Trading with Machine Learning Models¶

This tutorial will show how to train and backtest a machine learning price forecast model with *backtesting.py* framework. It is assumed you're already familiar with basic framework usage and machine learning in general.

For this tutorial, we'll use almost a year's worth sample of hourly EUR/USD forex data:

In [1]:

```
from backtesting.test import EURUSD, SMA data = EURUSD.copy() data
```

Loading BokehJS ...

Out[1]:

	Open	High	Low	Close	Volume
2017-04-19 09:00:00	1.07	1.07	1.07	1.07	1413
2017-04-19 10:00:00	1.07	1.07	1.07	1.07	1241
2017-04-19 11:00:00	1.07	1.07	1.07	1.07	1025
2017-04-19 12:00:00	1.07	1.07	1.07	1.07	1460
2017-04-19 13:00:00	1.07	1.07	1.07	1.07	1554
...	...	...	...	...	...
2018-02-07 11:00:00	1.23	1.24	1.23	1.24	2203
2018-02-07 12:00:00	1.24	1.24	1.23	1.23	2325
2018-02-07 13:00:00	1.23	1.23	1.23	1.23	2824
2018-02-07 14:00:00	1.23	1.23	1.23	1.23	4065
2018-02-07 15:00:00	1.23	1.23	1.23	1.23	6143

5000 rows × 5 columns

In supervised machine learning, we try to learn a function that maps input feature vectors (independent variables) into known output values (dependent variable):

$$ f\colon X \to \mathbf{y} $$

That way, provided our model function is sufficient, we can predict future output values from the newly acquired input feature vectors to some degree of certainty. In our example, we'll try to map several price-derived features and common technical indicators to the price point two days in the future. We construct model design matrix X below:

In [2]:

```
def BBANDS(data, n_lookback, n_std): """Bollinger bands indicator""" hlc3 = (data.High + data.Low + data.Close) / 3 mean, std = hlc3.rolling(n_lookback).mean(), hlc3.rolling(n_lookback).std() upper = mean + n_std*std lower = mean - n_std*std return upper, lower close = data.Close.values sma10 =
```

```
SMA(data.Close, 10) sma20 = SMA(data.Close, 20) sma50 = SMA(data.Close, 50) sma100 = SMA(data.Close,
100) upper, lower = BBANDS(data, 20, 2) # Design matrix / independent features: # Price-derived features
data['X_SMA10'] = (close - sma10) / close data['X_SMA20'] = (close - sma20) / close data['X_SMA50'] =
(close - sma50) / close data['X_SMA100'] = (close - sma100) / close data['X_DELTA_SMA10'] = (sma10 -
sma20) / close data['X_DELTA_SMA20'] = (sma20 - sma50) / close data['X_DELTA_SMA50'] = (sma50 - sma100)
/ close # Indicator features data['X_MOM'] = data.Close.pct_change(periods=2) data['X_BB_upper'] =
(upper - close) / close data['X_BB_lower'] = (lower - close) / close data['X_BB_width'] = (upper -
lower) / close data['X_Sentiment'] = ~data.index.to_series().between('2017-09-27', '2017-12-14') # Some
datetime features for good measure data['X_day'] = data.index.dayofweek data['X_hour'] = data.index.hour
data = data.dropna().astype(float)
```

Since all our indicators work only with past values, we can safely precompute the design matrix in advance. Alternatively, we would reconstruct the matrix every time before training the model.

Notice the made-up *sentiment* feature. In real life, one would obtain similar features by parsing news sources, Twitter sentiment, Stocktwits or similar. This is just to show input data can contain all sorts of additional explanatory columns.

As mentioned, our dependent variable will be the price (return) two days in the future, simplified into values 1 when the return is positive (and significant), -1 when negative, or 0 when the return after two days is roughly around zero. Let's write some functions that return our model matrix X and dependent, class variable $\mathbf{y}$ as plain NumPy arrays:

In [3]:

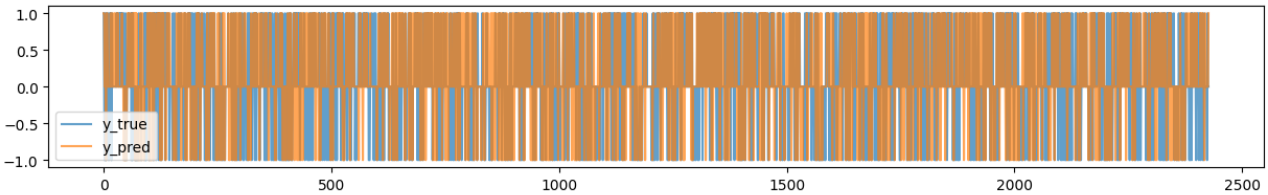
```
import numpy as np def get_X(data): """Return model design matrix X""" return
data.filter(like='X').values def get_y(data): """Return dependent variable y""" y =
data.Close.pct_change(48).shift(-48) # Returns after roughly two days y[y.between(-.004, .004)] = 0 #
Devalue returns smaller than 0.4% y[y > 0] = 1 y[y < 0] = -1 return y def get_clean_Xy(df): """Return
(X, y) cleaned of NaN values""" X = get_X(df) y = get_y(df).values isnan = np.isnan(y) X = X[~isnan] y =
y[~isnan] return X, y
```

Let's see how our data performs modeled using a simple k-nearest neighbors (kNN) algorithm from the state of the art scikit-learn Python machine learning package. To avoid (or at least demonstrate) overfitting, always split your data into *train* and *test* sets; in particular, don't validate your model performance on the same data it was built on.

In [4]:

```
import pandas as pd from sklearn.neighbors import KNeighborsClassifier from sklearn.model_selection
import train_test_split X, y = get_clean_Xy(data) X_train, X_test, y_train, y_test = train_test_split(X,
y, test_size=.5, random_state=0) clf = KNeighborsClassifier(7) # Model the output based on 7 "nearest"
examples clf.fit(X_train, y_train) y_pred = clf.predict(X_test) _ = pd.DataFrame({'y_true': y_test,
'y_pred': y_pred}).plot(figsize=(15, 2), alpha=.7) print('Classification accuracy: ', np.mean(y_test ==
y_pred))
```

```
Classification accuracy: 0.4210960032962505
```



We see the forecasts are all over the place (classification accuracy 42%), but is the model of any use under real backtesting?

Let's backtest a simple strategy that buys the asset for 20% of available equity with 20:1 leverage whenever the forecast is positive (the price in two days is predicted to go up), and sells under the same terms when the forecast is negative, all the while setting reasonable stop-loss and take-profit levels. Notice also the steady use of `data.df` accessor:

In [5]:

```
%%time from backtesting import Backtest, Strategy N_TRAIN = 400 class MLTrainOnceStrategy(Strategy): price_delta = .004 # 0.4% def init(self): # Init our model, a kNN classifier self.clf = KNeighborsClassifier(7) # Train the classifier in advance on the first N_TRAIN examples df = self.data.df.iloc[:N_TRAIN] X, y = get_clean_Xy(df) self.clf.fit(X, y) # Plot y for inspection self.I(get_y, self.data.df, name='y_true') # Prepare empty, all-NaN forecast indicator self.forecasts = self.I(lambda: np.repeat(np.nan, len(self.data)), name='forecast') def next(self): # Skip the training, in-sample data if len(self.data) < N_TRAIN: return # Proceed only with out-of-sample data. Prepare some variables high, low, close = self.data.High, self.data.Low, self.data.Close current_time = self.data.index[-1] # Forecast the next movement X = get_X(self.data.df.iloc[-1:]) forecast = self.clf.predict(X)[0] # Update the plotted "forecast" indicator self.forecasts[-1] = forecast # If our forecast is upwards and we don't already hold a long position # place a long order for 20% of available account equity. Vice versa for short. # Also set target take-profit and stop-loss prices to be one price_delta # away from the current closing price. upper, lower = close[-1] * (1 + np.r_[1, -1]*self.price_delta) if forecast == 1 and not self.position.is_long: self.buy(size=.2, tp=upper, sl=lower) elif forecast == -1 and not self.position.is_short: self.sell(size=.2, tp=lower, sl=upper) # Additionally, set aggressive stop-loss on trades that have been open # for more than two days for trade in self.trades: if current_time - trade.entry_time > pd.Timedelta('2 days'): if trade.is_long: trade.sl = max(trade.sl, low) else: trade.sl = min(trade.sl, high) bt = Backtest(data, MLTrainOnceStrategy, commission=.0002, margin=.05) bt.run()
```

```
CPU times: user 6.84 s, sys: 16.2 ms, total: 6.85 s Wall time: 6.84 s
```

Out[5]:

```
Start 2017-04-25 12:00:00 End 2018-02-07 15:00:00 Duration 288 days 03:00:00 Exposure Time [%] 79.41 Equity Final [$] 11604.55 Equity Peak [$] 12291.29 Commissions [$] 4124.02 Return [%] 16.05 Buy & Hold Return [%] 10.12 Return (Ann.) [%] 16.47 Volatility (Ann.) [%] 22.01 CAGR [%] 13.90 Sharpe Ratio 0.75 Sortino Ratio 1.28 Calmar Ratio 1.44 Alpha [%] 9.51 Beta 0.65 Max. Drawdown [%] -11.44 Avg. Drawdown [%] -1.45 Max. Drawdown Duration 84 days 22:00:00 Avg. Drawdown Duration 5 days 08:00:00 # Trades 353 Win Rate [%] 47.88 Best Trade [%] 0.56 Worst Trade [%] -0.54 Avg. Trade [%] 0.00 Max. Trade Duration 3 days 09:00:00 Avg. Trade Duration 0 days 19:00:00 Profit Factor 1.03 Expectancy [%] 0.00 SQN 0.80 Kelly Criterion 0.05 _strategy MLTrainOnceStrategy _equity_curve ... _trades Size Entr... dtype: object
```

In [6]:

```
bt.plot()
```

Out[6]:

GridPlot(id = 'p1427', …)

Despite our lousy win rate, the strategy seems profitable. Let's see how it performs under walk-forward optimization, akin to k-fold or leave-one-out cross-validation:

In [7]:

```
%%time class MLWalkForwardStrategy(MLTrainOnceStrategy): def next(self): # Skip the cold start period with too few values available if len(self.data) < N_TRAIN: return # Re-train the model only every 20 iterations. # Since 20 << N_TRAIN, we don't lose much in terms of # "recent training examples", but the speed-up is significant! if len(self.data) % 20: return super().next() # Retrain on last N_TRAIN values df = self.data.df[-N_TRAIN:] X, y = get_clean_Xy(df) self.clf.fit(X, y) # Now that the model is fitted,
```

```
# proceed the same as in MLTrainOnceStrategy super().next() bt = Backtest(data, MLWalkForwardStrategy, commission=.0002, margin=.05) bt.run()
```

```
CPU times: user 7.51 s, sys: 35.4 ms, total: 7.55 s Wall time: 7.51 s
```

Out[7]:

```
Start 2017-04-25 12:00:00 End 2018-02-07 15:00:00 Duration 288 days 03:00:00 Exposure Time [%] 71.72 Equity Final [$] 4872.65 Equity Peak [$] 10052.10 Commissions [$] 2686.16 Return [%] -51.27 Buy & Hold Return [%] 10.12 Return (Ann.) [%] -52.12 Volatility (Ann.) [%] 8.94 CAGR [%] -46.68 Sharpe Ratio -5.83 Sortino Ratio -3.28 Calmar Ratio -1.01 Alpha [%] -58.97 Beta 0.76 Max. Drawdown [%] -51.53 Avg. Drawdown [%] -51.53 Max. Drawdown Duration 265 days 00:00:00 Avg. Drawdown Duration 265 days 00:00:00 # Trades 324 Win Rate [%] 38.27 Best Trade [%] 0.36 Worst Trade [%] -0.53 Avg. Trade [%] -0.07 Max. Trade Duration 3 days 07:00:00 Avg. Trade Duration 0 days 18:00:00 Profit Factor 0.57 Expectancy [%] -0.07 SQN -3.77 Kelly Criterion -0.29 _strategy MLWalkForwardStr... _equity_curve ... _trades Size Entr... dtype: object
```

In [8]:

```
bt.plot()
```

Out[8]:

GridPlot(id = 'p1882', …)

Apparently, when repeatedly retrained on past `N_TRAIN` data points in a rolling manner, our basic model generalizes poorly and performs not quite as well.

This was a simple and contrived, tongue-in-cheek example that shows one way to use machine learning forecast models with *backtesting.py* framework. In reality, you will need a far better feature space, better models (cf. deep learning), and better money management strategies to achieve consistent profits in automated short-term forex trading. More proper data science is an exercise for the keen reader.

Some instant optimization tips that come to mind are:

- **Data is king.** Make sure your design matrix features as best as possible model and correlate with your chosen target variable(s) and not just represent random noise.
- Instead of modelling a single target variable y, model a multitude of target/class variables, possibly better designed than our "48-hour returns" above.
- **Model everything:** forecast price, volume, time before it "takes off", SL/TP levels, optimal position size ...
- Reduce false positives by increasing the conviction needed and imposing extra domain expertise and discretionary limitations before entering trades.

Also make sure to familiarize yourself with the full Backtesting.py API reference