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Bayesian Decision-Making in Candidate Assessment for Hiring[1]

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Abstract

This paper investigates the application of Bayesian decision theory in the context of organisational recruitment processes. Bayesian decision theory is a statistical framework that enables decision-makers to make rational choices by incorporating prior knowledge and updating it with new information. In enterprise recruiting, making informed decisions about candidate selection is crucial for optimising staffing outcomes and minimising potential risks. Traditional approaches often rely on subjective judgments and intuition, resulting in less-than-optimal outcomes. By adopting a Bayesian decision-making approach, organisations can enhance the objectivity and effectiveness of their recruitment processes. This paper discusses the fundamental concepts of Bayesian decision theory and demonstrates how it can improve candidate selection in enterprise recruiting. The suggested procedure starts with a traditional set of assessment tools, which provides a decision-maker with initial information about a candidate's abilities. This allows him to assess a prior probability distribution regarding the candidate's suitability for the position. In the second step, the candidate must pass professional tests, each of which can be successful or unsuccessful. This generates additional information for the decision-maker. Using the Bayesian technique, the procedure combines the prior probabilities with the test results to create a posterior distribution, ultimately leading to the likelihood of the candidate's suitability for a specific position. This suggested procedure can reduce the risk of hiring the wrong candidate.

Keywords: *Bayesian Technique, Probability Distribution, Prior Information, Posterior Information.*

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Introduction

The recruitment process is a crucial component of any organization's operations, as it significantly determines the quality of the workforce and ultimately affects business performance. Effective hiring practices are vital for attracting, selecting, and retaining top talent, which can drive innovation, competitiveness, and long-term success.

However, traditional recruitment methods often rely heavily on subjective judgments, intuition, and personal biases, leading to suboptimal decisions that can result in costly mistakes, poor fit, and reduced organizational effectiveness.

In the modern business landscape, where competition for skilled and qualified employees is intense, organizations face increasing challenges in making informed and data-driven hiring decisions. Traditional approaches, such as relying solely on interviews, resumes, and personal referrals, are no longer sufficient to evaluate candidate suitability, as they lack objectivity, accuracy, and consistency. Moreover, these methods often fail to account for the complexities of the job market, the dynamic nature of organizational needs, and the inherent uncertainty associated with evaluating candidate potential.

To overcome these limitations, organizations are increasingly seeking innovative, evidence-based approaches to inform their recruitment decisions. One such approach is Bayesian decision theory, a statistical framework that offers a rational and probabilistic method for making informed decisions under uncertainty. Bayesian decision theory has been widely applied in various fields, including economics, finance, and

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engineering, but its application in recruitment processes has been relatively underexplored.

This paper aims to bridge this gap by investigating the potential of Bayesian decision theory in improving employee selection and assessment for hiring. By leveraging Bayesian principles, organisations can formalise their decision-making processes, incorporate prior knowledge, and update their expectations with new information, ultimately leading to more informed and effective hiring decisions. This paper provides an overview of the fundamental concepts of Bayesian decision theory. It demonstrates its application in a recruitment context, highlighting the benefits and advantages of adopting this approach in improving candidate selection outcomes.

Using a Bayesian decision-making framework, this paper explores how organizations can enhance the objectivity, accuracy, and effectiveness of their recruitment processes. By integrating prior probabilities with new information generated from assessments and evaluations, decision-makers can update their expectations and make more informed decisions about candidate suitability. This approach can help reduce the risk of hiring the wrong candidate, improve staffing outcomes, and ultimately contribute to the long-term success of the organization.

In the following sections, we will explore the essence of Bayesian decision theory and its application in recruitment processes. We will discuss the limitations of traditional approaches, provide a suggested procedure for implementing Bayesian decision theory in enterprise recruiting, and highlight the benefits of adopting this approach to improving candidate selection outcomes.

The Bayesian Approach is effectively used in a broad set of business application areas. Hahn E. (2014) provides a comprehensive introduction to Bayesian methods, emphasizing their application in business analytics and decision-making. The book serves as a valuable resource for understanding and applying Bayesian inference in various business contexts. The focus of the book is on the comparison of Bayesian models, which are essential for guiding decision-making. The book also addresses practical issues such as handling missing data and referencing significant literature in the field. Additionally, it incorporates freely available software with code listings provided for practical application.

Ando, T. (2010), Grenadier S. and Malenko, A. (2010), Lohrke F., Carson C., Lockamy

A. (2018), Charness, G. and Levin, D. (2005), Savchuk V. (2023) consider various Bayesian approaches and techniques applicable to making business decisions.

It is not surprising that the Bayesian approach is used in HR, particularly in the recruiting process. Murphy K.R., Tam A.P. (2004) consider the application/selection process as a set of Bayesian opinion revision tasks, in which applicants obtain new information about the organization at each stage of the process and must integrate this information with their prior perceptions of the organization and the jobs. They use the Bayesian approach to provide valuable insights for understanding serial decisions of this type. It suggests that real-world decision-makers are too sensitive to the valence and insufficiently sensitive to the diagnosticity of the information they obtain from interviewers, assessors, etc., and that the effects of information obtained early in the process depends on both the applicant's state of perceived uncertainty and on the relationship between the applicant's preconceptions and this early information.

Ohnishi Y. and Sugaya S. (2022) propose an analytical framework for simultaneous estimation of candidates' true potential considering job interview rounds. The framework uses algorithms to extract unseen knowledge of candidates' true potential and interviewers' toughness as latent variables by analysing grade data from job interviews. The authors apply a Bayesian Hierarchical Model that successfully quantifies candidate potential and interviewers' toughness.

Kadar J. A., Agustono D., and Napitupulu D. (2018) demonstrate a good case for using the Naive Bayesian approach in the candidate selection process. The problem was formulated to estimate decision-making variables such as a candidate's potential and an interviewer's bias. They suggested a Bayesian model for calculating these variables and subsequently making decisions about a candidate.

1. Enterprise HR Challenges and Recruitment Process

The larger the company's size, the more acute the problem of the manager's compliance with the requirements and challenges of the position he is preparing to take.

In a small company centred around an entrepreneur-owner, the mistakes of managers, specialists, and line workers can be identified in time by the entrepreneur himself, who intervenes and makes the necessary adjustments. The functions that the entrepreneur delegates to his employees are not too complicated. These functions are more "broad" than "deep" and can be mastered by an employee of the company through experience accumulated during the work process. A mistake in appointing the "wrong" person to a position that does not require deep knowledge, versatile expertise, and broad corporate communication skills is usually not very noticeable. It is compensated by relatively simple requirements for positions and a safety net in the form of the vigilant oversight of the owner-entrepreneur. Therefore, the owner or director of a small business usually engages in the selection of new employees himself, relying more on his "like or dislike," referring to it with various terms: intuition, instinct, or "you have to try." Very rarely do conversations with small business entrepreneurs reveal any established approach to selecting or testing candidates for managerial or line vacancies. Almost always, there is a unique, colourful, and non-replicated way of evaluating a candidate. While there are some trivial checklists, tasks, or tests for knowledge of the basics or, conversely, the subtleties of the profession, there is no system in these methods because it is not needed at this level.

In a large company, the situation is much more complicated. It is impossible to constantly monitor and adjust the actions of

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hundreds or thousands of employees. All methods of monitoring employee effectiveness proposed in management involve periodic control of specific indicators or goals, giving employees greater autonomy in the intervals between control points. It is assumed that employees or managers act within the framework of established processes, which are generally reliable and help avoid major mistakes. For example, all purchases are controlled by the current approved budget of the business, which has undergone a complex system of considerations and approvals and thus has a high degree of expediency, reliability, and trust.

Another example is that quality control tools built into production processes prevent errors or defects from progressing further along the technological chain, significantly increasing the reliability of the entire technological process and reducing dependence on the human factor. In "real life," not all processes work so smoothly, and there are not many fortunate companies that have built their production and management processes with a high level of reliability. There is always room for independent actions by employees at any level, and each employee is expected to be able to solve or correct issues within their functions. Since the established processes in the company do not always run smoothly, managers usually encourage such initiatives. However, this is contingent upon the initiative being practical or rational and aligned with how the company solves such problems, reflecting an established culture. For example, if a supplier has delayed the delivery of components for the production line for an objective reason, an acceptable action would be to buy similar components from competitors at high prices. In contrast, stopping production to impose fines on the supplier is not deemed acceptable. Both solutions fall within the buyer's functions, but one will be encouraged by management and colleagues, while the other may lead to reprimand or job loss.

An employee in a large company must not only have a more profound knowledge of their professional field due to narrower specialisation but also possess more experience and communication skills in a large team. They must tend to act in a certain way in situations with a high degree of uncertainty when a process has failed, there is no direct command from the manager, or there are no regulations for such a situation. This refers to the ability of an employee to perceive the company's corporate culture and act by its guidelines. In a small company, there are more opportunities for an employee's adaptation during the work process. The company usually waits more patiently for a newcomer to acquire the minimum knowledge and experience necessary for daily work and adjust to the values of corporate culture. In a large company, such opportunities are practically non-existent, and having an entirely suitable candidate from the start is preferable. Thus, the requirements for the quality of personnel selection are significantly increased.

This is done by specialised employees for whom recruitment is part of their professional activities. These can be specialists in various functional blocks of the company and simultaneously at different levels of management. For the most challenging positions, third-party resources may be involved in recruiting or headhunting agencies. In any case, in a large company, the candidate selection process is quite structured and usually uses the following tools: the candidate's resume, review and verification of the recommendations provided, one or more interviews, and a probationary period.

These tools often form a simple linear sequence and are used together, one after the other, reducing the entire complex recruitment problem to a simple technology. First, the candidate's resume is considered, and then his experience is checked by studying references and contacting recommenders, followed by a series of interviews. After that, the employee undergoes a probationary period in the company, often under the supervision of his future manager. Of course, deviations toward simplification or complication of this technology are possible. For example, if this is the candidate's first job, his resume will not reveal much about him, and he is unlikely to provide recommendations. Therefore, the importance of the interview and a successful probationary period will be considerably higher in this case, with the overall opinion about the candidate primarily based on them. If, for example, the reputational factors of a candidate for the position of manager are significant, along with his professional knowledge and experience, the importance of a solid resume and a convincing list of references will increase significantly, and the interview may serve as an introduction.

It is also possible to complicate this technology. For example, a candidate may be required to pass tests or solve problems. Alternatively, they may be placed in a situation to identify their communication skills or stress resistance (the ethics of such methods are questionable). In particular, it is common for IT companies to test candidates by offering them an example to solve within a specific time frame. This example is usually related to the company's technologies and is designed to demonstrate the candidate's personal qualities, such as the ability to act under pressure, show acceptable work speed, and confirm familiarity with the professional tools they will use in their role. Such assessments significantly increase the employer's confidence in the candidate's knowledge, skills, and suitability for future tasks. These are good additions to the basic recruiting technology. We will return to them later.

The approach described above, along with its modifications, has one common drawback: the decision regarding the candidate's suitability is made quite subjectively. In fact, we are not far from the intuitive assessment of the head of a small business, which we discussed at the very beginning. However, a recruiter must be evidence- based. They must convince their manager or client of the proposal's validity for a particular candidate for the proposed position. This significantly impacts the process of studying and evaluating the candidate. The conclusions about their suitability should be evident to a layperson. Therefore, straightforward arguments are often used. For example: "Look, he has a great track record!" or "His referees are very authoritative! We called them all, and they confirmed their excellent opinion of the candidate." "The candidate performed exceptionally well in the interview! He is

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very charismatic and up to date with the latest news in our industry!"

However, a good resume is very subjective. This is simply because there are courses and "specialists" who specialize in writing good resumes. Reliable recommendations also depend heavily on the person reading them's perception of reliability and on a vast number of circumstances. A candidate may be charming and perform well in an interview, but this says almost nothing about their real abilities to work in a team or to perform a specific task.

The same story applies to the probationary period. During this time, the newcomer works under the guidance of his future boss in the production process, attempting to perform authentic tasks. Typically, his future manager evaluates him for the probationary period. The motivation for such an assessment can entirely depend on the newcomer's business qualities. Anything can lead the future manager to give a positive or negative evaluation of the candidate. This can include personal sympathy or antipathy, the need to quickly fill a vacancy, or the desire to keep the vacancy open because the wage fund is distributed among fewer employees. A fundamental lack of time may prevent the manager from closely observing the newcomer. There can be thousands of reasons, and it is often impossible to analyse them, leaving the person responsible for recruiting to rely on this uncertain opinion.

Another feature of the existing system is that it does not allow for improvement. It is presumed that the system will be enhanced through the experience gained by the individual responsible for recruitment. After working through dozens of these cycles with numerous candidates, they are expected to refine this process and make it more reliable. This means that the quality of candidates will improve because, at certain initial stages, even before the probationary period, the recruiter will filter out potentially unsuitable candidates. As we can observe, their sources for professional development are limited. Reading hundreds of resumes is unlikely to teach them anything significant. Communication with referees is rather dull and formal. Although interviews represent the most informative phase of the recruitment process, advanced skills are required to conduct them effectively and acquire new insights. Unfortunately, there is often insufficient time for a thorough interview. During the probationary period or afterwards, the recruiter might suggest completing a formal checklist, or the process may be reduced to the question, "Well, how is the newcomer? Has he shown himself?".

The existing system again leads us to the development of certain magical qualities of the person responsible for the selection, as was seen in the case of an entrepreneur in a small business. The recruiter develops a flair and the ability to adapt to circumstances and immediate requests from the company. Professional intuition does not develop or improve because there is no formal tool. Consequently, over time, the system becomes less reasoned, less transparent, and increasingly dependent on the personality and characteristics of the person responsible for the selection. They are becoming more inclined not towards qualitative candidate selection but rather towards creating a mass influx of candidates so the most suitable one can be chosen from a larger pool or placed in the company. This leads to higher staff turnover and less stable teams, with all the resulting consequences.

The problem with the current recruitment practice lies in its linearity and lack of high- quality feedback. This practice does not give the recruiter a reason to analyse their actions to improve effectiveness. It resembles a lottery: correct or incorrect, with vague arguments during and based on the process's results. This can be compared to a factory that produces TVs, where the assembly quality is determined at the end of the production line by turning on the TV after it has been assembled. There is no inspection of individual components, intermediate control points, or quality assurance tools. Thus, all the personnel on the assembly line work for a long time, and then, at the very end, there is a lottery: it may not turn on. If it does not turn on, it is unclear what to change or improve in the assembly line because there are no other control points apart from the endpoint.

If you ask the manager responsible for the selection at what stage of this technology, he has an opinion about the suitability or unsuitability of the candidate. Usually, two cases arise: either her own opinion does not appear at all, or (which is more common) it appears at the earliest stages. Unfortunately, the "first impression" rule works appropriately. The first telephone conversation, the writing style, the resume she liked, the first interview – such an unsubstantiated opinion is not easy to change in the future, even under severe circumstances. This adds even more subjectivity to the candidate's assessment.

Let's model a slightly different technology, adding only one additional element to the chain of actions: obtaining a prior judgment. Before each step of the assessment procedure, the recruiter will try to assume what would result from this step, that is, to give a specific prior assessment. Each step provides her with additional information regarding the candidate's suitability. She combines her prior assumption with the result of the current step and generates a posterior judgement regarding the candidate. This posterior information will serve as a prior one for the next step. The procedure can be repeated several times depending on the time and resources for the selection procedure.

The above considerations fully correspond to the Bayesian approach to decision- making. The only issue is whether to use appropriate quantitative metrics or base decisions on non-quantitative judgments.

2. Essentials of the Bayesian Technique

The essence of Bayesian thinking for decision-making is updating one's beliefs in light of new evidence. It's a continuous learning process in which one starts with a prior belief (prior distribution), observes new data, and then revises that belief to form a posterior belief (posterior distribution).

The following five points can present the Bayesian consideration for business decision-making.

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1. Every manager has her subjective judgment about a particular future event (the prior judgment):
- Whether an applicant possesses all necessary skills for a specific position.
- Whether a new project will be successful.
2. Is it possible to trust this judgment unequivocally?
- One can hardly do so because the manager's intuition may fail.
- The world is changing – experience may not be entirely acceptable or adequate.
3. What does she need to do to improve the reliability of the output? She should experiment (in the broad sense) and obtain new actual information.
- in a hiring process, she can test the applicant.
4. There is little time to conduct numerous experiments, which complicates decision- making. Thus, she cannot expect to receive comprehensive knowledge to make a decision.
5. Conclusion: She should decide by combining subjective prior information and a few results from the experiment.

This process can be fulfilled in two options: non-quantitative and quantitative.

The non-quantitative one doesn't require explicit metrics but rather a qualitative assessment of how the new evidence strengthens or weakens one's initial belief.

In the context of candidate assessment for hiring, this can be incredibly valuable, especially when dealing with qualities that are hard to quantify. Let us consider a possible procedure for deciding candidate suitability based on an interview scheme.

Before the interview, you review a candidate's resume and portfolio. Based on this, you form an initial impression. Maybe you think they're likely a good fit because their experience aligns well, or perhaps you're sceptical because of a gap in their employment history. This is your prior belief. It's not a number but a subjective judgment. Then, you interview the candidate and observe their communication skills, problem-solving abilities, cultural fit, and enthusiasm. These are your new pieces of evidence. Finally, you combine your prior beliefs with the latest evidence from the interview to form a revised judgment. Did the interview strengthen your initial positive impression? Did it alleviate your concerns about the employment gap? Or did the candidate perform poorly, weakening your initial positive assessment? This updated belief is your posterior, and it informs your hiring decision.

By applying Bayesian reasoning, even without precise numbers, hiring managers can make more informed decisions that consider the complete picture of a candidate's potential. The only drawback of such a procedure is that the manager responsible for selecting candidates cannot prove to someone else, such as her boss, who is responsible for overall company performance, in which the candidate will presumably play a crucial role.

It is well known that numbers are the best way to prove something to someone. The quantitative Bayesian technique effectively does this. From a practical standpoint, the Bayesian approach combines the following three statements.

Statement 1. The parameter of the system or model under study is assumed to be uncertain, and this uncertainty is modelled using random events or variables. Before observation, the prior probability distribution of the parameter is assumed to be known. It should be noted that we are now considering secondary randomness. Primary randomness models a primary random variable that describes a process or model. In the considered context, the role of the primary random event is played by the random event that an applicant will be successfully assessed to be selected for the required position. At the same time, secondary randomness describes the uncertainty of the hypothesis that he is suitable for the required position.

Statement 2. A posterior distribution is obtained by combining the prior distribution of the parameter (describing secondary randomness) with the results of the observation of the main random event. These observations are modelled by using the so-called likelihood function. This combining is made using the Bayes' rule.

Statement 3. A final decision is made by maximising the expected utility or minimising the losses associated with applying this rule. In the most practical application, the squared-error loss function is used, which leads to the estimation of the parameters or any of its functions as a posterior mean value.

Unlike classical decision theory, which assumes that the parameter of a probability distribution for the primary variable is non-random, Bayesian theory assumes that the parameter is random.

In the Bayesian methodology, the interpretation of judgments is always probabilistic and can be represented by means of:

- a frequency (objective) interpretation of probability, which is extremely rare since it requires many past experiences.
- rational degrees of certainty are mainly reduced to the mathematical expression of the absence of a priori knowledge.
- subjective beliefs refer to the researcher's attitude towards the phenomenon or system under study.

The areas of application of these methods practically do not intersect. In the first case, in the presence of many past observations, both rationalistic and subjectivist positions subjective the levels of belief inevitably coincide with relative frequencies. In the complete absence of knowledge, subjective levels of belief must coincide rational - rational ones,, i.e. with the need to accept a uniform prior distribution. In all other situations, and they are the exclusive majority subjective levels of belief are a unique way of presenting prior

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information.

The Bayesian theory's most challenging question is estimating subjective probabilities and quantifying subjective experiences.

Bayes' rule is the methodical basis of the transition process from prior information, formalised in the form of a prior distribution, to a posterior one by adding observation. This process can be represented as a sequential accumulation of information. At the initial stages of studying, a decision maker has some idea of the properties of the object under study. This view, in addition to non-formalized experience, includes empirical data obtained earlier with similar studies. During observation, new information appears as a data set that changes the object's properties' representation (probabilistic judgment). Thus, at the same time, there is a gradual revision and reassessment of the prior presentation. Moreover, at each moment, we can give a complete description of the properties of the object, and this description will be exhaustive in the sense that we have used all the available information for it. This process does not stop – it continues with each new observed result.

The following principles summarise the ideas of the Bayesian approach to modelling uncertainty.

1. The Bayesian approach follows probability axioms, which are the same as those for classical and frequency probability.
2. The Bayesian decision-maker has a complete set of probabilistic beliefs. In other words, she assigns a subjective probability to each proposition, *P(H).* A Bayesian decision-maker can assign a degree of belief about everything.
3. When exposed to new information, the event with conditional probability *P(A/H)* (the probability that A occurs, given that H is true), the Bayesian decision-maker changes his beliefs under new information according to Bayes' rule.

$$P(H/A) = \frac{P(H) \cdot P(A/H)}{P(A)}.$$

This rule works equally in the case of personalistic (classical) meaning of subjective probability as well as for rationalistic one assuming unique admissible probability assignment. The Bayesian approach postulates a subject-independent probability function. However, in both cases, the probabilities referred to are subjective in the sense that they depend on the information available to the subject rather than on the propensities or frequencies of the material world.

An extensive range of tasks for the Bayesian approach to risk assessment opens up economic and business applications. Since managers make many decisions based on subjective ideas and personal experience, it is often not economically feasible to perform expensive experiments that require diversifying resources and time. In this case, the manager needs a convenient and accurate methodology for assessing the risk of unfavourable events.

3. Quantitative Bayesian Model for Candidate Suitability

We consider the situation when an HR manager assesses a particular candidate as a standard part of hiring. She starts the assessment process with traditional actions, such as studying a resume and other available information. She also interviews the candidate. We consider this set of activities to be a preliminary phase. After its completion, the HR manager forms her subjective judgment about the candidate's suitability. After that, she suggests that the candidate take a test. The content of the test depends on the context of the enterprise. It might be a professional test with multiple-choice questions or a more complicated assignment demonstrating the candidate's suitability. This step can be repeated several times depending on the resources available. The candidate's suitability is determined by gathering all the available information.

The following steps formalise the model.

After completing the preliminary stage (resume, interview, etc.), the HR manager must assess the probabilities of these hypotheses *P(H1)* and *P(H2)*.

This assessment is subjective and based on the experience of the HR manager.

Step 2. Evaluation of the conditional probability

The HR manager instructs an enterprise field expert to examine the applicant by asking him to complete a specific task. Let *A* denote an event where the candidate will pass the test successfully. According to her experience and available statistics, the HR manager must assign two probabilities:

- *P(A/H1)* – a conditional probability of event *A* given the applicant corresponds to the position requirements (hypothesis H1),
- *P(A/H2)* – a conditional probability of event *A* given the applicant does not correspond to the position requirements (hypothesis H2).

Step 3. Evaluation of the posterior probability

There are two options for further scenario:

Option 1. Event A occurred – the applicant completed the test successfully. Using Bayes' theorem, the posterior probability of the applicant's suitability (hypothesis H1) is evaluated to be:

$$P(H_1/A) = \frac{P(H_1) \cdot P(A/H_1)}{P(A)},$$

where P(A) is estimated by the formula of total probability.

$(A) = (H_1) \cdot (A/H_1) + P(H_2) \cdot P(A/H_2).$

Option 2. Event A didn't occur, meaning an alternative event occurred when the applicant failed the test. According to Bayes' theorem, the posterior probability of the applicant's suitability (hypothesis H1) is

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$$P(H_1/\bar{A}) = \frac{P(H_1)\cdot P(\bar{A}/H_1)}{P(\bar{A})},$$

and again

$$P(\bar{A}) = P(H_1)\cdot P(\bar{A}/H_1) + P(H_2)\cdot P(\bar{A}/H_2).$$

The posterior probabilities (H_1/A) and $(H_1/\bar{A})$ serve as the criteria for making a decision regarding the suitability of the candidate.

We can repeat this procedure. The critical point is that the next iteration uses the posterior probabilities of the previous iteration as prior probabilities.

Let us consider the second iteration of the assessment procedure in the framework of the three-step procedure. The assessment manager suggests that the candidate pass one more test. Let B stand for the successful test result. In the first step, we assign a prior probability of the candidate's suitability, which we assign the posterior one after the third step of the first iteration (H_1/A).

In the second step, we must assign conditional probabilities for the hypothesis H_1 and H_2 to pass the test successfully. Let B stand for the successful test result. Then, we can see the results of the second step must be (B/H_1) and (B/H_2).

Finally, in the third step, using Bayes' rule, we compute the posterior probability of candidate suitability for both case: the candidate passed the test successfully B or he failed $\bar{B}$.

When B occurred, the applicant completed the test successfully, the posterior probability of his suitability is

$$P(H_1/B) = \frac{P(H_1/A)\cdot P(B/H_1)}{P(B)},$$

where the formula of total probability estimates *P(B).*

$(B) = (H_1/A)\cdot(B/H_1) + P(H_2/A)\cdot P(B/H_2).$

Otherwise, when the candidate fails

$$P(H_1/\bar{B}) = \frac{P(H_1/A)\cdot P(\bar{B}/H_1)}{P(\bar{B})},$$

where

$$P(\bar{B}) = P(H_1/A)\cdot P(\bar{B}/H_1) + P(H_2/A)\cdot P(\bar{B}/H_2).$$

Such a procedure can be repeated several times depending on its available resources.

4. A Numerical Example

Suppose that after studying all the information collected regarding the candidate and conducting an interview, the recruiter believes that the candidate corresponds to the requirements of a position with a probability of 0.8. Note that this is a relatively high assessment of the candidate, and apparently, he showed his best side. In terms of the procedure used, we have to assume $(H_1) = 0.8$, and $(H_2) = 1 - (H_1) = 0.2$.

In the next step, the recruiter sends the candidate to take the test. She asks the manager responsible for this test what the probability is of successfully passing if the candidate fits the position. Similarly, she asks for the same probability to be assigned if the candidate does not fit. The person responsible for testing is supposed to have sufficient experience and statistics to assess these probabilities.

In terms of our procedure, the recruiter asks to assign (A/H_1) and (A/H_2). Suppose these probabilities are assigned to be 0.6 and 0.1, respectively. The total probability of successfully passing the test, disregarding whether the candidate fits or does not fit the position, is calculated to be

$(A) = (H_1)\cdot(A/H_1) + P(H_2)\cdot P(A/H_2) = 0.8\cdot 0.6 + 0.2\cdot 0.1 = 0.50.$

In this example, the chance to pass a test is fifty to fifty.

Now, let's learn what happened while testing. Again, it would be two options. The first option is the candidate successfully passes the test. The question arises of how it changes the prior probability of suitability of the candidate. According to the Bayes' rule

$$P(H_1/A) = \frac{P(H_1)\cdot P(A/H_1)}{P(A)} = \frac{0.8\cdot 0.6}{0.5} = 0.96,$$

and this is an excellent estimate for the candidate. The positive conclusion arises immediately because the probability is almost a hundred persent.

But it is also possible that the candidate fails the test. What will be his chances? Again,
we use the Bayes' rule and obtain

$$P(H_1/\bar{A}) = \frac{P(H_1)\cdot P(\bar{A}/H_1)}{P(\bar{A})} = \frac{P(H_1)\cdot[1-P(A/H_1)]}{1-P(A)} = \frac{0.8\cdot 0.4}{1-0.5} = 0.64,$$

that is essentially less than the prior probability. Presumably, the recruiter would not recommend hiring the candidate. But she can give the candidate one more chance, sending him to the additional test. It might be a slightly different test with conditional probabilities of successful passing being assigned $(B/H_1) = 0.9$ and $(B/H_2) = 0.2$. To assess the total probability *P(B)* for the second test, we must use the posterior probabilities of the first iteration as a prior probability. It means that we must assume $(H_1) = 0.64$, and $(H_2) = 1 - (H_1) = 0.36$. As a result, the total probability of successfully passing the second test is calculated to be:

$(B) = (H_1/A)\cdot(B/H_1) + P(H_2/A)\cdot P(B/H_2) = 0.64\cdot 0.9 + 0.36\cdot 0.2 = 0.648.$

If the candidate passes the test successfully, he demonstrates the following posterior probability of his suitability:

$$P(H_1/B) = \frac{P(H_1/A)\cdot P(B/H_1)}{P(B)} = \frac{0.64\cdot 0.9}{0.648} = 0.89$$

and this can improve his value in the eyes of the recruiter. Otherwise, his chance of getting the position essentially drops,

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as we can see from the following estimation:

$$P(H_1/\bar{B}) = \frac{P(H_1/A)\cdot P(\bar{B}/H_1)}{P(\bar{B})} = \frac{P(H_1/A)\cdot[1-P(B/H_1)]}{1-P(B)} = \frac{0.64\cdot 0.1}{0.352} = 0.18.$$

The following picture demonstrates the dynamics of options for all possible series results from three tests. We can see that the candidate saves a chance to be approved if he successfully passes two of three tests. However, it depends on the severity of the requirements. If the critical probability is 0.75, then the two-from-three result is good for the candidate. If it is higher, say 0.85, the candidate has no chance.

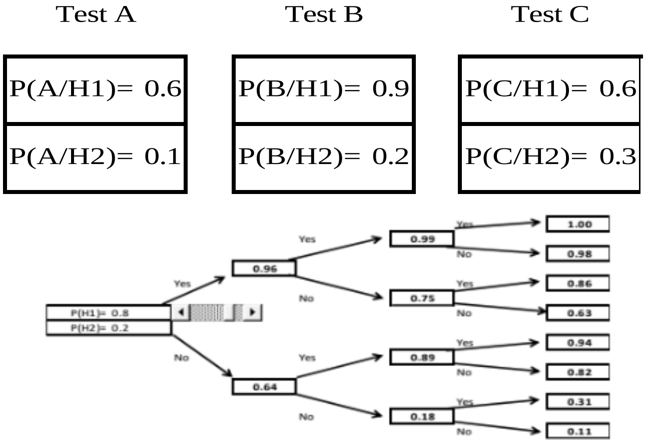

Fig. 1. Posterior estimates for (H_1) = 0.8.

The question arises of how a prior judgment affects the posterior probabilities. Suppose that after studying all the information collected regarding the candidate and an interview, a recruiter evaluates the candidate's abilities as weak and assesses him as 0.6. We can see from Figure 2 that the two-from-three result may not work for this prior probability.

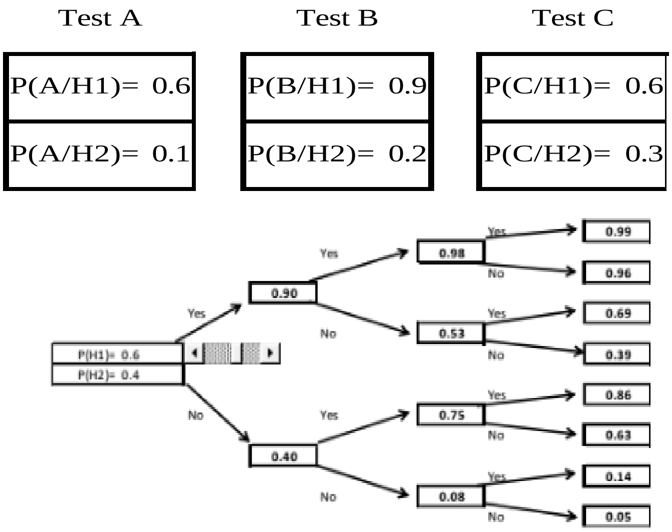

Fig. 2. Posterior estimates for (H_1) = 0.6.

As we can see, the algorithm is quite sensitive to the probability values used for estimation. Also, there is not much difference between a score of 0.75 and 0.8 when making a decision regarding a candidate. Therefore, such assessments are designed to provide greater confidence that she is not mistaken in her choice rather than simply replacing the recruiter and leaving her responsible for selecting the initial data.

5. Conclusion remarks

This paper has explored the application of Bayesian decision theory to enhance the candidate assessment process in hiring. By shifting from a linear, subjective evaluation process to a Bayesian framework, organizations can leverage prior knowledge and iteratively update their assessments based on new evidence gathered through interviews, tests, and other evaluation methods. This approach provides a structured, transparent, and adaptable methodology for making more informed hiring decisions, minimizing the impact of biases and subjective judgments.

The quantitative Bayesian model presented offers a practical framework for quantifying candidate suitability, allowing recruiters to move beyond vague impressions and articulate their evaluations with greater precision. While the selection of prior probabilities and the design of effective tests require careful consideration and domain expertise, the iterative nature of the Bayesian approach allows for continuous refinement and improvement of the assessment process. The numerical examples demonstrate the sensitivity of the model to different prior probabilities and test outcomes, highlighting the importance of careful data selection and interpretation. However, even with subjective prior probabilities, the framework provides a more robust and defensible decision-making process compared to traditional methods.

Further research could explore the application of Bayesian networks to model more complex relationships between candidate attributes and job requirements, incorporating multiple factors and dependencies. It would also be valuable to investigate the optimal design of tests and evaluation methods to maximize information gain and minimize uncertainty. Additionally, it would be beneficial to explore how the Bayesian approach can be integrated with existing HR systems and practices to facilitate wider adoption.

Ultimately, adopting a Bayesian approach to candidate assessment promises to reduce hiring errors, improve the quality of hires, and enhance overall organizational performance. By embracing a data-driven, iterative approach and fostering a probabilistic mindset amongst recruiters, organizations can move beyond intuition and subjectivity, making hiring decisions based on evidence and probabilistic reasoning. This transition will lead to a more effective, efficient, and equitable recruitment process, ultimately contributing to a more successful and adaptable workforce.

References

1. Ando, T. (2010). Bayesian Model Selection and Statistical Modeling. Boca Raton, FL: Chapman and Hall/CRC Press.
2. Charness, G. and Levin, D. (2005). "When optimal choices feel wrong: a laboratory study of Bayesian updating, complexity, and affect", American

Economic Review, Vol. 95 No. 4, pp. 1300-1309.

3. Grenadier S., Malenko, A., (2010). “A Bayesian approach to real options: the case of distinguishing between temporary and permanent shocks”, Journal of Finance, Vol. 65 No. 5, pp. 1949-1986.
4. Hahn E. D. (2014). *Bayesian Methods For Management and Business: Pragmatic Solutions For* Real *Problems.* Wiley & Sons, Inc.
5. Hansen, M., Perry, L. and Reese, C. (2004). “A Bayesian operationalisation of the resource-based view”, Strategic Management Journal, Vol. 25 No. 13, pp. 1279-1295.
6. Kadar J.A. , Agustono D., Napitupulu D. (2018). *Optimization of Candidate Selection Using Naive Bayes: Case Study in Company X.* IOP Conf. Series: Journal of Physics: 772–777.
7. Lohrke F., Carson C., Lockamy A. (2018). *Bayesian analysis in entrepreneurship decision-making research: Review and future directions*, Management Decision, Vol. 56 Issue: 5: 972-986.
8. Murphy K.R., Tam A.P. (2004). *The Decisions Job Applicants Must Make: Insights From a Bayesian Perspective.* International Journal of Selection and Assessment, v. 12. Blackwell Publishing: 66-74
9. Ohnishi Y., Sugaya S. (2022). *Applying Bayesian Hierarchical Probit Model to Interview Grade Evaluation*. arXiv:2003.11591v2.
10. Savchuk V. (2022). Making Decisions under Uncertainty: Value Chain Development. MPRA Paper No. 117213. https://mpra.ub.uni-muenchen.de/117213/
11. Savchuk V. (2023). *Bayesian Risk Assessment Technique for Economic Stress-Strength Models*,
12. Journal of Applied Economic Sciences, Volume XVIII, Winter, 4(82), 285–295.

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