Project 2: Crypto Golden Cross ML Algo Trading

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Overview

Trained support vector machine (SVM) model to make trading predictions, backtested the results, and evaluated its performance compared to that of a logistic regression model for BTC and ETH.

- **Technical indicators:**
  - FinTA 50 SMA x 200 SMA = Golden Cross
- **ML comparative analysis:**
  - Support Vector Machine model
  - Logistic Regression model
- **AWS chatbot:**
  - Front-end user interface for customers to chat in and purchase one of our trading models

Imports & Libraries

```
# Import the finta Python library and the TA module
from finta import TA
```

```
# Create a signals_df DataFrame
signals_df = trading_df.copy()

# Set the short window and long windows
short_window = 50
long_window = 200

# Add the SMA technical indicators for the short and long windows
signals_df["sma_fast"] = TA.SMA(signals_df, short_window)
signals_df["sma_slow"] = TA.SMA(signals_df, long_window)
```

- We used the Santiment (Sanpy) to retrieve the cryptocurrency data.
- We used the FinTA (Financial Technical Analysis) library to populate the golden cross indicator.
- We used Pandas to clean and format our datasets and Numpy and hvplot for financial analysis and visualizations.
- We imported StandardScaler, SVM, and LogisticRegression from SKlearn to standardize the data and populate the machine learning classifier models.

Bitcoin Data Analysis

BTC Golden Cross Model:

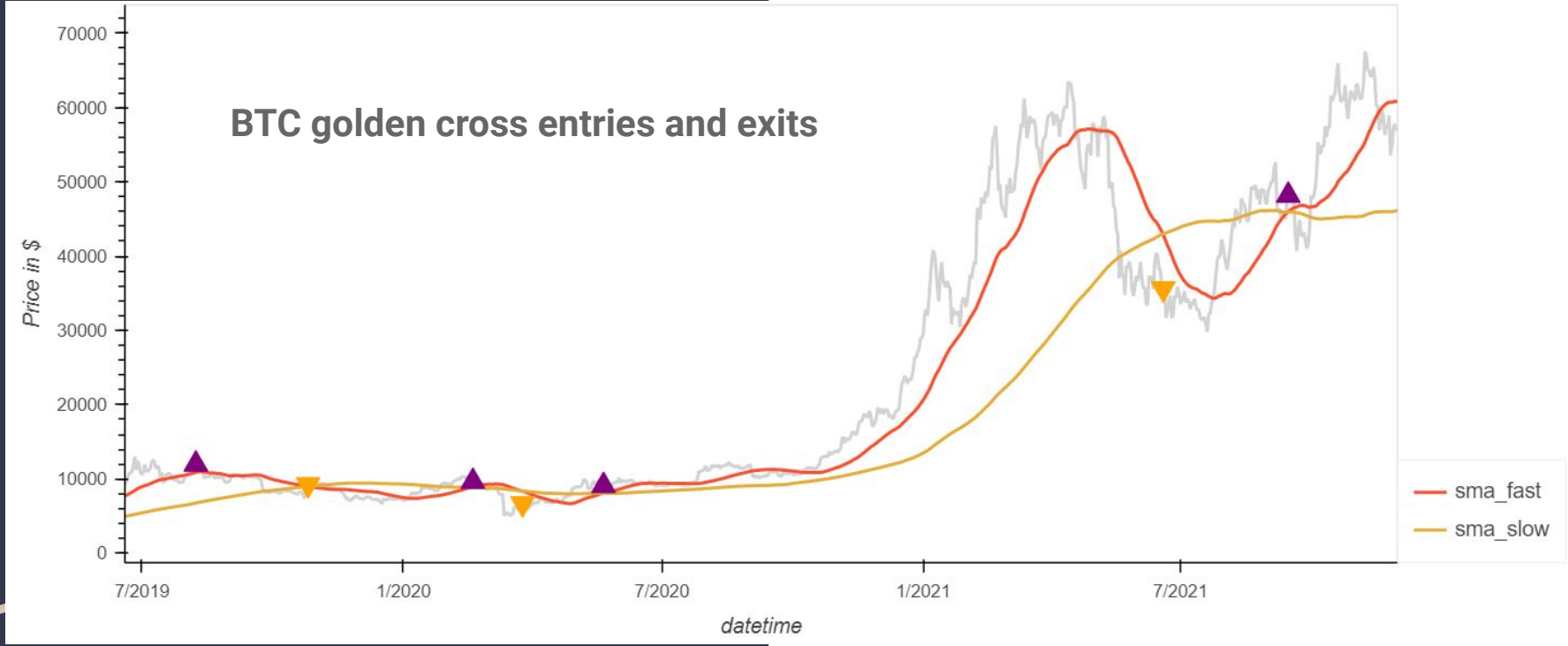
- Santiment BTC data time frame: 12/01/2018 - 12/01/2021 (3 years)
- FinTA 50 SMA x 200 SMA = Golden Cross
- 4 entries, 3 exits
- Split data into training and test datasets
- Standardized data using StandardScaler
- **Training** data **Support Vector Machine** model accuracy score = 60%
- **Training** data **Logistic Regression** model accuracy score = 54
- **Testing** data **Support Vector Machine** model accuracy score = 53%
    - Trading algorithm returns **outperforms** actual returns
- **Testing** data **Logistic Regression** model accuracy score = 48%

Ethereum Data Analysis

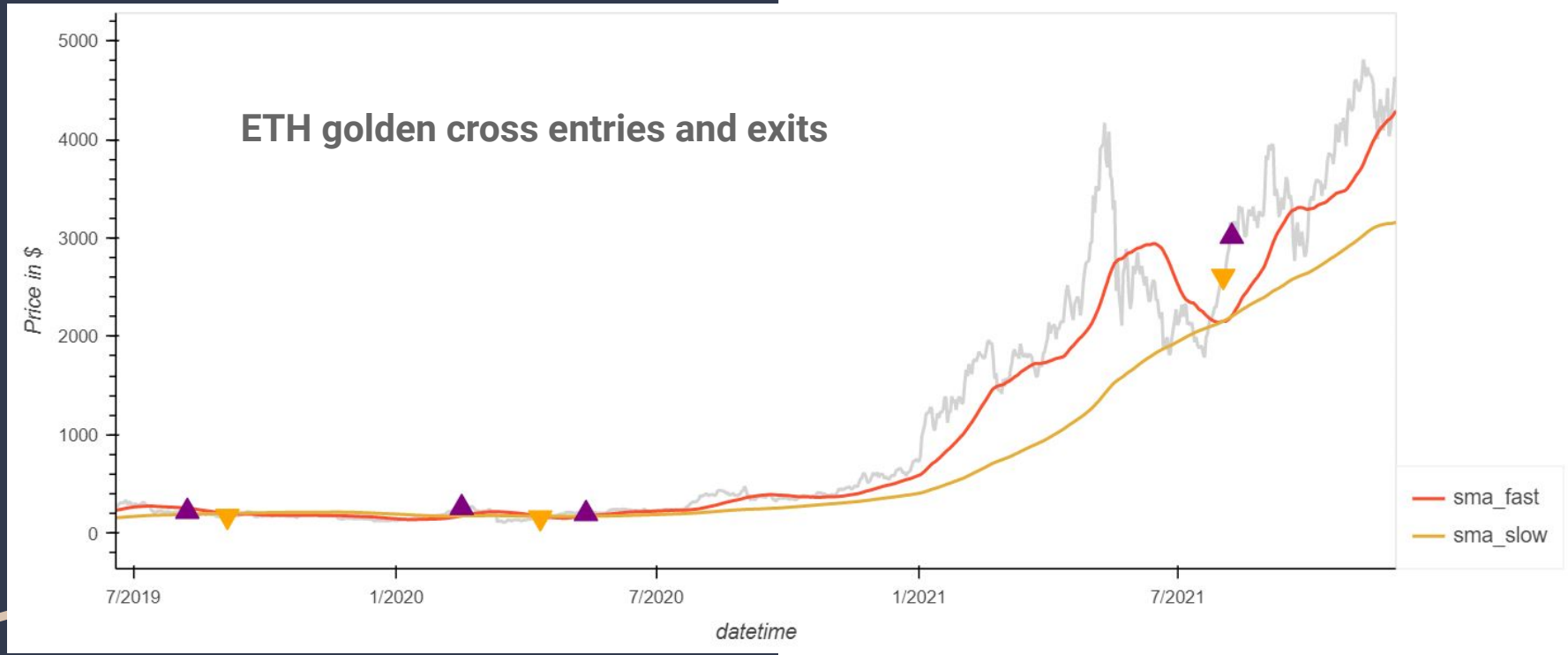
ETH Golden Cross Model:

- Santiment ETH data time frame: 12/01/2018 - 12/01/2021 (3 years)
- FinTA 50 SMA x 200 SMA = Golden Cross
- 4 entries, 3 exits
- Split data into training and test datasets
- Standardized data using StandardScaler
- **Training** data **Support Vector Machine** model accuracy score = 58%
- **Training** data **Logistic Regression** model accuracy score = 55%
- **Testing** data **Support Vector Machine** model accuracy score = 54%
    - Trading algorithm returns **underperforms** actual returns
- **Testing** data **Logistic Regression** model accuracy score = 45%

Data Exploration & Results Examples



Data Exploration & Results Examples



Data Exploration & Results Examples

Creating the Training Datasets

[16]:
```
# Imports
from pandas.tseries.offsets import DateOffset
```

[17]:
```
# Select the start of the training period
training_begin = X.index.min()

# Display the training begin date
print(training_begin)
```

```
2019-06-19 00:00:00+00:00
```

[18]:
```
# Select the ending period for the training data with an offset of 3 months
training_end = X.index.min() + DateOffset(months=3)

# Display the training end date
print(training_end)
```

```
2019-09-19 00:00:00+00:00
```

[19]:
```
# Generate the X_train and y_train DataFrames
X_train = X.loc[training_begin:training_end]
y_train = y.loc[training_begin:training_end]

# Display sample data
X_train.head()
```

[19]:

datetime	sma_fast	sma_slow
2019-06-19 00:00:00+00:00	7713.055810	4969.832575
2019-06-20 00:00:00+00:00	7795.545075	4996.768986
2019-06-21 00:00:00+00:00	7888.325162	5028.021115
2019-06-22 00:00:00+00:00	7986.993194	5061.745101
2019-06-23 00:00:00+00:00	8087.477265	5097.251982

BTC training datasets with an offset of 3 months

Data Exploration & Results Examples

Creating the Training Datasets

[14]:
```
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[15]:
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```

[17]:

datetime	sma_fast	sma_slow
2019-06-19 00:00:00+00:00	234.051936	158.616174
2019-06-20 00:00:00+00:00	236.269469	159.392705
2019-06-21 00:00:00+00:00	238.926172	160.322631
2019-06-22 00:00:00+00:00	241.754730	161.318462
2019-06-23 00:00:00+00:00	244.630754	162.345223

ETH training datasets with an offset of 3 months

Data Exploration & Results Examples

Creating the Testing Datasets

[20]:
```
# Generate the X_test and y_test DataFrames
X_test = X.loc[training_end:]
y_test = y.loc[training_end:]

# Display sample data
X_test.head()
```

[20]:

datetime	sma_fast	sma_slow
2019-09-19 00:00:00+00:00	10524.851472	8165.232394
2019-09-20 00:00:00+00:00	10520.490909	8197.356318
2019-09-21 00:00:00+00:00	10510.499681	8227.961461
2019-09-22 00:00:00+00:00	10495.424404	8258.779991
2019-09-23 00:00:00+00:00	10470.607194	8287.869189

Standardizing the Data

[21]:
```
# Imports
from sklearn.preprocessing import StandardScaler
```

[22]:
```
# Create a StandardScaler instance
scaler = StandardScaler()

# Apply the scaler model to fit the X-train data
X_scaler = scaler.fit(X_train)

# Transform the X_train and X_test DataFrames using the X_scaler
X_train_scaled = X_scaler.transform(X_train)
X_test_scaled = X_scaler.transform(X_test)
```

BTC testing datasets and standardizing the data with StandardScaler

Data Exploration & Results Examples

Creating the Testing Datasets

[18]:
```
# Generate the X_test and y_test DataFrames
X_test = X.loc[training_end:]
y_test = y.loc[training_end:]

# Display sample data
X_test.head()
```

[18]:

datetime	sma_fast	sma_slow
2019-09-19 00:00:00+00:00	194.433018	206.540982
2019-09-20 00:00:00+00:00	194.437851	206.994934
2019-09-21 00:00:00+00:00	194.390264	207.383026
2019-09-22 00:00:00+00:00	194.174721	207.747646
2019-09-23 00:00:00+00:00	193.759753	208.067080

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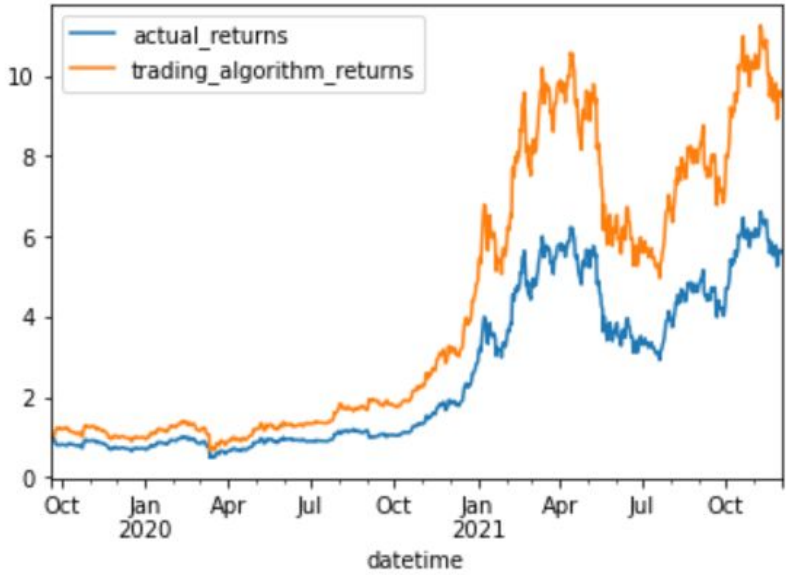
X_train_scaled = X_scaler.transform(X_train)
X_test_scaled = X_scaler.transform(X_test)
```

ETH testing datasets and standardizing the data with StandardScaler

Data Exploration & Results Examples

```
[29]: # Calculate and plot the cumulative returns for the `actual_returns` and the `trading_algorithm_returns`
      (1 + predictions_df[["actual_returns", "trading_algorithm_returns"]]).cumprod().plot()
```

```
[29]: <AxesSubplot:xlabel='datetime'>
```

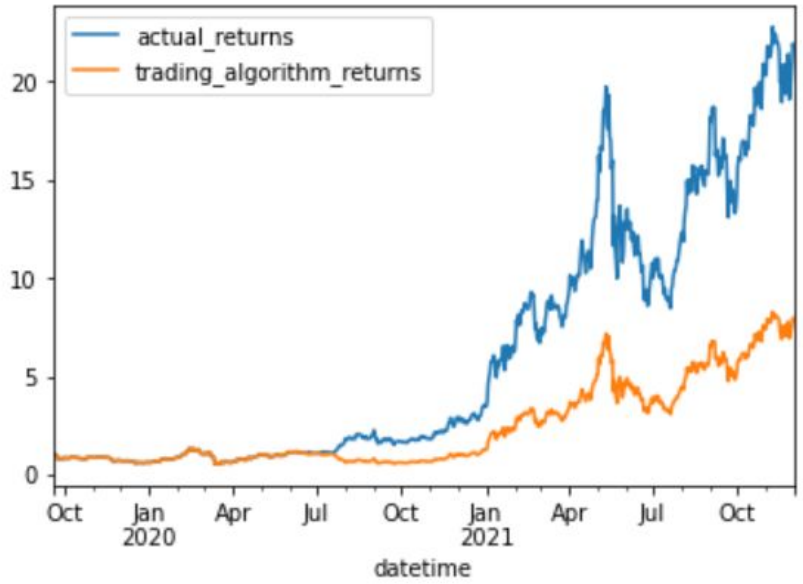


BTC SVM testing data model outperforms actual BTC returns

Data Exploration & Results Examples

```
[27]: # Calculate and plot the cumulative returns for the `actual_returns` and the `trading_algorithm_returns`
      (1 + predictions_df[["actual_returns", "trading_algorithm_returns"]]).cumprod().plot()
```

```
[27]: <AxesSubplot:xlabel='datetime'>
```



ETH SVM testing data model underperforms actual ETH returns

Data Exploration & Results Examples

[36]:
```
# Print the classification report for the Logistic Regression model using the test data
print("Logistic Regression Classification Report")
print(lr_testing_report)
```

```
Logistic Regression Classification Report
              precision    recall  f1-score   support

        -1.0       0.48      0.91      0.62       381
         1.0       0.55      0.10      0.17       424

    accuracy                           0.48       805
   macro avg       0.51      0.50      0.40       805
weighted avg       0.51      0.48      0.38       805
```

[37]:
```
# Print the classification report for the SVM model using the test data
print("SVM Classification Report")
print(svm_testing_report)
```

```
SVM Classification Report
              precision    recall  f1-score   support

        -1.0       0.53      0.14      0.22       381
         1.0       0.53      0.89      0.67       424

    accuracy                           0.53       805
   macro avg       0.53      0.51      0.44       805
weighted avg       0.53      0.53      0.45       805
```

The BTC SVM testing data model performs a bit better than the logistic regression model since it has a higher accuracy score (53% to 48%)

Data Exploration & Results Examples

[35]:
```
# Print the classification report for the Logistic Regression model using the test data
print("Logistic Regression Classification Report")
print(lr_testing_report)
```

```
Logistic Regression Classification Report
              precision    recall  f1-score   support

        -1.0       0.43      0.58      0.49       367
         1.0       0.49      0.34      0.40       438

    accuracy                           0.45       805
   macro avg       0.46      0.46      0.45       805
weighted avg       0.46      0.45      0.44       805
```

[36]:
```
# Print the classification report for the SVM model using the test data
print("SVM Classification Report")
print(svm_testing_report)
```

```
SVM Classification Report
              precision    recall  f1-score   support

        -1.0       0.47      0.05      0.10       367
         1.0       0.54      0.95      0.69       438

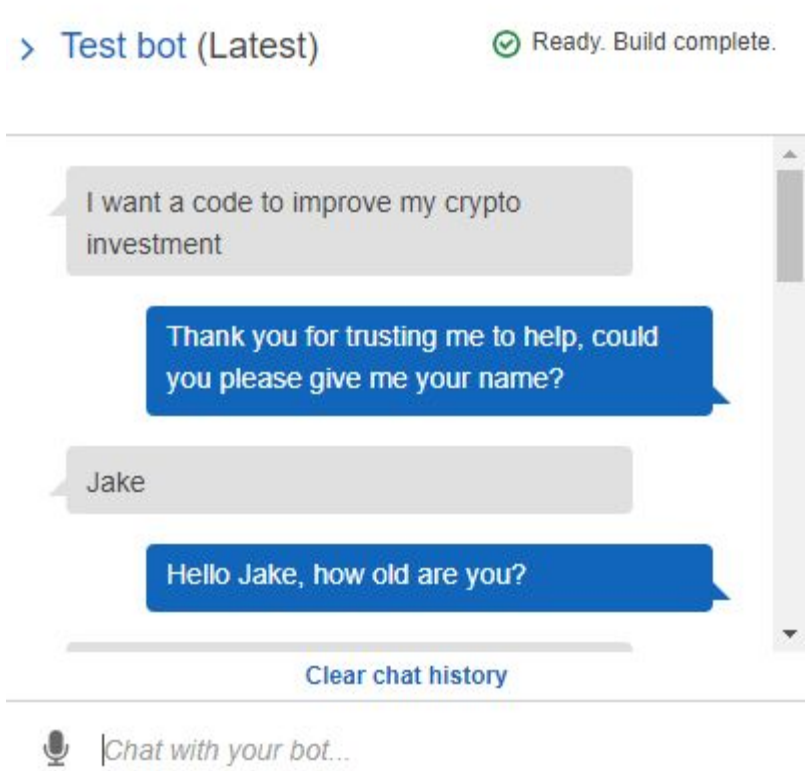
    accuracy                           0.54       805
   macro avg       0.50      0.50      0.39       805
weighted avg       0.51      0.54      0.42       805
```

The ETH SVM testing data model performs a bit better than the logistic regression model since it has a higher accuracy score (54% to 45%)

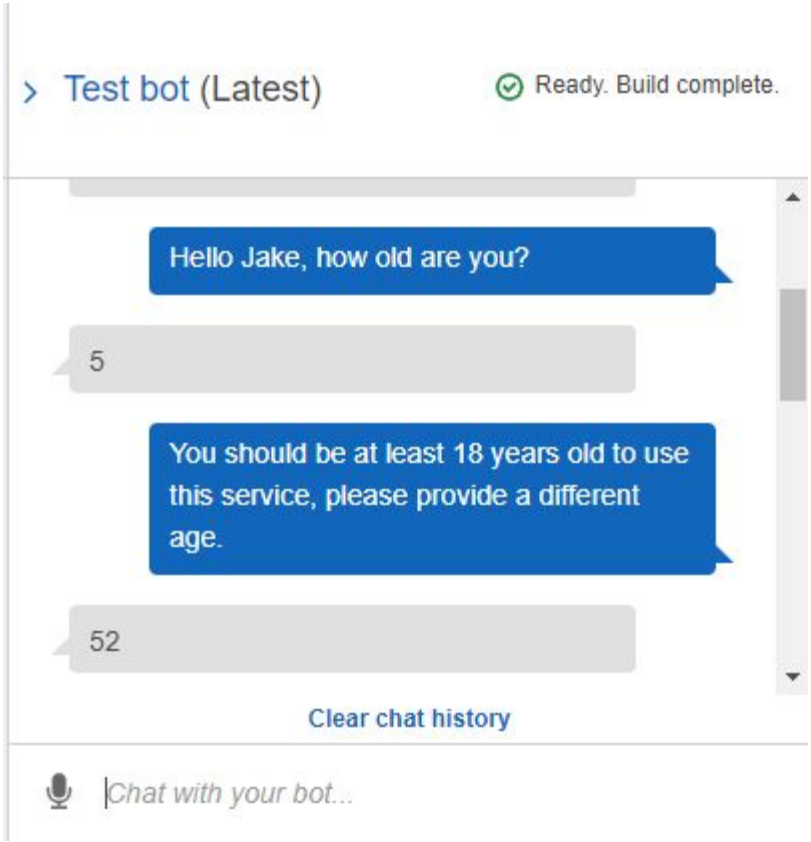
AWS Trading Bot

- Based on the technical indicators, the group decided to incorporate a trading bot.
- The investor initially answers basic questions.
- Based on the answers provided the bot makes an investment recommendation.

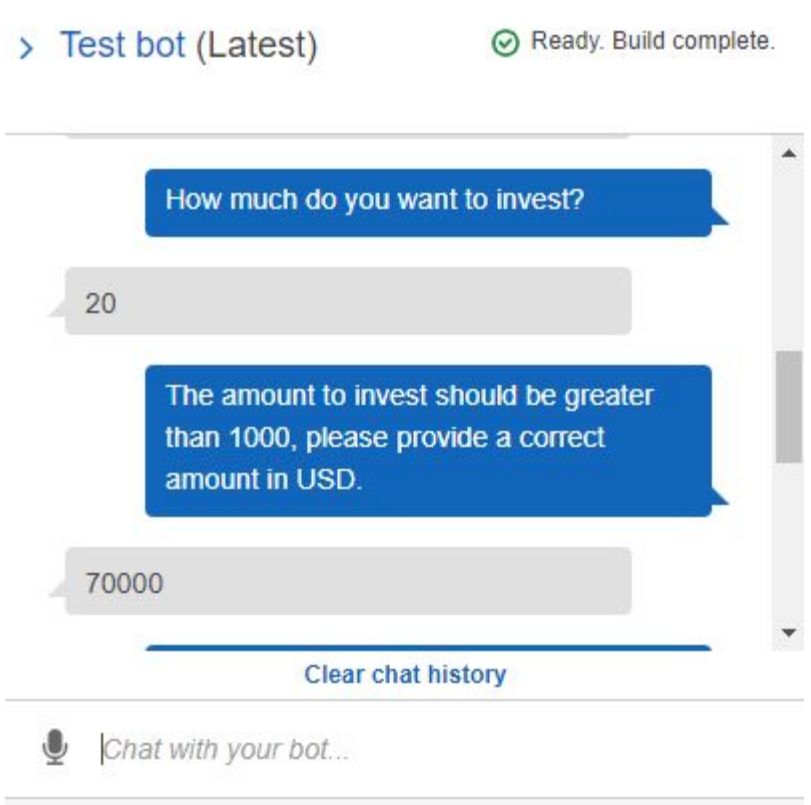
User Engagement



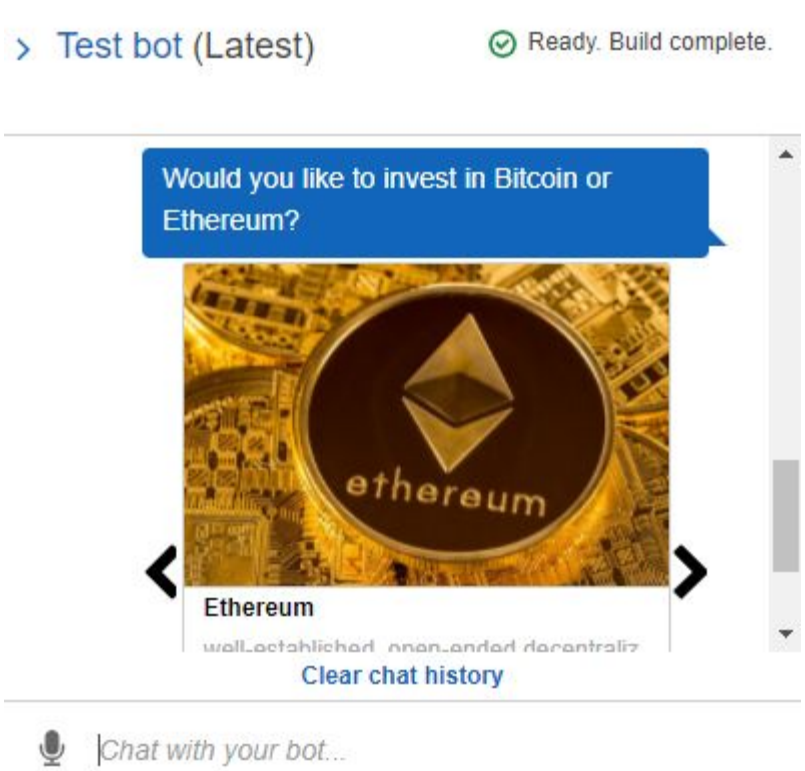
User Parameters



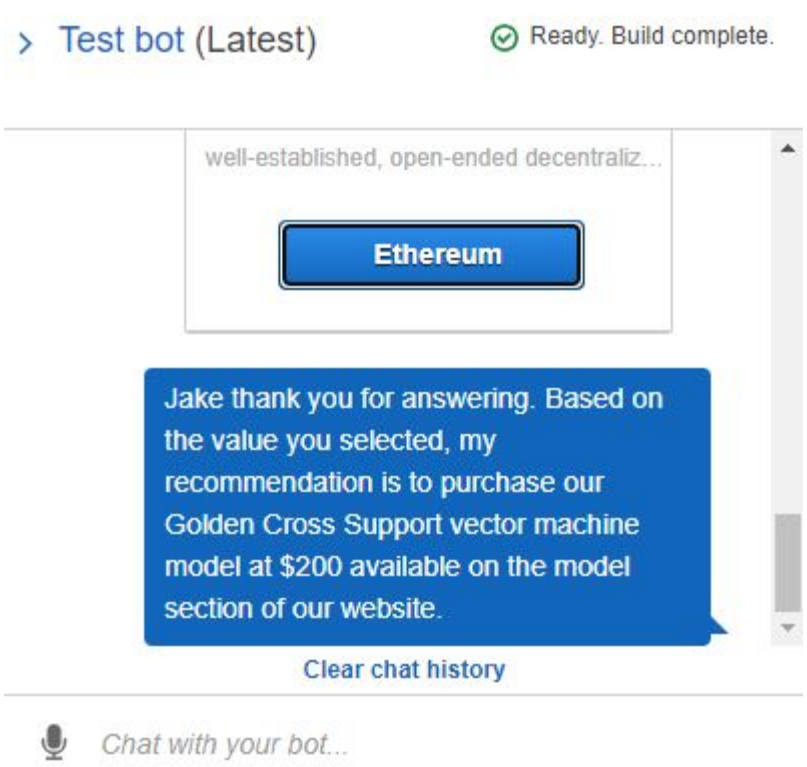
Initial Investment



Trading Bot Recommendation



Trading Bot


Test bot (Latest)
Ready. Build complete.
well-established, open-ended decentraliz...
Ethereum
Jake thank you for answering. Based on the value you selected, my recommendation is to purchase our Golden Cross Support vector machine model at $200 available on the model section of our website.
Clear chat history
Chat with your bot...

Postmortem

- The primary issue we faced was troubleshooting the trading bot.
- The training models created aren’t accurate and we struggled to adjust them for effective performance.

Questions?