034-arma-models-and-hyperparameter-tuning

May 9, 2022

3.4. ARMA Models

[1]:
```
import inspect
import time
import warnings

import matplotlib.pyplot as plt
import pandas as pd
import plotly.express as px
import seaborn as sns
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.arima.model import ARIMA

warnings.filterwarnings("ignore")
```

[2]:
```
VimeoVideo("665851728", h="95c59d2805", width=600)
```

[2]:
```
<IPython.lib.display.VimeoVideo at 0x7f6154791880>
```

1 Prepare Data

1.1 Import

Task 3.4.1: 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.

[3]:
```
client = MongoClient(host="localhost", port=27017)
db = client["air-quality"]
nairobi = db["nairobi"]
```

[4]:
```
def wrangle(collection, resample_rule="1H"):

    results = collection.find(
        {"metadata.site": 29, "metadata.measurement": "P2"},
        projection={"P2": 1, "timestamp": 1, "_id": 0},
    )

    # Read results 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 and forward-fill
    y = df["P2"].resample(resample_rule).mean().fillna(method="ffill")

    return y
```

[5]:
```
VimeoVideo("665851670", h="3efc0c20d4", width=600)
```

[5]:
```
<IPython.lib.display.VimeoVideo at 0x7f607760ff40>
```

Task 3.4.2: Change your `wrangle` function so that it has a `resample_rule` argument that allows the user to change the resampling interval. The argument default should be `"1H"`.

- What's an argument?
- Include an argument in a function in Python.

[6]:
```
# Check your work
func_params = set(inspect.signature(wrangle).parameters.keys())
assert func_params == set(
    ["collection", "resample_rule"]
), f"Your function should take two arguments: `'collection'`, `'resample_rule'`.
↪ Your function takes the following arguments: {func_params}"
```

Task 3.4.3: Use your wrangle function to read the data from the `nairobi` collection into the Series `y`.

[7]:
```
y = wrangle(nairobi, resample_rule="1H")
y.tail()
```

[7]:
```
timestamp
2018-12-31 22:00:00+03:00    7.060833
2018-12-31 23:00:00+03:00    7.854167
2019-01-01 00:00:00+03:00    9.755833
```

```
2019-01-01 01:00:00+03:00    12.665000
2019-01-01 02:00:00+03:00    18.803333
Freq: H, Name: P2, dtype: float64
```

[8]:
```
# Check your work
assert isinstance(y, pd.Series), f"`y` should be a Series, not a {type(y)}."
assert len(y) == 2928, f"`y` should have 2,928 observations, not {len(y)}."
assert (
    y.isnull().sum() == 0
), f"There should be no null values in `y`. Your `y` has {y.isnull().sum()}␣
↪null values."
```

1.2 Explore

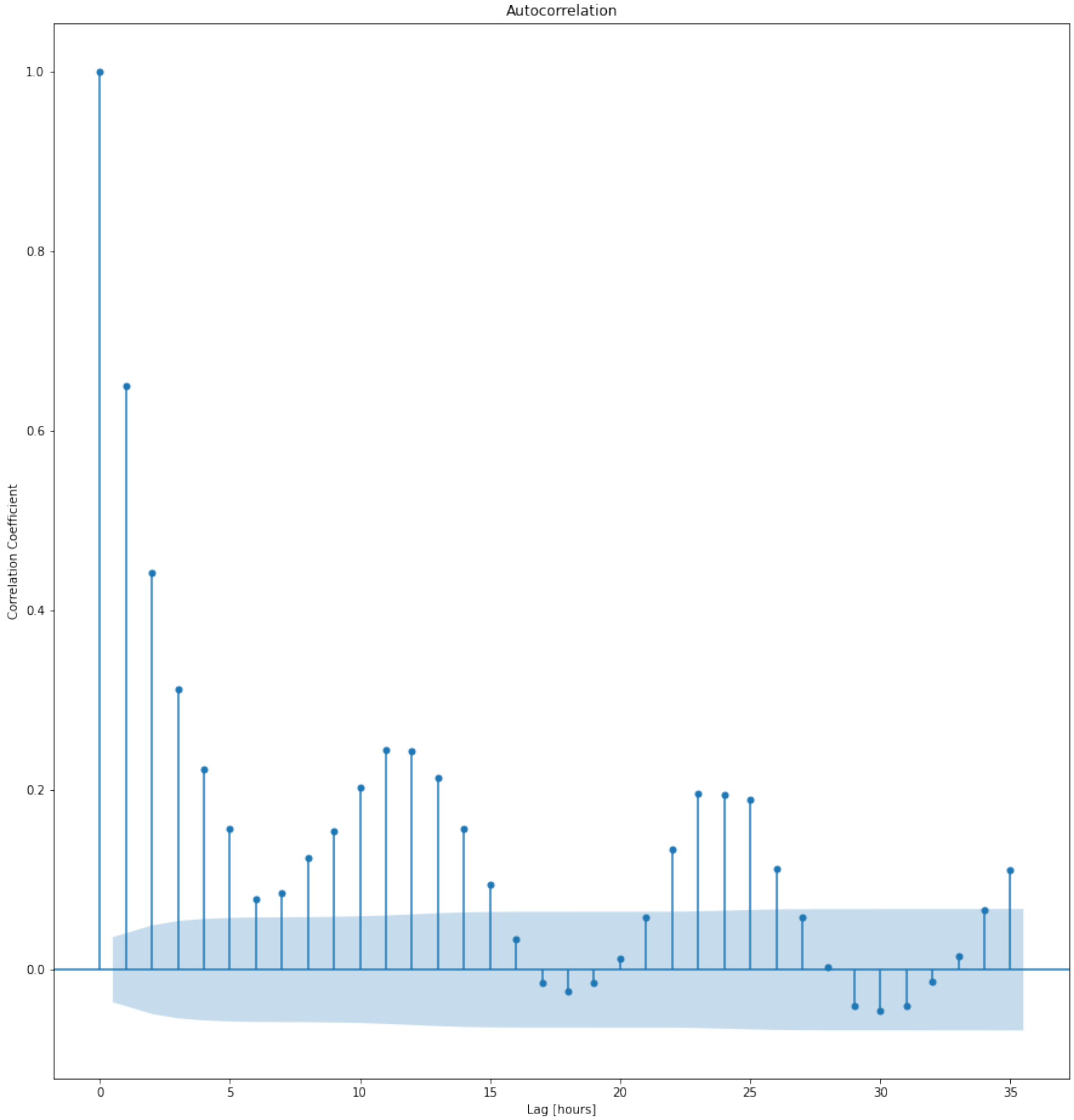
[9]:
```
VimeoVideo("665851654", h="687ff8d5ee", width=600)
```

[9]: <IPython.lib.display.VimeoVideo at 0x7f6075da2d30>

Task 3.4.4: 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=(15,16))
plot_acf(y, ax=ax)
plt.xlabel("Lag [hours]")
plt.ylabel("Correlation Coefficient");
```




```
[11]: VimeoVideo("665851644", h="e857f05bfb", width=600)
```

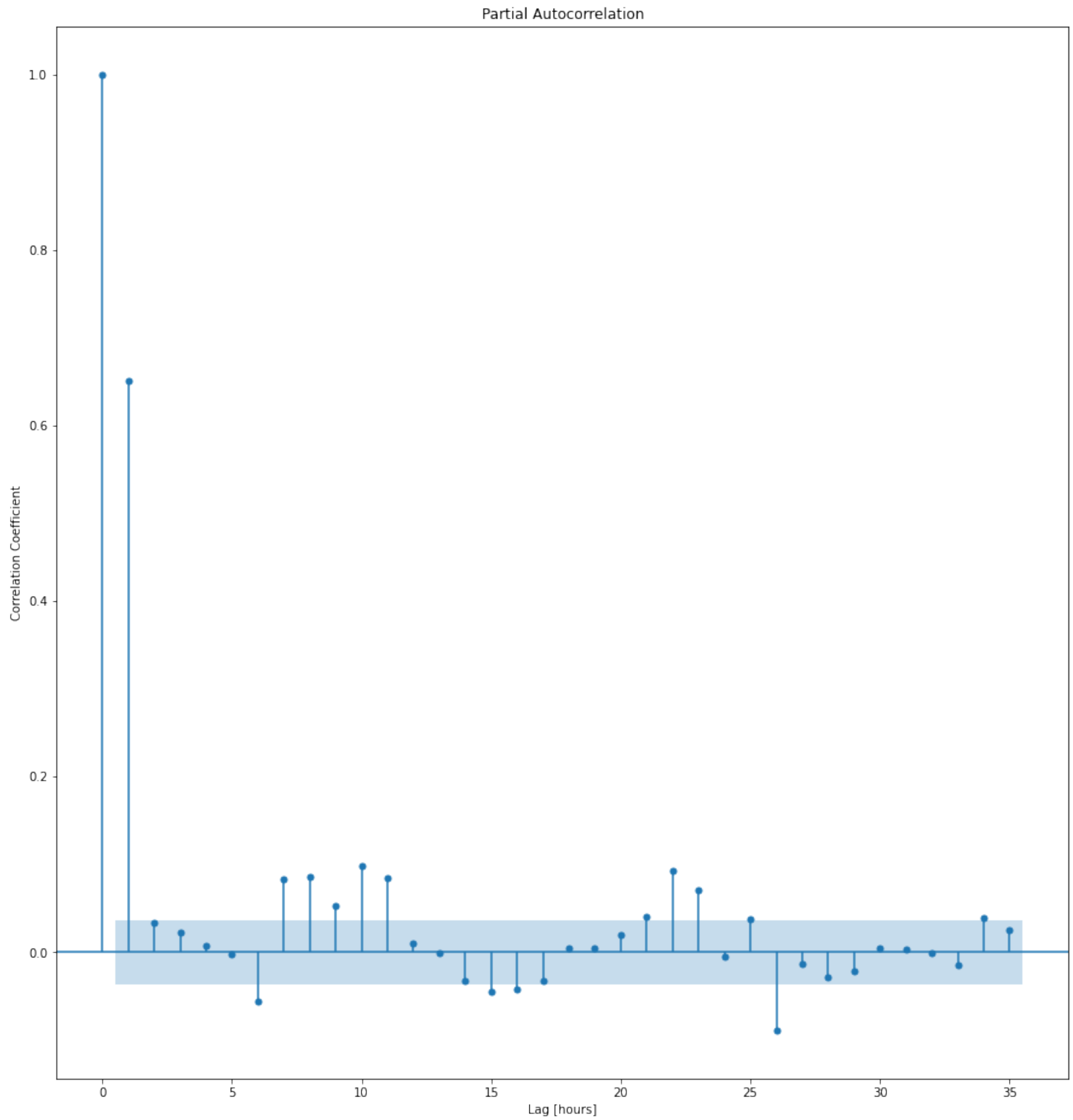
[11]: <IPython.lib.display.VimeoVideo at 0x7f6075d504f0>

Task 3.4.5: 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=(15,16))
      plot_pacf(y, ax=ax)
```

```
plt.xlabel("Lag [hours]")
plt.ylabel("Correlation Coefficient");
```



1.3 Split

Task 3.4.6: Create a training set `y_train` that contains only readings from October 2018, and a test set `y_test` that contains readings from November 1, 2018.

- Subset a DataFrame by selecting one or more rows in pandas.

[13]:
```
y_train =  y.get("2018-10")
y_test = y.get("2018-11-1")
```

```
#y_test.head()
```

[14]:
```
# Check your work
assert (
    len(y_train) == 744
), f"`y_train` should have 744 observations, not {len(y_train)}."
assert len(y_test) == 24, f"`y_test` should have 24 observations, not␣
↪{len(y_test)}."
```

2 Build Model

2.1 Baseline

Task 3.4.7: Calculate the baseline mean absolute error for your model.

[15]:
```
y_train_mean = y_train.mean()
y_train_pred = [y_train_mean] * len(y_train)
mae_baseline = mean_absolute_error(y_train, y_train_pred)
print("Mean P2 Reading:", round(y_train_mean, 2))
print("Baseline MAE:", round(mae_baseline, 2))
```

```
Mean P2 Reading: 10.12
Baseline MAE: 4.17
```

2.2 Iterate

[16]:
```
VimeoVideo("665851576", h="36e2dc6269", width=600)
```

[16]:
```
<IPython.lib.display.VimeoVideo at 0x7f6075cceca0>
```

Task 3.4.8: Create ranges for possible p and q values. `p_params` should range between 0 and 25, by steps of 8. `q_params` should range between 0 and 3 by steps of 1.

- What's a hyperparameter?
- What's an iterator?
- Create a range in Python.

[17]:
```
p_params = range(0,25,8)
q_params = range(0,3,1)
#list(p_params)
```

[18]:
```
VimeoVideo("665851476", h="d60346ed30", width=600)
```

[18]:
```
<IPython.lib.display.VimeoVideo at 0x7f6075c601f0>
```

Task 3.4.9: Complete the code below to train a model with every combination of hyperparameters in `p_params` and `q_params`. Every time the model is trained, the mean absolute error is calculated and then saved to a dictionary. If you're not sure where to start, do the code-along with Nicholas!

- What's an ARMA model?
- Append an item to a list in Python.
- Calculate the mean absolute error for a list of predictions in scikit-learn.
- Instantiate a predictor in statsmodels.
- Train a model in statsmodels.
- Write a for loop in Python.

[19]:
```python
# Create dictionary to store MAEs
mae_grid = dict()
# Outer loop: Iterate through possible values for `p`
for p in p_params:
    # Create key-value pair in dict. Key is `p`, value is empty list.
    mae_grid[p] = list()
    # Inner loop: Iterate through possible values for `q`
    for q in q_params:
        # Combination of hyperparameters for model
        order = (p, 0, q)
        # Note start time
        start_time = time.time()
        # Train model
        model = ARIMA(y_train, order=order).fit()
        # Calculate model training time
        elapsed_time = round(time.time() - start_time, 2)
        print(f"Trained ARIMA {order} in {elapsed_time} seconds.")
        # Generate in-sample (training) predictions
        y_pred = model.predict()
        # Calculate training MAE
        mae = mean_absolute_error(y_train, y_pred)
        # Append MAE to list in dictionary
        mae_grid[p].append(mae)

print()
print(mae_grid)
```

```
Trained ARIMA (0, 0, 0) in 0.39 seconds.
Trained ARIMA (0, 0, 1) in 0.41 seconds.
Trained ARIMA (0, 0, 2) in 1.3 seconds.
Trained ARIMA (8, 0, 0) in 10.4 seconds.
Trained ARIMA (8, 0, 1) in 41.9 seconds.
Trained ARIMA (8, 0, 2) in 77.5 seconds.
Trained ARIMA (16, 0, 0) in 38.31 seconds.
Trained ARIMA (16, 0, 1) in 133.39 seconds.
Trained ARIMA (16, 0, 2) in 195.01 seconds.
Trained ARIMA (24, 0, 0) in 108.08 seconds.
Trained ARIMA (24, 0, 1) in 126.22 seconds.
Trained ARIMA (24, 0, 2) in 242.93 seconds.

{0: [4.171460443827197, 3.3506427433555537, 3.1057222587888647], 8:
```

```
[2.9384480570404223, 2.9149008203151663, 2.908046094677133], 16:
[2.9201084726122, 2.929436207635203, 2.913638894139686], 24: [2.914390327277196,
2.9136013252035013, 2.89792511429827]}
```

[20]:
```
VimeoVideo("665851464", h="12f4080d0b", width=600)
```

[20]:
```
<IPython.lib.display.VimeoVideo at 0x7f6075c68520>
```

Task 3.4.10: Organize all the MAE's from above in a DataFrame names `mae_df`. Each row represents a possible value for q and each column represents a possible value for p.

- Create a DataFrame from a dictionary using pandas.

[21]:
```
mae_df = pd.DataFrame(mae_grid)
mae_df.round(4)
```

[21]:

	0	8	16	24
0	4.1715	2.9384	2.9201	2.9144
1	3.3506	2.9149	2.9294	2.9136
2	3.1057	2.9080	2.9136	2.8979

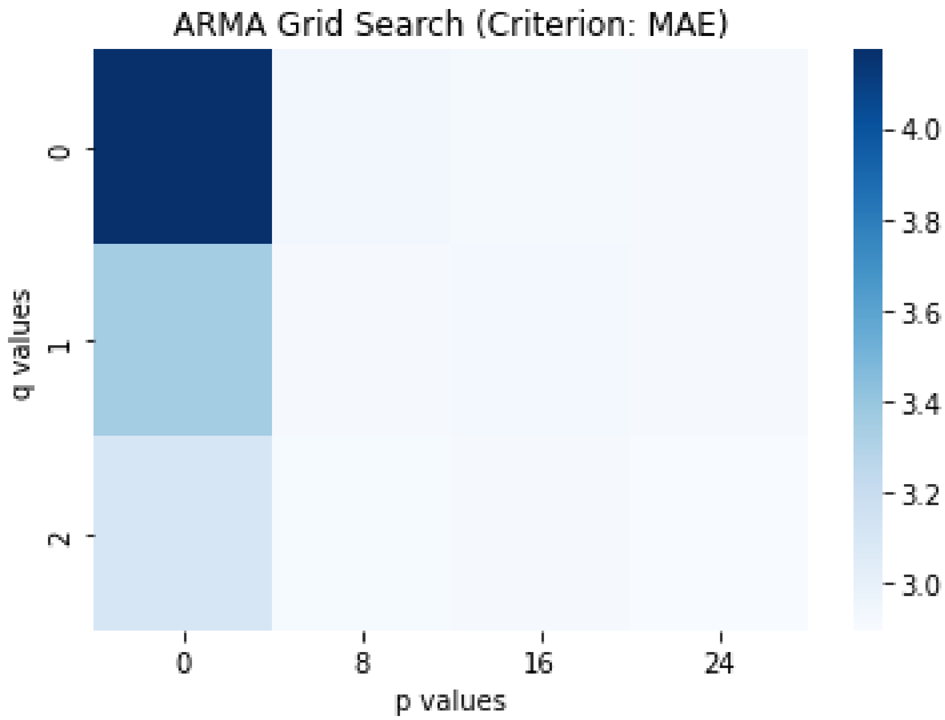
[22]:
```
VimeoVideo("665851453", h="dfd415bc08", width=600)
```

[22]:
```
<IPython.lib.display.VimeoVideo at 0x7f6075c686a0>
```

Task 3.4.11: Create heatmap of the values in `mae_grid`. Be sure to label your x-axis `"p values"` and your y-axis `"q values"`.

- Create a heatmap in seaborn.

[23]:
```
sns.heatmap(mae_df,cmap="Blues")
plt.xlabel("p values")
plt.ylabel("q values")
plt.title("ARMA Grid Search (Criterion: MAE)");
```



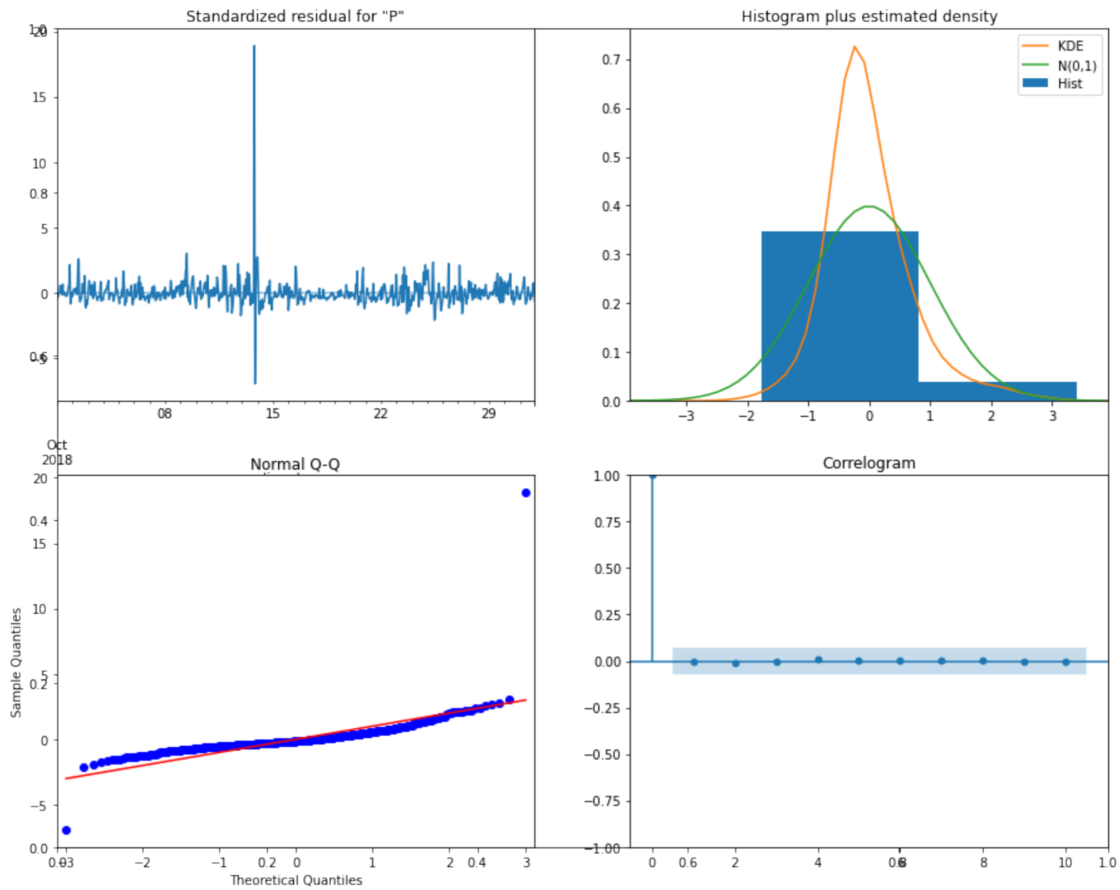
[24]:
```
VimeoVideo("665851444", h="8b58161f26", width=600)
```

[24]: <IPython.lib.display.VimeoVideo at 0x7f607760f2e0>

Task 3.4.12: Use the `plot_diagnostics` method to check the residuals for your model. Keep in mind that the plot will represent the residuals from the last model you trained, so make sure it was your best model, too!

- Examine time series model residuals using statsmodels.

[25]:
```
fig, ax = plt.subplots(figsize=(15, 12))
model.plot_diagnostics(fig=fig);
```



2.3 Evaluate

[26]:
```
VimeoVideo("665851439", h="c48d80cdf4", width=600)
```

[26]: `<IPython.lib.display.VimeoVideo at 0x7f6075c9c220>`

Task 3.4.13: Complete the code below to 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`. Choose the values for p and q that best balance model performance and computation time. Remember: This model is going to have to train 24 times before you can see your test MAE!

[31]:
```
y_pred_wfv = pd.Series()
history = y_train.copy()
for i in range(len(y_test)):
    model = ARIMA(history, order=(8,0,1)).fit()
    next_pred = model.forecast()
    y_pred_wfv = y_pred_wfv.append(next_pred)
    history = history.append(y_test[next_pred.index])
```

[30]:
```
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): 1.67
```

3 Communicate Results

[32]:
```
VimeoVideo("665851423", h="8236ff348f", width=600)
```

[32]:
```
<IPython.lib.display.VimeoVideo at 0x7f60744c8520>
```

Task 3.4.14: First, generate the list of training predictions for your model. Next, create a DataFrame `df_predictions` with the true values `y_test` and your predictions `y_pred_wfv` (don't forget the index). Finally, plot `df_predictions` using plotly express. Make sure that the y-axis is labeled `"P2"`.

- Generate in-sample predictions for a model in statsmodels.
- Create a DataFrame from a dictionary using pandas.
- Create a line plot in pandas.

[34]:
```
df_predictions = pd.DataFrame({"y_test":y_test, "y_pred_wfv":y_pred_wfv})
fig = px.line(df_predictions, labels={"value": "PM2.5"})
fig.show()
```
