btc-eth-neural-network-trading

October 12, 2024

1 Neural Networks For Market Trading

```
[11]: import vfinance as vf
      import pandas as pd
      import numpy as np
      from backtesting import Backtest, Strategy
      from xgboost import XGBClassifier, plot importance
      from sklearn.neural_network import MLPClassifier
      from sklearn.metrics import accuracy_score, confusion_matrix,_
      ⇔classification_report
      from matplotlib import pyplot as plt
      import pandas_ta as ta
      # Fetch BTC data
      df = yf.download("ETH-USD", start="2024-01-01", end="2024-10-12", interval="1d")
      df.reset_index(inplace=True)
      df.columns = ['Local time', 'Open', 'High', 'Low', 'Close', 'Adj Close',
       df = df.drop('Adj Close', axis=1)
      # Check for NA values and clean data
      df = df[df['Volume'] != 0]
      df.reset_index(drop=True, inplace=True)
      # Add RSI
      df["RSI"] = ta.rsi(df['Close'], length=16)
      # Check if RSI was added successfully
      print("Columns in DataFrame after adding RSI:")
      print(df.columns)
      df.dropna(inplace=True)
      df.reset_index(drop=True, inplace=True)
      # Ensure RSI is present
      if 'RSI' not in df.columns:
         raise KeyError("RSI column is missing from the DataFrame.")
```

```
print(df)
[********* 100%********** 1 of 1 completed
Columns in DataFrame after adding RSI:
Index(['Local time', 'Open', 'High', 'Low', 'Close', 'Volume', 'RSI'],
dtype='object')
   Local time
                      Open
                                  High
                                                Low
                                                          Close \
0
   2024-01-17
               2587.044678 2592.737061
                                                    2528.369385
                                        2508.432861
1
   2024-01-18
               2528.593262 2546.263916
                                        2426.135498
                                                    2467.018799
   2024-01-19
               2468.688965 2501.305176
                                        2414.710938
                                                    2489.498535
3
   2024-01-20 2489.847656 2489.847656
                                        2456.095703
                                                    2469.589111
4
   2024-01-21 2469.798584 2479.760498 2452.377686 2453.913086
263 2024-10-06
               2415.531738 2456.630615
                                        2407.099365 2439.957764
264 2024-10-07
               2439.944824 2520.406250
                                        2405.134277 2421.796631
265 2024-10-08
               2421.980957
                           2464.127441
                                        2400.510742 2439.840820
266 2024-10-09
               2439.840088 2470.913086
                                        2350.946533
                                                    2368.283447
267 2024-10-10 2368.273193
                           2417.288086 2329.784668 2383.857910
         Volume
                      RSI
0
    10441017520 58.512755
1
    11900028080 53.601379
2
    11405278376 55.075185
3
     5297826161 53.470659
4
     4578471955 52.193591
263
     8458690205 45.886015
264
    17414044416 44.870095
265
    14067361080 46.134008
266
    14954047093 42.055523
267
    15327769940 43.220866
```

2 Support and Resistance FUNCTIONS

[268 rows x 7 columns]

```
[2]: # Support and Resistance Functions
def support(df1, 1, n1, n2):
    for i in range(1 - n1 + 1, 1 + 1):
        if df1.Low[i] > df1.Low[i - 1]:
            return 0
    for i in range(1 + 1, 1 + n2 + 1):
        if df1.Low[i] < df1.Low[i - 1]:</pre>
```

```
return 0
return 1

def resistance(df1, 1, n1, n2):
    for i in range(1 - n1 + 1, 1 + 1):
        if df1.High[i] < df1.High[i - 1]:
            return 0

for i in range(1 + 1, 1 + n2 + 1):
        if df1.High[i] > df1.High[i - 1]:
            return 0

return 1
```

```
[3]: # Calculate necessary lists
     length = len(df)
     high = list(df['High'])
     low = list(df['Low'])
     close = list(df['Close'])
     open = list(df['Open'])
     bodydiff = [0] * length
     highdiff = [0] * length
     lowdiff = [0] * length
     ratio1 = [0] * length
     ratio2 = [0] * length
     def isEngulfing(1):
         row = 1
         bodydiff[row] = abs(open[row] - close[row])
         if bodydiff[row] < 0.000001:</pre>
             bodydiff[row] = 0.000001
         bodydiffmin = 0.002
         if (bodydiff[row] > bodydiffmin and bodydiff[row - 1] > bodydiffmin and
             open[row - 1] < close[row - 1] and
             open[row] > close[row] and
             (open[row] - close[row - 1]) \ge -0e-5 and close[row] < open[row - 1]):
             return 1
         elif (bodydiff[row] > bodydiffmin and bodydiff[row - 1] > bodydiffmin and
               open[row - 1] > close[row - 1] and
               open[row] < close[row] and</pre>
               (open[row] - close[row - 1]) <= +0e-5 and close[row] > open[row - 1]):
             return 2
         else:
             return 0
     def isStar(1):
         bodydiffmin = 0.0020
         row = 1
```

```
highdiff[row] = high[row] - max(open[row], close[row])
    lowdiff[row] = min(open[row], close[row]) - low[row]
    bodydiff[row] = abs(open[row] - close[row])
    if bodydiff[row] < 0.000001:</pre>
        bodydiff[row] = 0.000001
    ratio1[row] = highdiff[row] / bodydiff[row]
    ratio2[row] = lowdiff[row] / bodydiff[row]
    if ratio1[row] > 1 and lowdiff[row] < 0.2 * highdiff[row] and bodydiff[row]
 → bodydiffmin:
        return 1
    elif ratio2[row] > 1 and highdiff[row] < 0.2 * lowdiff[row] and__
 ⇒bodydiff[row] > bodydiffmin:
        return 2
    else:
        return 0
def closeResistance(l, levels, lim):
    if len(levels) == 0:
        return 0
    c1 = abs(df.High[l] - min(levels, key=lambda x: abs(x - df.High[l]))) <= lim</pre>
    c2 = abs(max(df.Open[1], df.Close[1]) - min(levels, key=lambda x: abs(x -

df.High[l]))) <= lim
</pre>
    c3 = min(df.Open[1], df.Close[1]) < min(levels, key=lambda x: abs(x - df.
 →High[1]))
    c4 = df.Low[1] < min(levels, key=lambda x: abs(x - df.High[1]))
    if (c1 or c2) and c3 and c4:
        return 1
    else:
        return 0
def closeSupport(l, levels, lim):
    if len(levels) == 0:
        return 0
    c1 = abs(df.Low[1] - min(levels, key=lambda x: abs(x - df.Low[1]))) <= lim
    c2 = abs(min(df.Open[1], df.Close[1]) - min(levels, key=lambda x: abs(x -
 \hookrightarrowdf.Low[1]))) <= lim
    c3 = max(df.Open[1], df.Close[1]) > min(levels, key=lambda x: abs(x - df.
 →Low[1]))
    c4 = df.High[1] > min(levels, key=lambda x: abs(x - df.Low[1]))
    if (c1 or c2) and c3 and c4:
        return 1
    else:
        return 0
```

```
[4]: # Generate signals
    n1 = 2
    n2 = 2
     backCandles = 30
     signal = [0] * length
     for row in range(backCandles, len(df) - n2):
         ss = \prod
         rr = []
         for subrow in range(row - backCandles + n1, row + 1):
             if support(df, subrow, n1, n2):
                 ss.append(df.Low[subrow])
             if resistance(df, subrow, n1, n2):
                 rr.append(df.High[subrow])
         if (isEngulfing(row) == 1 or isStar(row) == 1) and closeResistance(row, rr, __
      →150):
             signal[row] = 1
         elif (isEngulfing(row) == 2 or isStar(row) == 2) and closeSupport(row, ss,
             signal[row] = 2
         else:
             signal[row] = 0
     df['signal'] = signal
[5]: # Define strategy
     class MyCandlesStrat(Strategy):
         def init(self):
             super().init()
             self.signal1 = self.I(lambda: df['signal'])
         def next(self):
             super().next()
             if self.signal1 == 2:
                 sl1 = self.data.Close[-1] - 600
                 tp1 = self.data.Close[-1] + 450
                 self.buy(sl=sl1, tp=tp1)
             elif self.signal1 == 1:
                 sl1 = self.data.Close[-1] + 600
                 tp1 = self.data.Close[-1] - 450
                 self.sell(sl=sl1, tp=tp1)
[6]: # Run backtest
     bt = Backtest(df, MyCandlesStrat, cash=10_000, commission=.002)
     stat = bt.run()
     print(stat)
```

bt.plot()

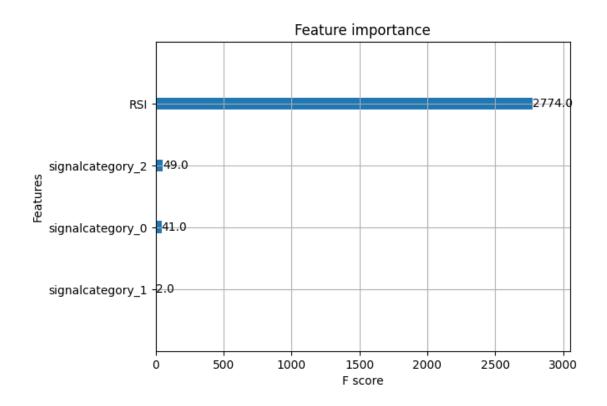
```
<ipython-input-6-136ea163cdb2>:2: UserWarning: Data index is not datetime.
    Assuming simple periods, but `pd.DateTimeIndex` is advised.
      bt = Backtest(df, MyCandlesStrat, cash=10_000, commission=.002)
    Start
                                                0.0
    End
                                              267.0
    Duration
                                              267.0
    Exposure Time [%]
                                         57.089552
    Equity Final [$]
                                       7824.428674
    Equity Peak [$]
                                      11369.631142
    Return [%]
                                        -21.755713
    Buy & Hold Return [%]
                                           -5.7156
    Return (Ann.) [%]
                                                0.0
    Volatility (Ann.) [%]
                                               NaN
    Sharpe Ratio
                                               NaN
    Sortino Ratio
                                               NaN
    Calmar Ratio
                                                0.0
    Max. Drawdown [%]
                                        -34.991396
    Avg. Drawdown [%]
                                        -18.787639
    Max. Drawdown Duration
                                             211.0
    Avg. Drawdown Duration
                                              108.0
    # Trades
                                                7.0
    Win Rate [%]
                                         42.857143
    Best Trade [%]
                                         15.914914
    Worst Trade [%]
                                        -19.355039
    Avg. Trade [%]
                                         -4.671989
    Max. Trade Duration
                                               57.0
    Avg. Trade Duration
                                         20.857143
    Profit Factor
                                          0.615687
    Expectancy [%]
                                         -3.559953
    SQN
                                         -0.637321
                                    MyCandlesStrat
    _strategy
                                          Equit...
    _equity_curve
    _trades
                                  Size EntryBa...
    dtype: object
    /usr/local/lib/python3.10/dist-packages/backtesting/_plotting.py:659:
    UserWarning: found multiple competing values for 'toolbar.active_drag' property;
    using the latest value
      fig = gridplot(
    /usr/local/lib/python3.10/dist-packages/backtesting/_plotting.py:659:
    UserWarning: found multiple competing values for 'toolbar.active_scroll'
    property; using the latest value
      fig = gridplot(
[6]: GridPlot(id='p1332', ...)
```

```
[7]: # Target flexible way
     pipdiff = 250
     SLTPRatio = 1
     def mytarget(barsupfront, df1):
         length = len(df1)
         high = list(df1['High'])
         low = list(df1['Low'])
         close = list(df1['Close'])
         open = list(df1['Open'])
         trendcat = [None] * length
         for line in range(0, length - barsupfront - 2):
             valueOpenLow = 0
             valueOpenHigh = 0
             for i in range(1, barsupfront + 2):
                 value1 = open[line + 1] - low[line + i]
                 value2 = open[line + 1] - high[line + i]
                 valueOpenLow = max(value1, valueOpenLow)
                 valueOpenHigh = min(value2, valueOpenHigh)
             if (valueOpenLow >= pipdiff) and (-valueOpenHigh <= (pipdiff /
      →SLTPRatio)):
                 trendcat[line] = 1 # downtrend
             elif (valueOpenLow <= (pipdiff / SLTPRatio)) and (-valueOpenHigh >=_
      →pipdiff):
                 trendcat[line] = 2 # uptrend
             else:
                 trendcat[line] = 0 # no clear trend
         return trendcat
     df['Target'] = mytarget(30, df)
     df.dropna(inplace=True)
     df.reset_index(drop=True, inplace=True)
```

```
df_model = df_model.drop(['signal'], axis=1)
     df_model = pd.concat([df_model, dfDummies], axis=1)
     # Check columns of df_model
     print("Columns in df_model after dummy variable creation:")
     print(df_model.columns)
     # Define attributes for modeling dynamically
     dummies_columns = [col for col in df_model.columns if col.
      ⇔startswith('signalcategory')]
     attributes = ['RSI'] + dummies_columns
     X = df_model[attributes]
     y = df_model['Target']
     # Split the data into training and test sets
     train_pct_index = int(0.7 * len(X))
     X_train, X_test = X[:train_pct_index], X[train_pct_index:]
     y_train, y_test = y[:train_pct_index], y[train_pct_index:]
     # Ensure all classes are covered
     all classes = sorted(y.unique())
     print(f"All classes: {all_classes}")
    Columns in df_model after dummy variable creation:
    Index(['RSI', 'Target', 'signalcategory 0', 'signalcategory 1',
           'signalcategory_2'],
          dtype='object')
    All classes: [0.0, 1.0, 2.0]
[9]: # XGBoost model
     xgb_model = XGBClassifier()
     xgb_model.fit(X_train, y_train)
     pred_train_xgb = xgb_model.predict(X_train)
     pred_test_xgb = xgb_model.predict(X_test)
     # Accuracy and metrics for XGBoost
     acc train xgb = accuracy score(y train, pred train xgb)
     acc_test_xgb = accuracy_score(y_test, pred_test_xgb)
     print('****XGBoost Results****')
     print(f'Train Accuracy: {acc_train_xgb:.4%}')
     print(f'Test Accuracy: {acc_test_xgb:.4%}')
     matrix_train_xgb = confusion_matrix(y_train, pred_train_xgb)
     matrix_test_xgb = confusion_matrix(y_test, pred_test_xgb)
     print("Train Confusion Matrix (XGBoost):")
     print(matrix_train_xgb)
```

```
print("Test Confusion Matrix (XGBoost):")
print(matrix_test_xgb)
report_train_xgb = classification_report(y_train, pred_train_xgb,_
  →labels=all_classes)
report_test_xgb = classification_report(y_test, pred_test_xgb,__
  ⇒labels=all classes)
print("Train Classification Report (XGBoost):")
print(report_train_xgb)
print("Test Classification Report (XGBoost):")
print(report_test_xgb)
plot_importance(xgb_model)
plt.show()
****XGBoost Results****
Train Accuracy: 99.3939%
Test Accuracy: 32.3944%
Train Confusion Matrix (XGBoost):
[[38 1 0]
[ 0 68 0]
 [ 0 0 58]]
Test Confusion Matrix (XGBoost):
[[ 0 0 18]
[10 17 20]
 [0 0 6]]
Train Classification Report (XGBoost):
              precision
                           recall f1-score
                                              support
         0.0
                             0.97
                   1.00
                                       0.99
                                                   39
         1.0
                   0.99
                             1.00
                                       0.99
                                                   68
         2.0
                   1.00
                             1.00
                                       1.00
                                                   58
                                       0.99
                                                   165
   accuracy
  macro avg
                   1.00
                             0.99
                                       0.99
                                                   165
                   0.99
                             0.99
                                       0.99
weighted avg
                                                   165
Test Classification Report (XGBoost):
              precision
                           recall f1-score
                                              support
         0.0
                   0.00
                             0.00
                                       0.00
                                                    18
                   1.00
                             0.36
                                       0.53
         1.0
                                                    47
         2.0
                   0.14
                             1.00
                                       0.24
                                                    6
                                       0.32
                                                   71
    accuracy
                                       0.26
                                                   71
  macro avg
                   0.38
                             0.45
```

weighted avg 0.67 0.32 0.37 71



```
[10]: # Neural Network model
      nn_model = MLPClassifier(hidden_layer_sizes=(50, 50, 60, 30, 9),
       →random_state=100, verbose=0, max_iter=1000, activation='relu')
      nn_model.fit(X_train, y_train)
      pred_train_nn = nn_model.predict(X_train)
      pred_test_nn = nn_model.predict(X_test)
      # Accuracy and metrics for Neural Network
      acc_train_nn = accuracy_score(y_train, pred_train_nn)
      acc_test_nn = accuracy_score(y_test, pred_test_nn)
      print('****Neural Network Results****')
      print(f'Train Accuracy: {acc_train_nn:.4%}')
      print(f'Test Accuracy: {acc_test_nn:.4%}')
      matrix_train_nn = confusion_matrix(y_train, pred_train_nn)
      matrix_test_nn = confusion_matrix(y_test, pred_test_nn)
      print("Train Confusion Matrix (Neural Network):")
      print(matrix_train_nn)
      print("Test Confusion Matrix (Neural Network):")
```

```
print(matrix_test_nn)
report_train_nn = classification_report(y_train, pred_train_nn,_
  ⇔labels=all_classes)
report_test_nn = classification_report(y_test, pred_test_nn, labels=all_classes)
print("Train Classification Report (Neural Network):")
print(report_train_nn)
print("Test Classification Report (Neural Network):")
print(report_test_nn)
****Neural Network Results****
Train Accuracy: 41.2121%
Test Accuracy: 66.1972%
Train Confusion Matrix (Neural Network):
[[ 0 39 0]
[ 0 68 0]
[ 0 58 0]]
Test Confusion Matrix (Neural Network):
[[ 0 18 0]
Γ 0 47 0]
 [0 6 0]]
Train Classification Report (Neural Network):
              precision
                           recall f1-score
                                              support
         0.0
                   0.00
                             0.00
                                       0.00
                                                    39
         1.0
                   0.41
                             1.00
                                       0.58
                                                    68
                   0.00
         2.0
                             0.00
                                       0.00
                                                    58
                                       0.41
                                                   165
    accuracy
                   0.14
                             0.33
                                        0.19
                                                   165
  macro avg
weighted avg
                   0.17
                             0.41
                                       0.24
                                                   165
Test Classification Report (Neural Network):
              precision
                           recall f1-score
                                              support
         0.0
                   0.00
                             0.00
                                       0.00
                                                    18
         1.0
                   0.66
                             1.00
                                       0.80
                                                    47
                   0.00
         2.0
                             0.00
                                       0.00
                                                     6
    accuracy
                                       0.66
                                                    71
                   0.22
                             0.33
                                       0.27
                                                    71
  macro avg
weighted avg
                   0.44
                             0.66
                                       0.53
                                                    71
```

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531: UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this

behavior.

_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
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UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parameter to control this behavior.

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UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
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/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1531:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this
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_warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))