

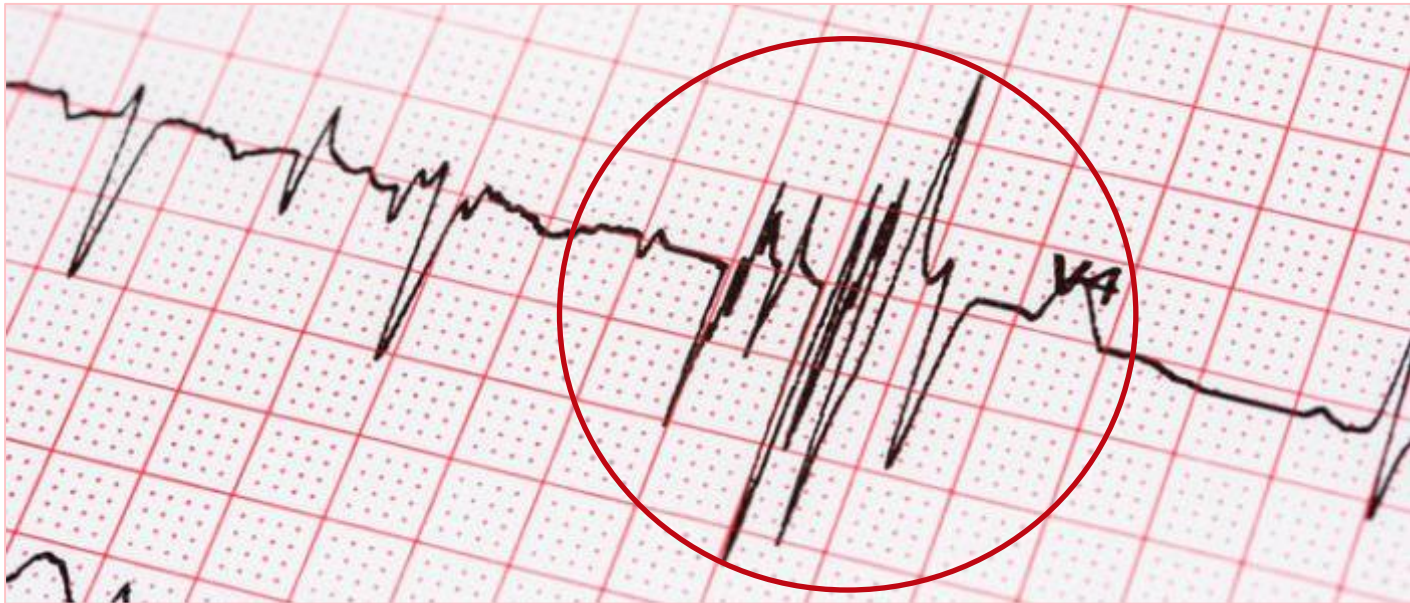
TRENDALYZE

We help financial companies understand and monetize
their granular transactional data via patterns search

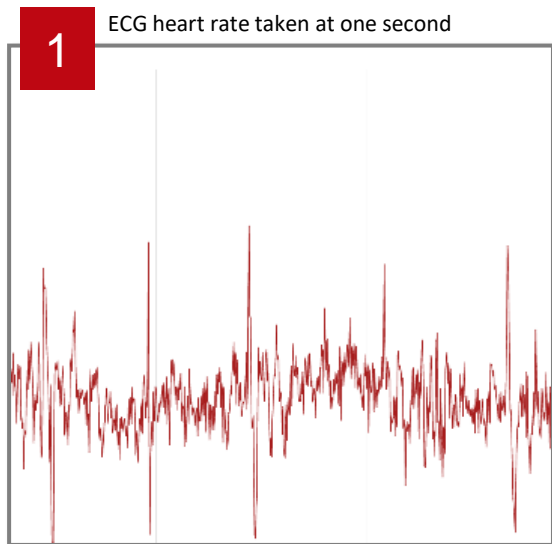


Why Trendalyze?

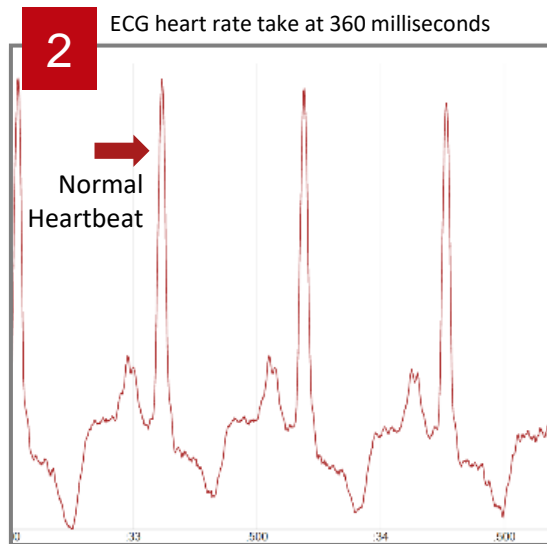
Today, every digital/digitized businesses runs on time-series (continuous) data. As it streams, it creates heartbeats. Just like an ECG, shapes in data contain vital, highly valuable insights. We built a platform where expert knowledge is augmented with machine power to detect and monetize patterns in high frequency, granular data.



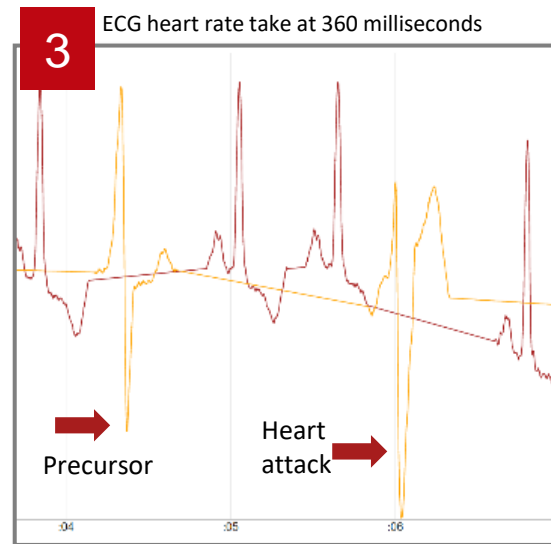
Example: How to Derive and Monetize Granular Data Value?



Meaningless pattern: The granularity is not low enough to recognize meaningful shapes



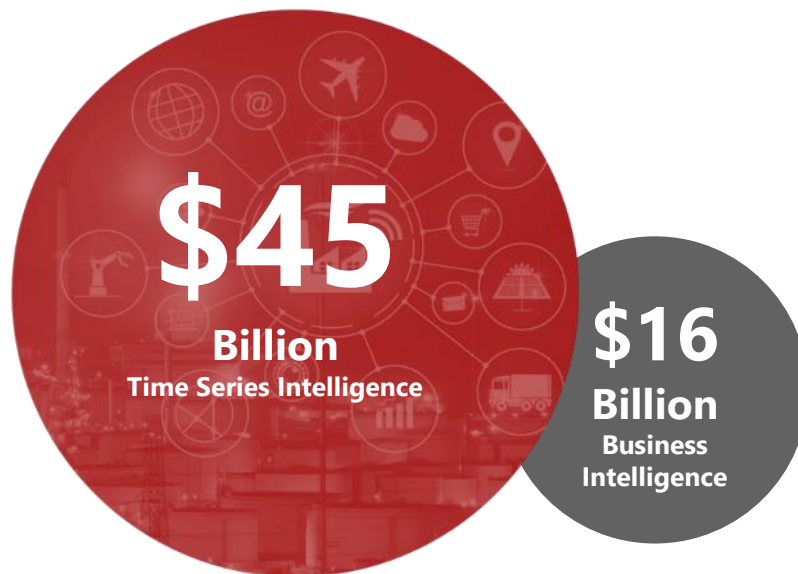
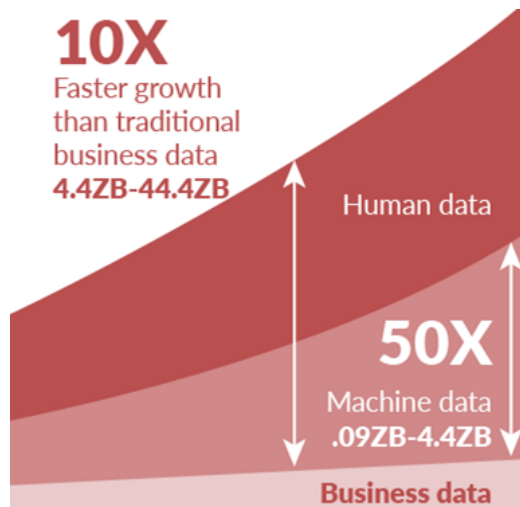
Recognizable pattern: Increasing the granularity reveals distinct meaning full shapes



Monetizable pattern: Patterns are monetized by learning and monitoring for different shapes

Why Granular Time-Series Data Matters?

Granular time series data is estimated to be growing 10-times faster and is already 50-times more than traditional business data. The hidden, repeating patterns in it offer valuable monetization opportunities. Market analysts expect the market for time series intelligence to be 3-times larger than the existing BI and analytics market.



Digital “Heartbeats” Exist in All Industries and Processes

Identifying “heartbeats” in continuous data is the next frontier of knowledge and value creation across all industries. Like ECG patterns, most patterns in granular data have diagnostic quality that allows companies to make or save money when monitoring for meaningful patterns identified by business professionals.

Applications In Key Verticals

Manufacturing



Healthcare



Fleet Management



Applications In Financial Services

Trading Surveillance



Price Manipulation



AML/Employee Fraud



Digital “Heartbeats” In Financial Services

Transactional data is one of the largest sources of digital “heartbeats”. Motifs can be identified in trading, AML records, mortgage origination, insider trading, etc.

Trading via Image Classification*

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Abstract

The art of systematic financial trading evolved with an array of approaches, ranging from simple strategies to complex algorithms all relying, primary, on aspects of time-series analysis (e.g., Murphy, 1999; De Prado, 2018; Tsay, 2005). Recently, after visiting the trading floor of a leading financial institution, we noticed that traders always execute their trade orders while observing images of financial time-series on their screens. In this work, we built upon the success in image recognition (e.g., Krizhevsky, Sutskever, and Hinton, 2012; Szepesvári et al., 2015; Zeiler and Fergus, 2014; Wang et al., 2017; Koch, Zemel, and Salakhutdinov, 2015; Le et al., Bengio, and Hinton, 2015) and examine the value in transforming the traditional time-series analysis to that of image classification. We create a large sample of financial time-series images encoded as candlestick (Box and Whisker) charts and label the samples following three algebraically-defined binary trade strategies (Murphy, 1999). Using the images, we train over a dozen machine-learning classification models and find that the algorithms are very efficient in recovering the complicated, multiscale label-generating rules when the data is represented visually. We suggest that the transformation of continuous numeric time-series classification problem to a vision problem is useful for recovering signals typical of technical analysis.

Introduction

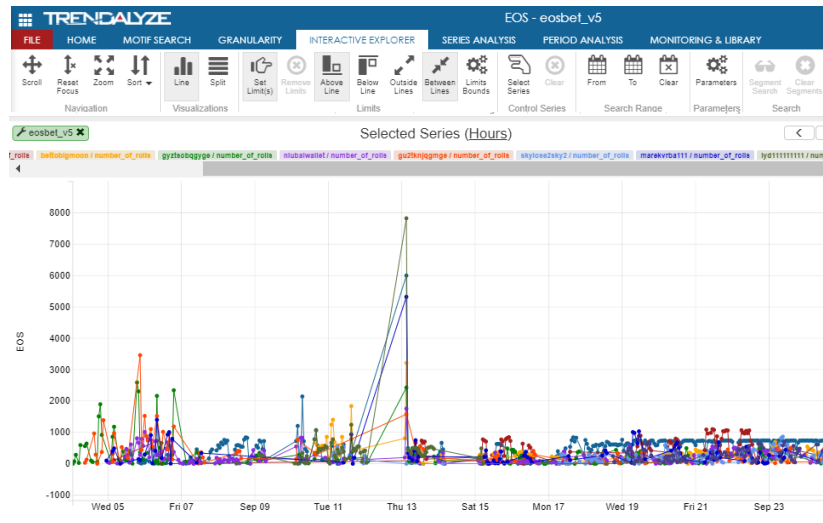
Traders in the financial markets execute buy and sell orders of financial instruments as stocks, mutual funds, bonds, and options daily. They execute orders while reading news reports and earning calls, but also while observing charts of time-series data that indicate the historical value of particular securities, or leading financial indices (see Fig. 1 for a typical workstation of a professional trader). More often,

algorithms process time-series data as a list of numerical data, aiming at detecting patterns as trends, cycles, correlations, etc. (e.g., De Prado, 2018; Tsay, 2005). In case a pattern is identified, the analyst can then construct an algorithm that will use the detected pattern (e.g., Wilks, 2011) to predict the expected future values of the sequence in hand (i.e., forecasting using exponential smoothing models, etc.).

Experienced traders with years of experience observing financial time-series charts and executing buy and sell orders start developing an intuition for market opportunities up to a point in which their intuition, based on observing charts, almost reflects the recommendation that their state-of-the-art model provides (personal communication with J.P. Morgan’s financial experts Jason Hunter, Joshua Younger, Alex Floman, and Veronica Bustamante). In this perspective, financial time-series analysis can be thought of as a visual process: when experienced traders look at a time-series data, they process and act upon the image instead of mentally executing algebraic operations on the sequence of numbers.



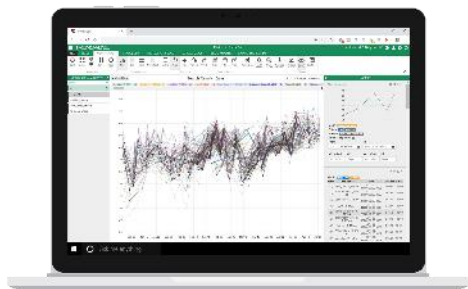
JPMorgan’s research on trading signals extraction and monitoring with neural networks. Motif discovery provides alternative approach that can leverage the traders’ expert knowledge.



Trendalyze pattern detection in ICO fraud (smurfing, layering, pump and dump). Trendalyze searches within 80 million active wallets, and passes suspects to crystalblockchain.com for risk scoring, thus minimizing the time and computational cost of scoring all active 80 million wallets.

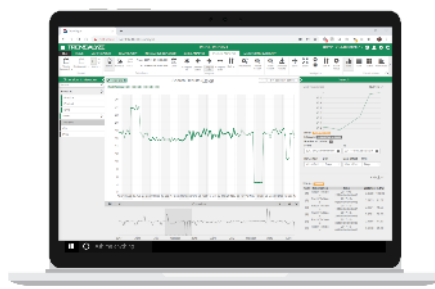
We Empower the Domain Experts to Do It Themselves

Trendalyze is a self-service platform for business users to mine, search for, monitor and predict motifs in time-series data. It works like Google, but instead of searching for sequences or letters, we search for time-series patterns.



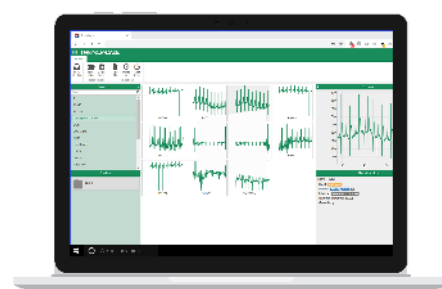
Motif Mining

Automatically discover clusters of distinct motifs in a large number of time-series data



Motif Search

Find similar, dissimilar, or correlated motifs across any number of measures, dimensions, and time-series

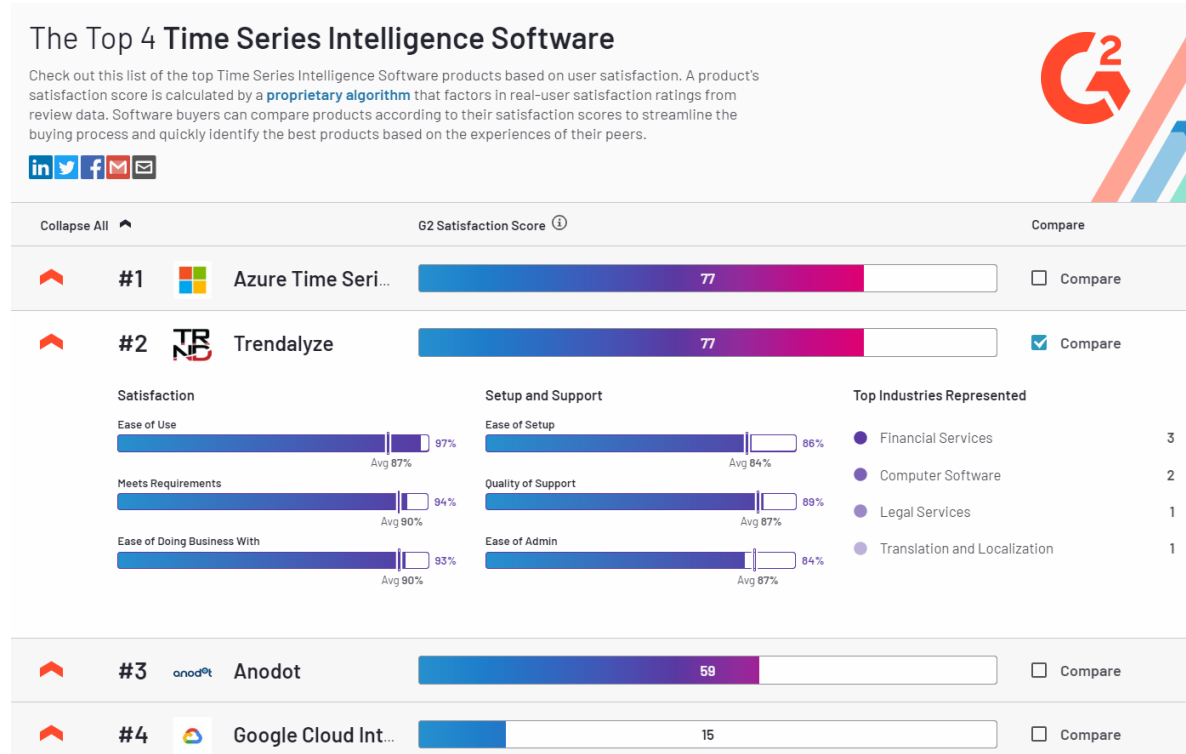


Motif Intelligence™

Monitor and configure intelligent predictions to make real-time actionable recommendations

Trendalyze Is Rated #2 Time Series Intelligence Software

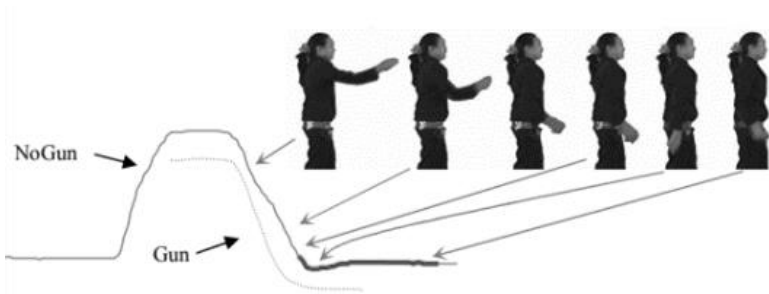
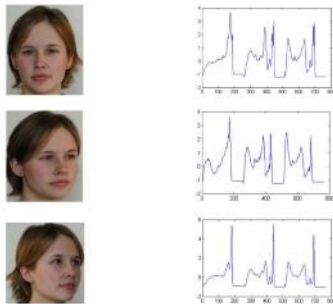
Our difference is in the approach and the unique UI/UX that makes Trendalyze the easiest to use



What is Our Approach & Methods?

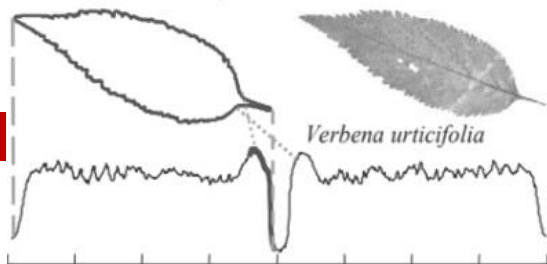
Trendalyze leverages shape learning, also referred to as “Motif Discovery”, as an alternative to statistical machine learning. The approach is growing in popularity because it can solve many problems in an easier and less complex way.

Face Detection

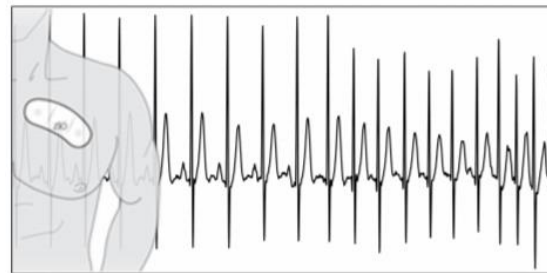


Gesture Detection

Object Detection



Process Monitoring



What Is the Key Advantage of Motif Discovery?

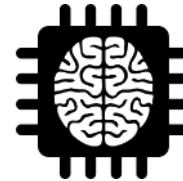
Shape learning works like the human brain. It learns fast from just a few examples. It requires minimal data for training and is more computationally efficient. Most importantly, it is understandable by business experts who can do it themselves. In analytics, self-service maximizes knowledge creation and data monetization.

How do humans and machines learn the differences between these two shapes?



Human Learning:

- Recognize shape differences immediately
- Learn the differences from a few examples
- Identify known shapes instantly



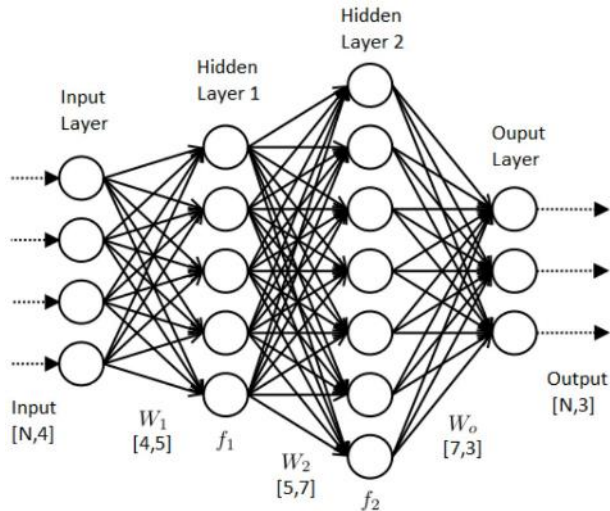
Machine Learning:

- Requires thousands of pictures to train the model
- All pictures have to be labeled precisely by humans
- Small shape differences confuse machines

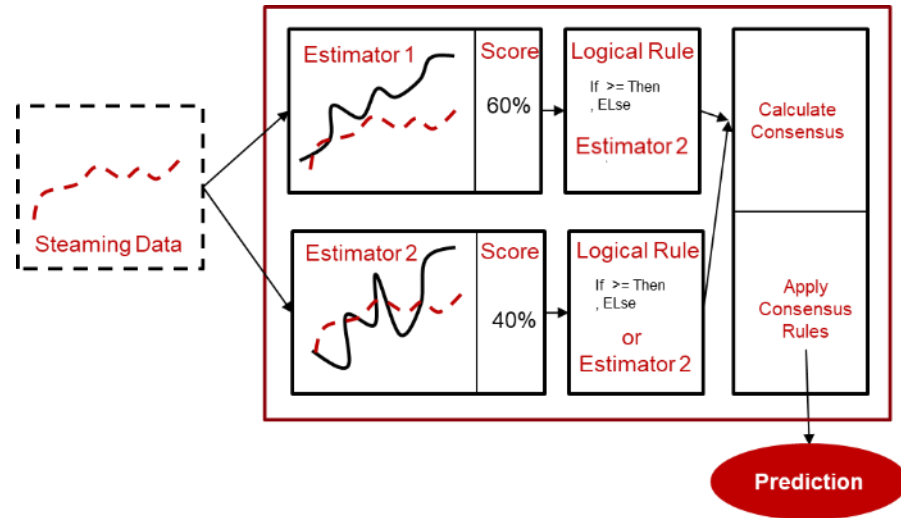
Trendlyze's Approach to Monitoring and Prediction

Trendlyze's artificial logical networks (ALN) are analogous to neural networks but are easier to configure by subject matter experts. Comparative studies show that ALNs deliver highly accurate results and deliver the advantage of transparency, fast time-to-market, and low computational costs when deployed in production applications.

Neural Network



Logical Network (patent pending)



This paper has been accepted and is currently in production.
It will appear shortly on 10.2196/24388
The final accepted version (not copyedited yet) is in [this tab](#).



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A Personalized Monitoring Model for Electrocardiogram (ECG) Signals: Diagnostic Accuracy Study

Rado Kotorov; Lianhua Chi; Min Shen

ABSTRACT

Background:

Lately, the demand for remote ECG monitoring has increased drastically because of the COVID-19 pandemic. To prevent the spread of the virus and keep individuals with less severe cases out of hospitals, more patients are having heart disease diagnosis and monitoring remotely at home. The efficiency and accuracy of the ECG signal classifier are becoming more important because false alarms can overwhelm the system. Therefore, how to classify the ECG signals accurately and send alerts to healthcare professionals in a timely fashion is an urgent problem to be addressed.

Objective:

The primary aim of this research is to create a robust and easy-to-configure solution for monitoring ECG signal in real-world settings. We developed a technique for building personalized prediction models to address the issues of generalized models because of the uniqueness of heartbeats [19]. In most cases, doctors and nurses do not have data science background and the existing Machine Learning models might be hard to configure. Hence a new technique is required if Remote Patient Monitoring will take off on a grand scale as is needed due to COVID-19. The main goal is to develop a technique that allows doctors, nurses, and other medical practitioners to easily configure a personalized model for remote patient monitoring. The proposed model can be easily understood and configured by medical practitioners since it requires less training data and fewer parameters to configure.

Financial Time Series Forecasting Based On Motif Discovery

A case study in foreign exchange rate

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Abstract—The objective of this research is to provide empirical evidence that motif discovery can be applicable to predict financial time series. Two prediction methods based on motif discovery (One Motif Approach and Integrated Motif Approach) are proposed, which apply adaptive dissimilarity index [6] with Complexity-Invariant Distance (CID) [2] as the similarity measure. This paper extends the work previously introduced by Ismailajala [12]. Tests are conducted based on relatively large financial time series datasets for foreign exchange rate, and result shows that the new prediction model is more efficient with less computational complexity and higher forecasting accuracy compared to previous model.

Keywords — motif discovery; financial time series; forecasting; adaptive dissimilarity index; CID; foreign exchange rate

1. INTRODUCTION

Time series forecasting is a common problem in various domains, including manufacturing, agriculture, retail, and tourism, etc. Among them, financial time series forecasting is extremely challenging and has been studied extensively for years. Except traditional statistical models, there are also models based on machine learning techniques, including artificial neural networks [17] and support vector machines [16] to predict financial time series.

II. LITERATURE REVIEW

Motif discovery has been widely studied in bioinformatics for detecting biosequences for years [23]. It can also be applied to medical data to detect anomalies in heart rhythm and blood pressure [22]. A time series motif is defined as a frequently recurrent pattern throughout the time series [20]. And motif discovery is the process of detecting and locating previously defined patterns in time series datasets [21]. An efficient motif discovery algorithm can be used as a data mining tool to summarize and analyze massive time series data.

Many of the motif discovery methods are based on searching a discrete approximation of the time series. To achieve dimensionality reduction, Agrawal et al. [1] used Discrete Fourier Transform (DFT) for processing similarity queries. Chan and Fu [4] contended that Discrete Wavelet Transform (DWT) can be effective in replacing DFT in many areas of study, including image [9], speech [14] and signal processing [13]. There are also algorithms utilizing Piecewise Aggregate Approximation (PAA) as the discretization technique [15][18][27]. Tanaka et al. [25] applied Principal Component Analysis (PCA) to reduce dimensions of data and discovered a motif based on Minimum Description Length (MDL) principle. More recently, there are series of algorithms based on Matrix Profile technique, which can improve the performance and increase the scalability of data [19][26]. In order to



European Union
European Regional
Development Fund

Joint R&D grant with University
College London for robotic surgery
gesture detection and optimization



Grant for chronic pain pattern
detection and management

Gesture Classification in Robotic Surgery using Recurrent Neural Networks with Kinematic Information

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INTRODUCTION

The integration of robotics in minimally-invasive surgery has witnessed remarkable increase over the previous decade. Breakthrough innovations in robotic technology, imaging and sensing facilitated the design of novel surgical systems for a number of different operations (laparoscopy, endovascular surgery). Prime example is the da Vinci Surgical System (dVSS; Intuitive Surgical Inc., Sunnyvale, CA, USA) used nowadays in many laparoscopic resection procedures (prostatectomy, cholecystectomy, nephrectomy) while it is constantly expanding to other surgical domains.

The use of robotic technology offers significant operational advantages like increased maneuverability, reduction of tremor and more precise tool positioning thus minimising intra-operative risk and trauma ultimately leading to a reduction in recovery times [3]. The continuous development of image-guided robotic surgery creates a need for new surgeons to go through analogous training for this type of surgery in order to master the necessary dexterous and technical skills. The currently practiced method of surgical training is heavily-based on expert supervision, with faculty surgeons reviewing and evaluating performance through manually assessing global rating scales and task specific checklists. The scoring procedure requires significant amount of time and it is also subjective and prone to interobserver variability. Subsequently, it has been advocated that novel objective methods, focusing on competency metrics should be developed for evaluating

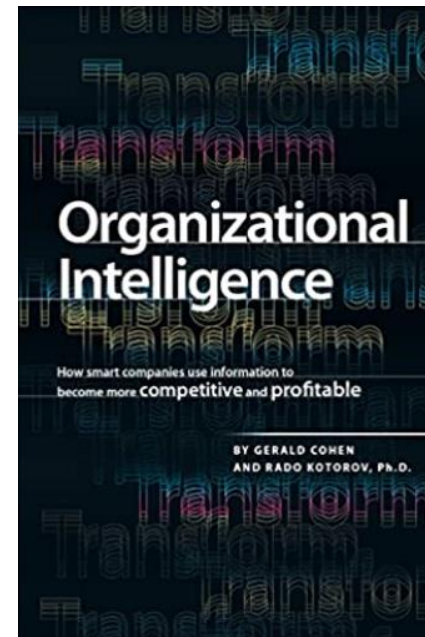
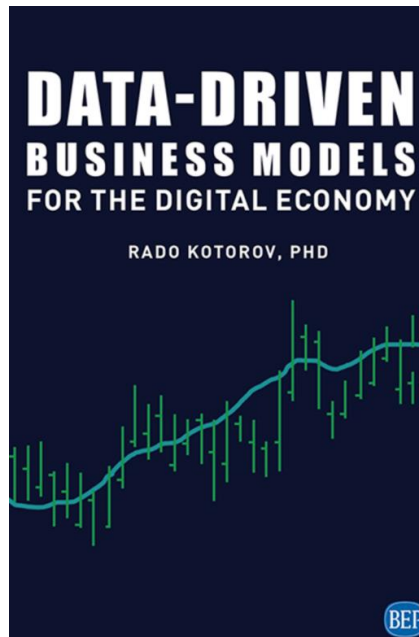
average classification accuracy for all three tasks when trained and tested with dVSS kinematic data from the same operator. Our preliminary work indicates that this type of artificial neural networks can be the building blocks in gesture classification systems which can form the basis for further developing automated skill assessment methods in robotic surgery.

MATERIALS AND METHODS

The JHU-ISI Gesture and Skill Assessment Working Set (JIGSAWS) is a publicly available surgical dataset comprising of video and kinematic data from the execution of three basic surgical tasks (suturing, knot tying and needle passing) with the dVSS on bench-top models by eight surgeons (subjects) of varying level of expertise [1, 2]. All subjects performed each task five times. The stereo video output of the dVSS endoscopic camera module was captured at 30fps in 640x480 resolution. The kinematic data contain 3D position, orientation, velocity and gripper angle values from both the master and slave, left and right manipulators totaling 76 motion-related parameters. The two datastreams are synchronised with the same sampling rate.



Figure 1. The three surgical tasks performed in JIGSAWS: from left to right – Suturing; Needle Passing; Knot Tying.



Trendalyze Team



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Co-Founder & CEO

Former Chief Innovation Officer at IBI, a BI and Data Management company with offices in 40 countries (investor Goldman Sachs). Key clients: USBank (20 million users), Fidelity, E*TRADE, Crédit Mutuel, RBC, Scotiabank, BBVA.



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Held Chair, CEO, COO roles for growth investments from Goldman Sacks and other PE firms. Managing Partner of IBM's Strategic Services consulting practice for Financial Services Industry.



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Former Research Scientist at IBM Research with a focus on AI for Blockchain. Lianhua has won numerous awards for best research papers. She also holds an associate professor position at La Trobe



We help companies understand
the pulse of their business.

Thank you.

