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ADVANCES IN GLOBAL SERVICES AND RETAIL MANAGEMENT

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Comparative Analysis of Tools for Matching Work-Related Skill Profiles With CV Data and Other Unstructured Data

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Abstract

Matching job candidates with job offerings is one of the most important business tasks and is crucial to the success of a company. But there is not much knowledge available about the quality of matchings processed automatically by software. With a specifically developed scoring system it becomes possible to make a statement about the quality of the matching results generated by three different tools, i.e., Textkernel, Joinvision and Sovren. A series of resumes is being matched against two concrete open job positions, one by Google and one by the University of Zurich. The results are then compared in detail with the human based assessment made by the authors. For the Post-Doctoral Researcher position at the University of Zurich the scoring results in general were weaker than for the Software Engineer position at Google. We found out that the success of a good matching depends mainly on the parsing of the CVs. The quality of CV information is depending on how it is structured and what the specific candidate's experience is. The different tools showed that the ranking of candidates is dependent on the number of keyword matches. In particular for the job offer at Google, the available CVs obviously included suitable candidates. Textkernel and Sovren were capable to parse the CVs and job description correctly and therefore achieved good results, whereas Joinvision failed to extract key information and consequently dropped to the last place in the ranking.

Keywords: job profiles, job matching, natural language processing

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Introduction

Matching job applicants with open positions is still one of the most important business tasks and is crucial to the success of a company. Some parts of the matching process have already been supported by techniques based on automatic text analysis in the past. Nevertheless, there is not much knowledge available about the quality of such matchings. This study gives a view on related research and identifies gaps in the relevant literature in Section 2. We outline the applied research methodology in detail in Section 3. With their specifically developed, proprietary scoring system we provide insights into the quality of the matching results. Section 4 describes the scoring system in detail.

The main focus in Section 5 is then on the evaluation of three leading commercial matching solutions. A differentiation of features is elaborated, and a series of resumes is being matched against two concrete open positions. The results are then compared in detail with the human based assessment made by the authors. This allows a ranking and statements about the usefulness of technological support within the candidate matching process.

Related Work

This section highlights the related literature. In general, a lot of papers can be found that focus on automatic analysis of text. Other studies work on the standardization of Curriculum Vitae (CVs) which can be a starting point for further automatic analysis. The literature shows good results for keyword extraction and counting.

Chandola et al. (2015) developed an online resume parsing system using text analytics. The system uses a rating scale for individual keywords. According to the extracted words, ratings low (1 point), medium (2 points) or high (3 points) are assigned and afterwards all ratings are summed up to derive the rank of each resume. In this paper, all the extracted words are assumed to be equally important. This is not necessarily the case as for some positions specific skills have different priorities or weightings, which the system of Chandola et al. (2015) does not take into consideration. Verma (2015) tries to recommend candidates according to given skill requirements in the form of keywords. In his Paper Verma (2015) uses term document matrix to extract relevant words from the resumes. A clustering methodology is used to find similar resumes and in a next step the importance of keywords is calculated according to the cluster. Finally, the appropriate rank is derived for given keywords.

Ankala & Karra (2016) introduce an algorithm to visualize the skillset of an aggregate group of people by analyzing their resumes. Hadoop, MapReduce, and R are used to extract key words, count the number of people that have the specific skill in their resume and visualize the results. No effort for parsing or matching with job offers is made (Ankala & Karra, 2016). Shivratri et al. (2015) built a system to standardize the format of resumes. In their tool, users can upload a resume in the form of .doc, .docx, .txt or .pdf. The whole document is analyzed and transformed in a standard form and saved to a database. The resume parser then reorganizes the available database in a streamlined and accessible way (Shivratri et al., 2015). Kopparapu (2010) follows the same approach and proposes a functional and automatic information extraction tool for both structured and unstructured resumes to aid electronic search. Natural language processing techniques and heuristics are used for the extraction of useful information from resumes.

Yu, Guan & Zhou (2005) elaborate on Resume Information Extraction with the so-called Cascaded Hybrid Model. Their work showed that such a model yields good results for the task of information extraction from resumes. Kudatarkar, Ramannavar & Sidnal (2015) define the concept of CV parsing. Their publication focuses on how to identify frequent item sets and understanding the user's intent. In their project, Celik et al (2013), worked on a system which enables free structured format of resumes to transform into an ontological structure model. Sadiq et al (2016) examine how to use Natural Language Processing (NLP) and Machine Learning (ML) to rank resumes. In addition, they want to compare the resume with the candidate's social profile to get a more genuine insight. They write about three generations of hiring systems, which could be a very interesting starting point for these studies.

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As seen in the selected literature above, there are also approaches discussed trying to rank CVs according to the number of chosen keywords using academic approaches. What is missing in current research is literature about the use of real commercialized products. This is the space which we want to fill with this paper.

Research Project Methodology

This section describes the methodological framework of this paper which is the foundation for the upcoming sections.

Background and Motivation

The success of a company is largely explained by the quality of the employees and therefore the quality of the human resources process. Hence the impact of improving this process with technological assistance is expected to be measurable in quantitative figures and qualitative factors. Our motivation is to identify the factors responsible for a successful matching of job candidates with job profiles to noticeably improve the company's performance. Therefore, the focus is on qualitative statements which lead to quantitative results.

Problem Statement

From the challenges discovered in the introduction phase and during the literature research, this document states the following problem: "A profound scoring system helps to understand and rate the quality of existing keyword matching solutions." Related to this, we want to answer the following research questions.

- What is the quality of keyword matchings for CVs taking into consideration the different requirement levels of job profiles?
- How can the quality be measured best?
- How can the matching quality be improved?

Research Method

A qualitative, analytical research approach is applied in this work. Multiple test cases are analyzed and presented in Section 5. Existing keyword matching solutions are described, real job profiles are being matched against CVs from real candidates and the results are shown for each solution. In the conclusion (Section 6) successful functionalities and gaps are presented focusing on the problem solution and the quality improvement.

Scope and Limitations

When thinking about the possibilities of CV matching improvement one can think about infinite solutions. Because of limitations in this paper, the focus is on the analysis of existing research and existing solutions. Nevertheless, the results will help the reader to find starting points to improve his or her hiring process.

Moreover, the paper covers only the results of commercial solutions in the area of semantic search. Besides commercial tools there is a variety of Open-Source Tools (Php, Python, R) publicly available through web platforms like GitHub and similar.

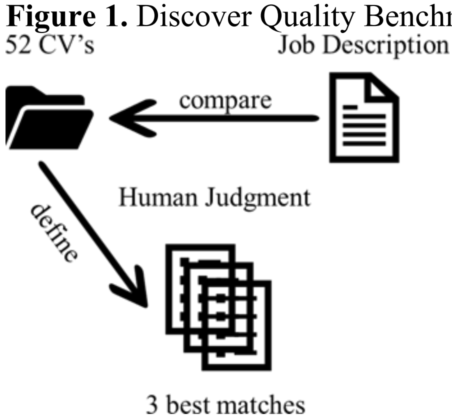
Scoring System

This section describes how the matching quality of each analyzed program is discovered. As every program delivers different outputs, a way has to be found to have a comparable scoring system. Moreover, an explanation of how the test will be performed to get comparable results is described.

Quality Benchmark

The basis for the comparison of the matching quality is a dataset of two different job offers and over 50 different CVs. To have a benchmark for further testing with the existing solutions, the three best matches to each job description are predefined. As there is no existing solution used to define the three top matches, this is done based on human judgment (see Figure 1). Based on this method, there is a total of six best matching CVs available for further comparison with the existing solutions.

Figure 1. Discover Quality Benchmark



A Comparison With Existing Solutions

The existing solutions use the same set of CVs as a starting point. The job description delivers the required skills which have to be fed into the input fields of the respective program. As the possible settings differ, the best has to be discovered first. This way, the existing solution is given the best possible chance to find the matches according to the job description and the matches are comparable with the benchmark.

As a result, depending on the existing solution, one or a set of matches is delivered. These matchings are then compared with the best three matches of the used job description based on human judgment. If the existing solutions deliver one or more CVs according to the benchmark, the quality can be considered as good. Moreover, the type outputs delivered by the programs is also qualitatively analyzed and cross compared. The following list summarizes the type of findings:

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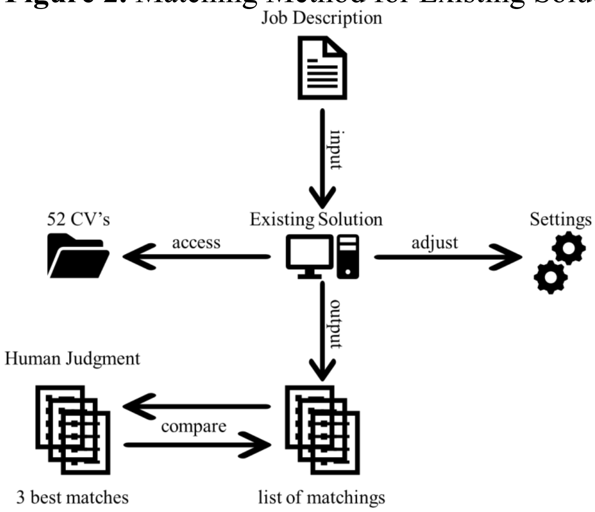
- Direct comparison with best matches of human judgment
- Quantitative quality measurement according to scoring table
- Analyze and cross compare possibilities of input adjustments
- Analyze and cross compare output types
- Only qualitative measurement (no points given)

Figure 2. Matching Method for Existing Solutions



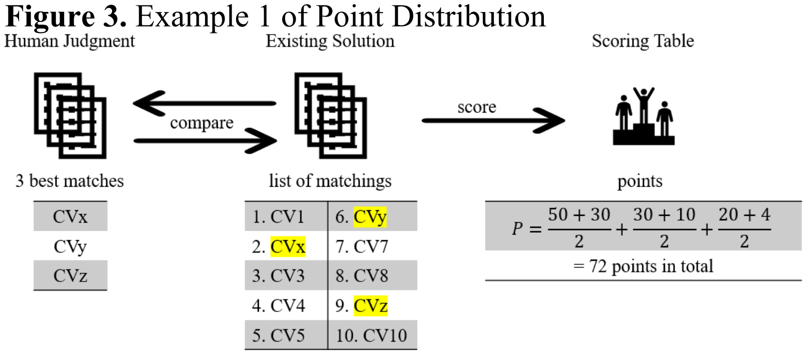
Point Distribution

For the quantitative quality measurement, the following scoring table was developed to allocate the points for the matchings. As shown in Table 1, 100 points can be achieved in maximum if the three best matches are in the top three and right order. If the matching order is not as determined by human judgment, the achievable number of points decreases by taking into consideration the distance to the maximum point of each match. The following example illustrates the point distribution (see Figure 3).

Table 1. Scoring Table

Rank	Points	Rank	Points
1	50	6	10
2	30	7	8
3	20	8	6
4	14	9	4
5	12	10	2

Figure 3. Example 1 of Point Distribution



It can be observed, that the better the matches are (near top 3) the more points are achieved. Moreover, it is distinguished between first best match, second best match and so on. This way, it is guaranteed to collect points as long as the match is in the list and the human judgment therefore is not a crucial criterion (e.g. 0 points if top 3 missed).

Case Studies

In this section, three existing solutions are examined. A pool of fifty-two CVs is used to find the best match for the following two open positions:

- Software Engineer, Google, Mountain View, California, USA.
- Post-Doctoral Researcher, Department of Psychology, University Zurich, Zurich, Switzerland.

To arrive at the three top matchings according to human judgement, for each CV, the authors provided evaluations of how well the candidate fits to the job profile as one would consider it in the HR (human resources) department of a real enterprise. Ratings from 0 (totally unsuitable) to 10 (perfectly matching) were assigned to each CV and then the average score was measured. The result is described below (names abbreviated).

- Software Engineer, Google: top candidates GS, ABS, MB
- Post-Doctoral Researcher, University of Zurich (UZH): top candidates EM, WAM, MB

In the conclusion section of each case study, the matching results are measured according to the methodology outlined in Section 4. A comparison and assessment of all the tools is conducted in Section 6.

A lot of research was done regarding existing commercial matching solutions. After identifying the most advanced and influential providers we contacted the respective sales department with an account request. The access was not granted by every company. Therefore, only the following three solutions were tested in detail:

- Textkernel
- Joinvision
- Sovren

After gaining insight into the functionalities with the help of a real world case it was clear that it has to be distinguished between two kinds of solutions. First, there are tools doing so-called semantic search and delivering complete matching results. Second, there are solutions supporting different and partial aspects of the hiring process, delivering the input for further proceeding. These are classified as so-called parsing solutions. In the following, we focus is on solutions in the area of semantic search.

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Textkernel

Solution Description

Textkernel is a R&D spin-off of the Universities of Tilburg, Antwerp and Amsterdam and was founded in 2001. Headquartered in Amsterdam with offices in Dusseldorf, Paris and Madrid, the company employs more than 120 people. The main focus of the company is in semantic understanding of documents and queries, advanced searching and matching as well as HR domain knowledge. Textkernel offers a variety of products targeting the aforementioned focus:

- Extract! (CV parser)
- Jobfeed! (aggregation of jobs found in the web)
- Search! (semantic search and talent sourcing)
- Match! (semantic job matching)

By combining the different solutions, Textkernel offers a powerful tool to accelerate the recruitment process of its customers (Textkernel, 2018). Textkernel has provided a test account for this report, consisting of the products Extract!, Search! and Match!. In a first step, the CVs have to be uploaded to the database. This happens with the CV parser. The CVs are uploaded one at a time, which is time consuming but more accurate as the CV and parsing output are compared side-by-side. Small parsing errors can be corrected and missing fields filled out.

The CVs are then available in the database and can be accessed with Search! for further processing. Besides the own uploaded CVs, Textkernel provides the access to various and well known social networks for professional contacts. However, this functionality is not in the scope of this report and therefore excluded. The functionality Match! can now be used to upload a job description. The program analyses and extracts key words within the job description and sets up the filter for matching the best CV. This filter can individually be adjusted, assuring the user to have full control within the matching process.

Matching Results

After uploading the document, Textkernel automatically sets up the initial filter with the keywords parsed out of the job description. The filter is divided into different sections and can be fine adjusted if necessary. With the given job description, some adjustments are necessary, e.g. activating optional criteria. Moreover, the weight of the criteria can be changed to either optional, required, or in between. For instance, according to the job description, the keyword mobile application development can be weighted the same as the keywords in "IT competencies". Furthermore, as the rating depends on the accordance of the keywords with the keywords of the CV, unnecessary keywords like "two" or "switch" can be deleted as they would worsen the result.

The results are then displayed with the used job description. The ranking is highlighted with a bar graph from 1 to 5 and sorted from best match to worst as all CVs which are uploaded are evaluated in this case. As previously mentioned, adjustments on the filter could have major impacts on the rating as the keywords are directly compared with the extracted ones from the CV. If the weighting of a keyword would be changed, a CV could reach a higher evaluation or would fall off the listing e.g. by changing a keyword of the filter to “essential”. The candidates can now be cross-compared for further evaluation where all positive keyword matches are highlighted.

For the Google job offer, there are only three candidates who receive two or more points. The best match achieves GS (3 points) followed by MB and AB (both 2 points). Due to the higher number of keyword matches by MB, he is ranked before AB. Another feature of Textkernel is the possibility to open the original CV as well as the parsed profile for corrections or additional information. For the post-doctoral researcher job offer the same steps as before are performed The initial filter is expanded by the required and essential criteria “PhD” and “English”. Additionally the search radius is turned off. Because of the essential criteria, only 13 results can be discovered. Following figure shows the result of the top 10 matching. Textkernel remembers GB as number one match (3 points) followed by HX and IR (both 2 points). Other than in the previous semantic search, more candidates are scored with two points.

When going through the ranking, it is noticeable that GS is listed twice. One possible cause could be a double parsing of the CV due to erroneous processing by the user of the tool. Since the rating has already been carried out, no changes were made. It should be noted at this point that an indication would be helpful if several identical CVs exist in the database.

Conclusion

The extraction of the keywords out of a job description works really well and only small changes to the filter have to be applied. Matching the keywords with the CVs in the database also works straight forward and the listing seems reasonable and understandable.

Therefore, the success of a good matching depends on the parsing of the CVs. If important keywords are missing, they will not be remembered in the search and actually good candidates could fall out of the listing.

The parsing process was not running perfectly as not every CV format and text was recognized. As the CVs have to be parsed one by another, missing information’s might be discovered and corrected but it is not guaranteed, especially if approximately 50 CVs have to be uploaded.

Nevertheless, the tool delivered good results. The points achieved according to the scoring table (Table 2). Textkernel ranks the same candidate on first rank. Only the second and third ranks are reversed. This results in a score smaller than 100 points, namely 95.

Table 2. Matching Result for UZH – Textkernel

Human Judgment		Rank achieved with Textkernel	Points
1.	GS	1.	50
2.	ABS	3.	25
3.	MB	2.	20

Table 3. Textkernel Scoring Table - University of Zurich

Human Judgment		Rank achieved with Textkernel	Points
1.	EM	4.	32
2.	WAM	Not recognized	0
3.	MB	10.	11

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Other than before, this result differs clearly from human judgment. The best match according to human judgment, EM, is ranked on fourth place whereas the third best match is ranked on the 10th place. Unfortunately the second best match, WAM, is not recognized by Textkernel. This results in a total of 42 points.

After investigating why the second best match was not recognized by Textkernel, the reason was discovered and located in the parsing process of the corresponding CV and the setting of the filter. According to the job description, the candidate must have a PhD and must speak English. Both pieces of information were missing in the database because the candidate did not mention his language skills and his PhD was still in progress.

Joinvision

Solution Description

Joinvision is an Austria based company that was founded in Vienna in 2006. In the beginning years, the focus lied on the operation of an online job portal for vacancies in engineering and IT with a specialization in freelancing. After the beginning years the focal point changed to self-developed parsing and matching technologies. In October 2016 Joinvision was acquired by JobCloud AG, a digital recruiting company in Switzerland. The product offering consists of the following individual parts:

- CVlizer (CV parser)
- JOBolizer (job offer parser)
- MatchPoint (searching and matching of candidates and jobs)
- HRexplorer package (combination of all three single solutions)

Further small modules are offered but not taken into consideration in this report (Joinvision, 2017). A test account for HRexlporer is the base for the following statements. Once logged in, there is the possibility to either upload candidate data in form of a CV or Job data in form of a job offer. Each file is then parsed into a standard form for a CV or Job offer respectively. The parsing is conducted by the mentioned components CVlizer and JOBolizer.

It is not only possible to upload and analyze own CV and Job data, the tool also provides a connection to index Adversdata and Jobfile, two job databases for Switzerland and Austria. Furthermore an interlinkage to Xing is built in to automatically scan for public candidate information of the social platform. As a next step MatchPoint is used to find the best candidate for a specific job offer. “MatchPoint is both an automated search and matching engine with sophisticated semantic capabilities, providing a one-click solution for matching the most suitable candidate profiles from any database to the most relevant job postings and vice versa” (Joinvision, 2017). For this process only the two mentioned job descriptions from Google and University of Zurich are in scope, all data from external partners like Xing or Jobfile are excluded.

Matching Results

At the beginning there is a hurdle to overcome. If the matching process for the Google job offer is conducted without making any changes and by just hitting the button called find suitable CVs the result is “no matches found”. Only when switching to the expert mode and turning the searching radius off, eight matches are displayed. The results are ranked, starting from the best to the worst match and rated with a number of stars from zero to six. In the case of the job as a Software Engineer at Google, candidate VB is the top match with a rating of three stars followed by GB scoring three stars too. The other candidates receive a score of less than three stars.

The result can then be analyzed in detail by looking at the profile matching. Job requirements and candidate skills are shown side by side and consents can be identified. Before going into the quality of the candidate match, findings for the parsing solutions are presented. What stands out is that the job description parser misses key information. In this case the employer, Google, is not recognized as well as the employment relationship is wrongly captured as holiday work.

Personal information and language skills from the CVs are parsed well but difficulties can be identified with differentiation between education and work experience. The CV parser confuses lecturing and teaching experience with the candidate’s education. Additionally, more general weaknesses can be found in the parsing of the CVs, namely missed information on acquired academic title, name and location of the university, name and location of the employer, duration of employment, contradictory information about a position or wrong translation. The quality of the information is different for every CV, depending on how it is structured and what the specific candidates experience is. The tool has features where manual corrections or additions can be made to reduce the possibility of wrong or bad matchings. In the test case of searching for a post-doctoral researcher, the results are less relevant, indicated by the low number of stars assigned. Additionally, nine results are displayed, compared to eight for the first matching. It can be concluded, that there is no fixed number of suiting candidates displayed.

What attracts attention is the top match, whose name is “Mathematical Sciences”, that is clearly a parsing error. When opening the details, the original resume can be accessed and the original name found out. The best match for the position according to Joinvision is HX. In this CV, the candidate name is mentioned in the heading and not in a separate section with a title like personal details. This can be a possible reason why the tool is not able to detect the correct name. HX is followed by GB as second best candidate. All the other candidates do not achieve star ratings.

Conclusion

The biggest issue with the tool Joinvision is the mistakes that are generated already at the parsing stage. To come to a reliable result, a lot of manual rework and corrections have to be done. Measuring the matching results against the human judgment, it can be found that Joinvision produces robust results only for the job description of the University of Zurich (Table 5).

Table 4. Joinvision Scoring Table - Google

Human Judgment		Rank achieved with Joinvision	Points
1.	GS	Not recognized	0
2.	ABS	7.	19
3.	MB	3.	20

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Joinvision ranks MB as number three match, equivalent to the result of human judgement. Furthermore, ABS is identified as 7th best result, compared to number two according to human assessment. GS, however, is not recognized by Joinvision. When counting the points in accordance with the scoring system, only 39 points are achieved, as the missing number one match has major impacts to the point distribution.

Table 5. Joinvision Scoring Table - University of Zurich

Human Judgment		Rank achieved with Joinvision	Points
1.	EM	9.	27
2.	WAM	3.	25
3.	MB	6.	15

The tool does have all the top three candidates in its output list of best matches. WAM is the third-best match according to Joinvision versus number two pursuant to human judgement. MB and EM are listed as number six and nine respectively. This leads to a total score of 67 points.

Sovren

Solution Description

Sovren is an American company founded in 1996. In its beginning days the company focused on staffing for financial and accounting markets. Later the business focus changed to being a software provider and later focusing on providing top-of-the-line job/resume parsing and AI matching software components (Sovren, 2018).

According to Cox (2018) Sovren does not feature a complete end user solution for its tools, but offer their services via API calls that clients build into their solutions. Their solutions include the following: Job Order and Resume Parser, AI Matching Engine, Resume Analyser and Sovren Quick Recruit.

The focus of the analysis for this paper will be on the Job Order and Resume Parser in combination with the AI Matching Engine to test the ability to find matching candidates to the two job profiles already mentioned.

As there is no available user interface and therefore no test account, the test of the solution is based on online test environment built into the website of the company. A job description can be uploaded and a number of CVs to be matched with it. Additionally, the website asks for guessing the best match, where a random CV is chosen. In the final step, a corporate or student e-mail address has to be provided and the results are instantly sent to the e-mail account and will be presented in the next section.

Matching Results

In the e-mail, a short summary on the parsed job description is provided, followed by the section with the matched candidates, sorted descending according to their relevance and matching quality to the job requirements. All candidates are listed in the matching section. The ten best matches are shown for the Software Engineer position. The top match provided by Sovren is GS, followed by ABS. In the e-mail, there is also a link provided to download the full JSON

(JavaScript Object Notation) results. When looking at the details, the solution of Sovren is very robust, the parsing results do not show any error and the matching is comprehensible.

The matching results for the Post-Doctoral Researcher position are as follows: The top match is ABS, pursued by IR and HX. In the results, the top ten candidates are listed according to their relevance for the job offering. In the next subsection, the quality of the results is assessed and discussed.

Conclusion

Sovren sees itself as leader in the space of resume and job order parsing and matching worldwide. Their technology configurability, scalable pricing, stability, and service accuracy are all unmatched in the industry and some of the largest resumes consuming organizations in the world run Sovren software (Cox, 2018). This self-statement can only be projected on the match with Google's job description:

Table 6. Sovren Scoring Table - Google

Human Judgment		Rank achieved with Sovren	Points
1.	GS	1.	50
2.	ABS	2.	30
3.	MB	Not recognized	0

The top two matches of Sovren are GS and ABS in this sequence. This result does exactly correspond to the human judgement. Only the third best match MB is not represented in the top ten results of Sovren. When using the scoring system, Sovren achieves 80 points.

Table 7. Sovren Scoring Table - University of Zurich

Human Judgment		Rank achieved with Sovren	Points
1.	EM	6.	30
2.	WAM	Not recognized	0
3.	MB	Not recognized	0

Sovren delivers weak results for this job description. Only one candidate in the top ten is corresponding with the top three applicants based on human judgement. The top match, EM, is listed as number six in the result output of Sovren. Therefore, a score of only 30 points is achieved. Possible causes are discussed in the next section.

Conclusions

In order to be able to make a statement about the quality of the matchings of the considered tools, the results are compared in Tables 8 and 9.

Table 8. Comparison of Matching Results – Google

Human Judgment		Rank achieved with Textkernel	Rank achieved with Joinvision	Rank achieved with Sovren
1.	GS	1.	Not recognized	1.
2.	ABS	3.	7.	2.
3.	MB	2.	3.	Not recognized
		= 95 points in total	= 39 points in total	= 80 points in total

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Table 9. Comparison of Matching Results – University of Zurich

Human Judgment		Rank achieved with Textkernel	Rank achieved with Joinvision	Rank achieved with Sovren
1.	EM	4.	9.	6.
2.	WAM	Not recognized	3.	Not recognized
3.	MB	10.	6.	Not recognized
		= 42 points in total	= 67 points in total	= 30 points in total

Matching results for the Post-Doctoral Researcher position at the University of Zurich are in general weaker than for the Software Engineer position at Google. This can be caused by the set of CVs that was randomly chosen by the authors. To a large extent, the 52 candidates are experienced in the fields of art or mathematics. Mathematicians correspond well with the position of a software engineer, whereas the artists do not match either of the job description's criteria. University of Zurich is looking for candidates with a degree in cognitive neuroscience or a related field and a proven track record of scientific output in the field. Therefore, even with human judgement it was extremely difficult to find a resilient match for the job description of the University of Zurich. Nevertheless statements about the quality of the tested software can be made. The success of a good matching firstly depends on the parsing of the CVs. If important keywords are missing, they will not be remembered in the search and actually good candidates could fall out of the listing. The quality of the information is different for every CV, depending on how it is structured and what the specific candidate's experience is. This fact makes it hard to parse each CV correctly without manual adjustments.

Secondly, the matching result depends on the keywords extracted out of the job description and the possibility to configure filters within the software tool. It seems clear how the ranking is made; the more keyword matches the higher the rank. The solutions only differentiate to a certain degree if the keywords matched are really relevant for the offered position. A good example is Textkernel where the filter can be adjusted and keywords weighted according to their relevance. Finally, as already outlined above, it was hard to find suitable candidates for the job description of the University of Zurich and the matches were strongly dependent on individual findings of the authors. Therefore, the existing solutions cannot replace this human judgment. This is underlined by the results, which are less relevant and partly incomprehensible.

In conclusion, and coming back to the problem statement, the scoring system helped to understand and rate the quality of the tested solutions. Especially for the job description of Google the available CVs obviously included suitable candidates. Textkernel and Sovren were capable of parsing the CVs and job description correctly and therefore achieved good results, whereas Joinvision failed to extract key information and consequently reached the last place. Nevertheless, none of the tools can be used to automatically parse and match candidates without human interaction. It must be noted that parsing processes have to be carried out carefully in order to always find the best suitable candidates. The scoring system and evaluation procedure introduced in this report can be used by HR departments to evaluate the most appropriate solution for their needs.

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