Big Data to Enable Global Disruption of the Grapevine-powered Industries

D5.3 – Trust-aware Decision Support System

DELIVERABLE NUMBER	D5.3
DELIVERABLE TITLE	Trust-aware Decision Support System
RESPONSIBLE AUTHOR	Katrien Verbert (KU Leuven)

GRANT AGREEMENT N.	780751	2
PROJECT ACRONYM	BigDataGrapes	
PROJECT FULL NAME	Big Data to Enable Global Disruption of the Grapevine-powered industries	
STARTING DATE (DUR.)	01/01/2018 (36 months)	
ENDING DATE	31/12/2020	
PROJECT WEBSITE	http://www.bigdatagrapes.eu/	
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WORKPACKAGE N.	TITLE	WP5	Leveraging Data Value	
WORKPACKAGE LEADER	KU Leuven	
DELIVERABLE N.	TITLE	D5.3	Trust-aware Decision Support System	
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DOCUMENT URL	http://www.bigdatagrapes.eu/	
DATE OF DELIVERY (CONTRACTUAL)	31 December 2018 (M12)	
DATE OF DELIVERY (SUBMITTED)	20 December 2018 (M12)	
VERSION	STATUS	1.0	Final	
NATURE	DEM (Demonstrator)	
DISSEMINATION LEVEL	PU (Public)	
AUTHORS (PARTNER)	Katrien Verbert (KU Leuven), Nyi Nyi Htun (KU Leuven)	
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VERSION	MODIFICATION(S)	DATE	AUTHOR(S)
0.1	Initial ToC and document structure	27/11/2018	Nyi-Nyi Htun (KU Leuven)
0.2	Introduction and System Descriptions	05/12/2018	Nyi-Nyi Htun (KU Leuven)
0.3	Internal revision	07/12/2018	Katrien Verbert (KU Leuven)
0.4	A complete draft	07/12/2018	Nyi-Nyi Htun (KU Leuven), Diego Rojo Garcia (KU Leuven)
0.5	2nd Draft	10/12/2018	Diego Rojo Garcia (KU Leuven), Nyi-Nyi Htun (KU Leuven)
0.6	Internal revision	11/12/2018	Katrien Verbert (KU Leuven)
0.7	3rd Draft	11/12/2018	Nyi-Nyi Htun (KU Leuven), Diego Rojo Garcia (KU Leuven)
0.8	Partner revision	19/12/2018	Florian Schlenz (GEOCLEDIAN), Stefan Scherer (GEOCLEDIAN)
1.0	Final version	20/12/2018	Nyi-Nyi Htun (KU Leuven)

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ACRONYMS LIST

WP	Work package
DSS	Decision support system
PA	Precision agriculture
UI	User interface
SVM	Support vector machine
JSON	JavaScript Object Notation

EXECUTIVE SUMMARY

In deliverable 5.3 of work package 5, we demonstrate a trust-aware decision support that uses visualisation techniques to explain the influence of input (predictor) variables on prediction outcomes. Research has shown that prediction models currently employed in agricultural decision support systems (DSS) remain opaque to users and hidden behind the software. This blackbox nature can often lead to users not trusting the system's decisions especially when the system fails to provide meaningful explanations. Previous work has expressed that explaining a model's predictions is an important approach for earning users' trust. Visualisation is a powerful technique to address this problem and can effectively communicate uncertainty emerging from both data and prediction models.

To demonstrate our decision support system, we used a wine quality dataset and linear regression, building on top of deliverable 4.3 where WP4 partners (CNR) used the same dataset to demonstrate a linear regression model. The dataset is based on red variants of the Portuguese "Vinho Verde" wine and contains 1599 instances of 11 physicochemical (inputs) variables and a sensory (the output) variable which is wine quality. A literature review was conducted to better understand visualisation techniques that have previously been developed based on this dataset. Based on the findings from this review, we selected two unique visualisations as a starting point, which are parallel coordinates and a waterfall plot. The two visualisations can clearly illustrate multidimensional data and the influence of each input variable by allowing us to arrange the variables accordingly (e.g. left to right and top to bottom respectively; see Figure 3). In this document, we present our decision support system with a substantial focus on the visualisation components and prediction model.

This document is structured as follows. Chapter 1 lays out an introduction to the deliverable describing the existing work and motivations. In Chapter 2, the visualisation components and prediction model of our DSS are described in detail together with their development framework. In Chapter 3, we provide a usage manual with instructions on how to reuse the components. This document concludes with Chapter 4 where a summary of the deliverable is underlined.

As the components are updated in the future with added visualisations and models, we will keep this document up to date accordingly. To keep track of such changes, please use this link: https://goo.gl/7zba2b.

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1 INTRODUCTION

Decision Support Systems (DSS) are designed to assist users with decision making activities when approaching uncertainty. In the field of agriculture, different stakeholders such as farmers, advisers and policymakers use DSS software tools to facilitate farm management and planning. Depending on the type of decision support required, data is first gathered from multiple sources including sensors, satellites and in-field observations, and analysed using a series of statistical models. The output is then presented to users in a number of ways such as tables and/or graphs. Many DSS are designed to support the concept of precision agriculture (PA) which seeks to provide a holistic approach to assist farmers with optimising resources [17]. McBratney et al. [14] defined PA as the "*kind of agriculture that increases the number of (correct) decisions per unit area of land per unit time with associated net benefits*". Thus, PA research concentrates on enabling users to make the right decisions in optimising resources in terms of space and time and leveraging yield.

Research has shown that user-centred development plays an essential role in fulfilling users' need for agricultural system modelling [12]. However, the models employed to date for agricultural DSS remain opaque to users and hidden behind the software [1, 9, 19, 24]. This often leads to trust issues, notably when suggestions coming from a DSS fail to provide meaningful explanations [21]. If users do not trust a model or a prediction, they are unlikely to use it in making important business decisions. Trust in a system is based on competence, benevolence, and integrity, just like trust in a person [13]. Ribeiro et al. [18] expressed two different (but related) definitions of trust related to models and predictions. These are 1) *trusting a prediction* meaning a user trusts an individual prediction sufficiently to take some action based on it, and 2) *trusting a model* meaning the user trusts a model to behave in reasonable ways if deployed. Both are directly affected by how much the user understands a model's behaviour. In fact, Ribeiro et al. [18] argued that explaining a model's predictions is a much more important aspect for earning a user's trust. Moreover, explanations should be not just accurate, but also easily understandable.

Visualisation is a powerful technique to bridge this gap, and has demonstrated its usefulness in PA [25] to clearly communicate uncertainty emerging from both data and prediction models [7]. Visually explaining a model's predictions can be as simple as highlighting important input variables. Figure 1 [18] and Figure 2 [4] are two examples of such a case. Both figures show how colour coding and charts can explain a model's predictions and the influence of each input variable on the final output.
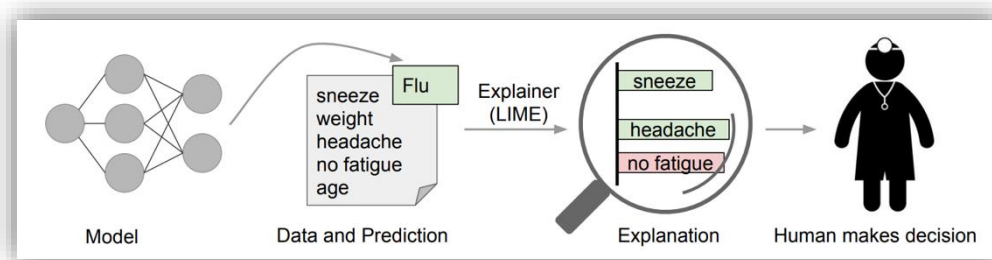

Figure 1: Explanation of a model which predicts flu based on the symptoms. Notice the use of simple colours: the green colour indicates that sneeze and headache are the primary indications of flu whereas the red colour indicates that having no fatigue is the evidence against flu [18].
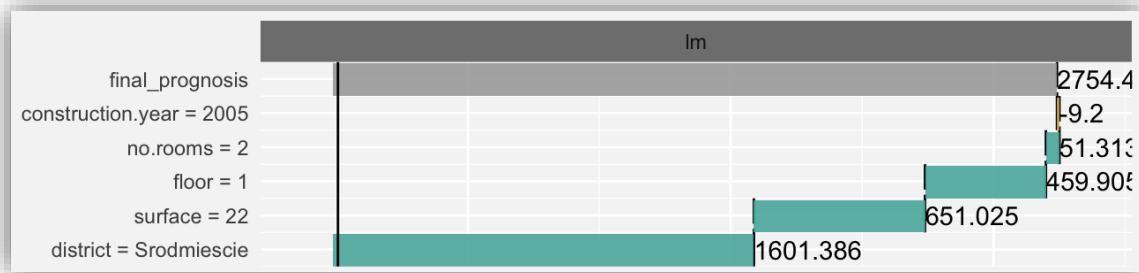
Figure 2: Explanation of a linear model that predicts house prices based on construction year, number of rooms, floor, surface area and district. The green bars indicate positive contributions of the input variables on the predicted price whereas the yellow bar (i.e. construction year) indicates negative contributions. [4].

Visualisation tools are explicitly designed to assist our visual system in handling detail that might otherwise require significant cognitive effort. For instance, visualisations provide information that can be easily perceived, recognised, and processed into inferences. Thus, undoubtedly, visualisations can assist users to better understand a model's prediction and the influence of variables on prediction outcomes.

For this deliverable, our goal is to develop a DSS that nurtures user trust. To achieve this goal, the system must be transparent, meaning it must be able to clearly communicate the prediction model with users and show differing effects of input variables on the model's output. Visualisation tools offer a good potential for these tasks as we have previously outlined in the systematic review of visualisation techniques[1]. We chose wine quality prediction as an example scenario to develop and demonstrate our first version of a trust-aware decision support system. This scenario has previously been used by WP4 partners (CNR) to demonstrate prediction models (see deliverable 4.3 at https://goo.gl/LLh5hi). As a starting point, we built our system on top of the red wine quality dataset (https://goo.gl/ynSP07) and used linear regression, as previously used by WP4 partners (CNR). The dataset is based on red variants of the Portuguese "Vinho Verde" wine. It contains 1599 instances of physicochemical (inputs) and sensory (the output) variables. The input variables are: fixed acidity, volatile acidity, citric acid, residual sugar, chlorides, free sulfur dioxide, total sulfur dioxide, density, pH, sulphates and alcohol. The output variable (based on sensory data) was quality which is scored between 0 and 10.

To find visualisation techniques that have previously been developed based on this dataset, we performed a review of all published papers that have cited this dataset and contain the following keywords: "visualisation", "visualization", "visual", "visualise", "visualize", "visualising" and "visualizing". We found a total of 139 papers using these criteria, of which 32 relevant papers were reviewed in detail. Results of our review indicate that a number of visualisation techniques have been used for this dataset, including scatterplot [6, 8, 16], parallel coordinates [26], biplot [5], star plot [11], multidimensional projection [3] and waterfall plot [22]. Amongst these visualisations, we selected parallel coordinates and a waterfall plot for this first version of the deliverable, as they can clearly show the influence of each variable by arranging the variables accordingly (e.g. left to right and top to bottom respectively; see Figure 3), something the remaining visualisations cannot accommodate. In the next section, we describe the system components, including the visualisations, and the development framework we employed.
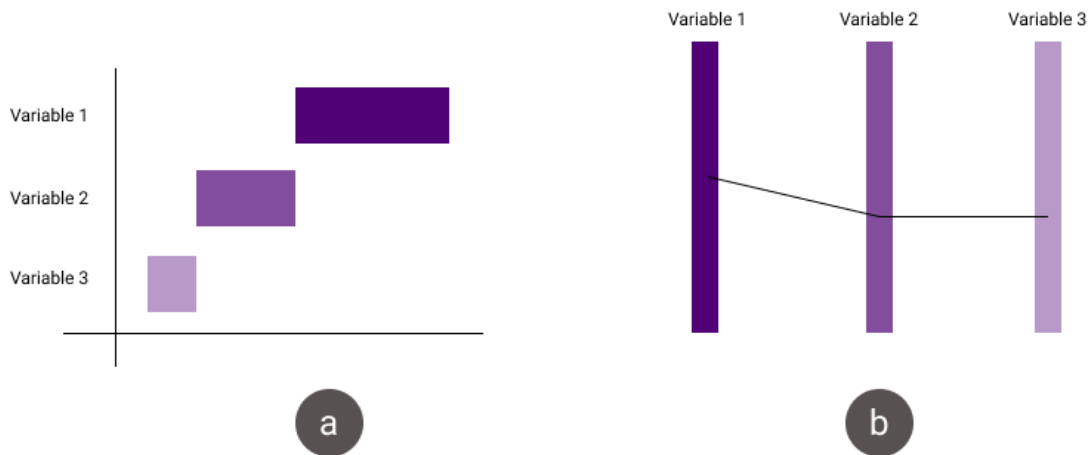

Figure 3: An example of a) waterfall plot and b) parallel coordinates showing the influence of input variables relative to each other. In both visualisations, the variables are arranged according to their influence on the output, i.e. top to bottom (a) and left to right (b), which is also indicated by varying colour intensity.

In line with participatory DSS development, visualisations can be especially practical and useful when following user-centred design approaches [10]. In fact, a number of qualitative PA studies highlighted the importance of using a participatory-design approach [2, 15] where the farmer's perspective is used as the central focus of the design. A key goal of such an approach is to support complex data analysis by adapting the tool according to the farmer needs [23]. Similarly, we aim to evaluate our system components and visualisations with experts of wine production. The evaluation results will inform us of UI improvements and practical requirements (if any) of a trust-aware decision support system.

2   SYSTEM DESCRIPTION

2.1   VISUALISATION COMPONENTS

One web component has been developed for each proposed visualisation: Regression Parallel Coordinates and Regression Waterfall. Both components are designed to help users understand the influence of the different variables on the prediction of any regression model. In the following sections, we will refer to the input or independent variables of the dataset as features and to the dependent variable that we want to predict as target variable.

Both components show information about the influence of the different features on the model target variable prediction. In the simplest scenario where the model is a linear regression (like we do in our system) this influence is global, i.e. with the model parameters we can know if a feature increases or decreases the target variable value for any value of the feature. But in more complex models, the influence of each feature changes depending on the value of that feature and of other features. So, to aid with the understanding of more complex models (e.g. neural networks or SVM) a linear regression can be used to locally approximate a complex model (see [22]). This linear regression would give us information about how the complex model works on the surroundings of a data-point of interest.

In the next subsection we will describe the data of the linear regression (either if it is the original model or the locally approximation model) that is needed by each visualisation component to help communicate the prediction model.

To make the linear regression model easier to understand, a preprocessing step that centres the training data must be applied. Then, the intercept of the linear regression can be interpreted as the predicted value of the *average* data, an observation that will have the mean value of the train dataset for each of the features.

2.1.1   Model Parameters

In this section we describe model parameters highlighting the data of the model and data-point of interest.

Feature data. For each feature of the model we will need to provide:
- Name: the name of the feature.
- Extent: minimum and maximum values of the feature on the dataset the linear regression model is trained on.
- Mean: mean value of the feature on the dataset the linear regression model is trained on. This is needed to be able to preprocess (centre) the data.
- Coefficient: the coefficient of linear regression for that feature.
- P-value: the probability that the feature and the target variable have no correlation.
- Data: the value of the feature on the data-point of interest, where we want to locally explain the model.

Target Name. We should provide the name of the target variable and its extent.
Intercept. The value of linear regression intercept (that can be interpreted as the predicted value of the *average* data).

The data model should be provided to each of the web components in a JSON format as following:

```
{
  "target": {
      "name": "Quality",
      "extent": [0, 10]
  },
  "intercept": 5.6375,
  "featureData": [
      {
      "p": 0.10990123004138723,
      "extent": [4.6, 15.6],
      "coef": 0.048289183405623715,
      "data": 5.6,
      "feature": "fixed.acidity",
      "mean": 8.258166666666664
      },
      {
      "p": 5.1727447125952114e-18,
      "extent": [8.4, 14],
      "coef": 0.27369521750081005,
      "data": 12.9,
      "feature": "alcohol",
      "mean": 10.439597222222217
      }
  ]
}
```
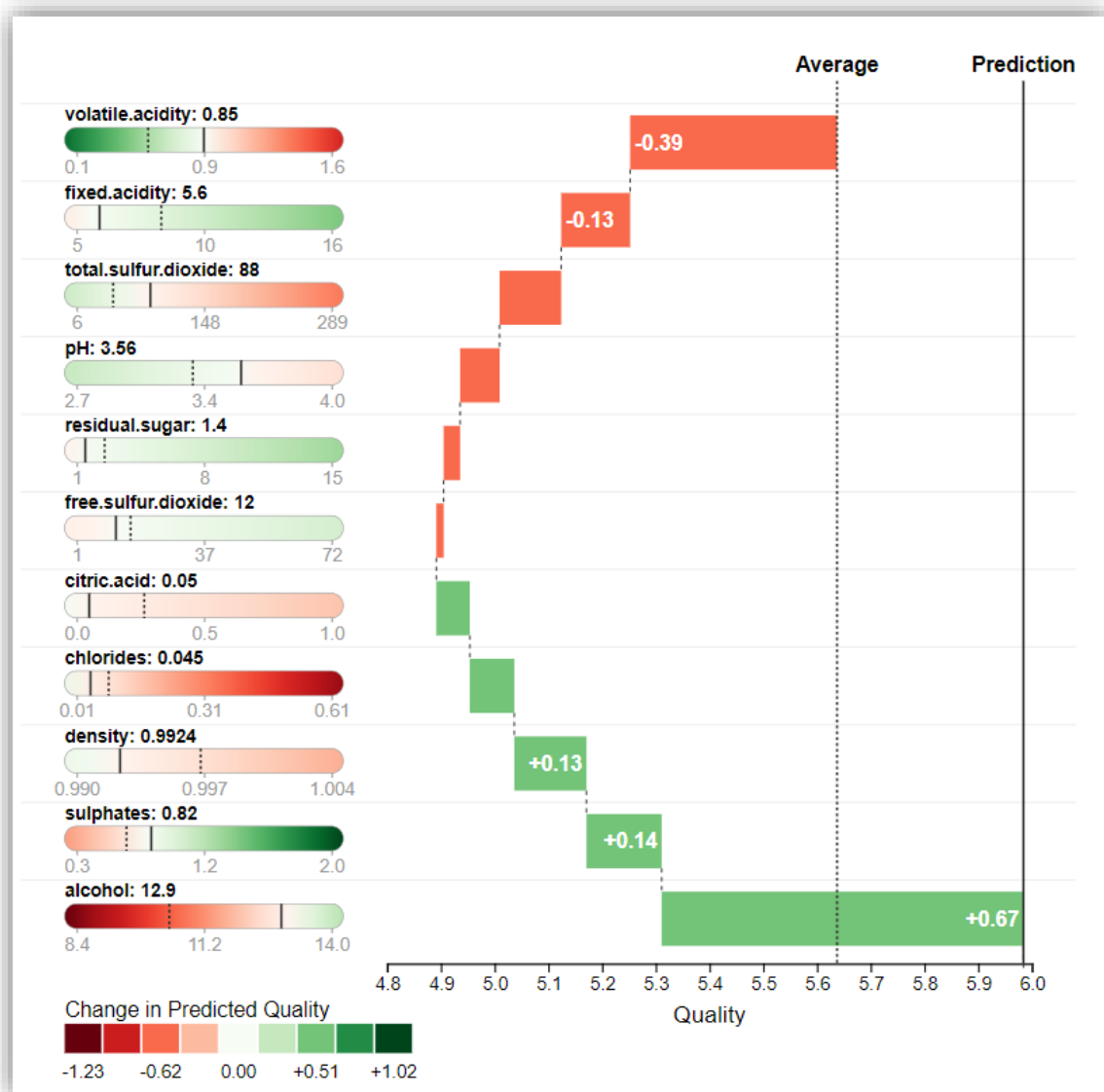
2.1.2   Regression Waterfall

Figure 4: Waterfall plot showing the distributions of input variables and the predicted wine quality.

The objective of the waterfall visualisation is to help users understand the contribution of each of the features of a regression model around a local data point. For instance, as we can see on the left side of Figure 4, the local data point has a volatile.acidity value of 0.859 , a fixed.acidity value of 5.6, etc. and an alcohol value of 12.9.

The main visualisation of this component is the waterfall plot on the right side. In this visualisation we can see the contribution (negative or positive) that leads to the final target variable prediction at the local point (i.e. quality prediction on Figure 4). So going from top to bottom we can see how starting from the value of the intercept (i.e. the predicted value of the *average* data) each feature contributes a certain quantity (e.g. volatile.acitidy contributes -0.40, sulphates contributes +0.14) to the predicted value at the local point.

In addition, on the left side of the visualisation we can see how modifying the value of each of the features can change (increase or decrease) the target variable prediction. The minimum and

maximum values are determined by the model data extent (e.g. sulphates extent goes from 0.3 to 2.0). In Figure 4, for example, increasing the value of sulphates to 2.0 will lead to an increase in the predicted quality of approximately 1.02 and decreasing the alcohol value to 8.4 will lead to a variation of predicted quality of approximately -1.23.

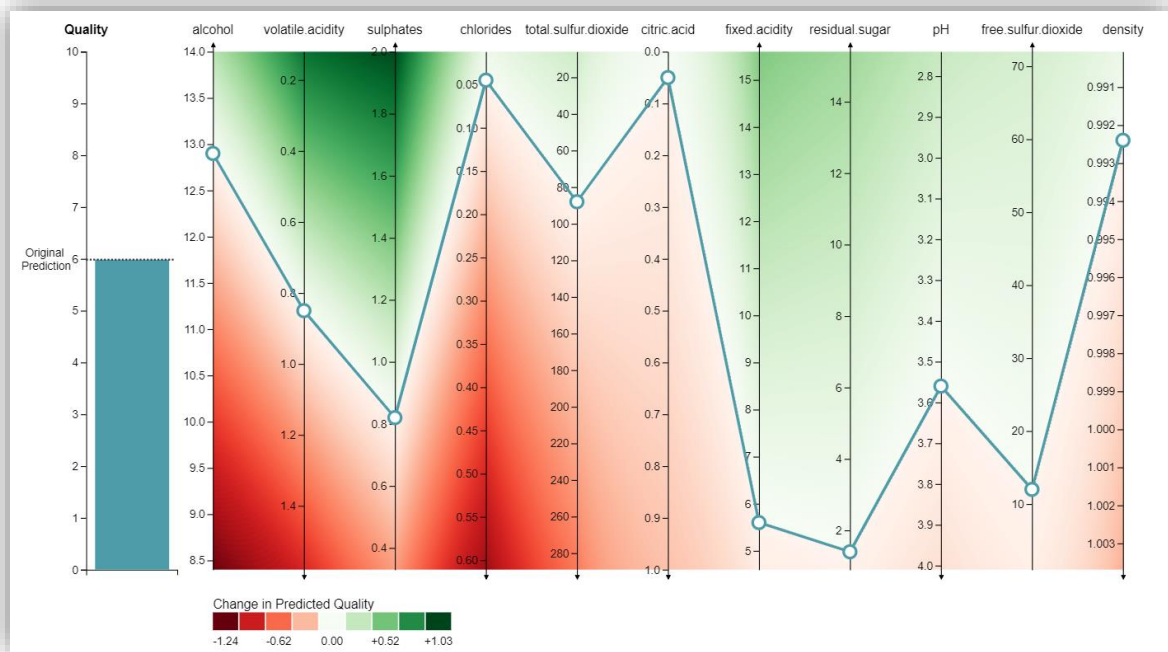### 2.1.3 Regression Parallel Coordinates

Figure 5: Parallel coordinates showing the distributions of input variables and the predicted wine quality in comparison to the baseline.

In the parallel coordinates visualisation, we don't have direct information about the concrete contribution of each feature to the target variable prediction. But we can easily see which attributes decrease the target variable value: the ones which axis are flipped (pointing downwards) like volatile.acidity or pH in Figure 5.

As in the regression waterfall we can see how modifying the value of each of the features can change (increase or decrease) the target variable prediction by looking at the colour next to each axis values. Again, the minimum and maximum values of the axis are determined by the model data extent (e.g. alcohol extent goes from 8.4 to 14.0). But in this component, we can also interact with each feature value by dragging the circles, allowing us to easily see how modifying multiple features values would change the target prediction value. For example, in Figure 5 we can see how decreasing the volatile.acidity value to 0.4 and increasing the sulphates value to 1.4 would raise the quality from approximately 6 to 7.
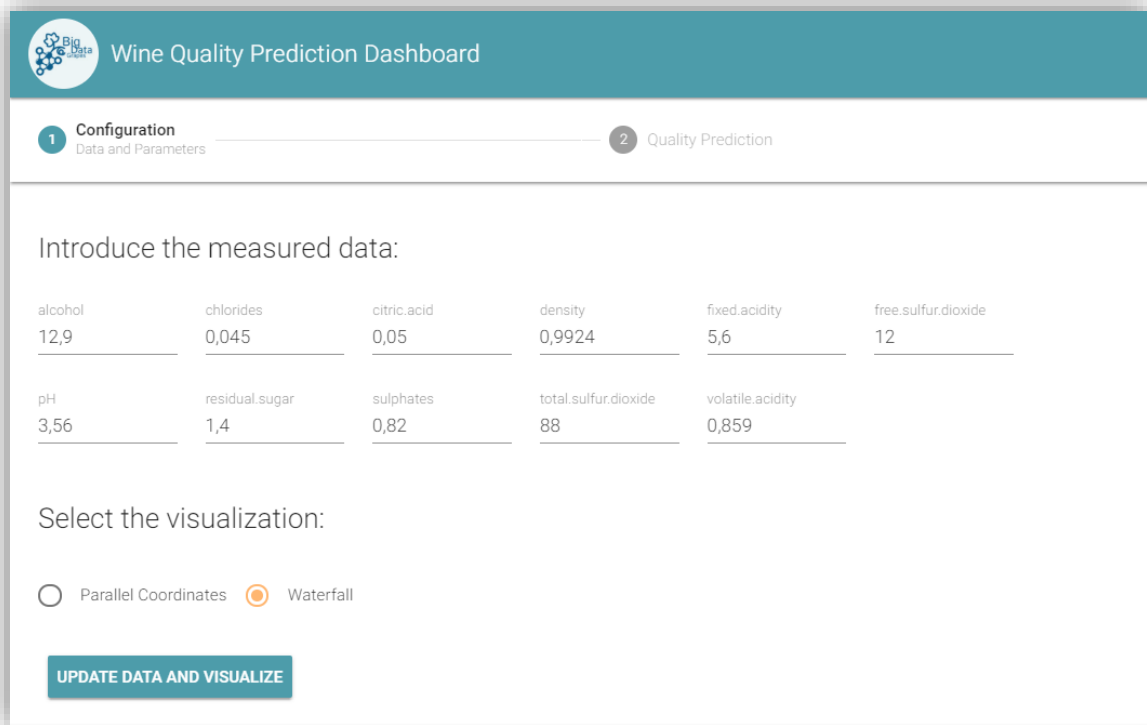
2.2 DASHBOARD

Figure 6: The dashboard interface accepts predictor variable values and visualises a wine quality prediction using parallel coordinates or waterfall diagram.

Dashboards are a collection of tools that provide an easy access to diverse visual components to display detailed data, providing a unified display to the decision-maker for interaction and exploration [20]. Our dashboard interface, as shown in Figure 6, provides access to the parallel coordinates and waterfall plot visualisations. As previously mentioned, the system behind the dashboard is built on top of the red wine quality dataset (https://goo.gl/ynSP07) using linear regression and preprocessing data by centring it. The dashboard simulates a real-world scenario where one would measure wine chemical properties and input the data in a configuration step. After that, the data can be visualised by selecting any of our visualisations described in the previous section, which will then help the user make decisions about the wine production process.

2.3 DEVELOPMENT FRAMEWORK

For the development of both Web Components[2] we have used the LitElement library from the Polymer Project[3]. The LitElement library provides a base class that uses lit-html (also from Polymer Project) to render and facilitate the management of properties and attributes. The visualizations elements have been developed with the aid of the d3.js[4], a javascript library for manipulating documents based on data, with high capabilities for the development of personalized visualizations.

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[2] https://www.webcomponents.org/

[3] https://www.polymer-project.org/

[4] https://d3js.org/

Both Web Components can be added to any web document easily with the two following lines of code:

```html
<!-- Load the components -->
<script type="module" src="path/to/viz-reg-parallel.js" defer></script>
<script type="module" src="path/to/viz-reg-waterfall.js" defer></script>

<!-- Use the components -->
<viz-reg-parallel></viz-reg-parallel>
< viz-reg-waterfall></viz-reg-waterfall>
```

The appearance of the Regression Waterfall or the Parallel Coordinates component can be personalized with the following attributes:

- width: the width space for the visualisation.
- height: the height space for the visualisation.
- scheme: the colour scheme for the *change in predicted quality*. In addition to the default green-red scheme, d3-scale-chromatic diverging schemes are available at: https://github.com/d3/d3-scale-chromatic#diverging.
- sort (only in viz-reg-waterfall): decide whether to order the features top-bottom by their contribution to the target variable (default) or by significance (i.e. p-value).

The aspect ratio of the Regression Waterfall is 1:1 and the Regression Parallel Coordinates is 16:9, so the visualization will centre on the width and height defined space.

The dashboard system has been built using the Vue[5] JavaScript Framework with the Vue CLI tools for development. Vue Material[6] components, which follow the Material Design[7] specs, have been used for the user interface elements.
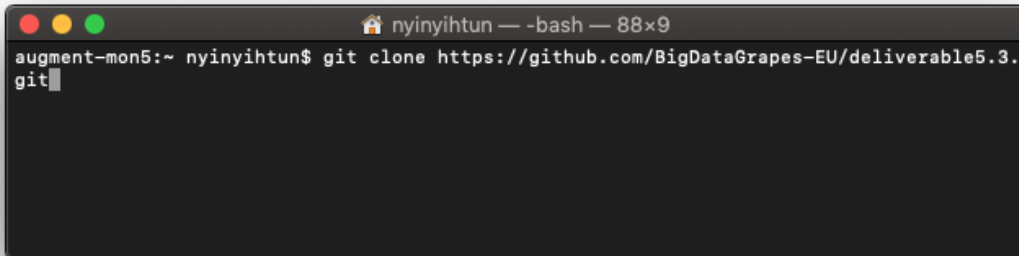
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[5] https://vuejs.org/

[6] https://vuematerial.io/

[7] https://material.io/design/

3 USAGE INSTRUCTIONS

A demo of the system is available at: https://bigdatagrapes-eu.github.io/deliverable5.3/. The source code of the system has been uploaded to github: https://github.com/BigDataGrapes-EU/deliverable5.3. Please follow the following steps to download the source code and serve locally.

Step 1.   Install npm with Node.js from https://www.npmjs.com/get-npm
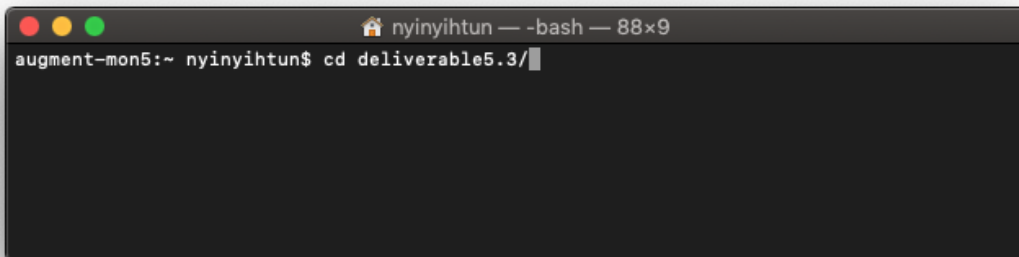
Step 2.   Download or clone the project:
`git clone https://github.com/BigDataGrapes-EU/deliverable5.3.git`

```
● ● ●                    🏠 nyinyihtun — -bash — 88×9
augment-mon5:~ nyinyihtun$ git clone https://github.com/BigDataGrapes-EU/deliverable5.3.
git█
```
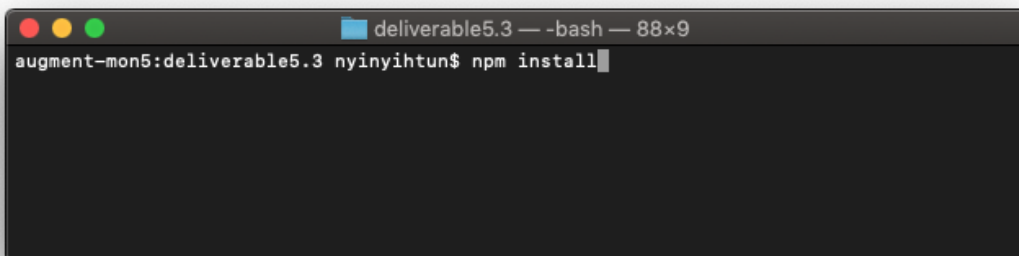
Step 3.   Navigate to the cloned/downloaded folder: `cd deliverable5.3`
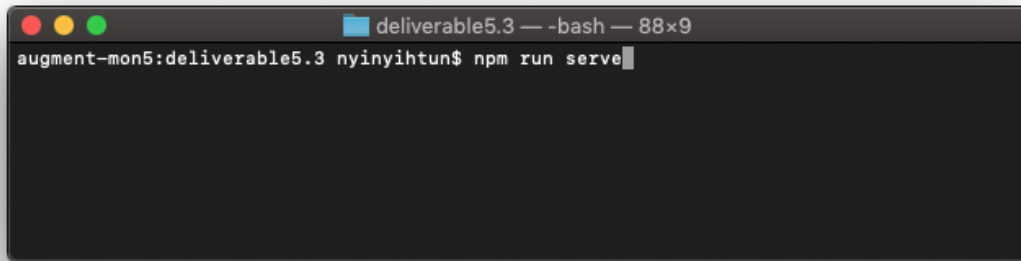
```
● ● ●                    🏠 nyinyihtun — -bash — 88×9
augment-mon5:~ nyinyihtun$ cd deliverable5.3/█
```

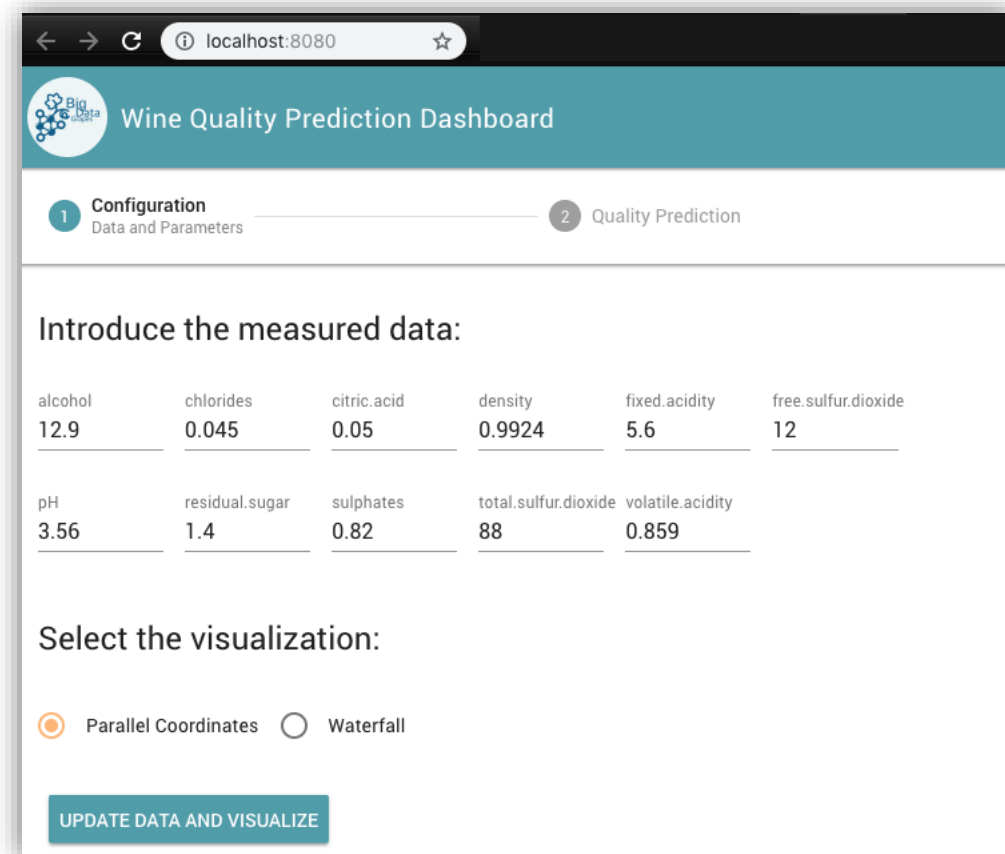Step 4.   Install dependencies: `npm install`

```
● ● ●                    📁 deliverable5.3 — -bash — 88×9
augment-mon5:deliverable5.3 nyinyihtun$ npm install█
```

Step 5.   Serve the project: npm run serve

Step 6.   Open http://localhost:8080 in browser

4 CONCLUSIONS

In this document, we presented our first version of a trust-aware decision support system, delivered under work package 5. Building upon a previous deliverable (D4.3) by WP4 partners (CNR), we designed our system with the aim to nurture user trust. To achieve this, the system explained model predictions and the influence of each input variable on final decisions. In this version of the system, we demonstrated two unique visualisations: parallel coordinates and a waterfall plot, to provide such explanations.

To ensure that the components can be easily reused by partners and to support plug-and-play, we built the system using Web Components [8]. Detailed explanations of the components and development framework have been presented in Chapter 2. We also provided sample codes for each of the components highlighting their usability. All of the codes have been published at the github repository of BigDataGrapes (https://github.com/BigDataGrapes-EU/deliverable5.3). A usage manual was provided in Chapter 3 with steps for obtaining the codes and serving the system.

For the next deliverable, we will focus on uncertainty and begin designing uncertainty-aware visual analytic components. In the meantime, we will also conduct evaluations of the visualisation components in our DSS. To do this, we have arranged a series of meetings with a pilot partner (INRA) and wine production experts from Pech-Rouge. In early 2019, we will begin our evaluations. With this system and uncertainty-aware visual analytic components, we aim to provide much needed assistance for various decision-making requirements in the grapevine-powered industry, especially for the prediction scenarios (i.e. B1, B2 and B3) highlighted in deliverable D2.1 (https://goo.gl/r4zxnb).

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[8] https://www.webcomponents.org/introduction

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