033-autoregressive-models

April 26, 2022

3.3. Autoregressive Models

[1]:
```
import warnings

import matplotlib.pyplot as plt
import pandas as pd
import plotly.express as px
from IPython.display import VimeoVideo
from pymongo import MongoClient
from sklearn.metrics import mean_absolute_error
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.ar_model import AutoReg

warnings.simplefilter(action="ignore", category=FutureWarning)
```

[2]:
```
VimeoVideo("665851858", h="e39fc3d260", width=600)
```

[2]: <IPython.lib.display.VimeoVideo at 0x7f9538768c40>

1 Prepare Data

1.1 Import

[3]:
```
VimeoVideo("665851852", h="16aa0a56e6", width=600)
```

[3]: <IPython.lib.display.VimeoVideo at 0x7f9538768ee0>

Task 3.3.1: Complete to the create a client to connect to the MongoDB server, assigns the `"air-quality"` database to `db`, and assigned the `"nairobi"` connection to `nairobi`.

- Create a client object for a MongoDB instance.
- Access a database using PyMongo.
- Access a collection in a database using PyMongo.

[4]:
```
client = MongoClient(host="localhost", port=27017)
db = client["air-quality"]
nairobi = db["nairobi"]
```

[5]:
```
VimeoVideo("665851840", h="e048425f49", width=600)
```

[5]: <IPython.lib.display.VimeoVideo at 0x7f94ea00db50>

Task 3.3.2: Change the `wrangle` function below so that it returns a Series of the resampled data instead of a DataFrame.

[6]:
```
def wrangle(collection):
    results = collection.find(
        {"metadata.site": 29, "metadata.measurement": "P2"},
        projection={"P2": 1, "timestamp": 1, "_id": 0},
    )

    # Read data into DataFrame
    df = pd.DataFrame(list(results)).set_index("timestamp")

    # Localize timezone
    df.index = df.index.tz_localize("UTC").tz_convert("Africa/Nairobi")

    # Remove outliers
    df = df[df["P2"] < 500]

    # Resample to 1hr window
    y = df["P2"].resample("1H").mean().fillna(method='ffill')

    return y
```

Task 3.3.3: Use your wrangle function to read the data from the `nairobi` collection into the Series `y`.

[7]:
```
y = wrangle(nairobi)
#y.shape
y.head()
```

[7]:
```
timestamp
2018-09-01 03:00:00+03:00    17.541667
2018-09-01 04:00:00+03:00    15.800000
2018-09-01 05:00:00+03:00    11.420000
2018-09-01 06:00:00+03:00    11.614167
2018-09-01 07:00:00+03:00    17.665000
Freq: H, Name: P2, dtype: float64
```

[8]:
```
# Check your work
assert isinstance(y, pd.Series), f"`y` should be a Series, not type {type(y)}"
assert len(y) == 2928, f"`y` should have 2928 observations, not {len(y)}"
assert y.isnull().sum() == 0
```

1.2 Explore

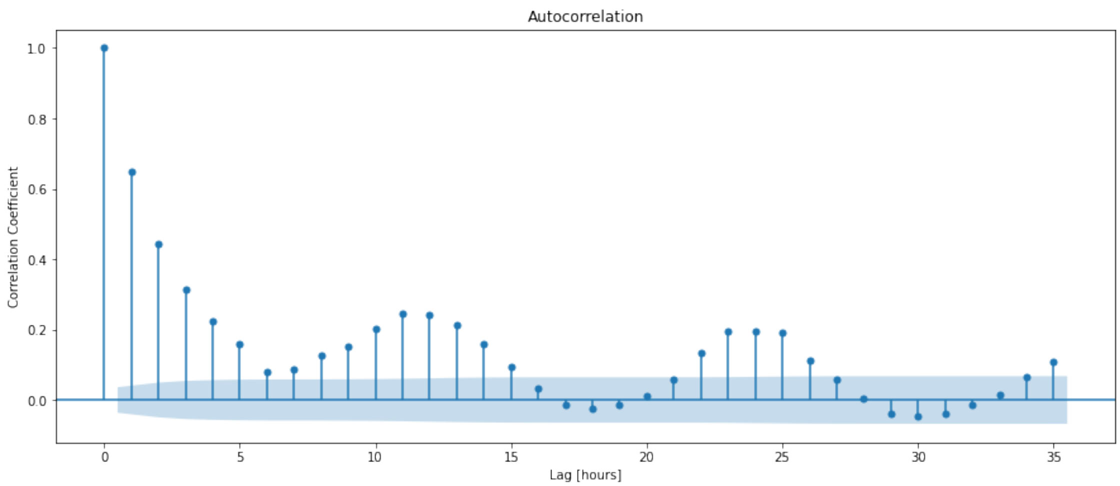
[9]:
```
VimeoVideo("665851830", h="85f58bc92b", width=600)
```

[9]: <IPython.lib.display.VimeoVideo at 0x7f94e9fa5c70>

Task 3.3.4: Create an ACF plot for the data in `y`. Be sure to label the x-axis as `"Lag [hours]"` and the y-axis as `"Correlation Coefficient"`.

- What's an ACF plot?
- Create an ACF plot using statsmodels

[10]:
```
fig, ax = plt.subplots(figsize=(15, 6))
plot_acf(y,ax=ax)
plt.xlabel("Lag [hours]")
plt.ylabel("Correlation Coefficient");
```



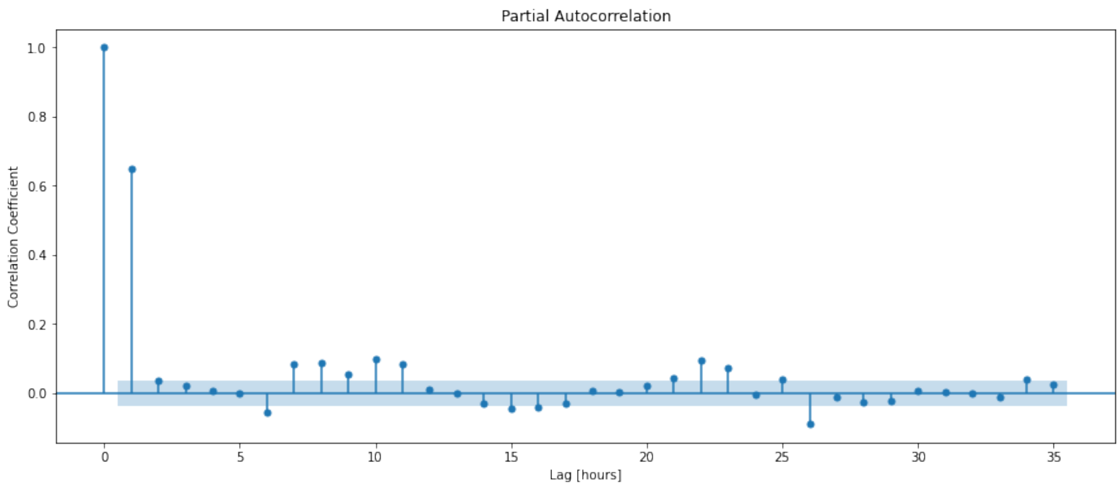
[11]:
```
VimeoVideo("665851811", h="ee3a2b5c24", width=600)
```

[11]: <IPython.lib.display.VimeoVideo at 0x7f945c75df10>

Task 3.3.5: Create an PACF plot for the data in `y`. Be sure to label the x-axis as `"Lag [hours]"` and the y-axis as `"Correlation Coefficient"`.

- What's an PACF plot?
- Create an PACF plot using statsmodels

[12]:
```
fig, ax = plt.subplots(figsize=(15, 6))
plot_pacf(y,ax=ax)
plt.xlabel("Lag [hours]")
plt.ylabel("Correlation Coefficient");
```



1.3 Split

[13]:
```
VimeoVideo("665851798", h="6c191cd94c", width=600)
```

[13]: <IPython.lib.display.VimeoVideo at 0x7f945c6bcc40>

Task 3.3.6: Split y into training and test sets. The first 95% of the data should be in your training set. The remaining 5% should be in the test set.

- Divide data into training and test sets in pandas.

[14]:
```
cutoff_test = int(len(y) * 0.95)

y_train = y.iloc[:cutoff_test]
y_test = y.iloc[cutoff_test:]
```

2 Build Model

2.1 Baseline

Task 3.3.7: Calculate the baseline mean absolute error for your model.

- Calculate summary statistics for a DataFrame or Series in pandas.

[15]:
```
y_train_mean = y_train.mean()
y_pred_baseline = [y_train_mean] * len(y_train)
mae_baseline = mean_absolute_error(y_train, y_pred_baseline)

print("Mean P2 Reading:", round(y_train_mean, 2))
print("Baseline MAE:", round(mae_baseline, 2))
```

```
Mean P2 Reading: 9.22
Baseline MAE: 3.71
```

2.2 Iterate

[16]:
```
VimeoVideo("665851769", h="94a4296cde", width=600)
```

[16]:
```
<IPython.lib.display.VimeoVideo at 0x7f9538768550>
```

Task 3.3.8: Instantiate an `AutoReg` model and fit it to the training data `y_train`. Be sure to set the `lags` argument to `26`.

- What's an AR model?
- Instantiate a predictor in statsmodels.
- Train a model in statsmodels.

[17]:
```
model = AutoReg(y_train,lags=26).fit()
```

[18]:
```
VimeoVideo("665851746", h="1a4511e883", width=600)
```

[18]:
```
<IPython.lib.display.VimeoVideo at 0x7f945c64b5b0>
```

[19]:
```
model.predict().isnull().sum()
```

[19]:
```
26
```

Task 3.3.9: Generate a list of training predictions for your model and use them to calculate your training mean absolute error.

- Generate in-sample predictions for a model in statsmodels.
- Calculate the mean absolute error for a list of predictions in scikit-learn.

[20]:
```
y_pred = model.predict().dropna()
training_mae = mean_absolute_error(y_train.iloc[26:],y_pred)
print("Training MAE:", training_mae)
```

```
Training MAE: 2.2809871656467036
```

[21]:
```
VimeoVideo("665851744", h="60d053b455", width=600)
```

[21]:
```
<IPython.lib.display.VimeoVideo at 0x7f944f9ebee0>
```

Task 3.3.10: Use `y_train` and `y_pred` to calculate the residuals for your model.

- What's a residual?
- Create new columns derived from existing columns in a DataFrame using pandas.

[23]:
```
#y_train_resid = y_train - y_pred
y_train_resid = model.resid
y_train_resid.tail()
```

[23]: timestamp
```
2018-12-25 19:00:00+03:00   -0.392002
2018-12-25 20:00:00+03:00   -1.573180
2018-12-25 21:00:00+03:00   -0.735747
2018-12-25 22:00:00+03:00   -2.022221
2018-12-25 23:00:00+03:00   -0.061916
Freq: H, dtype: float64
```

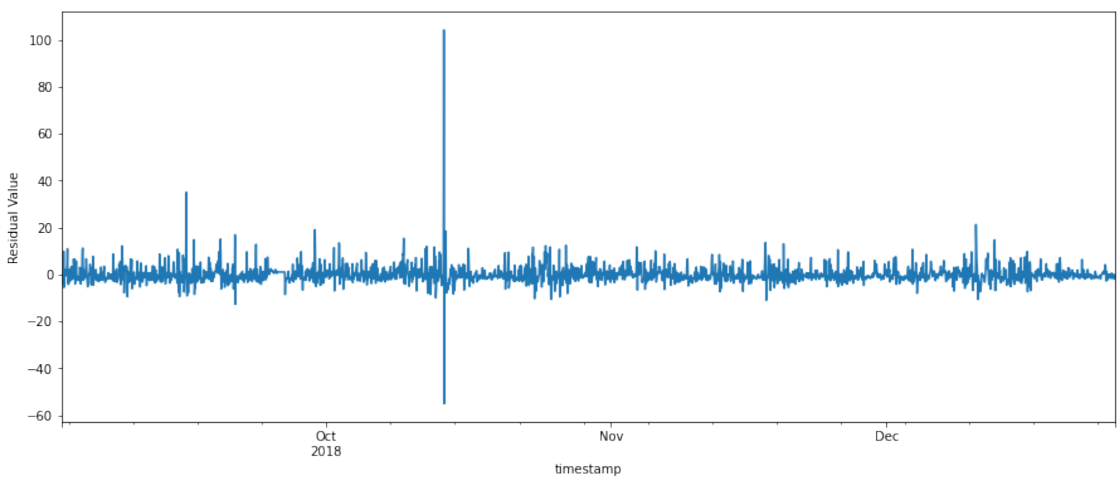
[24]:
```
VimeoVideo("665851712", h="9ff0cdba9c", width=600)
```

[24]: <IPython.lib.display.VimeoVideo at 0x7f9538756940>

Task 3.3.11: Create a plot of `y_train_resid`.

- Create a line plot using pandas.

[25]:
```
fig, ax = plt.subplots(figsize=(15, 6))
y_train_resid.plot(ylabel="Residual Value",ax=ax);
```



[26]:
```
VimeoVideo("665851702", h="b494adc297", width=600)
```

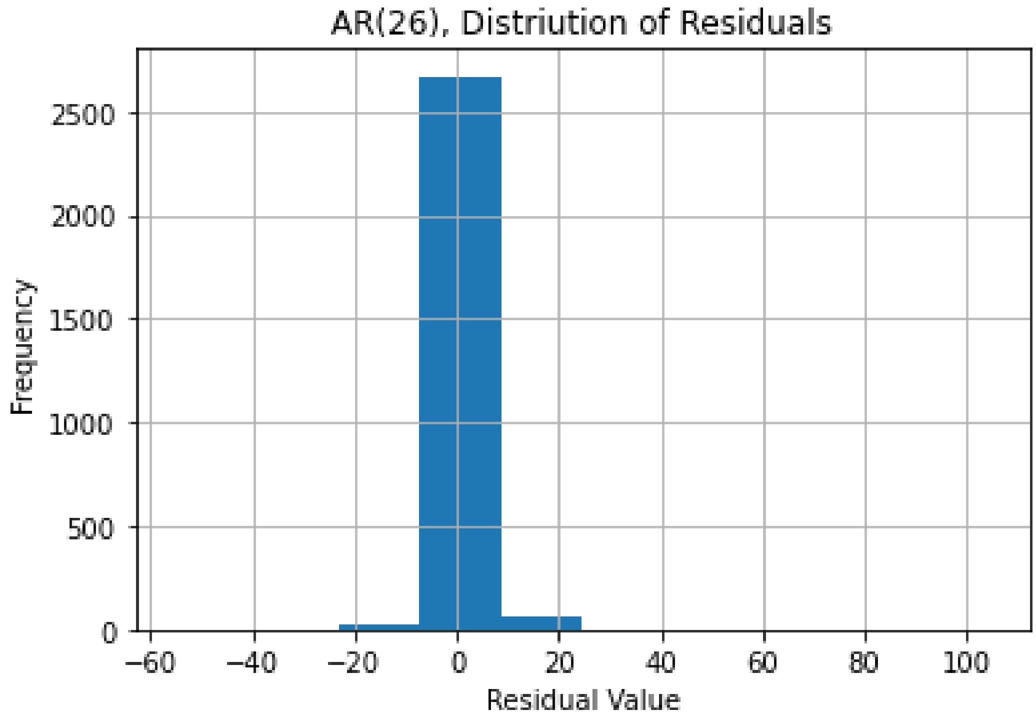
[26]: <IPython.lib.display.VimeoVideo at 0x7f945c510e50>

Task 3.3.12: Create a histogram of `y_train_resid`.

- Create a histogram using plotly express.

[28]:
```
y_train_resid.hist()
plt.xlabel("Residual Value")
plt.ylabel("Frequency")
plt.title("AR(26), Distriution of Residuals")
```

[28]: Text(0.5, 1.0, 'AR(26), Distriution of Residuals')



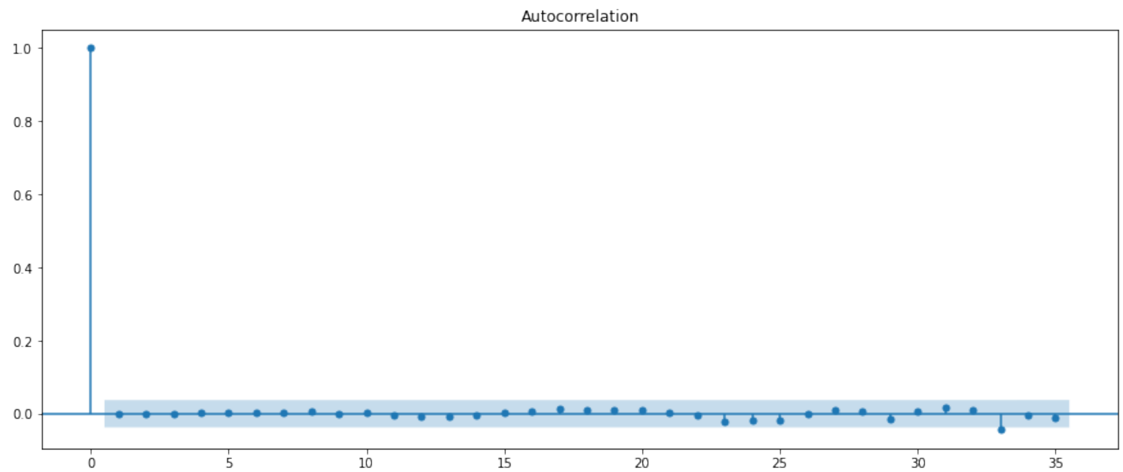
[29]:
```
VimeoVideo("665851684", h="d6d782a1f3", width=600)
```

[29]: <IPython.lib.display.VimeoVideo at 0x7f944d7a6940>

Task 3.3.13: Create an ACF plot of `y_train_resid`.

- What's an ACF plot?
- Create an ACF plot using statsmodels

[30]:
```
fig, ax = plt.subplots(figsize=(15, 6))
plot_acf(y_train_resid, ax=ax);
```



2.3 Evaluate

[31]:
```
VimeoVideo("665851662", h="72e767e121", width=600)
```

[31]: <IPython.lib.display.VimeoVideo at 0x7f944d8a39a0>

Task 3.3.14: Calculate the test mean absolute error for your model.

- Generate out-of-sample predictions using model in statsmodels.
- Calculate the mean absolute error for a list of predictions in scikit-learn.

[32]:
```
y_pred_test = model.predict(y_test.index.min(),y_test.index.max())
test_mae = mean_absolute_error(y_test, y_pred_test)
print("Test MAE:", test_mae)
```

```
Test MAE: 3.0136439495039054
```

Task 3.3.15: Create a DataFrame `test_predictions` that has two columns: `"y_test"` and `"y_pred"`. The first should contain the true values for your test set, and the second should contain your model's predictions. Be sure the index of `test_predictions` matches the index of `y_test`.

- Create a DataFrame from a dictionary using pandas.

[34]:
```
df_pred_test = pd.DataFrame(
    {"y_test": y_test, "y_pred": y_pred_test}, index=y_test.index
)
```

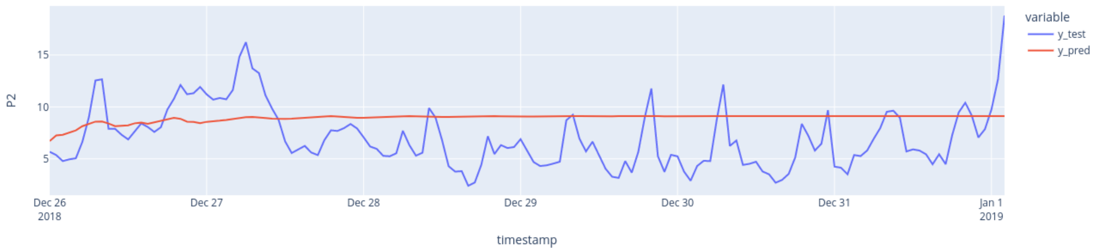
[33]:
```
VimeoVideo("665851628", h="29b43e482e", width=600)
```

[33]: <IPython.lib.display.VimeoVideo at 0x7f944fbf08b0>

Task 3.3.16: Create a time series plot for the values in `test_predictions` using plotly express. Be sure that the y-axis is properly labeled as `"P2"`.

- Create a line plot in plotly express.

[35]:
```
fig = px.line(df_pred_test, labels={"value": "P2"})
fig.show()
```



[36]:
```
VimeoVideo("665851599", h="bb30d96e43", width=600)
```

[36]: <IPython.lib.display.VimeoVideo at 0x7f950fe72e80>

Task 3.3.17: Perform walk-forward validation for your model for the entire test set `y_test`. Store your model's predictions in the Series `y_pred_wfv`.

- What's walk-forward validation?
- Perform walk-forward validation for time series model.

[48]:
```
%%capture

y_pred_wfv = pd.Series()
history = y_train.copy()
for i in range(len(y_test)):
    model = AutoReg(history, lags=26).fit()
    next_pred = model.forecast()
    y_pred_wfv = y_pred_wfv.append(next_pred)
    history = history.append(y_test[next_pred.index])
```

[37]:
```
VimeoVideo("665851568", h="a764ab5416", width=600)
```

[37]: <IPython.lib.display.VimeoVideo at 0x7f944fbf0340>

Task 3.3.18: Calculate the test mean absolute error for your model.

- Calculate the mean absolute error for a list of predictions in scikit-learn.

[49]:
```
test_mae = mean_absolute_error(y_test, y_pred_wfv)
print("Test MAE (walk forward validation):", round(test_mae, 2))
```

```
Test MAE (walk forward validation): 1.4
```

3 Communicate Results

[50]:
```
VimeoVideo("665851553", h="46338036cc", width=600)
```

[50]: <IPython.lib.display.VimeoVideo at 0x7f950fe72fa0>

Task 3.3.19: Print out the parameters for your trained model.

- Access model parameters in statsmodels

[51]:
```
print(model.params)
```

```
intercept    2.011432
P2.L1        0.587118
P2.L2        0.019796
P2.L3        0.023615
P2.L4        0.027187
P2.L5        0.044014
P2.L6       -0.102128
P2.L7        0.029583
P2.L8        0.049867
P2.L9       -0.016897
P2.L10       0.032438
P2.L11       0.064360
P2.L12       0.005987
P2.L13       0.018375
P2.L14      -0.007636
P2.L15      -0.016075
P2.L16      -0.015953
P2.L17      -0.035444
P2.L18       0.000756
P2.L19      -0.003907
P2.L20      -0.020655
P2.L21      -0.012578
P2.L22       0.052499
P2.L23       0.074229
P2.L24      -0.023806
P2.L25       0.090577
P2.L26      -0.088323
dtype: float64
```

[52]:
```
VimeoVideo("665851529", h="39284d37ac", width=600)
```

[52]: <IPython.lib.display.VimeoVideo at 0x7f950ec5cf40>

Task 3.3.20: Put the values for `y_test` and `y_pred_wfv` into the DataFrame `df_pred_test` (don't forget the index). Then plot `df_pred_test` using plotly express.

- Create a line plot in plotly express.

[53]:

```
df_pred_test = pd.DataFrame(
    {"y_test":y_test, "y_pred_wfv":y_pred_wfv}
)
fig = px.line(df_pred_test, labels={"value": "PM2.5"})
fig.show()
```