

Interactive Visualization of Correlations in High-Dimensional Streams

Bachelor's Thesis of

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(Yimin Zhang)

Abstract

A fundamental task of Data Mining is to estimate the correlation between the attributes of a data set. Knowing the relationship between a set of variables, one can infer useful knowledge about external, a priori unknown outcomes.

In contrast to static data, the data is often available as a stream, i.e., it is an infinite, ever evolving sequence of observations. Concepts learned at a certain time cannot be expected to hold in the future. Therefore, correlation estimation should be a continuous process.

Also, the data is often high-dimensional, i.e., it contains hundreds or thousands of dimensions. Besides the computational burden to estimate the correlation between many subsets, it becomes difficult for a human observer to extract knowledge from the results.

The task becomes even more difficult if one considers correlations between more than two variables, because the size of the result increases exponentially.

The aim of this bachelor thesis is to develop a graphical interface for data scientists, dedicated to the visualization of correlation in user-given data streams. With this interface, available for example as a web-service, users could provide their own data sets. Then, the system's backend would estimate the correlations, and provide a visualization of the results, for example, via force-directed graphs. Users will be able to interact in several ways with the interface, by setting parameters to tune the visualization. We will evaluate the benefits of our interface via controlled user studies.



Zusammenfassung

Die Abschätzung der Korrelation von Attribute in einer Datenmenge ist einer der grundlegenden Aufgaben von Data Mining. Wenn man die Beziehung von Variablen kennt, dann kann man einige nützliche Ausgaben über zusätzliche und unbekannte Informationen folgern.

Normalerweise sind die Daten als Datenfluss verfügbar, d.h. Es ist unendlich und sogar evolutionär. Die zur-zeitigen schon erkennende Begriffe und Resultaten kann man in der Zukunft nicht mehr benutzen. Deshalb muss die Abschätzung der Korrelation ständig werden.

Ein anderes Problem ist hohe Dimension. Die Daten enthalten oft mehr als 100 oder sogar 1000 Dimensionen, sodass es ist schwierig für das Rechnen der Daten. Es ist auch schwer für ein Mensch um Daten zu analysieren. Wenn es um die Korrelation über mehr als zwei Variablen geht, wächst das Rechnen der Datenmenge exponentiell an.

Das Ziel dieser Arbeit ist die Entwicklung von einer graphischen Schnittstelle für die Daten Wissenschaftler, um die Korrelation der Daten zu visualisieren. Mit dieser Schnittstelle, als zum Beispiel Web-Service, laden die Benutzer selbst Datenmenge hoch. Danach wird das Backend von System die Korrelationen von Attribute berechnen und eine Visualisierung von Daten ausgeben, zum Beispiel, durch Force-Directed Graph. Es ist auch möglich für die Benutzer mit der Schnittstelle Parameter aufzustellen, um die Visualisierung zu verbessern. Zum Schluss bewerten wir die Vorteile und Nachteile dieser Schnittstelle durch einige Anwendungsfälle.

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1 Introduction

1.1 Motivation

Correlation analysis aims at discovering and summarizing the relationship between the attributes of a data set. Knowing the relationship between a set of variables, one can infer useful knowledge about external, a priori unknown outcomes.

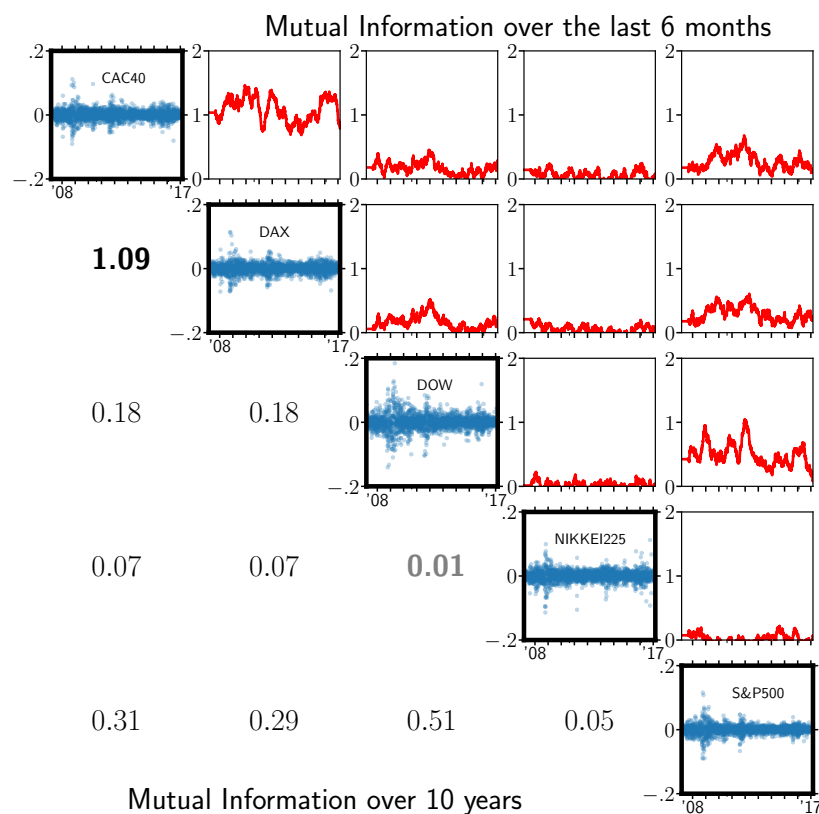


Figure 1.1: Mutual information between the return of financial indices

For example, we can measure the stock relationship via mutual information in a stock market that may undergo large fluctuations of stock prices. Figure 1.1 represents the Mutual Information between the return of important financial indices over 10 years over a sliding windows of 6 months. Such a correlation monitoring system could be of great help to a financial analysis.

As an instance, investing in low correlated market indices, such as CAC40 and NIKKEI, may be desirable minimize the risks of a portfolio: If one of the stock decreases, the other stock is unlikely to be affected too. This is how mutual information helps us to maximize our wealth.

Therefore, analyzing the correlation between different attributes helps us to understand their relationship. In general, the correlations between attributes remain same or change gradually. If the correlation structure changes brutally, which often indicates a sudden peak or valley, we can infer that one of the attributes may have an enormous change or the relationship between them may differ thoroughly. Figure 1.2 shows a simulation of "gradual" and "abrupt" changes for correlations.

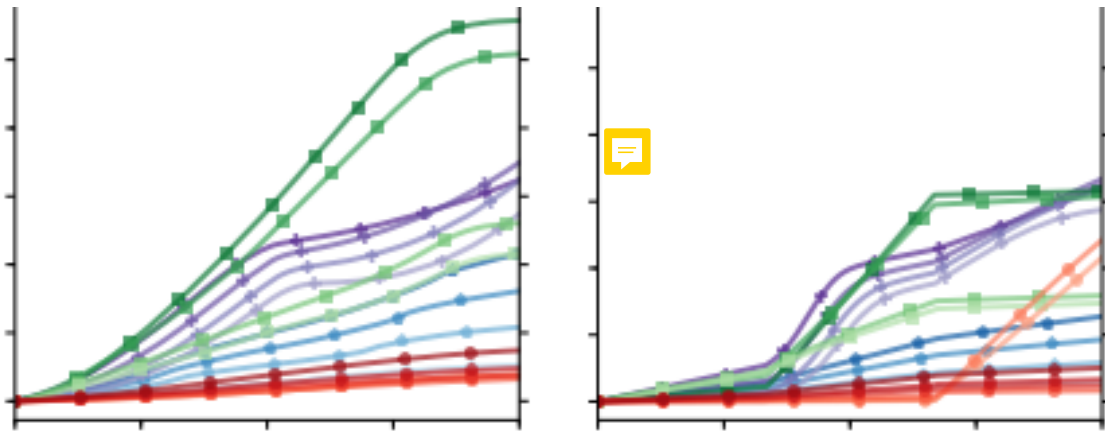


Figure 1.2: "Gradual" changes Vs "abrupt" changes for correlations

1.2 Challenges

The challenges of analyzing high-dimensional data streams is twofold: the evolving nature of streams and the high-dimensionality.

1.2.1 The evolving nature of streams

In contrast to static data, the data is often available as a stream, i.e., it is an infinite, ever evolving sequence of observations. As the concepts learned at a certain time cannot be expected to hold in the future, correlation analysis should be a continuous process.

1.2.2 The high-dimensionality

Also, the data is often high-dimensional, i.e., it contains hundreds or thousands of dimensions. In the case of streams with many dimensions, it is difficult to extract actionable insights from the correlation matrix, as the number of pairs of attributes increases quadratically and the coefficients evolve over time in unforeseen ways. For the pairwise correlation analysis of any data stream with n components, one needs to compute the correlation between $\frac{n * (n - 1)}{2}$ pairs, i.e., with $n = 5$, one needs to compute 10 pairs, with $n = 10$, one needs to compute 45 pairs, it becomes difficult and impossible to understand the result of the correlation analysis. The visualization of different number of pairs of attributes shown in Figure 1.3 illustrates this, which also indicates $O(n^2)$ of the time complexity.

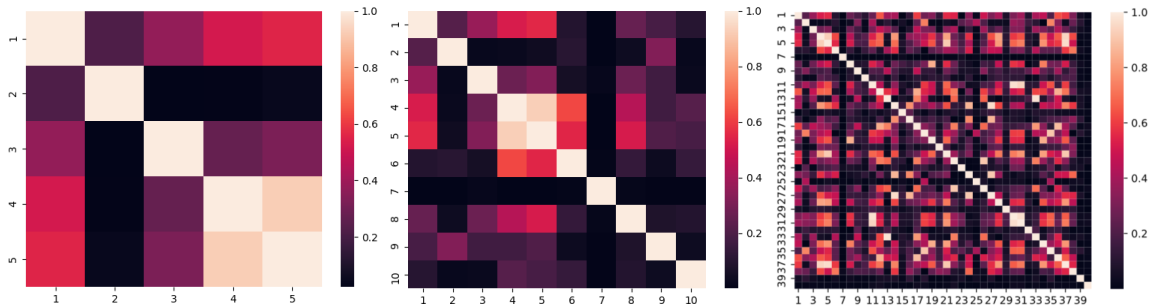


Figure 1.3: Visualization of different number of pairs of attributes

1.3 Goal of the thesis

The goal of this thesis is to propose and evaluate new tools for the interactive visualization of correlation in high-dimensional streams. In this thesis, we are going to answer the following three questions:

- What visualization methods are the most appropriate to visualize correlation?
- How can one visualize the evolution of correlation results?
- What are the desirable features of a correlation monitoring interface?

To answer these questions, we first search for some interactive visualization methods and then develop an interface to visualize correlations. This interface can be available in a browser and should be user friendly, which means that users provide their own data sets and the system's back-end calculates the correlations and then provides the visualization of the results, for example, via force-directed graphs. Users are also able to interact in several ways with this interface, such as setting parameters to tune the visualization. At last, we evaluate the benefits of our interface systematically via controlled user studies and discuss the advantages and disadvantages of each visualization method. Based on

the results, we discover the appropriate visualization methods of correlations in high-dimensional streams and the desirable features of the interactive interface.

1.4 Thesis outline

The process of investigation can be split into three parts, that is performing a literature review, developing a graphical interface and evaluating this interface, which also leads to the three parts of this thesis, the visualization methods, the design and implementation of interface, and the evaluation of this interface.

In Chapter 2, the first part of the thesis, we introduce some state-of-art methods for correlation visualization. Section 2.1 introduces the correlation matrix, which is the standard tool of performing the correlation analysis. In Section 2.2, Section 2.3 and Section 2.4, some other examples of data visualization are discussed.

In Chapter 3, we give an overview of parallel coordinates and scatterplot matrices as examples of multidimensional visualization techniques. Also, we introduce an interactive Framework for Exploring and Understanding Multivariate Correlations "FEXUM", which has something quite similiar to our work.

Chapter 4 is the main part of this thesis, which consists the design of the interface in Section 4.1 and the implementation of this interface in Section 4.2.

We introduce the evaluation of the developed interface in Chapter 5 ~~at the end, which is also the last part of this thesis.~~ Chapter 5 contains the experimental settings of controlled user studies for evaluation in Section 5.1 and the result in Section 5.2.

In the end, we summarize the whole thesis.

2 Visualization Methods

In this chapter, we first introduce the correlation matrix in Section 2.1 and then introduce some useful interactive visualization methods for correlations in Section 2.2, Section 2.3 and in Section 2.4.

2.1 Correlation Matrix

The most familiar measure of dependence between two quantities is the Pearson product-moment correlation coefficient [6], known as "Pearson's correlation coefficient". It is obtained by dividing the covariance of the two variables by the product of their standard deviations. The population correlation coefficient $\rho_{X,Y}$ between two random variables X and Y and standard deviations σ_X and σ_Y is defined as

$$\rho_{X,Y} = \text{corr}(X, Y) = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y} \quad (2.1)$$

where cov means covariance, and corr is a widely used alternative notation for the correlation coefficient. The Pearson correlation is defined only if both of the standard deviations are finite and non-zero.

The standard tool of correlation analysis is the computation of a correlation matrix, which is used to investigate the dependence between multiple variables at the same time.

2.2 Heatmap

A common visualization is the heatmap[7], which is originated in 2D displays of the values in a data matrix. The Figure 2.1 is a heatmap of a correlation matrix, in which the variables with strong correlation (high values) are printed in light colour and those with low correlation are in dark colour.

2.3 Force-Directed Graph

Also, Force-Directed Graph[4] is a useful visualization, which assigns forces among the set of edges and the set of nodes of a graph drawing. The purpose of it is to position the nodes of a graph in two-dimensional or three-dimensional space so that all the edges are of more or less equal length and there are as few crossing edges as possible. In such a

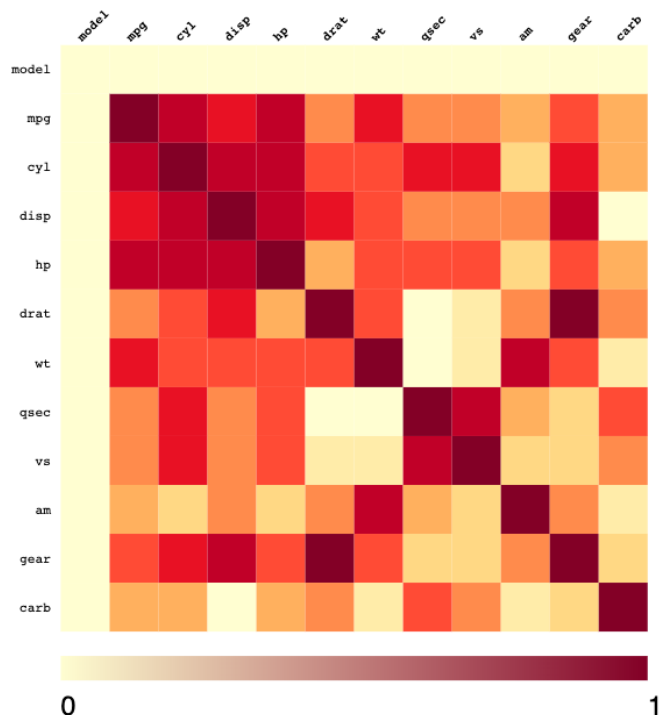


Figure 2.1: Correlation Matrix of a data set in heatmap

simulation, the forces are applied to the nodes, pulling them closer together or pushing them further apart. This can be used to simulate the relationship of different attributes throughout the time, in which the force is the representation of correlation matrix. The Figure 2.2 shows an example of Force-Directed Graph, which actually uses the same data set in Figure 2.1.

2.4 Bar Graph

A bar chart[3] or bar graph is a chart or graph that presents categorical data with rectangular bars with heights or lengths proportional to the values that they represent. The bars can be plotted vertically or horizontally. A vertical bar chart is sometimes called a line graph. One axis of the chart shows the specific categories being compared, and the other axis represents a measured value. Bar charts provide a visual presentation of categorical data. Categorical data is a grouping of data into discrete groups, such as months of the year, age group, shoe sizes, and animals. These categories are usually qualitative. The Figure 2.3 is an example of bar graph.



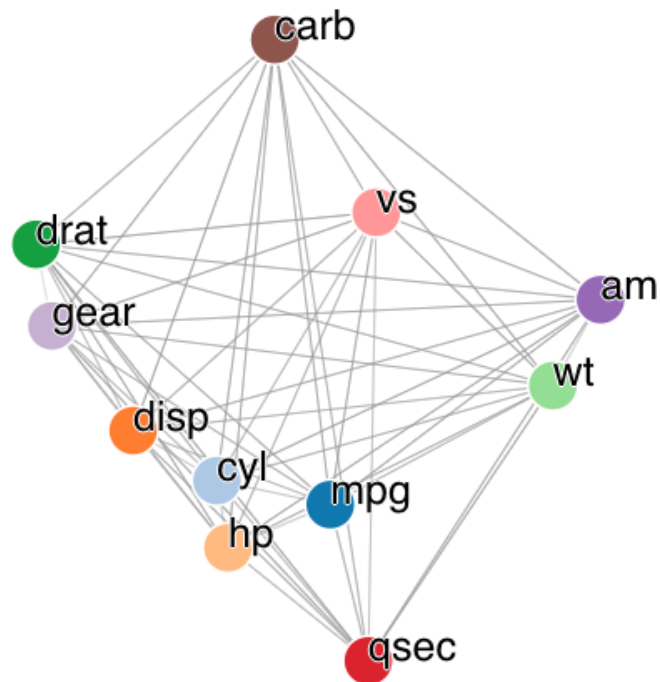


Figure 2.2: Force-Directed Graph

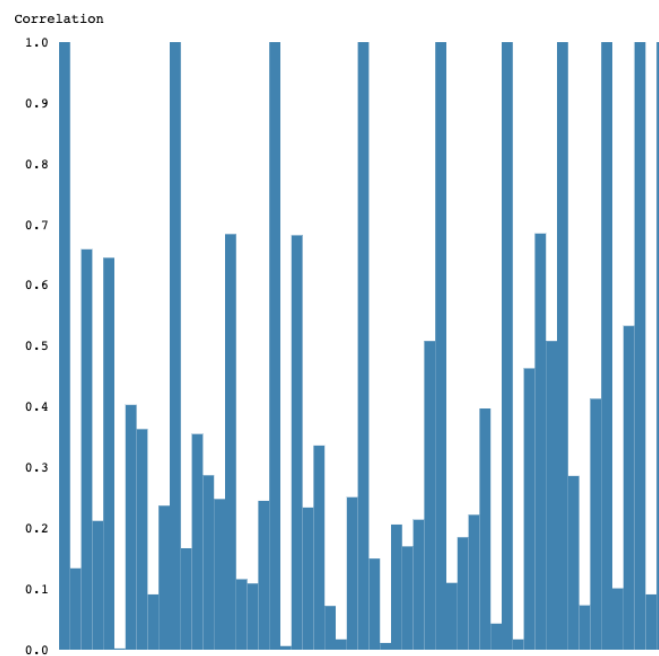


Figure 2.3: Bar Graph

3 Related Work

With the exponentially increasing amount of acquired multivariate data, several multi-dimensional visualization techniques have been proposed during the last decades. Parallel coordinates and scatterplot matrices are widely used to visualize multi-dimensional data sets. But these visualization techniques are insufficient when the number of dimensions grows, ~~as we have mentioned in Subsection 1.2.2.~~ To solve this problem, different approaches to preselect the best views or dimensions have been proposed in the last years. Georgia Albuquerque et al. [1] presented three new methods to explore multivariate data sets: a parallel coordinates matrix (Figure 3.1), in analogy to the well-known scatterplot matrix, a class-based scatterplot matrix that aims at finding good projections for each class pair (Figure 3.2), and an importance aware algorithm to sort the dimensions of scatterplot and parallel coordinates matrices. They aims at providing a visualization of the whole data set.

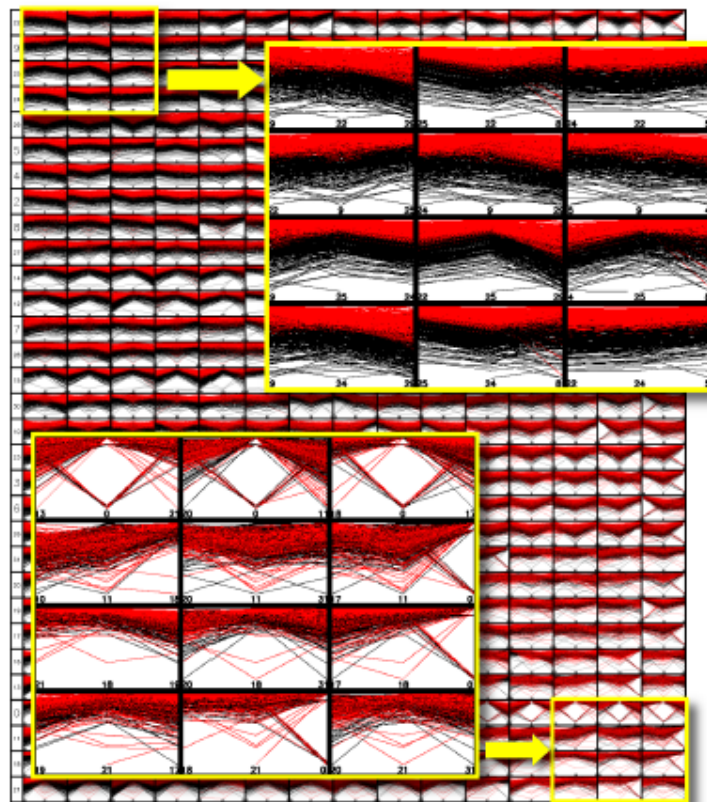


Figure 3.1: Parallel coordinates matrices for the data set

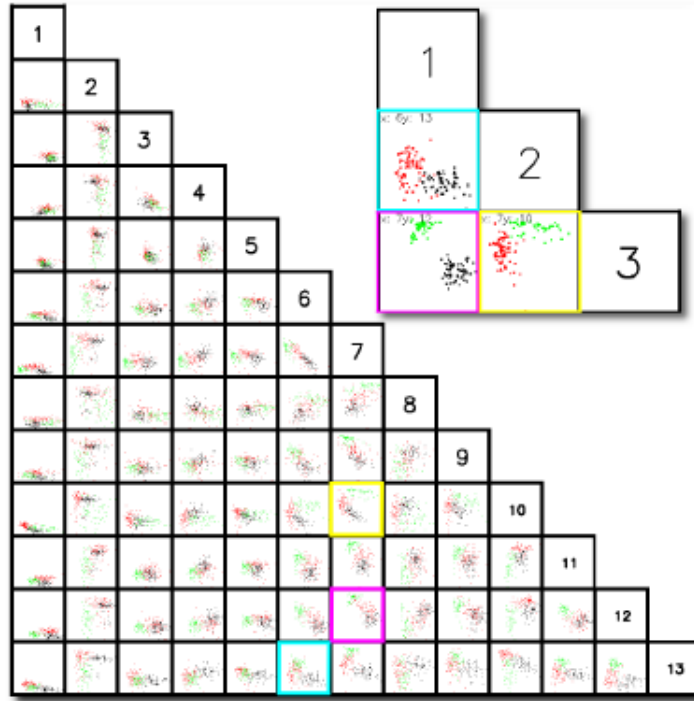


Figure 3.2: Class-based scatterplot matrices for the data set

In Section 1.1, we have pointed out the use and importance of correlation analysis between different attributes, which helps people to understand the relationship of attributes in a data set. Therefore, our interactive interface aims at providing a visualization of correlations for people.

As a high-dimensional data set may contain many redundant features, feature selection becomes an essential step for correlation analysis. Louis Kirsch et al. [2] developed an interactive Framework for Exploring and Understanding Multivariate Correlations (FEXUM) to simultaneously visualize all feature correlations to the target and pairwise correlations using Force-Directed-Graph. This visualization provides a layout in which a smaller distance between two features denotes a greater redundancy. In Figure 3.3, nodes represent features and weighted edges represent distances. FEXUM provides users with an understanding of how features interact with each other in terms of redundancy so that they can easily find influential value ranges in the analysis view and make feature selection.

~~What we are going to do~~ is to give the users an overview of all correlations in the data set. Instead of choosing a target attribute to focus on, our system represents the whole correlations of the data set. Unlike FEXUM, Force-Directed-Graph is not the only visualization method in our system. Heat map and Bar graphs are alternative visualization method for the users so that the users can choose **whichever they want** or think most suitable visualization method.

In Subsection 1.2.1, we have discussed that the correlation analysis should be a continuous process. FEXUM enables the users to upload their own data sets and visualize them.

However, in our system, the uploaded data set by users can be a data set of data stream so that the users can choose a period of time to perform the correlation analysis and visualization. Our goal is to visualize a concise but useful summary of correlations in the stream over time.



Figure 3.3: Features drawn using a force-directed graph (right), with the target highlighted in green. An analysis view of two features (left) for inspecting the correlations. (Color figure online)

4 Interface

To research questions, we develop an interface in a browser available as a web-service. The entire framework is open source and available [online](#). In Section 4.1, we describe the mock-up of this interface and its available functions. And we introduce the details of implementation in Section 4.2.



Interactive Visualization of Correlations in High-Dimensional Streams

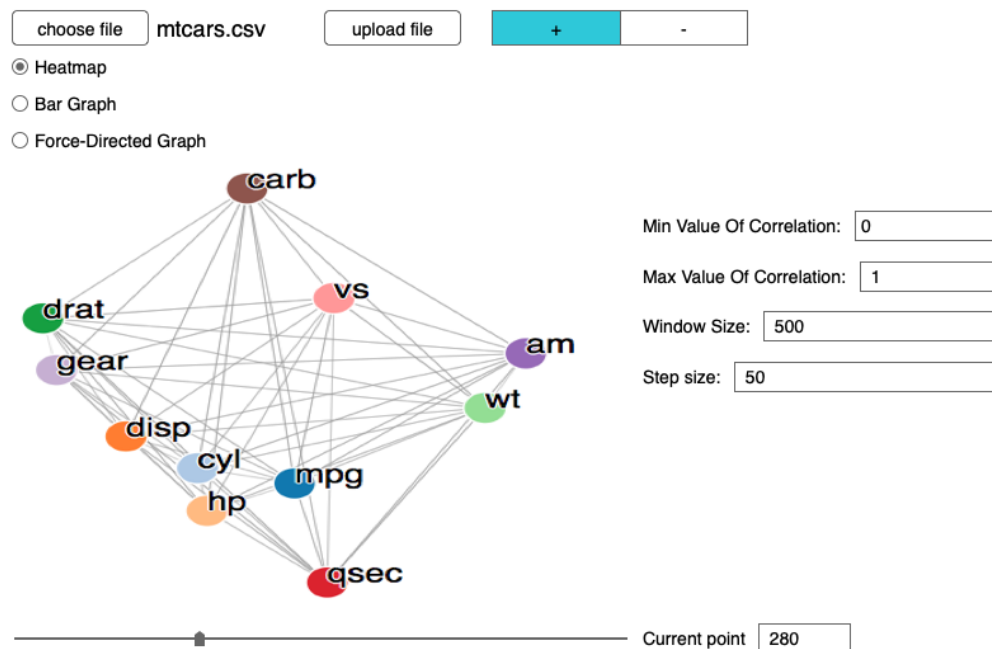


Figure 4.1: Mockup of the interface

4.1 Design

Figure 4.1 is the mock-up of this interface. This interface can be used with a wide range of data sets as csv files, supplied through upload by the user. After the calculation in the back-end, the visualization of data correlation is shown in the website, for example, via a force-directed graph. In the mock-up, a sliding window with start point and step size is supposed to be used to represent the continuous process of data throughout the time. Also, we have some simple user settings, such as changing the window size, setting the

minimum and maximum of correlation to be visualized.

4.2 Implementation

4.2.1 D3.js

D3.js (Data-Driven Documents)[5] is a data-driven JavaScript library for producing dynamic, interactive data visualizations in web browsers. It makes use of the widely implemented SVG, HTML5, and CSS standards and allows great control over the final visual result. SVG stands for Scalable Vector Graphics which is technically an XML based markup language. It is a great tool to display icons, logos, illustrations or charts, which is supported in all major browsers and requires no third-party lib because of owning the DOM interface;. In our project, we mainly use D3.js to implement the visualization of correlations in high-dimensional data streams.

Interactive Visualization of Correlations in High-Dimensional Streams

The interface includes a file upload section with a 'Choose file' button, a 'No file chosen' status, and an 'Upload' button with '+' and '-' icons. Below this are three radio buttons for visualization types: 'Heatmap' (selected), 'Bar Graph', and 'Force-Directed Graph'. There are four input fields: 'Minimum:' with value '0', 'Maximum:' with value '1', 'Window Size:' with value '0', and 'Step Size:' with value '0'. An 'Update the Graph' button is located below the 'Step Size' field. A yellow horizontal bar is positioned below the 'Update the Graph' button. At the bottom, there is a 'Current Point:' label followed by an input field containing the value '1'.

Figure 4.2: Overview of the interface

4.2.2 Details

The Figure 4.2 is an overview of our developed interface, which is available in a browser as a web-service. Users can press the "Choose file" button to upload their own data sets. After pressing the "upload" button, the data set will be calculated at the back-end. If the calculation of correlations is finished, a confirm window will pop up to inform the maximal window size of the current data set to the user. Also, the step size will be set to 1 and the window size will be set to the maximal window size after uploading the data set, see Figure 4.3. The width of the panel on the slider indicates the size of the current window. The window size represents the timestamp of the current data set. Combined with the step size, the user is able to get the visualization of a certain time period.

Interactive Visualization of Correlations in High-Dimensional Streams

Choose file: biolq20.csv Upload + -

☒ Heatmap
☐ Bar Graph
☐ Force-Directed Graph


Minimum: 0

Maximum: 1

Window Size: 86400

Step Size: 1

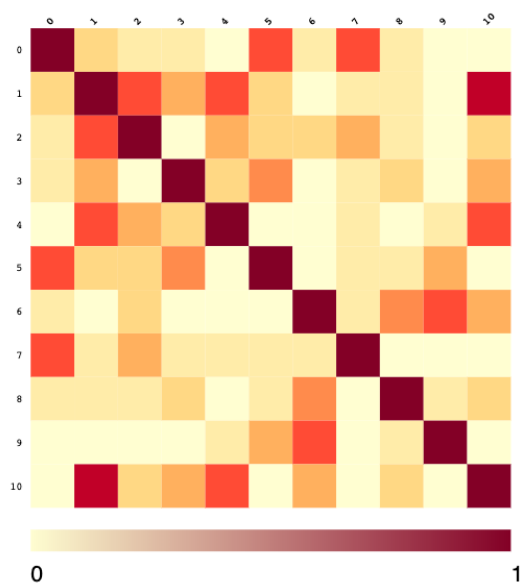
Update the Graph



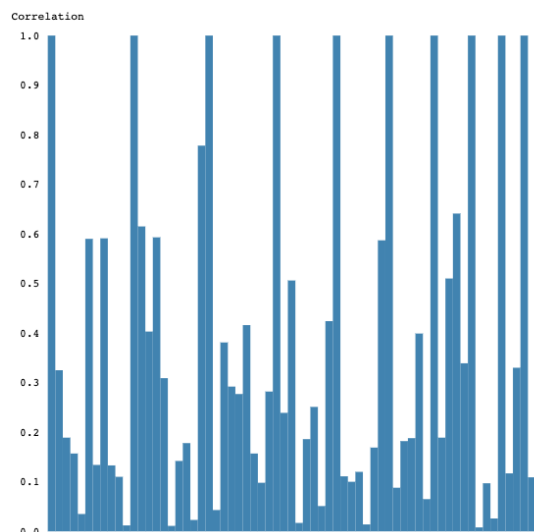
Current Point: 1

Figure 4.3: After uploading a csv file

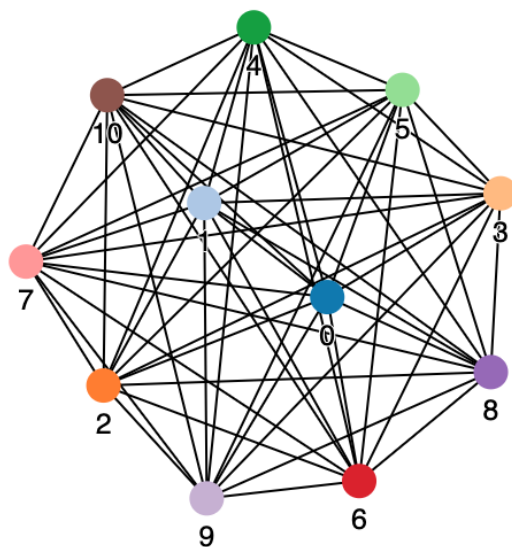
Our interface provides three visualization methods: heat map, bar graph and force directed graph. After selecting the corresponding radio button, a visualization will be drawn on the web site. The Figure 4.4 shows the three visualizations based on the same data set. Figure 4.4a is the heat map, Figure 4.4b is the bar graph and Figure 4.4c is the force directed graph. The user can also change the minimal and maximal correlation value they want to visualize, and slide the slider to see different time period of the current data set.



(a) Select Heatmap as visualization method



(b) Select Bar graph as visualization method



(c) Select Bar graph as visualization method

Figure 4.4: Select different visualization methods

5 Evaluation Via User Studies

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5.1 Experimental Settings

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5.2 Result

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6 Conclusion

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