Time to Question if We Should: Data-Driven and Algorithmic Tools in Public Employment Services

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Abstract. Algorithmic and data-driven systems have been introduced to assist Public Employment Services (PES) in various countries. However, their deployment has been heavily criticized. This paper is based on a workshop organized by a distributed team of researchers in AI ethics and adjacent fields, which brought together academics, system developers, representatives from the public sector, civil-society organizations, and participants from industry. We report on the workshop and analyze three salient discussion topics, organized around our research questions: (1) the challenge of representing individuals with data, (2) the role of job counsellors and data-driven systems in PES, and (3) questions around the interactions between job seeker, counsellor, and system. Finally, we consider lessons learned from the workshop and describe plans aiming at involving a multiplicity of stakeholders in a co-design process.

1 Introduction

Algorithmic and data-driven systems have been introduced to assist Public Employment Services (PES) in various countries (Desiere et al., 2018). Many of these systems are developed to support job counsellors in assessing and classifying job seekers as well as making decisions on the allocation of resources such as skills training and unemployment benefits (Allhutter et al., 2020a). However, their deployment has been heavily criticised (Kayser-Bril, 2019; Niklas, 2019; Epicenter, 2020), both in general terms and in relation to specific existing systems. To identify biases and potentially unjust outcomes, critical research in this field has explored the motivation behind systems' introduction, how specific design decisions are made, and how systems impact individuals and communities. Further points of discussion are the interaction between users and the system and how users' perspectives could be integrated into systems' development. An underlying question here is how the "user" is defined: are users defined only in terms of who operates the system, i.e., job counsellors, or could they be extended to include unemployed individuals seeking services, PES departments, and more broadly, states commissioning the development of such systems?

This paper is based on a workshop organized by a group of researchers working within European Computer Science departments on AI-ethics and adjacent fields with diverse disciplinary backgrounds, gathered around the topic of algorithmic and data-driven tools in PES. Our aim was to bring together people with very different perspectives and disciplinary backgrounds. Our work addresses the significant potential of algorithms to be beneficial to society, while also acknowledging the risks of applying technology-driven solutions to complex, long-standing societal issues.

The workshop took place online in May 2020. It comprised three keynote talks, a panel, and audience participation and discussion (see `https://people.cs.kuleuven.be/~bettina.berendt/PES`). The 37 participants were researchers, system developers, public servants, civic organizations' representatives from diverse academic disciplines, non-governmental organizations, industry, and the public sector. Disciplines included data science, psychology, sociology, machine learning, political science, and communication science. The workshop was conceived as a first step in engaging with these experts and obtaining interdisciplinary knowledge around five research questions:

1. What are general and field-specific factors that are decisive for finding a job and how can they be integrated into a model? (§ 3.1)
2. What tasks, skills, and expertise are inherent to the government job counsellor role and can they be replaced or augmented by technology? (§ 3.2)
3. What are the challenges in the interaction of job counsellors and job seekers with algorithmic decision-making systems? (§ 3.3)
4. What are important blind spots in existing conversations around PES and automation and how can they be addressed by future research? (Section 4)
5. What could a data-driven system for PES look like in an ideal world and what features and requirements would it have? (Section 4)

2 Related Work

Several European countries have already introduced different software-based tools for the profiling of job seekers. At the workshop, the systems designed for PES in Austria, the Netherlands and Flanders were discussed in depth.

Methods for profiling job seekers can be grouped into *administrative profiling, caseworker-based profiling* and *statistical profiling* (Barnes et al., 2015). Administrative profiling creates client groups based on administrative eligibility criteria, *e.g.* age and educational level. The systems in Poland (until 2019) and Flanders (until 2018) are examples of this. Caseworker-based profiling is based on the judgement of job counsellors, and is used in countries such as Germany and Switzerland. The current Flemish system could be characterized as advanced statistical, or AI-based, profiling (Desiere and Struyven, 2021). Statistical profiling uses statistical models to predict the chances of finding new employment. The three systems discussed in the workshop belong to this category, although they have quite different intended functions. The Dutch system calculates a probability of continued unemployment within 12 months. Based on this, job seekers are prioritized to receive face-to-face services (Desiere et al., 2019). The Austrian system is designed to categorize job seekers during an in-person interview with the counsellor who, during the assessment, decides whether to offer training or unemployment benefits to the job seeker (Allhutter et al., 2020b).

The reasoning for introducing such tools differs across countries. In the Netherlands, the profiling was introduced due to insufficient funding so that face-to-face services and further education or job training cannot be made available to every job seeker (Wijnhoven and Havinga, 2014). The Austrian system was introduced with three stated goals: (1) increasing efficiency and effectiveness of counselling, (2) improving the effectiveness of further job training and (3) standardizing the distribution of funding to avoid arbitrariness (Allhutter et al., 2020b). In Poland, the reasoning was rationalizing expenditure and customizing services to improve their quality (Jędrzej et al., 2015).

Despite different reasons for their introduction, all systems are framed as a tool to support job counsellors in job seeker assessment. However, in Austria, the *Arbeitsmarktchancen-Assistenz-System* (AMAS) algorithm has been broadly criticised as discriminatory, and concerns remain that even if the system's output is relegated to a role of *second opinion* rather than an automated decision, there is a possibility that it will become the *first opinion* in practical use (Allhutter et al., 2020b). Due to such criticism and a data-protection-based court order, the Austrian system has not (yet) been deployed beyond a test run. That such a so-called second opinion can become dominant has already been observed with the Polish profiling algorithm. Here, in 99.4% of cases the automatic profile was accepted by PES staff (Jędrzej et al., 2015), which means the system operated on an almost automated basis, even if counselors knew that the profile was erroneous (Sztandar-Sztanderska et al., 2021)

A recurrent criticism surrounding these systems is the risk of discrimination against certain groups, particularly migrants. In the new Flemish PES system, people with "foreign origin" are more likely to be misclassified as high risk on long term unemployment. Although sensitive information such as citizenship status of a job seeker is omitted, other variables such as language skills are used as proxies (Desiere and Struyven, 2021). Allhutter et al. (2020b) raise similar concerns about AMAS. Particularly women with a migration background have a high probability of being classified as having low chances to find new employment which shows pre-existing societal bias encoded in the system.

3 Key Themes

A continuous and wide-ranging discussion took place throughout the workshop, amongst invited speakers and audience members. We used a semantic approach to thematic analysis to identify common themes, topics, and ideas that where discussed and documented in the notes, which we will discuss in this section.

3.1 Representing Humans With Data: Impacts of Choices Made

Our first question addresses the tension present in systems that reduce the full biography, background, and skills of individuals to a numerical value or other simplified structure, aimed at supporting and optimizing decision-making processes. Some argue that the use of algorithmic tools that allow for systematic and consistent procedures for decision making is fairer than potentially subjective human judgement (Kleinberg et al., 2018). However, a representation of a person's biographical background translated into computational terms will always require some sort of simplification, or 'imperfect surrogate' (Davis et al., 1993) of contextual and personal factors surrounding one's future employability.

This tension is very clearly illustrated with the AMAS algorithm. This algorithm was described as stemming from value-laden choices that have been made with limited explanation, *e.g.* the choice to measure care obligations only for women. These choices embed specific social values in the system, which is evidenced by the historical inequalities reflected in the AMAS scores, where women in technical occupations, women with migration backgrounds and other marginalized groups systematically receive lower "integration value" scores. Along with issues with the choice of the variables themselves, decisions surrounding the simplification of data into categorical variables, and including a large number of binary variables were similarly unexplained. As the data is used to group individuals who then must be treated similarly, improper variable selection and oversimplified variable representation increase the likelihood that people in very different situations and with very different backgrounds can be placed in the same group. This gave rise to concern that the system is actually not designed for adaptability to the inevitable complexities, variety, and exceptional situations existing within the unemployed population and the job market.

3.2 Explicit, Implicit, and Undefined Roles

When examining data-driven tools for PES, particularly those meant to automate tasks done by governmental job counsellors, we should consider the conceptualization of the counsellors' role behind the system's design. While the roles of counsellors vary between countries, and even how the role is interpreted and carried out varies between individuals, the notion of counsellor often appears oversimplified as a distributor or gatekeeper. This is reflected in the fact that data-driven tools for PES are often presented as methods to optimize the distribution of human and financial resources. With our second question, we explore the complex roles that counsellors currently fulfil, to better understand the tasks that automation aims to replace. We also investigate the limits of automation for such tasks and the systems' potentials to augment counsellors' capabilities.

A common framing in the discussion around resource distribution and decision making focuses on whether algorithmic systems can offer higher levels of fairness and accuracy than human decision makers. While humans may indeed be biased and make mistakes, algorithmic systems too can output errors at scale, sometimes invisibly. In the Austrian AMAS, human discretion is required to judge the system's output, which contradicts with AMAS as a neutral and accurate decision maker in comparison to human job counsellors (Allhutter et al., 2020b). However, at the workshop, it was argued that a better approach to the dichotomy humans vs. machines could be a workflow of humans and machines working together (see § 3.3).

3.3 Impacts of Interactions within Sociotechnical Systems

One of the important aspects of human-machine collaboration is intelligibility: it is hard for job counsellors to judge systems' outputs if they do not know what the base for the score provided by the system is. Nuances are present in the different approaches adopted by the Austrian AMAS, where counsellors are given a single score with a very limited explanation, and the Dutch Work Profiler, which gives more extensive information about the data-driven output. In this sense, it was claimed that the Work Profiler is an early-assessment, non-prescriptive instrument and that counsellors are prompted to focus on individual service delivery. It was also pointed out that the system should at least provide some information or warning about forms of discrimination that could take place in the interaction between counsellors and job seekers.

Beyond these differences, fundamental aspects revolve around questions such as what the introduction of a new system promises and how humans are trained to interact with the system. For instance, if the system is said to provide neutral outputs and job counsellors are trained not to question the system, the risk exists that a 'human in the loop' system becomes fully automated and that unfair outcomes will be detected only after they have caused harm.

Further concerns centered around purposes of the introduction of systems that are not explicitly stated during implementation. Specifically, concerns around systems' potential for surveillance emerged. We saw examples from Poland regarding the monitoring and controlling of counsellors, e.g. overruling an automated decision was recorded. Regarding the job seeker, the Austrian AMAS monitors the attendance of appointments and this record as a predictor.

4 Lessons Learned and Next Steps

Implications for Future Design Processes To address some of the blind spots that were not covered by the discussions presented here, our future work will focus on two co-design workshops: The first will focus on the job seekers, where people who had (possibly unsatisfactory) experiences interacting with PES could provide input. The second will gather counsellors, as both views are important and both groups will interact with PES systems. One question is what values and emotions workshop participants associate with existing systems and, hypothetically, with a prototype system. The results of these workshops should flow into recommendations on which aspects should be implemented or changed.

Specific Recommendations The *first* takeaway from the workshop discussion is that data-driven systems should not be seen as decision makers but rather as advisors, given the risks of automated decision making in PES. This is rooted in the conceptualization of data as information, and of data-driven technologies as information sharing tools. Algorithmic tools are very effective at uncovering patterns in data, including patterns of bias existing in that data. To this end, algorithmic tools used in an advisory role could be helpful. For instance, if an individual has an uncommon job or experience, a system could inform the individual how many people like them are there and what previous experiences, intervention choices and outcomes were. We see potential to use data-driven systems to providing actionable information based on all shared experiences.

The *second* observation emerging from the discussion refers to the relationship between data-driven tools and labor markets. On the one hand, participants agreed with the fact that such systems could potentially help job seekers to improve their chances in the job market, for example by suggesting training programs. On the other hand, on a macro level, software could also be used to better understand and predict the job market and its near-term future development. Although long-term labor market prediction is not explicitly within the scope of tools currently developed and deployed in PES, these systems do have the power to potentially shape the labor market. We argue that it is crucial to involve all stakeholders in designing systems with such far-reaching consequences.

The *third* workshop takeaway refers to aspects of human intervention. Especially the role of job counsellors remained central throughout the discussion. Participants saw value in expanding imaginaries around counsellors' role beyond that of gatekeeper. Others argued that counsellors are mediators between the system and job seekers and that this role is essential to make sure system outputs are seen as recommendations, not final decisions. We thus argue that counsellors' training should reinforce the idea that system outputs can be contested.

Finally, discussing contestation paths and the role of people leads to the observation that there are indeed interactions that cannot be properly replaced by software. With several bias and fairness-related issues present in all of the systems discussed throughout the workshop and with the many trade-offs involved in the development of such systems, we question whether one should build data-driven profiling tools for Public Employment Services at all. Instead, PES could leverage data science for skill-building, market analyses, and other purposes.

5 Conclusion

With our work, we discuss the implementation of data-driven tools in PES towards a consideration of the normativities that get inscribed in technical systems and how systems also (re)produce normativities. We believe that this conversation cannot take place without the participation of all stakeholders. Involving users and potentially impacted communities in system design and development as well as discussing contestation and refusal paths emerge as urgent next steps.

Bibliography

Doris Allhutter, Florian Cech, Fabian Fischer, Gabriel Grill, and Astrid Mager. 2020a. Algorithmic Profiling of Job Seekers in Austria: How Austerity Politics Are Made Effective. *Frontiers in Big Data* 3 (Feb. 2020). https://doi.org/10.3389/fdata.2020.00005 Publisher: Frontiers.

Doris Allhutter, Astrid Mager, Florian Cech, Fabian Fischer, and Gabriel Grill. 2020b. *Der AMS Algorithmus - Eine Soziotechnische Analyse des Arbeitsmarktchancen-Assistenz-Systems (AMAS).* Technical Report. Wien: ÖAW, ITA 2020-02. http://epub.oeaw.ac.at/?arp=0x003bfdf3/

Sally-Anne Barnes, Sally Wright, P Irving, and I Deganis. 2015. Identification of latest trends and current developments in methods to profile jobseekers in European public employment services: final report. *Directorate-General for Employment, Social Affairs and Inclusion, European Commission, Brussels* (2015).

Randall Davis, Howard Shrobe, and Peter Szolovits. 1993. What Is a Knowledge Representation? *AI Magazine* 14, 1 (March 1993), 17–17. https://doi.org/10.1609/aimag.v14i1.1029 Number: 1.

Sam Desiere, Kristine Langenbucher, and Ludo Struyven. 2018. Profiling tools for early identification of jobseekers who need extra support. Policy Brief on Activation Policies. http://www.oecd.org/employment/activation.htm,

Sam Desiere, Kristine Langenbucher, and Ludo Struyven. 2019. Statistical profiling in public employment services: An international comparison. (Feb. 2019). https://doi.org/10.1787/b5e5f16e-en Publisher: OECD.

Sam Desiere and Ludo Struyven. 2021. Using Artificial Intelligence to classify Jobseekers: The Accuracy-Equity Trade-off. *Journal of Social Policy* 50, 2 (April 2021), 367–385. https://doi.org/10.1017/S0047279420000203

Epicenter. 2020. Warum der polnische "Ams"-Algorithmus gescheitert ist. https://epicenter.works/content/warum-der-polnische-ams-algorithmus-gescheitert-ist Accessed on 16 Aug. 2021.

Niklas Jędrzej, Karolina Sztandar-Sztanderska, and Katarzyna Szymielewicz. 2015. Profiling the Unemployed in Poland: Social and Political Implications of Algorithmic Decision Making. (Oct. 2015). https://panoptykon.org/sites/default/files/leadimage-biblioteka/panoptykon_profiling_report_final.pdf

Nicolas Kayser-Bril. 2019. Austria's employment agency rolls out discriminatory algorithm, sees no problem. AlgorithmWatch. https://algorithmwatch.org/en/austrias-employment-agency-ams-rolls-out-discriminatory-algorithm/ Accessed on 16 Aug. 2021.

Jon Kleinberg, Jens Ludwig, Sendhil Mullainathan, and Cass R Sunstein. 2018. Discrimination in the Age of Algorithms. *Journal of Legal Analysis* 10 (Dec. 2018), 113–174. https://doi.org/10.1093/jla/laz001

Jedrzej Niklas. 2019. Poland: Government to scrap controversial unemployment scoring system. AlgorithmWatch. https://algorithmwatch.org/en/poland-government-to-scrap-controversial-unemployment-scoring-system/ Accessed on 16 Aug. 2021.

Karolina Sztandar-Sztanderska, Michał Kotnarowski, and Marianna Zieleńska. 2021. Czy Algorytmy Wprowadzają w Błąd? Metaanaliza Algorytmu Stosowanego Do Profilowania Bezrobotnych w Polsce. *Studia Socjologiczne* 1 (2021), 89–116. Issue 240.

Martijn A Wijnhoven and Harriët Havinga. 2014. The Work Profiler: A digital instrument for selection and diagnosis of the unemployed. *Local Economy* 29, 6-7 (2014), 740–749. https://doi.org/10.1177/0269094214545045

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