Computational Intelligence and Deep Learning Group (CIDL)
AIIA Lab, Dept. of Informatics, Aristotle University of Thessaloniki
&
Datascouting, Greece

CRYPTOSENTIMENT: A DATASET AND BASELINE FOR SENTIMENT-AWARE DEEP REINFORCEMENT LEARNING FOR FINANCIAL TRADING

Loukia Avramelou, Paraskevi Nousi, Nikolaos Passalis, Stavros Doropoulos, Anastasios Tefas

Presentation Outline

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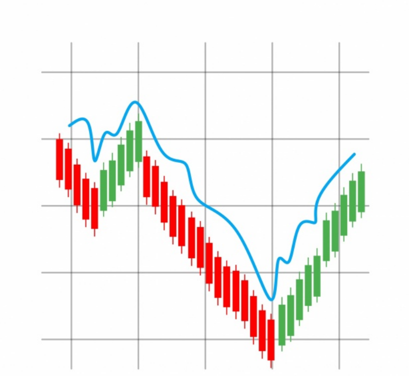
Introduction

- **Financial Trading** refers to purchasing and selling financial assets for profit.
- Financial assets can be stocks, cryptocurrencies assets etc.
- Predicting financial market activity allows achieving **profitable trades**.

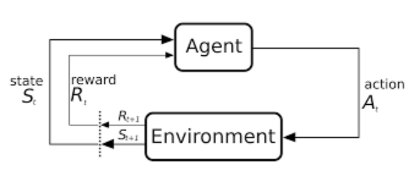
- **Automated Financial Trading** is the task in which algorithms perform financial trading actions without the involvement of humans.
- We can train a machine learning model using historical price data in order to maximize profit.

- The exponential growth of deep learning models in a wide range of fields has as a result the development of financial trading neural networks.
- **Deep Learning** models have provide a variety of approaches that focus in these kind of tasks.
- **Deep Supervised Learning** and **Deep Reinforcement Learning** techniques are used mainly for automated financial trading.

- **Deep Supervised Learning** approaches financial trading problems as regression or classification problems.
- The model either predicts the next price value, either the next price movements (up, down, same) or the next most profitable action (buy, sell or exit).
- In this case, labeled data must be gathered for either regression or classification problems.



- In **Deep Reinforcement Learning** , an agent learns to interact with its environment, decides on the best trading strategy and is rewarded according on the amount of profit that accumulates, without the need of labeled data.



Sentiment features

- Most deep learning models use only price-related features.
- Sentiment features, reflecting the public opinion about financial assets, have positive impact in models performance.
- This kind of information can be extracted from online articles or social media platforms.

Contributions

1. We provide a **publicly available dataset: CryptoSentiment** containing fine-grained sentiment analysis data about cryptocurrency market collected by different online sources.
2. We investigate whether using **sentiment information** is **advantageous** for training deep reinforcement learning agents for cryptocurrency trading.

CryptoSentiment Dataset

- Text examples have been collected based on **keywords** related to cryptocurrency from various online sources, such as online articles and social media platforms.

Table 1: Example of cryptocurrencies along with keywords used in the collection of text from online sources

Cryptocurrency	Keywords
XRPUSDT	'Ripple', 'XRP', 'Chris Larsen', 'Jed McCaleb'
BTCUSDT	'Bitcoin', 'BTC', 'XBT', 'Satoshi Nakamoto'
ETHUSDT	'Ethereum', 'ETH', 'Vitalik Buterin'
EOSUSDT	'EOS.IO', 'EOS', 'Dan Larimer'
NEOUSDT	'NEO', 'Da Hongfei', 'Erik Zhang'
XMRUSDT	'Monero', 'XMR', 'Monero Core Team'
XLMUSDT	'Stellar', 'XLM', 'Jed McCaleb'

FINBERT SENTIMENT ANALYZER

- Text samples are passed from FinBERT sentiment analyzer.
- FinBERT is a pre-trained sentiment analysis model based on BERT.
- General sentiment analyzers often can't generalize in domain-specific tasks with complex vocabulary, such as finance, medical or law.
- It is trained using financial news and predicts 3-class sentiment labels (positive, neutral, negative)

- **Sentiment score** is calculated as : $s = o_p - o_n$
- Positive text -> 1 / Neutral text -> 0 / Negative text -> -1
- **235,907** sentiment scores for 14 different cryptocurrencies gathered from various online sources, such as news articles and social media, that exceed the 3,000,000 documents from 17-08-2017 to 12-02-2022.
- We extracted text documents from more than 30 online sources.

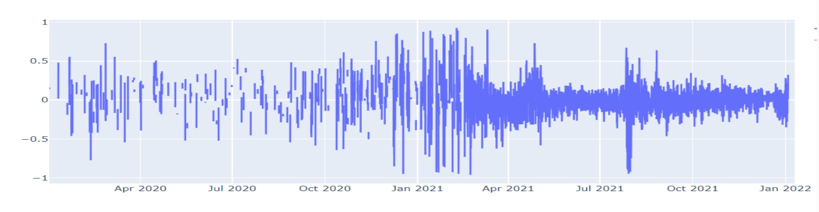


Figure 1: Sentiment values from 2020 to 2022.

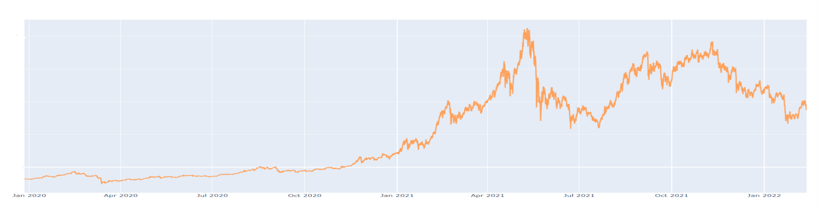


Figure 2: BTC price data from 2020 to 2022.

Deep Reinforcement Learning Pipeline

Features

- We used data from 14 cryptocurrency - USDT pairs, XRPUSDT, BTCUSDT, ETHUSDT, EOSUSDT, ADAUSDT, NEOUSDT, TRXUSDT, XMRUSDT, XLMUSDT, WAVESUSDT, ETCUSDT, VETUSDT, BTCBUSDT, ATOMUSDT
- As features, we use price features, such as percentage differences and volatility of high, close and low prices, sentiment score and time features in order to encode time.

- Price features are extracted from OHLC price data.

Feature	Description
Prices differences	$p(t) - p(t-1) \in \mathbb{R}$
Standardized price differences	$[\frac{p_c(t)-p_l(t)}{p_c(t)}, \frac{p_h(t)-p_c(t)}{p_c(t)}] \in \mathbb{R}^2$
High/Low value to close price	$[\frac{p_h(t)}{p_c(t-1)} - 1, \frac{p_l(t)}{p_c(t-1)} - 1] \in \mathbb{R}^2$
Volatility of high and low prices	$\frac{p_h(t)}{p_l(t)} \in \mathbb{R}$
Closing price volatility	$\mathbb{E}_t\left(x_p(t) - \mathbb{E}_t(x_p(t))\right)^2 \in \mathbb{R}$

Time Features

- Time features are extracted from time-related data.

Feature	Description
Day features	$[sin(\frac{2\pi i_m}{60\times 24}), cos(\frac{2\pi i_m}{60\times 24})]^T \in \mathbb{R}^2$
Week features	$[sin(2\pi i_w), cos(2\pi i_w)]^T \in \mathbb{R}^2$
Month features	$[sin(2\pi i_{mo}), cos(2\pi i_{mo})]^T \in \mathbb{R}^2$
Year features	$[sin(2\pi i_y), cos(2\pi i_y)]^T \in \mathbb{R}^2$

- Sentiment features are extracted from CryptoSentiment data.

Feature	Description
Previous sentiment	$s(t-1) \in \mathbb{R}$

Pipeline

- A **Long Short Term Memory** (LSTM) model with **Proximal Policy Optimization** is used.
- **Profit and Loss** (PnL) metric is used as agent reward and it is calculated as:

$$\mathrm{PnL} = \sum_{t=1}^{N} \delta_t p_t - |\delta_t - \delta_{t-1}|c, \tag{1}$$

where N denotes the total duration of the back-testing period (number of time-steps), p_t is the return at time step t, c is the commission paid for realizing profits/losses and δ_t is an index variable used to indicate the current position, which is defined as:

$$\delta_t = \begin{cases} -1, \text{if agent holds a short position at time-step t} \\ 1, \text{if agent holds a long position at time-step t} \\ 0, \text{if the agent is not in the market at time-step t} \end{cases} . \tag{2}$$

Experimental Evaluation

Experimental Setup

- The DRL agent is a LSTM model of 32 neurons followed with a 3 neurons actor and critic with dropout probability set to 0.2.
- Learning rate is initialized as $5 * 10^{-5}$ and commission punishment is set to $2 * 10^{-5}$.
- The optimizer used was RAdam Optimizer.
- We used data before 25-07-2021 for training and data from 25-07-2021 to 12-02-2022 for testing.
- PnL metric is used for evaluation of agent's performance.

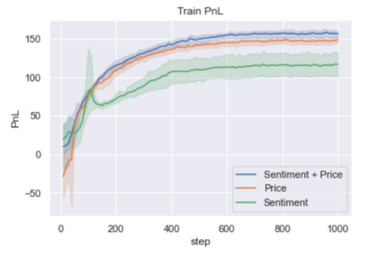


Table 2: Mean train and test PnL after DRL agent training

	Test PnL	**Train PnL**
Sentiment-only	6.69 ± 6.43	116.92 ± 20.58
Price only	9.68 ± 4.93	149.08 ± 5.37
Price + Sentiment	$\mathbf{10.55 \pm 1.16}$	$\mathbf{156.68 \pm 5.38}$

DRL Trading Agent

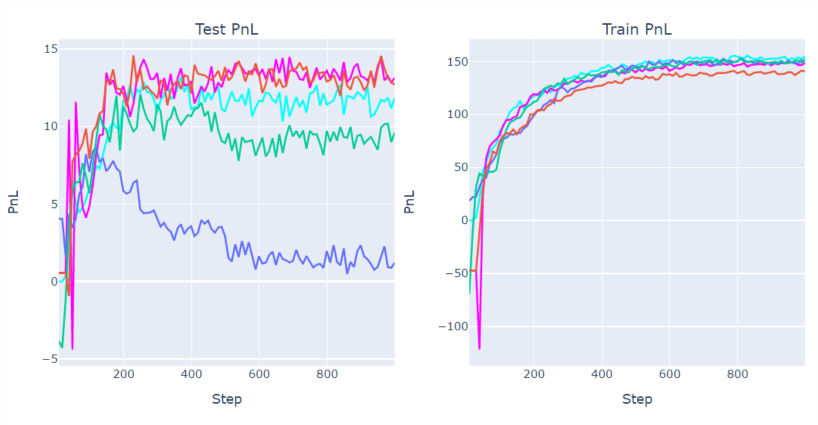


Figure 3: Test and train Pnl during DRL agent training. Features that are used are only - price features. Each curve represents a different run

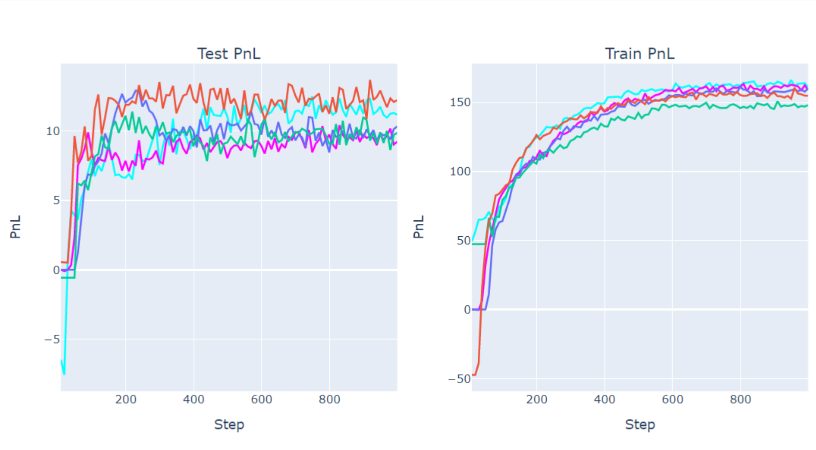


Figure 4: Test and train Pnl during DRL agent training. Features that are used are price - sentiment features. Each curve represents a different run

Figure 5: Test and train Pnl during DRL agent training. Features that are used are sentiment features. Each curve represents a different run

Figure 6: Agents behavior during test period.

Conclusions & Future Work

Conclusions

- We provided a dataset of sentiment scores that represent public opinion of cryptocurrencies from online sources.
- We investigated the impact of sentiment information in training of DRL agents for financial trading.

Future Work

- How additional sentiment values effect agents learning trading strategies ?
- Is sentiment beneficial in other domains other than cryptocurrency trading ?

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DeepFinance

Με τη συγχρηματοδότηση της Ελλάδας και της Ευρωπαϊκής Ένωσης

Thank you!
Any Questions?