Programming Assignment 3

UP feature and ensemble models exploration continues from the jump-start code below.

MSDS 451 Feature Engineering

Financial Machine Learning: Adding Features to the Mix

Thomas W. Miller, August 25, 2025

Overview

We again use machine learning classifiers, including tree-based ensemble boosting and bagging methods, to predict the direction of oil futures (up or down) using a number of lagged price features. In particular, we look at daily closing spot prices for West Texas Intermediate (ticker WTI) with lags of one to seven days, as well as features based on opening, closing, high, and low price points, and daily trading volume.

Tree-based ensemble models for predicting the direction of daily returns set the stage for testing the predictive utility of additional features. The domain of potential features or leading indicators is wide, including those associated with other price series, economic indicators, international events, securities filings, analyst and news reports, and media measures. Here we explore a set of nine features defined from a range of exchange-traded funds (ETFs).

The model-building process demonstrated here can be employed for any asset or portfolio of assets.

The model building process involves these steps:

- Define price-based features for the target asset.
- Define binary features (Up or not Up) for other assets, economic measures, market measures, worldwide events, and media measures.
- Fit an ensemble model to the full set of features within a time series cross-validation design using a tree-structured ensemble with hyperparameters set to their default values. Note the test set classification performance in predicting movement (Up or not Up) in the target asset.
- Utilized randomized search across key hyperparameters to determine "best" settings.
- Use a hold-out test set to evaluate model performance with "best" hyperparameter settings.
- Rank the importance of features from the model evaluation, and select the best features for subsequent model development.
- Repeat the model-building process, adding new features to the mix.

Import Libraries

We draw on Python packages for data manipulation and modeling. Most important are Polars, a high-performance alternative to Pandas for data manipulation, and Scikit-Learn for machine learning study design and modeling algorithms.

```
!pip install catboost
```

```
Collecting catboost
  Downloading catboost-1.2.8-cp312-cp312-manylinux2014_x86_64.whl.metadata (1.2 kB)
Requirement already satisfied: graphviz in /usr/local/lib/python3.12/dist-packages (from catboost) (0.21)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.12/dist-packages (from catboost) (3.10.0)
Requirement already satisfied: numpy<3.0,>=1.16.0 in /usr/local/lib/python3.12/dist-packages (from catboost) (2.0.2)
Requirement already satisfied: pandas>=0.24 in /usr/local/lib/python3.12/dist-packages (from catboost) (2.2.2)
Requirement already satisfied: scipy in /usr/local/lib/python3.12/dist-packages (from catboost) (1.16.1)
Requirement already satisfied: plotly in /usr/local/lib/python3.12/dist-packages (from catboost) (5.24.1)
Requirement already satisfied: six in /usr/local/lib/python3.12/dist-packages (from catboost) (1.17.0)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.12/dist-packages (from pandas>=0.24->catboost) (2.9.0.pc
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.12/dist-packages (from pandas>=0.24->catboost) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.12/dist-packages (from pandas>=0.24->catboost) (2025.2)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.12/dist-packages (from matplotlib->catboost) (1.3.3)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.12/dist-packages (from matplotlib->catboost) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.12/dist-packages (from matplotlib->catboost) (4.59.1)
Requirement already satisfied: kiwisolver>=1.3.1 in /usr/local/lib/python3.12/dist-packages (from matplotlib->catboost) (1.4.9)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.12/dist-packages (from matplotlib->catboost) (25.0)
Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.12/dist-packages (from matplotlib->catboost) (11.3.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.12/dist-packages (from matplotlib->catboost) (3.2.3)
Requirement already satisfied: tenacity>=6.2.0 in /usr/local/lib/python3.12/dist-packages (from plotly->catboost) (8.5.0)
```

```
Downloading catboost-1.2.8-cp312-cp312-manylinux2014_x86_64.whl (99.2 MB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 99.2/99.2 MB 7.9 MB/s eta 0:00:00
Installing collected packages: catboost
Successfully installed catboost-1.2.8
```

```
import os
# Ignore warnings
import warnings
warnings.filterwarnings('ignore')
warnings.simplefilter(action='ignore', category=FutureWarning)

# datetime functions needed for filtering across DataFrames with differing time frame
from datetime import datetime, timezone

# Import Python Packages for data manipulation, data pipelines, and databases
import numpy as np
import pyarrow # foundation for polars
import polars as pl # DataFrame work superior to Pandas

# Plotting
import matplotlib.pyplot as plt
# Display static plots directly in the notebook output
%matplotlib inline
# create stylized visualizations, including heat maps
import seaborn as sns

# Preprocessing
from sklearn.preprocessing import MinMaxScaler, StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.model_selection import (RandomizedSearchCV,
                                    TimeSeriesSplit)
from sklearn.model_selection import cross_validate

# utilized in all possible subsets classification work
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import log_loss

# needed for randomized search
from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import randint, uniform

# metrics in xgboost tuning and final model evaluation
from sklearn.metrics import (accuracy_score,
                             classification_report,
                             roc_curve,
                             roc_auc_score,
                             RocCurveDisplay,
                             ConfusionMatrixDisplay,
                             confusion_matrix,
                             precision_score,
                             recall_score,
                             f1_score
                            )

from sklearn.ensemble import AdaBoostClassifier

from catboost import CatBoostClassifier

# XGBoost Package... more complete than SciKit-Learn boosting methods
import xgboost as xgb
from xgboost import XGBRegressor, XGBClassifier, plot_importance

from sklearn.ensemble import RandomForestClassifier

import warnings
# Suppress warnings for cleaner output
warnings.filterwarnings('ignore')
```

Retrieve Data

In previous work, we retrieved price data for WTI and nine ETFs from Yahoo Finance. The code for WTI is shown in the next commented-out cell.

```
'''
Previous work to retrieve data from Yahoo Finance had this structure for each of the ETFs in the study

symbol = 'WTI'
start_date = '2000-01-01'
end_date = '2025-08-19'

ticker = yf.Ticker(symbol)
historical_data = ticker.history(start = start_date, end = end_date, period = '1mo')
print(historical_data)

print("type of historical_data", type(historical_data))

historical_data.to_csv("wti_daily_data.csv")
'''
```

```
'\nPrevious work to retrieve data from Yahoo Finance had this structure for each of the ETFs in the study\n\nsymbol = \'WTI\'\nstart_da
te = \'2000-01-01\'\nend_date = \'2025-08-19\'\n\nticker = yf.Ticker(symbol)\nhistorical_data = ticker.history(start = start_date, end
= end_date, period = \'1mo\')\nprint(historical_data)\n\nprint("type of historical_data", type(historical_data))\n\nhistorical_data.to_
```

Polars DataFrame Development

The following code cell demonstrates Polars use with the time series DataFrame for our selected market/ticker, WTI.

```
wti = pl.read_csv("/content/wti_daily_data.csv", try_parse_dates=True)

# check the original schema
print(wti.schema)

# drop useless columns Dividends and StockSplits
wti = wti.drop(['Dividends', 'StockSplits'])

# create lag price features
wti = wti.with_columns((pl.col('Close')).shift().alias('CloseLag1'))
wti = wti.with_columns((pl.col('CloseLag1')).shift().alias('CloseLag2'))
wti = wti.with_columns((pl.col('CloseLag2')).shift().alias('CloseLag3'))

# create high-minus-low (HML) for day and its lags
wti = wti.with_columns((pl.col('High') - pl.col('Low')).alias('HML'))
wti = wti.with_columns((pl.col('HML')).shift().alias('HMLLag1'))
wti = wti.with_columns((pl.col('HMLLag1')).shift().alias('HMLLag2'))
wti = wti.with_columns((pl.col('HMLLag2')).shift().alias('HMLLag3'))

# create a net change for the day as the open minus closing price OMC
# also create the corresponding lag metrics
wti = wti.with_columns((pl.col('Open') - pl.col('Close')).alias('OMC'))
wti = wti.with_columns((pl.col('OMC')).shift().alias('OMCLag1'))
wti = wti.with_columns((pl.col('OMCLag1')).shift().alias('OMCLag2'))
wti = wti.with_columns((pl.col('OMCLag2')).shift().alias('OMCLag3'))

# create volume lag metrics
wti = wti.with_columns((pl.col('Volume')).shift().alias('VolumeLag1'))
wti = wti.with_columns((pl.col('VolumeLag1')).shift().alias('VolumeLag2'))
wti = wti.with_columns((pl.col('VolumeLag2')).shift().alias('VolumeLag3'))

# compute 10-day exponential moving averages of closing prices
# compute acround CloseLag1 to avoid any "leakage" in explanatory variable set
# note also the 10-day buffer between train and test in time-series cross-validation
wti = wti.with_columns((pl.col('CloseLag1').ewm_mean(half_life=1,ignore_nulls=True)).alias('CloseEMA2'))
wti = wti.with_columns((pl.col('CloseLag1').ewm_mean(half_life=2,ignore_nulls=True)).alias('CloseEMA4'))
wti = wti.with_columns((pl.col('CloseLag1').ewm_mean(half_life=4,ignore_nulls=True)).alias('CloseEMA8'))

# log daily returns
wti = wti.with_columns(np.log(pl.col('Close')/pl.col('CloseLag1')).alias('LogReturn'))

# set volume features to Float64 for subsequent use in Numpy arrays
wti = wti.with_columns(
    pl.col('Volume').cast(pl.Float64).round(0),
    pl.col('VolumeLag1').cast(pl.Float64).round(0),
    pl.col('VolumeLag2').cast(pl.Float64).round(0),
    pl.col('VolumeLag3').cast(pl.Float64).round(0),
    )

# round other features to three decimal places for reporting and subsequent analytics
wti = wti.with_columns(
```

```
    pl.col('Open').round(3),
    pl.col('High').round(3),
    pl.col('Low').round(3),
    pl.col('Close').round(3),
    pl.col('CloseLag1').round(3),
    pl.col('CloseLag2').round(3),
    pl.col('CloseLag3').round(3),
    pl.col('HML').round(3),
    pl.col('HMLLag1').round(3),
    pl.col('HMLLag2').round(3),
    pl.col('HMLLag3').round(3),
    pl.col('OMC').round(3),
    pl.col('OMCLag1').round(3),
    pl.col('OMCLag2').round(3),
    pl.col('OMCLag3').round(3),
    pl.col('CloseEMA2').round(3),
    pl.col('CloseEMA4').round(3),
    pl.col('CloseEMA8').round(3))

# no correction for class imbalance in this analysis
# define binary target/response 1 = market price up since previous day, 0 = even or down
wti = wti.with_columns(pl.when(pl.col('LogReturn')>0).then(pl.lit(1)).otherwise(pl.lit(0)).alias('Target'))

# save to external comma-delimited text file for checking calculations in Excel
wti.write_csv("wti-with-computed-features.csv")
```

```
Schema({'Date': Datetime(time_unit='us', time_zone='UTC'), 'Open': Float64, 'High': Float64, 'Low': Float64, 'Close': Float64, 'Volume':
```

Descriptive Statistics for Price Features

```
# Drop the rows with null values such as the initial lag rows
wti = wti.drop_nulls()

# Descriptive statistics
wtiStatistics = wti.drop('Date').describe()

print(wtiStatistics.columns)

wtiStatisticsToPrint = wtiStatistics.transpose(include_header=True).drop(['column_1', 'column_5', 'column_7'])

print(wtiStatisticsToPrint.schema)

with pl.Config(
    tbl_rows = 60,
    tbl_width_chars = 200,
    tbl_cols = -1,
    float_precision = 3,
    tbl_hide_dataframe_shape = True,
    tbl_hide_column_data_types = True):
    print(wtiStatisticsToPrint)
```

```
['statistic', 'Open', 'High', 'Low', 'Close', 'Volume', 'CloseLag1', 'CloseLag2', 'CloseLag3', 'HML', 'HMLLag1', 'HMLLag2', 'HMLLag3', '
Schema({'column': String, 'column_0': String, 'column_2': String, 'column_3': String, 'column_4': String, 'column_6': String, 'column_8'
```

column	column_0	column_2	column_3	column_4	column_6	column_8
statistic	count	mean	std	min	50%	max
Open	5169.0	9.888208357515962	8.24379751138907	1.105	6.597	44.596
High	5169.0	10.104958405881215	8.390030911332957	1.145	6.784	44.626
Low	5169.0	9.646586767266395	8.068196720476314	1.028	6.4	43.235
Close	5169.0	9.871213774424453	8.228563569925155	1.047	6.592	44.172
Volume	5169.0	1748263.726059199	1829939.6046243927	34700.0	1177400.0	40429700.0
CloseLag1	5169.0	9.873441671503192	8.22790431775934	1.047	6.592	44.172
CloseLag2	5169.0	9.87565660669375	8.22725538628012	1.047	6.592	44.172
CloseLag3	5169.0	9.877919326755658	8.226617508094625	1.047	6.592	44.172
HML	5169.0	0.4583662217063263	0.43874669689562873	0.029	0.327	4.129
HMLLag1	5169.0	0.4583936931708261	0.43872807289866955	0.029	0.327	4.129
HMLLag2	5169.0	0.45853685432385377	0.43871551870478587	0.029	0.327	4.129
HMLLag3	5169.0	0.4587094215515574	0.43873022336223927	0.029	0.327	4.129
OMC	5169.0	0.016985683884697237	0.37995566715807194	-3.223	0.01	3.705
OMCLag1	5169.0	0.016974656606693762	0.3799555359557333	-3.223	0.01	3.705
OMCLag2	5169.0	0.01702050686786613	0.3799653728485099	-3.223	0.01	3.705
OMCLag3	5169.0	0.01715302766492551	0.3800928215711145	-3.223	0.01	3.705
VolumeLag1	5169.0	1748148.5974076223	1829989.5770774593	34700.0	1176900.0	40429700.0
VolumeLag2	5169.0	1748359.3538402012	1829930.1201336666	34700.0	1177400.0	40429700.0

VolumeLag3	5169.0	1750131.4954536662	1833301.7931244925	34700.0	1178000.0	40429700.0
CloseEMA2	5169.0	9.875673437802282	8.219729461746063	1.111	6.614	43.432
CloseEMA4	5169.0	9.878829560843492	8.210186049750966	1.136	6.624	43.018
CloseEMA8	5169.0	9.885304314180692	8.190856957522218	1.157	6.649	42.696
LogReturn	5169.0	-0.00039874914065335176	0.04178042201340917	-0.2644790687687591	0.0	0.3488180995786815
Target	5169.0	0.4778487134842329	0.4995574042820073	0.0	0.0	1.0

Base Feature List Defined on WTI Pricing Alone

Features or explanatory variables, also known as an independent variables, are used to predict the values of target variables. The initial list of featrues includes the price-based features defined above, everything except the continuous response **LogReturn** if we wanted to employ regression and the binary response **Target** for classification, which is the focus of this project. This complete feature list is used in evaluating all methods.

We retain Date and Target at this point... Date is needed to select across WTI and the many ETFs. Target is needed as the response in training. These will be dropped from the training features set later.

```
# Select Features for the Model, exclude current day price variables ... no "leakage"
# note for moving averages, we have excluded the current day, and provide a 10-day gap
# so these may be included in the set
wti = wti.drop(['LogReturn', 'Open', 'High', 'Low', 'Close', 'Volume', 'HML', 'OMC'])
wti.head()
```

shape: (5, 17)

Date	CloseLag1	CloseLag2	CloseLag3	HMLLag1	HMLLag2	HMLLag3	OMCLag1	OMCLag2	OMCLag3	VolumeLag1	VolumeLag2	VolumeLag3
datetime[μs, UTC]	f64	f64	f64	f64	f64	f64	f64	f64	f64	f64	f64	f64
2005-02-02 05:00:00 UTC	13.196	13.189	13.406	0.232	0.79	0.942	-0.007	0.217	0.725	656500.0	1.7768e6	9.8135e6
2005-02-03 05:00:00 UTC	13.196	13.196	13.189	0.152	0.232	0.79	0.029	-0.007	0.217	265300.0	656500.0	1.7768e6
2005-02-04 05:00:00 UTC	13.225	13.196	13.196	0.087	0.152	0.232	0.0	0.029	-0.007	303200.0	265300.0	656500.0
2005-02-07 05:00:00 UTC	13.189	13.225	13.196	0.275	0.087	0.152	0.072	0.0	0.029	361100.0	303200.0	265300.0
2005-02-08 05:00:00 UTC	13.218	13.189	13.225	0.196	0.275	0.087	0.152	0.072	0.0	161900.0	361100.0	303200.0

Read Data for Nine Exchange Traded Funds

The following code cells read data from nine exchange-traded funds (ETFs) selected to cover a wide range of asset classes. All of these funds have about a billion or more assets under management (AUM). We note the range of dates covered in each ETF DataFrame. Later we will ensure that the same date ranges are covered by WTI and the nine ETFs. Beginning dates vary, but all time series end on August 19, 2025.

For each selected ETF, we compute a variable named **Up** that is 1 if the price of the ETF went up the previous day, zero if not.

```
# work with SPY data
spy = pl.read_csv("/content/spy_daily_data.csv", try_parse_dates=True)

# drop useless columns Dividends, StockSplits, and CapitalGains
spy = spy.drop(['Dividends', 'StockSplits', 'CapitalGains'])

spy = spy.with_columns((pl.col('Close')).shift().alias('CloseLag1'))
spy = spy.with_columns((pl.col('CloseLag1')).shift().alias('CloseLag2'))
spy = spy.with_columns(pl.when(pl.col('CloseLag1')>pl.col('CloseLag2')).then(pl.lit(1)).otherwise(pl.lit(0)).alias('SPYUp'))
# check the schema
print(spy.schema)

# Drop initial lag row
spy = spy.drop_nulls()

spyStatistics = spy.describe()
print(spyStatistics.columns)
spyStatisticsToPrint = spyStatistics.transpose(include_header=True).drop(['column_1', 'column_5', 'column_6', 'column_7'])
print(wtiStatisticsToPrint.schema)
```

```
with pl.Config(
    tbl_rows = 60,
    tbl_width_chars = 200,
    tbl_cols = -1,
    float_precision = 3,
    tbl_hide_dataframe_shape = True,
    tbl_hide_column_data_types = True):
    print(spyStatisticsToPrint)

# print a few records at the beginning of the DataFrame
print(spy.head())
```

```
Schema({'Date': Datetime(time_unit='us', time_zone='UTC'), 'Open': Float64, 'High': Float64, 'Low': Float64, 'Close': Float64, 'Volume':
['statistic', 'Date', 'Open', 'High', 'Low', 'Close', 'Volume', 'CloseLag1', 'CloseLag2', 'SPYUp']
Schema({'column': String, 'column_0': String, 'column_2': String, 'column_3': String, 'column_4': String, 'column_6': String, 'column_8'
```

column	column_0	column_2	column_3	column_4	column_8
statistic	count	mean	std	min	max
Date	6444	2012-10-26 16:36:45.027933+00:…	null	2000-01-05 05:00:00+00:00	2025-08-19 04:00:00+00:00
Open	6444.0	190.82591842184576	144.02936415534128	50.113057480959675	645.989990234375
High	6444.0	191.92668889779023	144.7563930674051	51.62493276253082	646.1900024414062
Low	6444.0	189.6269088728895	143.23284984431902	49.48618592302649	642.6799926757812
Close	6444.0	190.84933958343657	144.06736661670922	50.23106002807617	644.9500122070312
Volume	6444.0	105232386.51458721	90179712.63917024	1436600.0	871026300.0
CloseLag1	6444.0	190.76379166087477	143.96436701907055	50.23106002807617	644.9500122070312
CloseLag2	6444.0	190.67826132712196	143.85915506172498	50.23106002807617	644.9500122070312
SPYUp	6444.0	0.5446927374301676	0.4980371984141425	0.0	1.0

shape: (5, 9)

Date --- datetime[μs, UTC]	Open --- f64	High --- f64	Low --- f64	…	Volume --- i64	CloseLag1 --- f64	CloseLag2 --- f64	SPYUp --- i32
2000-01-05 05:00:00 UTC	88.657974	89.6677	86.955297	…	12177900	88.539185	92.142517	0
2000-01-06 05:00:00 UTC	88.459986	89.6479	87.272072	…	6227200	88.697571	88.539185	1
2000-01-07 05:00:00 UTC	88.895594	92.340546	88.737205	…	8066500	87.272072	88.697571	0
2000-01-10 05:00:00 UTC	92.657303	93.073073	91.885159	…	5741700	92.340546	87.272072	1
2000-01-11 05:00:00 UTC	92.380116	92.558303	90.915022	…	7503700	92.657303	92.340546	1

```
# work with GLD data
gld = pl.read_csv("/content/gld_daily_data.csv", try_parse_dates=True)

# drop useless columns Dividends, StockSplits, and CapitalGains
gld = gld.drop(['Dividends', 'StockSplits', 'CapitalGains'])

gld = gld.with_columns((pl.col('Close')).shift().alias('CloseLag1'))
gld = gld.with_columns((pl.col('CloseLag1')).shift().alias('CloseLag2'))
gld = gld.with_columns(pl.when(pl.col('CloseLag1')>pl.col('CloseLag2')).then(pl.lit(1)).otherwise(pl.lit(0)).alias('GLDUp'))
# check the schema
print(gld.schema)

# Drop initial lag row
gld = gld.drop_nulls()

gldStatistics = gld.describe()
print(gldStatistics.columns)
gldStatisticsToPrint = gldStatistics.transpose(include_header=True).drop(['column_1', 'column_5', 'column_6', 'column_7'])
print(wtiStatisticsToPrint.schema)
with pl.Config(
    tbl_rows = 60,
    tbl_width_chars = 200,
    tbl_cols = -1,
    float_precision = 3,
    tbl_hide_dataframe_shape = True,
    tbl_hide_column_data_types = True):
    print(gldStatisticsToPrint)

# print a few records at the beginning of the DataFrame
print(gld.head())
```

```
Schema({'Date': Datetime(time_unit='us', time_zone='UTC'), 'Open': Float64, 'High': Float64, 'Low': Float64, 'Close': Float64, 'Volume':
['statistic', 'Date', 'Open', 'High', 'Low', 'Close', 'Volume', 'CloseLag1', 'CloseLag2', 'GLDUp']
Schema({'column': String, 'column_0': String, 'column_2': String, 'column_3': String, 'column_4': String, 'column_6': String, 'column_8'
```

column	column_0	column_2	column_3	column_4	column_8
statistic	count	mean	std	min	max
Date	5218	2015-04-04 10:38:49.858183+00:…	null	2004-11-22 05:00:00+00:00	2025-08-19 04:00:00+00:00
Open	5218.0	132.1412112242237	51.52670299042503	41.029998779296875	317.489990234375
High	5218.0	132.77317369738134	51.70272920655233	41.36000061035156	317.6300048828125
Low	5218.0	131.45804141663464	51.31802554569786	41.02000045776367	315.0400085449219
Close	5218.0	132.14241081638417	51.533912524483476	41.2599983215332	316.2900085449219
Volume	5218.0	9420078.114220008	6644238.186068209	319300.0	93804200.0
CloseLag1	5218.0	132.09248939242204	51.49232280202278	41.2599983215332	316.2900085449219
CloseLag2	5218.0	132.0421693442927	51.44969185599339	41.2599983215332	316.2900085449219
GLDUp	5218.0	0.5298965120735915	0.49915323048311416	0.0	1.0

shape: (5, 9)

Date --- datetime[μs, UTC]	Open --- f64	High --- f64	Low --- f64	…	Volume --- i64	CloseLag1 --- f64	CloseLag2 --- f64	GLDUp --- i32
2004-11-22 05:00:00 UTC	44.75	44.970001	44.740002	…	11996000	44.779999	44.380001	1
2004-11-23 05:00:00 UTC	44.880001	44.919998	44.720001	…	3169200	44.950001	44.779999	1
2004-11-24 05:00:00 UTC	44.93	45.049999	44.790001	…	6105100	44.75	44.950001	0
2004-11-26 05:00:00 UTC	45.25	45.599998	45.060001	…	3097700	45.049999	44.75	1
2004-11-29 05:00:00 UTC	45.099998	45.5	45.080002	…	3759000	45.290001	45.049999	1

```
# work with VGT data
vgt = pl.read_csv("/content/vgt_daily_data.csv", try_parse_dates=True)

# drop useless columns Dividends, StockSplits, and CapitalGains
vgt = vgt.drop(['Dividends', 'StockSplits', 'CapitalGains'])

vgt = vgt.with_columns((pl.col('Close')).shift().alias('CloseLag1'))
vgt = vgt.with_columns((pl.col('CloseLag1')).shift().alias('CloseLag2'))
vgt = vgt.with_columns(pl.when(pl.col('CloseLag1')>pl.col('CloseLag2')).then(pl.lit(1)).otherwise(pl.lit(0)).alias('VGTUp'))
# check the schema
print(vgt.schema)

# Drop initial lag row
vgt = vgt.drop_nulls()

vgtStatistics = vgt.describe()
print(vgtStatistics.columns)
vgtStatisticsToPrint = vgtStatistics.transpose(include_header=True).drop(['column_1', 'column_5', 'column_6', 'column_7'])
print(wtiStatisticsToPrint.schema)
with pl.Config(
    tbl_rows = 60,
    tbl_width_chars = 200,
    tbl_cols = -1,
    float_precision = 3,
    tbl_hide_dataframe_shape = True,
    tbl_hide_column_data_types = True):
    print(vgtStatisticsToPrint)

# print a few records at the beginning of the DataFrame
print(vgt.head())
```

```
Schema({'Date': Datetime(time_unit='us', time_zone='UTC'), 'Open': Float64, 'High': Float64, 'Low': Float64, 'Close': Float64, 'Volume':
['statistic', 'Date', 'Open', 'High', 'Low', 'Close', 'Volume', 'CloseLag1', 'CloseLag2', 'VGTUp']
Schema({'column': String, 'column_0': String, 'column_2': String, 'column_3': String, 'column_4': String, 'column_6': String, 'column_8'
```

column	column_0	column_2	column_3	column_4	column_8
statistic	count	mean	std	min	max
Date	5421	2014-11-08 04:40:16.602103+00:…	null	2004-02-03 05:00:00+00:00	2025-08-19 04:00:00+00:00
Open	5421.0	167.88651112658872	165.87005650920398	25.400250326119036	710.0499877929688
High	5421.0	169.15025730560342	167.19942905975995	26.273459632207647	710.8800048828125
Low	5421.0	166.46979142040922	164.35842233160983	24.68993342530967	704.0
Close	5421.0	167.9006570834688	165.88368753316217	25.04936981201172	707.2899780273438

Volume	5421.0	360279.91145545105	400808.0053902826	0.0	6564500.0
CloseLag1	5421.0	167.78119283618796	165.74161113685028	25.04936981201172	707.2899780273438
CloseLag2	5421.0	167.65927450781356	165.59152803560164	25.04936981201172	707.2899780273438
VGTUp	5421.0	0.5543257701531082	0.4970857990731627	0.0	1.0

shape: (5, 9)

Date --- datetime[μs, UTC]	Open --- f64	High --- f64	Low --- f64	…	Volume --- i64	CloseLag1 --- f64	CloseLag2 --- f64	VGTUp --- i32
2004-02-03 05:00:00 UTC	40.925945	40.942719	40.774989	…	231100	41.194313	41.160759	1
2004-02-04 05:00:00 UTC	39.83571	39.83571	39.709911	…	51000	40.942719	41.194313	0
2004-02-05 05:00:00 UTC	40.003442	40.003442	39.709913	…	2600	39.709911	40.942719	0
2004-02-06 05:00:00 UTC	40.17116	40.716278	40.17116	…	1000	39.91119	39.709911	1
2004-02-09 05:00:00 UTC	40.791757	40.917555	40.607254	…	3200	40.716278	39.91119	1

```
# work with VB data
vb = pl.read_csv("/content/vb_daily_data.csv", try_parse_dates=True)

# drop useless columns Dividends, StockSplits, and CapitalGains
vb = vb.drop(['Dividends', 'StockSplits', 'CapitalGains'])

vb = vb.with_columns((pl.col('Close')).shift().alias('CloseLag1'))
vb = vb.with_columns((pl.col('CloseLag1')).shift().alias('CloseLag2'))
vb = vb.with_columns(pl.when(pl.col('CloseLag1')>pl.col('CloseLag2')).then(pl.lit(1)).otherwise(pl.lit(0)).alias('VBUp'))
# check the schema
print(vb.schema)

# Drop initial lag row
vb = vb.drop_nulls()

vbStatistics = vb.describe()
print(vbStatistics.columns)
vbStatisticsToPrint = vbStatistics.transpose(include_header=True).drop(['column_1', 'column_5', 'column_6', 'column_7'])
print(wtiStatisticsToPrint.schema)
with pl.Config(
    tbl_rows = 60,
    tbl_width_chars = 200,
    tbl_cols = -1,
    float_precision = 3,
    tbl_hide_dataframe_shape = True,
    tbl_hide_column_data_types = True):
    print(vbStatisticsToPrint)

# print a few records at the beginning of the DataFrame
print(vb.head())
```

```
Schema({'Date': Datetime(time_unit='us', time_zone='UTC'), 'Open': Float64, 'High': Float64, 'Low': Float64, 'Close': Float64, 'Volume':
['statistic', 'Date', 'Open', 'High', 'Low', 'Close', 'Volume', 'CloseLag1', 'CloseLag2', 'VBUp']
Schema({'column': String, 'column_0': String, 'column_2': String, 'column_3': String, 'column_4': String, 'column_6': String, 'column_8'
```

column	column_0	column_2	column_3	column_4	column_8
statistic	count	mean	std	min	max
Date	5421	2014-11-08 04:40:16.602103+00:…	null	2004-02-03 05:00:00+00:00	2025-08-19 04:00:00+00:00
Open	5421.0	106.9052813338388	62.1452158206943	23.633474085495507	258.1815273395355
High	5421.0	107.60790542830034	62.54629697613005	24.28031945289275	260.4463040442688
Low	5421.0	106.04389329572601	61.673058648440175	19.9520221629505	257.5090323220884
Close	5421.0	106.86636685982025	62.11471701676378	23.546703338623047	258.69580078125
Volume	5421.0	491339.45766463754	522990.5325407978	200.0	9288100.0
CloseLag1	5421.0	106.82761647115882	62.09329247825284	23.546703338623047	258.69580078125
CloseLag2	5421.0	106.78877441576543	62.07172201176196	23.546703338623047	258.69580078125
VBUp	5421.0	0.5366168603578676	0.49870340245454003	0.0	1.0

shape: (5, 9)

Date --- datetime[μs, UTC]	Open --- f64	High --- f64	Low --- f64	…	Volume --- i64	CloseLag1 --- f64	CloseLag2 --- f64	VBUp --- i32
2004-02-03	36.107417	36.18088	36.048645	…	1200	36.14415	35.997215	1

05:00:00 UTC								
2004-02-04 05:00:00 UTC	35.872324	35.872324	35.299305	…	1600	36.048645	36.14415	0
2004-02-05 05:00:00 UTC	35.549099	35.622565	35.336054	…	4000	35.299305	36.048645	0
2004-02-06 05:00:00 UTC	35.615208	36.254341	35.615208	…	2000	35.409519	35.299305	1
2004-02-09 05:00:00 UTC	36.511441	36.636328	36.504093	…	2900	36.254341	35.409519	1

```
# work with IVE data
ive = pl.read_csv("/content/ive_daily_data.csv", try_parse_dates=True)

# drop useless columns Dividends, StockSplits, and CapitalGains
ive = ive.drop(['Dividends', 'StockSplits', 'CapitalGains'])

ive = ive.with_columns((pl.col('Close')).shift().alias('CloseLag1'))
ive = ive.with_columns((pl.col('CloseLag1')).shift().alias('CloseLag2'))
ive = ive.with_columns(pl.when(pl.col('CloseLag1')>pl.col('CloseLag2')).then(pl.lit(1)).otherwise(pl.lit(0)).alias('IVEUp'))
# check the schema
print(ive.schema)

# Drop initial lag row
ive = ive.drop_nulls()

iveStatistics = ive.describe()
print(iveStatistics.columns)
iveStatisticsToPrint = iveStatistics.transpose(include_header=True).drop(['column_1', 'column_5', 'column_6', 'column_7'])
print(wtiStatisticsToPrint.schema)
with pl.Config(
    tbl_rows = 60,
    tbl_width_chars = 200,
    tbl_cols = -1,
    float_precision = 3,
    tbl_hide_dataframe_shape = True,
    tbl_hide_column_data_types = True):
    print(iveStatisticsToPrint)

# print a few records at the beginning of the DataFrame
print(ive.head())
```

```
Schema({'Date': Datetime(time_unit='us', time_zone='UTC'), 'Open': Float64, 'High': Float64, 'Low': Float64, 'Close': Float64, 'Volume':
['statistic', 'Date', 'Open', 'High', 'Low', 'Close', 'Volume', 'CloseLag1', 'CloseLag2', 'IVEUp']
Schema({'column': String, 'column_0': String, 'column_2': String, 'column_3': String, 'column_4': String, 'column_6': String, 'column_8'
```

column	column_0	column_2	column_3	column_4	column_8
statistic	count	mean	std	min	max
Date	6343	2013-01-08 00:46:19.883336+00:…	null	2000-05-31 04:00:00+00:00	2025-08-19 04:00:00+00:00
Open	6343.0	74.6655833423332	46.11985052593699	21.26051340242963	203.21139722740784
High	6343.0	75.06144188464853	46.32247720139887	22.014917670226524	203.8427634546091
Low	6343.0	74.22128225486621	45.922028399013676	20.797465831147417	202.95489456330537
Close	6343.0	74.66454975014508	46.129873687318245	21.3702449798584	203.3889617919922
Volume	6343.0	677624.5940406747	792860.168455924	400.0	20403600.0
CloseLag1	6343.0	74.63817534400859	46.10495666736668	21.3702449798584	203.3889617919922
CloseLag2	6343.0	74.61178671650268	46.080269741101944	21.3702449798584	203.3889617919922
IVEUp	6343.0	0.5344474223553524	0.49885128818986785	0.0	1.0

shape: (5, 9)

Date --- datetime[μs, UTC]	Open --- f64	High --- f64	Low --- f64	…	Volume --- i64	CloseLag1 --- f64	CloseLag2 --- f64	IVEUp --- i32
2000-05-31 04:00:00 UTC	34.549207	34.899005	34.549207	…	12200	34.567142	34.046928	1
2000-06-01 04:00:00 UTC	34.890046	35.257782	34.836231	…	25400	34.827251	34.567142	1
2000-06-02 04:00:00 UTC	35.858717	35.93047	35.751087	…	10000	35.257782	34.827251	1
2000-06-05 04:00:00 UTC	35.786959	35.786959	35.544792	…	15500	35.751087	35.257782	1
2000-06-06 04:00:00 UTC	35.508916	35.544792	35.508916	…	4100	35.589638	35.751087	0

```python
# work with XLI data
xli = pl.read_csv("/content/xli_daily_data.csv", try_parse_dates=True)

# drop useless columns Dividends, StockSplits, and CapitalGains
xli = xli.drop(['Dividends', 'StockSplits', 'CapitalGains'])

xli = xli.with_columns((pl.col('Close')).shift().alias('CloseLag1'))
xli = xli.with_columns((pl.col('CloseLag1')).shift().alias('CloseLag2'))
xli = xli.with_columns(pl.when(pl.col('CloseLag1')>pl.col('CloseLag2')).then(pl.lit(1)).otherwise(pl.lit(0)).alias('XLIUp'))
# check the schema
print(xli.schema)

# Drop initial lag row
xli = xli.drop_nulls()

xliStatistics = xli.describe()
print(xliStatistics.columns)
xliStatisticsToPrint = xliStatistics.transpose(include_header=True).drop(['column_1', 'column_5', 'column_6', 'column_7'])
print(wtiStatisticsToPrint.schema)
with pl.Config(
    tbl_rows = 60,
    tbl_width_chars = 200,
    tbl_cols = -1,
    float_precision = 3,
    tbl_hide_dataframe_shape = True,
    tbl_hide_column_data_types = True):
    print(xliStatisticsToPrint)

# print a few records at the beginning of the DataFrame
print(xli.head())
```

```
Schema({'Date': Datetime(time_unit='us', time_zone='UTC'), 'Open': Float64, 'High': Float64, 'Low': Float64, 'Close': Float64, 'Volume':
['statistic', 'Date', 'Open', 'High', 'Low', 'Close', 'Volume', 'CloseLag1', 'CloseLag2', 'XLIUp']
Schema({'column': String, 'column_0': String, 'column_2': String, 'column_3': String, 'column_4': String, 'column_6': String, 'column_8'
```

column	column_0	column_2	column_3	column_4	column_8
statistic	count	mean	std	min	max
Date	6444	2012-10-26 16:36:45.027933+00:…	null	2000-01-05 05:00:00+00:00	2025-08-19 04:00:00+00:00
Open	6444.0	47.13428678572114	33.75933048208735	11.236274653018539	155.07000732421875
High	6444.0	47.445254711260986	33.95744459372276	11.497583816634966	155.14999389648438
Low	6444.0	46.80200222742193	33.55937913538951	10.989484954974614	154.07000732421875
Close	6444.0	47.13715054336207	33.76749713408024	11.149171829223633	154.99000549316406
Volume	6444.0	8557567.116697703	7392044.013283453	400.0	79118200.0
CloseLag1	6444.0	47.1164178205972	33.74450283125619	11.149171829223633	154.99000549316406
CloseLag2	6444.0	47.09581460485097	33.72157067152891	11.149171829223633	154.99000549316406
XLIUp	6444.0	0.5332091868404718	0.4989346455594378	0.0	1.0

shape: (5, 9)

Date --- datetime[μs, UTC]	Open --- f64	High --- f64	Low --- f64	…	Volume --- i64	CloseLag1 --- f64	CloseLag2 --- f64	XLIUp --- i32
2000-01-05 05:00:00 UTC	17.728652	17.807798	17.550574	…	129200	17.758335	18.262877	0
2000-01-06 05:00:00 UTC	17.679196	17.9661	17.609944	…	54000	17.679186	17.758335	0
2000-01-07 05:00:00 UTC	18.124382	18.599257	18.124382	…	32900	17.916634	17.679186	1
2000-01-10 05:00:00 UTC	18.698189	18.757548	18.539897	…	122500	18.599257	17.916634	1
2000-01-11 05:00:00 UTC	18.658613	18.658613	18.361816	…	109800	18.599257	18.599257	0

```python
# work with XLU data
xlu = pl.read_csv("/content/xlu_daily_data.csv", try_parse_dates=True)

# drop useless columns Dividends, StockSplits, and CapitalGains
xlu = xlu.drop(['Dividends', 'StockSplits', 'CapitalGains'])

xlu = xlu.with_columns((pl.col('Close')).shift().alias('CloseLag1'))
xlu = xlu.with_columns((pl.col('CloseLag1')).shift().alias('CloseLag2'))
xlu = xlu.with_columns(pl.when(pl.col('CloseLag1')>pl.col('CloseLag2')).then(pl.lit(1)).otherwise(pl.lit(0)).alias('XLUUp'))
# check the schema
print(xlu.schema)
```

```
# Drop initial lag row
xlu = xlu.drop_nulls()

xluStatistics = xlu.describe()
print(xluStatistics.columns)
xluStatisticsToPrint = xluStatistics.transpose(include_header=True).drop(['column_1', 'column_5', 'column_6', 'column_7'])
print(wtiStatisticsToPrint.schema)
with pl.Config(
    tbl_rows = 60,
    tbl_width_chars = 200,
    tbl_cols = -1,
    float_precision = 3,
    tbl_hide_dataframe_shape = True,
    tbl_hide_column_data_types = True):
    print(xluStatisticsToPrint)

# print a few records at the beginning of the DataFrame
print(xlu.head())
```

```
Schema({'Date': Datetime(time_unit='us', time_zone='UTC'), 'Open': Float64, 'High': Float64, 'Low': Float64, 'Close': Float64, 'Volume':
['statistic', 'Date', 'Open', 'High', 'Low', 'Close', 'Volume', 'CloseLag1', 'CloseLag2', 'XLUUp']
Schema({'column': String, 'column_0': String, 'column_2': String, 'column_3': String, 'column_4': String, 'column_6': String, 'column_8'
```

column	column_0	column_2	column_3	column_4	column_8
statistic	count	mean	std	min	max
Date	6444	2012-10-26 16:36:45.027933+00:…	null	2000-01-05 05:00:00+00:00	2025-08-19 04:00:00+00:00
Open	6444.0	31.894989147350113	19.721009673760992	6.889745684259615	87.3499984741211
High	6444.0	32.123881544096875	19.861535759212497	7.41416278528114	87.66999816894531
Low	6444.0	31.650661453103062	19.573122239135174	6.736037375918337	86.12999725341797
Close	6444.0	31.89608001967974	19.7271434580805	6.885226726531982	87.31999969482422
Volume	6444.0	8837735.055865921	7372839.575100792	3200.0	90263100.0
CloseLag1	6444.0	31.88441676186302	19.717318739292757	6.885226726531982	87.31999969482422
CloseLag2	6444.0	31.8729350237577	19.707778243189146	6.885226726531982	87.31999969482422
XLUUp	6444.0	0.5335195530726257	0.49891388733682634	0.0	1.0

shape: (5, 9)

Date --- datetime[μs, UTC]	Open --- f64	High --- f64	Low --- f64	…	Volume --- i64	CloseLag1 --- f64	CloseLag2 --- f64	XLUUp --- i32
2000-01-05 05:00:00 UTC	11.165537	11.248862	11.018116	…	273400	10.921968	11.26168	0
2000-01-06 05:00:00 UTC	11.178358	11.178358	11.050166	…	34500	11.197585	10.921968	1
2000-01-07 05:00:00 UTC	11.197586	11.274501	11.146309	…	46200	11.178358	11.197585	0
2000-01-10 05:00:00 UTC	11.268088	11.345003	11.248859	…	15500	11.274501	11.178358	1
2000-01-11 05:00:00 UTC	11.261679	11.261679	11.107849	…	25700	11.312955	11.274501	1

```
# work with SLV data
slv = pl.read_csv("/content/slv_daily_data.csv", try_parse_dates=True)

# drop useless columns Dividends, StockSplits, and CapitalGains
slv = slv.drop(['Dividends', 'StockSplits', 'CapitalGains'])

slv = slv.with_columns((pl.col('Close')).shift().alias('CloseLag1'))
slv = slv.with_columns((pl.col('CloseLag1')).shift().alias('CloseLag2'))
slv = slv.with_columns(pl.when(pl.col('CloseLag1')>pl.col('CloseLag2')).then(pl.lit(1)).otherwise(pl.lit(0)).alias('SLVUp'))
# check the schema
print(slv.schema)

# Drop initial lag row
slv = slv.drop_nulls()

slvStatistics = slv.describe()
print(slvStatistics.columns)
slvStatisticsToPrint = slvStatistics.transpose(include_header=True).drop(['column_1', 'column_5', 'column_6', 'column_7'])
print(wtiStatisticsToPrint.schema)
with pl.Config(
    tbl_rows = 60,
    tbl_width_chars = 200,
    tbl_cols = -1,
    float_precision = 3,
```

```
    tbl_hide_dataframe_shape = True,
    tbl_hide_column_data_types = True):
    print(slvStatisticsToPrint)

# print a few records at the beginning of the DataFrame
print(slv.head())
```

```
Schema({'Date': Datetime(time_unit='us', time_zone='UTC'), 'Open': Float64, 'High': Float64, 'Low': Float64, 'Close': Float64, 'Volume':
['statistic', 'Date', 'Open', 'High', 'Low', 'Close', 'Volume', 'CloseLag1', 'CloseLag2', 'SLVUp']
Schema({'column': String, 'column_0': String, 'column_2': String, 'column_3': String, 'column_4': String, 'column_6': String, 'column_8'
```

column	column_0	column_2	column_3	column_4	column_8
statistic	count	mean	std	min	max
Date	4856	2015-12-23 02:12:58.418451+00:…	null	2006-05-02 04:00:00+00:00	2025-08-19 04:00:00+00:00
Open	4856.0	19.84649361829585	6.487981729697927	8.710000038146973	47.619998931884766
High	4856.0	20.0214888811897	6.55865103290389	9.050000190734863	48.349998474121094
Low	4856.0	19.649800242859214	6.395723154542012	8.449999809265137	46.54999923706055
Close	4856.0	19.840868817129873	6.487317455039558	8.850000381469727	47.2599983215332
Volume	4856.0	15420806.878088962	16683460.219457056	1039000.0	295400000.0
CloseLag1	4856.0	19.83675020118129	6.484757133225693	8.850000381469727	47.2599983215332
CloseLag2	4856.0	19.832479608314237	6.481893562087745	8.850000381469727	47.2599983215332
SLVUp	4856.0	0.5168863261943987	0.4997662319131529	0.0	1.0

shape: (5, 9)

Date --- datetime[μs, UTC]	Open --- f64	High --- f64	Low --- f64	…	Volume --- i64	CloseLag1 --- f64	CloseLag2 --- f64	SLVUp --- i32
2006-05-02 04:00:00 UTC	14.245	14.4	14.1	…	12511000	13.87	13.812	1
2006-05-03 04:00:00 UTC	14.45	14.464	13.413	…	15141000	14.365	13.87	1
2006-05-04 04:00:00 UTC	13.95	14.287	13.68	…	11075000	13.925	14.365	0
2006-05-05 04:00:00 UTC	14.0	14.03	13.75	…	6586000	14.0	13.925	1
2006-05-08 04:00:00 UTC	13.8	14.0	13.506	…	9453000	13.995	14.0	0

```
# work with USO data
uso = pl.read_csv("/content/uso_daily_data.csv", try_parse_dates=True)

# drop useless columns Dividends, StockSplits, and CapitalGains
uso = uso.drop(['Dividends', 'StockSplits', 'CapitalGains'])

uso = uso.with_columns((pl.col('Close')).shift().alias('CloseLag1'))
uso = uso.with_columns((pl.col('CloseLag1')).shift().alias('CloseLag2'))
uso = uso.with_columns(pl.when(pl.col('CloseLag1')>pl.col('CloseLag2')).then(pl.lit(1)).otherwise(pl.lit(0)).alias('USOUp'))
# check the schema
print(uso.schema)

# Drop initial lag row
uso = uso.drop_nulls()

usoStatistics = uso.describe()
print(usoStatistics.columns)
usoStatisticsToPrint = usoStatistics.transpose(include_header=True).drop(['column_1', 'column_5', 'column_6', 'column_7'])
print(wtiStatisticsToPrint.schema)
with pl.Config(
    tbl_rows = 60,
    tbl_width_chars = 200,
    tbl_cols = -1,
    float_precision = 3,
    tbl_hide_dataframe_shape = True,
    tbl_hide_column_data_types = True):
    print(usoStatisticsToPrint)

# print a few records at the beginning of the DataFrame
print(uso.head())
```

```
Schema({'Date': Datetime(time_unit='us', time_zone='UTC'), 'Open': Float64, 'High': Float64, 'Low': Float64, 'Close': Float64, 'Volume':
['statistic', 'Date', 'Open', 'High', 'Low', 'Close', 'Volume', 'CloseLag1', 'CloseLag2', 'USOUp']
Schema({'column': String, 'column_0': String, 'column_2': String, 'column_3': String, 'column_4': String, 'column_6': String, 'column_8'
```

column	column_0	column_2	column_3	column_4	column_8

statistic	count	mean	std	min	max
Date	4869	2015-12-13 15:52:11.238447+00:…	null	2006-04-12 04:00:00+00:00	2025-08-19 04:00:00+00:00
Open	4869.0	207.56218537914114	172.12513325570848	17.280000686645508	952.6400146484375
High	4869.0	209.87204556632614	174.16241714493188	18.0	953.3599853515625
Low	4869.0	205.02635254098982	169.7785603051359	16.8799991607666	932.0
Close	4869.0	207.54419582231404	172.08918039384076	17.040000915527344	939.8400268554688
Volume	4869.0	3012812.4988704044	4036484.7365261046	14888.0	124913013.0
CloseLag1	4869.0	207.64140263532167	172.14643555816238	17.040000915527344	939.8400268554688
CloseLag2	4869.0	207.73813501876296	172.20317777305166	17.040000915527344	939.8400268554688
USOUp	4869.0	0.5103717395769152	0.49994375754988574	0.0	1.0

shape: (5, 9)

Date --- datetime[μs, UTC]	Open --- f64	High --- f64	Low --- f64	…	Volume --- i64	CloseLag1 --- f64	CloseLag2 --- f64	USOUp --- i32
2006-04-12 04:00:00 UTC	545.76001	550.47998	542.47998	…	156038	545.599976	544.159973	1
2006-04-13 04:00:00 UTC	540.0	551.919983	539.200012	…	70088	542.719971	545.599976	0
2006-04-17 04:00:00 UTC	553.599976	559.200012	549.440002	…	114713	550.559998	542.719971	1
2006-04-18 04:00:00 UTC	560.799988	568.400024	556.559998	…	115338	558.320007	550.559998	1
2006-04-19 04:00:00 UTC	564.640015	577.280029	563.919983	…	98725	566.0	558.320007	1

```
# Find earliest date that can be used across all DataFrames
minDateAll = max(min(wti['Date']),min(spy['Date']),min(gld['Date']),
                 min(vgt['Date']),min(vb['Date']),min(ive['Date']),
                 min(xli['Date']),min(xlu['Date']),min(slv['Date']),min(uso['Date']))

print("minimum Date on which to select, minDateAll:", minDateAll)
```

minimum Date on which to select, minDateAll: 2006-05-02 04:00:00+00:00

```
# find latest date across all DataFrames

maxDateAll = min(max(wti['Date']),max(spy['Date']),max(gld['Date']),
                 max(vgt['Date']),max(vb['Date']),max(ive['Date']),
                 max(xli['Date']),max(xlu['Date']),max(slv['Date']),max(uso['Date']))

print("maximum Date on which to select, axDateAll:", maxDateAll)
```

maximum Date on which to select, axDateAll: 2025-08-19 04:00:00+00:00

```
# select training data from minDateAll to 2024-12-31, test data all dates in 2025
beginTrain = minDateAll
endTrain = datetime(2024, 12, 31, tzinfo=timezone.utc)
beginTest = datetime(2025, 1, 1, tzinfo=timezone.utc)
endTest = maxDateAll
wtiTrain = wti.filter((pl.col('Date')>=beginTrain) & (pl.col('Date')<=endTrain))
wtiTest = wti.filter((pl.col('Date')>=beginTest) & (pl.col('Date')<=endTest))

print("Beginning of wti training set")
print(wtiTrain.head())
print("End of wti training set")
print(wtiTrain.tail())
print("Beginning of wti test set")
print(wtiTest.head())
print("End of wti test set")
print(wtiTest.tail())
```

UTC

UTC								
2024-12-30 05:00:00 UTC	1.579	1.54	1.501	…	1.544	1.525	1.559	1

Beginning of wti test set
shape: (5, 17)

Date --- datetime[μs, UTC]	CloseLag1 --- f64	CloseLag2 --- f64	CloseLag3 --- f64	…	CloseEMA2 --- f64	CloseEMA4 --- f64	CloseEMA8 --- f64	Target --- i32
2025-01-02 05:00:00 UTC	1.628	1.638	1.579	…	1.61	1.579	1.581	1
2025-01-03 05:00:00 UTC	1.746	1.628	1.638	…	1.678	1.628	1.607	0
2025-01-06 05:00:00 UTC	1.727	1.746	1.628	…	1.702	1.657	1.626	0
2025-01-07 05:00:00 UTC	1.619	1.727	1.746	…	1.66	1.646	1.625	0
2025-01-08 05:00:00 UTC	1.599	1.619	1.727	…	1.63	1.632	1.621	1

End of wti test set
shape: (5, 17)

Date --- datetime[μs, UTC]	CloseLag1 --- f64	CloseLag2 --- f64	CloseLag3 --- f64	…	CloseEMA2 --- f64	CloseEMA4 --- f64	CloseEMA8 --- f64	Target --- i32
2025-08-13 04:00:00 UTC	1.74	1.71	1.72	…	1.729	1.731	1.737	0
2025-08-14 04:00:00 UTC	1.74	1.74	1.71	…	1.734	1.733	1.737	0
2025-08-15 04:00:00 UTC	1.74	1.74	1.74	…	1.737	1.735	1.737	0
2025-08-18 04:00:00 UTC	1.71	1.74	1.74	…	1.724	1.728	1.733	1
2025-08-19 04:00:00 UTC	1.74	1.71	1.74	…	1.732	1.731	1.734	0

Define the WTI Target for Training and Test Sets

Using the dates defined by looking across all ETFs and the WTI time series.

```
# Define and examine the target for classification model development
print(wtiTrain['Target'].value_counts())
yTrain = np.array(wtiTrain['Target'])

print(wtiTest['Target'].value_counts())
yTest = np.array(wtiTest['Target'])
```

shape: (2, 2)

Target --- i32	count --- u32
1	2227
0	2471

shape: (2, 2)

Target --- i32	count --- u32
1	72
0	85

Remove Target from WTI Data Sets

The initial feature set will include price features from WTI. Having obtained the Target from both the training and test data for WTI, we remove it from the WTI feature set in both the training and test sets.

```
# Having extracted the Target from the WTI training and test sets, we can delete it from the set of features
XTrain = wtiTrain.drop(['Target'])
XTrain.head()

XTest = wtiTest.drop(['Target'])
XTest.head()
```

shape: (5, 16)

Date	CloseLag1	CloseLag2	CloseLag3	HMLLag1	HMLLag2	HMLLag3	OMCLag1	OMCLag2	OMCLag3	VolumeLag1	VolumeLag2	VolumeLag3
datetime[μs, UTC]	f64	f64	f64	f64	f64	f64	f64	f64	f64	f64	f64	f64
2025-01-02 05:00:00 UTC	1.628	1.638	1.579	0.059	0.108	0.098	0.0	-0.029	-0.01	2.2437e6	3.6429e6	2.5184e6
2025-01-03 05:00:00 UTC	1.746	1.628	1.638	0.128	0.059	0.108	-0.078	0.0	-0.029	3.4821e6	2.2437e6	3.6429e6
2025-01-06 05:00:00 UTC	1.727	1.746	1.628	0.088	0.128	0.059	0.039	-0.078	0.0	1.4409e6	3.4821e6	2.2437e6
2025-01-07 05:00:00 UTC	1.619	1.727	1.746	0.167	0.088	0.128	0.128	0.039	-0.078	2.5746e6	1.4409e6	3.4821e6
2025-01-08	1.599	1.619	1.727	0.098	0.167	0.088	0.029	0.128	0.039	2.2995e6	2.5746e6	1.4409e6

```
# filter by date for all the ETF DataFrames, defining training and test sets

spyTrain = spy.filter((pl.col('Date')>=beginTrain) & (pl.col('Date')<=endTrain))
spyTest = spy.filter((pl.col('Date')>=beginTest) & (pl.col('Date')<=endTest))

gldTrain = gld.filter((pl.col('Date')>=beginTrain) & (pl.col('Date')<=endTrain))
gldTest = gld.filter((pl.col('Date')>=beginTest) & (pl.col('Date')<=endTest))

vgtTrain = vgt.filter((pl.col('Date')>=beginTrain) & (pl.col('Date')<=endTrain))
vgtTest = vgt.filter((pl.col('Date')>=beginTest) & (pl.col('Date')<=endTest))

vbTrain = vb.filter((pl.col('Date')>=beginTrain) & (pl.col('Date')<=endTrain))
vbTest = vb.filter((pl.col('Date')>=beginTest) & (pl.col('Date')<=endTest))

iveTrain = ive.filter((pl.col('Date')>=beginTrain) & (pl.col('Date')<=endTrain))
iveTest = ive.filter((pl.col('Date')>=beginTest) & (pl.col('Date')<=endTest))

xliTrain = xli.filter((pl.col('Date')>=beginTrain) & (pl.col('Date')<=endTrain))
xliTest = xli.filter((pl.col('Date')>=beginTest) & (pl.col('Date')<=endTest))

xluTrain = xlu.filter((pl.col('Date')>=beginTrain) & (pl.col('Date')<=endTrain))
xluTest = xlu.filter((pl.col('Date')>=beginTest) & (pl.col('Date')<=endTest))

slvTrain = slv.filter((pl.col('Date')>=beginTrain) & (pl.col('Date')<=endTrain))
slvTest = slv.filter((pl.col('Date')>=beginTest) & (pl.col('Date')<=endTest))

usoTrain = uso.filter((pl.col('Date')>=beginTrain) & (pl.col('Date')<=endTrain))
usoTest = uso.filter((pl.col('Date')>=beginTest) & (pl.col('Date')<=endTest))
```

```
# verify consistent shapes of DataFrames
print("Train DataFrame shapes:")
print("wtiTrain.shape: ", wtiTrain.shape)
print("spyTrain.shape: ", spyTrain.shape)
print("gldTrain.shape: ", gldTrain.shape)
print("vgtTrain.shape: ", vgtTrain.shape)
print("vbTrain.shape: ", vbTrain.shape)
print("iveTrain.shape: ", iveTrain.shape)
print("xliTrain.shape: ", xliTrain.shape)
print("xluTrain.shape: ", xluTrain.shape)
print("slvTrain.shape: ", slvTrain.shape)
print("usoTrain.shape: ", usoTrain.shape)
```

```
print("usoTrain.shape: ", usoTrain.shape)
# verify consistent shapes of DataFrames
print("Test DataFrame shapes:")
print("wtiTest.shape: ", wtiTest.shape)
print("spyTest.shape: ", spyTest.shape)
print("gldTest.shape: ", gldTest.shape)
print("vgtTest.shape: ", vgtTest.shape)
print("vbTest.shape: ", vbTest.shape)
print("iveTest.shape: ", iveTest.shape)
print("xliTest.shape: ", xliTest.shape)
print("xluTest.shape: ", xluTest.shape)
print("slvTest.shape: ", slvTest.shape)
print("usoTest.shape: ", usoTest.shape)
```

```
Train DataFrame shapes:
wtiTrain.shape:  (4698, 17)
spyTrain.shape:  (4698, 9)
gldTrain.shape:  (4698, 9)
vgtTrain.shape:  (4698, 9)
vbTrain.shape:  (4698, 9)
iveTrain.shape:  (4698, 9)
xliTrain.shape:  (4698, 9)
xluTrain.shape:  (4698, 9)
slvTrain.shape:  (4698, 9)
usoTrain.shape:  (4698, 9)
Test DataFrame shapes:
wtiTest.shape:  (157, 17)
spyTest.shape:  (157, 9)
gldTest.shape:  (157, 9)
vgtTest.shape:  (157, 9)
vbTest.shape:  (157, 9)
iveTest.shape:  (157, 9)
xliTest.shape:  (157, 9)
xluTest.shape:  (157, 9)
slvTest.shape:  (157, 9)
usoTest.shape:  (157, 9)
```

```
# Add Up indicator variables to the wti DataFrames
wtiTrainETF = wtiTrain
wtiTrainETF = wtiTrainETF.with_columns(spyTrain['SPYUp'])
wtiTrainETF = wtiTrainETF.with_columns(gldTrain['GLDUp'])
wtiTrainETF = wtiTrainETF.with_columns(vgtTrain['VGTUp'])
wtiTrainETF = wtiTrainETF.with_columns(vbTrain['VBUp'])
wtiTrainETF = wtiTrainETF.with_columns(iveTrain['IVEUp'])
wtiTrainETF = wtiTrainETF.with_columns(xliTrain['XLIUp'])
wtiTrainETF = wtiTrainETF.with_columns(xluTrain['XLUUp'])
wtiTrainETF = wtiTrainETF.with_columns(slvTrain['SLVUp'])
wtiTrainETF = wtiTrainETF.with_columns(usoTrain['USOUp'])
print(wtiTrainETF.schema)
print(wtiTrainETF.head())

wtiTestETF = wtiTest
wtiTestETF = wtiTestETF.with_columns(spyTest['SPYUp'])
wtiTestETF = wtiTestETF.with_columns(gldTest['GLDUp'])
wtiTestETF = wtiTestETF.with_columns(vgtTest['VGTUp'])
wtiTestETF = wtiTestETF.with_columns(vbTest['VBUp'])
wtiTestETF = wtiTestETF.with_columns(iveTest['IVEUp'])
wtiTestETF = wtiTestETF.with_columns(xliTest['XLIUp'])
wtiTestETF = wtiTestETF.with_columns(xluTest['XLUUp'])
wtiTestETF = wtiTestETF.with_columns(slvTest['SLVUp'])
wtiTestETF = wtiTestETF.with_columns(usoTest['USOUp'])
print(wtiTestETF.schema)
print(wtiTestETF.head())
```

```
Schema({'Date': Datetime(time_unit='us', time_zone='UTC'), 'CloseLag1': Float64, 'CloseLag2': Float64, 'CloseLag3': Float64, 'HMLLag1':
shape: (5, 26)
```

Date --- datetime[μs, UTC]	CloseLag1 --- f64	CloseLag2 --- f64	CloseLag3 --- f64	…	XLIUp --- i32	XLUUp --- i32	SLVUp --- i32	USOUp --- i32
2006-05-02 04:00:00 UTC	32.19	31.062	30.669	…	1	0	1	1
2006-05-03 04:00:00 UTC	33.471	32.19	31.062	…	1	1	1	1
2006-05-04 04:00:00 UTC	33.158	33.471	32.19	…	1	0	0	0
2006-05-05 04:00:00 UTC	35.013	33.158	33.471	…	1	1	1	0
2006-05-08 04:00:00 UTC	33.645	35.013	33.158	…	1	1	0	0

```
Schema({'Date': Datetime(time_unit='us', time_zone='UTC'), 'CloseLag1': Float64, 'CloseLag2': Float64, 'CloseLag3': Float64, 'HMLLag1':
shape: (5, 26)
```

Date --- datetime[μs, UTC]	CloseLag1 --- f64	CloseLag2 --- f64	CloseLag3 --- f64	…	XLIUp --- i32	XLUUp --- i32	SLVUp --- i32	USOUp --- i32
2025-01-02 05:00:00 UTC	1.628	1.638	1.579	…	0	0	0	1
2025-01-03 05:00:00 UTC	1.746	1.628	1.638	…	0	1	1	1
2025-01-06 05:00:00 UTC	1.727	1.746	1.628	…	1	1	1	1
2025-01-07 05:00:00 UTC	1.619	1.727	1.746	…	0	0	1	0
2025-01-08 05:00:00 UTC	1.599	1.619	1.727	…	0	0	1	1

```
# we can now drop Date and Target from wti training and test sets
# as we now have the full set o features for training and testing
wtiTrainETF = wtiTrainETF.drop(['Date','Target'])
wtiTestETF = wtiTestETF.drop(['Date','Target'])
```

```
trainStatistics = wtiTrainETF.describe()
print(wtiTrainETF.columns)
trainStatisticsToPrint = trainStatistics.transpose(include_header=True).drop(['column_1', 'column_5', 'column_6', 'column_7'])
print(trainStatisticsToPrint.schema)
with pl.Config(
    tbl_rows = 60,
    tbl_width_chars = 200,
    tbl_cols = -1,
    float_precision = 3,
    tbl_hide_dataframe_shape = True,
    tbl_hide_column_data_types = True):
    print(trainStatisticsToPrint)

# print a few records at the beginning of the DataFrame
print(wtiTrainETF.head())
```

```
['CloseLag1', 'CloseLag2', 'CloseLag3', 'HMLLag1', 'HMLLag2', 'HMLLag3', 'OMCLag1', 'OMCLag2', 'OMCLag3', 'VolumeLag1', 'VolumeLag2', 'V
Schema({'column': String, 'column_0': String, 'column_2': String, 'column_3': String, 'column_4': String, 'column_8': String})
```

column	column_0	column_2	column_3	column_4	column_8
statistic	count	mean	std	min	max
CloseLag1	4698.0	9.434744146445293	7.903321463290654	1.047	44.172
CloseLag2	4698.0	9.441019795657727	7.9087858952326995	1.047	44.172
CloseLag3	4698.0	9.447220093656876	7.91400686144687	1.047	44.172
HMLLag1	4698.0	0.45111323967645806	0.43053528722285817	0.029	4.129
HMLLag2	4698.0	0.4514563644103873	0.4308960144294226	0.029	4.129
HMLLag3	4698.0	0.45179480630055346	0.4312426208526598	0.029	4.129
OMCLag1	4698.0	0.01769391230310771	0.37248492041266446	-3.223	3.705
OMCLag2	4698.0	0.017589186888037466	0.3725618641070302	-3.223	3.705
OMCLag3	4698.0	0.01758407833120477	0.37256294191238093	-3.223	3.705
VolumeLag1	4698.0	1846607.4499787143	1858696.1408019532	52700.0	40429700.0
VolumeLag2	4698.0	1846130.779054917	1858810.9684406945	52700.0	40429700.0
VolumeLag3	4698.0	1845878.9272030653	1858934.5724908514	52700.0	40429700.0
CloseEMA2	4698.0	9.441036824180502	7.901227922219755	1.156	43.432
CloseEMA4	4698.0	9.450132183908048	7.900732474686015	1.285	43.018
CloseEMA8	4698.0	9.46854576415496	7.899496747575	1.382	42.696
SPYUp	4698.0	0.5506598552575565	0.49747990726518226	0.0	1.0
GLDUp	4698.0	0.5259684972328651	0.4993783325710364	0.0	1.0
VGTUp	4698.0	0.5576841209025117	0.49671426317032225	0.0	1.0
VBUp	4698.0	0.5357598978288634	0.49877267659502655	0.0	1.0
IVEUp	4698.0	0.5340570455512984	0.4988918682142226	0.0	1.0
XLIUp	4698.0	0.5398041719880801	0.49846616338488664	0.0	1.0
XLUUp	4698.0	0.5363984674329502	0.4987264730981392	0.0	1.0
SLVUp	4698.0	0.5163899531715623	0.4997844912621346	0.0	1.0
USOUp	4698.0	0.511068539804172	0.4999306820015263	0.0	1.0

shape: (5, 24)

CloseLag1 --- f64	CloseLag2 --- f64	CloseLag3 --- f64	HMLLag1 --- f64	…	XLIUp --- i32	XLUUp --- i32	SLVUp --- i32	USOUp --- i32
32.19	31.062	30.669	1.128	…	1	0	1	1
33.471	32.19	31.062	1.681	…	1	1	1	1
33.158	33.471	32.19	1.375	…	1	0	0	0
35.013	33.158	33.471	1.688	…	1	1	1	0
33.645	35.013	33.158	1.899	…	1	1	0	0

```
testStatistics = wtiTestETF.describe()
print(wtiTestETF.columns)
testStatisticsToPrint = testStatistics.transpose(include_header=True).drop(['column_1', 'column_5', 'column_6', 'column_7'])
print(testStatisticsToPrint.schema)
with pl.Config(
    tbl_rows = 60,
    tbl_width_chars = 200,
    tbl_cols = -1,
    float_precision = 3,
    tbl_hide_dataframe_shape = True,
    tbl_hide_column_data_types = True):
    print(testStatisticsToPrint)

# print a few records at the beginning of the DataFrame
print(wtiTestETF.head())
```

```
['CloseLag1', 'CloseLag2', 'CloseLag3', 'HMLLag1', 'HMLLag2', 'HMLLag3', 'OMCLag1', 'OMCLag2', 'OMCLag3', 'VolumeLag1', 'VolumeLag2', 'V
Schema({'column': String, 'column_0': String, 'column_2': String, 'column_3': String, 'column_4': String, 'column_8': String})
```

column	column_0	column_2	column_3	column_4	column_8
statistic	count	mean	std	min	max
CloseLag1	157.0	1.583496815286624	0.23880529630030126	1.096	2.346
CloseLag2	157.0	1.5828471337579617	0.23851536438187623	1.096	2.346
CloseLag3	157.0	1.5820127388535032	0.23829673344386137	1.096	2.346
HMLLag1	157.0	0.08693630573248408	0.05223058853366095	0.03	0.398
HMLLag2	157.0	0.08730573248407644	0.052172748365944654	0.03	0.398
HMLLag3	157.0	0.08761146496815288	0.05209331490177502	0.03	0.398
OMCLag1	157.0	0.004267515923566881	0.06086306426616007	-0.119	0.288
OMCLag2	157.0	0.004210191082802551	0.06089029983030787	-0.119	0.288
OMCLag3	157.0	0.003891719745222931	0.060832639225176156	-0.119	0.288
VolumeLag1	157.0	1774694.2675159236	1436394.6061296004	469000.0	9514600.0
VolumeLag2	157.0	1793519.1082802548	1441411.6644551635	469000.0	9514600.0
VolumeLag3	157.0	1805398.7261146498	1439638.7979587486	469000.0	9514600.0
CloseEMA2	157.0	1.582611464968153	0.2311157066659726	1.111	2.235
CloseEMA4	157.0	1.5808598726114649	0.2211442694956234	1.136	2.122
CloseEMA8	157.0	1.5780191082802548	0.20381714628488098	1.157	1.988
SPYUp	157.0	0.5668789808917197	0.4970926415014129	0.0	1.0
GLDUp	157.0	0.5796178343949044	0.49519988886944	0.0	1.0
VGTUp	157.0	0.5605095541401274	0.4979133332299239	0.0	1.0
VBUp	157.0	0.4968152866242038	0.5015898291312316	0.0	1.0
IVEUp	157.0	0.5414012738853503	0.49987749601678194	0.0	1.0
XLIUp	157.0	0.535031847133758	0.5003673319951818	0.0	1.0
XLUUp	157.0	0.5668789808917197	0.4970926415014129	0.0	1.0
SLVUp	157.0	0.535031847133758	0.5003673319951818	0.0	1.0
USOUp	157.0	0.4840764331210191	0.5013455681821809	0.0	1.0

shape: (5, 24)

CloseLag1 --- f64	CloseLag2 --- f64	CloseLag3 --- f64	HMLLag1 --- f64	…	XLIUp --- i32	XLUUp --- i32	SLVUp --- i32	USOUp --- i32
1.628	1.638	1.579	0.059	…	0	0	0	1
1.746	1.628	1.638	0.128	…	0	1	1	1
1.727	1.746	1.628	0.088	…	1	1	1	1
1.619	1.727	1.746	0.167	…	0	0	1	0
1.599	1.619	1.727	0.098	…	0	0	1	1

```
# Standardize features in the training data
featureNames = wtiTrainETF.columns
print("Feature names correspond to Numpy array columns:",featureNames)
scaler = StandardScaler()
XTrain = scaler.fit_transform(np.array(wtiTrainETF))
```

```
Feature names correspond to Numpy array columns: ['CloseLag1', 'CloseLag2', 'CloseLag3', 'HMLLag1', 'HMLLag2', 'HMLLag3', 'OMCLag1', 'OM
```

```
# Standardize features for hold-out test set
featureNames = wtiTestETF.columns
print("Feature names correspond to Numpy array columns:",featureNames)
scaler = StandardScaler()
XTest = scaler.fit_transform(np.array(wtiTestETF))
```

```
Feature names correspond to Numpy array columns: ['CloseLag1', 'CloseLag2', 'CloseLag3', 'HMLLag1', 'HMLLag2', 'HMLLag3', 'OMCLag1', 'OM
```

```
# Defining training features and target for tree-structured ensemble modeling (XGBoost)
```

```
# Defining training features and target for tree-structured ensemble modeling (XGBoost)
X = XTrain  # the full training data set with ETS Up indicators
y = yTrain  # the cloned values just computed


# Splitting the X (XTrain) and y (yTrain) data
# into cross-validation train and test sets
# within the Scikit-Learn framework using TimeSeriesSplit
# with a gap, for the number of samples to exclude from
# the end of each train set and before the next test set.
tscv = TimeSeriesSplit(gap=10, n_splits=5)

all_splits = list(tscv.split(X, y))
train_0, test_0 = all_splits[0]
train_1, test_1 = all_splits[1]
train_2, test_2 = all_splits[2]
train_3, test_3 = all_splits[3]
train_4, test_4 = all_splits[4]

# examine the objects created for cross-validation splits
print("type(all_splits):", type(all_splits), " outer list length", len(all_splits))
print()
print("train_0 has",len(train_0),"with indices from ",min(train_0),"to",max(train_0))
print("test_0 has",len(test_0),"with indices from ",min(test_0),"to",max(test_0))
print()
print("train_1 has",len(train_1),"with indices from ",min(train_1),"to",max(train_1))
print("test_1 has",len(test_1),"with indices from ",min(test_1),"to",max(test_1))
print()
print("train_2 has",len(train_2),"with indices from ",min(train_2),"to",max(train_2))
print("test_2 has",len(test_2),"with indices from ",min(test_2),"to",max(test_2))
print()
print("train_3 has",len(train_3),"with indices from ",min(train_3),"to",max(train_3))
print("test_3 has",len(test_3),"with indices from ",min(test_3),"to",max(test_3))
print()
print("train_4 has",len(train_4),"with indices from ",min(train_4),"to",max(train_4))
print("test_4 has",len(test_4),"with indices from ",min(test_4),"to",max(test_4))

# to see all indices we can uncomment these statements
# print("elements of all_splits list of lists,\n shows index numbers for each the five lists")
# print(all_splits)
```

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

train_0 has 773 with indices from  0 to 772
test_0 has 783 with indices from  783 to 1565

train_1 has 1556 with indices from  0 to 1555
test_1 has 783 with indices from  1566 to 2348

train_2 has 2339 with indices from  0 to 2338
test_2 has 783 with indices from  2349 to 3131

train_3 has 3122 with indices from  0 to 3121
test_3 has 783 with indices from  3132 to 3914

train_4 has 3905 with indices from  0 to 3904
test_4 has 783 with indices from  3915 to 4697
```

```
model = XGBClassifier(objective='binary:logistic', n_estimators=1000, random_state=2025)


# Evaluate a Classification Model Within the Time Series Cross-Validation Design
# Prior to executing a full-blown search for the "best" classification model,
# we test the cross-validation design on a binary classification model,
# revising code provided in online documentation for Scikit-Learn:
# Time-related feature engineering. In particular,
# we define appropriate metrics for assessing classification performance.
def evaluate(model, X, y, cv, model_prop=None, model_step=None):
    cv_results = cross_validate(
        model,
        X,
        y,
        cv=cv,
        scoring=["accuracy"],
        return_estimator=model_prop is not None,
    )
    if model_prop is not None:
        if model_step is not None:
            values = [
```

```
                getattr(m[model_step], model_prop) for m in cv_results["estimator"]
            ]
        else:
            values = [getattr(m, model_prop) for m in cv_results["estimator"]]
        print(f"Mean model.{model_prop} = {np.mean(values)}")
    accuracy = -cv_results["test_accuracy"]

    # print used in earlier testing
    # print(
    #    f"Mean Accuracy:     {-accuracy.mean():.3f} +/- {accuracy.std():.3f}\n"
    # )
    return (-accuracy.mean(), accuracy.std())

evaluate(model, X, y, cv=tscv, model_prop="n_estimators")
```

```
Mean model.n_estimators = 1000.0
(np.float64(0.4947637292464878), np.float64(0.02598091670999012))
```

```
# print results from evaluate for the model with default hyperparameter settings
accuracyMean, accuracyStd = evaluate(model, X, y, cv=tscv, model_prop="n_estimators")
print(
        f"Mean Accuracy:     {accuracyMean:.3f} +/- {accuracyStd:.3f}\n"
     )
```

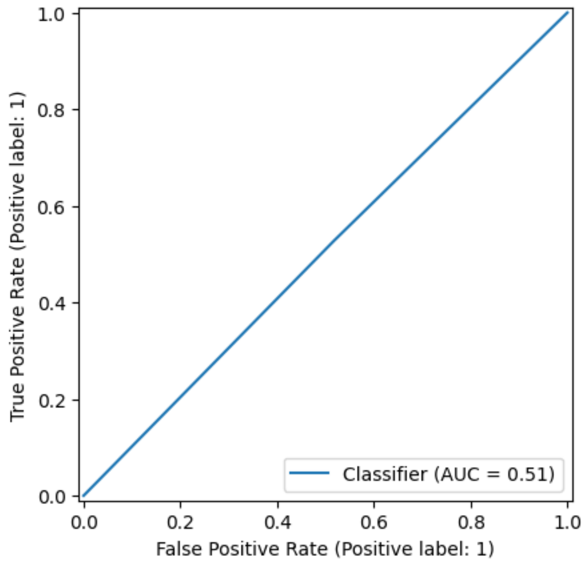
```
Mean model.n_estimators = 1000.0
Mean Accuracy:     0.495 +/- 0.026
```

```
# Randomized search to find the best set of hyperparameters

param_dist = {
    'max_depth': randint(3, 10),
    'min_child_weight': randint(1, 10),
    'subsample': uniform(0.5, 1),
    'learning_rate': uniform(0.01, 0.1),
    'n_estimators': randint(100, 1000),
}
xgb_model = xgb.XGBClassifier(objective='binary:logistic', use_label_encoder=False, eval_metric='logloss', random_state=2025)

random_search = RandomizedSearchCV(
    estimator=xgb_model,
    param_distributions=param_dist,
    n_iter=100, # Number of parameter settings that are sampled.
    scoring='accuracy',
    cv = TimeSeriesSplit(gap=10, n_splits=5),
    random_state=2025,
    n_jobs=-1 # Use all available cores
)

random_search.fit(X, y)

print("Best parameters:", random_search.best_params_)
print("Best score:", random_search.best_score_)
```

```
Best parameters: {'learning_rate': np.float64(0.05637364430976246), 'max_depth': 6, 'min_child_weight': 1, 'n_estimators': 691, 'subsamp
Best score: 0.5106002554278416
```

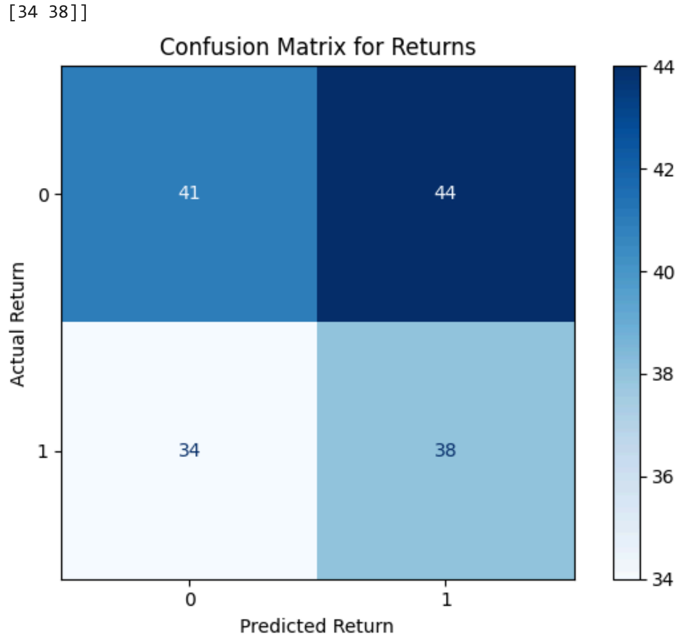
```
# Evaluate Model Classification Performance in the Test Set with "Best" hyperparameter settings
# final model evaluation
finalModel = XGBClassifier(objective='binary:logistic', eval_metric='logloss', random_state=2025,
                          max_depth = 6, min_child_weight = 1, subsample = 0.5970606684977592, learning_rate = 0.05637364430976246, n_estima

finalModel.fit(X, y) # fit to the training data
ypred = finalModel.predict(XTest) # predictions on the hold-out test data
RocCurveDisplay.from_predictions(yTest, ypred)
```

```
<sklearn.metrics._plot.roc_curve.RocCurveDisplay at 0x7ebc004bf740>
```




```
print("Confusion Matrix")
print(confusion_matrix(yTest, ypred))
disp = ConfusionMatrixDisplay.from_predictions(yTest, ypred,
                              display_labels =["0","1"],
                                              cmap = plt.cm.Blues)
plt.title("Confusion Matrix for Returns")
plt.xlabel("Predicted Return")
plt.ylabel("Actual Return")
plt.tight_layout()
plt.show()
```

```
Confusion Matrix
[[41 44]
 [34 38]]
```




```
print(classification_report(yTest, ypred, labels = ["0","1"]))
```

```
              precision    recall  f1-score   support

           0       0.55      0.48      0.51        85
           1       0.46      0.53      0.49        72

   micro avg       0.50      0.50      0.50       157
   macro avg       0.51      0.51      0.50       157
weighted avg       0.51      0.50      0.50       157
```

```
# Assess and print feature importances
model.fit(X, y)
print(model.feature_importances_)
```

```
[0.0485498  0.05014864 0.04153407 0.04655541 0.0437216  0.04683292
 0.04472881 0.04442059 0.04525414 0.04386874 0.04124043 0.04550721
 0.04161915 0.04029098 0.04140518 0.03696298 0.03331797 0.04327295
 0.03996009 0.0403973  0.03649111 0.03022377 0.03888723 0.03480893]
```

Ranking Features by Importance

This completes the exploration of additional features being added to the mix. Now we identify which of those features are most important in classifying the next day's return direction (up or even/down).

```
featureNames = wtiTrainETF.columns
print("Feature names correspond to Numpy array columns:",featureNames)

# Get feature importances
importances = np.round(model.feature_importances_, decimals = 3)

# Create Polars DataFrame
importanceDF = pl.DataFrame({"feature": featureNames, "importance": importances})

with pl.Config(
    tbl_rows = 60):
    print(importanceDF.sort("importance", descending=True))
```

```
Feature names correspond to Numpy array columns: ['CloseLag1', 'CloseLag2', 'CloseLag3', 'HMLLag1', 'HMLLag2', 'HMLLag3', 'OMCLag1', 'OM
shape: (24, 2)
```

feature --- str	importance --- f32
CloseLag2	0.05
CloseLag1	0.049
HMLLag1	0.047
HMLLag3	0.047
VolumeLag3	0.046
OMCLag1	0.045
OMCLag3	0.045
HMLLag2	0.044
OMCLag2	0.044
VolumeLag1	0.044
VGTUp	0.043
CloseLag3	0.042
CloseEMA2	0.042
VolumeLag2	0.041
CloseEMA8	0.041
CloseEMA4	0.04
VBUp	0.04
IVEUp	0.04
SLVUp	0.039
SPYUp	0.037
XLIUp	0.036
USOUp	0.035
GLDUp	0.033
XLUUp	0.03

Repeat the Modeling Process

For subsequent model development, we can retain the top features and then run additional tests with new features using the procedure demonstrated in this analysis

References

- [yfinance GitHub]
- [yfinance Documentation]
- [Polars Online User Guide]
- [Build Polars Database]

- [YouTube. Polars and Time Series: What It Can Do, and How to Overcome Any Limitation]()
- [Awesome Quant: Python for Quantiative Finance]()
- [Cross-validation]()
- [TimeSeriesSplit]()
- [RandomizedSearchCV]()
- [Hyperparameter Tuning]()
- [Metrics and Scoring]()
- [Introduction to Boosted Trees]()
- [XGBoost documentation]()
- [XGBoost in Python documentation]()
- [Auto-Sklearn for AutoML in an Scikit-Learn Environment]().

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
# list of the ETF tickers
etfs = ['spy', 'gld', 'ive', 'slv', 'uso', 'vb', 'vgt', 'xli', 'xlu']
etf_dfs = {}

# Loop through each ETF to reate the 'Up' feature
for etf in etfs:
    file_path = f"/content/{etf}_daily_data.csv"
    try:
        df = pl.read_csv(file_path, try_parse_dates=True)
        # Drop irrelevant columns
        df = df.drop(['Dividends', 'StockSplits'])
        # Create lagged closing price for previous day
        df = df.with_columns(pl.col('Close').shift(1).alias('CloseLag1'))
        # Create the 'Up' feature based on yesterday's price
        df = df.with_columns(
            (pl.col('Close').shift(-1) > pl.col('Close')).alias(f'{etf}Up').cast(pl.Int32)
        )
        etf_dfs[etf] = df
    except pl.ColumnNotFoundError as e:
        print(f"Column missing in {etf}: {e}. Skipping this ETF.")
    except Exception as e:
        print(f"Error processing {etf}: {e}. Skipping this ETF.")

if 'spy' in etf_dfs:
    print(etf_dfs['spy'].head())
```

shape: (5, 9)

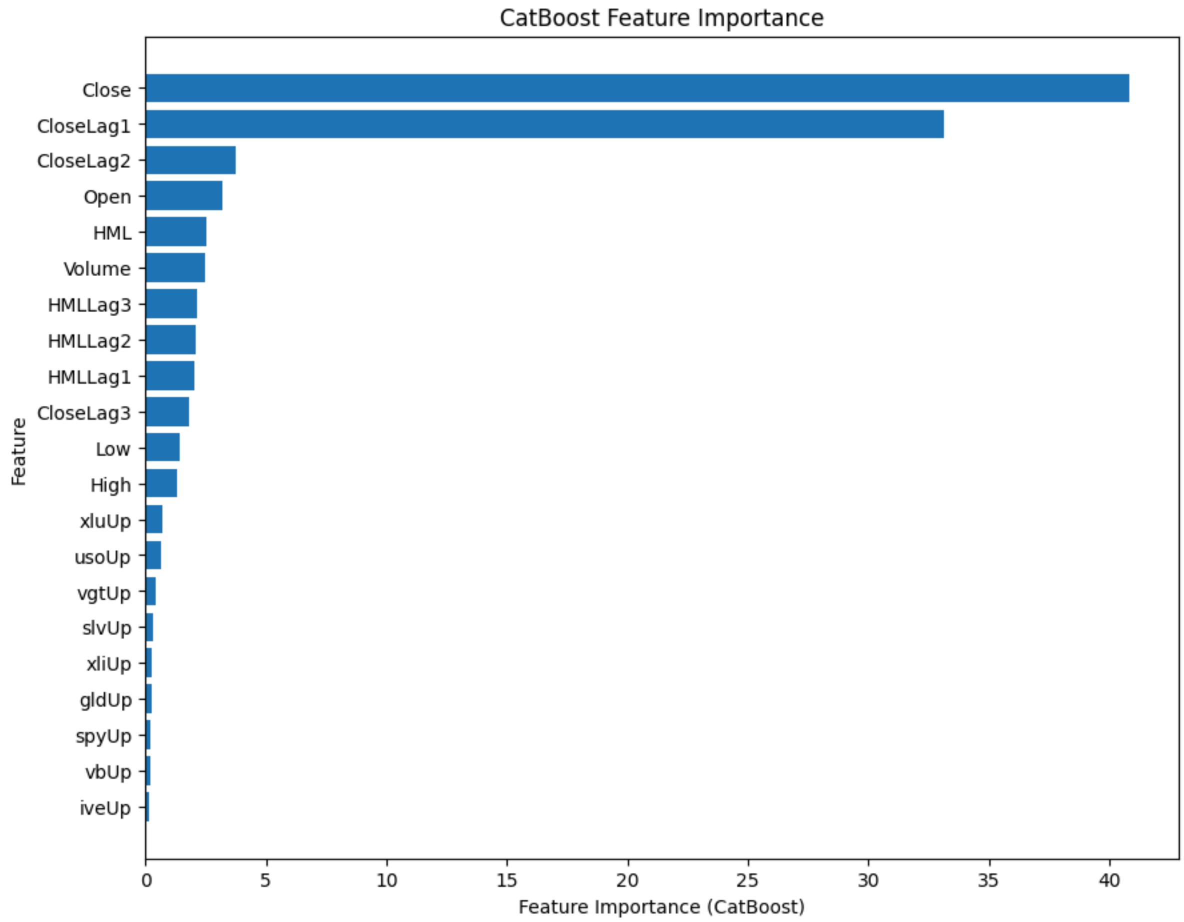
Date --- datetime[μs, UTC]	Open --- f64	High --- f64	Low --- f64	…	Volume --- i64	CapitalGains --- f64	CloseLag1 --- f64	spyUp --- i32
2000-01-03 05:00:00 UTC	93.924388	93.924388	91.152589	…	8164300	0.0	null	0
2000-01-04 05:00:00 UTC	90.934811	91.271387	88.46989	…	8089800	0.0	92.142517	1
2000-01-05 05:00:00 UTC	88.657974	89.6677	86.955297	…	12177900	0.0	88.539185	0
2000-01-06 05:00:00 UTC	88.459986	89.6479	87.272072	…	6227200	0.0	88.697571	1
2000-01-07 05:00:00 UTC	88.895594	92.340546	88.737205	…	8066500	0.0	87.272072	1

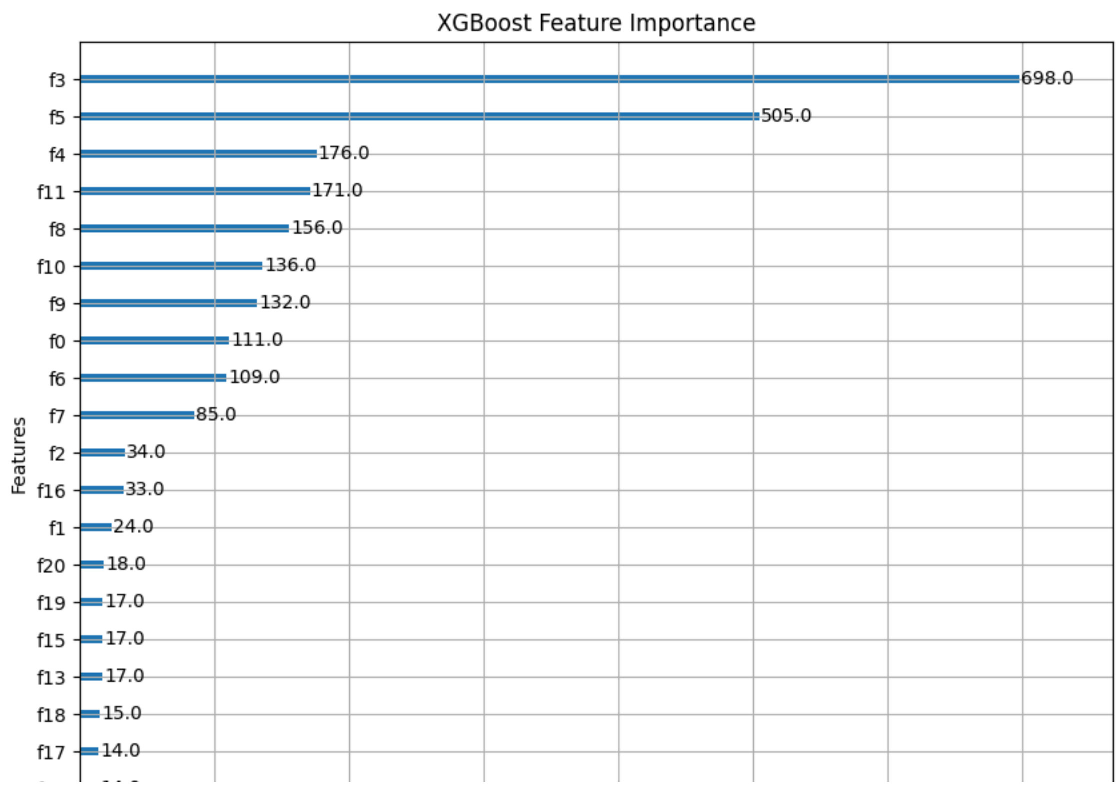
```
#  read prepared wti
wti = pl.read_csv("/content/wti-with-computed-features.csv", try_parse_dates=True)

# merge WTI with each ETF df
for etf, df in etf_dfs.items():
    wti = wti.join(df.select(['Date', f'{etf}Up']), on='Date', how='left')
```

```python
# drop NAs
wti = wti.drop_nulls()

# separate features and target
etf_features = [f'{etf}Up' for etf in etfs]
base_features = wti.columns[1:13]
X_columns = base_features + etf_features

X = wti.select(X_columns).to_numpy()
y = wti['Target'].to_numpy()
dates = wti['Date'].to_numpy()


# TimeSeriesSplit with a gap to prevent look-ahead bias
tscv = TimeSeriesSplit(n_splits=5, gap=10)

# initialize CatBoost and XGBoost
models = {
    'CatBoost': CatBoostClassifier(verbose=0, random_state=42),
    'XGBoost': XGBClassifier(random_state=42, eval_metric='logloss', use_label_encoder=False)
}

# Train and evaluate each model using cross-validation
for name, model in models.items():
    print(f"Training and evaluating {name}...")
    cv_results = cross_validate(model, X, y, cv=tscv, scoring=['accuracy', 'roc_auc'], return_train_score=False)
    print(f"{name} Cross-Validation Results:")
    print(f"  Accuracy: {cv_results['test_accuracy'].mean():.4f} +/- {cv_results['test_accuracy'].std():.4f}")
    print(f"  AUC: {cv_results['test_roc_auc'].mean():.4f} +/- {cv_results['test_roc_auc'].std():.4f}")
```

```
Training and evaluating CatBoost...
CatBoost Cross-Validation Results:
  Accuracy: 0.6494 +/- 0.0917
  AUC: 0.7146 +/- 0.1055
Training and evaluating XGBoost...
XGBoost Cross-Validation Results:
  Accuracy: 0.7046 +/- 0.0631
  AUC: 0.7749 +/- 0.0824
```

```python
# Re-fit CatBoost model on the full dataset to get feature importance
catboost_model = CatBoostClassifier(verbose=0, random_state=42)
catboost_model.fit(X, y)

# Get feature importance and feature names
feature_importance = catboost_model.get_feature_importance()
sorted_idx = np.argsort(feature_importance)
sorted_features = np.array(X_columns)[sorted_idx]

# Plot feature importance for CatBoost
plt.figure(figsize=(10, 8))
plt.barh(sorted_features, feature_importance[sorted_idx])
plt.xlabel("Feature Importance (CatBoost)")
plt.ylabel("Feature")
plt.title("CatBoost Feature Importance")
plt.show()

# Re-fit XGBoost model on the full dataset to get feature importance
xgboost_model = XGBClassifier(random_state=42, eval_metric='logloss', use_label_encoder=False)
xgboost_model.fit(X, y)

# Plot feature importance for XGBoost
plt.figure(figsize=(10, 8))
plot_importance(xgboost_model, ax=plt.gca())
plt.title("XGBoost Feature Importance")
plt.show()
```


CatBoost Feature Importance
Feature
Close
CloseLag1
CloseLag2
Open
HML
Volume
HMLLag3
HMLLag2
HMLLag1
CloseLag3
Low
High
xluUp
usoUp
vgtUp
slvUp
xliUp
gldUp
spyUp
vbUp
iveUp
0
5
10
15
20
25
30
35
40
Feature Importance (CatBoost)


XGBoost Feature Importance
Features
f3
f5
f4
f11
f8
f10
f9
f0
f6
f7
f2
f16
f1
f20
f19
f15
f13
f18
f17
698.0
505.0
176.0
171.0
156.0
136.0
132.0
111.0
109.0
85.0
34.0
33.0
24.0
18.0
17.0
17.0
17.0
15.0
14.0