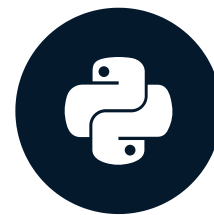


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# Time-delayed features and auto- regressive models

MACHINE LEARNING FOR TIME SERIES DATA IN PYTHON



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Science

# The past is useful

- Timeseries data almost always have information that is *shared between timepoints*
- Information in the past can help predict what happens in the future
- Often the features best-suited to predict a timeseries are previous values of the same timeseries.

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# A note on smoothness and auto-correlation

- A common question to ask of a timeseries: how smooth is the data.
- AKA, how correlated is a timepoint with its neighboring timepoints (called **autocorrelation**).
- The amount of auto-correlation in data will impact your models.

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# Creating time-lagged features

- Let's see how we could build a model that uses values in the past as input features.
- We can use this to assess how auto-correlated our signal is (and lots of other stuff too)

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# Time-shifting data with Pandas

```
print(df)
```

```
df
0    0.0
1    1.0
2    2.0
3    3.0
4    4.0
```

```
# Shift a DataFrame/Series by 3 index values towards the past
print(df.shift(3))
```

```
df
0    NaN
1    NaN
2    NaN
3    0.0
4    1.0
```

# Creating a time-shifted DataFrame

```
# data is a pandas Series containing time series data
data = pd.Series(...)
```

```
# Shifts
shifts = [0, 1, 2, 3, 4, 5, 6, 7]
```

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```
# Create a dictionary of time-shifted data
many_shifts = {'lag_{}'.format(ii): data.shift(ii) for ii in shifts}
```

```
# Convert them into a dataframe
many_shifts = pd.DataFrame(many_shifts)
```

# Fitting a model with time-shifted features

```
# Fit the model using these input features
model = Ridge()
model.fit(many_shifts, data)
```

. Ridge "many\_shifts" "data" 가 . Ridge 가

# Interpreting the auto-regressive model coefficients

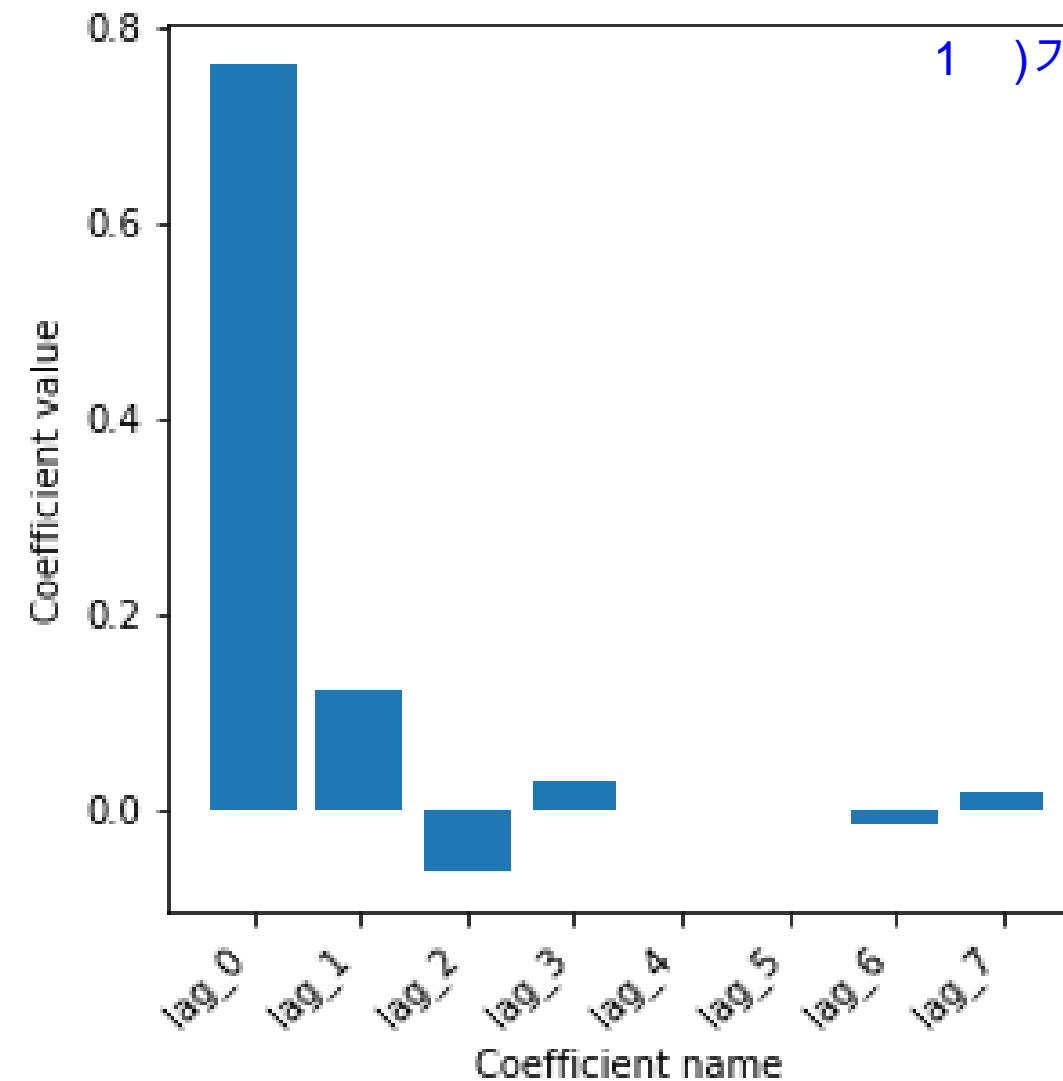
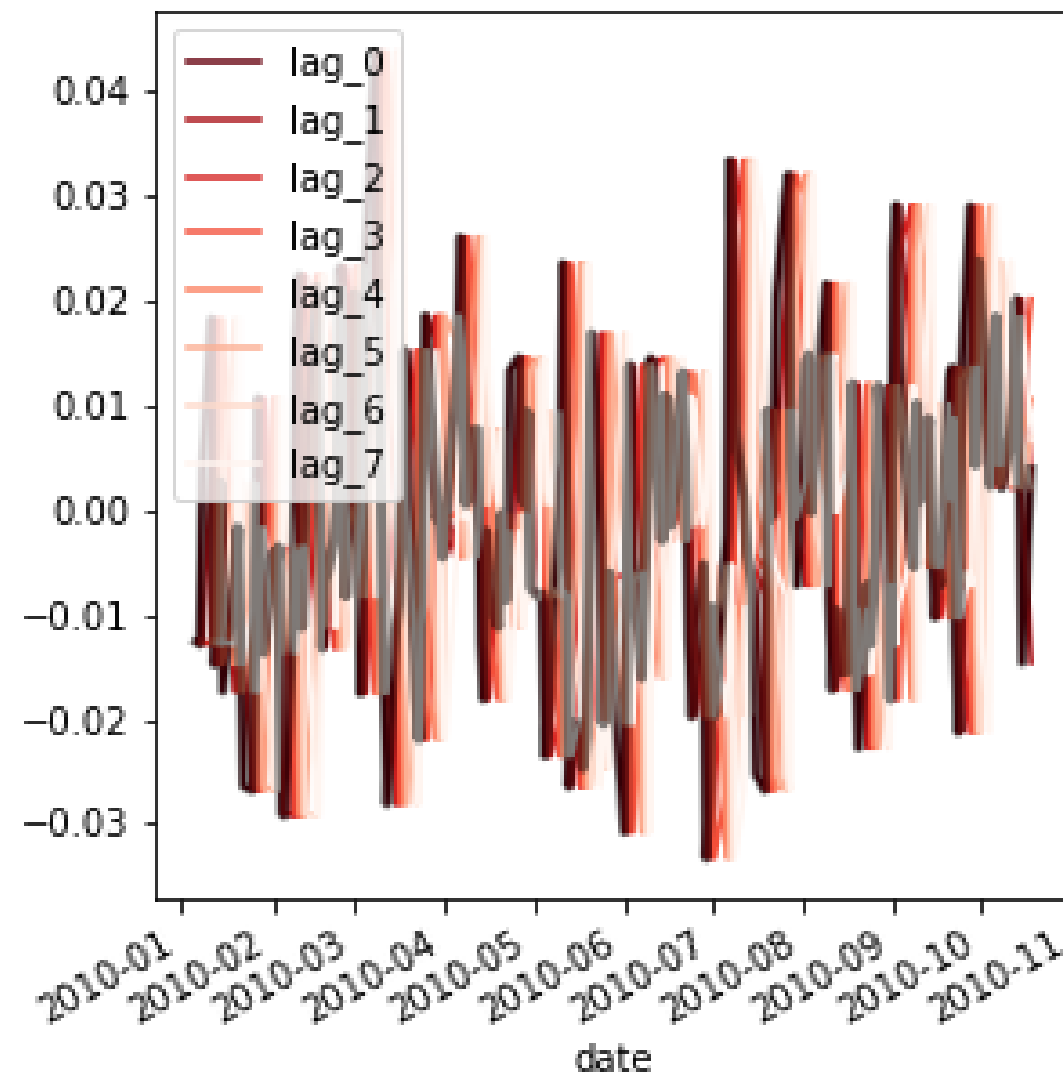
```
# Visualize the fit model coefficients
fig, ax = plt.subplots()
ax.bar(many_shifts.columns, model.coef_)
ax.set(xlabel='Coefficient name', ylabel='Coefficient value')

# Set formatting so it looks nice
plt.setp(ax.get_xticklabels(), rotation=45, horizontalalignment='right')
```

Matplotlib



# Visualizing coefficients for a rough signal

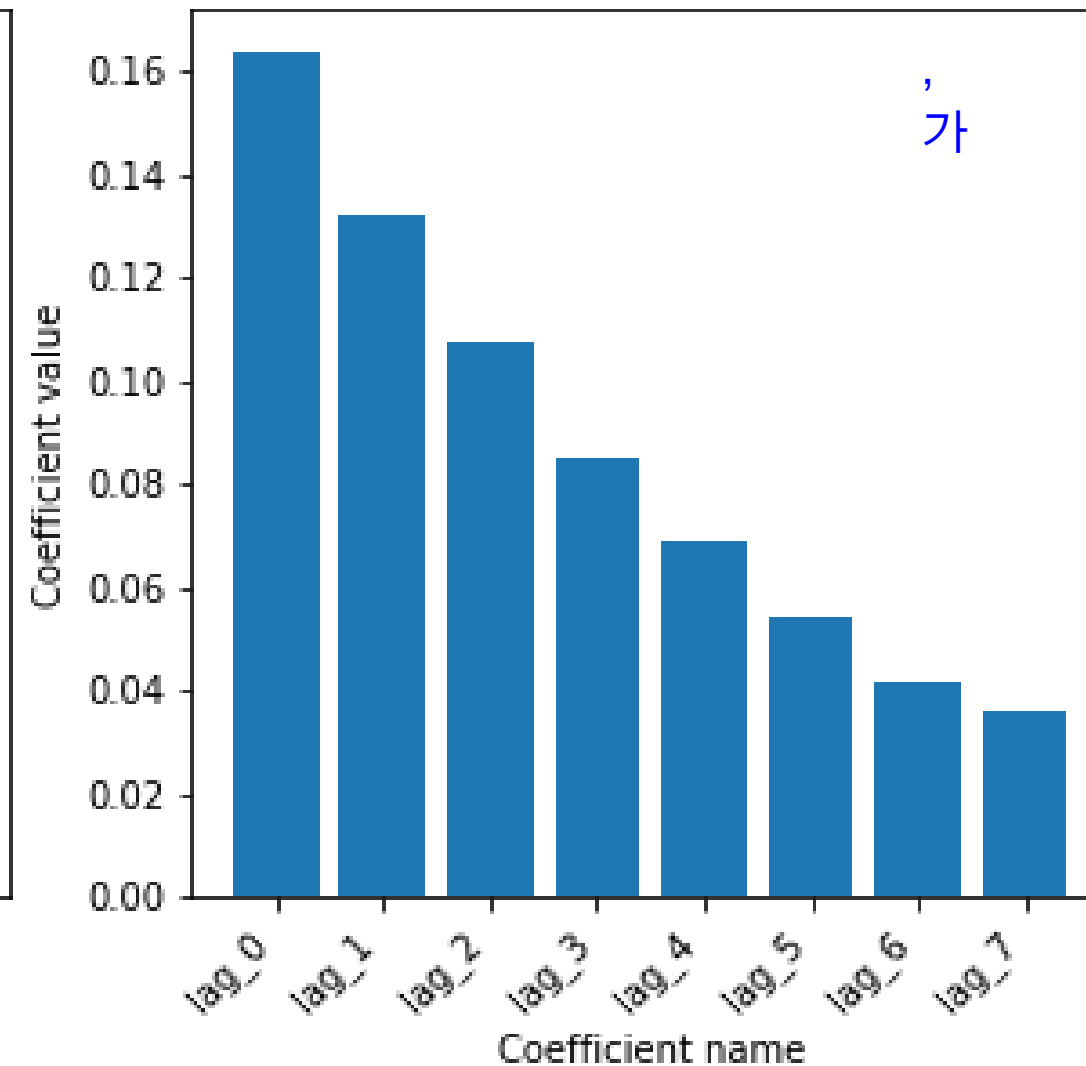
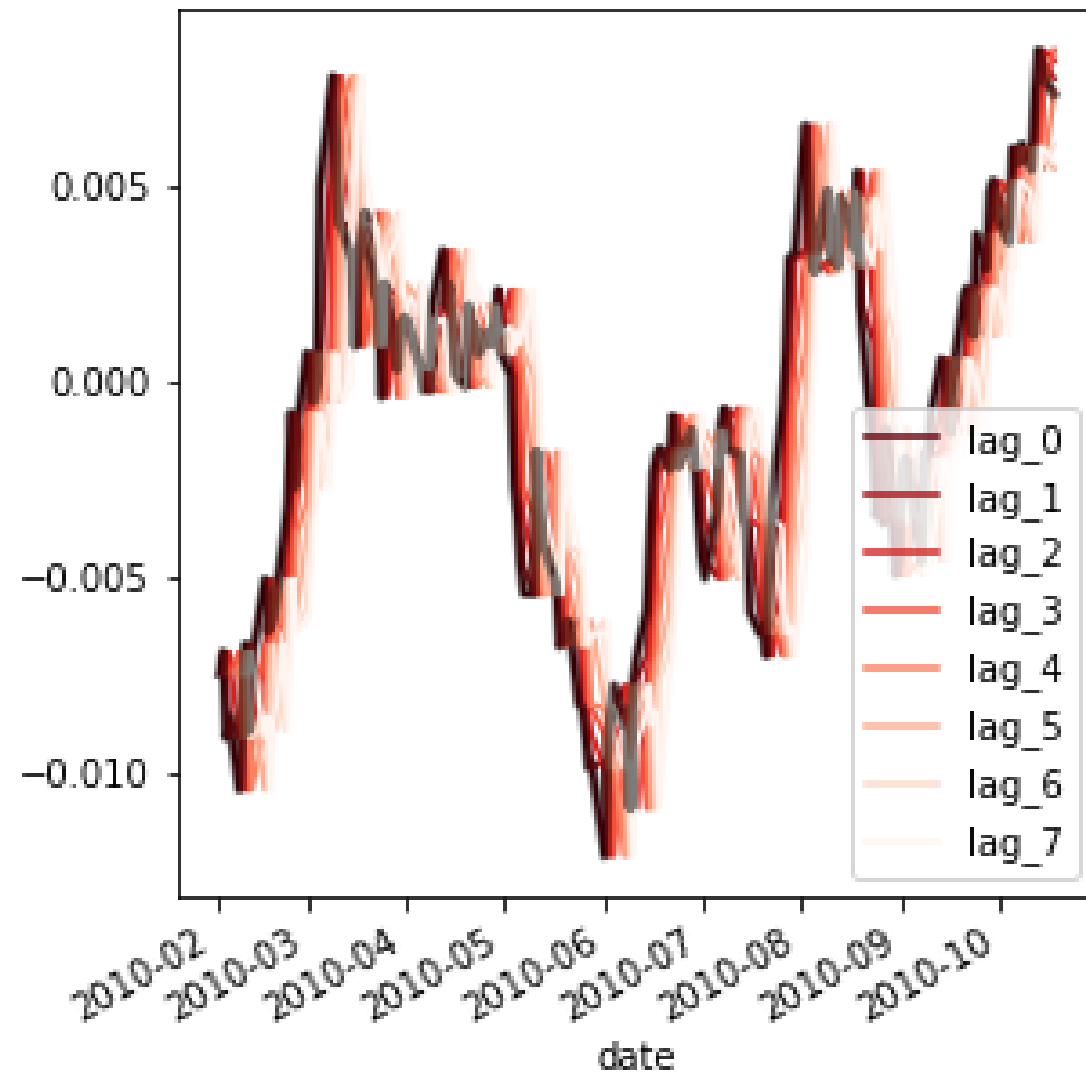


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# Visualizing coefficients for a smooth signal



# Let's practice!

MACHINE LEARNING FOR TIME SERIES DATA IN PYTHON

# Cross-validating timeseries data

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# Cross validation with scikit-learn

```
# Iterating over the "split" method yields train/test indices
for tr, tt in cv.split(X, y):
    model.fit(X[tr], y[tr])
    model.score(X[tt], y[tt])
```

Scikit - learn

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# Cross validation types: KFold

- `KFold` cross-validation splits your data into multiple "folds" of equal size
- It is one of the most common cross-validation routines

```
from sklearn.model_selection import KFold
cv = KFold(n_splits=5)
for tr, tt in cv.split(X, y):
    ...
```

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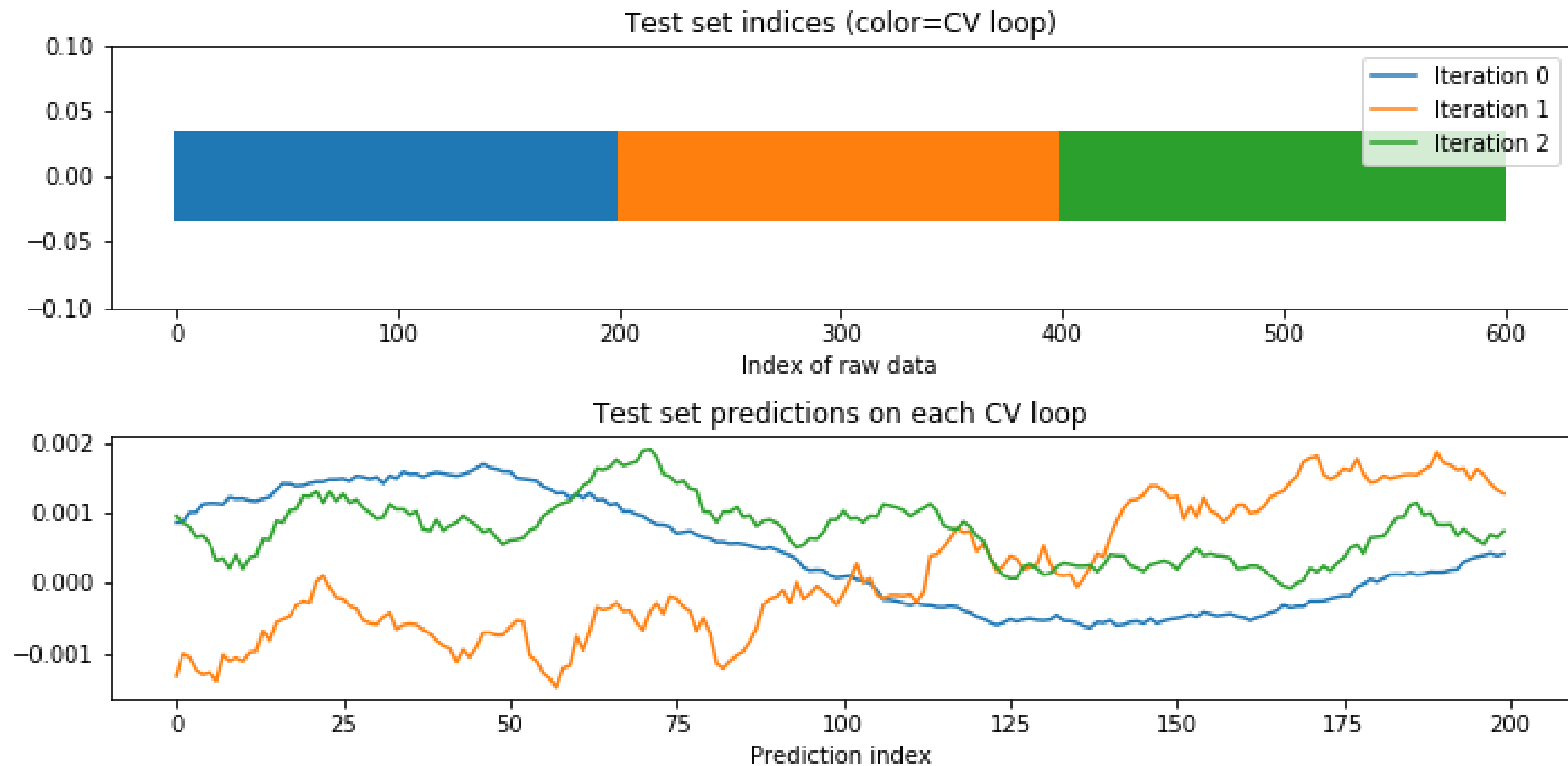
# Visualizing model predictions

```
fig, axs = plt.subplots(2, 1)

# Plot the indices chosen for validation on each loop
axs[0].scatter(tt, [0] * len(tt), marker='_', s=2, lw=40)
axs[0].set(ylim=[-.1, .1], title='Test set indices (color=CV loop)',
           xlabel='Index of raw data')

# Plot the model predictions on each iteration
axs[1].plot(model.predict(X[tt]))
axs[1].set(title='Test set predictions on each CV loop',
           xlabel='Prediction index')
```

# Visualizing KFold CV behavior



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# A note on shuffling your data

- Many CV iterators let you shuffle data as a part of the cross-validation process.
- This only works if the data is i.i.d., which timeseries usually is **not**.
- You should *not* shuffle your data when making predictions with timeseries.

```
from sklearn.model_selection import ShuffleSplit

cv = ShuffleSplit(n_splits=3)
for tr, tt in cv.split(X, y):
    ...
```

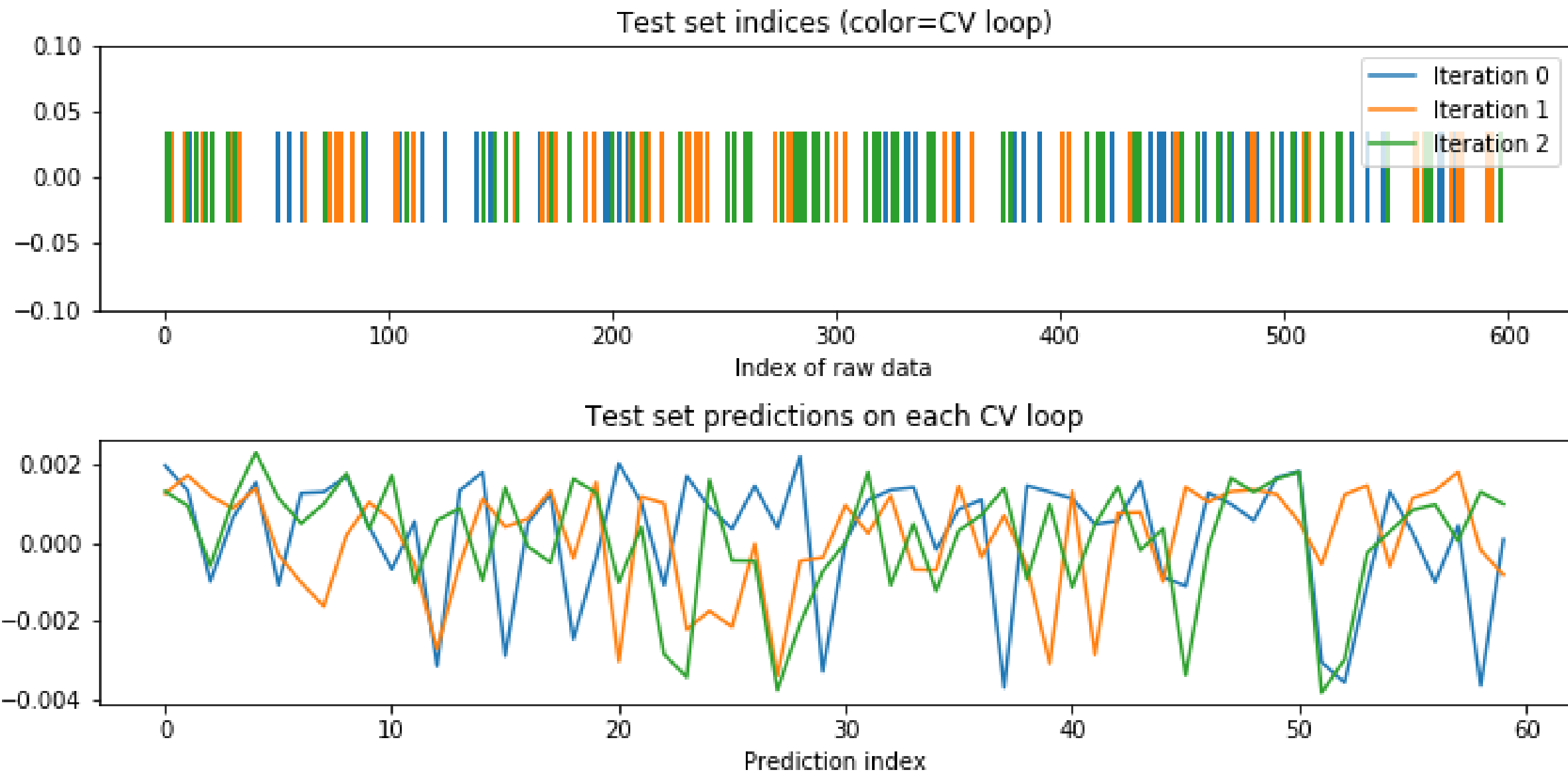
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"ShuffleSplit"

# Visualizing shuffled CV behavior



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# Using the time series CV iterator

- Thus far, we've broken the linear passage of time in the cross validation
- However, you generally **should not** use datapoints in the future to predict data in the past
- One approach: Always use training data from the **past** to predict the **future**

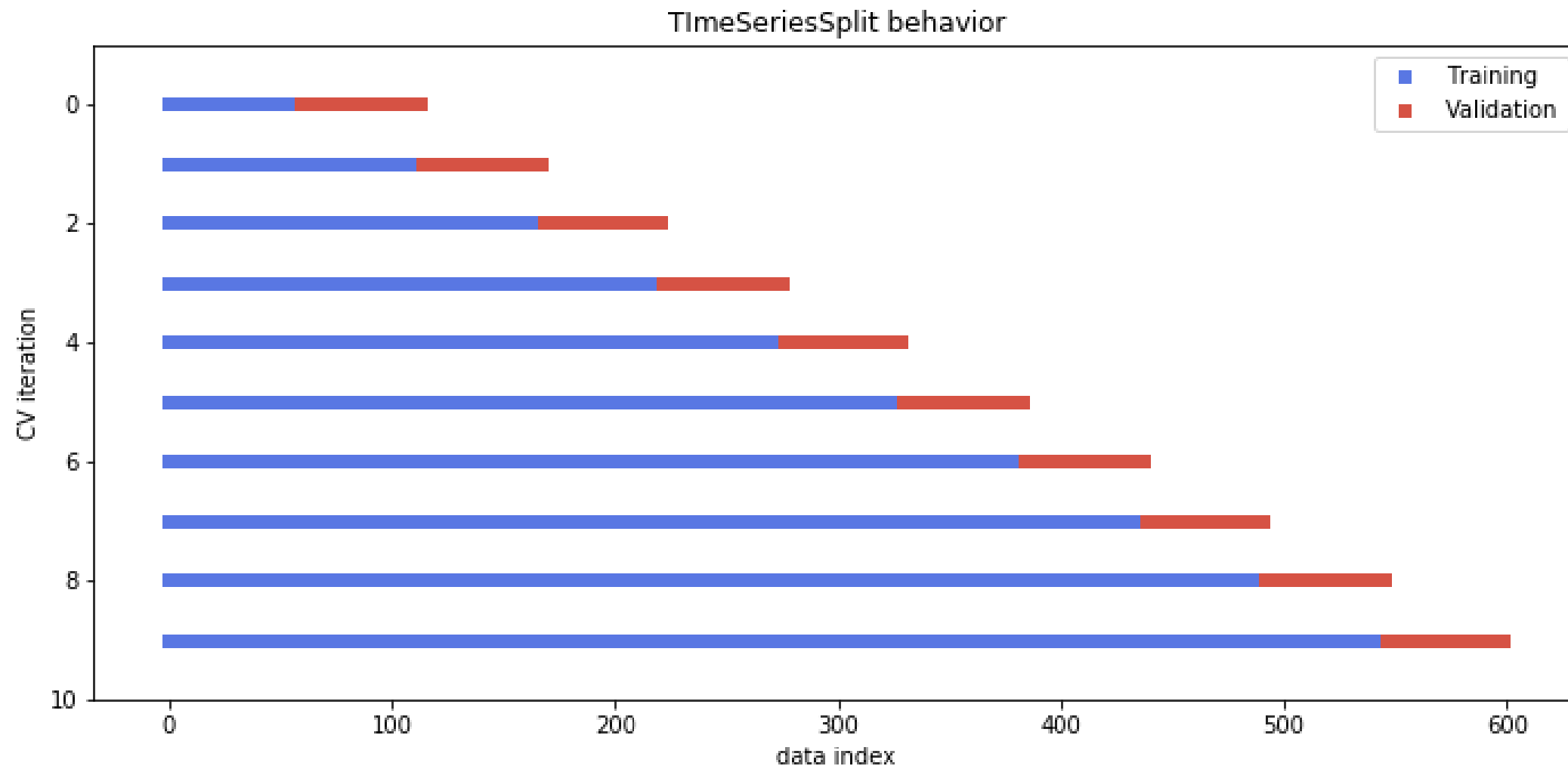
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# Visualizing time series cross validation iterators

```
# Import and initialize the cross-validation iterator
from sklearn.model_selection import TimeSeriesSplit      Scikit - learn      TimeSeriesSplit
cv = TimeSeriesSplit(n_splits=10)

fig, ax = plt.subplots(figsize=(10, 5))
for ii, (tr, tt) in enumerate(cv.split(X, y)):
    # Plot training and test indices
    l1 = ax.scatter(tr, [ii] * len(tr), c=[plt.cm.coolwarm(.1)],
                    marker='_', lw=6)
    l2 = ax.scatter(tt, [ii] * len(tt), c=[plt.cm.coolwarm(.9)],
                    marker='_', lw=6)
    ax.set(ylim=[10, -1], title='TimeSeriesSplit behavior',
           xlabel='data index', ylabel='CV iteration')
    ax.legend([l1, l2], ['Training', 'Validation'])
```

# Visualizing the TimeSeriesSplit cross validation iterator



TimeSeriesSplit CV

# Custom scoring functions in scikit-learn

```
def myfunction(estimator, X, y):  
    y_pred = estimator.predict(X)  
    my_custom_score = my_custom_function(y_pred, y)  
    return my_custom_score
```

Scikit - learn

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# A custom correlation function for scikit-learn

```
def my_pearsonr(est, X, y):  
    # Generate predictions and convert to a vector  
    y_pred = est.predict(X).squeeze()  
  
    # Use the numpy "corrcoef" function to calculate a correlation matrix  
    my_corrcoef_matrix = np.corrcoef(y_pred, y.squeeze())  
  
    # Return a single correlation value from the matrix  
    my_corrcoef = my_corrcoef[1, 0]  
    return my_corrcoef
```

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# Let's practice!

MACHINE LEARNING FOR TIME SERIES DATA IN PYTHON



# Stationarity and stability

MACHINE LEARNING FOR TIME SERIES DATA IN PYTHON



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# Stationarity

- Stationary time series do not change their statistical properties over time
- E.g., mean, standard deviation, trends
- Most time series are non-stationary to some extent

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# Model stability

- Non-stationary data results in variability in our model
- The statistical properties the model finds may change with the data
- In addition, we will be less certain about the correct values of model parameters
- How can we quantify this?

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# Cross validation to quantify parameter stability

- One approach: use cross-validation
- Calculate model parameters on each iteration
- Assess parameter stability across all CV splits

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# Bootstrapping the mean

- Bootstrapping is a common way to assess variability
- The bootstrap:
  1. Take a random sample of data **with replacement**
  2. Calculate the mean of the sample
  3. Repeat this process many times (1000s)
  4. Calculate the percentiles of the result (usually 2.5, 97.5)

The result is a *95% confidence interval* of the mean of each coefficient.

# Bootstrapping the mean

```
from sklearn.utils import resample

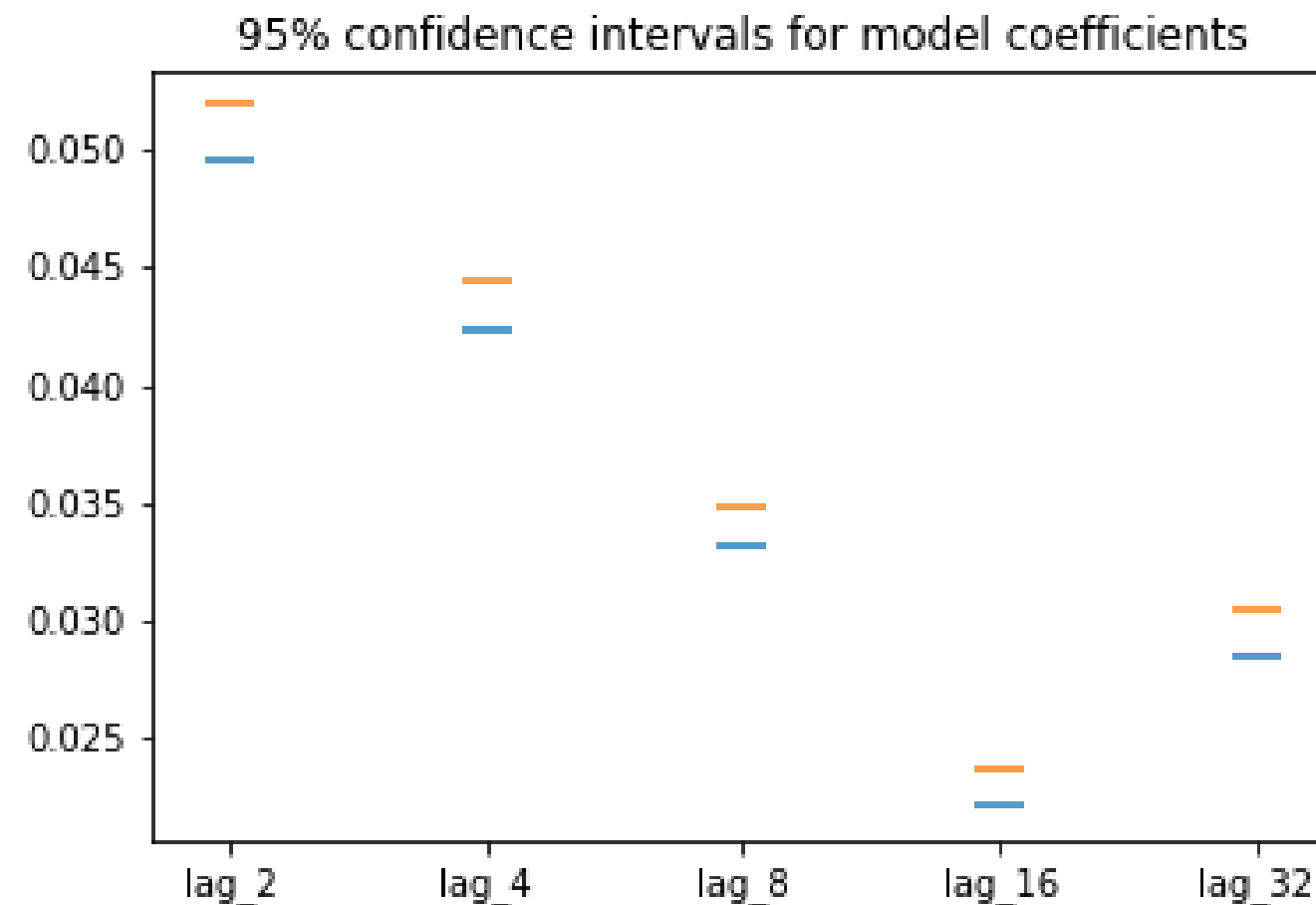
# cv_coefficients has shape (n_cv_folds, n_coefficients)
n_boots = 100
bootstrap_means = np.zeros(n_boots, n_coefficients)
for ii in range(n_boots):
    # Generate random indices for our data with replacement,
    # then take the sample mean
    random_sample = resample(cv_coefficients)
    bootstrap_means[ii] = random_sample.mean(axis=0)

# Compute the percentiles of choice for the bootstrapped means
percentiles = np.percentile(bootstrap_means, (2.5, 97.5), axis=0)
```

numpy 가 .  
skikit - learn  
numpy  
- 5 97 - 5  
95%  
2

# Plotting the bootstrapped coefficients

```
fig, ax = plt.subplots()
ax.scatter(many_shifts.columns, percentiles[0], marker='_', s=200)
ax.scatter(many_shifts.columns, percentiles[1], marker='_', s=200)
```



가 95%



# Assessing model performance stability

- If using the TimeSeriesSplit, can *plot* the model's score over time.
- This is useful in finding certain regions of time that hurt the score
- Also useful to find non-stationary signals

TimeSeriesSplit

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# Model performance over time

```
def my_corrcoef(est, X, y):  
    """Return the correlation coefficient  
    between model predictions and a validation set."""  
    return np.corrcoef(y, est.predict(X))[1, 0]  
  
# Grab the date of the first index of each validation set  
first_indices = [data.index[tt[0]] for tr, tt in cv.split(X, y)]  
  
# Calculate the CV scores and convert to a Pandas Series  
cv_scores = cross_val_score(model, X, y, cv=cv, scoring=my_corrcoef)  
cv_scores = pd.Series(cv_scores, index=first_indices)  
  
cross_val_score  
cross_val_score
```

# Visualizing model scores as a timeseries

```
fig, axs = plt.subplots(2, 1, figsize=(10, 5), sharex=True)

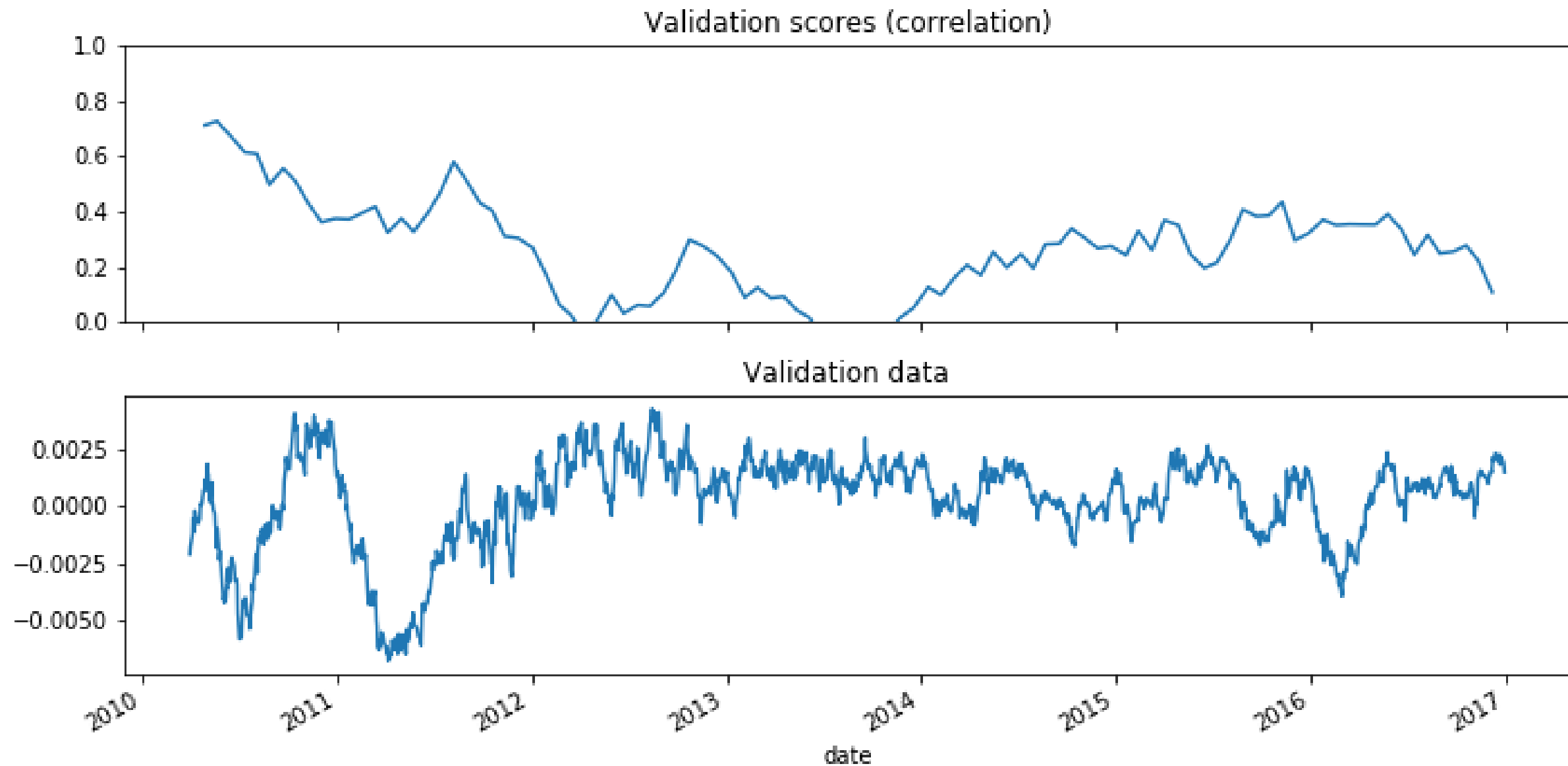
# Calculate a rolling mean of scores over time
cv_scores_mean = cv_scores.rolling(10, min_periods=1).mean()
cv_scores.plot(ax=axs[0])
axs[0].set(title='Validation scores (correlation)', ylim=[0, 1])

# Plot the raw data
data.plot(ax=axs[1])
axs[1].set(title='Validation data')
```

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matplotlib .

# Visualizing model scores



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# Fixed windows with time series cross-validation

```
# Only keep the last 100 datapoints in the training data
window = 100

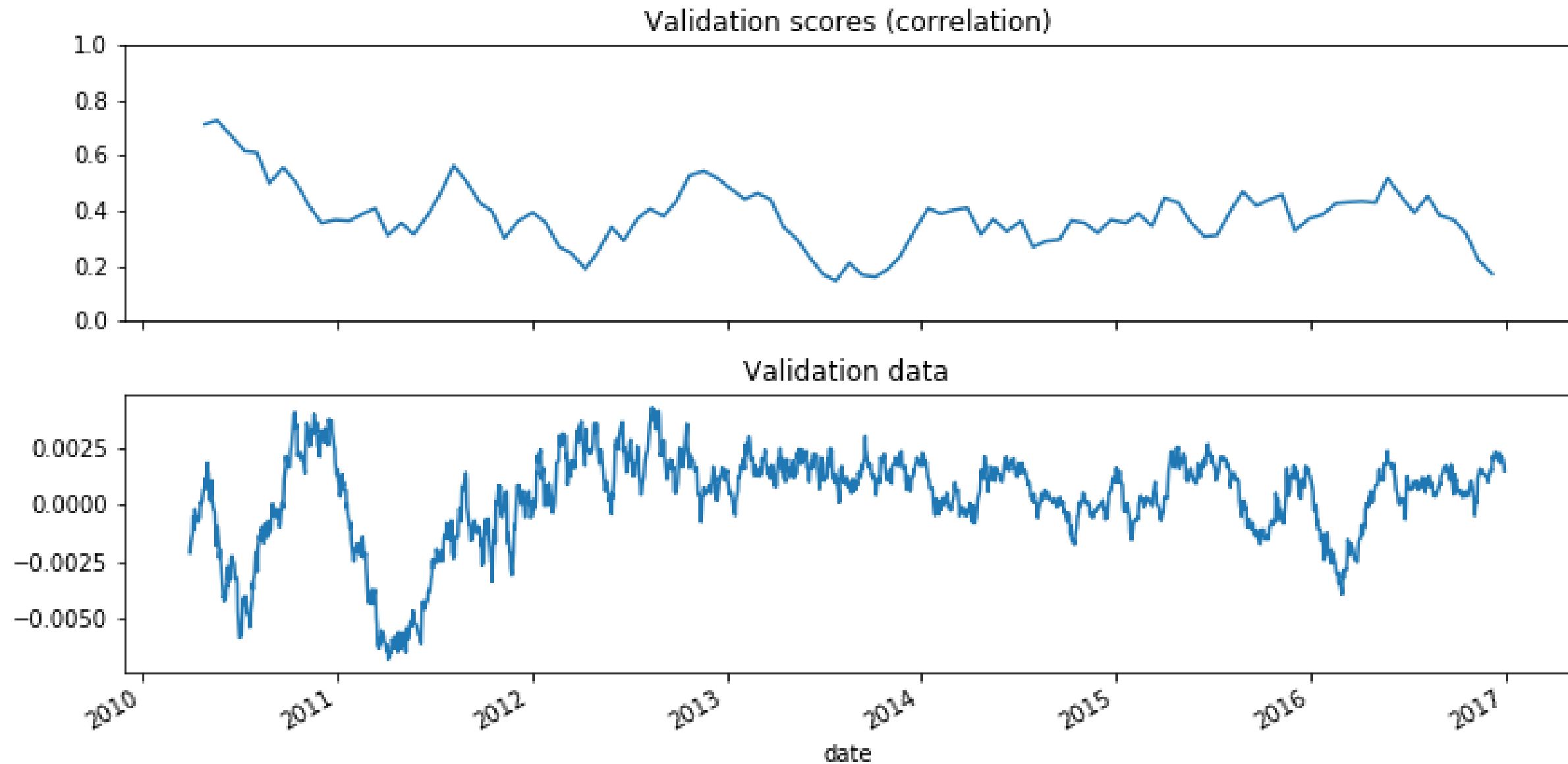
# Initialize the CV with this window size
cv = TimeSeriesSplit(n_splits=10, max_train_size=window)
```

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. max\_train\_size

# Non-stationary signals



# Let's practice!

MACHINE LEARNING FOR TIME SERIES DATA IN PYTHON

# Wrapping-up

MACHINE LEARNING FOR TIME SERIES DATA IN PYTHON



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# Timeseries and machine learning

- The many applications of time series + machine learning
- Always visualize your data first
- The scikit-learn API standardizes this process

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# Feature extraction and classification

- Summary statistics for time series classification
- Combining multiple features into a single input matrix
- Feature extraction for time series data

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# Model fitting and improving data quality

- Time series features for regression
- Generating predictions over time
- Cleaning and improving time series data

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# Validating and assessing our model performance

- Cross-validation with time series data (don't shuffle the data!)
- Time series stationarity
- Assessing model coefficient and score stability

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# Advanced concepts in time series

- Advanced window functions
- Signal processing and filtering details
- Spectral analysis

# Advanced machine learning

- Advanced time series feature extraction (e.g., tsfresh )
- More complex model architectures for regression and classification
- Production-ready pipelines for time series analysis

```
" tsfresh , . . . 가 , "
```

# Ways to practice

- There are a lot of opportunities to practice your skills with time series data.
- Kaggle has a number of time series predictions challenges
- Quantopian is also useful for learning and using predictive models others have built.

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# Let's practice!

MACHINE LEARNING FOR TIME SERIES DATA IN PYTHON