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On the Problem of Human Bias in the Management of the Organization's Personnel

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Abstract. *In recent years, of all the resources involved in the organization in the implementation of production processes or the provision of services, managers have paid more attention to human resources. Experts argue that investing in human capital generates more revenue for companies than even modern technology. Therefore, to achieve optimal efficiency and productivity in today's highly competitive environment, organizations must use effective methods of managing human resources. In the organization's personnel management system, when recruiting personnel, a subjective approach takes place when evaluating the applicant accepted for a vacant workplace in the organization. The aim of this study is to use modern innovative deep learning models to eliminate recruitment manager bias by increasing the flexibility of filtering parameters by implementing an adversarial autocoder. A person's bias in the personnel management process, in particular when hiring managers inadvertently favor candidates who have similar experiences or values to their own, is a recurring issue that businesses often deal with. The hypothesis of the study is that, having studied the personnel management model in the Kazakhstan branch of the audit and consulting company KPMG in Almaty with 25 years of experience with more than 100 employees, it will be possible to more accurately assess the applicant's participant through an adaptable scale factor of various parameters, including career progress, organizational features and potential risks. Deep and adversarial autocoders were evaluated and contrasted with the Naive Bayes reference classifier. The data were pretreated (cleaning, merging, denoising) as well as optimized for the neural network used in deep learning. Metrics derived from the confounding matrix were matched and the results showed that the adversarial autocoder produced better results and that deep learning models tended to be superior in terms of digital prognostic analysis.*

Keywords: *autoencoder, deep and adversarial autoencoders, HR management, recruitment human factors, human bias, deep learning, deep learning engine, predictive modeling, staff potential assessment, KPMG audit firm, KPMG adversarial hiring algorithm.*

Introduction

In today's highly competitive business environment, it is essential for organizations to have effective personnel management strategies in place to ensure maximum efficiency and productivity [1].

However, one of the persistent issues organizations faces is the presence of human bias in the personnel management process [2], particularly where recruiters may unconsciously prefer candidates with similar backgrounds, experiences, or values to their own, creating an unfair and discriminatory workplace for employees [3]. Usually, Human Resource managers are accountable for the efficient organization of the organizational human resources, however, their contribution to the allocation process, in time-series comparison, tends to diminish with the emergence of the digitalized predictive analysis [4].

Research Question: Will the integration of autoencoder deep learning assist in the elimination of human bias at the stage of personnel recruitment?

Research Objectives: Eliminating the human bias in the recruitment process by simultaneously enhancing the flexibility of the filtering parameters through the implementation of the autoencoder.

Research Rationales: The hypothesis for this study assumes that training the model on the experience of 25 years of one organization that has more than a hundred workers will provide a better estimation of the applicant's participant through flexible weighting of the multiple parameters in terms of career progression, idiosyncratic risks of the organization and potential risks.

Research Contributions: This work's contribution is not limited to the adaptation of autoencoder deep learning in the framework of human resource management, it also brings value to the personnel management schemes in the developing nations since the utilized model was tested and trained on Kazakhstan's KPMG brunch.

Literature review

Effect of the digital era on personnel management: existing limitations

One of the most prominent directions in which predictive regression has been vastly implemented is the estimation of expected risks attributed to the workers [5,6,7,8]. In this case, the predictive modeling provides a new foundation for the assessment of the company's goodwill and workers' intangible contributions, which would have been challenging to estimate based on the human assessment.

Predictive modeling is a type of data analysis that uses algorithms to identify patterns in a data set, allowing organizations to make more informed decisions about potential hires [2]. With this approach, it is possible to assess a potential worker's skills and competencies [9], by taking into account a variety of factors such as job performance, employee engagement, and retention rates. While existing predictive modeling methods allow following the unbiased procedure, they lack accuracy in the filtering process. Overcompensation in creating the credible engine resulted in the impossibility to process complex information about the applications, meaning that the absence of specific keywords in the resume may cause the entire elimination regardless of the possible potential from other not defined variables [10].

This work aims to propose a possible solution for the mentioned limitation by providing a new method of personnel management, particularly, for the hiring process, that utilizes the deep learning algorithm in the potential assessment stage.

Deep Learning: Autoencoder

Before moving to further analysis, it is reasonable to define the core meaning of the deep learning and the fundamental neural network. Neural networks, as can be seen form the naming, mimic the behavior, and outlay of the human brain [11]. In the same way, as the learning processes are yet to be entirely understood by medicine, the Artificial Intelligence possess the «black box» of hidden layers allowing to train the program for understanding the nonlinear relationship. There are various adaptations and branching of the deep learning, among them the autoencoder in the specific interest of this paper. It is the unsupervised learning mechanism that allows to restore the input values through deep learning. Prior to 2006, neural networks with several hidden layers were challenging to train and seldom used [12]. However, the development of Stacked AutoEncoders (SAEs) made it possible to train several layers without supervision before fine-tuning them under supervision to address pattern recognition problems [13].

The difference from the accepted artificial neural network underlines in the availability of the latent space within the black box of the code that allows to have a better understanding of the clandestine processes in the hidden layers [14]. The operational system is similar to the re-constructurer that aims to identify the main patters responsible for the global parameters. As it can be seen from the Figure 1.

The framework of consists of the encoder and decoder that are respectively responsible for input and output. An encoder learns the data representation in lower-dimension space, (i.e., extracting the most salient features of the data), whereas a decoder learns to reconstruct the original data based on the learned representation by the encoder. The weights are chosen to minimize the sum of squared differences between the output and the input.

Methods

Data collection

This study has collected data from one of the big four company KPMG's brunch located in Almaty, Kazakhstan. The obtained data included the person-

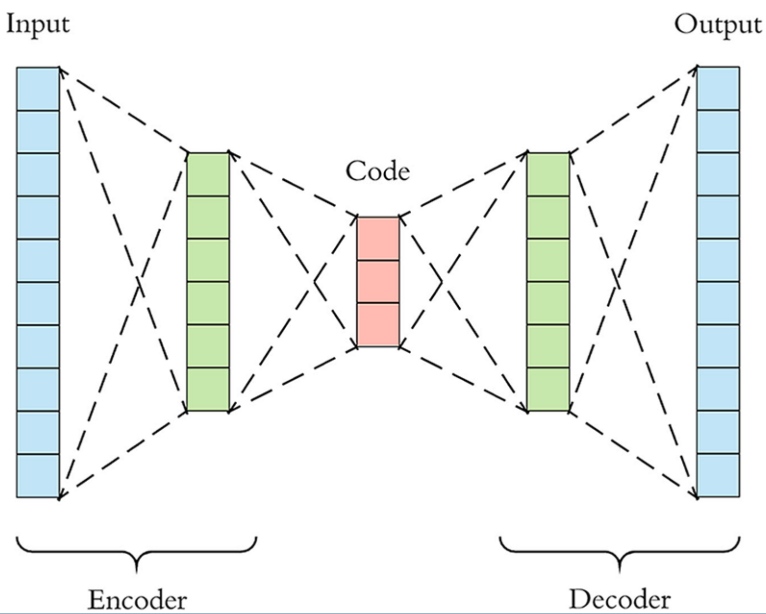

Figure 1 – The outlay of the autoencoder [15]

nel evaluation criteria from the year of foundation – 1996, and the recent assessment, until 2021. The considered evaluation forms contained the wide range of metrics related to the personal working capabilities, career progression, teamwork cooperativity, and soft skills level. On average, the value of the participants had the normal distribution in terms of age, gender and performance variation.

Data preparation

Overall, initial data included 3750x50 dimensions, rows for participants and the columns for the conditions assessed. The preprocessing step included the statistical wandering, evaluation of the two-sample t-test on the significance difference between chosen parameters and the correlation estimations. The data preparations steps were required to evaluate the availability of the interconnected variables and the corresponding dimensions reduction. Some of the parameters were in the discrete form (e.g., 1 to 5 assessment criteria), whereas others were presented in the form of continuous data (e.g., speed and time related evaluations). Such variability required pinpoint working direction and data normalization. Working strategy for the former value were based on the dropping of the missing values, while in the latter case the unavailable information was replaced with the mean value of the parameter.

Normalization was performed in the range of [-1,1] time-series wise. The overview of the entire preprocessing can be seen on the Figure 2. The circularity of the process is justified with the different starting point for various assessment criteria, yet regardless of the point of commencement, all of the 5 steps consequently implemented. Depicted data merging refer to the combination of the preliminary application data (e.g., resume, cover letter) with the working performance assessment, and with demographical covariates (e.g., gender and age). Covariates will be implemented as controlling factors into the deep learning model.

Data Processing

There are several available mechanisms of implementing the deep learning into the personnel management, hence, to arrive at the objective and weighted conclusion and response for the aforementioned research question, it is reasonable to conduct a cross-section comparison of the machine learning mechanisms: deep stacked autoencoder vs. adversarial autoencoder. Furthermore, the existing simplistic classifier – Naïve Bayer – will be also utilized as the controlling points.

Deep Stacked Autoencoder

Considering the abundant number of assessment variables (n = 50), the usage of advanced – deep – stack autoencoder is justified. The deep autoencoder is able to learn complex features from the data without any labeled examples and can then be used to produce a representation of the data that is much more accurate than traditional methods through the hierarchical multiple layer iterations. The step-by-step operational process:

1. Encoding the extracted values from the KPMG. Both before job placing and after for the entire period of 25 years. The input is given through deterministic mapping, meaning that the function will return the same type of return any time the unchanged input is provided.

2. The second level encoding is the crucial feature of the deep stacked autoencoder that differentiates it from the ordinary version. The same compression

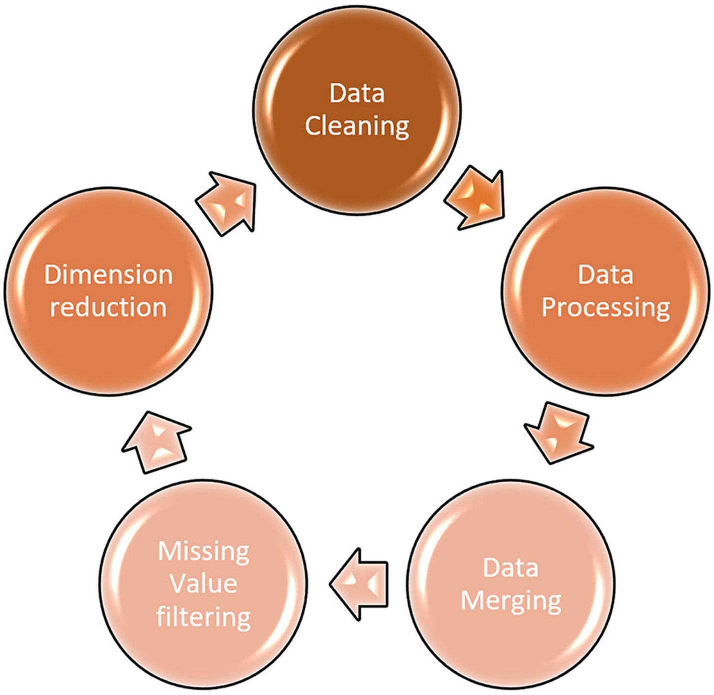

Figure 2 – The data preparation process

process is performed on the output from the first encoding.

3. Deriving the latent space to see the optimization level of the derived patterns from the encoder.

4. Utilizing the exponential growth function to the depicted features simultaneously with the integrated loss function for the cross-entropy identification.

5. Assessing the performance of the reconstructed results from the decoder.

The reconstruction of the input may show the performance of the autoencoder itself, however, the evaluation on the deep learning efficiency requires additional iterations on the testing set. The available data for this and consequent stages will be split based on the 70/30 ratio for training and testing.

Adversarial Autoencoder

The adversarial autoencoder is one of the adaptations of the stack version that has been created with the additional feature of encoder tricking. This type of deep learning allows to input the data that was not in the form of the initial training set, which was not possible in the case of deep stack autoencoder. Both types of the autoencoder have the same processing sequence. The discriminating factors here are rooted in the flexibility of input values and in the error estimation process.

In case of the deep stacked autoencoder the error rate is positively correlated with the performance of the machine learning, meaning that if the error is high on the testing set, the approach does not provide sufficient foundation to replace the biased employee recruitment. However, in case of the adversarial autoencoder, the reverse condition is true. Since the new input will be from the training sample regardless of the true origin, the error rate is the needed coefficient of estimations. The latter one is included in this study because it is assumed that in order to utilize the program in the perspective of assessment of future candidates, the historical performance based trained program will not provide credible results. Thus, the model that can ignore the time value of the series (past or future) may be more efficient.

Naive Bayes Classifier

Naive Bayes classifier is a supervised machine learning algorithm that is used for classification tasks. Mainly, the probability of an event can be estimated from the frequency of past events. Naive Bayes classifier makes a strong assumption that all features are independent of each other, which simplifies the calculation of the probability of an event.

Results and Discussions

Data preprocessing resulted in the decreased number of samples and the direction reduction of predictive variables leaving the final matrix in the form of 3597x37 (previously 3750x50). The deep learning code was run on MATLAB, and the performance of the model was estimated based on the confusion matrix results.

Data preprocessing

The noise identification was performed successfully through finding the hidden state dynamics and equating it with the original one. The function utilized is based on the hidden Markov modeling, where the observed information (performance of the workers in the long-term perspective) was influences by the unobservable, but present variables – employee's information from the application period. The denoising was performed successfully allowing to smooth the original discrete values with minimal valuable information lose. The main function in use for this section is the hmmtrain MATLAB that evaluates the transition and emission probabilities.

Deep Learning Model

After finding the parameters for layers, option's parameters were also adjusted several times, and the best obtained result showed the validation rate of the 96.89% (option d).

Optimization of the deep learning model

Option	Number of layers	Filters of the added layers, correspondingly	Paddings, correspondingly	Validation rate
a	3	3,3,3	8,16,32	92.29%
b	4	3,3,3,10	8,16,32,8	93.83%
c	5	3,3,3,5	8,16,32,8	90.73%
d	5	3,3,3,5,5	8,16,32,8,16	96.89%
e	5	3,3,3,5,10	8,16,32,8,8	86.38%
f	5	3,3,3,5,10	8,16,32,8,16	87.32%
g	4	3,3,3,10	8,16,32,16	84.24%
h	4	3,3,3,8	8,16,32,8	82.73%
i	4	3,3,3,20	8,16,32,8	84.62%
j	5	3,3,3,20,20	8,16,32,8,16	86.14%
k	6	3,3,3,20,20,20	8,16,32,8,16,32	89.70%
l	5	3,3,3,15,20	8,16,32,8,16	86.29%

The reproducibility of the conditions that were found for the deep autoencoder were altered accordingly to fit the model of adversarial autoencoder.

Functioning comparison

The error rate, accuracy and precision for each of the three models were calculated using the probability estimation of confusion matrix. The original table form of the confusion matrix is presented on the Figure 3.

The confusion matrix values have the sum equal to the number of predictive variables for the employee assessment.

The obtained results regarding true negative and true positive re-constructions were separately calculated for the performance assessment measures.

The results obtained showed that the Naive Bayes classifier, which was used as a control model and represents the existing predictive modeling, had the lowest performance compared to deep learning engines. The only values where the classifier was responsible for the greatest value were the false positive rate and false discovery rate, meaning that the program makes high rate of errors and misclassify the negative results as positive. Such type of error is considerably impactful for the topic of recruitment process and personnel management, because of high probability to hire a low potential worker due to the misinterpretation. Based on the mentioned rationales, it is reasonable to conclude that the Naïve Bayes classifier can be eliminated from the further analysis.

Both tested conditions had relatively satisfactory performance, however the deep model was superior in terms of sensitivity, negative predictive value, and false negative rate. While it may be assumed that the high rates in the firstly mentioned parameters will be sufficient, in terms of human recourse management high level of false negative rate is a significant drawback. The probable missed opportunity on talents due to false classification have high opportunity cost for the major international enterprises like KPMG.

In comparison to the deep learning model, the adversarial algorithm high specificity, precision, accuracy, and low false negative, false positive rates, meaning that this model is the most optimal one for the enhancing the recruitment process in Almaty KPMG.

Conclusion

This study has conducted a comprehensive review of the existing issues in the personnel management strategies and revealed the issue of existing humane bias in the recruitment process and the abundancy of the noisy human resource data that result in poor predictive modeling mechanisms with low flexibility. The issue was attempted to be resolved through the implementation of deep learning models of autoencoder. Two types of autoencoder – deep and adversarial – were tested and compared to the control Naïve Bayes classifier. The object of this study included the longitude dataset of 25 years with over 3750 employee's information of prior recruitment potential and annual assessments during the working period. The data went through the preprocessing (cleaning, merging, denoising) and the optimization for the deep learning's neural network. The comparative result of the metrics obtained from the confusion matrix revealed the general superiority of the deep learning models with regards to the digital predictive analysis, and the greatest results for the adversarial autoencoder.

This works contribution includes following factors:

- development of justifiably superior personnel recruitment model;
- elimination of human bias by replacing the manual evaluation process to the automated, objective one;
- increasing the competence of resource allocation through providing the working force and time efficient analytical model;
- generating the flexible framework that can be

		Predicted	
		Negative **(N)** -	Positive **(P)** +
Actual	Negative -	True Negative **(TN)**	**False Positive (FP) Type I Error**
	Positive +	**False Negative (FN) Type II Error**	True Positive **(TP)**

Figure 3 – A. The confusion matrix [15]

easily retrained with the new covariate and conditions. Equally possible to keep the model up to date by including the most recent employees' information to the neural network;

- possibility to generalize the model to the other audit companies of Kazakhstan.

The limitations of this study are based on the limited regional coverage – one country that may create overfitting in the future if the program will be attempted to be broaden to other nations. The future studies can be navigated to resolve the stated limitation or to the reversely advancement of the model to more specific parts of the organization – training to assess the candidate from the precise department.

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Ұйымның персоналын басқарудағы адами бейімділік мәселесі туралы

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Аңдатпа. *Соңғы жылдары өндірістік процестерді енгізу немесе қызмет көрсету кезінде ұйымға тартылған барлық ресурстардың ішінде менеджерлер адам ресурстарына көбірек көңіл бөлуде. Сарапшылардың пікірінше, адами капиталға инвестиция салу компанияларға тіпті заманауи технологияларға қарағанда көбірек табыс әкеледі. Сондықтан, бүгінгі бәсекеге қабілетті ортада оңтайлы тиімділік пен өнімділікке қол жеткізу үшін ұйымдар адам ресурстарын басқарудың тиімді әдістерін қолдануы керек. Ұйымның персоналды басқару жүйесінде персоналды іріктеу кезінде ұйымдағы бос жұмыс орнына қабылданған кандидатты бағалау кезінде субъективті тәсіл орын алады. Бұл зерттеудің мақсаты бәсекелес автокодерді енгізу арқылы сүзу параметрлерінің икемділігін арттыру арқылы персоналды іріктеу бойынша менеджердің біржақтылығын жою үшін терең оқытудың заманауи инновациялық модельдерін пайдалану болып табылады. Персоналды басқару* *процесінде адамның біржақтылығы, атап айтқанда, жалдау менеджерлері өздеріне ұқсас тәжірибесі немесе құндылықтары бар үміткерлерге байқаусызда артықшылық бергенде, кәсіпорындар жиі кездесетін қайталанатын мәселе болып табылады. Зерттеудің гипотезасы мынада: 100-ден астам қызметкермен 25 жылдық тәжірибесі бар бір компанияның Персоналды басқару моделін зерттей отырып, мансаптық өсуді, ұйымдастырушылық ерекшеліктерді және ықтимал тәуекелдерді қоса алғанда, әртүрлі параметрлердің бейімделетін масштабты коэффициенті арқылы қатысушы үміткерді дәлірек бағалауға болады. Терең және қарсылас автокодерлер бағаланды және аңғал Байес анықтамалық классификаторымен салыстырылды. Деректер алдын ала өңделген (тазалау, біріктіру, шуды азайту) және терең оқытуда қолданылатын нейрондық желі үшін оңтайландырылған. Араластыру матрицасынан алынған көрсеткіштер салыстырылды және нәтижелер бәсекелес автокодер жақсы нәтиже беретінін және терең оқыту үлгілері цифрлық болжамдық талдаудан асып түсетінін көрсетті.*

Кілт сөздер: *автоэнкодер, терең және қарсылас автоэнкодерлер, HR-менеджмент, адами факторларды тарту, адамның бейімділігі, терең білім, терең оқыту қозғалтқышы, болжамды модельдеу, қызметкерлердің әлеуетін бағалау, KPMG аудиторлық фирмасы, KPMG қарсыластық жалдау алгоритмі.*

К проблеме человеческого предубеждения в управлении персоналом организации

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Аннотация. *В последние годы из всех ресурсов, задействованных в организации при осуществлении производственных процессов или оказании услуг, руководители все больше внимания уделяют человеческим ресурсам. Эксперты утверждают, что инвестиции в человеческий капитал приносят компаниям больше дохода, чем даже современные технологии. Поэтому для достижения оптимальной эффективности и производительности в сегодняшней высококонкурентной среде организации должны использовать эффективные методы управления человеческими ресурсами. В системе управления персоналом организации при подборе персонала имеет место субъективный подход при оценке претендента, принятого на вакантное рабочее место в организации. Целью данного исследования является использование современных инновационных моделей глубокого обучения для устранения предвзятости менеджера по подбору персонала за счет повышения гибкости параметров фильтрации путем внедрения состязательного автокодера. Предвзятость человека в процессе управления персоналом, в частности, когда менеджеры по найму непреднамеренно отдают предпочтение кандидатам, имеющим схожий опыт или ценности, является повторяющейся проблемой, с которой часто сталкиваются предприятия. Гипотеза исследования заключается в том, что, изучив модель управления персоналом одной компании с 25-летним стажем с численностью сотрудников более 100 человек, можно будет более точно оценить участника-соискателя через адаптируемый масштабный коэффициент различных параметров, в том числе карьерный рост, организационные особенности и возможные риски. Глубокие и состязательные автокодеры были оценены и сопоставлены с эталонным классификатором наивного Байеса. Данные были предварительно обработаны (очистка, слияние, шумоподавление), а также оптимизированы для нейронной сети, используемой в глубоком обучении. Метрики, полученные из смешанной матрицы, были сопоставлены, и результаты показали, что состязательный автокодер дает лучшие результаты и что модели глубокого обучения, как правило, лучше с точки зрения цифрового прогностического анализа.*

Ключевые слова: *автоэнкодер, глубинные и состязательные автоэнкодеры, управление персоналом, подбор человеческого фактора, предвзятость человека, глубокое обучение, механизм глубокого обучения, прогнозное моделирование, оценка потенциала персонала, аудиторская фирма КПМГ, алгоритм состязательного найма KPMG.*

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