HW8

January 19, 2022

1 HW8

Copy class example.

[1]:
```
data_location = 'sqlite:///../../data/data.db'
```

[2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from functools import reduce

import pickle
```

[3]:
```
def vol_ohlc(df, lookback=10):
    o = df.open
    h = df.high
    l = df.low
    c = df.close

    k = 0.34 / (1.34 + (lookback+1)/(lookback-1))
    cc = np.log(c/c.shift(1))
    ho = np.log(h/o)
    lo = np.log(l/o)
    co = np.log(c/o)
    oc = np.log(o/c.shift(1))
    oc_sq = oc**2
    cc_sq = cc**2
    rs = ho*(ho-co)+lo*(lo-co)
    close_vol = cc_sq.rolling(lookback).sum() * (1.0 / (lookback - 1.0))
    open_vol = oc_sq.rolling(lookback).sum() * (1.0 / (lookback - 1.0))
    window_rs = rs.rolling(lookback).sum() * (1.0 / (lookback - 1.0))
    result = (open_vol + k * close_vol + (1-k) * window_rs).apply(np.sqrt) * np.
 ↪sqrt(252)
    result[:lookback-1] = np.nan

    return result
```

[4]:
```
def plot_learning_curve(
    estimator,
    title,
    X,
    y,
    axes=None,
    ylim=None,
    cv=None,
    n_jobs=None,
    train_sizes=np.linspace(0.1, 1.0, 5),
    scoring=None
):
    if axes is None:
        _, axes = plt.subplots(1, 3, figsize=(20, 5))

    axes[0].set_title(title)
    if ylim is not None:
        axes[0].set_ylim(*ylim)
    axes[0].set_xlabel("Training examples")
    axes[0].set_ylabel("Score")

    train_sizes, train_scores, test_scores, fit_times, _ = learning_curve(
        estimator,
        X,
        y,
        cv=cv,
        n_jobs=n_jobs,
        train_sizes=train_sizes,
        return_times=True,
        scoring=scoring,
    )
    train_scores_mean = np.mean(train_scores, axis=1)
    train_scores_std = np.std(train_scores, axis=1)
    test_scores_mean = np.mean(test_scores, axis=1)
    test_scores_std = np.std(test_scores, axis=1)
    fit_times_mean = np.mean(fit_times, axis=1)
    fit_times_std = np.std(fit_times, axis=1)

    # Plot learning curve
    axes[0].grid()
    axes[0].fill_between(
        train_sizes,
        train_scores_mean - train_scores_std,
        train_scores_mean + train_scores_std,
        alpha=0.1,
        color="r",
    )
```

```
    axes[0].fill_between(
        train_sizes,
        test_scores_mean - test_scores_std,
        test_scores_mean + test_scores_std,
        alpha=0.1,
        color="g",
    )
    axes[0].plot(
        train_sizes, train_scores_mean, "o-", color="r", label="Training score"
    )
    axes[0].plot(
        train_sizes, test_scores_mean, "o-", color="g", label="Cross-validation␣
↪score"
    )
    axes[0].legend(loc="best")

    # Plot n_samples vs fit_times
    axes[1].grid()
    axes[1].plot(train_sizes, fit_times_mean, "o-")
    axes[1].fill_between(
        train_sizes,
        fit_times_mean - fit_times_std,
        fit_times_mean + fit_times_std,
        alpha=0.1,
    )
    axes[1].set_xlabel("Training examples")
    axes[1].set_ylabel("fit_times")
    axes[1].set_title("Scalability of the model")

    # Plot fit_time vs score
    fit_time_argsort = fit_times_mean.argsort()
    fit_time_sorted = fit_times_mean[fit_time_argsort]
    test_scores_mean_sorted = test_scores_mean[fit_time_argsort]
    test_scores_std_sorted = test_scores_std[fit_time_argsort]
    axes[2].grid()
    axes[2].plot(fit_time_sorted, test_scores_mean_sorted, "o-")
    axes[2].fill_between(
        fit_time_sorted,
        test_scores_mean_sorted - test_scores_std_sorted,
        test_scores_mean_sorted + test_scores_std_sorted,
        alpha=0.1,
    )
    axes[2].set_xlabel("fit_times")
    axes[2].set_ylabel("Score")
    axes[2].set_title("Performance of the model")

    return plt
```

[5]:
```python
ohlc = pd.read_sql('SELECT * FROM ohlc', data_location)
ohlc.shape
```

[5]: (11627, 9)

[6]:
```python
ohlc.head()
```

[6]:
```
                    ts      open      high       low     close       volume  \
0  2021-11-01 00:00:00  61421.37  61669.14  61239.60  61343.68   256.433869
1  2021-11-01 01:00:00  61346.17  61709.82  61171.22  61610.93   332.481185
2  2021-11-01 02:00:00  61610.94  61779.87  61299.89  61333.17   314.250720
3  2021-11-01 03:00:00  61333.17  61457.28  60050.00  60589.06  1059.931358
4  2021-11-01 04:00:00  60590.23  60655.00  59752.92  59971.89   621.419878

      volumeUSD token chain
0  1.575751e+07   BTC   BTC
1  2.044558e+07   BTC   BTC
2  1.935390e+07   BTC   BTC
3  6.414625e+07   BTC   BTC
4  3.744744e+07   BTC   BTC
```

[7]:
```python
ohlc.describe()
```

[7]:
```
               open          high           low         close        volume  \
count  11627.000000  11627.000000  11627.000000  11627.000000  1.162700e+04
mean    5708.198992   5737.512791   5676.641523   5706.967946  7.782893e+05
std    16518.161143  16599.532113  16430.972527  16514.731530  2.057505e+06
min        0.999900      1.000000      0.995100      0.999900  6.713000e+00
25%        4.555900      4.611000      4.496050      4.554350  2.565695e+03
50%       92.590000     93.710000     91.000000     92.600000  4.624230e+04
75%      307.924500    309.700000    305.501000    307.796500  1.768436e+05
max    68638.470000  69000.000000  68456.500000  68639.630000  3.978895e+07

          volumeUSD
count  1.162700e+04
mean   9.847622e+06
std    1.769057e+07
min    1.960784e+03
25%    9.664755e+05
50%    3.420994e+06
75%    1.068309e+07
max    3.988035e+08
```

[8]:
```python
tokens = ohlc.token.unique()
```

[9]:
```python
def df_merge(left, right):
    return pd.merge(left, right, on='ts', how='inner')
```

```python
X = reduce(df_merge, [
    (lambda df:
    (
        df
        .assign(
            vol=vol_ohlc(df).fillna(0),
            ret=df.close.pct_change()
        )[['ts', 'vol', 'ret']]
        .rename(columns={
            col: f'{col}_{token}' for col in ['ts', 'vol', 'ret'] if col != 'ts'
        })
    ))(ohlc[ohlc.token == token])
    for token in tokens
]).set_index('ts')
```

[10]:
```python
X.shape
```

[10]: (1057, 22)

[11]:
```python
X.tail()
```

[11]:
```
                      vol_BTC   ret_BTC   vol_ETH   ret_ETH  vol_USDT  \
ts
2021-12-14 20:00:00  0.136358  0.004810  0.158369  0.005961  0.002463
2021-12-14 21:00:00  0.142237  0.019797  0.170096  0.016737  0.002652
2021-12-14 22:00:00  0.151148  0.010414  0.172081  0.004623  0.002684
2021-12-14 23:00:00  0.149424 -0.000302  0.170257 -0.003195  0.002823
2021-12-15 00:00:00  0.143079 -0.001448  0.159883 -0.000641  0.002816

                     ret_USDT   vol_SOL   ret_SOL   vol_ADA   ret_ADA  …  \
ts                                                                     …
2021-12-14 20:00:00    0.0001  0.216740  0.002798  0.225286  0.014437  …
2021-12-14 21:00:00    0.0000  0.218492  0.025892  0.224116  0.012141  …
2021-12-14 22:00:00    0.0000  0.246122  0.015624  0.232362  0.009295  …
2021-12-14 23:00:00    0.0001  0.238235 -0.010027  0.231115 -0.000157  …
2021-12-15 00:00:00    0.0000  0.228867  0.002517  0.220068 -0.007715  …

                     vol_AVAX  ret_AVAX  vol_ATOM  ret_ATOM   vol_CRV  \
ts
2021-12-14 20:00:00  0.239258  0.008227  0.254118 -0.000471  0.255464
2021-12-14 21:00:00  0.241603  0.019207  0.254350  0.019303  0.263456
2021-12-14 22:00:00  0.268875  0.026851  0.253472  0.012933  0.270895
2021-12-14 23:00:00  0.301778  0.032506  0.245708 -0.009576  0.268758
2021-12-15 00:00:00  0.296444  0.005576  0.234522 -0.003223  0.242546

                      ret_CRV  vol_AAVE  ret_AAVE  vol_COMP  ret_COMP
```

```
ts
2021-12-14 20:00:00  0.003049  0.207758  0.009387  0.284268  0.006813
2021-12-14 21:00:00  0.021277  0.222014  0.022490  0.281497  0.017473
2021-12-14 22:00:00  0.023810  0.220598  0.006242  0.275083  0.009868
2021-12-14 23:00:00 -0.011628  0.219474 -0.003013  0.271229 -0.000864
2021-12-15 00:00:00 -0.002941  0.213360  0.001659  0.246067 -0.001027

[5 rows x 22 columns]
```

[12]:
```
y = X.ret_SOL.shift(-1)[:-1]
X = X[:-1]
```

[13]:
```
X.shape
```

[13]:
```
(1056, 22)
```

[14]:
```
y.shape
```

[14]:
```
(1056,)
```

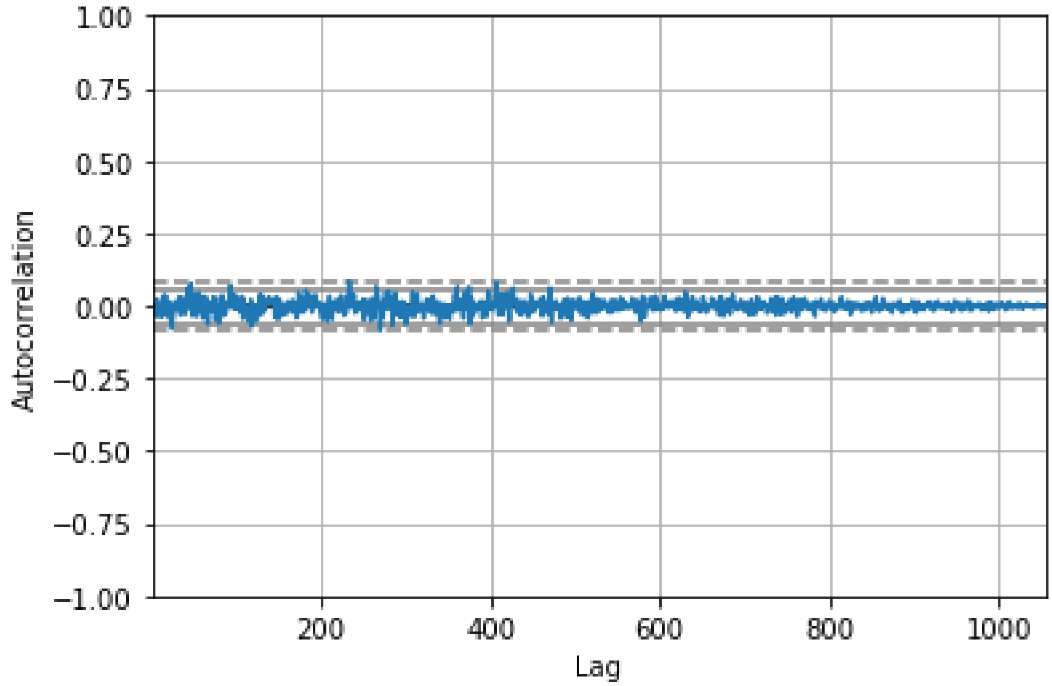
[15]:
```
y.describe()
```

[15]:
```
count    1056.000000
mean       -0.000156
std         0.012010
min        -0.053429
25%        -0.007444
50%        -0.000503
75%         0.006740
max         0.048298
Name: ret_SOL, dtype: float64
```

[16]:
```
from pandas.plotting import scatter_matrix, autocorrelation_plot
```

[17]:
```
autocorrelation_plot(y[1:])
```

[17]:
```
<AxesSubplot:xlabel='Lag', ylabel='Autocorrelation'>
```



[18]:
```
X.head()
```

[18]:
```
                     vol_BTC   ret_BTC  vol_ETH   ret_ETH  vol_USDT  ret_USDT  \
ts
2021-11-01 00:00:00      0.0       NaN      0.0       NaN       0.0       NaN
2021-11-01 01:00:00      0.0  0.004357      0.0  0.006874       0.0    0.0000
2021-11-01 02:00:00      0.0 -0.004508      0.0 -0.005322       0.0   -0.0002
2021-11-01 03:00:00      0.0 -0.012132      0.0 -0.013126       0.0    0.0001
2021-11-01 04:00:00      0.0 -0.010186      0.0 -0.010679       0.0    0.0000

                     vol_SOL   ret_SOL  vol_ADA   ret_ADA  …  vol_AVAX  \
ts                                                         …
2021-11-01 00:00:00      0.0       NaN      0.0       NaN  …       0.0
2021-11-01 01:00:00      0.0  0.027359      0.0  0.003203  …       0.0
2021-11-01 02:00:00      0.0 -0.009879      0.0 -0.008667  …       0.0
2021-11-01 03:00:00      0.0 -0.021692      0.0 -0.007618  …       0.0
2021-11-01 04:00:00      0.0 -0.003039      0.0 -0.006903  …       0.0

                     ret_AVAX  vol_ATOM  ret_ATOM  vol_CRV   ret_CRV  \
ts
2021-11-01 00:00:00       NaN       0.0       NaN      0.0       NaN
2021-11-01 01:00:00 -0.006346       0.0  0.008193      0.0  0.000725
2021-11-01 02:00:00 -0.006231       0.0 -0.025419      0.0 -0.031791
2021-11-01 03:00:00 -0.005329       0.0 -0.013943      0.0 -0.010431
```

```
2021-11-01 04:00:00 -0.008667       0.0 -0.020046      0.0  0.004514

                     vol_AAVE  ret_AAVE  vol_COMP  ret_COMP
ts
2021-11-01 00:00:00       0.0       NaN       0.0       NaN
2021-11-01 01:00:00       0.0  0.008043       0.0 -0.002281
2021-11-01 02:00:00       0.0 -0.009171       0.0 -0.006020
2021-11-01 03:00:00       0.0 -0.013301       0.0 -0.022273
2021-11-01 04:00:00       0.0 -0.016452       0.0 -0.024002

[5 rows x 22 columns]
```

[19]:
```
pd.isnull(X).sum()
```

[19]:
```
vol_BTC     0
ret_BTC     1
vol_ETH     0
ret_ETH     1
vol_USDT    0
ret_USDT    1
vol_SOL     0
ret_SOL     1
vol_ADA     0
ret_ADA     1
vol_DOT     0
ret_DOT     1
vol_AVAX    0
ret_AVAX    1
vol_ATOM    0
ret_ATOM    1
vol_CRV     0
ret_CRV     1
vol_AAVE    0
ret_AAVE    1
vol_COMP    0
ret_COMP    1
dtype: int64
```

[20]:
```
{col: y.corr(X[col]) for col in X.columns if X[col].dtype != 'object'}
```

[20]:
```
{'vol_BTC': 0.028693550573573322,
 'ret_BTC': -0.01384862380414729,
 'vol_ETH': 0.023571512894692854,
 'ret_ETH': 0.030649212659338242,
 'vol_USDT': 0.0068501801913109055,
 'ret_USDT': -0.04440085499052747,
 'vol_SOL': 0.03485259726638475,
```

```
 'ret_SOL': -0.029855064193406503,
 'vol_ADA': 0.03888023343700738,
 'ret_ADA': 0.00024928333961420914,
 'vol_DOT': 0.05904076845167186,
 'ret_DOT': 0.008193946995455023,
 'vol_AVAX': 0.041408511560781514,
 'ret_AVAX': 0.01691945028976705,
 'vol_ATOM': -0.0022346077856851467,
 'ret_ATOM': 0.05546161881659773,
 'vol_CRV': 0.019828890149893356,
 'ret_CRV': -0.005844145396121428,
 'vol_AAVE': 0.0360507780728068,
 'ret_AAVE': 0.019895686732066185,
 'vol_COMP': 0.059842585308615054,
 'ret_COMP': 0.020113141490153072}
```

[21]:

```
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import QuantileTransformer
from sklearn.decomposition import PCA
from sklearn.impute import SimpleImputer

from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer

from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.linear_model import Ridge

from sklearn.model_selection import cross_validate
from sklearn.model_selection import TimeSeriesSplit
from sklearn.metrics import mean_squared_error, make_scorer

from sklearn.model_selection import learning_curve
```

[22]:

```
class FeatureSelector(BaseEstimator, TransformerMixin):
    def __init__(self, columns):
        self.columns = columns

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        return X[self.columns]
```

[23]:

```
def evaluate_model(model, X, y, test_size=0.2):
    cv = TimeSeriesSplit(n_splits=int(y.shape[0] * test_size), test_size=1)
```

```
    scorer = make_scorer(mean_squared_error, greater_is_better=False,␣
↪squared=False)

    return np.mean(cross_validate(model, X, y, cv=cv, scoring=scorer,␣
↪n_jobs=-1)['test_score'])
```

The class example determines the best model as folloing with n_components = 20 and alpha=0.1.

[24]:
```
pipeline = Pipeline([
    ('impute', SimpleImputer(missing_values=np.nan, strategy='constant',␣
↪fill_value=0.)),
    ('scale', StandardScaler()),
    ('pca', PCA(n_components=20)),
    ('model', Ridge(alpha=0.1))
])

evaluate_model(pipeline, X, y)
```

[24]: -0.008575141851714433

Based on the class model, I replace StandardScalar() with other preprocessing methods first but find no difference among them. So I keep using StandardScaler(). Then, according to the diagram under section Estimator Choice, I follow the instructions and try linear SVR model instead of RidgeRegression. From https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVR.html, there are two free parameters: C and epsilon. Since I'm using linear SVR, I tune C parameter only.

[25]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import QuantileTransformer
from sklearn.svm import SVR

pipeline = Pipeline([
    ('impute', SimpleImputer(missing_values=np.nan, strategy='constant',␣
↪fill_value=0.)),
    ('scale', StandardScaler()),
    ('pca', PCA()),
    ('model', SVR())
])

test_size = 0.2
cv = TimeSeriesSplit(n_splits=int(y.shape[0] * test_size), test_size=1)
scorer = make_scorer(mean_squared_error, greater_is_better=False, squared=False)

search = GridSearchCV(pipeline, {
    'model__kernel': ['linear'],
    'pca__n_components': [1, 5, 10, 20, 22],
    'model__C': [.01, .05, .1, .5, 1, 5, 10]
}, scoring=scorer, refit=True, cv=cv, n_jobs=-1)
```

```
search.fit(X, y)
```

[25]:
```
GridSearchCV(cv=TimeSeriesSplit(gap=0, max_train_size=None, n_splits=211,
test_size=1),
             estimator=Pipeline(steps=[('impute',
                                        SimpleImputer(fill_value=0.0,
                                                      strategy='constant')),
                                       ('scale', StandardScaler()),
                                       ('pca', PCA()), ('model', SVR())]),
             n_jobs=-1,
             param_grid={'model__C': [0.01, 0.05, 0.1, 0.5, 1, 5, 10],
                         'model__kernel': ['linear'],
                         'pca__n_components': [1, 5, 10, 20, 22]},
             scoring=make_scorer(mean_squared_error, greater_is_better=False,
squared=False))
```

[26]:
```
search.best_params_
```

[26]:
```
{'model__C': 0.01, 'model__kernel': 'linear', 'pca__n_components': 1}
```

[27]:
```
best_model = search.best_estimator_
```

[28]:
```
evaluate_model(best_model, X, y)
```

[28]:
```
-0.008546201345938906
```

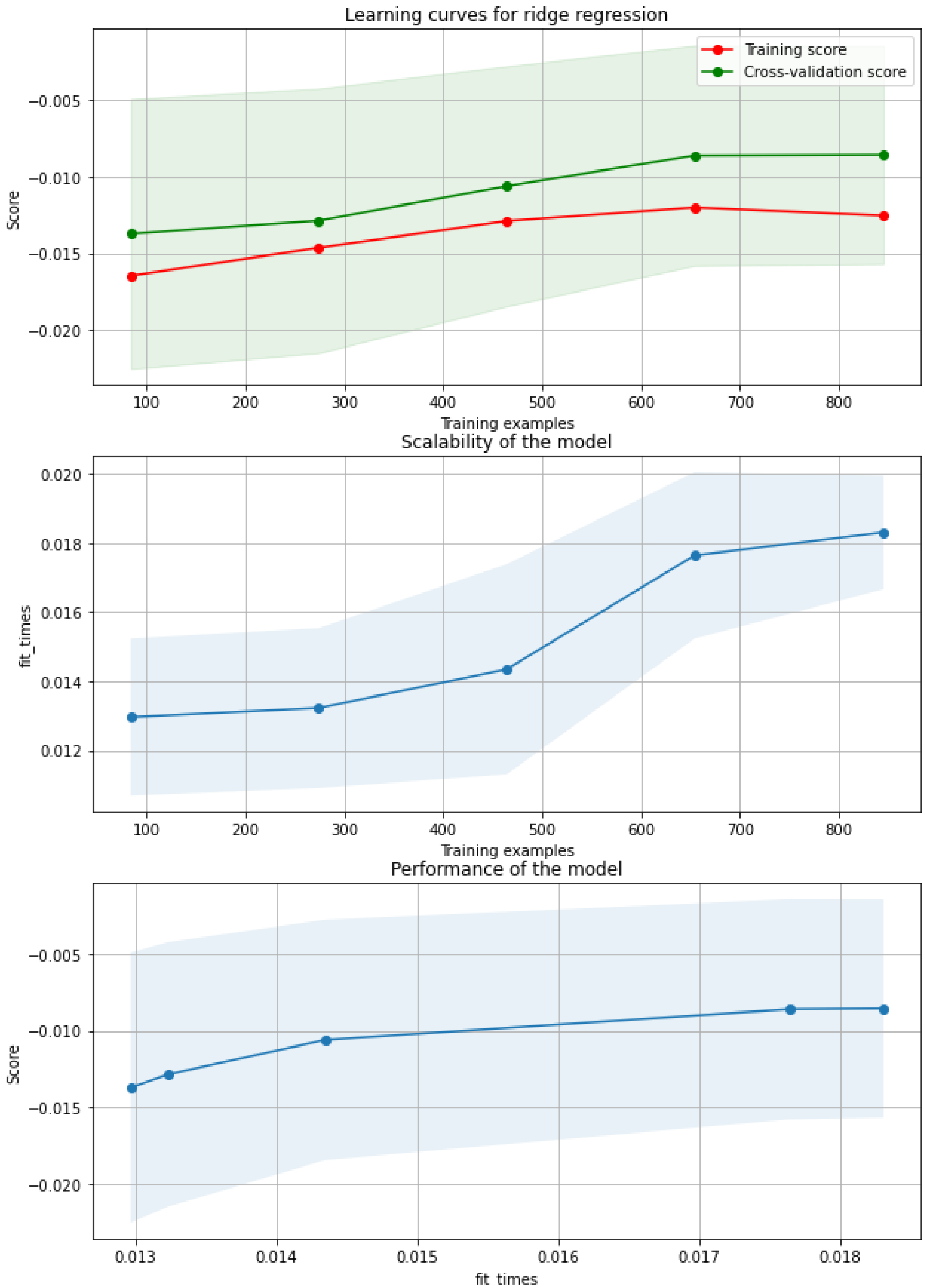
The average cross-validated RMSE is slighly better than the class model. Check the learning curve and save the model.

[29]:
```
fig, axes = plt.subplots(3, 1, figsize=(10, 15))

title = "Learning curves for ridge regression"

plot_learning_curve(
    best_model, title, X, y, axes=axes, cv=cv, n_jobs=4, scoring=scorer
)
```

[29]:
```
<module 'matplotlib.pyplot' from 'C:\\ProgramData\\Anaconda3\\lib\\site-
packages\\matplotlib\\pyplot.py'>
```



[30]:
```
pickle.dump(best_model, open('best_model.pkl', 'wb'))
```

[31]:
```
loaded_model = pickle.load(open('best_model.pkl', 'rb'))
```

[32]:
```
loaded_model == best_model
```

[32]: False

[33]:
```
loaded_model.predict(X.iloc[[-1]])
```

[33]: array([-0.00256548])

[34]:
```
best_model.predict(X.iloc[[-1]])
```

[34]: array([-0.00256548])

[35]:
```
best_model
```

[35]:
```
Pipeline(steps=[('impute', SimpleImputer(fill_value=0.0, strategy='constant')),
                ('scale', StandardScaler()), ('pca', PCA(n_components=1)),
                ('model', SVR(C=0.01, kernel='linear'))])
```

[36]:
```
loaded_model
```

[36]:
```
Pipeline(steps=[('impute', SimpleImputer(fill_value=0.0, strategy='constant')),
                ('scale', StandardScaler()), ('pca', PCA(n_components=1)),
                ('model', SVR(C=0.01, kernel='linear'))])
```

[37]:
```
evaluate_model(best_model, X, y)
```

[37]: -0.008546201345938906

[38]:
```
evaluate_model(loaded_model, X, y)
```

[38]: -0.008546201345938906

[ ]:
```
```