Asian Institute of Management
Master of Science in Data Science – Machine Learning

Predicting the XAU-USD Foreign Exchange Prices using Machine Learning

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Abstract

XAU-USD or gold price in US Dollars is the most volatile currency pair in the foreign exchange (forex) market. Forex trading is the largest financial market in the world with a daily average of $5 trillion. In the Philippines, forex trading lags in terms of popularity and awareness as compared to other trading or investment options. In this paper, the researchers use real hourly price data from a foreign forex broker to predict the gold price. The data has approximately 16,000 observations with multiple technical indicators use as features. Feature engineering was performed to add features in the study based on the knowledge from a forex trading school. Various machine learning models were employed, and Linear Support Vector Machine was chosen which attained a 65% accuracy with a 58% precision macro score. A trade simulation was run using the last six months of the dataset and resulted a 54% return on investments. Long Short-Term Memory (LSTM) may increase the accuracy of the model and improve the simulated profit. The results provide an evidence to the great potential of forex trading as a better alternative for income generation for individuals.

***Keywords**: Classification; Foreign Exchange (Forex); Forex Trading; Machine Learning; XAU-USD*

1. Introduction

Foreign Exchange (Forex) is the largest financial market in the world with a daily average of $5 trillion each day versus the largest stock market, New York Stock Exchange, which averages $75 billion. This amount of money is equivalent to five Apple, Inc companies. Forex is a decentralized market, meaning there is no one physical location where investor go to buy or sell currencies. Individuals or retailers can trade forex anywhere and anytime through your laptop, tablet or phone as long as you are connected online. Unlike stock exchanges, forex is open 24 hours 5 days a week.

In essence, there are two markets in forex. There is the interbank market, where banks, hedge funds, governments and corporations are and the other one is retail who are the individuals. People can open begin trading with a $100. Forex brokers provide favorable leverage that with a small amount of money, you can trade large trades. This market is the most volatile with the highest return possible but the highest risk of losing money as well.

Traders use the term PIP or *Percentage in Point* in computing the gains or losses of each trade. It is the unit of change in a currency pair. A pip is the smallest price change that a given exchange rate can make and every money pair has a corresponding value. For example, the price of gold is 1500.10 and the trader bet for a long at $0.03, after a while the price of gold increased to 1501.10 or by 100 pips thus the trader's profit is $3.00 (100 * 0.03). Other forex brokers allow other currencies for trading (e.g. euro and sing dollars). It is calculated as

$$Profit\ or\ Loss\ =\ PIP\ \times\ Amount\ being\ purchased.$$

Stop loss is use as an order that is set to reduce losses. A transaction trend describes the direction of the market movement which is either upward or downward. For an uptrend, there are more sellers than buyers which creates a resistance level while a downtrend means there are more buyers than sellers creating a support level.

Most professional forex traders average up to 10% a month of profit. Compounded in a year this amounts to approximately 213% profit, assuming that this is net of all the losses. For most, this may seem unrealistic that if this is possible why not everyone just trade forex and will not need to work. Forex is easy to do and not much brain power to execute but human emotion is what hinders a person to maximize the potential profit due mainly to greed and fear. The saying practice makes perfect applies to this kind of profession as well by doing back testing of chosen trading strategy.

XAU-USD or the price of gold in US dollars is the main focus of the study. Since the 1970s, overall, the price of gold has been on an upward with a couple of reversals in the 1980s and 2011.

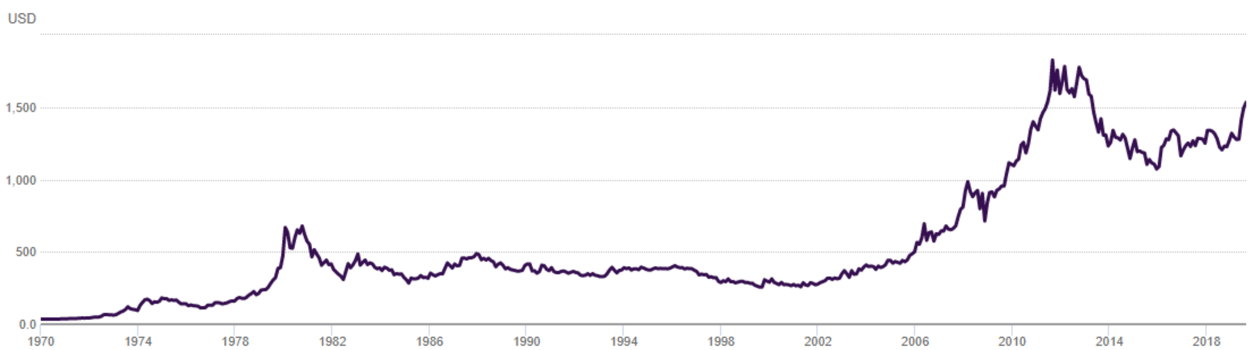

Figure 1. Historical Price of Gold (1970 – 2019)

2. Related Work

One of the most answered foreign exchange problems is the prediction of forex rates (determining whether it will go up or down) of currency pairs. This is a classification solution with binary values as outputs. Another approach is to treat it as a time series data and the technique usually used is Auto Regressive Integrated Moving Average (ARIMA). However, according to Baasher and Mohamed, who did a study on forex trend classification using machine learning techniques, ARIMA is an unvaried model in general. It is performed with the assumption that the time series data is linear and stationary. According to Deboeck, G.J., forex has noisy data which makes it a challenging time series forecasting problem.[8] Since financial time series are inherently noisy and unstable, it is tough to enhance forecasting accuracy. To mitigate this disadvantage, B. Zhang has conducted a study on LSTM (Long Short-Term Memory) application to financial forecasting model. It has presented superior forecasting capacity which backs up the idea that machine learning performs better in non-linear time series forecasting.[7]

The downside of statistical models lies in their innate linear form and as a result, non-linear models have been explored. Studies indicate that neural networks perform better than statistical models occasionally and of all learning algorithms, recursive neural network (RNN) works better with sequence dependency.[3,4] Long Short-Term Memory (LSTM) is under the RNN algorithm, which may greatly simplify exchange rates forecasting. It combines the scoring process and threshold value selecting process instead of separate processes.[6] Therefore, all these unique features enable LSTM to perform well in time series forecasting.

2.1 Support Vector Machine (SVM) Model

Non-linear prediction problems can also be solved by SVM models even though there are limited publications that use this algorithm for financial time-series forecasting[10], it has been reported as a powerful technique. SVM models avoid issues such as over-fitting problems. It seems to be difficult to solve a non-linear training dataset, but the solution is to map the data onto a higher dimensional space (so-called feature space) in where the linear hyperplane can separate the dataset in two classes.

3. Dataset

The whole data set, which was collected from Hotforex, a foreign forex broker, contains actual hourly prices starting from September 10, 2015 up to June 15, 2018 for a total of 16,298 observations. The raw features available were the open, high, low, and close prices, and the volume. Other indicators were also calculated from the raw features:

a. Ceiling price – highest price of the previous day
b. Floor price – lowest price of the previous day
c. Short Term Moving Average (5 hours)
d. Short Term Moving Average (21 hours)
e. Mid Term Moving Average (number of hours)[1]
f. Long Term Moving Average (number of hours)[1]
g. Trigger[1]

After calculating the moving averages, a number of observations were left with null values since the long term moving average can only be calculated starting from the 84th observation. The dataset for modelling therefore starts at September 15, 2015 at 15:00H.

3.1 Feature Selection and Engineering

The features described above cannot be directly used for modelling since they will cause the model to predict the forex trend using features that are in the same time period. Features for modelling were generated from the lagged values of the original features.

For this study, a 21-hour window was used to account for the short term price movements. The previous 21, open, high, low, and close prices were added in the lagged features. The previous

[1] Details for this indicator is omitted as it is covered by a non-disclosure agreement

moving averages (short term only) and trigger values were also included. Lastly, standard deviations and ratios for the moving averages were also added.

3.2 Setting the Target

The objective for the model is to predict if the forex price will increase by 300 pips within the succeeding 4 hours. The target labels for this objective was generated by taking the difference between highest price attained in the next 4 hours (since a sell can be automated as long as the target price was reached) and the previous closing price. This value was labelled 1 if it exceeded $3.3 (330 pips) to account for the difference and spread in buying and selling prices.

3.3 Train-Test Split

Even if the model built was a classifier, the data was split based on time periods. This ensures that the model is trained without seeing data from the future. It also allows simulation for consecutive time periods.

The training set used ranged from September 15, 2015 0:00H up to January 18, 2018 0:00H. The testing set used was for the succeeding months: January 18, 2018 0:00H up to June 15, 2018 24:00H. The split was prepared to have a full 6-months for the testing set (June 16 and 17, 2018 were weekends).

4. Exploratory Data Analysis

The whole dataset is on an upward trend but mostly ranging with numerous dips. Gold price was ranging since the reversal in 2011 up to 2018

Figure 2. Historical Price of Gold (Sep 2015 – Jun 2018)

5. Methods

A classifier which recommends trades was used in this study. This classifier will recommend a trade (class 1) if in the next four hours, the forex price is predicted to reach at least 300 pips higher than the previous closing price. Otherwise, the classifier will not recommend a trade (class 0).

The models considered for the classification are the following:

a. Logistic Regression (L2 regularization)
b. Linear Support Vector Machine (L2 regularization)
c. Random Forest Classifier
d. Gradient Boosting Classifier

The parameters for each classifier were tuned using sklearn's grid search cross validation function with a 'precision_macro' scoring. The scoring maximizes the true positives and true negatives predicted by the model, making it more reliable.

After identifying the best model, a trade simulation was run using the testing set[2]. The estimated profits was then calculated using the predictions and stoploss assumptions.

6. Results and Discussion

6.1 Oversampling and Modelling

Oversampling using SMOTE was done first since the training set was unbalanced (65% class 0 – 35% class 1). The default parameters were used from the imblearn.oversampling library. The models were then trained using the resampled training set and the scores were evaluated based on the test set predictions. The hyperparameters used for tuning each model are shown below:

Table 1. Model Tuning Hyperparameters

Model	Hyperparameter	Range Tested
Logistic Regression (L2)	C	0.001 – 1
Linear Support Vector Machine (L2)	C	$1x10^{-5}$ – 0.01
Random Forest	max_depth	8 – 10
	n_estimators	100 – 200
Gradient Boost	max_depth	8 – 10
	n_estimators	100 – 200

The following results were attained after tuning:

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[2] Details on the simulation will be discussed in the trade simulation section

Table 2. Model Tuning Results

Model	Accuracy	Precision Macro
Logistic Regression (L2)	64%	58%
Linear Support Vector Machine (L2)	65%	58%
Random Forest	65%	56%
Gradient Boost	63%	53%

The accuracy attained from all models were below the heuristic target for the PCC (1.25 x 54%) which is 67.8%. However, these results are still better than guessing trades at random. The effectiveness of this model could be further analyzed through the trade simulation.

The best model was found the be the Linear Support Vector Machine with L2 regularization. It attained a 65% accuracy with a 58% precision macro score.

```
              precision    recall  f1-score

           0       0.74      0.76      0.75
           1       0.42      0.39      0.40

    accuracy                           0.65
   macro avg       0.58      0.58      0.58
weighted avg       0.64      0.65      0.64
```

Figure 3. Linear SVM with L2 Regularization Classification Report

The figure above shows that the model was able to predict bad trades (class 0) correctly, 74% (precision) of the time. It was also able to predict 76% (recall) of the bad trades. This is good since we can be certain that when the model predicts a class 0, we refrain from trading.

However, the precision and recall were lower for class 1 (42% and 39%, respectively). This means that trade recommendations only have a 42% chance of being correct and that the model was only able to find 39% of the good trades. We leave our model at this since we cannot try to increase the precision at the expense of a lower recall. A higher precision may mean that we are more certain about our trades but the lower recall would mean that we are losing more opportunities to trade.

We resolve the low precision by implementing a stop loss amount during trading. A stop loss is normally implemented by traders to prevent them from losing to much from dips in the exchange.

6.2 Trade Simulation

A trade simulation was prepared using the best performing model. The simulation was done for the testing set which covers the days between January 18, 2018 and June 15, 2018 (6 months). This ensures that the model is not recommending trades for forex movements that it has already seen before.

Since the best model was only able to achieve 42% precision for the recommended trades (class 1), a stoploss was placed in every trade. The stoploss price was placed at around 100 pips which is 1/3 of the target selling price (300 pips). This ensures that the losses from wrong predictions could still be covered. The table below shows the parameters used for the simulation:

Table 3. Trade Simulation Parameters

Simulation Parameter	Value	Description
Starting Equity	$ 100,000	Starting equity for the simulation
Stoploss	$ -1 (100 pips)	Stoploss target to prevent losing too much equity on wrong predictions
Selling Price	$ +3.3 (330 pips)	Target selling price based on the model prediction
Bet	(Current Equity)/10,000	Portion of the equity to be placed on bet during trading. The total win/loss will be calculated using the bet based on the change in pips

The bet placed at every trade was calculated as an industry practice for conservative trading. It prevents the trader from making trades with too high of a risk. A sample trade gain/loss calculation can be found on the appendix.

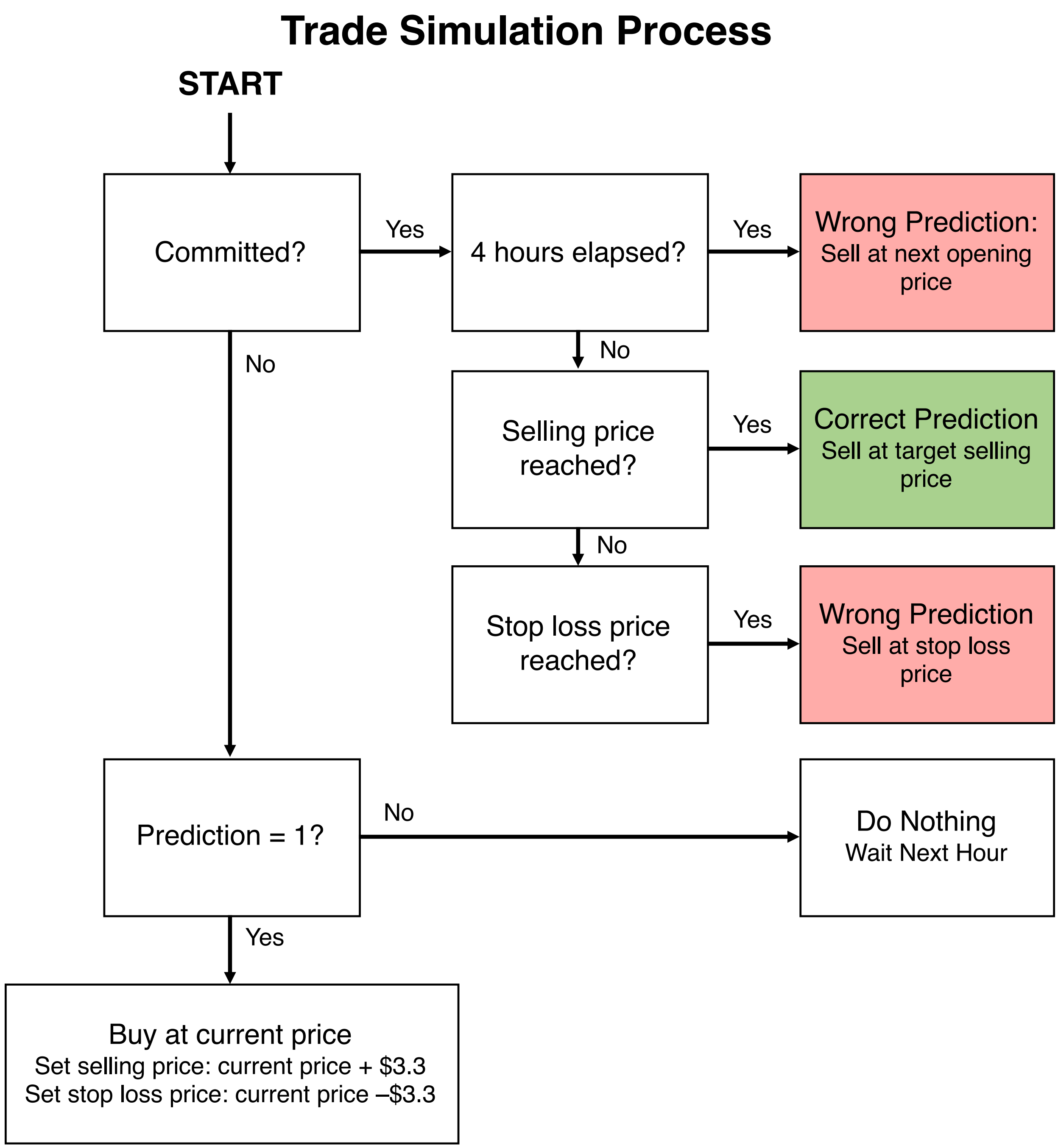

Figure 4. Trade Simulation Process Flow

The process flow above was followed for simulating the trades between January – June 2018. In the process, we only committed one (1) trade at a time for simplicity. In the real-world scenario, it is possible to commit multiple trades at any given time.

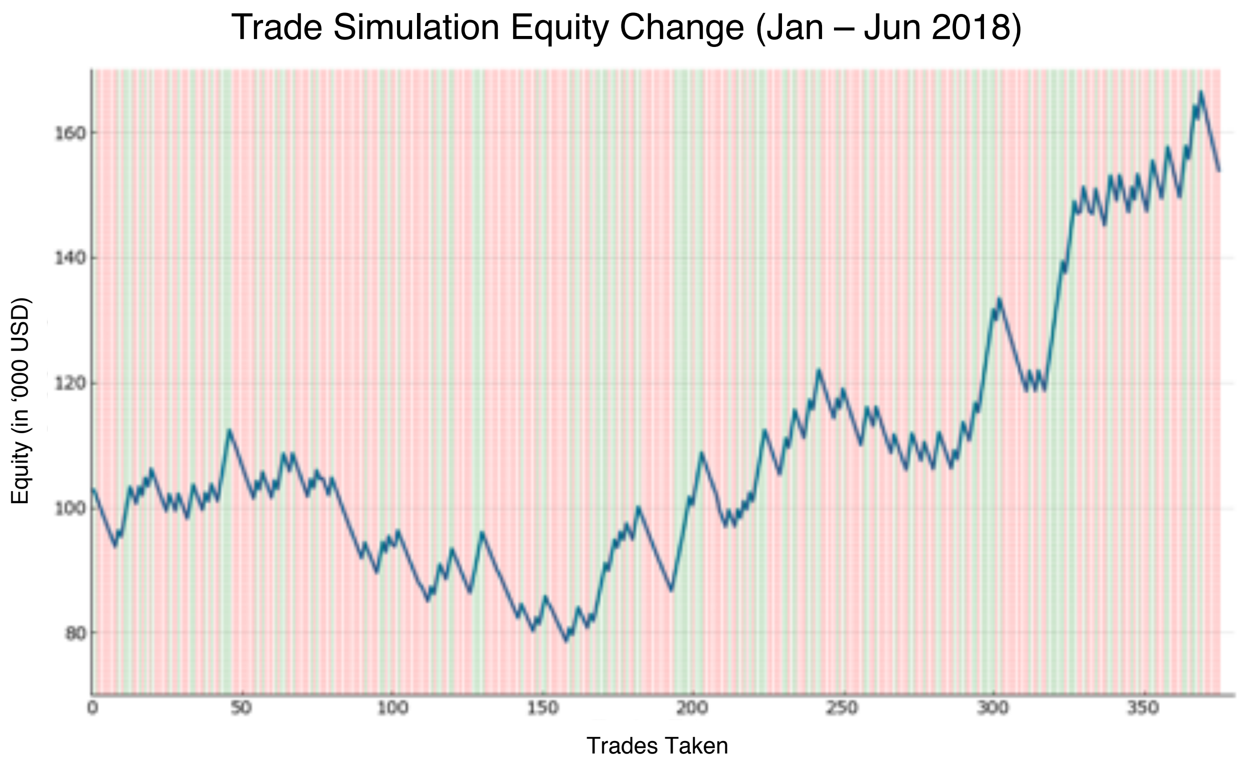

Figure 5. Trade Simulation Results

The predictions made from the linear support vector machine model resulted in a total profit of \$53,855 (54% in 6 months). This is equivalent to an 8% month-on-month growth. These returns are within the average monthly returns of a professional forex trader which ranges between 1-10% per month (admiralmarkets.com). It could also be observed that a larger portion of the trades caused losses which could be attributed to incorrect predictions. However, using the stop loss of 100 pips, the losses were still covered by the correct predictions.

Over the 6-month period, it was also observed that only 375 trades were taken. This is caused by the low recall of the model (39%). We were also unable to trade in some consecutive hours since the simulation process we ran only commits one (1) trade at a time. The simulation could be improved by accepting simultaneous trades.

7. Conclusion and Recommendations

Implementation of machine learning models could help predict the trends in forex prices despite their volatility, thereby, resulting to potential gain or profit. This is especially useful for amateur traders who could be in conflict between emotions and logic during trading.

By implementing a linear support vector machine in the trade simulation, a profit of 54% in 6 months was found to be possible. This is at around 8% monthly returns from continuous trading. As some forex trading softwares allows scripting to automate their trades, it is entirely possible to retrain an updated model using latest 2019 data and other deep learning algorithms such as Long

Short Term Memory to improve accuracy. These models can then be implemented for automated trading.

Forex trading also allows short selling which helps traders to earn from down trends. Therefore, the model could be further improved by converting it into a multinomial classifier. The model could then recommend no trade, trade (uptrend), and trade (downtrend). This would give more trading opportunities for the trader.

Forex trading can be a better investment over stocks and fixed income for retailers. With the right strategy and discipline, an individual can gain profit of 1% with one trade per week and compounding it for 52 weeks in a year, it is equivalent to 66%.

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Appendix

Sample Trade Simulation Results

	buy	target	stop_loss	sell	bet	delta	equity
2018-01-18 04:00:00	1325.92	1328.92	1324.92	1328.92	0.010000	2.700000	102.700000
2018-01-18 16:00:00	1330.09	1333.09	1329.09	1329.09	0.010270	-1.335100	101.364900
2018-01-18 18:00:00	1329.71	1332.71	1328.71	1328.71	0.010136	-1.317744	100.047156
2018-01-19 04:00:00	1330.67	1333.67	1329.67	1329.67	0.010005	-1.300613	98.746543
2018-01-19 12:00:00	1335.61	1338.61	1334.61	1334.61	0.009875	-1.283705	97.462838
2018-01-19 16:00:00	1334.18	1337.18	1333.18	1333.18	0.009746	-1.267017	96.195821
2018-01-22 13:00:00	1333.63	1336.63	1332.63	1332.63	0.009620	-1.250546	94.945276
2018-01-23 15:00:00	1336.51	1339.51	1335.51	1335.51	0.009495	-1.234289	93.710987
2018-01-23 17:00:00	1334.16	1337.16	1333.16	1337.16	0.009371	2.530197	96.241184
2018-01-24 03:00:00	1340.78	1343.78	1339.78	1342.05	0.009624	-0.933539	95.307644
2018-01-24 11:00:00	1347.05	1350.05	1346.05	1350.05	0.009531	2.573306	97.880951
2018-01-24 13:00:00	1349.70	1352.70	1348.70	1352.70	0.009788	2.642786	100.523736
2018-01-24 16:00:00	1352.21	1355.21	1351.21	1355.21	0.010052	2.714141	103.237877
2018-01-25 10:00:00	1361.13	1364.13	1360.13	1360.13	0.010324	-1.342092	101.895785
2018-01-25 16:00:00	1360.18	1363.18	1359.18	1359.18	0.010190	-1.324645	100.571140

<u>First trade (2018-01-18 04:00:00) calculation:</u>

For each trade, the bet will be based on the starting equity:

$$Starting\ Equity = \$100$$

$$Bet = \frac{\$100}{10{,}000} = 0.1$$

Once the models gives a trade recommendation, we buy at the current price and set the target price (+ 300 pips)

$$Buying\ Price = \$\ 1{,}325.92$$

$$Target\ Selling\ Price = \$\ 1{,}328.92$$

$$1\ pip = \$\ 0.01$$

$$change = 300\ pips$$

After reaching the target price, the current holdings are sold, accounting for the difference in buying and selling prices (30 pips). We profit based on the bet amount.

$$profit = 0.01 \times (300\, pips - 30\, pips) = \$2.7$$

$$total\ equity = \$100 + \$2.7 = \$102.7$$