Cross Validation in Time Series

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1 Cross Validation in Time Series

This notebook answers the question: > DS2: What cross-validation technique would you use on a time series data set?

1.1 Cross Validation (CV)

- Technique we use for tuning hyperparameters
- two most common:
  - k-fold cross validatio
  - hold-out cross validation

1.2 Why CV is different with Time Series?

Traditional techniques will fail because:

1.2.1 Temporal Dependencies

- data must be split to avoid leakages
- test must only withhold data about events that occur chronologically after the events
- k-fold CV will not work in this case
- use hold-out CV but split temporally
- given in image below, the red dots correspond to the test/validate observation which occurs temporally after the blue training observations

1.2.2 Arbitrary Choice of Test Set

- results in test set error being a poor estimate of error on an independent test set
- use nested cross validation to address this

1.3 Nested Cross Validation

- uses two loops - outer and inner
- outer loop:
  - used for error estimation
  - here data is split into train and test set
- inner loop:
  - parameter tuning
  - data is split into train and validation set

1.4 Nested CV Methods for a Time Series

1.4.1 Predict Second Half

- only one train-test split
- suffers from the limitation of an arbitrarily-chosen test set
- the validation set is chronologically subsequent to the training subset

1.4.2 Day Forward-Chaining

- aka rolling-origin-recalibration evaluation
- successively consider each day as the test set and assign all previous data into the training set.
- E.g if our dataset has five days, then we would produce three different training and test splits, as shown below:

1.4.3 Regular Day Forward-Chaining

- utilizes day forward-chaining
- but splits now also contain data from each participant in our dataset

1.4.4 Polpulation-informed Day Forward-Chaining

- takes advantaged of independence between different participants' data
- the test and validation sets only contain data from one participant and all data from all other participants in the dataset are allowed in the training set

1.5 Monthly Sunspot Dataset

- This dataset describes a monthly count of the number of observed sunspots for just over 230 years (1749-1983).
- The source of the dataset is credited as Andrews & Herzberg (1985).

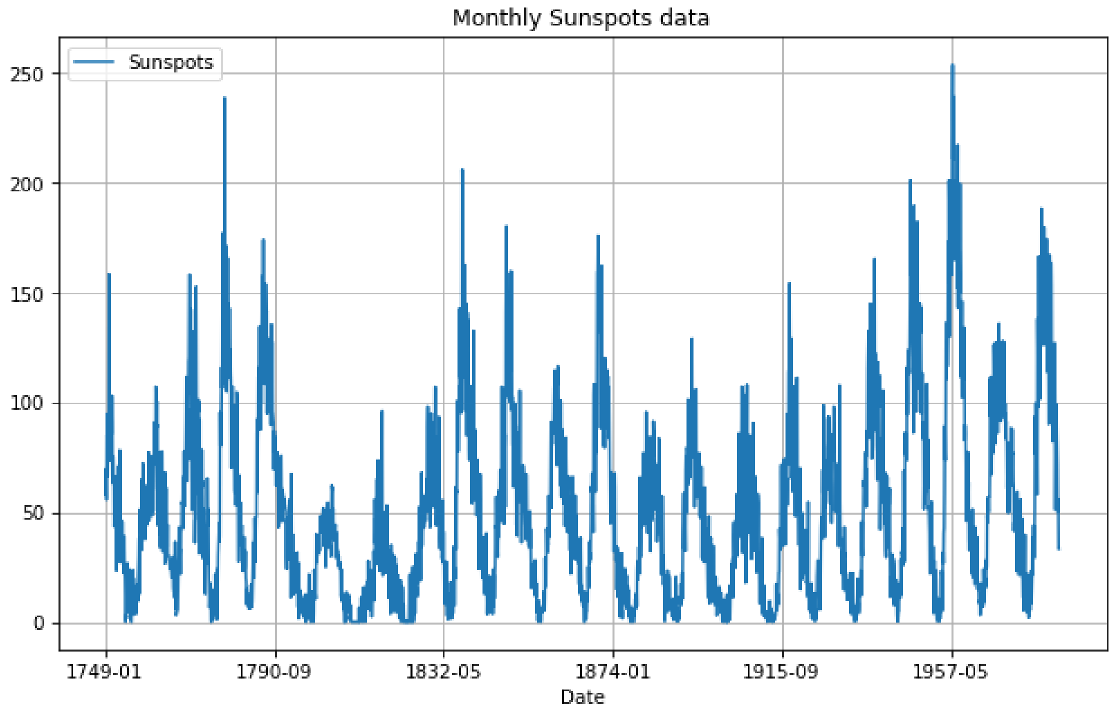
[1]:
```
# importing libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```
# loading data

series = pd.read_csv('data/monthly-sunspots.csv', header=0, index_col=0)
series.head(5)
```

[2]:
```
         Sunspots
Month
1749-01      58.0
1749-02      62.6
1749-03      70.0
```

```
1749-04      55.7
1749-05      85.0
```

[3]:
```
# displaying plot

fig = plt.figure(figsize=(10, 6), dpi=75)
series.plot(ax = plt.gca())
plt.title('Monthly Sunspots data')
plt.xlabel('Date')
plt.grid()
plt.show()
```

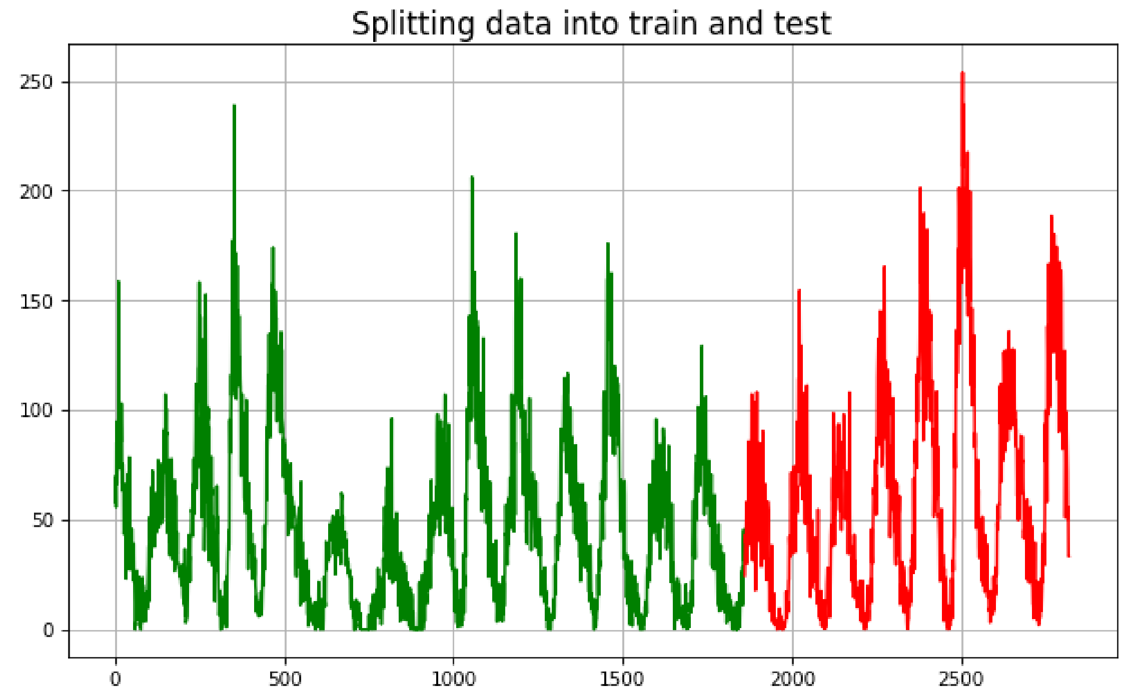


1.5.1 Train Test Temporal Split

[4]:
```
X = series.values

# 66% train set; 34% test size
train_size = int(len(X) * 0.66)
train, test = X[0:train_size], X[train_size:len(X)]

print('Observations: %d' % (len(X)))
print('Training Observations: %d' % (len(train)))
print('Testing Observations: %d' % (len(test)))
```

```
plt.figure(figsize=(10, 6), dpi=75)
plt.plot(train, color = 'green')
plt.plot([None for i in train] + [x for x in test], color = 'red')
plt.title("Splitting data into train and test", fontsize=16)
plt.grid()
plt.show()
```

```
Observations: 2820
Training Observations: 1861
Testing Observations: 959
```



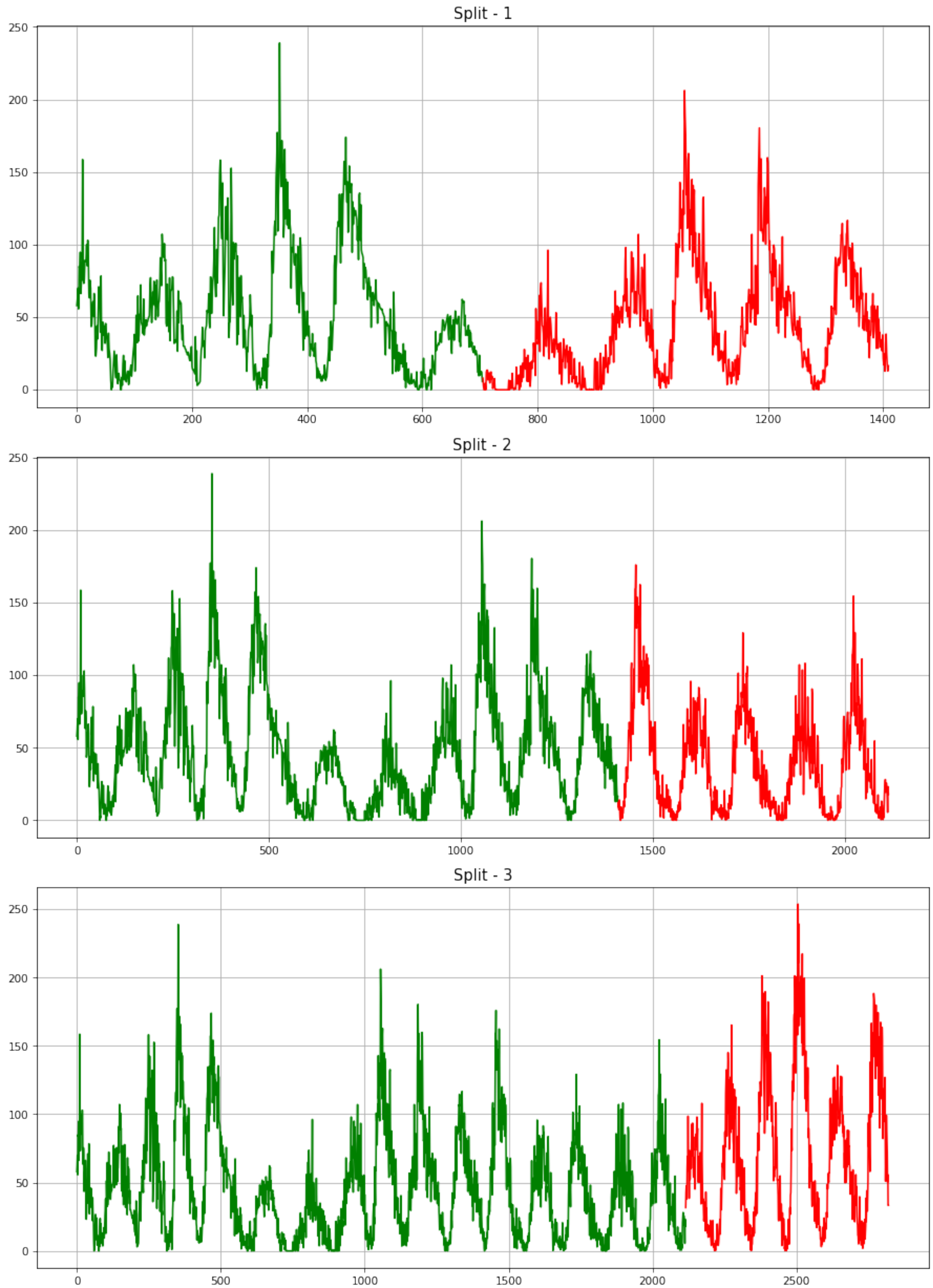
1.5.2 Multple Train-Test Splits for nested CV methods

[5]:
```
from sklearn.model_selection import TimeSeriesSplit

# three splits for the outer loop
splits = TimeSeriesSplit(n_splits=3)
fig = plt.figure(1, figsize = (12, 6*3), dpi = 75)
fig.suptitle("Splitting data into 3 outer loops", fontsize=16)
index = 1

for train_index, test_index in splits.split(X):
    train = X[train_index]
    test = X[test_index]
```

```python
    print('Observations: %d' % (len(train) + len(test)))
    print('Training Observations: %d' % (len(train)))
    print('Testing Observations: %d' % (len(test)))

    ax = fig.add_subplot(310 + index)
    ax.set_title('Split - {}'.format(str(index)), fontsize=14)
    ax.plot(train, color = 'green')
    ax.grid()
    ax.plot([None for i in train] + [x for x in test], color = 'red')
    index += 1

plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.show()
```

```
Observations: 1410
Training Observations: 705
Testing Observations: 705
Observations: 2115
Training Observations: 1410
Testing Observations: 705
Observations: 2820
Training Observations: 2115
Testing Observations: 705
```

Splitting data into 3 outer loops



1.6 Which method to choose?

A comparsion among each method is given in the table below:

Ideally, we would want to choose population-informed day forward-chaining whenever each participant's data is independent of one another. Despite being computationally expensive, it's the most unbiased estimate of generalization error.

1.7 References

1. TowardsDataScience - Time Series Nested Cross-Validation
2. Rob J Hyndman - Cross-validation for time series
3. Machine Learning Mastery - How To Backtest Machine Learning Models for Time Series Forecasting