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Bachelors Thesis

Implementation of application for visualization of regularities and randomness in data

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Contents

Keywords

Pateikiamas terminų sąrašas (jei reikia)

Abstract

Santraukos tekstas rašto darbo kalba...

Santrauka

Darbo pavadinimas kita kalba

This is a summary in English...

Introduction

Signals can be observer all around us. For example, measuring the time taken between a weight-driven pendulum clock's ticks produces a signal. It does not require a great deal of effor to image how such a signal behaves. We would expect the clock's pendulum to swing back and forth, each time travelling a minutely shorter distance until the pendulum stops completely. Analysis of even a part of such a signal can help us determine the pendulum's position far into future.

Now consider a more complex siganl: the rates of a stock market. People have been analyzing this data for decades, grasping to predict its future state. For the scope of this paper, we defined the term signal processing as *the science of analyzing time-varying processes* [14].

In this thesis we analyzed the non-triviality of digital sygnals. Certain signals can be classified as simple (relatively trivial), like the aforementioned clock's pendulum. A more complex (non-trivial) signal would be the rates of a stock exchange.

1 Signal processing and Recurrence plot

1.1 Signal processing

A signal is a function that conveys information about the behaviour of a system or attributes of some phenomenon [16]. For example, measuring the time taken between a weight-driven pendulum clock's ticks produces signal. In turn, for the scope of this paper, we defined the term signal processing as *the science of analyzing time-varying processes* [14]. By processing a signal we analyzed the non-triviality of a given signal. Analyzing a signal reveals that some signals have properties that can be categorized.

1.2 Signal property categories

We have considered the following categories:

1. Stationary and non stationary signals
2.

Signals have varying properties. Some consist of simple repetitions while others have no apparent patterns. For example, measuring the time taken between a weight-driven pendulum clock's ticks produces a relatively simple (trivial) signal.

2 Web application development

This project is aimed at creating a web application allowing one to interact with the recurrence plot algorithm in a user friendly manner. The project offers a feature of classifying data based on the generated plot using convolutional neural networks. This is an effort to further spread the popularity of this algorithm and help users intuitively grasp how it behaves.

2.1 Analysis of analogous tools

As of the date of publishing, only one tool was located capable of generating a recurrence plot online [15]. There are multiple implementations of the recurrence plot in Python as well as other languages, but none offer the ability to classify data based on the generated image.

It is noteworthy, that the aforementioned implementations require at least a minimal undertanding of software programming, a computing machine and specific software to compile and run the code. This is laborious and is not likely to attract new users to experiment with algorithm. Based on these factors, a decision was made to create a web based application that requires as little user knowledge to get started with the algorithm as possible.

2.2 Architecture

This project uses the microservices. Microservices are small autonomous services deployed independently, with a single and clearly defined purpose [12]. This design approach was chosen due to the flexibility and scalability associated with the architecture. The nature of microservices allows one to easily test, modify or out right replace each one of the components giving more freedom to the developer. The project ecosystem consists of the following microservices:

1. Front end web application
2. Back end for the web application
3. Python web server for plotting operations

Communication between microservices is performed via HTTP requests. In general, a query with JSON body is sent to a service and a JSON response along side an image attachment is returned. Figure 1 illustrates the microservice architecture of the project and data flow among services.

2.2.1 Project structure

The project is structured so that each microservice resides in an independent directory:

- app/
  - src/
    - components/
  - public/
- server/

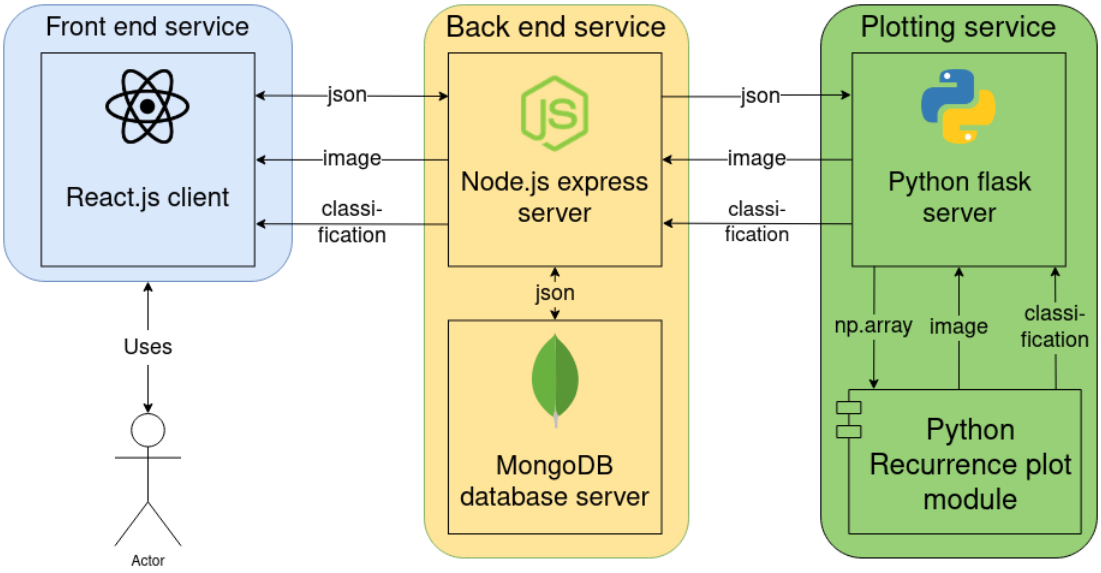


Figure 1. Microservice architecture structure

  - db/
  - public/
  - utils/
- plotter/
  - jupyter/

As the name suggests - `/app/` directory contains the front end ReactJS application. The NodeJS express[1] server resides inside the `/server/` directory. Meanwhile, `/plotter/` contains all of the Python source code. That includes the flask [2] web server, the recurrence plot module, jupyter notebooks for convolutional neural network model development and scripts for model training data generation.

2.2.2 Project workflow

We will now cover an example workflow of the application as per figure 1.

When first opening the app, a request is sent to the back end to fetch a list of existing plot data. The user selects an entry from the list and fills in remaining parameters for generating a recurrence plot. A request with select data ID is sent to the back end microservice. The back end service fetches data from the database and forwards it to the plotting service. The plotting service generates an image, then runs the image through a convolutional neural network to get classification data. Finally, the plotting service send the image along with classification data back to the back end service, which in turn forwards it to the front end service. The front end service displays the image and classification data.

2.3 Microservices

The tools used for microservice development were largely open-sourced and relatively modern. Front end and Back end services were written in javascript based environments - React JS and

Node JS respectively. These choises were made due to the widespread use of javascript in modern web application development providing a large pool of open-sourced libraries and tools.

On the other hand python was the tool used to develop the plotting service. It is known to perform better on data handling and machine learning than javascript alternatives [13]. Both Python and Node JS have certain strengths and thus have appropriate community driven libraries and modules to reinforce their leverages in appropriate operations.

2.3.1 Front end microservice

The front end service is developed using React - A JavaScript library for building user interfaces [11]. SASS is used for styling the apllication due to the intuitive syntax it provides [9]. The microservice utilizes the Node Package Manager [6]. From the NPM registry, two open sourced libraries are used:

- node-fetch - A module that brings window.fetch to Node.js [5].
- query-string - a tool for building HTTP query string [8].

These libraries were used to facilitate communication via HTTP requests with the back end server.

Following the best practices of React development, the app is broken down into reuseable components. Figure 2 indicates the application structure denoting components with the standard JSX component notation `<component />`. We will be using this notation to refeter to JSX components.

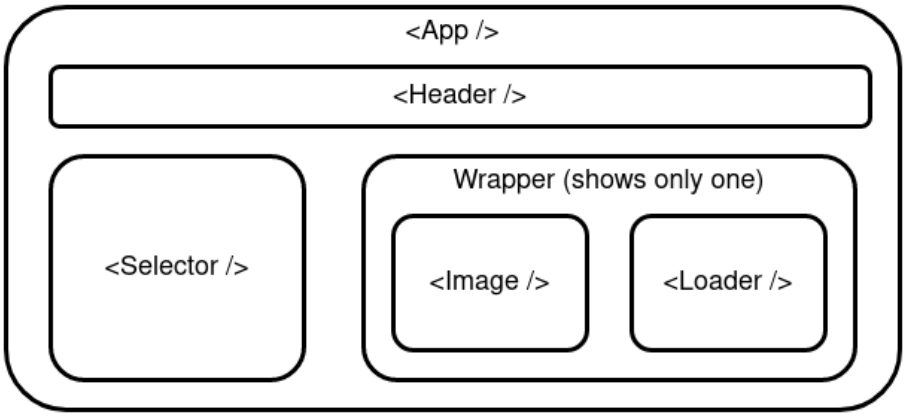


Figure 2. React app component structure

Figure 2 indicates that a root `<App />` component wraps the whole application. Initially, only the `<Header />`, `<Selector />` and `<Loader />` components are visible to the user. The `<Selector />` component sends an HTTP GET request to the backend service to retrieve a list of available plot data. This list is displayed inside the `<Selector />` for the user to pick from. A user must select a data entry and may add optional plotting parameters. Submitting the `<Selector />` form sends an HTTP GET request to the back end service. The backend service returns a JSON with the location of the generated recurrence plot image and additional parameters. After handling the server response - the `<Loader />` component is replaced by the `<Image />`. During any further plot requests, the `<Image />` is briefly replaced by the `<Loader />` component to indicate that a request is being processed.

2.3.2 Back end microservice

The backend microservice also utilizes libraries provided by the Node Package Manager. The service runs on an Node JS express server [1]. The server handles all requests from the front end service. Server endpoints cover the following operations:

- CRUD operations for plot data stored inside the MongoDB database
- Requests to generate a recurrence plot using the plotting service

The express server communicates with the database server by making use of an open sourced MongoDB object modeling library - mongoose [4]. The service itself does not generate any plot data, but merely acts as an intermediary between the front end service, the MongoDB database and the plotting service.

2.3.3 Plotter microservice

The plotter microservice handles requests to generate and classify recurrence plots. The service utilizes numpy[7], scipy[10] and matplotlib[3] open sourced python libraries.

The service consists of 3 main parts:

1. Flask - a python web framework
2. Recurrence plot module
3. Data classification model

The flask service handles HTTP requests with JSON data as input. The service processes the input and generates an image using the recurrence plot module. Image is passed through the convolutional neural network to get the image classification. An HTTP response is then sent containing the classification data and the generated image as an attachment.

2.4 Recurrence plot module

The recurrence plot module is a Python implementation of the algorithm used to generate a recurrence plot. The module creates a `RecurrencePlot` object. The object takes in several parameters as input allowing one to customize the following features of the generated plot:

- D - signal dimension
- d - signal delay
- compare_mode - evaluation metric: euclidean and maximum
- target - Prefered pixel percentage of the recurrence plot
- deviation - allowed deviation for final pixel percentage

As output the module returns the name of the asset in the local storage. The object can also be manipulated to retrieve various other metrics about the recurrence plot.

3 Data classification model

A recurrence plot reveals certain information about the singal. After some practice a human can identify whether a given signal exhibits signs of periodity and / or stationarity, has a trend or seems to be random in nature. The goal of this model is to determine some the aforementioned characteristics of a signal by analyzing the reucrrence plot generated by it.

3.1 Generating training data

It is common knowledge that one requires data to train a convolutional neural network. The accuracy of a data model heavily weighs on the quality of training data and labeling. After a brief search for publicly available, labeled and categorized data suitable for training a recurrence plot model, a decision was made for this data to be generated synthetically.

3.1.1 Training data methodologies

The source code for generating training assets if written is python programming language. Open sourced libraries utilized for the creation of assets are listed in section 2.3.3. All of the following signals and their graphs are generated by utilizing the aforementioned libraries and the recurrence plot module. For every signal a complementary graph image is generated to help visualise the data which resulted in the recurrence plot. Due to the module flexibility every chaotic and periodic asset had randomised values for D - Dimension and d - delay. In addition, most aspects of each graph had a randomised flaoting point number be added or subtracter. This aided in generating a more diverse set of training assets. The number of assets chosen was arbitraty - 1000 sygnals for each training label. That amounts to a total of 3000 recurrence plot images used for training the CNN. The source code for generating assets and associated graphs is inside the `/plotter/generate-cnn-assets.py` file.

3.1.2 Choosing classification features

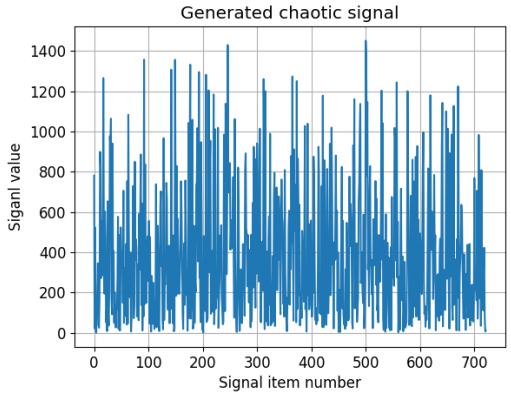
Before generating the data it is important to recognize what the convolutional neural network is expected to learn from it. The *what can it learn?* aspect of a CNN is mostly limited by the labeled data we can provide. A choise was made to classify plot images into one of the three groups:

- Plotted signal is chaotic
- Plotted signal has a trend
- Plotted signal has is periodic

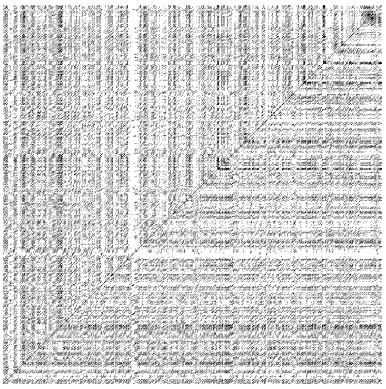
We will explore the reasoning of this decision by exploring the limitations of generating labeled signals.

3.1.3 Chaotic signal

A relatively simple signal to identify is a chaotic signal. Chaotic, means it has no distinguishable pattern - random. This signal can be generated rather easily - by calling a random number generator for each entry in the signal. It is also advantageous, that chaotic signal does not trigger any other feature attribute except for stationarity. A chaotic signal tends to have a high level of stationary

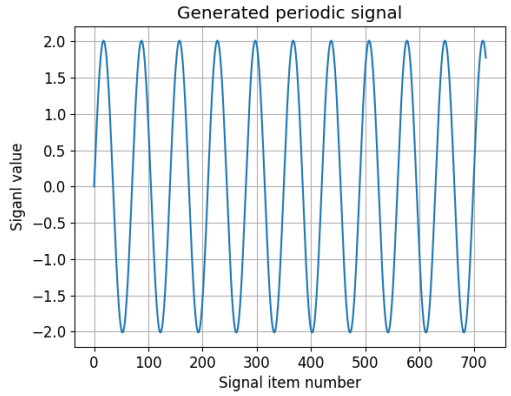


(a) Chaotic signal

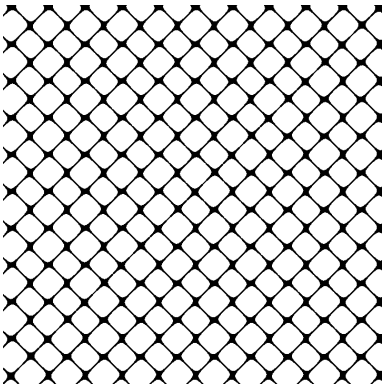


(b) Recurrence plot. Pixel target=17.5%, D=2, d=1

Figure 3. Chaotic signal and recurrence plot generated by it



(a) Sine wave signal



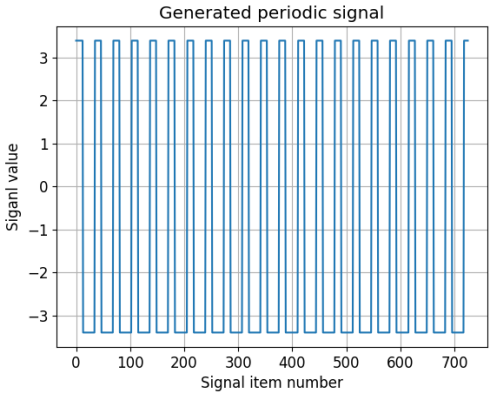
(b) Recurrence plot. Pixel target=17.5%, D=3, d=2

Figure 4. Periodic sine wave form signal and recurrence plot generated by it

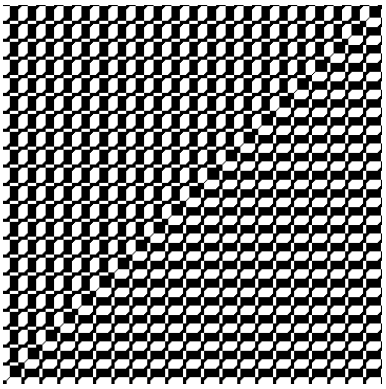
meaning it is dispersed fairly evenly across the recurrence plot. Figure 3 displays a signal (a) and the generated recurrence plot (b) from the training set. This signal is labeled as chaotic and is one of the signals used for training the convolutional neural network.

3.1.4 Periodic signal

For a human, identifying a signal with a periodic characteristic is not too strenuous either. Unfortunately we cannot consider the periodicity of a signal without considering the stationarity of it. Stationarity is generally observed by the homogeneity of a signal. In layman terms - how evenly the pixels are spread across the recurrence plot. Looking back at figure 3 we can see that a chaotic signal is highly stationary as the pixels are spread fairly evenly. Figure 4 illustrates a signal (a) from the periodic training set and the recurrence plot (b) that is generated from it. We can see that this siganl forms a grid pattern. The pattern stretches across the whole image therefore this signal is also stationary. It would be difficult to generate periodic data that is not stationary, but the same applies to chaotic data. This is the reason why stationarity is not one of the attributes measured by the model. Determining the level of periodicity is beyond the scope of this particular neural netowrk.

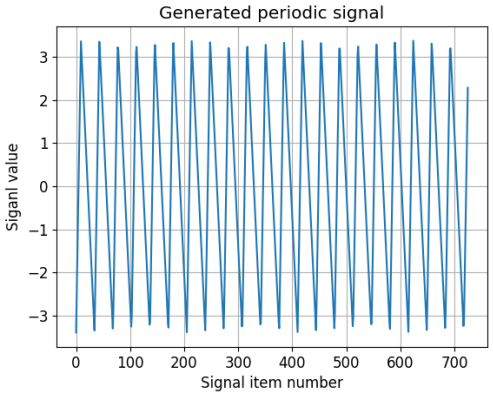


(a) Square wave signal

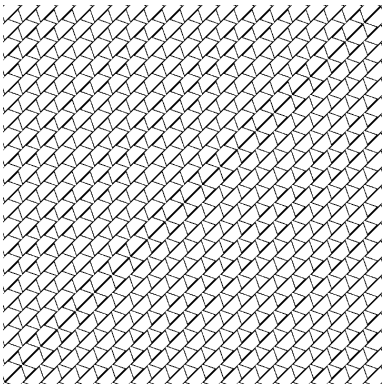


(b) Recurrence plot. Pixel target=17.5%, D=4, d=2

Figure 5. Periodic square wave form signal and recurrence plot generated by it



(a) Sawtooth wave signal



(b) Recurrence plot. Pixel target=17.5%, D=4, d=2

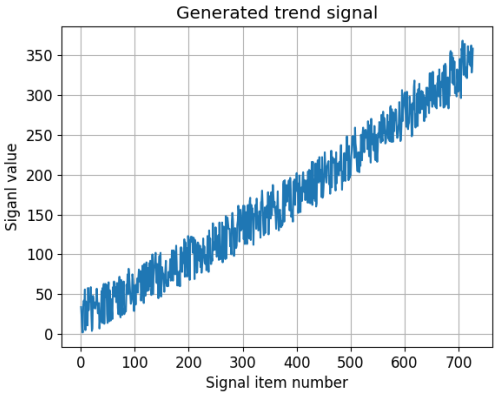
Figure 6. Periodic sawtooth wave form signal and recurrence plot generated by it

A periodic signal wave can have difference forms. The signal in figure 4 is generated from a sine wave. To provide the model with more diverse training data - two additional distinct wave functions were used to generate the training data. Figure 5 illustrates a signal with a square wave. See the signal wave (a) on the left and generated recurrence plot on the right (b). The final waveform to be used for periodic images is the sawtooth waveform. Figure 6 illustrates the wave signal (a) and the recurrence plot generated (b) using it.

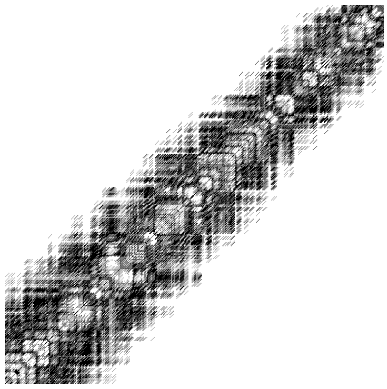
3.1.5 Signal with a trend

A trend signal is quite distinguishable by it's tendency to be less stationary than the previous two. Recurrence plot of a non synthetic trend signal appears to center aruond the diagonal simetry line and tends to have an increasing width towards either side of the image. Figure 7 illustrates an example trend signal (a) and the recurrence plot generated using it (b). This is one of the labeled samples used in training the convolutional neural netowrk.

These signals are generated by using a randomly generated data starting point. Then generating an integer within a given range to simulate increasing or decreasing data. Finally slightly increasing the average signal value by a flat value multiplied by an exponent. This allows synthetic trend



(a) Trend signal



(b) Recurrence plot. Pixel target=17.5%, D=4, d=2

Figure 7. Trend signal and recurrence plot generated by it

data to either increase linearly or exponentially. Looking closely to figure 7 image on the left we can see that the trend data exhibits an exponentially increasing in values. The exponent is picked to be small so that the synthetic signal appears more natural.

3.2 Data processing

Conclusions and Recommendations

Išvados bei rekomendacijos.

Ateities tyrimų planas

Pristatomi ateities darbai ir/ar jų planas, gairės tolimesniems darbams....

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Appendices

Dokumentą sudaro du priedai: A priede ....

A Pirmojo priedo pavadinimas

Pirmojo priedo tekstas ...

B Antrojo priedo pavadinimas

Antrojo priedo tekstas ...