

ARTIFICIAL INTELLIGENCE IN HUMAN RESOURCE MANAGEMENT

Abstract

A kind of gap exists between the reality and promises of AI in the field of Human Resource Management and also it gives suggestions related to the progress which can be made for further improvements. Four challenges have been identified in HR practices while using the techniques of HR practices:

- Restrictions which are been imposed by small type of data sets
- Employee reaction to management via data based algorithms
- Complexity of HR phenomena
- Questions ethically related with the constraints of fairness and legal constraints

We suggest practical solutions to these issues, focusing on the over lying three concepts – randomization, cognitive kind of reasoning and formalization of process which might prove efficient economically and appropriate socially for applying data analytics in the process of staff administration.

Keywords: Artificial Intelligence, Human Resource Management, Machine Learning, Data Management

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I. INTRODUCTION

The rate at which business jargon shifted from BD i.e Big Data to ML i.e. Machine Learning to AI i.e. artificial intelligence is astounding. There exists a tie between reality and orotundity, on the other hand, it shows a kind of different issue. Many of the businesses are failing while making any headway in developing capabilities of data analytics: forty-one percent of CEOs on the ground think that they are nowhere equipped to employ the new technology of data analytics, while only four percent claims that they are prepared to large extent.

Unoriginally, the term "AI" leads to a large technological category which enables the computer-system to execute responsibilities which would ordinarily need the intellect of humans, such as capacity of making decisions. The approach we are having is more focused, concentrating towards the subclass of AI systems that depends primarily upon the enhanced availability of data for the task which is predictable. Over the last few years, there exists significant developments related to the fields of recognition of patterns and NLP i.e natural language processing as well. Deep learning with neural networks has grown more frequent in some data-rich environments, bringing us closer to real AI, which reflects robots' ability to emulate versatile human decision making. Nonetheless, few firms have even entered the big data stage in terms of staff management, where they ensure the delivery of more sophisticated judgments which are expressed loudly and consistently. Only 22% of organizations believe they have implemented analytics in HR i.e. Human Resources (LinkedIn 2018), and it is unclear how advanced the analytics are in those firms.

On the contrary, the data analytics potential is visible more in industries like marketing segment. While there are several issues to be addressed, they are differentiated just with the clarity, as of conjectures towards the customers who will buy the products and the kind of amendments in its presentation effects the sales of such kind. The quantity of an notations like product sales of various specific kinds over time throughout the nation, for example - is quite huge as per the use of big data approaches viable. No doubt marketing is not very much ethical dilemmas, the premises that businesses need to aim for offering more of their products are accepted extensively, as is the impression that businesses will try to persuade more and more consumers to buy the product.

AI can be used effectively to human resource issues which comprises of lots of hurdles. They rely ranging from the practicality to the conceptual task, which involves the datum that the kind of analysis data science uses when applied to people have very severe kind of illogicalities because of the criteria that humanities usually ponder relevantly for making any kind of judgments which are meaningful in consideration to individuals. Following points can be considered for the same:

1. On certain kind of complexities of HR like what constitutes a "good employee." Such kind of a "good employee." That edifice has numerous magnitudes and gauging it precisely for most jobs is difficult
2. The complexities of HR outcomes is one of the main issue like the thing which constitutes a "good employee." Gauging the numerous magnitudes of edifice precisely is difficult for most of the jobs. Validity and reliability issues are the issues due to which most extensively used performance assessment ratings, metric has been challenged

heavily. Also many employers are biased and are abandoning them entirely. It is difficult to separate the collective and individual performance as other tasks are linked with decently complex jobs. (pfeffer and Sutton 2006).

3. By data science standards, data sets of human resources are typically fairly tiny. Transaction made by its clients were compared and it was observed that even a huge corporation may have small staff. Furthermore, rare observations were made from many interesting outcomes like people being fired for poor performance. Data science tools performed badly when somewhat infrequent occurrences were forecasted.
4. As such important ramifications for society and individuals have been made by the consequences of human resource choices (like who gets hired or fired), fairness concerns – in terms of distribution and procedure – take precedence. Companies way of selection have been limited by extensive legislative frameworks.
5. A variety of complex socio-psychological issues shared by staff members have influenced the decisions of employment, like apparent justice, relational and legal expectations and personal worth and status, organizational and individual outcomes are also influenced by all of them. As a consequence, Justifying and explaining one's activities is far more crucial than in others disciplines

Determining who to recruit to show these concerns has imagined the implementation of an algorithm. In such cases as in customary, an algorithm that depends upon the characteristics of workers and their performance at work in the current staff has been generated because of the use of algorithm from machine learning. Even if a casual relationship between job and sex performance could be shown, an algorithm that says to hire more white men as performance of job may be a biased indicator can be distrusted, distortion of present staff could be done on the characteristics how we hired them in the past(e.g., hiring of few women), and significant problems would be created for us by acting on it.

If algorithm is instead based on a more objective criterion, like fired for a bad performance, to justify the development of an effective algorithm, the number of such examples in a normal organization is far too tiny. Furthermore, if the substance of hiring algorithm is learnt by applicants, their behaviors are likely different in interviews, algorithm is rendered to useless. Most of the applicants, for example, answer of the question is already known “what is your worst characteristic” contributing the non-negative attribute “I work too hard.”

It is also believed that as a decision-making process, randomization can also be valuable (as to its challenges and apparent fairness may face in reaching legitimate and fair conclusions). Points are based on view on encounters with practitioners and knowledge of current practice, in the year 2018, a workshop was held and from 20 major US firms, leaders of workforce analytics functions and data science faculty were brought together.

II. THE AI LIFE CYCLE:

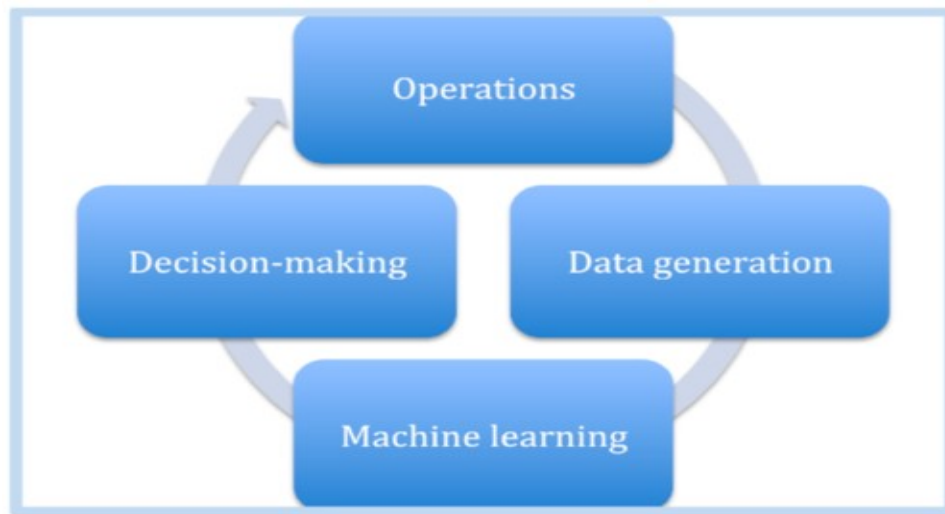


Figure 1: AI Life Cycle: Operations, Data Generation, Machine Learning, and Decision-Making.

III. OPERATIONS

Such as how a company employs staff, occurrence of interest has been described. HR performs so many activities that entail so much money, it is one of the explanations for the interest in using data science tools to HR. US economy's approximately 60% of all spending is on labour. In the service industry, the figure is substantially greater. The following are the most typical human resource operations, along with the accompanying workforce analytic tasks of prediction:

The term "machine learning" (ML) refers to a varied range of approaches that may modify and acquire knowledge through the data to construct algorithms which do more effectively, efficiently at a task, generally forecast. Machine learning algorithms in commercial situations has been primarily used and has been "supervised" uses, in which a machine learning algorithm has been established by the data scientist, decides a suitable metrics for evaluating the algorithm's precision, and prepares the algorithm via its training specimen. A number of the finest and most popular forecasting algorithms, like random forest and logistic regression, derive predicted inconsistent that is important through the numerical connections between the data that has been observed. Preliminary model's accuracy on the criterion of sample until it reaches the level of satisfaction. On the experimental sample, the last version of the model is run, sample is serving as the ultimate assessment of the models quantity along the accuracy if the predictions on this sample.

Such algorithms vary significantly with typical methodologies employed in human resources. In the subject of workplace psychology, which has traditionally concentrated on the decisions which are related human resource, and its hiring for example, might examine various descriptive hypotheses on the relationship between job performance and individual predictors. The investigator selects the variables and hypothesis to investigate. The technique

generates employing insights such as a test at a time, such as association among character assessment works, scores efficiency, and the relationship between job success and education in another exercise, and moves on.

Human Resource Operations	Tasks Of Predictions
Electing –discovering potential prospects also convincing them to relate	Do we attract qualified aspirant?
Selecting –deciding who must be offered jobs	Do we hire people who prove to be the better worker?
Enrollment -introducing a new worker in a company	What techniques help new hired workers become more fast and useful?
Preparation	Which measures are appropriate with regard to people, and do they increase productivity?
Performance management –recognizing both excellent and terrible conduct	Do our habits lead to better work efficiency?
Advancement –deciding who will be elevated	Can we forecast individuals who can excel in new responsibilities?
Retention	May we forecast who will move on and regulate the degree of maintenance?
Benefits of Employees	Determination of the benefits which are most important to employees in order to know what to propose when there are options and what to propose them and what are the implications of that benefits?

On the other hand, machine learning developed a single algorithm that takes into account large amount of factor. The theoretical literature linked with the topic may not contain variables, the examiner s even not investigating the relationship between any the outcome being predicted and any one variable or is not hypothesizing. Indeed, exploration of non-traditional aspects is one of the appeals of machine learning as rather than advance the theory of the subject on which the researcher is based by presenting evidence on specific idea, the goal is to create a better forecast.

IV. ADDRESSING AI CHALLENGES IN HR

A Step at a time, this part delves into the four broad hurdles to AI stated in the Introduction: the complexity of HR phenomena, tiny data sets, ethical and regulatory limits, and employee attitudes to AI-management. To make these issues more manageable, we describe them in the context of the specific stages of the AI Life Cycle when they are most important. .

V. GENERATION OF DATA

In terms of data, not all aspects of HR actions are measured; not all operational details leave digital traces that can be collected; and not all traces left can be captured. Operations Data creation Machine learning Decision-making 9 is extracted and converted to a useful format at a low cost. Employers, for example, may not trace the ways through which

applicants contact them, such as referrals vs. visiting our website vs. job sites, and so on. Most firms collect a limited quantity of data on candidates and do not keep it for those who are screened out. These options limit the types of analyses that can be run and the conclusions that can be reached.

Employers might benefit from lessons learned in domains such as performance management when confronting the difficulty of data generation:

- Compile data from numerous perspectives and across time. Digital HR technologies, for example, provide speedy real-time reviews among colleagues utilizing mobile devices.
- Perfect performance measures do not exist, therefore do not expect them. It is preferable to select reasonable measurements and stick with them in order to observe trends and changes in outcomes rather than fiddle with systems in order to get the perfect measure.
- Integrate HR data with business and financial data from the company to examine the implications of HR practices and outcomes on business unit performance.

As per the database concerns, analyzing a topic in HR for the first time can be costly. As a result, data analytics managers must be cautious about where to "place bets" when combining data for analysis, let alone when gathering fresh data. How do managers choose which HR questions to explore, especially since so few have been investigated previously? The final step in determining what to analyze is an audit of what data is required to answer the research question and how difficult it is to collect. For example, if an organization wants to apply a machine-learning algorithm in hiring, it must have previous data on unsuccessful job candidates, which many employers do not keep. Because the data are not available, it may be impossible to answer critical issues that data science is well-suited to answering.

VI. SMALL DATA

As it is a critical issue for human resource analytics. Because they do not have a large workforce, most firms do not hire enough people, nor do they conduct enough performance reviews or collect enough additional data points for their current workforce to deploy machine learning techniques. According to the machine learning literature, having access to more data provides significant advantages in terms of predicting accuracy. (Fortuny, Martens, and Provost 2014).

When a formal procedure reveals significant disputes about causal elements, one approach would be to generate extra data via randomized experiments to verify causal assumptions. Google became recognized for conducting studies on a wide range of HR phenomena, from the best number of interviews per job candidate to the optimal size of the cafeteria meal plate. If talks, trials, and leadership persuasion do not result in a reasonable consensus on the causal model that yields the desired outcome, AI-analyses are likely to be unproductive and should be avoided until more or better evidence is available.

Employee Reactions to Data Collection Efforts: All HR analytical efforts should be concerned with the possibility that employees may skew their responses and the data in accordance with their perceptions of how the data will be used. As a result, there is a need for

alternate data sources that can be considered to be more reliable. This information is used in hiring decisions and in determining "flight risk" or retention issues. 14 Banks have long examined email data for indications of fraudulent behavior and are subject to stricter laws demanding control of workers. They are already using it to find further issues as well. For instance, the occurrence of words like "harassment" in email traffic may lead to the opening of an internal investigation to identify issues at work.

The greatest predictors, according to some of the companies at our workshop, did not come from traditional psychology-based discoveries but rather from data sources like social media. These companies indicated that they had developed models for predicting flight risk. Many employers believed that their own use of social media violated moral principles; others believed that using employee-related data was acceptable as long as it was anonymized but that using natural language algorithms to track sentiment in email messages was unethical.

Utilizing "authentic" data from email or social media traffic presents a practical challenge because it is unclear just how "authentic" the data actually is. It is undoubtedly true that people do not always craft their social media posts with the intention of influencing employers, but few people would assume that those posts are always sincere. They are often created to present a person in a way that is different from how they actually are: postings about vacation cruises outweigh ones about doing the laundry, despite the fact that most of us spend much more time on the latter.

VII. MACHINE LEARNING STAGE

It's possible that a machine learning (ML) algorithm will perform better than any other hiring algorithm an organization has used in the past. The fact that the majority of the predictors recommended in that research, such as personality and IQ scores, predict job performance so poorly (a typical validity coefficient of .30, for example, translates to explaining nine percent of the variance in performance), creates a significant opportunity for data analytics to perform better. This is a reasonable criticism of prior research in human resources. It will as its objective is to just predict and it is not constrained to a narrow set of singular results, as with a personality test.

As was already mentioned, it can be difficult to find good data to create an algorithm with. The vendor community frequently takes the approach of developing an algorithm based on the characteristics of a client firm's "best performers," as they are simpler to find, because clients rarely have data on employee performance in which they feel confident. After that, applications are evaluated using that algorithm. Take the vendor, for instance, who assists clients in conducting video interviews. Controversial algorithms built using the facial expressions seen in those videos are now a part of its offering. Job prospects are evaluated based on how closely their expressions resemble those of the algorithms, which are trained on data from high achievers at the client company.

VIII. DECISION-MAKING STAGE

When decision-makers attempt to use the predictions generated by machine learning, they face three basic obstacles. The first is about fairness and legal considerations, the second is about the algorithm's inexplicability, and the third is about how employees will respond to algorithmic conclusions.

IX. FAIRNESS

There are many issues surrounding fairness in the HR setting. The knowledge that any algorithm is probably going to look backward is one of these. For instance, if historical discrimination is present in the data used to develop a hiring algorithm, the model is likely to favor white men disproportionately. The demographic diversity—or lack thereof—present in the historical data runs the risk of being reproduced by actions utilizing those algorithms. This is a common issue that led to the biased hiring decisions made by Amazon, as previously mentioned. The algorithm was choosing men over women even though sex was not present in the candidate dataset, choosing men over attributes associated with women, such as taking "women's studies" courses.

X. EXPLAIN ABILITY

Explain ability, in this case the degree to which employees comprehend the standards utilized for data-based judgments, is closely tied to the idea of fairness. Even though we may not always agree with its implications, a straightforward seniority decision rule—more senior employees are given preference over less senior ones—is simple to understand and feels impartial. Employees find it far more challenging to comprehend a machine learning algorithm based on a weighted mixture of 10 performance-related parameters, especially when they naturally compare results to one another and are unable to understand the underlying causes of variance. This issue is well known to professors who have to explain to students why their grade differs from that of a buddy who they think submitted a similar response. The complexity of an algorithm increases its accuracy while also making it harder to comprehend and explain.

The Oncology application of IBM Watson is a well-known illustration of the value of explain ability to users. Oncologists expressed strong opposition to this program since it was challenging to comprehend how the system arrived at its conclusions. Due to the lack of transparency, it was challenging for medical professionals to accept and implement the system's suggestions when it differed with the doctor's evaluation. (Bloomberg 2018).

Explain ability is anticipated to become crucial for the effective application of machine learning technologies, particularly in "high stakes" scenarios, such as those that affect people's lives—or their jobs. Due to a flood of government and commercial investment focused on explainable AI, we anticipate significant advancement in this field in the upcoming years. For instance, a large program on explainable artificial intelligence (XAI) has just been begun by the US Defense Advanced Research Projects Agency (DARPA), which is renowned for successfully sponsoring innovative IT research. Deliverables, software toolkits, and computational models are anticipated by 2021.

XI. EMPLOYEE REACTIONS TO ALGORITHMIC DECISIONS

Employee experiences and behavior are unavoidably impacted by changes in formal decision-making of the kind connected with the introduction of algorithms. We may gain a lot from Scientific Management's attempts to create the best decision rules in this area. Human experiments and a priori engineering ideas served as the foundation for employment policies and judgments regarding work structure. Although they may have been far more effective than earlier methods, employees despised them vehemently, which resulted in a period of

unrest and confrontation between workers and management. From the standpoint of front-line employees and their managers, the scenario might have resembled the AI model we present here: decisions would be handed down from another department in the organization, the justification for them would be that they were the most effective that science could offer, understanding the basis of the decision is extremely difficult, and trying to alter them would simply be a mistake.

XII. DISCUSSION AND CONCLUSIONS

The development of specialized AI systems in the fields of healthcare, the automotive industry, social media, advertising, and marketing is moving quickly, even though general-purpose AI is still a long way off in any area of human endeavor. Even on the first stage of the AI road, which is decisions guided by algorithms, there has been much less progress in the area of personnel management. We pinpoint four causes for this: the complexity of HR phenomena, data issues from HR operations, fairness and legal restrictions, and employee responses to AI-management.

The first principle that can be applied to solving these problems at various stages of the AI Life Cycle is causal reasoning. Lack of concepts of causality makes it far more challenging to create the datasets required for analysis because the development of algorithms depends on association rather than causation: we need more data because we are unsure of what to choose. Fairness and explainability difficulties are considerably aided by causal reasoning. While causal reasoning has advantages, there are also disadvantages. In cases when we lack causal models, employers must first accept the higher expenses (resulting from the requirement for more data) and poorer predictive power of algorithms, and they must endeavor to create an agreement over causal assumptions prior to modeling. These difficulties help to explain why the data science community is quite dubious about AI systems that can reason causally.

The second principle that can aid in making decisions using algorithms is randomization. In order to establish causality, randomizing an algorithm's inputs is similar to experimentation. Second, selecting an HR outcome at random based on an algorithm's probability prediction in cases where we are unable to make accurate predictions acknowledges the algorithm's intrinsic inaccuracy and the stochastic character of HR outcomes. Employees may believe that randomization, such as tossing a coin, results in more equitable outcomes when there is ambiguity.

Building sound algorithms also requires formalizing processes. It guarantees that the parties are aware of any assumptions incorporated into algorithms, the costs associated with developing them, and the potential difficulties posed by personnel who are negatively impacted by them. Formalization can facilitate the process rather than impose pressure (Adler and Borys 1996). An key consideration is whether the HR function has to be restructured in order to implement the changes we recommend. Without a doubt, HR leaders must comprehend and support the Data Generation and Machine Learning phases of the AI Life Cycle. An HR Department should be able to quantify its contribution to the bottom line of the company in monetary terms thanks to the integration of HR data with business and financial data.

Line managers will also need to update their skill set. For them, AI should be seen as "augmented intelligence," or the deliberate use of workforce analytics data to decision-making. In order to systematically update managerial ideas with new information, the literature on evidence-based management suggests using a Bayesian method (Barends and Rousseau 2018). We see it as a good starting point for managing AI as well.

The majority of organizational action is impacted by the conflict between the logic of efficiency and that of appropriateness (March and Simon 1993). The need for efficiency and concerns about justice may not always coincide in the HR field. The conceptual and practical insights presented in this study should advance AI-management in HR on both the appropriateness and efficiency fronts.

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