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D1.5 Demand and supply analysis report

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Change Log

Version	Date	Amended by	Changes
0.1	20/11/2017	Alexander Mikroyannidis	Outline and responsibilities of contributors.
0.2	11/12/2017	Erik Novak, Inna Novalija	Content input.
0.3	10/01/2018	Diego Collarana, Simon Scerri	Content input.
0.4	11/01/2018	Alexander Mikroyannidis	Version for internal review.
0.5	25/01/2018	Alexander Mikroyannidis	Revised version.
1.0	26/01/2018	Alexander Mikroyannidis	Final QA.

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1. Executive Summary

WP1 primarily deals with the design and execution of a series of studies on the demand for data science training. These studies have produced an evidence base of demand for data science training as well as listing gaps in any existing training across Europe. The results of this study have been analysed in order to inform the iterations of the proposed curricula (WP2) and resultant training (WP3).

Following the outcomes of the M18 project review, WP1 has been amended to also include an analysis of the supply of learning resources, in order to match the identified demand. The results of this demand and supply analysis are reflected in the EDSA dashboard. Supply information is collected semi-automatically, with a focus on relevant institutions from Europe as well as online offerings. The information is analysed automatically to identify relevant skills, which are then mapped to job descriptions.

This deliverable reports the types of supply analyses conducted in relation to the demand analysis and how this work has been implemented in the EDSA dashboard. This deliverable also describes how the demand and supply data are presented in the dashboard and how users are able to interact with this data in order to explore the current demand and supply.

2. Introduction

In today's job market the required skills are constantly evolving. This can be seen in more technical fields such as web development and data science where new tools and libraries are developed and available to the public with an increasing rate. This is visible in both research and industry sectors where a job position might require a previously unseen skill and the applicant needs to learn it to be qualified. Finding the courses that would give the skill knowledge can be tedious and does not guarantee its sufficiency.

The EDSA dashboard[1] connects the job market skill demand with the courses that give the required skill knowledge. The EDSA dashboard enables users to search for their desired job position, find out what is the required skill set and which are the appropriate learning materials and courses to acquire the missing skills. We have focused on job positions that require data science skills and courses that are provided by acknowledged course providers. Additionally, the dashboard shows the most demanded skills and hiring location for the given results.

The main contributions of the EDSA dashboard are a) creating a sizable data set of data science related job postings containing the job postings title, description, locations and other information, and b) developing a dashboard which for a given query shows relevant job postings as well as courses and lectures which give the appropriate skills. The dashboard is daily updated with new job postings showing the most recent changes. Basic statistics such as the most popular job locations and skills are also shown.

The remainder of this deliverable is organised as follows. First, an overview of the user interface of the dashboard is provided, followed by an in-depth look into the back-end architecture. We then present the mechanisms behind harvesting various types of data for the dashboard, namely jobs, skills and courses. Finally, the user evaluation of the dashboard is presented and the deliverable is concluded.

3. Dashboard user interface

The EDSA dashboard allows users to explore both the current data science skills demand and supply. Users of this dashboard are able not only to explore the current demand in the data science market, but also find learning materials and training relevant to the skills they will need to secure a specific job position. Additionally, users are supported in building personalised learning pathways, consisting of courses and learning materials that will help them reach their learning goals.

In particular, the EDSA dashboard allows users to:

- View the current demand for data science jobs and skills across Europe.
- Filter demand by required skills and region.
- View trends and statistics regarding data science jobs and skills for a given timeframe.
- Explore the current supply of courses and learning materials that will help them acquire certain skills.
- Build personalised learning pathways towards acquiring certain skills.

The following figures show different views of the EDSA dashboard. Figure 1 shows a job search performed via the dashboard. This view is deliberately kept as simple as possible. In this view, queries typed into the search box at the top result in a simple list of related data science jobs. Selecting any job results in additional details of the post being displayed. The toolbar below the query entry box allows users to add or remove additional views.

[1] http://edsa-project.eu/resources/dashboard/

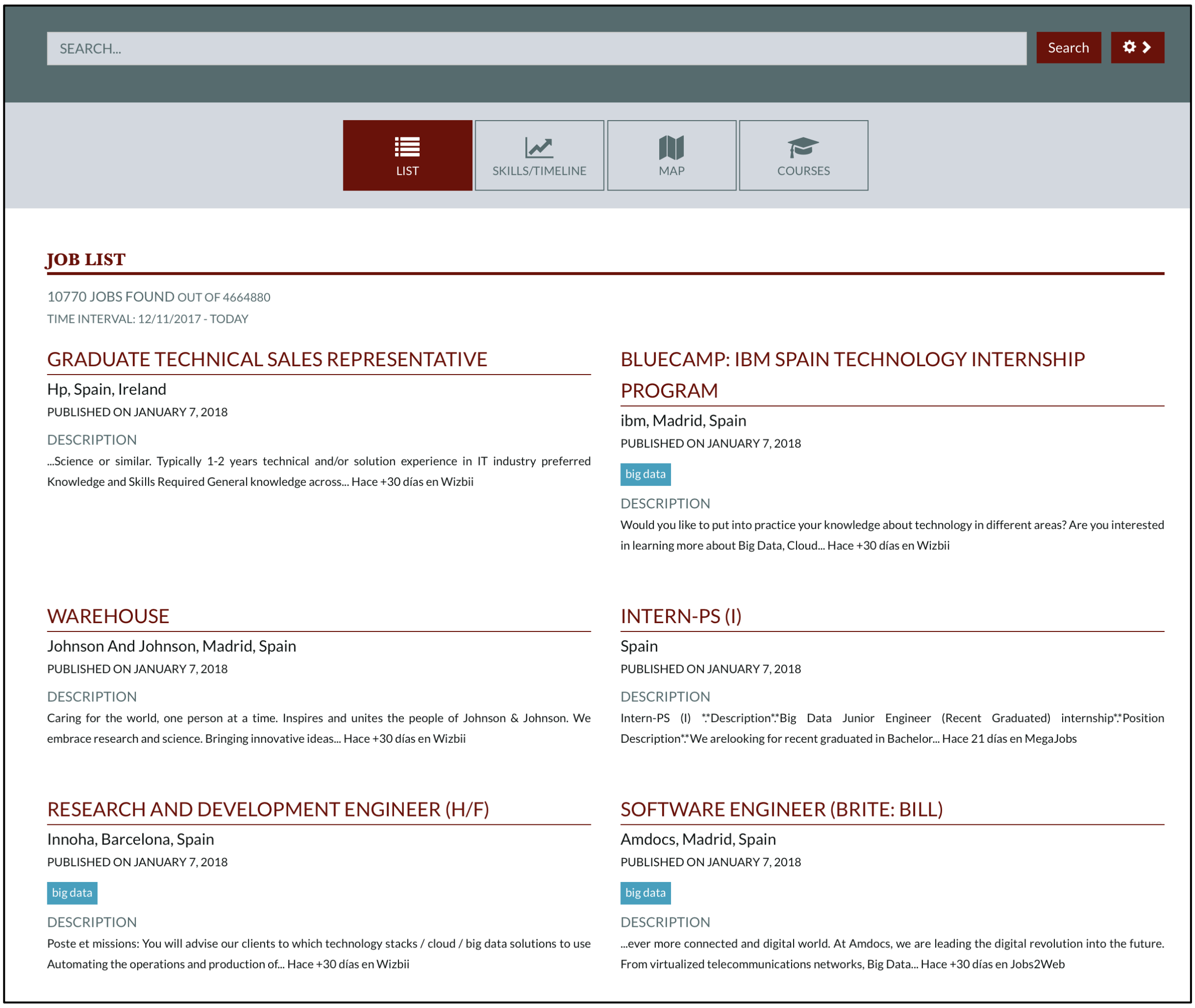

Figure 1: Job search in the EDSA dashboard.

In Figure 2, a map view has been selected. Google maps are used for the map view incorporating zoom facilities. Selecting any anchor point in the map brings up details about the job. In Figure 3, the courses view has been selected. The courses view shows recommended courses related to the query, which are offered by the EDSA project consortium and external organisations. This view also displays recommended learning pathways based on the performed search.

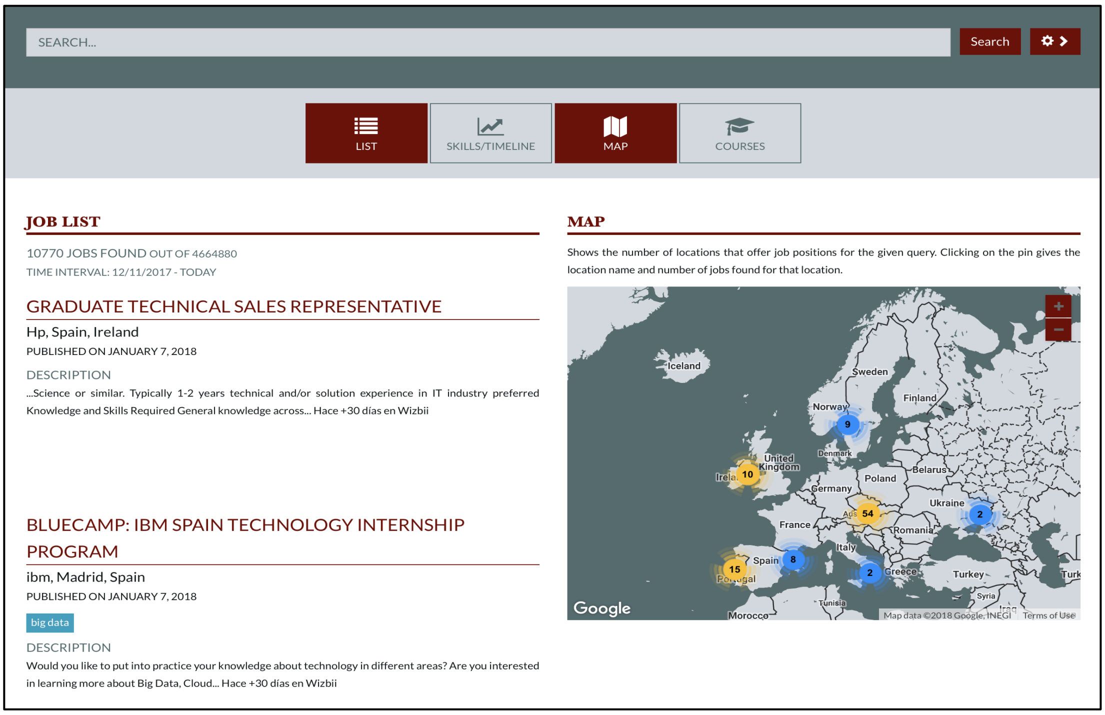

Figure 2: Job search with the map view selected.

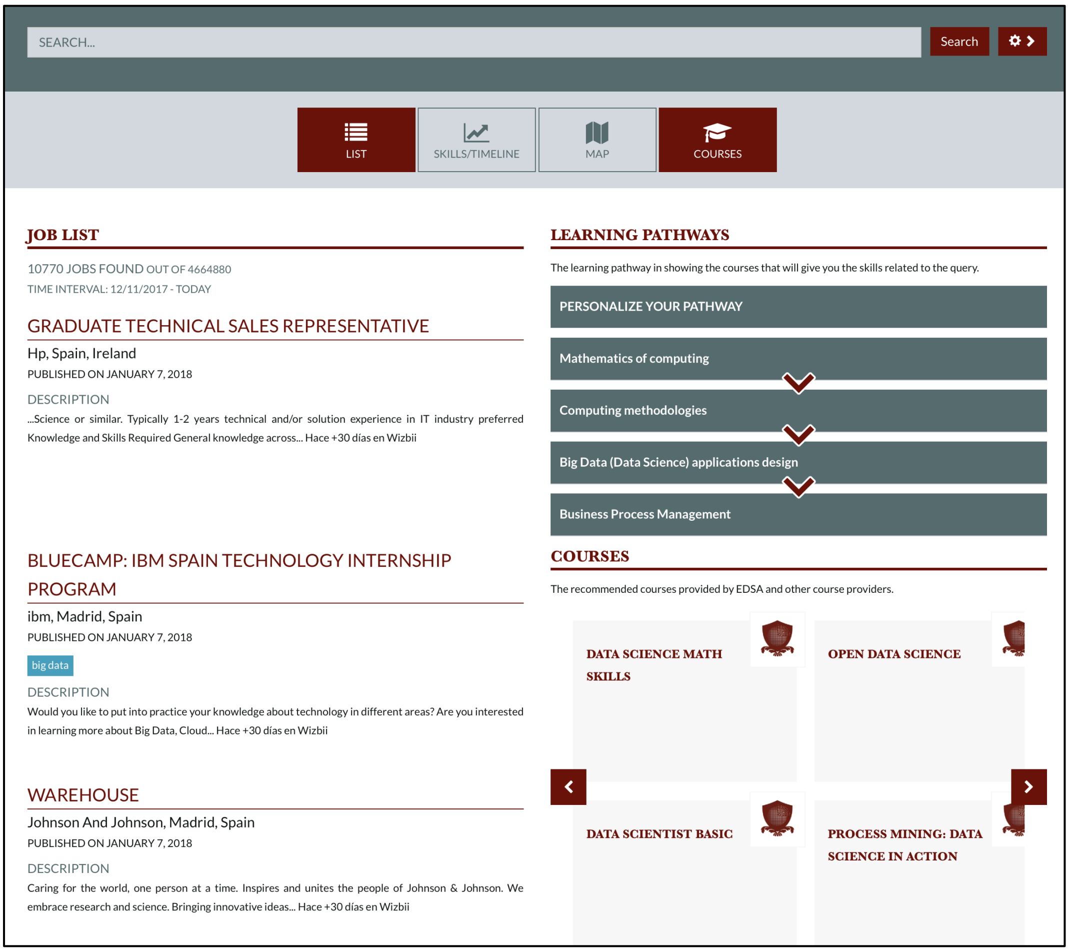

Figure 3: Job search with the courses view selected.

Figure 4 shows additional filters that users can enable when searching. These filters allow users to specify the required skills, the location of jobs, as well as the start and end time of job adverts.

Figure 4: The dashboard search filters.

The EDSA dashboard not only allows users to explore the current listings of jobs and associated learning resources, but also structures the recommended learning resources into learning pathways, which can be further customised and personalised by users. In order to build their personalised pathways, users of the dashboard start by searching for certain job positions. Based on their searches, the dashboard recommends courses and learning pathways for gaining the required skills. Users may follow these pathways or further personalise them by visiting the EDSA courses portal.[2]

Figure 5 shows the list of data science learning pathways currently offered by the EDSA courses portal. These pathways have been adapted from the EDISON Data Science Framework[3] and consist of recommended data science topics, as well as courses for acquiring certain sets of skills related to these topics. Users can use these pathways as templates in order to build their own pathways by adding courses, monitoring their progress towards completing their pathways, as well as reflecting on the contents of the pathways and on what they have learned, as shown in Figure 6.

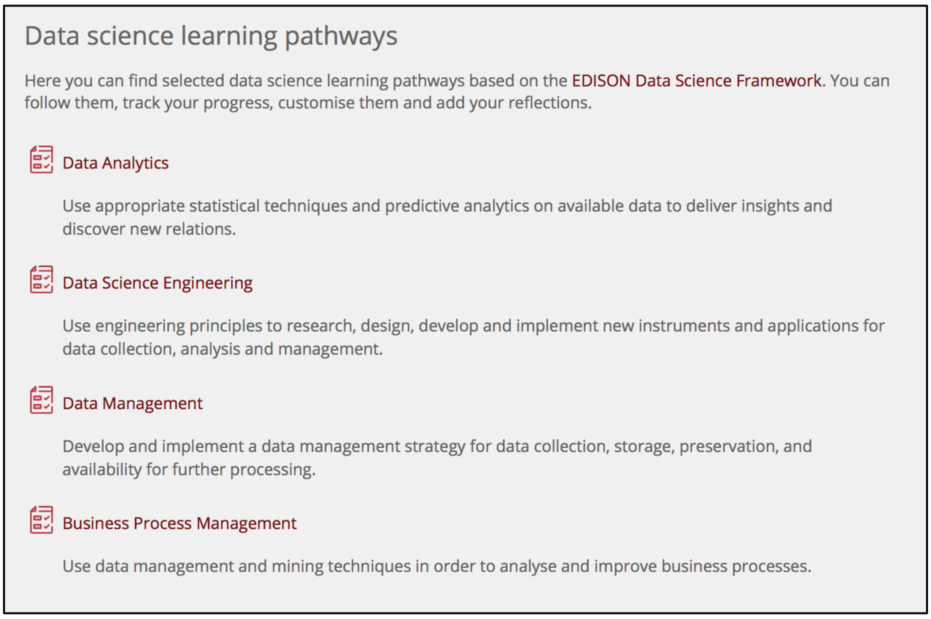

Figure 5: Data science learning pathways in the EDSA courses portal.

[2] http://courses.edsa-project.eu

[3] http://edison-project.eu/edison/edison-data-science-framework-edsf

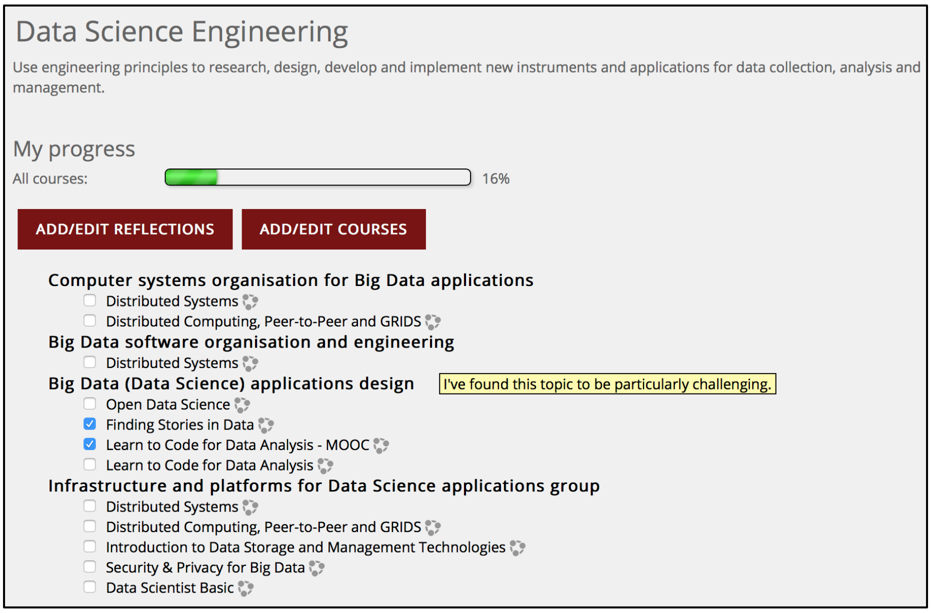

Figure 6: Building a personalised learning pathway.

4. Dashboard software architecture

In this section, we present the content retrieval methodology and describe the different components of the dashboard. The content is retrieved by inserting a query text in the search input. The user may add additional query conditions by selecting the Data Science skills, locations, countries and a time interval in which the job postings were published. Upon submitting, the query is used to fetch the content that matches the conditions. While all query values are used for retrieving job postings, only the input text and skills are used for retrieving the courses and video lectures content. Since courses and video lectures are available online the location and time interval are irrelevant for retrieving the supply content.

To retrieve the content, we first need to set an appropriate index. The job posting data set is indexed by Wikipedia concepts, Data Science skills, locations, countries and published date while the course and lecture data sets are indexed only by Wikipedia concepts. The query text is sent through wikification to acquire Wikipedia concepts which are used for retrieving the relevant content. Next, additional query conditions are used to filter out the content. The remaining content is used to calculate the most demanded skills and hiring locations. Finally, the query results are returned and used to update the dashboard components. This process is developed using QMiner [1], a data analytics platform for processing large-scale real-time streams containing structured and unstructured data.

The dashboard is composed of different components. The largest component is a list of job postings. Each job posting is presented by its extracted information, including the Data Science skills extracted from the title and description. Figure 7 shows an example of a job posting in the list. Since Wikifier supports cross and multi-linguality the list consists of job postings written in different languages.

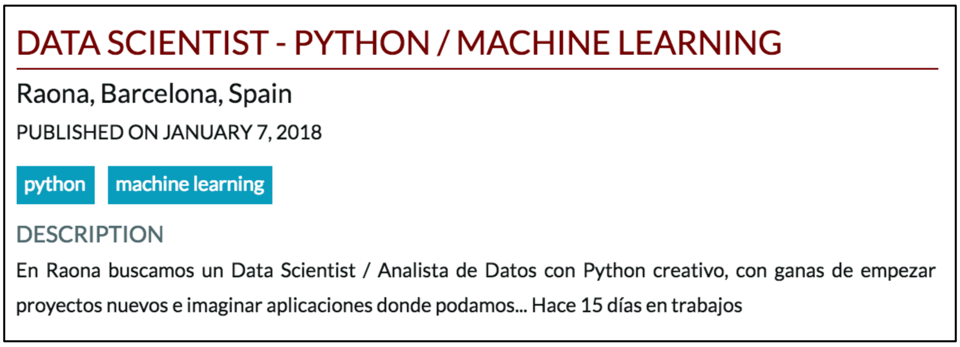

Figure 7: Example of a job posting returned by the query "machine learning". Even though the job posting is written in Spanish the methodology finds it relevant.

If the user does not have the required skill set it can be acquired by enrolling into courses shown in the course list. The list shows courses offered by different online course providers that are relevant to the users input query. Figure 3 (section 3) shows the component containing the course list. Left and right arrows are used to navigate through the list where each course is presented by its name and a course provider. Additionally, the user can watch lectures to get a deeper understanding of a problem. Similar to courses the video lectures list shows relevant content found on VideoLectures.NET. Clicking the lecture redirects the user to the video lecture homepage.

The dashboard also shows them most demanded skills and job posting timeline. The timeline shows how the ratio between queried and all job postings changed since the start of the year 2016. Additionally, this shows a trend of the skill demand in the queried job posting subset. Figure 8 shows the visualizations used to show the skill demand and timeline.

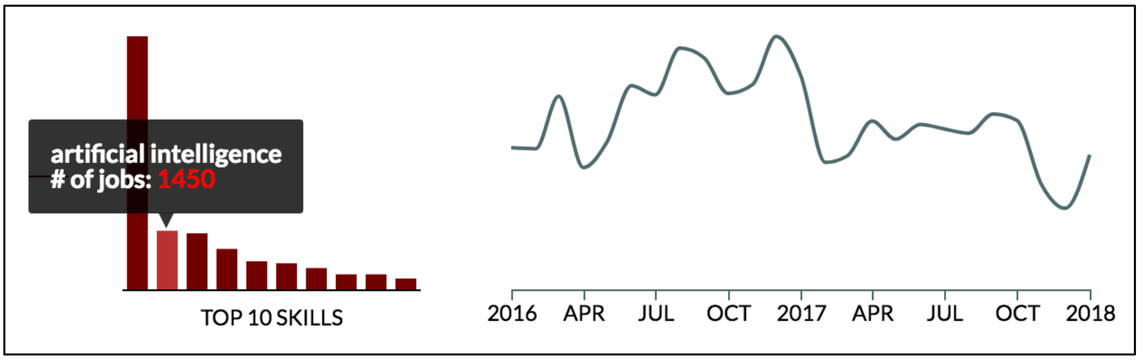

Figure 8: On the left the ten most demanded skills histogram, and on the right the number of job positions timeline, for the query "machine learning". Hovering over the histogram column shows the number of queried jobs demanding the skill.

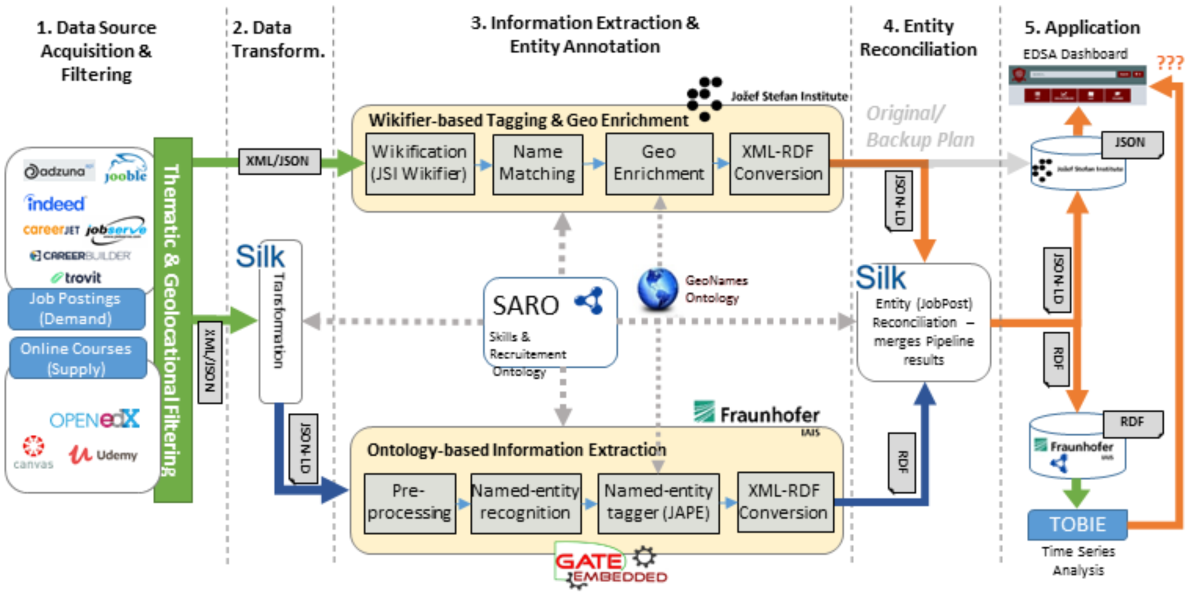

Figure 9: The EDSA Data acquisition process.

The EDSA data acquisition process, shown in Figure 9, consists of two parallel pipelines that operate on the extracted (and transformed) demand and supply data. The Wiki-based Tagging and Geo-enrichment (WTG) pipeline shown on the top (responsible: JSI) complements the Ontology-based Information Extraction (OBIE) pipeline shown below (responsible: Fraunhofer), by discovering new skills that are not known to the ontology (SARO[4]). At the moment, these need to be manually added to be recognised in the future. The OBIE pipeline relies on a customised GATE[5] pipeline. The OBIE pipeline is better in terms of precision, whereas the WTG pipeline compensates for incomplete recall.

The results from both pipelines are integrated using the Silk Framework,[6] so that all the knowledge discovered is attached to the same data. Following the entity reconciliation process, results are stored for direct access by the EDSA dashboard. Separately, a snapshot of the dataset is routinely stored in order to enable time series analysis (the results are not integrated in the EDSA dashboard).

4.1 Harvesting jobs

Open job positions can be found using job search services. These services aggregate job postings by location, sector, applicant qualifications and skill set or type. One such service is Adzuna,[7] a search engine for job ads which mostly covers English speaking countries. Another service is Trovit,[8] a leading search engine for classified ads in Europe and Latin America. The service is available in 13 different languages and provides listings of jobs as well as cars, real estate and other products. When applying for a job position the applicant requires to have a certain skill set. If the requirements are not fulfilled, he can enrol in courses to get the missing skills. Additionally, watching certain lectures can

[4] http://vocol.iais.fraunhofer.de/saro/

[5] https://gate.ac.uk/

[6] http://silkframework.org/

[7] https://www.adzuna.com/

[8] https://www.trovit.com/

give a deeper understanding of a particular problem which can increase the probability of getting accepted for a job position.

Jooble[9], Indeed[10] and XING[11] have also been integrated as additional sources for demand data (routine extraction of job postings). Table 1 summarises all demand sources.

Table 1: Summary of demand sources.

Demand Data Source	***Responsible for Integration in Dashboard***
Adzuna	JSI
Trovit	JSI
Jooble	Fraunhofer
Indeed	Fraunhofer
XING	Fraunhofer

Since we needed a continuous flow of data, we developed a pipeline for acquiring job postings, courses and lectures. This will allow us to provide the dashboard, presented above, with the most recent data. For job postings we targeted the portals like Adzuna with an emphasis on positions in Data Science.

For data acquisition and enrichment, we collected data either using dedicated APIs, including Adzuna API,[12] as well as custom web crawlers. The data was formatted to JSON to aid further processing and enrichment.

The next step of data preprocessing is wikification - identifying and linking textual components to the corresponding Wikipedia pages [2]. This is done using Wikifier,[13] which also supports cross and multi-linguality enabling extraction and annotation of relevant information from job postings, courses and video lectures in different languages. Wikification will allow us to search for job postings, courses and lectures in multiple languages.

Next, we use the Skill and Recruitment Ontology (SARO) [3] to extract Data Science skills from job postings. For each job posting we match the Wikipedia concepts with the skills found in SARO ontology and declare the matched concepts as Data Science skills. These skills are then added to the job posting profile. Finally, to allow searching by locations and countries the job postings were further enriched by using GeoNames[14] ontology to include the latitude and longitude and the corresponding GeoNames ID and the location name.

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9 https://jooble.org

10 https://indeed.com/

11 https://www.xing.com/jobs

12 https://developer.adzuna.com/

13 http://wikifier.org/

14 http://www.geonames.org/

The job postings data set contains almost 3.3M job postings acquired in the period of 18 months. Job postings were located for 144 different countries, the majority of them from Europe. Figure 10 shows the top fifteen countries with most found job postings. The UK dominates other countries with 906k job postings, followed by France with almost 539k.

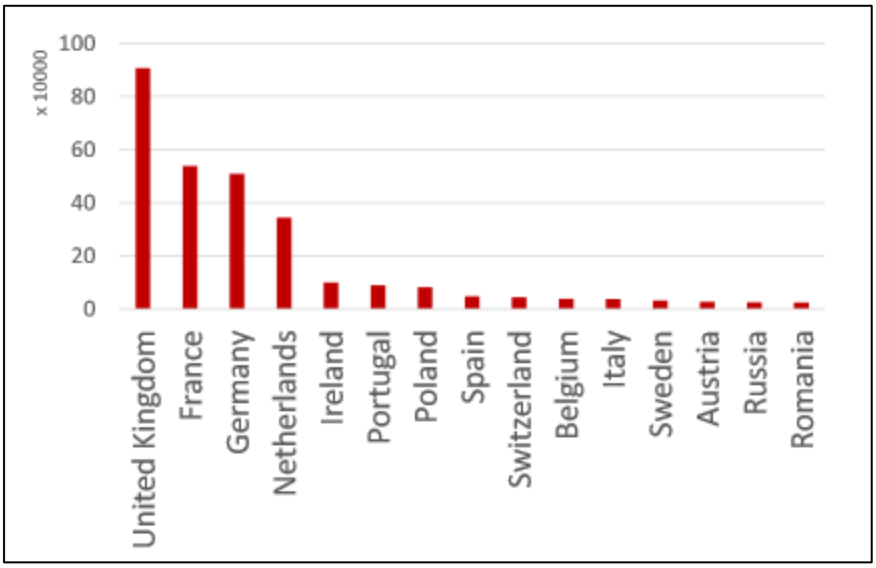


Figure 10: Top fifteen countries with most found job postings. The greatest number of job postings were found for UK, followed by France and Germany.

4.2 Harvesting skills

There were 650 unique Data Science skills extracted from the data set. These include soft skills, such as leadership and management, knowledge of a particular domain, such as machine learning and artificial intelligence, and programming languages. Figure 11 shows the most demanded skills in the data set.

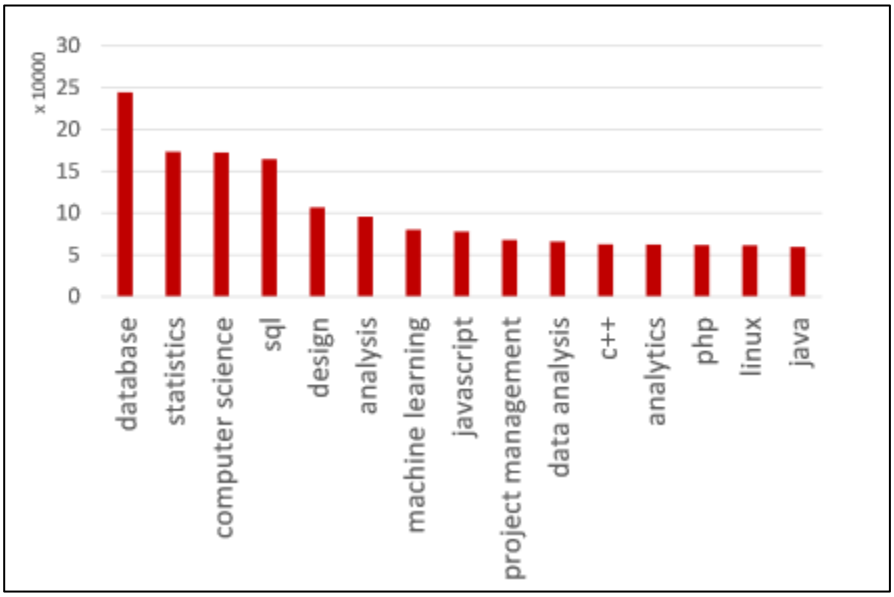


Figure 11: Top fifteen most demanded skills. They are mostly comprised of high-level skills, such as "database" and "computer science", and specific programming languages.

4.3 Harvesting courses

For courses we targeted different course providers, including Coursera,[15] providing courses from top universities, and Hackr.io,[16] a service which finds the best online programming courses & tutorials. We also targeted VideoLectures.NET to acquire video lectures containing the Data Science tag. The tags are given manually by the VideoLectures team.

Canvas[17], edX[18] and Udemy[19] have also been integrated as additional sources for supply data (routine extraction of relevant courses). Table 2 summarizes all supply sources.

Table 2: Summary of supply sources.

Demand Data Source	***Responsible for Integration in Dashboard***
Coursera	JSI
VideoLectures	JSI
Canvas	Fraunhofer
edX	Fraunhofer
Udemy	Fraunhofer

The course data set contains information for over 63k courses, including their title, description and course providers. The data set is comprised of over 8k courses available online and 55k offline courses. Figure 12 shows the distribution of online courses by course providers. The most courses were acquired from Coursera with above 4k, followed by Hackr.io at 2k.

[15] https://www.coursera.org/

[16] https://hackr.io/

[17] https://www.canvas.net/

[18] https://www.edx.org/

[19] https://www.udemy.com/

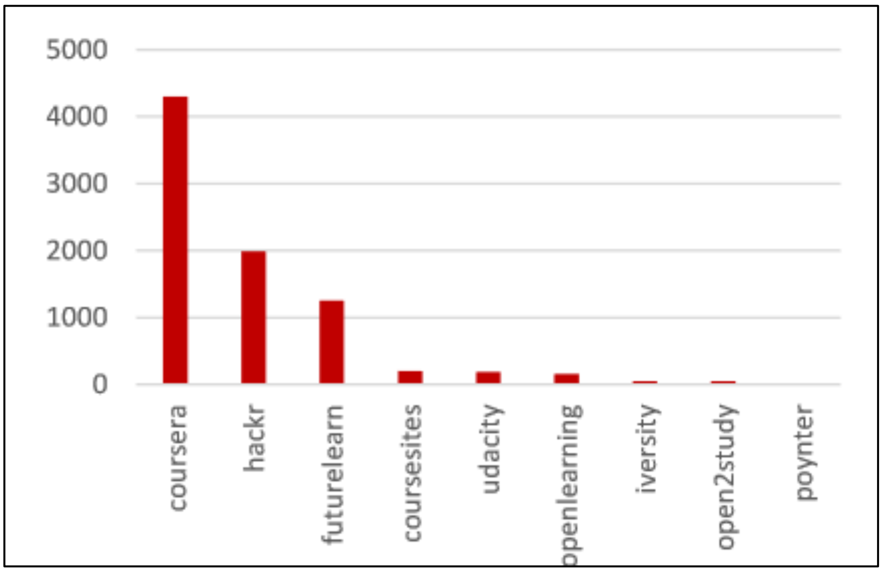


Figure 12: The distribution of online courses by course providers. The most courses were acquired from Coursera, followed by Hackr.io.

VideoLectures.NET[20] is an award-winning free and open access educational video lectures repository. It contains videos of individual lectures as well as lectures given at renown conferences.

We acquired a data set of over 20k lectures published on VideoLectures.NET. It contains information about the lectures available on the video repository including title and description and link to the lecture.

5. Dashboard evaluation

5.1 Evaluation Goals

In order to validate the usability and usefulness of the EDSA Dashboard, we conducted a formative usability evaluation. The evaluation was performed to identify to what the foreseen users can:

1. Easily perform basic tasks such a search for a job or understand the learning paths.
2. Find the dashboard easy and enjoyable to use.

The following tasks were identified beforehand, and they defined the evaluation exercise. The evaluators were asked to:

1. **Search/Identification**
   T1. Search for a relevant data science Job in Germany

   T2. Search for a job based on specific skills (e.g. Python and Java)

   T3. Identify what steps are missing in one's learning path to become a data scientist

2. **Analysis/Exploration**
   T4. Analyse which country has more suitable job offers

   T5. Identify which are the top 3 relevant skills for a data scientist

[20] http://videolectures.net/

5.2 Evaluation Setup

Number of participants

6 Student Assistants (Data Science area) from Fraunhofer IAIS participated in the evaluation.

Moderator

1 moderator carried out the evaluation. The moderator was open to discussion with the participants, explaining the objective of the tasks without giving any additional instructions on how to complete a task.

Dashboard version

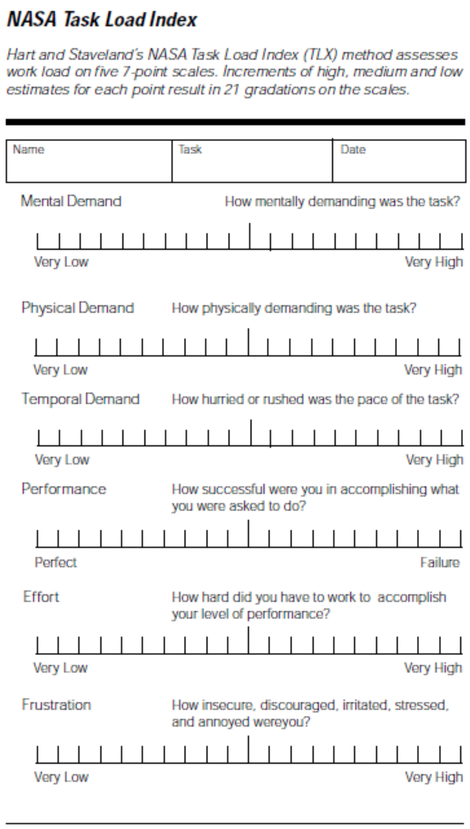
The version used during the was the last deployment on 22.11.2017

http://edsa-project.eu/resources/dashboard/

Metrics

We defined the following evaluation metrics:

1. **NASA Task Load Index (TLX)[21]:** In all cases we used the standard NASA Task Load Index (TLX) to measure workload in loosely time-constrained tasks.
2. **Thinking Aloud protocol** [4] to uncover usability issues.
3. To measure the usability, we will use a simplified version of **Post-Study Usability Questionnaire (PSSUQ)** [5].



NASA Task Load Index

Hart and Staveland's NASA Task Load Index (TLX) method assesses work load on five 7-point scales. Increments of high, medium and low estimates for each point result in 21 gradations on the scales.

Name	Task	Date

Mental Demand — How mentally demanding was the task?
Very Low — Very High

Physical Demand — How physically demanding was the task?
Very Low — Very High

Temporal Demand — How hurried or rushed was the pace of the task?
Very Low — Very High

Performance — How successful were you in accomplishing what you were asked to do?
Perfect — Failure

Effort — How hard did you have to work to accomplish your level of performance?
Very Low — Very High

Frustration — How insecure, discouraged, irritated, stressed, and annoyed wereyou?
Very Low — Very High

Figure 13: The NASA Task Load Index used during the Dashboard usability evaluation.

[21] https://humansystems.arc.nasa.gov/groups/tlx/

The Post-Study Usability Questionnaire
Version 3

		Strongly agree 1	2	3	4	5	6	Strongly disagree 7	NA
1	Overall, I am satisfied with how easy it is to use this system.	O	O	O	O	O	O	O	O
2	It was simple to use this system.	O	O	O	O	O	O	O	O
3	I was able to complete the tasks and scenarios quickly using this system.	O	O	O	O	O	O	O	O
4	I felt comfortable using this system.	O	O	O	O	O	O	O	O
5	It was easy to learn to use this system.	O	O	O	O	O	O	O	O
6	I believe I could become productive quickly using this system.	O	O	O	O	O	O	O	O
7	The system gave error messages that clearly told me how to fix problems.	O	O	O	O	O	O	O	O
8	Whenever I made a mistake using the system, I could recover easily and quickly.	O	O	O	O	O	O	O	O
9	The information (such as online help, on-screen messages and other documentation) provided with this system was clear.	O	O	O	O	O	O	O	O
10	It was easy to find the information I needed.	O	O	O	O	O	O	O	O
11	The information was effective in helping me complete the tasks and scenarios.	O	O	O	O	O	O	O	O
12	The organization of information on the system screens was clear.	O	O	O	O	O	O	O	O
13	The interface* of this system was pleasant.	O	O	O	O	O	O	O	O
14	I liked using the interface of this system.	O	O	O	O	O	O	O	O
15	This system has all the functions and capabilities I expect it to have.	O	O	O	O	O	O	O	O
16	Overall, I am satisfied with this system.	O	O	O	O	O	O	O	O

**The "interface" includes those items that you use to interact with the system. For example, some components of the interface are the keyboard, the mouse, the microphone, and the screens (including their graphics and language).*

Figure 14: The Post-Study Usability Questionnaire used during the Dashboard usability evaluation.

Procedure

The moderator carried out the experiment at each participant's desks, in order to provide a comfortable environment for them. The evaluation introduction also gave some background of the EDSA project, before explaining the tasks requested. Participants were told to speak freely and loud what they are thinking during their attempts to carry out the tasks in the EDSA Dashboard; all the while, the moderator took note of all their remarks. After each task, the NASA TLX questionnaire was given to each participant. At the end of all tasks, the PSSUQ questionnaire was also filled out by the participants.

No time limit was applied but the participants were asked to stop attempting to complete the tasks when they gave up. The time required was recorded, but no timer was shown to the participants so as not to introduce time pressure for the participants while performing the task.

5.3 Evaluation Results and Discussion

In general, all the evaluation showed positive scores, indicating that the participants were able to complete the tasks and the workload demand using the Dashboard was low. Additionally, the usability scores showed an overall user satisfaction with the Dashboard.

The most prominent difficulty in the Dashboard's use was the intuitiveness during first use, but this showed signs of improvement when performing the next tasks. A How-to Video for new users is therefore highly recommended.

Figure 15 shows the results of the NASA TLX. Overall, all the NASA indexes indicate a positive result, Task 3 and 5 were the ones with the lowest level of required effort. In contrast, Task 1 showed the highest level of frustration, although this may be related to the lack of guidance at first use (see above).

Task 4 was the task that required most effort to accomplish and with the lowest performance of all tasks. In general, the map view proved to be somewhat confusing, as well as the interpretation of its values.

	T1		T2		T3		T4		T5	
	M	STD	M	STD	M	STD	M	STD	M	STD
Mental Demand	15.08	13.30	19.05	13.75	15.08	13.59	20.63	23.27	12.70	5.26
Physical Demand	18.25	17.48	14.29	13.47	14.29	13.47	13.49	13.59	10.32	6.96
Temporal Demand	26.98	20.33	34.13	15.89	20.63	12.80	24.60	16.36	20.63	8.98
Performance	25.40	16.65	19.84	17.26	11.90	7.14	30.16	32.37	11.11	5.94
Effort	27.78	24.19	29.37	19.52	13.49	5.08	30.16	25.74	11.11	6.54
Frustration	29.37	22.24	23.81	17.39	13.49	10.07	19.84	24.03	8.73	3.27

Figure 15: Workload analytics from Task 1 (T1) - Task 5 (5). Mean (M) and Standard deviation (STD) are calculated. Green tones show positively lowest ratings, and red tones the opposite higher ratings.

Figure 16 shows the boxplot of the NASA TLX score in terms of performance. The users were asked to rate how successful they felt accomplishing a task, from Perfect to Failure. Overall all the tasks were completed. Task 4 was the only one (1 user) that failed to be completed.

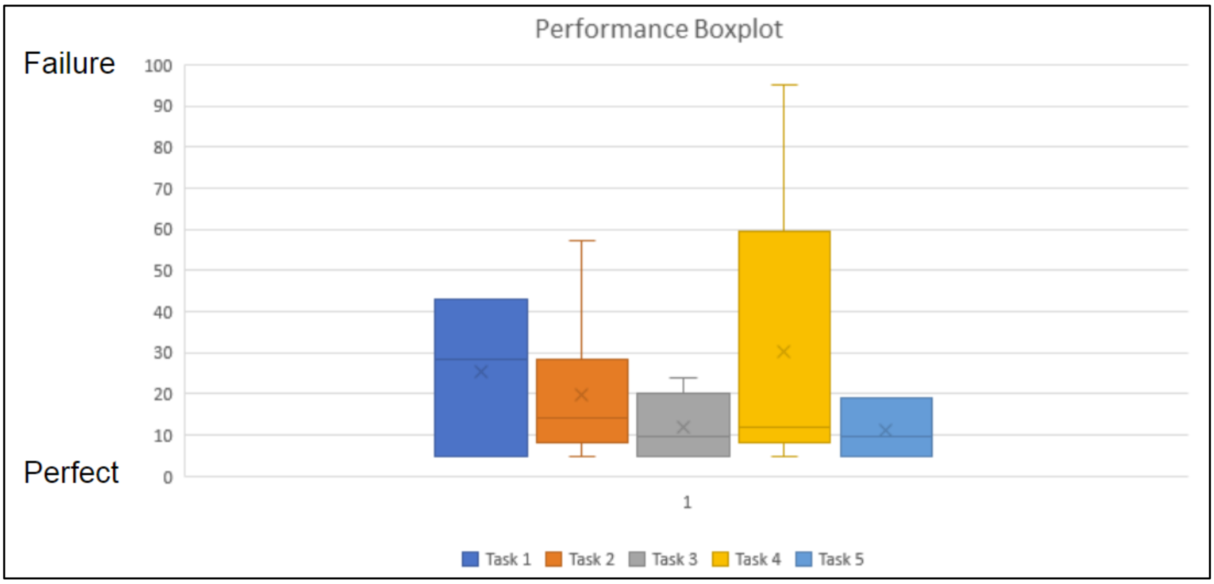


Figure 16: Boxplot of self-perceived success in accomplishing each task, according to NASA LTX results.

Figure 17 shows the boxplot of the NASA TLX score in terms of frustration. The users were asked to rate how frustrated they felt while performing the task. Overall the mean of users felt low frustration while using the Dashboard. Task 1, 2 show some exceptions which may be related to the effect of first-use. Task 4 shows a higher degree of frustration related to the user who could not complete the task (as shown in Figure 16).

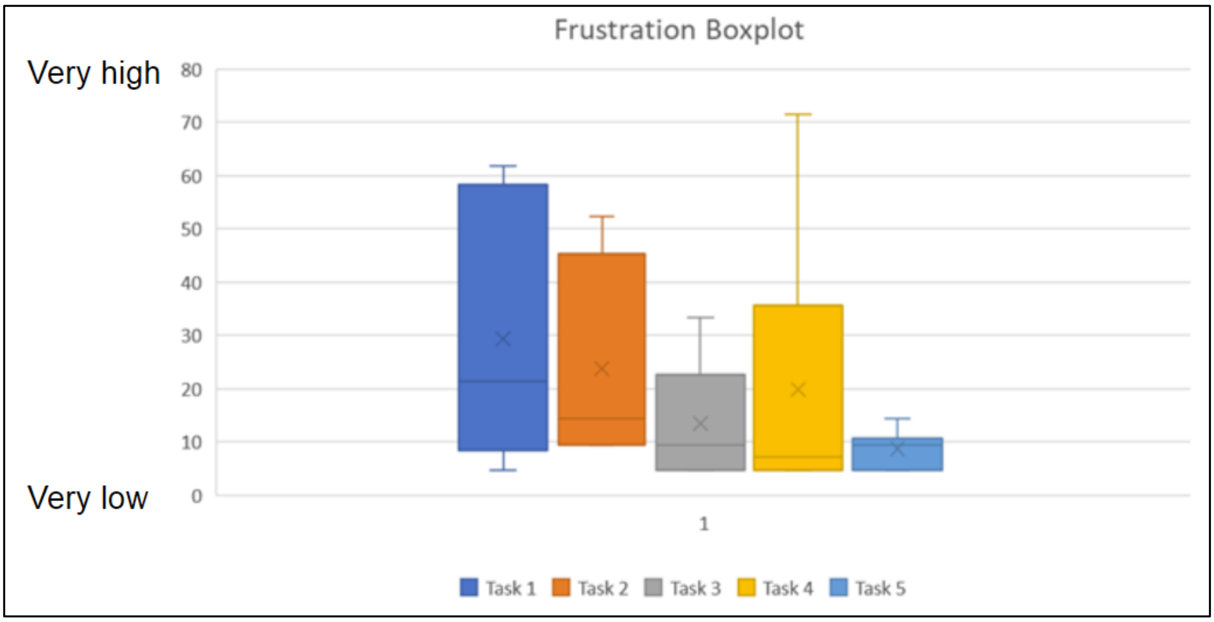


Figure 17: Boxplot of how insecure, discouraged, irritated, stressed, and annoyed were the participants during the task execution, according to NASA LTX results.

Figure 18 shows the results of the PSSUQ questionnaire about the general usability of the Dashboard. All the shown dimensions achieved good scores, showing that the Dashboard is usable and participants found it easy to learn, and were satisfied with it.

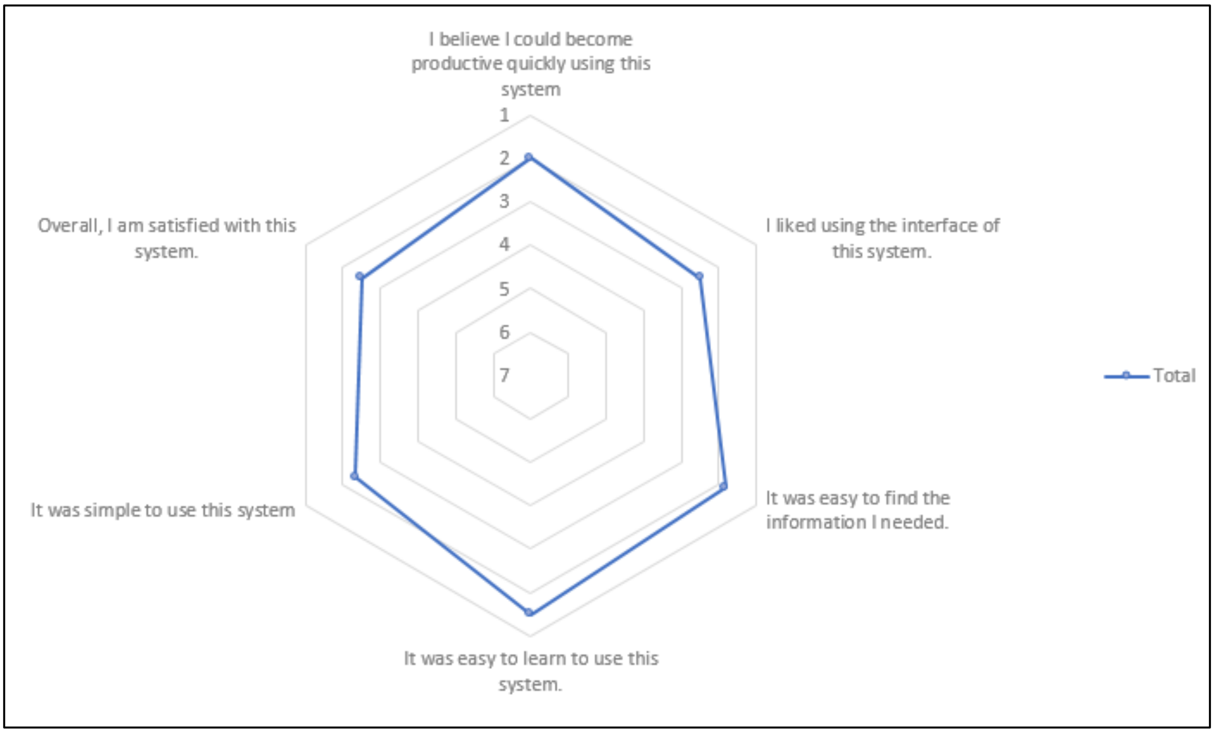


Figure 18: Post-Study Usability Questionnaire (PSSUQ)

The most relevant Think Aloud remarks gathered during the evaluation process were:

1. Most users had problems locating the search query fields.
2. Most users had positive reaction to Learning Pathways once they located it.
3. Most users were confused with the purpose of the buttons on top of the page.

6. Conclusion

Linking the demand for data science skills with the supply of learning resources that offer these skills is crucial for bridging the data science skills gap. Towards this goal, EDSA has developed an interactive dashboard that enables its users to explore both the current data science skills demand and supply.

This deliverable has presented the types of supply analyses conducted in relation to the demand analysis and how this work has been implemented in the EDSA dashboard. In particular, this deliverable has described how the demand and supply data are presented in the EDSA dashboard and how users are able to interact with this data in order to explore the current demand and supply.

The main contributions of this work are: a) creating a sizable data set of data science related job postings containing the job postings title, description, locations and other information, and b) developing a dashboard that offers relevant job postings for a given query, as well as courses and learning pathways for gaining the appropriate skills. The dashboard is updated daily with new job postings and courses and will continue to be maintained beyond the lifetime of the project, thus offering a sustainable service to the data science community.

It should be noted that the dashboard will continue to be maintained and further developed after the end of the project. Further improvements will include the addition of a time series analysis based on the data being collected, which is to be implemented by Fraunhofer. More details about this planned work are provided in the Project Exploitation Report (D5.4). Additionally, usability issues that were identified in the evaluation of the dashboard, such as usability improvements of the map view and the search query fields as well as other layout issues, will be taken upon by the team that will continue to support the dashboard after the project's end.

7. References

[1] B. Fortuna, J. Rupnik, J. Brank, C. Fortuna, V. Jovanoski, M. Karlovcec, B. Kazic, K. Kenda, G. Leban, A. Muhic, et al. qminer: Data analytics platform for processing streams of structured and unstructured data, software engineering for machine learning workshop. In Neural Information Processing Systems, 2014.

[2] L. Ratinov, D. Roth, D. Downey, and M. Anderson. Local and global algorithms for disambiguation to wikipedia. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies-Volume 1, pages 1375–1384. Association for Computational Linguistics, 2011.

[3] E. Sibarani, S. Scerri, N. Mousavi, and S. Auer. Ontology-based skills demand and trend analysis, July 2016.

[4] Joseph S. Dumas and Janice C. Redish. 1999. A Practical Guide to Usability Testing (1st ed.). Intellect Books, Exeter, UK.

[5] J. R. Lewis. IBM computer usability satisfaction questionnaires: psychometric evaluation and instructions for use". In: International Journal of Human-Computer Interaction 7.1 (1995), pp. 57.