CPI_Timeseries

November 12, 2022

0.0.1 1. Import required libraries

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
import datetime
```

[2]:
```
%matplotlib inline
warnings.filterwarnings('ignore')
sns.set_style("darkgrid")
```

[3]:
```
import sklearn
from sklearn.metrics import mean_squared_error
```

0.0.2 2. Read and Cleanup Data

[4]:
```
data = pd.read_csv('cpiai.csv')
data.head()
```

[4]:

	Date	Index	Inflation
0	1913-01-01	9.8	0.00
1	1913-02-01	9.8	0.00
2	1913-03-01	9.8	0.00
3	1913-04-01	9.8	0.00
4	1913-05-01	9.7	-1.02

[5]:
```
data.tail()
```

[5]:

	Date	Index	Inflation
1208	2013-09-01	234.149	0.12
1209	2013-10-01	233.546	-0.26
1210	2013-11-01	233.069	-0.20
1211	2013-12-01	233.049	-0.01
1212	2014-01-01	233.916	0.37

[6]:
```
data.shape
```

[6]:
```
(1213, 3)
```

[7]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1213 entries, 0 to 1212
Data columns (total 3 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       1213 non-null   object
 1   Index      1213 non-null   float64
 2   Inflation  1213 non-null   float64
dtypes: float64(2), object(1)
memory usage: 28.6+ KB
```

[8]:
```
data.describe()
```

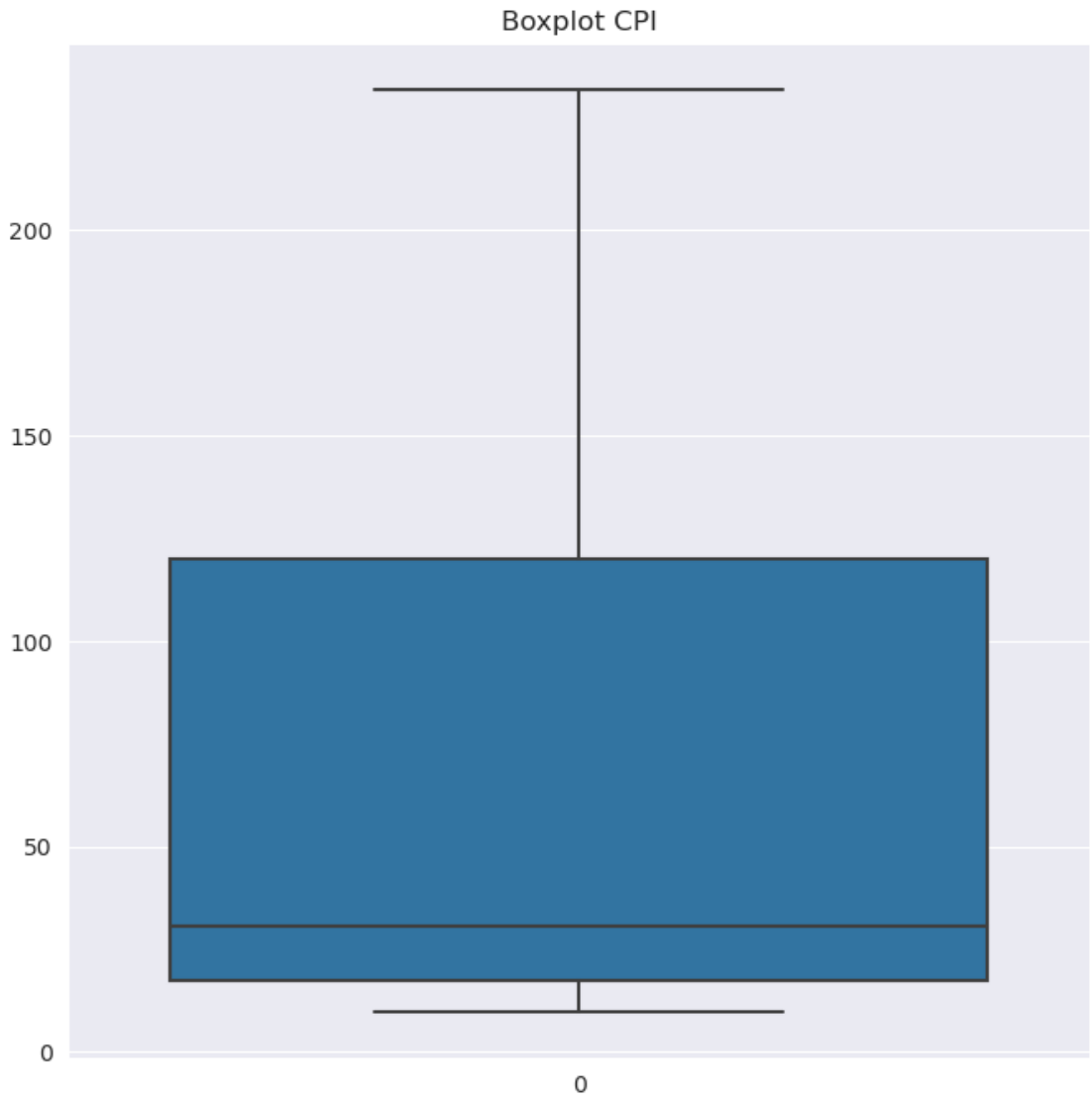
[8]:

	Index	Inflation
count	1213.00000	1213.000000
mean	70.36088	0.264106
std	68.90227	0.661618
min	9.70000	-3.160000
25%	17.30000	0.000000
50%	30.70000	0.240000
75%	120.20000	0.560000
max	234.14900	5.880000

[9]:
```
data.isnull().sum()
```

[9]:
```
Date         0
Index        0
Inflation    0
dtype: int64
```

[10]:
```
plt.figure(figsize=(8,8))
plt.title('Boxplot CPI')
sns.boxplot(data['Index'])
plt.savefig('Boxplot.jpg')
plt.show()
```



[11]:
```
data['Year'] = pd.DatetimeIndex(data['Date']).year
data.head()
```

[11]:

	Date	Index	Inflation	Year
0	1913-01-01	9.8	0.00	1913
1	1913-02-01	9.8	0.00	1913
2	1913-03-01	9.8	0.00	1913
3	1913-04-01	9.8	0.00	1913
4	1913-05-01	9.7	-1.02	1913

[12]:
```
data['Month'] = pd.DatetimeIndex(data['Date']).month
data.head()
```

[12]:

	Date	Index	Inflation	Year	Month
0	1913-01-01	9.8	0.00	1913	1
1	1913-02-01	9.8	0.00	1913	2
2	1913-03-01	9.8	0.00	1913	3
3	1913-04-01	9.8	0.00	1913	4
4	1913-05-01	9.7	-1.02	1913	5

[13]:
```
ndata = data.groupby(['Date'])['Index','Inflation'].median().reset_index()
ndata.head()
```

[13]:

	Date	Index	Inflation
0	1913-01-01	9.8	0.00
1	1913-02-01	9.8	0.00
2	1913-03-01	9.8	0.00
3	1913-04-01	9.8	0.00
4	1913-05-01	9.7	-1.02

[14]:
```
ndata = pd.DataFrame(ndata)
ndata = ndata.set_index(['Date'])
```

[15]:
```
ndata.head()
```

[15]:

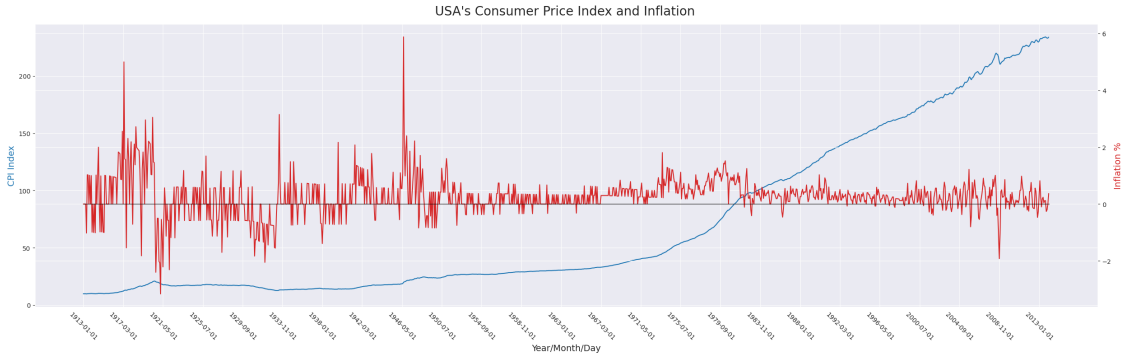
Date	Index	Inflation
1913-01-01	9.8	0.00
1913-02-01	9.8	0.00
1913-03-01	9.8	0.00
1913-04-01	9.8	0.00
1913-05-01	9.7	-1.02

[16]:
```
ndata.index.dtype
```

[16]:
```
dtype('O')
```

[17]:
```
fig, ax = plt.subplots(figsize=(25,8))
plt.suptitle("USA's Consumer Price Index and Inflation", fontsize=20)
plt.xticks(np.arange(0, len(data['Date'])+1, 50),rotation = -45)

ax.plot(ndata['Index'],label='Index')
ax.set_xlabel("Year/Month/Day", fontsize = 14)
ax.set_ylabel("CPI Index", color='C0' , fontsize = 14)

ax2 = ax.twinx()
ax2.plot(ndata['Inflation'],label='Inflation', color = 'C3')
ax2.hlines(y=0, xmin=0, xmax=len(data['Date']),linewidth=0.75, color='black')

ax2.set_ylabel("Inflation %", color='C3', fontsize = 14)
```

```
plt.tight_layout()
```



[18]:
```
cdata = data.groupby(['Date'])['Index'].median().reset_index()
cdata = pd.DataFrame(cdata)
cdata = cdata.set_index(['Date'])
```

[19]:
```
cdata.head()
```

[19]:

Date	Index
1913-01-01	9.8
1913-02-01	9.8
1913-03-01	9.8
1913-04-01	9.8
1913-05-01	9.7

[20]:
```
from pylab import rcParams
from scipy.fftpack import fftfreq
import statsmodels.api as sm

decomposition = sm.tsa.seasonal_decompose(cdata,model='additive',period=12)
```

[33]:
```
fig, (ax1,ax2,ax3,ax4) = plt.subplots(4,1, figsize=(18,12),sharex=True)
plt.suptitle("Additive Seasonal Decomposition", fontsize=20)
plt.tight_layout()
decomposition.observed.plot(ax=ax1,ylabel='Observed',color='C0')
ax1.set_ylabel("Observed", color='C0')
decomposition.trend.plot(ax=ax2,ylabel='Trend',color='C1')
ax2.set_ylabel("Trend", color='C1')
decomposition.seasonal.plot(ax=ax3,ylabel='Seasonal',color='C2')
ax3.set_ylabel("Seasonal", color='C2')
decomposition.resid.plot(ax=ax4,ylabel='Residual',color='C3')
ax4.set_ylabel("Residual", color='C3')
ax4.hlines(y=0, xmin=0, xmax=len(data['Date']),linewidth=0.75,color='Black')
```

```
plt.xticks(np.arange(0, len(data['Date'])+1, 50),rotation = 0); #The use of ;␣
↪to silence print in console
plt.savefig('Additive_Seasonal_Decomposition.jpg',dpi=400, bbox_inches =␣
↪"tight")
```

0.0.3 Building an ARIMA Model for Forcasting in Python

0.0.4 Augmented Dickey-Fuller (ADF) test: To inference if the time series is stationary or not using p-values

[22]:
```
from statsmodels.tsa.stattools import adfuller
adf_test = adfuller(cdata)
print(adf_test)
print('ADF Statistic: %f' % adf_test[0])
print('Critical Values @ 0.05: %.2f' % adf_test[4]['5%'])
print('p-value: %f' % adf_test[1])
```

```
(3.3042221177526567, 1.0, 14, 1198, {'1%': -3.4358202562873807, '5%':
-2.8639555777313683, '10%': -2.568056097446774}, 561.4948359334458)
ADF Statistic: 3.304222
Critical Values @ 0.05: -2.86
p-value: 1.000000
```

0.0.5 Kwiatkowki-Phillips-Schmidt-Shin (KPSS) test

[23]:
```
from statsmodels.tsa.stattools import kpss
from statsmodels.tools.sm_exceptions import InterpolationWarning
warnings.simplefilter('ignore', InterpolationWarning)

kpss_test = kpss(cdata)
print(kpss_test)
print('KPSS Statistic: %f' % kpss_test[0])
print('Critical Values @ 0.05: %.2f' % kpss_test[3]['5%'])
print('p-value: %f' % kpss_test[1])
```

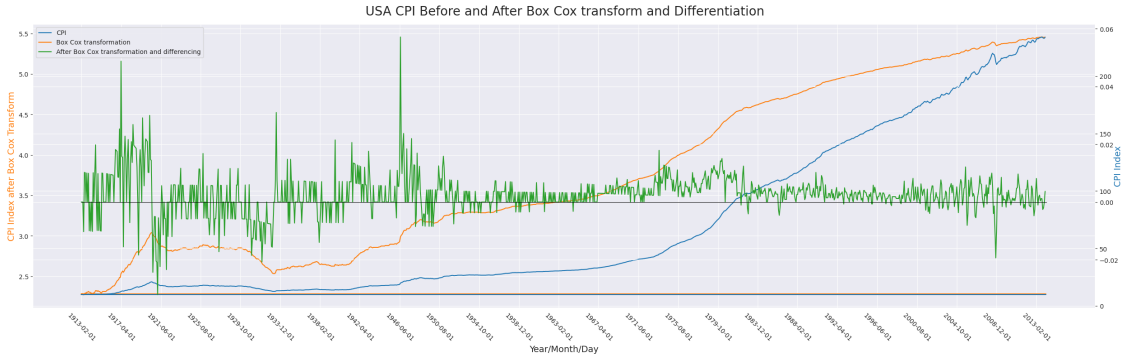
```
(4.965084323361918, 0.01, 20, {'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%':
0.739})
KPSS Statistic: 4.965084
Critical Values @ 0.05: 0.46
p-value: 0.010000
```

Inference: p-value is less than 0.05. This means that the series is not stationary

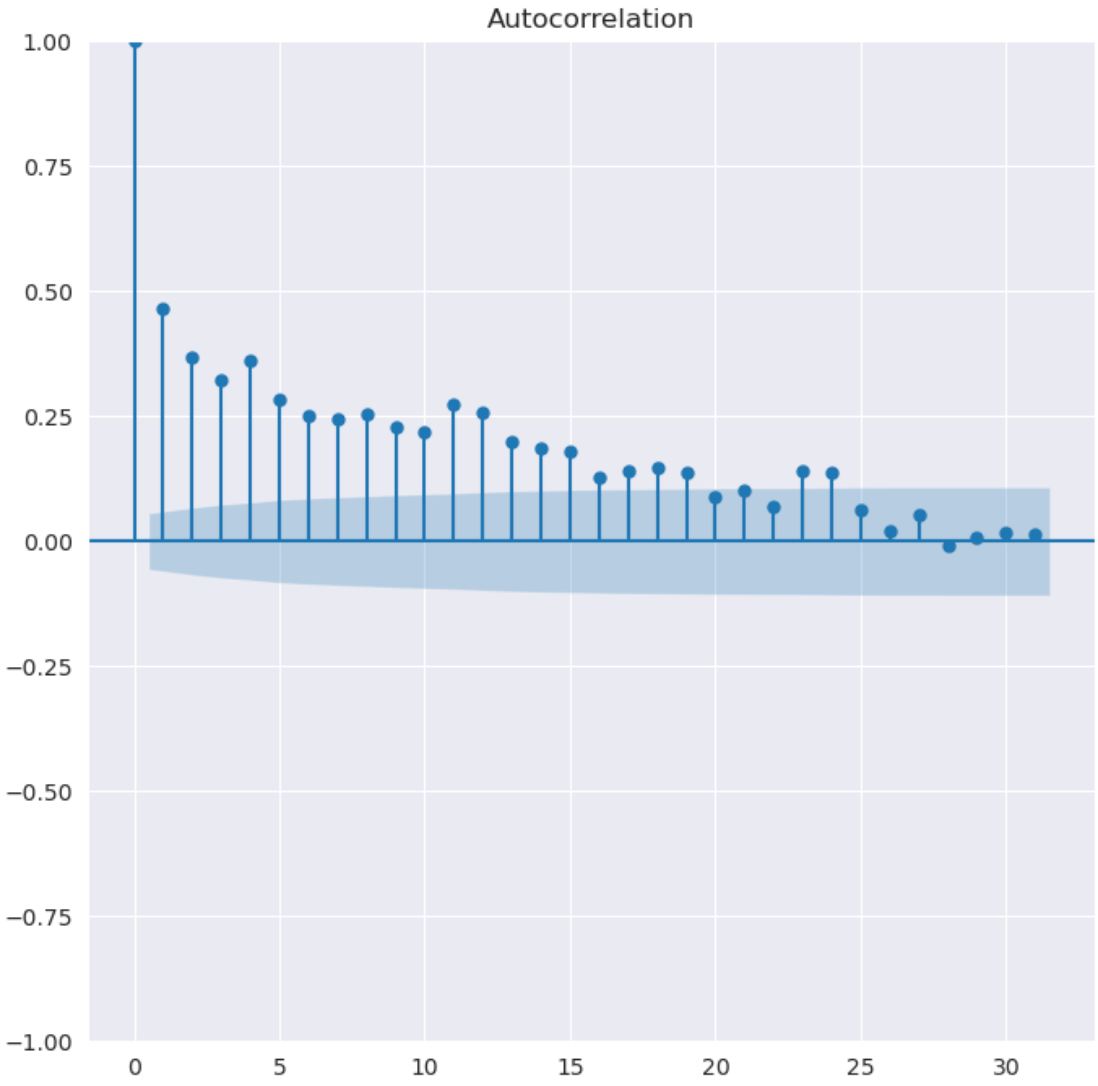
0.0.6 Box Cox transformation to make variance constant

[24]:
```
from scipy.stats import boxcox
# Transforms non-gaussian distribution data into gaussian distribution / normal␣
 ↪distribution
data_boxcox = pd.Series(boxcox(cdata['Index'], lmbda=0))
data_boxcox_diff = pd.Series(data_boxcox - data_boxcox.shift(), cdata.index)
data_boxcox_diff.dropna(inplace=True)



fig, ax = plt.subplots(figsize=(25,8))
plt.suptitle('USA CPI Before and After Box Cox transform and Differentiation',␣
 ↪fontsize=20)
plt.xticks(np.arange(0, len(data['Date'])+1, 50),rotation = -45);

ax.plot(data_boxcox, label = 'Box Cox transformation', color = 'C1')
ax.set_xlabel("Year/Month/Day", fontsize = 14)
ax.set_ylabel("CPI Index after Box Cox Transform", color='C1' , fontsize = 14)

ax2 = ax.twinx()
ax2.plot(cdata, label = 'CPI')
ax2.set_ylabel("CPI Index", color='C0' , fontsize = 14)

ax3 = ax.twinx()

ax3.plot(data_boxcox_diff, label='After Box Cox transformation and␣
 ↪differencing',color='C2')
```

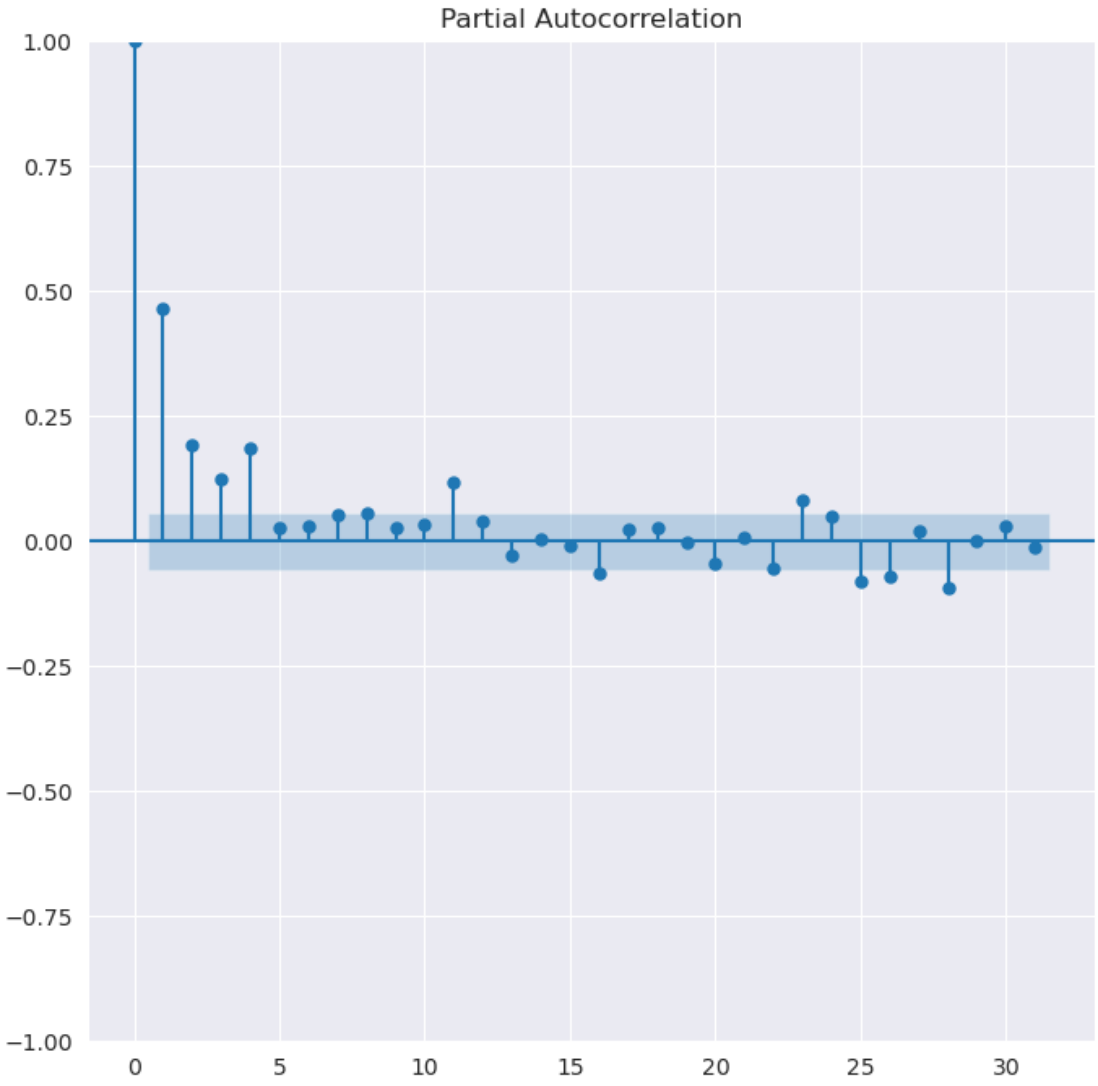
```
ax3.hlines(y=0, xmin=0, xmax=len(data['Date']),linewidth=0.75, color='black')

handles, labels = [(a + b + c) for a, b,c in zip(ax2.
  ↪get_legend_handles_labels(),ax.get_legend_handles_labels(),ax3.
  ↪get_legend_handles_labels())]
plt.legend(handles, labels, loc='upper left')

plt.tight_layout()
plt.savefig('BoxCox.jpg')
```



[25]:
```
from statsmodels.graphics.tsaplots import plot_acf

with plt.rc_context():
    plt.rc("figure", figsize=(8,8))
    plot_acf(data_boxcox_diff)
    plt.savefig('Autocorrelation.jpg')
```



[26]:
```
from statsmodels.graphics.tsaplots import plot_pacf
with plt.rc_context():
    plt.rc("figure", figsize=(8,8))
    plot_pacf(data_boxcox_diff)
    plt.savefig('Partial_Autocorrelation.jpg')
```



0.1 Fit an ARIMA model

0.1.1 Fit on all% Data

[27]:
```
from sklearn.model_selection import train_test_split

train, test= train_test_split(cdata, test_size=0.2,shuffle=False)

print(f"No. of training examples: {train.shape[0]}")
print(f"No. of testing examples: {test.shape[0]}")
```

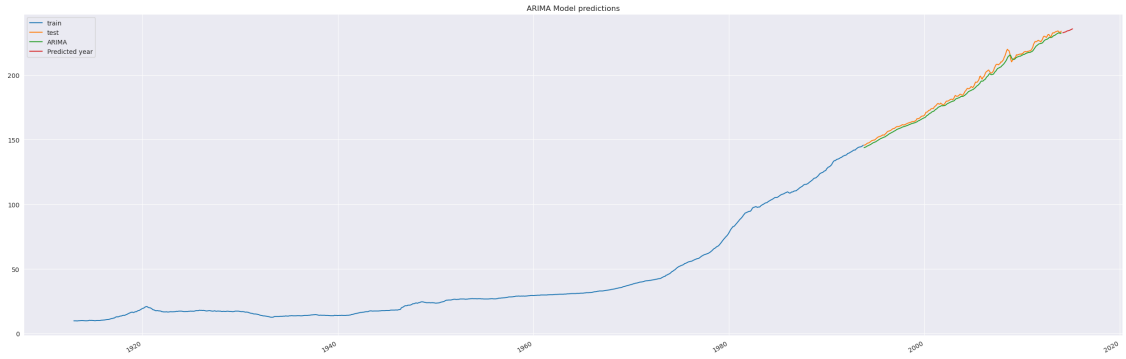
```
No. of training examples: 970
No. of testing examples: 243
```

[28]:
```
import warnings
warnings.filterwarnings('ignore');

from statsmodels.tsa.arima.model import ARIMA
model = ARIMA(data_boxcox_diff, order=(6,1,15))
model_fit = model.fit()
```

[29]:
```
#Recover original time series
y_hat_ar = data_boxcox_diff.copy()
y_hat_ar['ar_forecast_boxcox_diff'] = model_fit.predict(data_boxcox_diff.index.
 ↪min(), data_boxcox_diff.index.max())
y_hat_ar['ar_forecast_boxcox'] = y_hat_ar['ar_forecast_boxcox_diff'].cumsum()
y_hat_ar['ar_forecast_boxcox'] = y_hat_ar['ar_forecast_boxcox'].
 ↪add(data_boxcox[0])
y_hat_ar['ar_forecast'] = np.exp(y_hat_ar['ar_forecast_boxcox'])
```

[30]:
```
future_predict = model_fit.predict(start = len(ndata),end = (len(ndata))+12)
future_predict = future_predict.cumsum()
future_predict = np.exp(future_predict.add(data_boxcox[0]))
future_predict = future_predict * (data['Index'].max()/future_predict.mean())
```

[31]:
```
train.index = pd.to_datetime(train.index)
test.index = pd.to_datetime(test.index)
plt.figure(figsize=(25,8))

plt.plot(train, label='train',color='C0')
plt.plot(test, label='test',color='C1')
y_hat_ar_df = y_hat_ar['ar_forecast'][test.index.min():].to_frame()
plt.plot(y_hat_ar_df, label='ARIMA',color='C2')
future_predict.plot(label='Predicted year',color='C3')


plt.legend(loc='best')

plt.title('ARIMA Model predictions')
plt.tight_layout()
plt.savefig('AM_Predictions.jpg')
```


ARIMA Model predictions
train
test
ARIMA
Predicted year
200
150
100
50
0
1920
1940
1960
1980
2000
2020

[ ]: