





Hana Rizvić

Advanced Analytics Team Lead



Renee Ahel

Freelance Data Scientist

- ABOUT US
- MORE ABOUT IOLAP AND DSC
- FUTURE MEETUPS

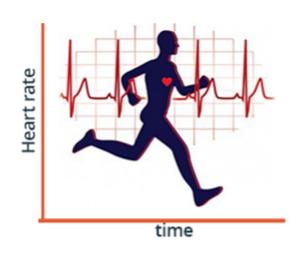
AGENDA



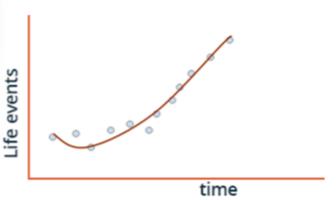
- What are time series?
- Overview of usage
- Overview of methods
- Main components and properties of time series
- SARIMA explained



Notion of a real world event as an abstraction of a sequence of timely activities.



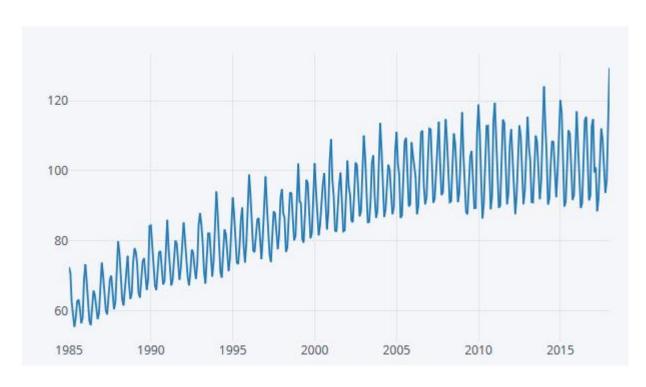




TIME SERIES EXAMPLES

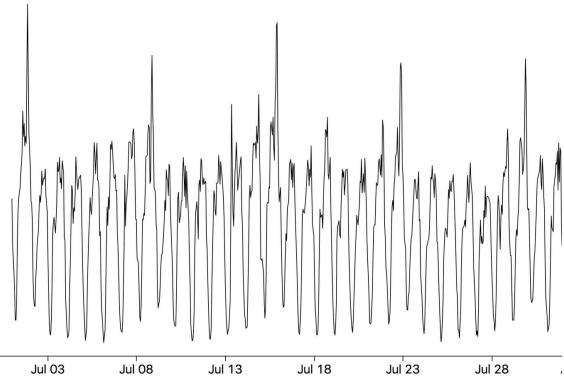


Energy production Jan 1985 – Sep 2018



https://fred.stlouisfed.org/series/IPG2211A2N

Hourly sum of Uber trips in July 2017



iOLAP, Inc. 2018 - All Rights Reserved

FOR WHAT IS USED



In terms of statistics, econometrics, finance, meteorology...

Short – term predictions

Planning and scheduling: equipment, personnel, financial, levels of inventory, personnel etc

Medium – term predictions

Budgeting purposes mostly – require predictions of economic and industry variables

Long term predictions

Needed for capital expansion plans, selecting R&D projects, launching new products, formulating long-term goals

Trend tracking

Changes in trend due to newly introduced factors – marketing campaigns, environmental changes

OVERVIEW OF METHODS AND DIVISIONS



Frequency domain

Time domain

Assumptions

By look and count

Spectral analysis

Autocorrelation

Parametric

Linear and non-linear

Wavelet analysis

Crosscorrelation Non-Parametric Uni- or Multivariate

$$Y_t = b_0 + b_1 Y_{t-1} + b_2 Y_{t-2} + \dots + b_p Y_{t-p} + e_t$$

$$Y_t' = Y_t - Y_{t-1}$$

$$Y_t = b_0 + b_1 e_{t-1} + b_2 e_{t-2} + \dots + b_q e_{t-q} + e_t$$

ARIMA(p,d,q) + Seasonal = ARIMA(p,d,q)(P,D,Q)

COMPONENTS

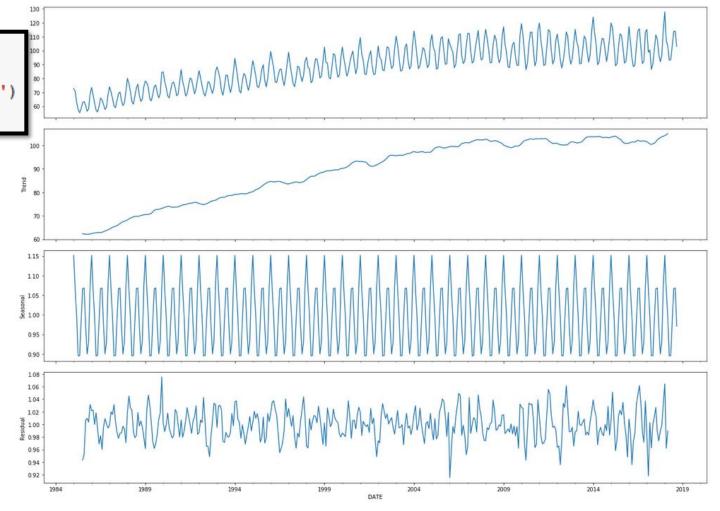


data.index = pd.to_datetime(data.index)
from statsmodels.tsa.seasonal import seasonal_decompose
result = seasonal_decompose(data, model='multiplicative')
fig = result.plot()

DATA = Trend X Seasonal X Error

DATA = Trend + Seasonal + Error

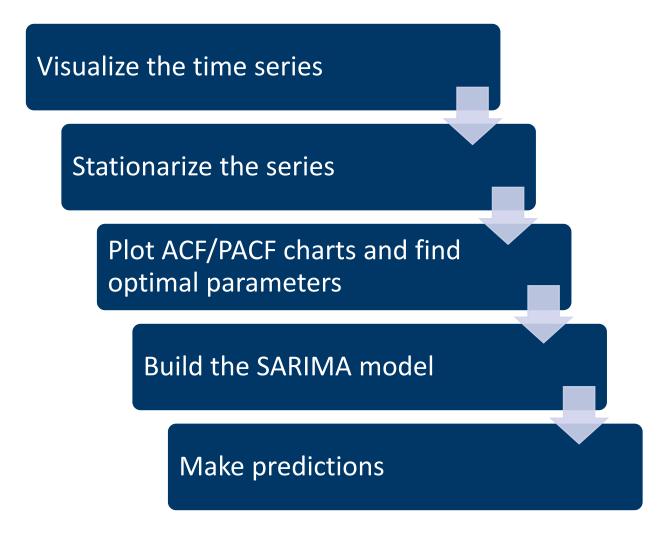
Additive or Multiplicative?



PROCESS FLOW

iOLAP, Inc. 2018 - All Rights Reserved





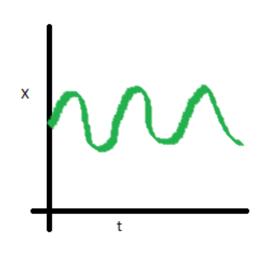
10

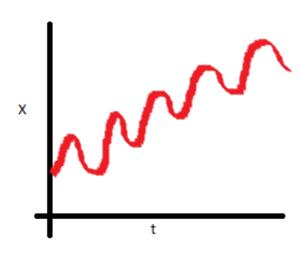
STATIONARITY



11

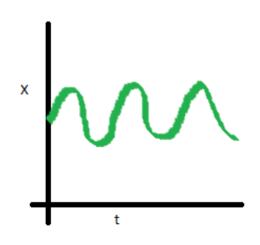
- Unit roots
- Augmented Dickey Fuller test



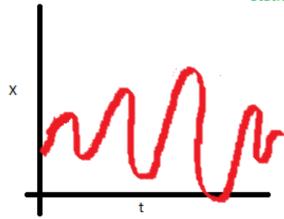


Stationary series

Non-Stationary series



Stationary series

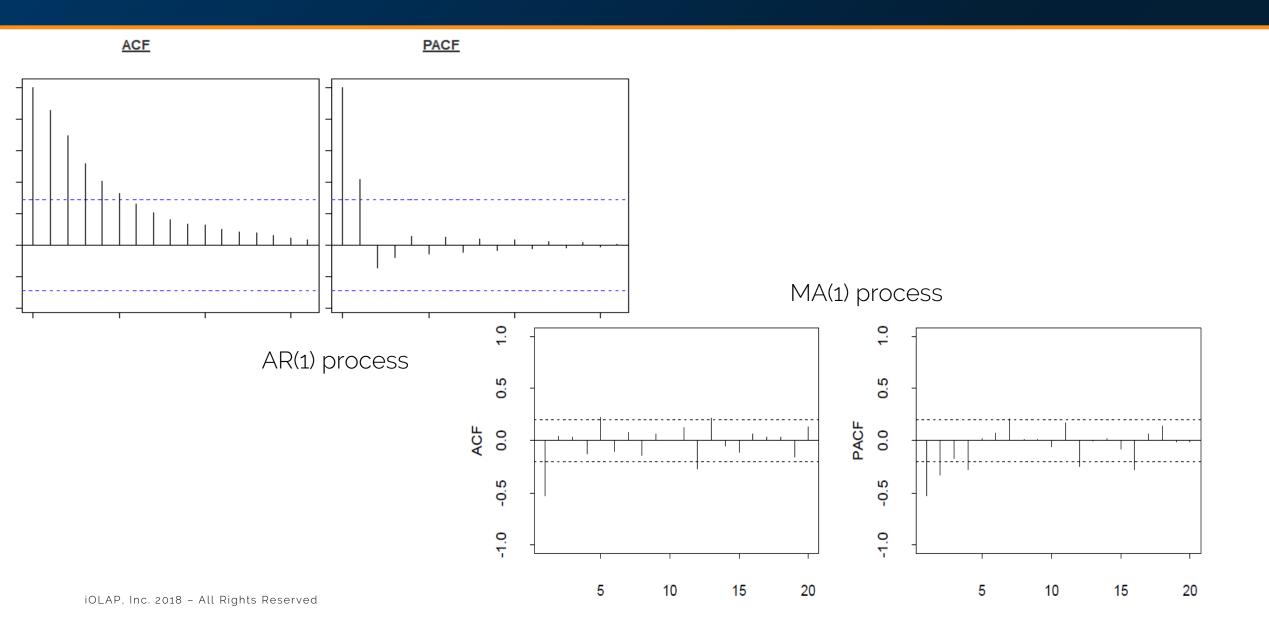


Non-Stationary series

iOLAP, Inc. 2018 - All Rights Reserved

ACF AND PACF





```
from pyramid.arima import auto arima
train = data.loc['1985-01-01':'2016-12-01']
test = data.loc['2017-01-01':]
stepwise model = auto arima(train, start p=1, start q=1,
                           max p=3, max q=3, m=12,
                           start P=0, seasonal=True,
                           d=1, D=1, trace=True,
                           error action='ignore',
                           suppress warnings=True,
                           stepwise=True)
print(stepwise model.aic())
```

ARIMA(p,d,q)(P,D,Q)

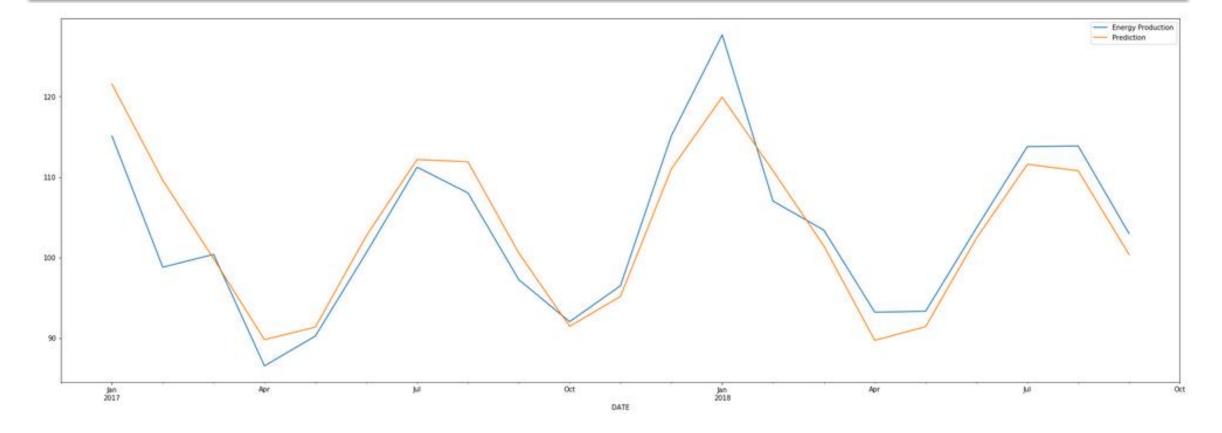
```
Fit ARIMA: order=(0, 1, 2) seasonal_order=(2, 1, 1, 12); AIC=1696.141, BIC=1723.555, Fit time=3.047 seconds Fit ARIMA: order=(2, 1, 2) seasonal_order=(2, 1, 1, 12); AIC=1689.560, BIC=1724.806, Fit time=8.076 seconds Fit ARIMA: order=(1, 1, 1) seasonal_order=(2, 1, 1, 12); AIC=1686.438, BIC=1713.852, Fit time=5.175 seconds Fit ARIMA: order=(1, 1, 3) seasonal_order=(2, 1, 1, 12); AIC=1689.153, BIC=1724.399, Fit time=8.269 seconds
```

```
print(str('ARIMA')+str(stepwise_model.order)+str(stepwise_model.seasonal_order))
ARIMA(1, 1, 2)(2, 1, 1, 12)
```

SARIMA - PREDICTION

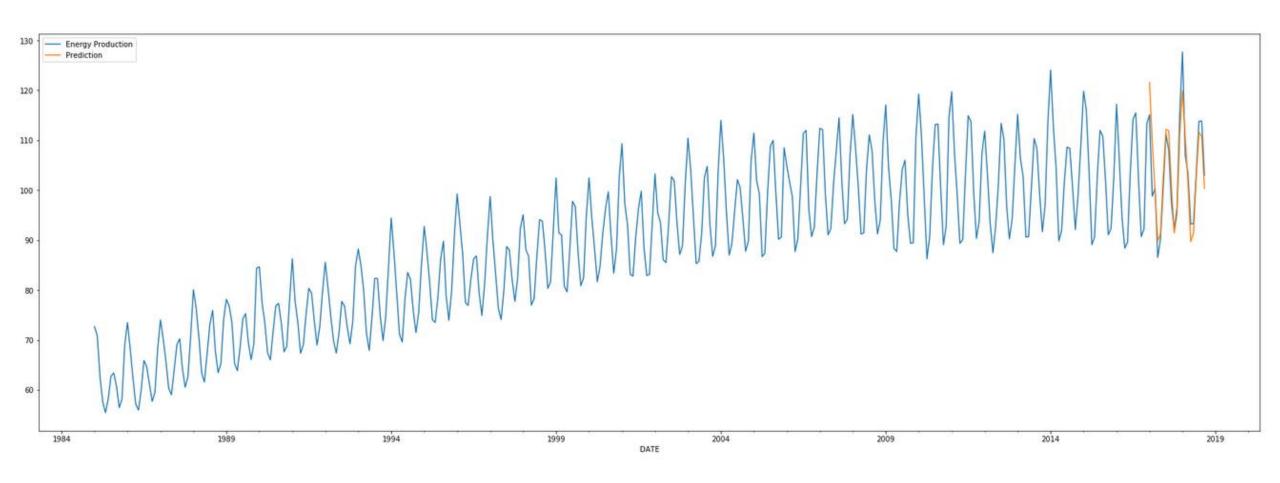


```
stepwise_model.fit(train)
future_forecast = stepwise_model.predict(n_periods=len(test))
future_forecast = pd.DataFrame(future_forecast,index = test.index,columns=['Prediction'])
pd.concat([test,future_forecast],axis=1).plot()
```



SARIMA - FINAL





iOLAP, Inc. 2018 - All Rights Reserved

RECOMMENDED READING



- Forecasting : methods and applications
 - Spyros Makridakis, Steven C. Wheelwright, Victor E. McGee
- Practical Time Series Analysis
 - By Avishek and Prakash
- Time Series Analysis: Forecasting and Control (3rd Edition)
 - Box et al.

