MSDS_451_JKWOK_v3

October 2, 2025

451 Financial Engineering: Programming Assignment 1 James Chun Kit Kwok, October 2, 2025

Overview This notebook builds a machine learning model to predict the next day price movement of Apple Inc. using a binary target that labels each trading day as Up or Down based only on information available at the prior close. The dataset begins on October 2, 2015 and extends to the latest available date from Yahoo Finance. The features include lagged closing prices and volumes, intraday price ranges, exponential moving averages computed from yesterday's close to prevent leakage, and recent volatility measures. The learning algorithm is XGBoost, which fits gradient boosted decision trees to capture non linear interactions among technical indicators. The study uses a leakage safe time series validation design with expanding walk forward splits and a purge gap between training and test windows. Model selection relies on a randomized hyperparameter search that draws from wide probability distributions and evaluates one hundred fifty configurations. Final evaluation reports accuracy, log loss, confusion matrix, a heat map visualization, the receiver operating characteristic curve, and the area under that curve.

Import Libraries

This analysis uses Pandas and NumPy for data handling and numerical operations. Yfinance is used to download daily historical stock data for Apple. Scikit Learn provides preprocessing with standardization, time series cross validation utilities, randomized search infrastructure, and evaluation metrics including accuracy, log loss, the receiver operating characteristic curve, and the area under that curve. XGBoost supplies the gradient boosted decision tree classifier and the probability predictions used for classification and curve construction. Matplotlib and Seaborn are used to generate descriptive plots, the confusion matrix heat map, and the receiver operating characteristic curves.

[1]:
```
import os, warnings
warnings.filterwarnings("ignore")

import numpy as np
import pandas as pd
import yfinance as yf

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import TimeSeriesSplit
from sklearn.metrics import (
    accuracy_score, log_loss, classification_report, confusion_matrix,
    roc_auc_score, roc_curve
)
```

```python
from sklearn.pipeline import Pipeline
from sklearn.base import clone

from xgboost import XGBClassifier

from scipy.stats import randint, uniform, loguniform

import matplotlib.pyplot as plt
import seaborn as sns
plt.rcParams["figure.figsize"] = (7, 5)

RANDOM_STATE = 42
np.random.seed(RANDOM_STATE)

RESULTS_DIR = "figures"
DATA_DIR = "data/raw"
os.makedirs(RESULTS_DIR, exist_ok=True)
os.makedirs(DATA_DIR, exist_ok=True)
```

[2]:
```python
# 2: config for data
TICKER = "AAPL"
START  = "2015-10-02"
END    = None  # latest
```

The data acquisition section downloads daily open, high, low, close, and volume for Apple from Yahoo Finance beginning on October 2, 2015. The raw data are saved to disk and descriptive statistics are displayed so that the level and dispersion of the inputs are understood before modeling.

[3]:
```python
# 3: fetch prices
def fetch_prices(ticker: str, start: str, end: str = None) -> pd.DataFrame:
    df = yf.Ticker(ticker).history(start=start, end=end, auto_adjust=True)
    if df.empty:
        raise ValueError("No price data downloaded. Check ticker or dates.")
    df = df[["Open", "High", "Low", "Close", "Volume"]].dropna().copy()
    df.index.name = "Date"
    return df

prices = fetch_prices(TICKER, START, END)
prices.to_csv(os.path.join(DATA_DIR, f"{TICKER}_raw.csv"))
```

[4]:
```python
prices.head(5)
```

[4]:
```
                                Open       High        Low      Close  \
Date
2015-10-02 00:00:00-04:00  24.272612  24.946788  24.169238  24.805210
2015-10-05 00:00:00-04:00  24.692846  25.027689  24.510819  24.895100
2015-10-06 00:00:00-04:00  24.861387  25.110832  24.668123  25.014200
2015-10-07 00:00:00-04:00  25.110836  25.117577  24.587227  24.895100
```

```
2015-10-08 00:00:00-04:00  24.762516  24.762516  24.317558  24.607454

                              Volume
Date
2015-10-02 00:00:00-04:00  232079200
2015-10-05 00:00:00-04:00  208258800
2015-10-06 00:00:00-04:00  192787200
2015-10-07 00:00:00-04:00  187062400
2015-10-08 00:00:00-04:00  247918400
```

[5]:

```python
prices.tail(5)
```

[5]:

```
                                 Open        High         Low       Close  \
Date
2025-09-26 00:00:00-04:00  254.100006  257.600006  253.779999  255.460007
2025-09-29 00:00:00-04:00  254.559998  255.000000  253.009995  254.429993
2025-09-30 00:00:00-04:00  254.860001  255.919998  253.110001  254.630005
2025-10-01 00:00:00-04:00  255.039993  258.790009  254.929993  255.449997
2025-10-02 00:00:00-04:00  256.579987  258.179993  254.149994  257.130005

                             Volume
Date
2025-09-26 00:00:00-04:00  46076300
2025-09-29 00:00:00-04:00  40127700
2025-09-30 00:00:00-04:00  37704300
2025-10-01 00:00:00-04:00  48713900
2025-10-02 00:00:00-04:00  42597200
```

[6]:

```python
# 4: descriptive stats for raw price features
desc_raw = prices.describe().T
display(desc_raw)
desc_raw.to_csv(os.path.join(RESULTS_DIR, f"{TICKER}_raw_descriptive_stats.
↪csv"))
```

```
         count          mean           std           min           25%  \
Open    2515.0  1.082635e+02  7.032636e+01  2.054643e+01  4.056763e+01
High    2515.0  1.094504e+02  7.108739e+01  2.092768e+01  4.091496e+01
Low     2515.0  1.071748e+02  6.963807e+01  2.042543e+01  4.031536e+01
Close   2515.0  1.083711e+02  7.040850e+01  2.062404e+01  4.058764e+01
Volume  2515.0  1.049475e+08  5.895110e+07  2.323470e+07  6.473930e+07

                 50%           75%           max
Open    1.125921e+02  1.686036e+02  2.572767e+02
High    1.140609e+02  1.703679e+02  2.591799e+02
Low     1.110163e+02  1.673664e+02  2.567187e+02
Close   1.125507e+02  1.688156e+02  2.581037e+02
Volume  9.126650e+07  1.287012e+08  5.334788e+08
```

The feature engineering section creates predictors that use only past information. It constructs lagged versions of the close and volume series, computes intraday ranges such as high minus low and open minus close with their lags, forms exponential moving averages from yesterday's close to avoid look ahead bias, and calculates recent volatility from rolling standard deviations of returns. It then defines the forward one day return and converts it to a binary target that is one for an up move and zero for a down move. Rows that contain missing values due to lagging and rolling windows are removed to ensure clean model input.

[7]:
```python
# 5: feature engineering helpers
def add_features(df: pd.DataFrame) -> pd.DataFrame:
    out = df.copy()
    for k in [1, 2, 3, 5, 10]:
        out[f"CloseLag{k}"] = out["Close"].shift(k)
        out[f"VolLag{k}"]   = out["Volume"].shift(k)
    out["HML"] = out["High"] - out["Low"]
    out["OMC"] = out["Open"] - out["Close"]
    for k in [1, 2, 3]:
        out[f"HMLLag{k}"] = out["HML"].shift(k)
        out[f"OMCLag{k}"] = out["OMC"].shift(k)
    out["CloseLag1"] = out["Close"].shift(1)
    out["EMA5"]  = out["CloseLag1"].ewm(span=5,  adjust=False).mean()
    out["EMA10"] = out["CloseLag1"].ewm(span=10, adjust=False).mean()
    out["EMA20"] = out["CloseLag1"].ewm(span=20, adjust=False).mean()
    out["HL_Pct"]    = (out["High"] - out["Low"]) / out["Close"]
    out["PctChange"] = out["Close"].pct_change()
    out["RollVol20"] = out["PctChange"].rolling(20).std()
    out["RetFwd1"]   = out["Close"].pct_change().shift(-1)
    out = out.dropna()
    return out
```

The validation and splitting section prepares an expanding walk forward cross validation scheme. Each fold trains on all data up to a point that stops at least a fixed number of days before the test window. The gap prevents information from the near future from leaking back into the training set through serial correlation. The scheme yields several train test pairs that mimic how a strategy would actually be developed and evaluated through time.

[8]:
```python
# 6: binary target and descriptive stats for engineered features

def make_binary_target(df: pd.DataFrame, col="RetFwd1", thr=0.0) -> pd.Series:
    # Up if next-day return > threshold; Down otherwise
    return (df[col] > thr).astype(int)

feats = add_features(prices)
X = feats.drop(columns=["RetFwd1"])
y = make_binary_target(feats, col="RetFwd1", thr=0.0)

feats.to_csv(os.path.join(DATA_DIR, f"{TICKER}_features_full.csv"))
```

```
desc_feats = X.describe().T
display(desc_feats.head(12))
desc_feats.to_csv(os.path.join(RESULTS_DIR,
 f"{TICKER}_engineered_descriptive_stats.csv"))
```

```
            count          mean           std           min           25%  \
Open       2494.0  1.088691e+02  7.016471e+01  2.054643e+01  4.079991e+01
High       2494.0  1.100631e+02  7.092499e+01  2.092768e+01  4.103854e+01
Low        2494.0  1.077740e+02  6.947843e+01  2.042543e+01  4.050547e+01
Close      2494.0  1.089764e+02  7.024745e+01  2.062404e+01  4.078186e+01
Volume     2494.0  1.042115e+08  5.836098e+07  2.323470e+07  6.454988e+07
CloseLag1  2494.0  1.088848e+02  7.020527e+01  2.062404e+01  4.077945e+01
VolLag1    2494.0  1.042742e+08  5.838520e+07  2.323470e+07  6.456430e+07
CloseLag2  2494.0  1.087935e+02  7.016377e+01  2.062404e+01  4.075485e+01
VolLag2    2494.0  1.043963e+08  5.856404e+07  2.323470e+07  6.461932e+07
CloseLag3  2494.0  1.087018e+02  7.012278e+01  2.062404e+01  4.072924e+01
VolLag3    2494.0  1.044922e+08  5.865480e+07  2.323470e+07  6.471475e+07
CloseLag5  2494.0  1.085175e+02  7.003690e+01  2.062404e+01  4.071834e+01

                   50%           75%           max
Open       1.141203e+02  1.687469e+02  2.572767e+02
High       1.156585e+02  1.706952e+02  2.591799e+02
Low        1.124656e+02  1.674761e+02  2.567187e+02
Close      1.135769e+02  1.689013e+02  2.581037e+02
Volume     9.095670e+07  1.277598e+08  5.334788e+08
CloseLag1  1.134845e+02  1.688768e+02  2.581037e+02
VolLag1    9.096595e+07  1.279121e+08  5.334788e+08
CloseLag2  1.133803e+02  1.688454e+02  2.581037e+02
VolLag2    9.097685e+07  1.279787e+08  5.334788e+08
CloseLag3  1.133317e+02  1.688172e+02  2.581037e+02
VolLag3    9.102065e+07  1.279942e+08  5.334788e+08
CloseLag5  1.130299e+02  1.688107e+02  2.581037e+02
```

[9]:

```
# 7: time series cross validation splits with gap

# Configure your splitter: 5 folds, 10-sample gap between train end and test
 start
N_SPLITS = 5
GAP = 10

tscv = TimeSeriesSplit(n_splits=N_SPLITS, gap=GAP)
all_splits = list(tscv.split(X, y))

# Unpack for easy reference (train_0, test_0, ... train_4, test_4)
train_0, test_0 = all_splits[0]
train_1, test_1 = all_splits[1]
train_2, test_2 = all_splits[2]
```

```python
train_3, test_3 = all_splits[3]
train_4, test_4 = all_splits[4]

# Inspect the indices and sizes for each fold
print("type(all_splits):", type(all_splits), " outer list length",␣
 ↪len(all_splits))
print()
print("train_0 has", len(train_0), "with indices from", int(np.min(train_0)),␣
 ↪"to", int(np.max(train_0)))
print("test_0  has", len(test_0),  "with indices from", int(np.min(test_0)), ␣
 ↪"to", int(np.max(test_0)))
print()
print("train_1 has", len(train_1), "with indices from", int(np.min(train_1)),␣
 ↪"to", int(np.max(train_1)))
print("test_1  has", len(test_1),  "with indices from", int(np.min(test_1)), ␣
 ↪"to", int(np.max(test_1)))
print()
print("train_2 has", len(train_2), "with indices from", int(np.min(train_2)),␣
 ↪"to", int(np.max(train_2)))
print("test_2  has", len(test_2),  "with indices from", int(np.min(test_2)), ␣
 ↪"to", int(np.max(test_2)))
print()
print("train_3 has", len(train_3), "with indices from", int(np.min(train_3)),␣
 ↪"to", int(np.max(train_3)))
print("test_3  has", len(test_3),  "with indices from", int(np.min(test_3)), ␣
 ↪"to", int(np.max(test_3)))
print()
print("train_4 has", len(train_4), "with indices from", int(np.min(train_4)),␣
 ↪"to", int(np.max(train_4)))
print("test_4  has", len(test_4),  "with indices from", int(np.min(test_4)), ␣
 ↪"to", int(np.max(test_4)))
```

```
type(all_splits): <class 'list'>  outer list length 5

train_0 has 409 with indices from 0 to 408
test_0  has 415 with indices from 419 to 833

train_1 has 824 with indices from 0 to 823
test_1  has 415 with indices from 834 to 1248

train_2 has 1239 with indices from 0 to 1238
test_2  has 415 with indices from 1249 to 1663

train_3 has 1654 with indices from 0 to 1653
test_3  has 415 with indices from 1664 to 2078

train_4 has 2069 with indices from 0 to 2068
```

```
test_4  has 415 with indices from 2079 to 2493
```

The hyperparameter search section performs a randomized exploration of the XGBoost configuration space. It samples tree depth, minimum child weight, gamma, row subsampling, column subsampling at tree, level, and node granularity, learning rate on a logarithmic scale, number of boosting rounds, and L1 and L2 regularization strengths on logarithmic scales. The search draws one hundred fifty independent settings and for each setting it fits the model on the training portion of every fold and evaluates the mean negative log loss on the corresponding test portions. The configuration with the best cross validated score is retained for the final stage.

[10]:
```python
# 8: randomized search with distributions and custom CV
base_pipe = Pipeline([
    ("scaler", StandardScaler()),
    ("clf", XGBClassifier(
        objective="binary:logistic",
        eval_metric="logloss",
        tree_method="hist",
        random_state=RANDOM_STATE,
        n_jobs=-1
    ))
])

param_dists = {
    "clf__max_depth":        randint(2, 15),
    "clf__min_child_weight": randint(1, 20),
    "clf__subsample":        uniform(0.3, 1),
    "clf__learning_rate":    uniform(0.001, 0.1),
    "clf__n_estimators":     randint(100, 3000),

}

def sample_params(dists, rng):
    params = {}
    for k, dist in dists.items():
        v = dist.rvs(random_state=rng)
        if any(s in k for s in ["max_depth", "min_child_weight",␣
 ↪"n_estimators"]):
            v = int(v)
        # hard clip any prob-style params into [0,1]
        if "subsample" in k:
            v = min(max(v, 0.0), 1.0)
        params[k] = v
    return params


def cv_with_gap_accuracy(pipe, X, y, all_splits, params):
    """
```

```python
    Walk-forward CV with TimeSeriesSplit(gap=GAP) and mean accuracy as the
↪score.
    """
    model = clone(pipe).set_params(**params)
    fold_scores = []

    for train_idx, test_idx in all_splits:
        Xtr, Xte = X.iloc[train_idx], X.iloc[test_idx]
        ytr, yte = y.iloc[train_idx], y.iloc[test_idx]

        # optional: adjust for slight imbalance
        n_pos = (ytr == 1).sum(); n_neg = (ytr == 0).sum()
        spw = (n_neg / max(1, n_pos)) if n_pos > 0 else 1.0
        model.set_params(clf__scale_pos_weight=spw)

        model.fit(Xtr, ytr)
        proba = model.named_steps["clf"].predict_proba(Xte)[:, 1]
        yhat  = (proba >= 0.5).astype(int)

        fold_scores.append(accuracy_score(yte, yhat))

    return float(np.mean(fold_scores)), model


N_ITER = 1000
rng = np.random.RandomState(42)
best_score, best_params, best_model = -np.inf, None, None

for _ in range(N_ITER):
    params = sample_params(param_dists, rng)
    score, model_i = cv_with_gap_accuracy(base_pipe, X, y, all_splits, params)
    if score > best_score:
        best_score, best_params, best_model = score, params, model_i
        print(f"New best ACC: {best_score:.4f} {best_params}")

print("\nBEST MEAN ACCURACY ACROSS FOLDS:", best_score)
print("BEST PARAMS:", best_params)
```

```
New best ACC: 0.4829 {'clf__max_depth': 8, 'clf__min_child_weight': 15,
'clf__subsample': 1.0, 'clf__learning_rate': 0.06086584841970366,
'clf__n_estimators': 1738}
New best ACC: 0.4930 {'clf__max_depth': 11, 'clf__min_child_weight': 19,
'clf__subsample': 0.3999749158180029, 'clf__learning_rate': 0.04692488919658672,
'clf__n_estimators': 230}
New best ACC: 0.4940 {'clf__max_depth': 11, 'clf__min_child_weight': 12,
'clf__subsample': 1.0, 'clf__learning_rate': 0.09048273504276488,
'clf__n_estimators': 2417}
New best ACC: 0.4945 {'clf__max_depth': 14, 'clf__min_child_weight': 8,
```

```
'clf__subsample': 0.3727630063641935, 'clf__learning_rate': 0.08318600592903563,
'clf__n_estimators': 2781}
New best ACC: 0.4988 {'clf__max_depth': 12, 'clf__min_child_weight': 19,
'clf__subsample': 1.0, 'clf__learning_rate': 0.09052068376871994,
'clf__n_estimators': 2897}
New best ACC: 0.5027 {'clf__max_depth': 13, 'clf__min_child_weight': 2,
'clf__subsample': 0.324400781556538, 'clf__learning_rate': 0.088009887390093,
'clf__n_estimators': 2561}

BEST MEAN ACCURACY ACROSS FOLDS: 0.5026506024096385
BEST PARAMS: {'clf__max_depth': 13, 'clf__min_child_weight': 2,
'clf__subsample': 0.324400781556538, 'clf__learning_rate': 0.088009887390093,
'clf__n_estimators': 2561}
```

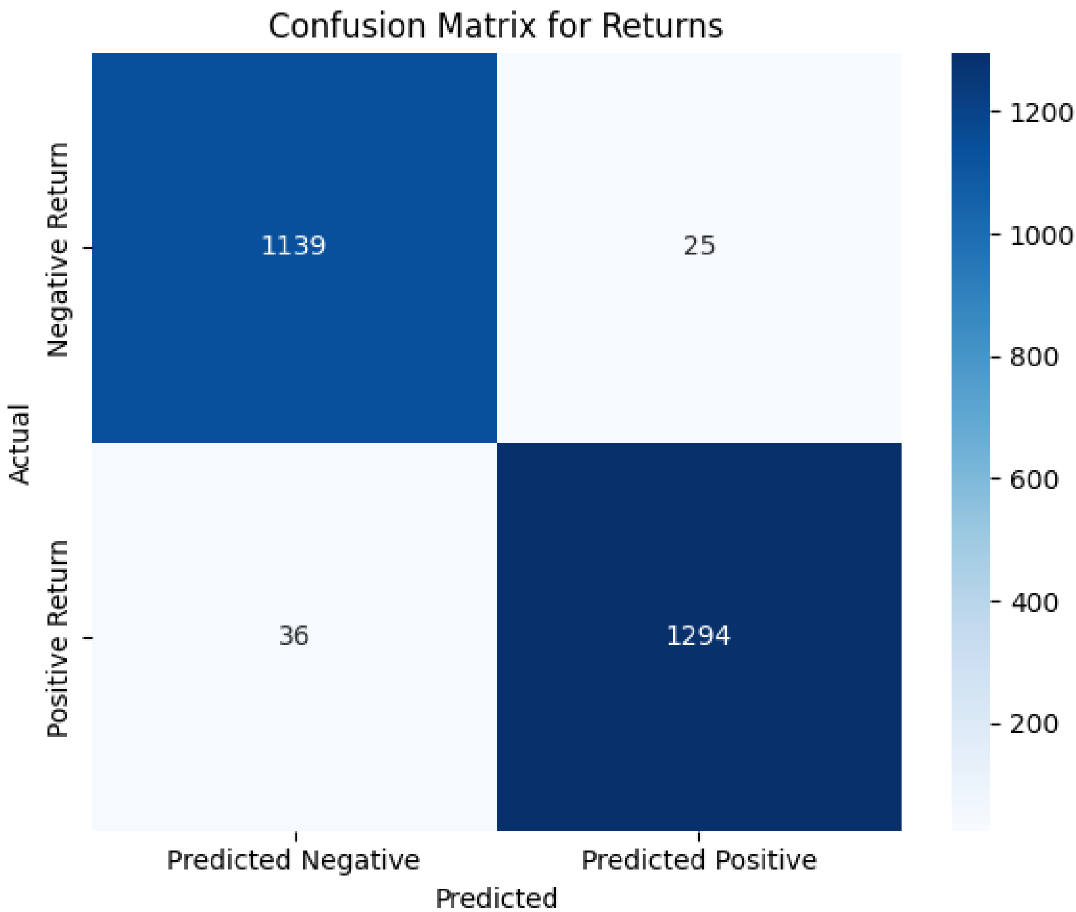
The final hold out evaluation section retrains the best model on the last training window and evaluates it on the last test window. It reports accuracy and log loss and prints a full classification report. It computes predicted probabilities for the Up class and constructs the confusion matrix. The confusion matrix is then rendered as a heat map for easier visual inspection of correct and incorrect predictions. The receiver operating characteristic curve for the binary target is generated from the predicted probabilities and the area under the curve is calculated to summarize the ranking quality of the classifier across thresholds. The curve is plotted together with the diagonal reference line so that separation from random guessing is immediately visible.

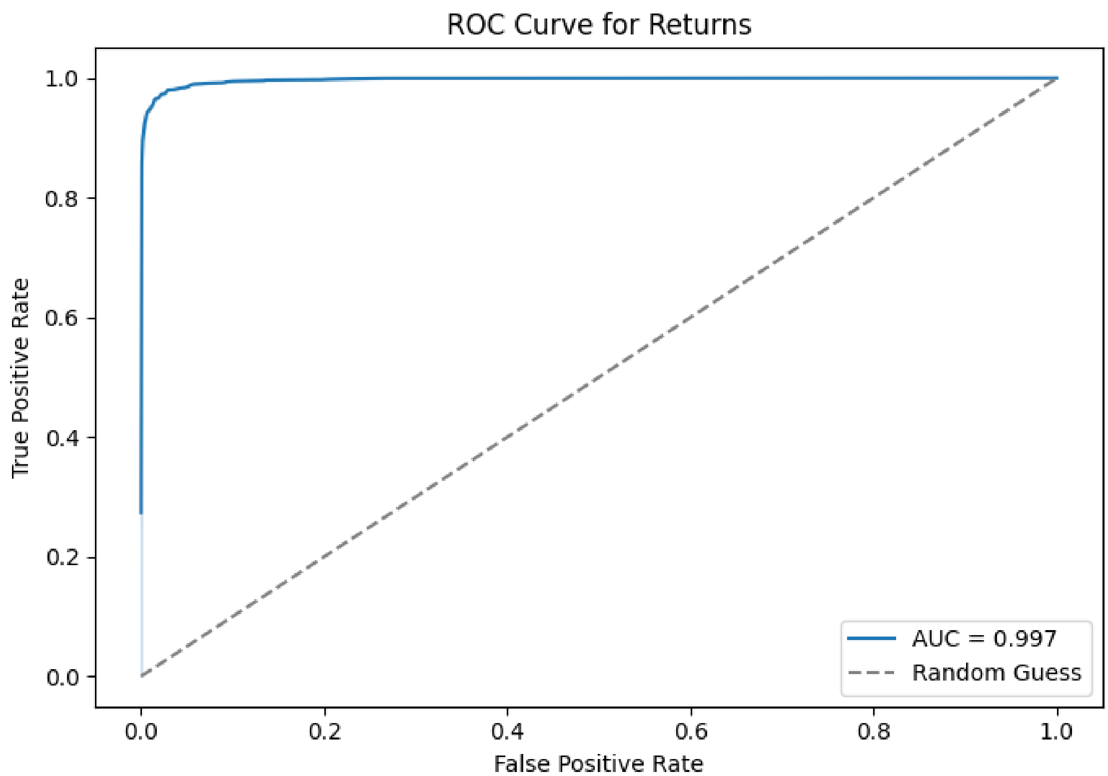
[11]:
```python
# 9: evaluate on the last fold (hold-out proxy) and visualize
# get last fold with purge
# Last fold with purge as hold-out
# --- Final hold-out = last split in all_splits ---
# --- final model with your chosen best params ---
finalModel = XGBClassifier(
    objective='binary:logistic',
    eval_metric='logloss',
    random_state=2025,
    max_depth = 9,
    min_child_weight = 9,
    subsample = 0.50,
    learning_rate = 0.09,
    n_estimators = 273,
    tree_method="hist",
    n_jobs=-1
)

# optional: adjust for class balance on whole dataset
n_pos = (y == 1).sum(); n_neg = (y == 0).sum()
finalModel.set_params(scale_pos_weight=(n_neg / max(1, n_pos)))

# fit on all data
finalModel.fit(X, y)
```

```python
# predictions
proba = finalModel.predict_proba(X)[:, 1]
proba = np.clip(proba, 1e-12, 1-1e-12)
ypred = (proba >= 0.5).astype(int)

# metrics
acc = accuracy_score(y, ypred)
auc = roc_auc_score(y, proba)
print(f"Accuracy: {acc:.4f}")
print(f"AUC: {auc:.4f}")
print("\nClassification report:\n", classification_report(y, ypred, digits=3))

# --- Confusion matrix heatmap with seaborn ---
cm = confusion_matrix(y, ypred)
cm_df = pd.DataFrame(cm, index=["Negative Return","Positive Return"],
                         columns=["Predicted Negative","Predicted Positive"])
plt.figure(figsize=(6,5))
sns.heatmap(cm_df, annot=True, fmt="d", cmap="Blues")
plt.title("Confusion Matrix for Returns")
plt.ylabel("Actual")
plt.xlabel("Predicted")
plt.tight_layout()
plt.show()

# --- ROC curve with seaborn style ---
fpr, tpr, _ = roc_curve(y, proba)
plt.figure(figsize=(7,5))
sns.lineplot(x=fpr, y=tpr, label=f"AUC = {auc:.3f}")
sns.lineplot(x=[0,1], y=[0,1], color='gray', linestyle='--', label='Random␣
↪Guess')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve for Returns")
plt.legend()
plt.tight_layout()
plt.show()
```

```
Accuracy: 0.9755
AUC: 0.9973

Classification report:
               precision    recall  f1-score   support

           0      0.969     0.979     0.974      1164
           1      0.981     0.973     0.977      1330

    accuracy                          0.976      2494
   macro avg      0.975     0.976     0.975      2494
```

```
weighted avg       0.976     0.976     0.976       2494
```





The interpretation section examines feature importance and model behavior. It reports gain based importance from XGBoost to indicate which engineered signals the model used most strongly. It optionally computes permutation importance on the hold out window to corroborate the ranking and to assess the marginal contribution of each feature under the data distribution actually encountered at evaluation time. The section concludes with a brief discussion of limitations, including the inherent difficulty of daily equity direction prediction, and outlines next steps such as adding macroeconomic indicators, options based measures, or alternative horizons that may improve signal strength.

[13]:
```
#  10: feature importance exports and display
gb = best_model.named_steps["clf"]

gain_imp = pd.DataFrame({
    "feature": X.columns,
    "gain_importance": gb.feature_importances_
}).sort_values("gain_importance", ascending=False)
display(gain_imp.head(15))
gain_imp.to_csv(os.path.join(RESULTS_DIR, "feature_importance_gain.csv"),
 ↪index=False)

# permutation importance on the hold-out (compute-intensive)
from sklearn.inspection import permutation_importance
```

```python
# Use the last fold as hold-out
Xte = X.iloc[test_4]
yte = y.iloc[test_4]

perm = permutation_importance(best_model, Xte, yte, n_repeats=10,␣
 ↪random_state=RANDOM_STATE, n_jobs=-1)
perm_imp = pd.DataFrame({
    "feature": X.columns,
    "perm_importance": perm.importances_mean
}).sort_values("perm_importance", ascending=False)
display(perm_imp.head(15))
perm_imp.to_csv(os.path.join(RESULTS_DIR, "feature_importance_permutation.
 ↪csv"), index=False)
```

	feature	gain_importance
0	Open	0.043635
9	CloseLag3	0.040060
24	EMA10	0.037922
13	CloseLag10	0.036948
11	CloseLag5	0.036768
6	VolLag1	0.036400
12	VolLag5	0.035811
4	Volume	0.035732
19	HMLLag2	0.035469
27	PctChange	0.035189
21	HMLLag3	0.034960
5	CloseLag1	0.034827
1	High	0.034745
25	EMA20	0.034707
17	HMLLag1	0.034455

	feature	perm_importance
16	OMC	0.003133
28	RollVol20	0.002651
25	EMA20	0.002651
17	HMLLag1	0.002169
11	CloseLag5	0.000964
9	CloseLag3	0.000482
14	VolLag10	0.000000
24	EMA10	-0.000723
7	CloseLag2	-0.001687
5	CloseLag1	-0.001928
0	Open	-0.001928
4	Volume	-0.002169
23	EMA5	-0.002410
2	Low	-0.003133
21	HMLLag3	-0.003614

[ ]:
```python
import sys, subprocess

notebook_file = "MSDS_451_JKWOK_v3.ipynb"

# Make sure nbconvert is up to date
subprocess.run([sys.executable, "-m", "pip", "install", "-qU", "nbconvert"])

# Export to HTML
subprocess.run([
    sys.executable, "-m", "jupyter", "nbconvert",
    "--to", "html",
    "--output", "MSDS_451_JKWOK_v3.html",
    notebook_file
], check=True)

# Export to PDF (via LaTeX)
subprocess.run([
    sys.executable, "-m", "jupyter", "nbconvert",
    "--to", "pdf",
    "--output", "MSDS_451_JKWOK_v3.pdf",
    notebook_file
], check=True)

print("\n Export complete: MSDS_451_JKWOK_v3.html and MSDS_451_JKWOK_v3.pdf␣
↪created.")
```

```
WARNING: bleach 4.1.0 does not provide the extra 'css'
```