

The Optimal Stopping Problem and Beta-Binomial Distribution in Workforce Management

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1 Abstract

This paper considers the Optimal Stopping Problem in which a decision maker (DM) is given a set of n randomly arranged choices that are ranked from worst to best. The DM must pick the best choice with a single decision. In Section 3, this article applies the Optimal Stopping Problem to the context of a company hiring employees, then derives the optimal stopping point. In Section 4, given that a specific employee is hired and is evaluated via multiple binomial trials, this paper derives the Beta-Binomial distribution model that tracks an employee's true value, the probability that he or she succeeds at a given task, with a confidence value.

2 Introduction

Medium to large businesses constantly face a problem: deciding whom to hire in an endless pool of applicants, and continuously tracking an employee's performance over their career. Both problems include a common mathematical structure—confidence. For hiring, one must be confident that a worthy applicant will be selected, and for evaluation, one must be confident in their belief that a select employee is high-performing.

Section 3 addresses the hiring decision by deriving the optimal stopping threshold for the Optimal Stopping Problem. E. B. Dynkin (1963), as cited in [1], applied the Markov stopping time theory to the problem, where the decision maker (DM) blindly rejects the first $r - 1, \{r \in \mathbb{N}\}$ choices and picks the relative best choice in the remaining applicants. Then, the optimal stopping point $\frac{r}{n}$ is $\frac{1}{e}$ as $n \rightarrow \infty$.

Section 4 picks up on Section 3 and introduces Bayes' Theorem to track $P(H)$, which primarily depends on an employee's true value, the success rate of an employee on tasks. Then, from the Bayes' Theorem, we derive the Beta-Binomial distribution model that computes an employee's true value with a confidence

value.

The remainder of this paper is organized as follows: Section 3 develops the optimal stopping model and its solution. Section 4 introduces Bayes' Theorem within the context of evaluating an employee and derives the Beta-Binomial distribution model. Section 5 concludes.

3 The Optimal Stopping Problem for Hiring

3.1 Problem Statement

According to [1], the Optimal Stopping Problem has the following features:

1. There is one employee position available.
2. The number n of applicants is known.
3. The applicants are interviewed sequentially in random order, each order being equally likely.
4. It is assumed that the decision maker (DM) can rank all the applicants from best to worst without ties. The decision to accept or reject an applicant must be based only on the relative ranks of those applicants interviewed so far.
5. An applicant once rejected cannot later be recalled.
6. The DM is very particular and will be satisfied with nothing but the very best. (That is, their payoff is 1 if they choose the best of the n applicants and 0 otherwise.)

3.2 The Monotone Threshold Rule

E. B. Dynkin (1963), as discussed in Ferguson's historical review of the problem [1], considered this problem as the application of the Markov stopping times, and proved that the solution follows a monotone threshold structure: reject the first $r - 1 \in (0, n - 1]$, applicants, then accept the next relative best applicant.

Relative best ranking is a rank compared to all the previous applicants, no matter if they are within $r - 1$.

3.3 The Solution

If the j -th applicant be the overall best applicant out of the n applicants $\{j \in (0, \infty), n \rightarrow \infty\}$, the probability, $\phi(r)$, that the DM picks the j -th applicant is:

$$\phi(r) = \sum_{j=r}^n P(j\text{-th applicant is the best and the DM selects them})$$

Note that we can sum each probabilities because the events are pairwise disjoint. Additionally, j begins at r because the first $r-1$ applicants are rejected according the monotone threshold rule discussed in the previous subsection.

Let A_j be the event that the j -th applicant is the best overall. Let B_j be the event that the DM picks that applicant. Since $P(A \times B) = P(A) \times P(B|A)$,

$$\phi(r) = \sum_{j=r}^n P(A_j) \times P(B_j|A_j)$$

$P(A_j) = \frac{1}{n}$. $P(B_j|A_j) = \frac{r-1}{j-1}$. The latter event cannot happen if there exists a relatively best applicant who is not the best applicant between positions r to n . Therefore, $P(B_j|A_j)$ must account that there are no applicant that will make the DM pick an applicant that is not the overall best applicant. Therefore, $P(B_j|A_j)$ can be interpreted as the probability that the relatively best applicant is within the positions 1 to $r-1$, who gets automatically rejected. Then,

$$\phi(r) = \sum_{j=r}^n \left(\frac{1}{n}\right) \left(\frac{r-1}{j-1}\right)$$

Now that we have the function, our sole task is to find the value of r such that $\phi(r)$ is a maximum. For optimization, we must transform ϕ into an integral, take the derivative of the integral, and find the root of the derivative.

Note that if n is a reasonable finite number less than approximately 1000, r can be found by calculating $\phi(r)$ for every $r \in (1, n)$, and picking out an r that gives a maximum value for $\phi(r)$.

As $n \rightarrow \infty$, it is plausible that

$$\phi(r) \approx \sum_{j=r}^n \left(\frac{1}{n}\right) \left(\frac{r}{j}\right)$$

If we multiply $\frac{n}{n}$ to the expression,

$$\phi(r) = \sum_{j=r}^n \left(\frac{1}{n}\right) \left(\frac{n}{j}\right) \left(\frac{r}{n}\right) = \left(\frac{1}{n}\right) \left(\frac{r}{n}\right) \sum_{j=r}^n \frac{n}{j}$$

Consider a number line with domain $[0, 1]$. $\phi(r)$ essentially "sweeps" the number line from $\frac{r}{n}$ to $\frac{n}{n}$, with the interval $\frac{1}{n}$. The position on the number line can be represented by $\frac{j}{n}$. This is approximately an integral with the differential $\frac{1}{n}$, lower limit $\frac{r}{n}$, and upper limit $\frac{n}{n}$, or 1.

Let $x = \frac{r}{n}$, $t = \frac{j}{n}$, and $dt = \frac{1}{n}$. Then,

$$\phi(r) = \sum_{j=r}^n \left(\frac{1}{n}\right) \left(\frac{n}{j}\right) \left(\frac{r}{n}\right) = \left(\frac{1}{n}\right) \left(\frac{r}{n}\right) \sum_{j=r}^n \frac{n}{j} \approx x \int_x^1 \frac{1}{t} dt \text{ as } n \rightarrow \infty.$$

Evaluating the integral gives

$$\phi(r) \approx x[\ln(t)]_x^1 \quad (1)$$

$$= x[\ln(1) - \ln(x)] \quad (2)$$

$$= -x \ln(x) \quad (3)$$

To find the value of x such that $\phi(r)$ is a maximum, we take the derivative of (3) and set it equal to zero.

$$\phi'(r) \approx \frac{d}{dx}[-x \ln(x)] \quad (4)$$

$$= -\ln(x) + [-x(\frac{1}{x})] \quad (5)$$

$$= -\ln(x) - 1 \quad (6)$$

Setting $\phi'(r)$ equal to 0,

$$\phi'(r) = 0 \quad (7)$$

$$-\ln(x) - 1 = 0 \quad (8)$$

$$\ln(x) = -1 \quad (9)$$

$$x = \frac{r}{n} = \frac{1}{e} \quad (10)$$

The solution provides us with two pieces of information: the number of applicants that the DM should initially reject depends on the total number of n applicants, and the fraction of applicants the DM should initially reject (to maximize the probability that the next relative best applicant is the best overall applicant) converges to $\frac{1}{e}$ as $n \rightarrow \infty$.

3.4 Simulation

To verify the result of Section 3.3 independently of analytical derivation, we simulate the hiring process 5000 times using $n = 1000$. For each trial, the first r out of 1000 applicants are rejected. Then, if a relative best applicant who is not the overall best applicant is selected, the trial returns failure. On the other hand, if the overall best applicant is picked, the trial returns success. After 5000 trials, the $P(\text{Success})$ is recorded and plotted. This is repeated for each $r \in [1, n]$.

The above simulation generates a following comparison:

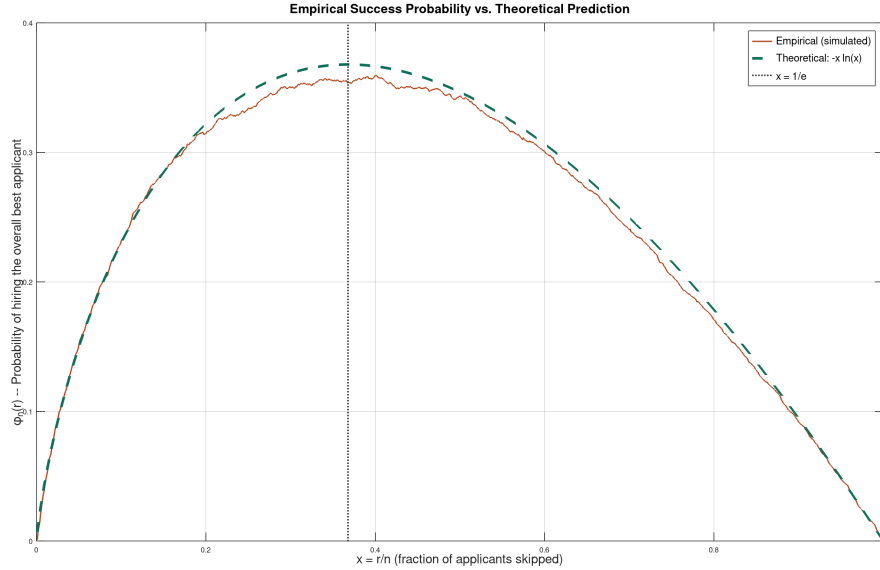


Figure 1: Visual comparison between theoretical prediction and empirical data

The empirical data closely tracks the theoretical prediction across the full range of x (Figure 1). From the data, the empirical maximum occurred at $\frac{r}{n} \approx 0.400$, while the theoretical maximum occurred at $\frac{r}{n} \approx 0.367$ —a difference caused by the finite value of n used in the trials.

The Optimal Stopping Problem, in this context, answers the question of when to commit to a hiring decision, given that information about applicants arrives sequentially and cannot be revisited once passed over. Once this decision has been made and an applicant is hired, another question arises: how should the company continue to learn about that employee’s actual performance, given that performance data also arrives sequentially? The remainder of this paper turns to this second question.

4 Bayes’ Theorem and the Beta-Binomial Distribution Model for Employee Evaluation

4.1 Motivation

Now that an employee has been hired, the probability $P(H)$ that that employee is high-performing should be tracked—that way, a company is able to model how their belief about a specific employee’s ability evolves as evidence accumulates. In this section, we describe the procedure for tracking $P(H)$ using Bayes’ Theorem, and starting from said theorem, we derive the Beta-Binomial distribution that models the success/failure data of an employee on tasks.

4.2 Bayes' Theorem in the Context of Employee Evaluation and Sequential Update

Let H be the hypothesis, which is that an employee is high-performing. Let E be the evidence, which is that an employee succeeds in a given task. Then, we can define the following probabilities:

1. $P(H)$
2. $P(H^c)$
3. $P(E|H)$
4. $P(E|H^c)$
5. $P(E^c|H)$
6. $P(E^c|H^c)$
7. $P(H|E)$

Note that in Bayes' Theorem, $P(H)$ is the prior, $P(E|H)$ is the likelihood, $P(H|E)$ is the posterior, and $P(E)$ is the probability of the event (which, in our context, is an employee succeeding in a task). This is also known as the normalizing constant.

According to Bayes' Theorem, the following is true [3]:

$$P(H|E) = \frac{P(H)P(E|H)}{P(H)P(E|H) + P(H^c)P(E|H^c)} = \frac{P(H)P(E|H)}{P(E)}$$

Let it be known that $P(E|H)$, $P(E^c|H)$, and their complements are constants, because the model only considers one case of H —this will be further explained in the following subsection.

In the context of workforce management, the above probability can be interpreted as the probability that an employee is high-performing given that he or she succeeds in a task.

Bayes' Theorem allows a sequential update—that is, the computed $P(H|E)$ becomes the next $P(H)$, or the posterior becomes the next prior. This way, the model allows prior beliefs to be updated to a new value after every trial, where the new value depends on the result of the trial.

Then, we can write a recursive formula for $P(H|E)_{i+1}$, the probability that an employee is high-performing given that he or she succeeds in a given task, after $i \in [0, \infty)$ tasks.

$$P(H|E)_{i+1} = \begin{cases} \frac{P(H)_i P(E|H)}{P(H)_i P(E|H) + P(H^c)_i P(E|H^c)} & \text{if task } i+1 \text{ succeeds} \\ \frac{P(H)_i P(E^c|H)}{P(H)_i P(E^c|H) + P(H^c)_i P(E^c|H^c)} & \text{if task } i+1 \text{ fails} \end{cases}$$

$P(H)_0$ is given as the company's initial prior—their guess of the probability that an employee is high-performing, before any evaluation takes place. Additionally, $P(H)_{i+1} = P(H|E)_i$.

4.3 The Beta-Binomial Distribution for Modeling T with a Confidence Value

The Beta-Binomial model we are about to derive considers H as not a case but as a real number. In the previous model, H was a single event that an employee is high-performing; therefore, $P(H)$ was also a single value—the probability that an employee is high-performing. This model’s version of H is $T \in [0, 1]$ —also previously referenced in this paper as the true value. As $T \rightarrow 0$, one assumes that the employee is low-performing, and as $T \rightarrow 1$, one assumes that the employee is high-performing. After k tasks, let s be the number of successes and f be the number of failures. Then, the likelihood $P(E|H)$ from the previous subsection can be modeled by the function

$$L(T) = \binom{k}{s} T^s (1 - T)^f$$

Note that the binomial distribution was used because we assume that the employee can either only succeed or fail a given task. Because the Beta distribution is known to be the natural conjugate prior of binomial distribution, we can model the prior $P(H)$ from the previous subsection with the following function ρ .

Let $\alpha, \beta \in \mathbb{N}$ such that $\frac{\alpha}{\alpha+\beta} = P(H)_0$. Then,

$$\rho(T) = \frac{T^{\alpha-1} (1 - T)^{\beta-1}}{B(\alpha, \beta)}$$

The Beta function in the denominator makes the above function a probability density function, meaning that $\int_0^1 \rho(T) dT = 1$, which must be true because the probability that an employee’s T is within $[0, 1]$ is 1.

Note that $\rho(T)$ may seem like it is the end of the derivation as it is a function that models the true value with confidence value (which is our goal), but it does not consider the likelihood $L(T)$ —therefore, the derivation is yet to be done.

According to Bayes’ Theorem, it is true that

$$\text{Posterior} \propto \text{Prior} \times \text{Likelihood}$$

Therefore, the new posterior ψ is related to the following:

$$\psi(T) \propto L(T) \times \rho(T) \tag{11}$$

$$= \binom{k}{s} T^s (1 - T)^f \times \frac{T^{\alpha-1} (1 - T)^{\beta-1}}{B(\alpha, \beta)} \tag{12}$$

$$= \frac{\binom{k}{s}}{B(\alpha, \beta)} T^{\alpha+s-1} (1 - T)^{\beta+f-1} \tag{13}$$

Next, take $P(E)$ into consideration. In the previous subsection, $P(E)$ was defined as

$$P(H) \times P(E|H) + P(H^c) \times P(E|H^c)$$

Because it was the sum of all the possible probabilities of hypotheses multiplied by the likelihood.

In this subsection, because $T \in [0, 1]$, we have an indefinite number of hypotheses and their complements to consider. Therefore, our new probability of the event ω , or the normalizing constant, is

$$\omega = \int_0^1 L(T)\rho(T) dT \quad (14)$$

$$= \int_0^1 \frac{\binom{k}{s}}{B(\alpha, \beta)} T^{\alpha+s-1} (1-T)^{\beta+f-1} dT \quad (15)$$

$$= \frac{\binom{k}{s}}{B(\alpha, \beta)} \int_0^1 T^{\alpha+s-1} (1-T)^{\beta+f-1} dT \quad (16)$$

$$= \frac{\binom{k}{s}}{B(\alpha, \beta)} B(\alpha + s, \beta + f) \quad (17)$$

In (17), the integral was simply replaced with the Beta function.

According to Bayes' Theorem,

$$Posterior = \frac{Prior \times Likelihood}{Probability of the Event}$$

Therefore, our new posterior is

$$\psi(T) = \frac{\rho(T) \times L(T)}{\omega(T)} \quad (18)$$

$$= \frac{\frac{\binom{k}{s}}{B(\alpha, \beta)} T^{\alpha+s-1} (1-T)^{\beta+f-1}}{\frac{\binom{k}{s}}{B(\alpha, \beta)} B(\alpha + s, \beta + f)} \quad (19)$$

$$= \frac{T^{\alpha+s-1} (1-T)^{\beta+f-1}}{B(\alpha + s, \beta + f)} \quad (20)$$

The above is the Beta-Binomial distribution curve that models T with a confidence value [2].

In this model, as data of success/failures accumulate, the Beta distribution narrows down to a specific T , in which the probability that an employee's T is within $k \in \mathbb{R}$ is

$$\int_{T-k}^{T+k} \psi(T) dT$$

Note that since ψ is a probability density function, the following is true:

$$\int_0^1 \psi(T) dT = 1$$

4.4 Simulation

To illustrate how $\psi(T)$ behaves as data accumulates, we simulate an employee completing a series of similar-difficulty tasks and track the evolving model. In the simulation with n employee evaluations, we assign T to be 0.7 and α, β such that $\frac{\alpha}{\alpha+\beta} = 0.3$. Additionally, the probability of the most likely T after n evaluations was calculated by performing a Riemann Sum over $[T - 0.02, T + 0.02]$.

In Figures 2-5, T^* represents the T value with the highest probability density after n trials.

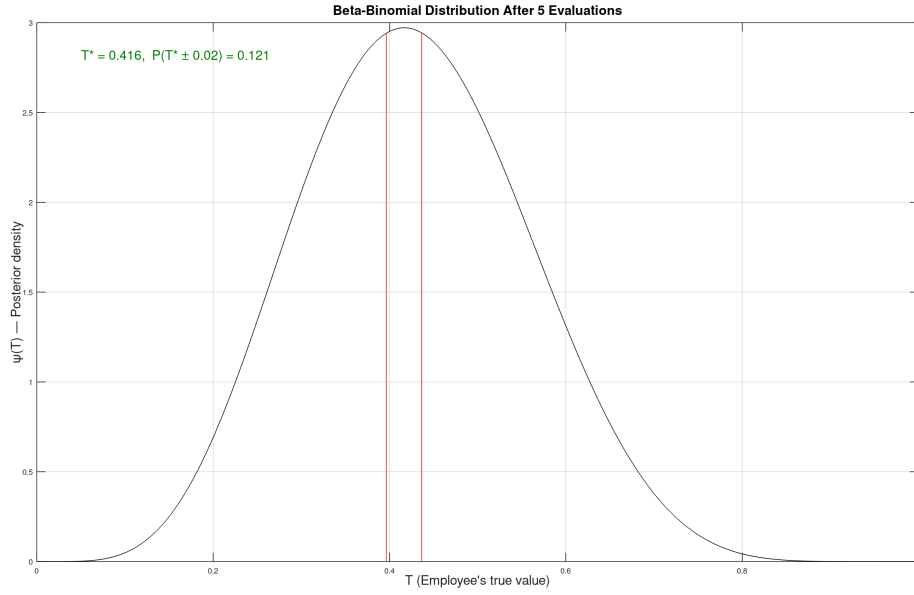


Figure 2: $n = 5$

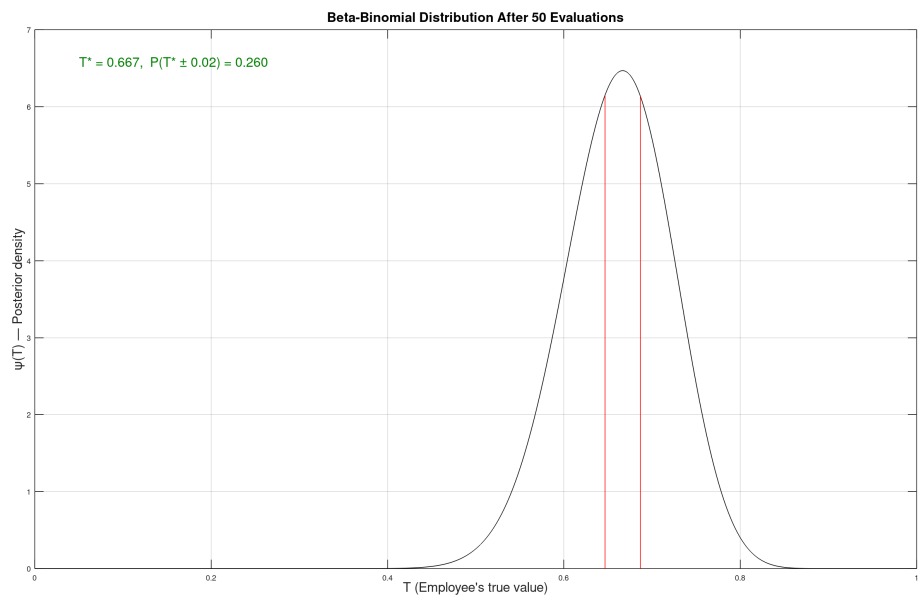


Figure 3: $n = 50$

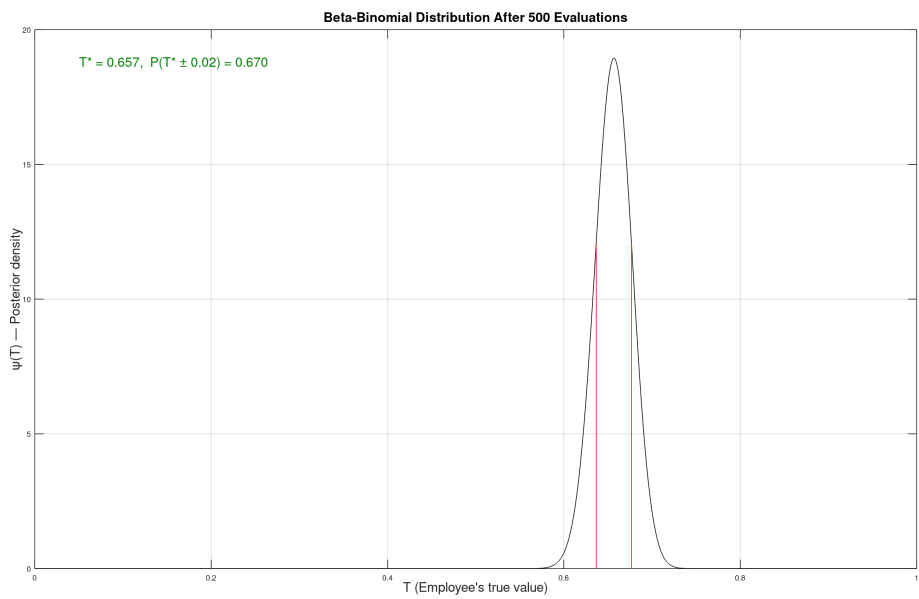


Figure 4: $n = 500$

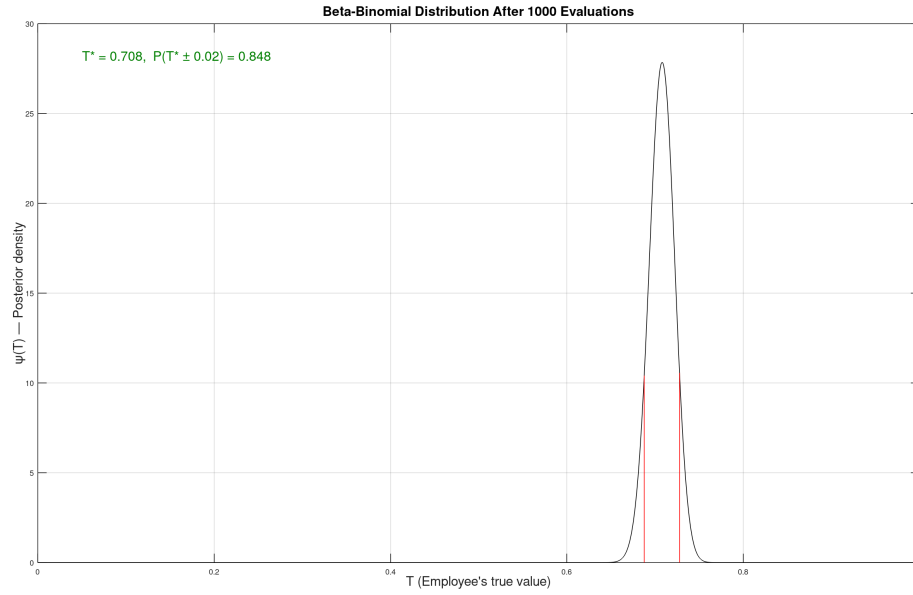


Figure 5: $n = 1000$

The evolution of the model as data accumulated is shown below, at $n = 1000$. Note that all conditions were constant.

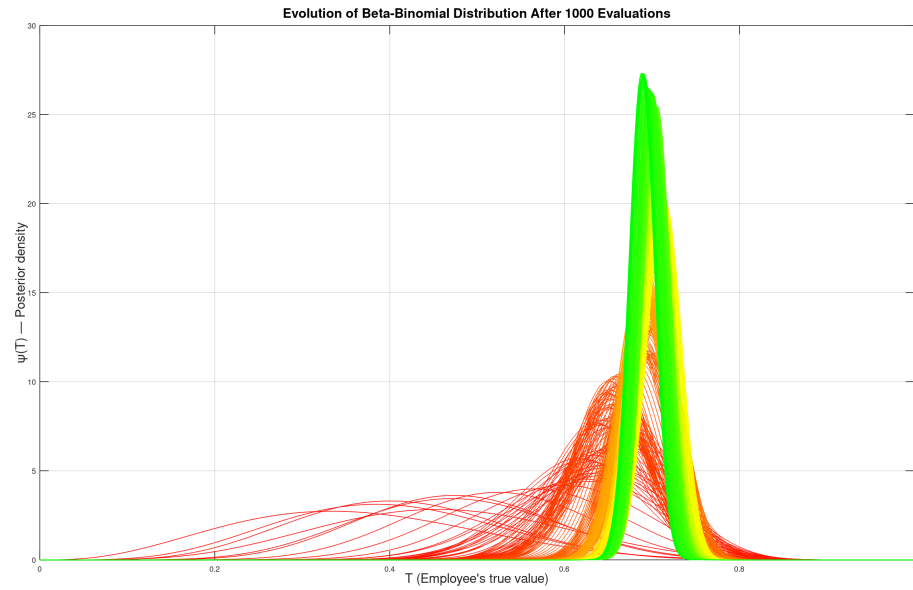


Figure 6: The evolution of the Beta-Binomial distribution after 1000 evaluations.

5 Conclusion

5.1 Summary

This paper examined two decision problems in workforce management: deciding whom to hire, and evaluating that employee once hired. Confidence played a central role in both, although in different senses.

In Section 3, confidence took the form of a single judgment—what is the optimal stopping point that will maximize one’s confidence in picking the overall best applicant? We showed that the optimal stopping point depends on the number of applicants, and also that the fraction of candidates to reject, $\frac{r}{n}$, converges to $\frac{1}{e}$ as $n \rightarrow \infty$, which was confirmed empirically via simulation (Figure 1).

In Section 4, confidence updated itself as data accumulated. From Bayes’ Theorem applied to workforce management, we extended the single case of H into a continuous distribution of $T \in [0, 1]$. Then, using the fact that Binomial likelihood’s conjugacy prior is the Beta distribution, we derived the Beta-Binomial model $\psi(T)$ for the evolving estimation of T with a confidence value. Unlike a single point estimate, as the number n of evaluations increase, the accuracy of T increases, as well as its confidence—this way, companies don’t just know whether an employee is high-performing or not; they know the exact numerical value of an employee’s performance.

We then displayed $\psi(T)$ via simulation in Figures 2-6, with 6 being the visual record of the changing distribution as data accumulated.

5.2 Limitations and Ethical Concerns

In the industry, the solution to the Optimal Stopping Problem would be scarcely utilized, as the problem was not designed for real-world hiring purposes. Unless a company is placed under a heavy time limit, the traditional way of evaluating applicants one by one is the best method of picking an overall best applicant.

The final model of Section 4 has quite a few limitations: first, every task an employee performs is assumed to be of similar difficulty. In practice, this is impossible, unless the tasks given are categorized on difficulty by the company before-hand. Second, this paper does not address in detail how the initial prior values for $\psi(T)$, α and β , should be chosen. A poorly chosen prior could distort early estimates before sufficient amount of data accumulates. Third, the model assumes that tasks have binary outcomes, while real performance results are frequently multidimensional. Therefore, extra attention may be required to ensure that the model accurately predicts overall performance of an employee.

Furthermore, this paper’s model reduces an employee’s value to a single quantity, T . Reducing a human performance to a scalar can obscure other various dimensions—collaboration, mentorship, development, etc.—that play a role in determining an employee’s worth. Therefore, a model like this should not be mistaken as a complete account of an employee’s value; instead, it should be treated as the general overview of an employee’s accuracy and skill, similar

to how tests are the close estimate of a student’s knowledge and accuracy.

5.3 Future Work

Future work related to this paper’s topic will cover the case where tasks are not of the same difficulty, which was a primary limitation for the Beta-Binomial distribution we derived in this paper. In the above scenario, tasks will be assigned a value $V \in [0, 1]$ that represents their difficulty—1 being extremely difficult, and 0 being extremely easy. Additionally, we will consider the issue of choosing an accurate initial prior. Finally, the realistic multidimensional results that an employee produces will also be taken into account, essentially addressing all the limitations listed in the previous subsection.

Although the Optimal Stopping Problem and its solution may not be implemented in the industry, the Beta-Binomial distribution model can be modified further in a way that, in the future, it may be ready for practical application.

References

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- [2] Howell, E. (2022, August 26). Bayesian conjugate priors simply explained. *Towards Data Science*. <https://towardsdatascience.com/bayesian-conjugate-priors-simply-explained-747218be0f70/>
- [3] Azad, K. (n.d.). An intuitive (and short) explanation of Bayes’ theorem. *BetterExplained*. <https://betterexplained.com/articles/an-intuitive-and-short-explanation-of-bayes-theorem/>
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- [4] Sanderson, G. (2019). Bayes theorem, the geometry of changing beliefs [Video]. *3Blue1Brown*, YouTube. <https://youtu.be/HZGCoVF3YvM>
- [5] Collings, I. (n.d.). What is a probability density function (PDF)? [Video]. *Iain Explains Signals, Systems, and Digital Comms*, YouTube. <https://www.youtube.com/watch?v=jUFbY5u-DMs>

A Code for the Empirical Simulation of The Optimal Stopping Problem

Listing 1: Matlab code for the Optimal Stopping Problem used to generate Figure 1.

```
clear; clc; close all;
```

```

n = 1000;
trials = 5000;

success_count = zeros(1, n);
r_values = 1:n;

for t = 1:trials
    perm = randperm(n);    % random arrival order of ranks 1..n
    running_max = cummax(perm);
    is_record = [true, perm(2:end) > running_max(1:end-1)];

    position_of_best = find(is_record, 1, 'last');

    vals = Inf(1, n);
    vals(is_record) = find(is_record);
    next_record = fliplr(cummin(fliplr(vals)));

    success_this_trial = (next_record == position_of_best);
    success_count = success_count + success_this_trial;
end

empirical = success_count / trials;

% theoretical curve
x = linspace(0.001, 1, 500);
theoretical = -x .* log(x);

figure;
plot(r_values/n, empirical, 'Color', [0.71 0.27 0.11], 'LineWidth', 1);
hold on;
plot(x, theoretical, '—', 'Color', [0.06 0.43 0.34], 'LineWidth', 2);
plot([1/e 1/e], [0 0.4], ':', 'Color', [0.2 0.2 0.2], 'LineWidth', 1.2);
xlabel('x = r/n (fraction of applicants skipped)', 'fontsize', 17);
ylabel('phi_n(r) — Probability of hiring the overall best applicant', 'font...');
title('Empirical Success Probability vs. Theoretical Prediction', 'fontsize', ...);
legend('Empirical (simulated)', 'Theoretical: -x ln(x)', 'x = 1/e', 'Location', ...);
grid on;

[peak_val, peak_idx] = max(empirical);
fprintf(" Empirical optimal r/n = %.4f (theoretical 1/e = %.4f)\n", peak_idx/n, ...);

```

B Code for the Visualization of the Beta-Binomial Model

Listing 2: Matlab code for the Beta-Distribution model used to generate Figure 2-5. To generate Figure 6, follow the directions on the first lines of comments.

%TO GENERATE FIGURE 6, DE-COMMENT THE FOLLOWING:

```

    %if mod(i,2) == 0
        %if i<500
            % colors = [1 (1/500)*i 0]; %start: [1 0 0] end: [1 1 0]

        %endif

        %if i>=500
            % colors = [2-((1/500)*i) 1 0]; %start: [1 1 0] end: [0 1 0]
        %endif

    %endif

    %AND COMMENT THE FOLLOWING:
    %plot([x(lower_idx), x(lower_idx)], [0, y(lower_idx)], 'r-'); hold on;
    %plot([x(upper_idx), x(upper_idx)], [0, y(upper_idx)], 'r-'); hold off;

    %label_str = sprintf('T* = %.3f,
P(T*      %.2f) = %.3f', T_star, x(upper_idx)-x(lower_idx), prob_near_peak);

    %text(0.05, 0.95, label_str, 'Units', 'normalized', ...
        %    'HorizontalAlignment', 'left', 'VerticalAlignment', 'top', ...
        %    'FontSize', 17, 'Color', [0 0.5 0]);

clear;clc;close all
dp=0.001;
maxd = 0;
al = 3;
be = 7;
true_value = 0.7;
x=linspace(0,1,1/dp);

for i=1:1000
    y = ((x.^(al-1)).*(1-x).^(be-1))/(beta(al, be));

    colors = [0 0 0]

    %if mod(i,2) == 0
        %if i<500
            % colors = [1 (1/500)*i 0]; %start: [1 0 0] end: [1 1 0]

```

```

    %endif

    %if i>=500
        % colors = [2-((1/500)*i) 1 0]; %start: [1 1 0] end: [0 1 0]
    %endif

%endif

plot(x, y, 'Color', colors); hold on; grid on;

[peak_val, peak_idx] = max(y);
T_star = x(peak_idx);

window_width = dp;
window_scale = (1/dp)/50;
lower_idx = max(1, peak_idx - window_scale);
upper_idx = min(length(x), peak_idx + window_scale);
prob_near_peak = sum(y(lower_idx:upper_idx)) * dp;

plot([x(lower_idx), x(lower_idx)], [0, y(lower_idx)], 'r-'); hold on;
plot([x(upper_idx), x(upper_idx)], [0, y(upper_idx)], 'r-'); hold off;

label_str = sprintf('T*=%%.3f, P(T*=%%.2f)=%.3f', T_star, x(upper_idx), y(upper_idx));

text(0.05, 0.95, label_str, 'Units', 'normalized', ...
    'HorizontalAlignment', 'left', 'VerticalAlignment', 'top', ...
    'FontSize', 17, 'Color', [0 0.5 0]);

r=randi([1 10]);
if and((r/10)>=0.1, (r/10)<=true_value)
    al = al + 1;
endif
if and((r/10)>true_value, (r/10)<=1)
    be = be + 1;
endif

xlabel('T-(Employee''s-true-value)', 'fontsize',17)
ylabel('\psi(T)-Posterior-density', 'fontsize',17)
title(sprintf('Evolution-of-Beta-Binomial-Distribution-After-%.d-Evaluations', d))
pause(0.01)
end

```