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Some Advice for Psychologists Who Want to Work With Computer Scientists on Big Data

Cornelius J. König
Saarland University, Saarbrücken, Germany, ckoenig@mx.uni-saarland.de

Andrew M. Demetriou
Delft University of Technology, Delft, The Netherlands, andrew.m.demetriou@gmail.com

Philipp Glock
PRECIRE Technologies GmbH, Aachen, Germany, philipp.glock@precire.com

Annemarie M. F. Hiemstra
Erasmus University Rotterdam, The Netherlands, hiemstra@essb.eur.nl

Dragos Iliescu
University of Bucharest, Romania, dragos.iliescu@fpse.unibuc.ro

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Authors
Cornelius J. König, Andrew M. Demetriou, Philipp Glock, Annemarie M. F. Hiemstra, Dragos Iliescu, Camelia Ionescu, Markus Langer, Cynthia C. S. Liem, Anja Linnenbürger, Rudolf Siegel, and Ilias Vartholomaios

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Some Advice for Psychologists Who Want to Work With Computer Scientists on Big Data

Cornelius J. König[1], Andrew M. Demetriou[2], Philipp Glock[3], Annemarie M. F. Hiemstra[4], Dragos Iliescu[5], Camelia Ionescu[6], Markus Langer[1], Cynthia C. S. Liem[2], Anja Linnenbürger[3], Rudolf Siegel[1], and Ilias Vartholomaios[7]

1. Saarland University, Saarbrücken, Germany
2. Delft University of Technology, Delft, The Netherlands
3. PRECIRE Technologies GmbH, Aachen, Germany
4. Erasmus University, Rotterdam, The Netherlands
5. University of Bucharest, Romania
6. TestCentral, Bucharest, Romania
7. Owiwi, Athens, Greece

ABSTRACT

This article is based on conversations from the project "Big Data in Psychological Assessment" (BDPA) funded by the European Union, which was initiated because of the advances in data science and artificial intelligence that offer tremendous opportunities for personnel assessment practice in handling and interpreting this kind of data. We argue that psychologists and computer scientists can benefit from interdisciplinary collaboration. This article aims to inform psychologists who are interested in working with computer scientists about the potentials of interdisciplinary collaboration, as well as the challenges such as differing terminologies, foci of interest, data quality standards, approaches to data analyses, and diverging publication practices. Finally, we provide recommendations preparing psychologists who want to engage in collaborations with computer scientists. We argue that psychologists should proactively approach computer scientists, learn computer scientific fundamentals, appreciate that research interests are likely to converge, and prepare novice psychologists for a data-oriented scientific future.

KEYWORDS

personnel assessment, computer science, artificial intelligence, interdisciplinarity

With digitized information and communication becoming more commonplace, massive amounts of unstructured data from a variety of data sources (Big Data) have become available, challenging the traditional ways of assessing personnel (Oswald, Behrend, Putka, & Sinar, 2020). In the computer science domain, techniques for making sense of big data have been developed and are sometimes referred to as "data science." Key techniques employ machine learning and broader artificial intelligence techniques, which seek to find pattern and relationships in datasets through utilizing mathematics and statistics. In personnel assessment, novel data collection tools such as sensors (e.g., cameras, wearables) require a deeper understanding of how the data collection methods work, what kind of data structure emerges, and how to handle this data (see, e.g., Landers, 2019). Some specific examples from research on personnel selection and assessment cover automatic analyses of accomplishment records (Campion, Campion, Campion, & Reider, 2016), attempts to use big data approaches to automatize talent management decisions (cf., Campion, Campion, & Campion, 2018), and highly automated conduction and evaluation of telephone and video interviews (cf. Langer, König, & Hemsing, 2020). In all of this, there lies a vast untapped potential for psychologists and computer scientists, as we claim that both sides can benefit from interdisciplinary cooperation.

Until recently, however, psychology and data-driven computer science efforts run mostly parallel but not intertwined, therefore interdisciplinary potentials remain untapped. Specifically, psychologists seem to not have a

Corresponding author:
Cornelius J. König
Universität des Saarlandes, AE Arbeits- und Organisationspsychologie, Campus A1 3, D-66123 Saarbrücken, Germany
Email: ckoenig@mx.uni-saarland.de

strong tradition of collaborating with computer scientists and vice versa (Chamorro-Premuzic, Akhtar, Winsborough, & Sherman, 2017). Thus, the goal of this article is to offer guidance for psychologists who want to delve into the field of data science and work with computer scientists by explaining the differences between both fields and highlighting their similarities. Although our main audience are researchers with a psychological background, many of the described challenges should also be relevant for computer scientists, data scientists, and practitioners from both fields.

This article is mainly based on our experience in working together in a project called "Big Data in Psychological Assessment" (BDPA). It was funded by the European Union and brought together psychologists and computer scientists from both academia and practice, from different countries. In addition, most of the authors have worked on interdisciplinary projects (see, e.g., Gebhard et al., 2019) and on connecting the worlds of psychology and machine learning (see Liem et al., 2018). Wherever possible, we cite relevant research to show that the contents of this article are more than anecdotes. Up front, we must highlight a caveat: our potential overgeneralization throughout this article, as our attempts to accessibly describe mean differences between computer scientists and psychologists ignore the large amount of within-group variance.

Why Should You Be Interested in Collaborating With Computer Scientists?

First, computer science has developed exciting new processes and tools that can be used to generate and gather data. For example, web scraping allows for efficient gathering of a vast amount of online data about a large variety of people from around the world (Landers, Brusso, Cavanaugh, & Collmus, 2016). Sensors in wearables and smartphones allow unobtrusive collection of large scale longitudinal and behavioral data (cf. Langer, Schmid Mast, Meyer, Maass, & König, 2019). An important advantage is that these approaches can augment self-reports, helping to overcome common methodological issues (e.g., common method bias and social desirable responding) and thus increasing ecological validity of findings (cf. Youyou, Kosinski, & Stillwell, 2015). However, these computer scientific processes and tools have their own challenges regarding data collection, management, and analysis. Computer scientists are much more accustomed to working with large stores of unstructured data from different sources, whereas psychologists might initially start to think about hiring an army of students to manually structure given data by traditional means.

Second, this new kind of data analyzed by computer scientists can be a playing field for testing psychological theories. For example, Levashina and Campion offered their faking in interviews theory in 2006 and built it primarily on paper-and-pencil self-report data. Novel data gathering opportunities now allow the analysis of faking behavior with video and audio data collection methods, and thus enable behavior-based testing of their theoretical arguments. For instance, this allows for testing of dynamic impression management assumptions such as that ingratiation from applicants affects interviewers' behavior (Langer, König, & Scheuss, 2019).

Third, and most important, the benefits of interdisciplinary work will be mutual for psychology and for computer science. In particular, computer scientists have already attempted contributions to fields that have been typical areas of psychology, for example personality trait identification (e.g., Gupta & Chatterjee, 2013), the diagnosis of mental disorders (e.g., Liu et al., 2015), and even personnel selection (e.g., Chen, Cheng, & Hung, 2016). Data-driven domains in computer science, including many applied artificial intelligence/machine learning domains, might profit from psychology's rich tradition of conducting carefully designed studies with human subjects, and psychologists' focus on reliable and valid data gathering methods, therefore giving opportunities for stronger empirical scientific foundations and better data quality (e.g., Lipton & Steinhardt, 2019). Furthermore, psychologists have studied biases and fairness issues in a variety of settings for decades (e.g., in the personnel decision-making process, see for instance Harvey, 1938), which is a current and highly relevant topic for computer scientists (e.g., Olteanu, Castillo, Diaz, & Kıcıman, 2019). For psychologists, potentials unfold when employing novel data gathering tools, cleaning unstructured data from various sources for further analyses, and using alternative data analysis approaches that are still uncommon within psychological practice and research (e.g., decision trees, and deep learning approaches).

Common Challenges When Psychologists Collaborate With Computer Scientists

Terminologies

Both disciplines have their own language. In particular, people new to the field of computer science (i.e., psychologists) might carelessly use current buzzwords interchangeably—like *algorithms*, *artificial intelligence*, and *machine learning*—without understanding the differences between them (but see Liem et al., 2018, for an explanation). At the same time, important concepts in psychological measurement, such as reliability and validity, may be taught as part of methodology courses in computer science but do not form a core part of computer science curricula. Thus, asking your computer science colleagues for construct validity evidence for a particular variable or for an estimate of its retest reliability might result in blank faces. As a consequence, psychologists may need to educate their computer science collaborators on psychometrical concepts and at the same time to broaden their own understanding of data scientific concepts (e.g., sensitivity and specificity of classification decisions in confusion matrices).

Foci of interest

Another challenge is that the work of computer scientists and of psychologists have different foci: Whereas psychologists are predominantly interested in explaining a phenomenon (e.g., faking in personnel selection situations), computer scientists in data-driven research are typically interested in achieving high prediction accuracies for relevant outcomes (see Shmueli, 2010, and Yarkoni & Westfall, 2017). This difference in focus has important implications. For example, many studies of psychologists are about single or multiple mediators (or even moderated mediation), or try to assess the relative importance of well-known and validated predictors, hoping that this explains psychological mechanisms. Computer scientists, however, care about prediction accuracy regardless of whether there are tens, hundreds or even millions of variables in a prediction model of which many might not be interpretable by humans. Although including these variables may improve a model's accuracy, it also makes understanding such models difficult for humans and may not lead to insights about *why* one model performs better than another. The difference in focus also implies that computer scientists try to find efficient ways of predicting an outcome by flexibly choosing different kinds of algorithms, comparing their performance and efficiency, and exploring which one offers the best prediction accuracy without putting too much effort in trying to keep the relations between inputs and outputs explainable (but see recent developments in the area of explainable artificial intelligent where increasing explainability is the goal; Ribeiro, Sing, & Guestrin, 2016).

Consequently, when the main focus is on prediction accuracy, it matters less whether an algorithmic model and the "why" behind its outcomes are explainable or not, because there seems to be a trade-off between explainability and predictive accuracy (Rudin, 2019). Deep neural networks, for instance, develop their internal structure from input data, and this structure might not even be accessible or too complex for our limited human cognition. Alternatively, if more explainable algorithms (e.g., decision-tree based algorithms; Guidotti, Monreale, Ruggieri, Turini, Giannotti, & Pedreschi, 2018) are used, such algorithms might only achieve predictive accuracy comparable to deep neural networks when the input data and internal relations within the algorithms grow to a level of complexity that is also not accessible to human processing (Lipton & Steinhardt, 2019). In contrast, psychologists would probably sacrifice prediction accuracy (i.e., less explained variance) for including only predictors that matter theoretically and that they can readily interpret for having an algorithm that relates predictor variables and outcomes in an optimal way.

Data collection and analysis

Both disciplines have different research traditions with varying kinds of data. Computer scientists use large, noisy, multimodal, and high-dimensional field data. "Large" can mean terabytes of data and millions of measurements; noise can be due to various sources of errors that naturally occur in field data (e.g., scraped data from Twitter, and physical noise of sensors); multimodal can mean that relevant information is encoded in various modalities, for instance as a mixture of visual and audio material. Commonly, this kind of data is of very high dimensionality too—each measurement relates to a low-level observation (e.g., image content is encoded as pixel intensities, and audio content is encoded as dynamic intensities over time, as captured by a microphone). Often, the data involve time series, especially if video or audio is involved, which yet again increases the dimensionality of an observation (e.g., if an audio signal is recorded at 44.1 kHz, that means that 44,100 intensity values are recorded per second, so 30 seconds of audio would yield 1.3 million consecutive intensity values). Thus, a classical validation study of a psychological questionnaire with five scores per 200 participants, two control variables (e.g., two other selection procedures), and one outcome variable (e.g., supervisors' performance ratings) will look unusual to computer scientists, whose datasets may include data from thousands of people from various data sources and with multiple observations per person.

Furthermore, computer scientists might have a different mindset regarding quality dimensions of input and output variables. For example, the "ChaLearn Looking at People 2016 First Impressions" challenge, where teams competed to predict hirability and personality from videos, used YouTube self-presentation videos (Ponce-López et al., 2016). These videos were then rated by crowd-sourced workers after watching these videos using single-item hirability and single-item personality ratings. Psychologists would likely have wished to analyze videos of real (or at least hypothetical) applicants answering standardized interview questions. Furthermore, psychologists probably would have preferred that the crowd workers assessed constructs such as hirability and personality with multiple items. This contrasts the data generation step of computer scientists and psychologists. Where computer scientists will try to generate data and insights out of already existing material, psychologists will try to optimize data quality by generating their pool of data, often within laboratory studies, that will naturally include less data than what already exists online.

Not only are large data sets necessary for using certain data scientific approaches, large data sets are also important because computer scientists prefer to evaluate their solutions by comparing a training sample to a hold-out (test) sample (see Yarkoni & Westfall, 2017). This means that data are divided into two (or more) parts, with one being used as the training sample (on which the parameters of the algorithm may be tuned) and the others being used to validate the algorithm (Putka, Beatty, & Reeder, 2018). Whether such tests with hold-out samples are an appropriate strategy to validate solutions is, by the way, a different question. This might be an inappropriate strategy because both samples are automatically fairly similar to each other but not necessarily representative for future (potential) applications of a resulting algorithm. For example, if data in the training and the hold-out sample always include videos only from a specific angle, changing the angle for another application might heavily affect prediction accuracy. At the same time, psychology's current replication crisis (e.g., Shrout & Rodgers, 2018) indicates that psychology is not good at producing generalizable results either and that overfitting (in the language of computer scientists) is prevalent within psychology (Putka et al., 2018).

Finally, psychologists interested in collaborating with computer scientists should realize that data requirements for further analyses may differ. For instance, when using video data, psychologists will be interested in observable behavior to meaningfully assess a given psychological construct. Requirements for the data then cover eliciting relevant behavior in a standardized way and creating the conditions to assess it (e.g., sufficient sound, person facing camera). Computer scientists may have different requirements for video data to be able to analyze them, such as similarity between the single videos in terms of the number of pixels in a frame, the positioning of the camera, lighting conditions, the contrast of the person and the background, and the signal-to-noise ratio. Moreover, psychologists should be aware of the many, many steps that are necessary to turn such large, noisy, multidimensional, and time-series data into a usable data set; many data science practitioners spend most of their time pre-processing data, whereas applying different algorithms to the data only requires a small share of the daily work.

Publication styles

Computer scientists and psychologists have different publications styles. Whereas researchers from psychology try to publish in high-impact journals, computer science researchers are rather focused on publishing in the proceedings of high-impact conferences (e.g., Vrettas & Sanderson, 2015). This has two important implications. First, a collaborative project between computer scientists and psychologists might lead to a publication that only counts for one side. In particular, evaluators of the performance of academic psychologists might likely ignore conference proceedings, whereas evaluators of the performance of academic computer scientists might likely not give much weight to a journal publication. Thus, collaborators should try to reach compromises. Alternatively, it might also be possible that the same data collection effort leads to one publication in computer science conference proceedings where the focus is to describe the algorithm engineering process and to one publication in a psychological journal with a focus on describing the psychological processes that are involved, although researchers are well-advised to openly communicate such double use of data.

Second, publication style differences lead to important differences in publishing tradition. Contributions to proceedings are often shorter in length (with full papers frequently being restricted to a maximum of 8–10 double-column pages) and have faster review processes (with most reviews being available after ~3 months). Author response opportunities ("rebuttals") are also limited: If available, the response window for authors typically is no longer than a working week, and the rebuttal response will be restricted to giving clarifications in response to reviewer comments within a given word/page limit but not by revising the paper itself. Furthermore, conferences have regular deadlines, making deadline rushes (i.e., intense and long working hours before the end of the deadline; König & Kleinmann, 2005), a phenomenon that seems to be more common in computer science than in psychology. All of this makes the publishing process in computer science faster than in psychology, where papers might, for instance, be rejected after a second revision and 18 months. Furthermore, authors in computer science are considerably more likely to be employed outside academia.

Last, computer scientists are used to publishing their preprints on arXiv, which is a large platform to upload your preprints (e.g., 13.302 new preprints only in November 2019). ArXiv preprints are discoverable and citable. This tendency of uploading preprints reflects the interest of computer scientists to show it was them who had a particular idea first. At the same time, the quality of the content of the preprints can be questionable, as uploaded content is not guaranteed to have gone through internal or external peer review processes. Recently, PsyArXiv has started to become a kind of counterpart of arXiv for psychologists. Although the submission rate to PsyArXiv is far lower than its big brother, preprints on PsyArXiv are increasingly used to gather feedback prior to formal submissions to journals. Although getting friendly reviews on those preprints prior to submissions is a great idea, preprint articles should be handled cautiously—advice that should be pronounced for novice researchers in psychology and computer science.

Differences in tools used for work

Psychologists interested in working together with computer scientists should be open to learning LaTeX as a tool to typeset articles. Unlike Microsoft's Word, LaTeX is not a WYSIWYG software (What You See Is What You Get). This means that within LaTeX, authors write plain text and annotate it with small commands (much like in an easy programming language). Scientists who would like to write collaboratively can use online LaTeX editors such as Overleaf. LaTeX makes writing equations and typesetting easy and is the standard in most computer scientific publication and working cultures. For example, most computer science conferences require submissions formatted with their own LaTeX templates. Note, however, that there is empirical research from psychology showing that using LaTeX can slow down users (Knauff & Nejasmic, 2014).

Furthermore, psychologists should prepare themselves that computer scientists do not work with SPSS. It certainly helps to be familiar with R or Python as these languages and many of their associated tools are open source, incorporate better ways to handle large scale unstructured data (especially Python), and offer more convenient and reproducible ways of sharing algorithms as well as a very engaged community where users help each other on platforms such as StackOverflow. Adapting this behavior of making research efforts more transparent might be one of the most fruitful inspirations that psychologists can get from computer scientists.

Gender imbalance

A final comment on potential challenges when working together with computer scientists concerns gender distribution in the two fields. Computer science, including its data-driven subdisciplines, continues to be dominated by men, and the male dominance seems to be particularly strong in this field (Berman & Bourne, 2015; Holman, Stuart-Fox, & Hauser, 2018). In contrast, industrial and organizational psychology is fairly gender balanced (König, Fell, Kellnhofer, & Schui, 2015). We are not sure what the implications of this fact are, but it is likely something of which one should be aware.

Similarities Between Computer Scientists and Psychologists

Despite the challenges that might occur when computer scientists and psychologists collaborate, there are also important similarities. First and foremost, our own experience tells us that both areas are fairly pragmatic. "Sure, one could dream about better datasets, but let's start working anyway"—such an approach seems to be easily acceptable for both. Second, data play a major role for both disciplines. Third, most psychologists and computer scientists will share a preference for field data. Fourth, both fields are distant enough from each other that it is fairly simple to acknowledge that one does not know exactly what the other does and is able to do. This is in contrast to other fields that might try to reduce psychological phenomena to questions to more basic levels (e.g., biological processes). Finally, both research traditions often try to answer similar research questions when studying human behavior. By trying to answer these questions, psychologists and computer scientists often times stumble upon similar challenges (e.g., fairness issues and data quality issues) and research questions that need to be addressed in an empirical way. This is where both research traditions can help each other to overcome issues that the respective other discipline has stumbled upon years ago.

Implications: What Can You Do?

Be creative

Our first advice is to be creative: Computer scientific methods may offer you new and innovative ways to develop your research further. Think about how your research questions may be answered by using big data or alternative statistical models (e.g., using machine learning techniques) to analyze your data.

Talk

Our second advice is to talk to colleagues from computer science. They might be surprised that you approach them, but this direct approach might be the easiest way to get in contact. Understand that you may use different words as they do but still mean similar things, and in our experience, you will find them welcoming.

Learn

Our third advice is to make a step towards computer scientists and their perspective. Try to learn the basics of a programming languages such as Python (or at least R). Get a feeling of what basic programming is already able to offer and what kind of questions might require more effort (or collaboration with computer/data scientists). Furthermore, try to learn the basic concepts and terminology common within computer science and how these relate to and/or contrast psychological concepts (e.g., "ground truth" can be considered a type of criterion; see Liem et al., 2018, for an overview).

Sell

You might not be the only person who wants to collaborate with people from the computer science department. Do not approach them with ideas such as "hey we have an idea for an app and need someone with programming skills." Rather, approach them with interesting research questions where there is potential to achieve even better research results through interdisciplinary collaboration.

Prepare

This advice addresses those who teach personnel assessment at psychology or business schools: Prepare the future generation of assessment specialists for the advancement of computer science and/or machine learning and artificial intelligence. Although predicting the future is difficult, it is probably not far fetched to say that the field of personnel selection will be influenced by developments within computer science rather more than less in the future. If we want our students to understand these developments, if we want to make them interested in data science, if we want to foster research capitalizing on the collaboration between psychology and computer science, they need to have at least a basic understanding of it. Enabling this has been the goal of the project Big Data in Psychological Assessment (BDPA), and its funding by the European Union has allowed the authors of this article to develop various teaching materials regarding exactly the topic of providing a basic understanding of data science. These materials are free to use and downloadable from their Open Science Framework webpage https://osf.io/v6rn4/.

Conclusion

Computer scientific approaches might spark innovation and creativity in the field of personnel assessment. In fact, data scientific approaches (in laypeople's language often referred to algorithms and artificial intelligence) already support decisions in daily work in human resource departments (Oswald et al., 2020). Psychologists interested in assessment should get involved into this development, collaborate with computer scientists, and educate themselves and their future generations in order to be ready to shape the computer scientific future in personnel assessment.

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