Trademindx - Artificial Intelligence for Cryptocurrency Trading

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Abstract. *Trademindx* (later simply referred to as “the system”) aims to facilitate trading decisions through applied natural-language processing, sentiment analysis and machine learning algorithms. Built as a micro-services based distributed architecture, its primary function is to analyse large volumes of data and provide clear trading indicators to the client in real-time.

1. Introduction

The system combines natural-language processing, sentiment analysis and machine learning algorithms to classify large volumes of data into clear (BUY, SELL or HOLD) trading signals for the trader in real-time. The default approach is implemented using a sentiment analyzer plus a maximum entropy (MaxEnt) algorithm with *feedback.* The former quantifies sentiment. The latter applies a multinomial logistic regression model [1] to categorise data and continually improve accuracy.

One of the design features of the system is that there is no requirement to train the model. In this respect, it differs quite significantly from other machine learning implementations. The system uses its own unique algorithms to **train itself**, generating models, checking results against known data and subsequently refining those models. The system is by design, in a state of continuous automated machine learning, constantly adjusting and updating it's internal models, thus improving accuracy.

Simply put, Trademindx crunches huge amounts of data and tells you which cryptocurrencies to invest in, attempting to maximize your returns.

The approach of self-training has an additional knock-on effect of removing any human bias introduced when categorising initial training set data. This is further reinforced by the use of maximum entropy. Instead, the system simply starts to learn, recognise patterns, identify features, deduce correlations, build models and test them — continuously.

Moreover, the system aims to provide more granular outputs which are not necessarily binary (positive/negative). The system can provide more complex outcomes which may include additional characteristics such as time horizons — e.g. *buy and hold for 1 month*. However for simplicity, the initial implementation provides buy, sell or hold outputs with a fixed 24hr time horizon.

2. High-level Algorithm Overview

- Opinion moves the market.
- Can Artificial Intelligence sense opinion?
- And, can AI predict the market before it moves?

What impacts the price of precious metals, currencies, cryptocurrencies, stocks? Some may think it's the money invested, but this is not the case. It is driven by opinion. To be more precise, it is opinion and consensus.

Since it is generally accepted, let's just take it is as a baseline assumption: opinion moves the market.

What if you could model the set of traders participating in a particular market and deduce their overall consensus on opinion? What do you get? A super trader. That trader can clearly predict the market movements correctly. Now it's just a case of building such a trader with AI technology.

There's an obvious problem, not all traders are actively commenting on social media or forums! However, we can assume that we are taking a slice of the market and most traders are consuming some sort of information when making trading decisions. We then have to attempt to model how that information is being analyzed by traders.

3. Applying Artificial Intelligence

AI can be used to measure opinion to a statistical degree of confidence.

In order to attempt to measure opinion, we need to source raw information from a number of sources, apply Natural Language Processing (NLP) to make sense of it, turning it into data that can be processed by a machine. Then, we apply sentiment analysis plus machine learning algorithms to derive trading signals. Raw information sources include:

- News articles
- Twitter feeds
- Reddit posts
- Other social media feeds
- Forum threads
- Even GitHub repository activity
- And of course, market data feeds from cryptocurrency exchanges

Once we get the raw data, we run it through a sentiment analyzer which allocates a sentiment measure. For example:

```
SentimentConfidence {
    id='5a53bc72ca3ec40fb2bd9bbd',
    ticker='ETH',
    positiveSentiment=57.0,
    negativeSentiment=23.0,
    neutralSentiment=20.0,
    compoundSentiment=100.0,
    numberOfSamples=781
}];
```

In the case above, the system has deduced that at that specific moment in time, after analyzing 781 samples of discreet data, Ethereum has an overall positive sentiment — with a 57% degree of confidence. We then repeat this for all other cryptocurrencies that we want to analyze. We then track sentiment as it changes in real-time.

Research has shown that sentiment analysis algorithms are approaching high degrees of accuracy. Our sentiment analyzer is based on VADER — Valence Aware Dictionary and sEntiment Reasoner, which has been shown to produce highly accurate results, even in social media contexts.

Market data sources providing volumes and price ticks are still relatively open in the cryptocurrency space, with exchanges freely publishing near real-time or even real-time feeds, which is in direct contrast to mature forex and stock markets. So our market data sources are abundant.

Furthermore, what makes the cryptocurrency market such an interesting domain to analyze, is the relative immaturity which leads to high volatility.

Market moves are often triggered by announcements, news articles, support by social influencers and even rumours. This often happens very quickly, so if an AI algorithm could sense changing opinion, then this could in turn provide a trading advantage. And of course, a trading advantage has intrinsic monetary value — profit.

As well as taking sentiment data, we also take our input data and attempt to build AI models and then refine those models using feedback. This is where machine learning comes in. We back test our models against known market moves and then continuously re-calibrate those models, thereby attempting to improve accuracy. The model starts off vague but gets more refined as time moves on and more data becomes known.

Lets consider a more concrete example. So say our current model for Ether, predicts that based on certain characteristics found in our data, we expect the price of Ether to rise within the next 24 hours. We make note of that, wait 24 hours and check if that was the case or not. We then use this information to refine the model. This is what we mean by feedback .This “predict and test” happens all the time — continuously.

At any given time, we take the most up-to-date model, combine it with our sentiment data and use it to form a trading signal — BUY, SELL or HOLD.

For our models, we have decided to use Maximum Entropy (MaxEnt) modelling which has been shown to produce more accurate results than Naive Bayes. However, in the future models can be swapped out if others are deemed to be more accurate.

4. Use Cases

We envisage day traders and investors using the system, can gain insights into the social sentiment currently in the market before they execute their trades. This may help with decision making and provide increased returns while lowering risk. We see multiple use cases for the data provided by the system by:

- Individual investors
- Quant traders
- Global macro hedge funds
- Online exchanges
- Research analysts
- Risk managers
- Economists

Once AI can be built to predict market moves, the possibilities are then torn wide open for algorithmic trading in the cryptocurrency markets by hooking our AI into existing exchange APIs and running different trading strategies based on the trading signals.

Perhaps our AI can even be hooked into more traditional forex and stock markets too. The principles are similar.

5. Maximum Entropy (MaxEnt)

entropy noun *lack of order or predictability; gradual decline into disorder*

MaxEnt works by extracting a set of weighted features from the input. Each feature corresponds to a constraint on the model. The MaxEnt model is the model with the maximum entropy of all the models that satisfy the constraints.

The baseline principle being that if we choose a model with less entropy we would add information constraints to the model that would not be justified by the evidence available to us. Choosing a MaxEnt model is motivated by the desire to preserve as much uncertainty as possible thus removing any bias [2]. More formally, the maximum entropy principle states that [4]:

…in making inferences on the basis of partial information we must use that probability distribution which has the maximum entropy subject to whatever is known.

Additionally, the reasons for using MaxEnt are as follows:

- Near state-of-the-art level of accuracy when classifying complex data sets
- Simple features have been proven to successfully approximate complex relationships
- MaxEnt is able to output the accuracy/confidence of the classification

Further mathematical details are outside the scope of this introductory document but the reader is encouraged to refer to the references section for further details concerning MaxEnt [1], [2], [3].

6. TaaS: Trademindx As A Service

During 2017 we have seen the introduction of AI systems into large financial organisations with varying degrees of complexity and autonomy [5]. This trend is highly likely to continue.

The system can also be thought of as a service*,* that can be used as a springboard to provide any organisation their first AI implementation in the shortest possible timeframe. It is heavily customisable to meet complex client requirements. Although the core system provides a default set of behaviours, these are non-opinionated, in the sense that they can be overridden or augmented to provide custom behaviours. This is achieved by well-designed generic core services controlled by parameters.

Additionally, as it is designed as a set of distinct RESTful services, it can be hooked into any client infrastructure to provide AI capability in existing applications and can be run on-prem, private cloud or public cloud or a hybrid. Having a set of distinct micro-services also lends itself to auto-scaling.

Once the models have been sufficiently self-trained and calibrated there is no reason why it cannot supplement existing algorithmic trading systems. The system can also be readily used to classify any set of documents.

7. Application to Cryptocurrencies

In the first instance, the system has been applied to Bitcoin (BTC) [6] and all other altcoins with a large market capitalisation (more that $100mm). The implementation is designed in such a way as to facilitate introduction of additional cryptocurrencies into the system with relative ease.

Previous attempts to deduce market sentiment analysis for Bitcoin have been made [7],[8]. The approaches have broadly utilised binary (positive/negative) approaches to categorisation with explicitly declared training data sets.

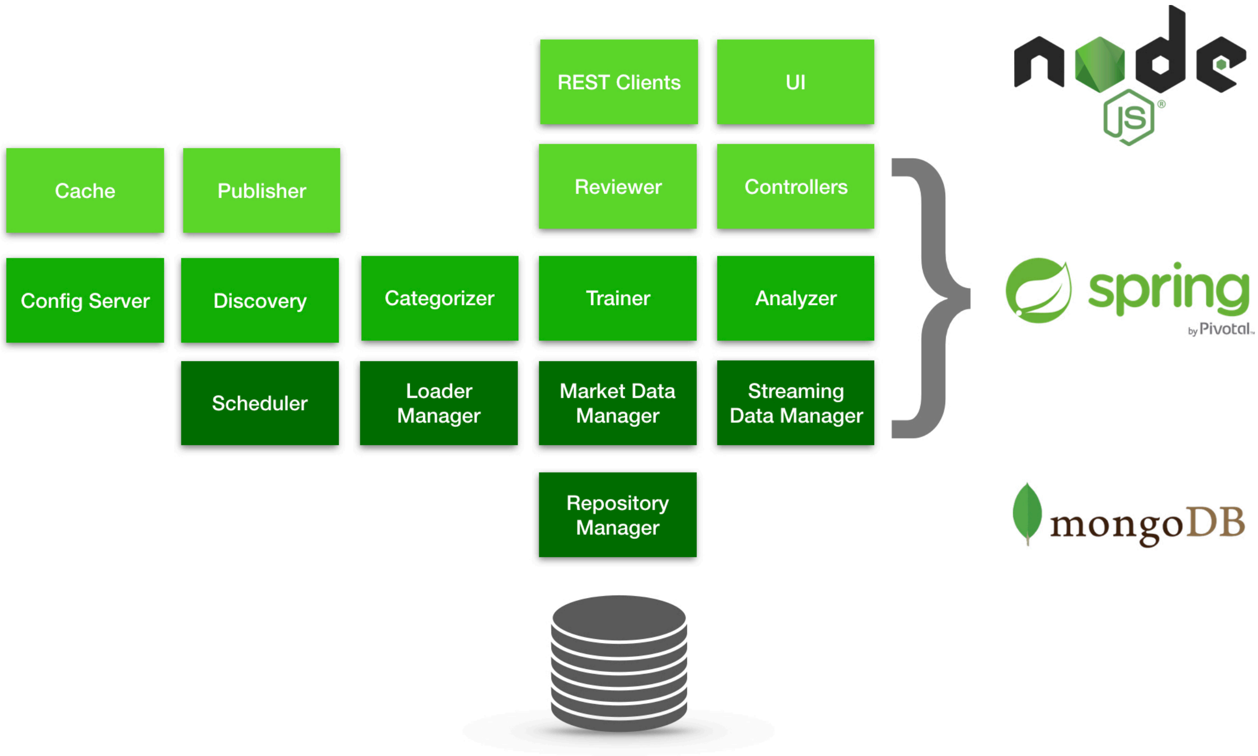
The application to this particular area is of particular interest because it is likely to yield interesting results in high volatility markets that are heavily influenced by news, opinion and perhaps even rumour [9]. Moreover near real-time market data is readily available from public APIs (exchanges).

8. Application to Other Markets

The system is flexible enough that it can be applied to *any* market data sources, *any* data feeds and *any* financial instruments with minimum customisation by utilising core generic services outlined in the next section. In fact, it can broadly be applied to *any* sentiment categorisation problem.

We anticipate being able to apply the system to forex, equity [10,11] and commodity markets as well as cryptocurrencies.

9. Core Services



10. Core Services Description

Config server	Holds configuration parameters for all services
Discovery service	Allows services to be discoverable in the system
Repository Manager	Persists raw input data, market data, categorised data, training sets, models, financial products, and result sets
Loader Manager	Loads data from known data sources into store as raw data
Market Data Manager	Manages life-cycle of intraday and historical market data
Streaming Data Manager	Manages real-time streaming data sources
Categorizer	Retrieves raw data, applies categorisation algorithms and saves result sets
Trainer	Trains models based on known data sets and categorisation results
Analyzer	Retrieves appropriate models and applies them to real-time data as it arrives, generating results for the clients
Reviewer	Reviews previously generated results by the analyzer against known market data
Scheduler	Orchestrates all events in all services
Publisher	Manages topics and distributes events between services and clients
Cache	Manages in-memory caching of frequently accessed data such as models
Controllers	Expose REST endpoints and delegate requests from clients to underlying services
User Interface (UI)	Real-time web-based UI for visualising results

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