Average')
plt.legend(loc='best')
plt.title('Original vs. Moving Average')
plt.show()
```



Δt und Summe Δt

[33]:
```
#t_array = test_DF.Quart.values.tolist()
t_array = range(1, len(moving_average_list))

delta_t_list, delta_t_power_liste, sum_delta_t_power_liste = delta_t(t_array)
#print(delta_t_list, delta_t_power_liste, sum_delta_t_power_liste)
```

Δz und Summe Δz

[34]:
```
z_array = test_DF.Revs.values.tolist()
#z_array = np.log(z_array)

delta_z_list = delta_z(z_array, exp=True)
#delta_z_list
```

$\Delta t \Delta z$ und Summe $\Delta t \Delta z$

[35]:
```
delta_zt_liste, sum_delta_zt_liste = delta_z__delta_t(delta_t_list,␣
 ↪delta_z_list)
#print(delta_zt_liste, sum_delta_zt_liste)
```

Parameter a und b

[36]:
```
a, b = calc_ab(np.log(z_array), t_array, delta_zt_liste,␣
 ↪sum_delta_t_power_liste)
print(b, a)
```

```
0.060843189848590565 1.3542838464764335
```

Prognosewerte für die 1. bis letze Periode

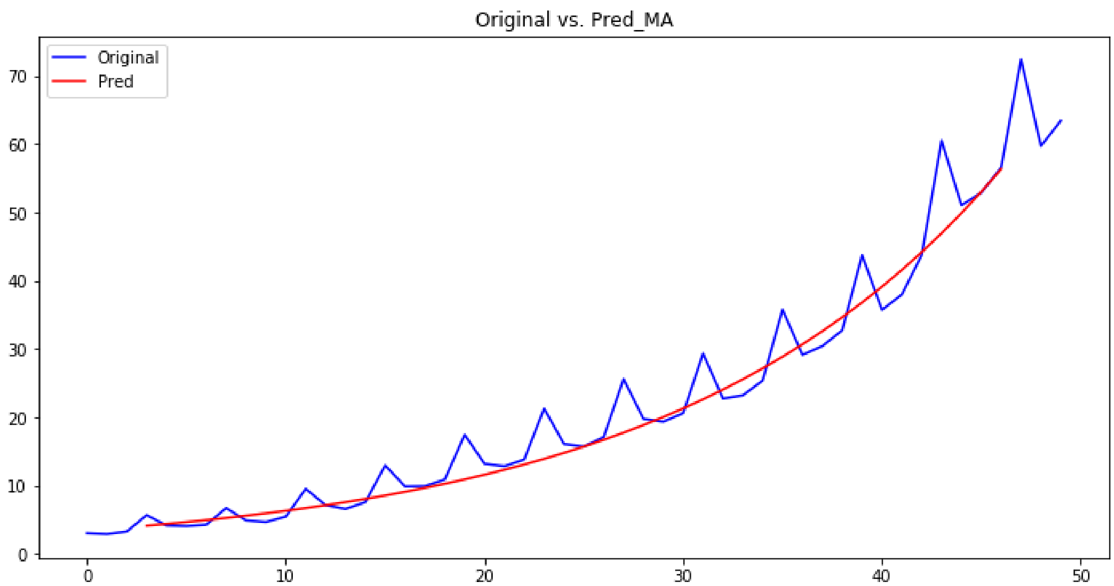
[37]:
```
#prediction_for_list = range(1,13)
prediction_for_list = range(1,len(test_DF.Revs) + 1)
z_array = z_array

prediction_list_MA = predict(a, b, prediction_for_list, exp=True)
#prediction_list_MA
```

DataFrame-Erweiterung und plotten der Prognosewerte auf Basis MA

[38]:
```
test_DF['Pred_MA'] = prediction_list_MA
```

[39]:
```
orig = plt.plot(rev_DF.Revs, color='blue', label='Original')
pred = plt.plot(test_DF.Quartal, test_DF.Pred_MA, color='red', label='Pred')
plt.legend(loc='best')
plt.title('Original vs. Pred_MA')
plt.show()
```



1.6.3 Hinzufügen der Saisonkomponente

Residuen berechnen

[40]:
```
residual_list = calc_residual(revenues, moving_average_list)
#residual_list
```

Saisonkomponenten berechnen

[41]:
```
seasonal_components = get_seasonal_components(residual_list)
#seasonal_components
```

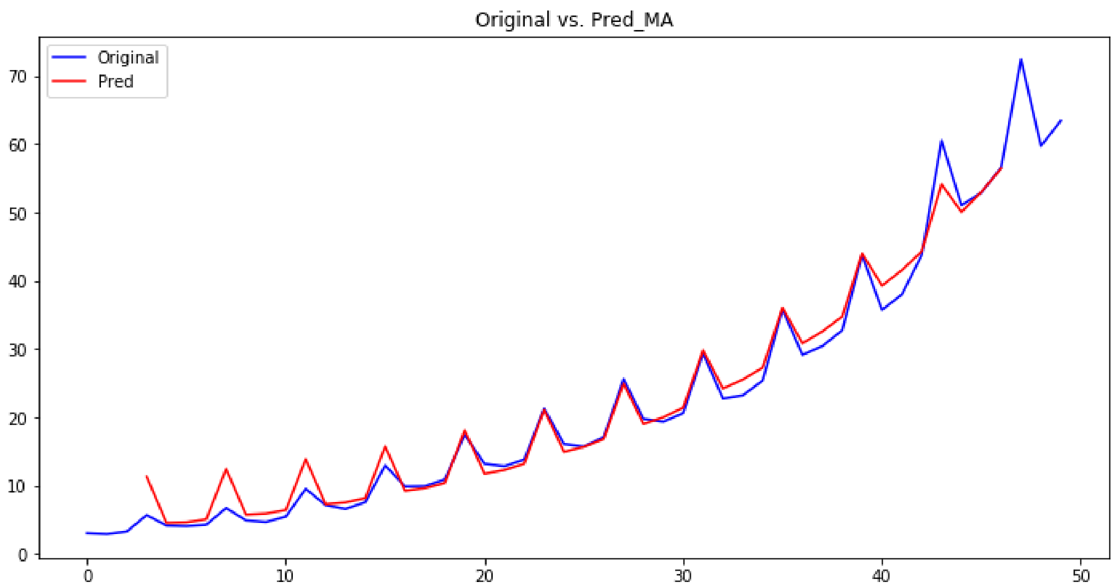
Saisonkomponente auf Moving-Average draufrechnen

[42]:
```
ma_saison_list = add_saison(prediction_list_MA, seasonal_components)
#ma_saison_list
```

DataFrame-Erweiterung und plotten der Prognosewerte auf Basis MA + Saisonkomponente

[43]:
```
test_DF['Pred_MA_Sasion'] = ma_saison_list
```

[44]:
```
orig = plt.plot(rev_DF.Revs, color='blue', label='Original')
pred = plt.plot(test_DF.Quartal, test_DF.Pred_MA_Sasion, color='red',␣
 ↪label='Pred')
plt.legend(loc='best')
plt.title('Original vs. Pred_MA')
plt.show()
```



1.6.4 Bestimmtheitsmaß berechnen

[45]:
```
z_array = rev_DF.Revs.values.tolist()
z_array = z_array[3:len(z_array) - 3]

r = r_power(z_array, ma_saison_list)
r
```

[45]: 0.9438841841147938