Computational Modeling: Talent vs. Luck

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1 Introduction

"Success is not luck, but only the result of blood, sweat and tears" [KontraK, 2015]. This is a quote from a well-known German rapper who tries to convince his audience of a career similar to "from dishwasher to millionaire". Populist politicians also use the image of hard work and talent to replace social policy with self-optimisation of the population. In our meritocratic Western Society, it is good manners to believe in success through ability. The question arises whether talent and hard work really play such an important role in a person's career, or is it not rather luck? The paper "Talent versus Luck: The Role of Randomness in Success and Failure" by Alessandro Pluchino, Alessio Emanuele Biondo, and Andrea Rapisarda explores the impact of randomness on success, challenging the meritocratic view [PLUCHINO et al., 2018].

The authors present the discrepancy between the normal distribution of talent and intelligence (Gaussian distribution) and the highly skewed distribution of wealth (Pareto law), with few individuals amassing significant wealth while the majority remain poor. This gap suggests the presence of an overlooked factor influencing success. Through the TvL model (Talent versus Luck), the paper quantifies the role of luck in achieving success, demonstrating that while talent is necessary, it is not sufficient.

In the following report, I would like to summarise the authors' findings and critically examine the model. In the last chapter, I show how I adapted the authors' model based on the criticism. The code can be found in the Github repository https://github.com/Raphaaella/Computational-Modeling—Talent-vs.-Luck.

2 The Model

The paper uses an agent-based model to simulate careers over a 40-year period, showing how talent and luck interact to produce the observed distribution of success.

2.1 Talent

Talent in this paper encompasses personal qualities such as intelligence, skills, smartness, effort, willfulness, hard work, and risk-taking. It represents inherent or acquired capabilities that an individual possesses. Talent is assumed to follow a Gaussian (Normal) distribution. Mathematically, this can be expressed as:

$$T \sim \mathcal{N}(\mu_T, \sigma_T^2)$$

where μ_T is the mean talent level and σ_T^2 is the variance.

Success

Success is proxied by wealth in the paper. It reflects the outcomes and accomplishments that individuals attain over their careers. Success is shown to follow a power-law (Pareto) distribution. This distribution is characterized by a small number of individuals achieving very high levels of success (or wealth), while the majority remain relatively unsuccessful. Mathematically, this can be expressed as:

$$P(X > x) \propto x^{-\alpha}$$

where α is a positive constant, and X represents the level of success.

Luck

Luck represents random, uncontrollable events that can significantly impact an individual's level of success. These events can be positive (lucky) or negative (unlucky) and can drastically alter the career trajectory of an individual. The probability of successfully capitalizing on a lucky event is proportional to the individual's talent.

2.2 Event Points

At each time step in the simulation, which represents a six-month period, event points move randomly across the simulated world. Lucky events, if they intersect with an individual's position, provide an opportunity for the individual to double their capital, but only if their talent level is sufficient to take advantage of the opportunity. Conversely, unlucky events halve an individual's capital when they intersect, regardless of the individual's talent. These events are distributed randomly, and their interactions with individuals are contingent on the probabilities defined by the model.

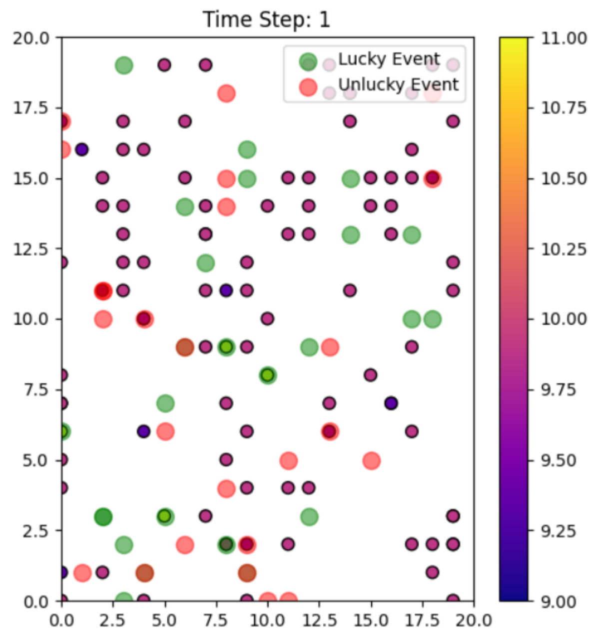


Figure 1: 100 Agents randomly distributed in a grid

3 Results

Interaction between Talent, Success, and Luck

According to the model talent alone does not guarantee success; rather, luck plays a crucial role in determining the most successful individuals. The findings reveal that success often follows a power-law distribution, where a few individuals accumulate disproportionate wealth, largely due to fortunate circumstances. The most successful individuals are often not the most talented but those who have experienced the most favorable sequences of luck. This suggests that success is not purely meritocratic but significantly influenced by random factors.

3.1 Research Funding Scenarios

Serendipity, or accidental discoveries, is often a crucial factor in scientific breakthroughs. The authors mention historical examples like the discovery of penicillin and radioactivity, emphasizing the unpredictable nature of such discoveries. Current funding strategies focused on excellence may overlook the potential of less promising but innovative research. The TvL model is used to simulate various funding scenarios to identify the most effective strategies:

- Egalitarian Criterion (equal distribution of funds among all researchers)
- Elitarian Criterion (funding only the most successful individuals based on past performance)
- Mixed Criterion (a combination of merit-based and equal distribution)
- Selective Random Criterion (random selection of individuals for funding)

Simulations show that egalitarian distribution is the most efficient strategy, doubling the success rate of talented individuals. Random strategies also perform well, indicating that funding diversity can lead to greater innovation and success. The environment, such as the average education level and social stimuli, significantly impacts the success of individuals. Two scenarios were analyzed: increasing the standard deviation of talent distribution (benefits the highly talented but increases inequality) and raising the average talent level (enhances overall success and reduces inequality). The authors concludes that diverse and egalitarian funding strategies, combined with a stimulating environment, are crucial for maximizing the potential of talented individuals. These strategies help counterbalance the role of luck, ensuring broader opportunities for success and fostering innovation.

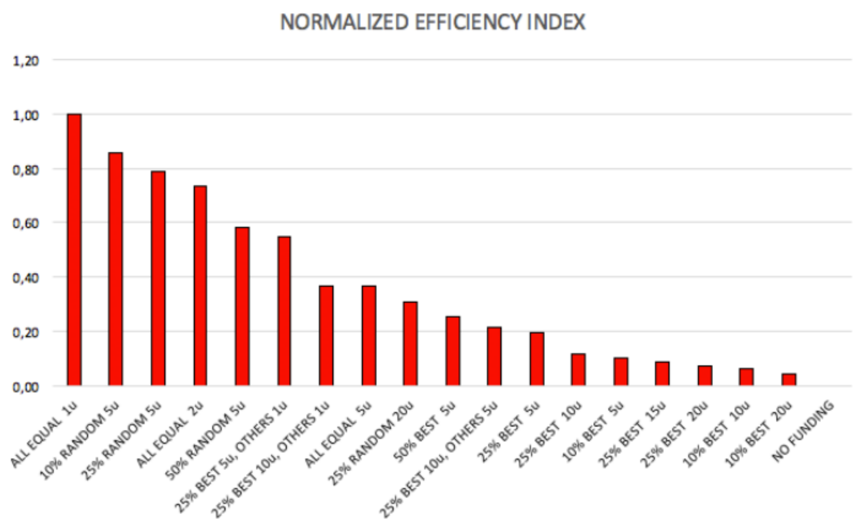


Figure 2: Normalized e±ciency index for several funding strategies. Figure 11, page 21 [PLUCHINO et al., 2018]

The provided plot further substantiates these arguments by illustrating the Normalized Efficiency Index for various funding strategies, thereby visualizing their relative effectiveness in promoting success among talented individuals. The vertical axis measures the normalized efficiency index, which quantifies the effectiveness of each funding strategy relative to the most efficient strategy, set at 1.0. The horizontal axis lists different funding strategies, ranging from egalitarian approaches to selective and random ones. The plot reveals that the egalitarian strategy, which distributes funds equally among all individuals (ALL EQUAL 1u, 2u, 5u), consistently ranks the highest in normalized efficiency. This indicates that distributing funds equally is the most effective approach in enhancing overall success. Random strategies (10% RANDOM, 25% RANDOM) also show high efficiency, suggesting that random distribution of funds can effectively promote success. Mixed strategies, which combine merit-based and egalitarian distribution (25% BEST, OTHERS), are moderately efficient, indicating they can still be effective but not as much as purely egalitarian or random approaches. On the other hand, selective meritocratic strategies (10% BEST, 25% BEST, 50% BEST) are the least efficient, reinforcing the chapter's argument that distributing funds based on past success is not as effective. The "No Funding" scenario represents the baseline with the lowest efficiency index, highlighting the importance of funding strategies in promoting success.

In summary, the paper highlights the role of randomness in success, challenging the traditional meritocratic paradigm. It underscores the importance of considering luck in assessments of success and calls for more equitable and effective strategies in resource allocation to foster true meritocracy and innovation. The authors argue that current meritocratic practices, which reward individuals based on past successes, may favor those who were simply luckier, rather than more talented. The paper suggests alternative funding strategies that could better promote innovation and diversity, such as distributing resources more evenly or randomly, rather than concentrating them among the already successful.

4 Critique

A central sentence of the authors in the results section of the simulation is: "although there is an absence of correlation between success and talent coming out of the simulations, there is also a very strong correlation between success and luck" [PLUCHINO et al., 2018] It can be clearly criticised that this correlation is simply the result of the construction of the model itself. A lucky event point plus a minimum availability of talent leads to a doubling of capital by model definition. A correlation between talent and success and a correlation between luck and success can therefore not be compared because the two components play a different role in the simulation.

Another point is the vague definition of the term "talent" in the paper. Talent is described in broad terms such as intelligence, ability, cleverness, effort, stubbornness, hard work and risk-taking, but it is not clearly defined or measured. Talent is a very complex theoretical concept that requires in-depth analysis. The inclusion of actual survey data could have provided a more valid basis for the model.

Additionally, the model assumes that all agents start with the same initial capital. This assumption overlooks the critical impact of socio-economic differences on individuals' career trajectories. In reality, individuals do not start on an equal footing; socio-economic background, access to resources, and inheritance significantly influence one's ability to capitalize on talent and luck. By ignoring these disparities, the model simplifies the complexities of real-world success and fails to account for the structural inequalities that can perpetuate advantage or disadvantage, regardless of talent or luck.

Furthermore talent is time-independent in this model. In reality, talent can evolve over time due to factors such as education, training, experience, and personal development. By treating talent as a static attribute, the model does not account for the dynamic nature of personal growth and skill acquisition.

Another critique is the lack of consideration for the feedback loops between success and further lucky opportunities. Success in real life often leads to additional opportunities and resources, which can further amplify an individual's trajectory. This positive feedback loop is not reflected in the model, which treats each event and its impact on capital independently of past successes.

5 Modified Simulation

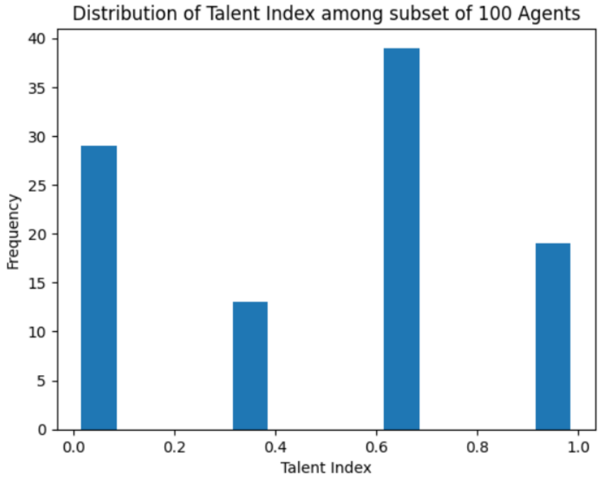
In an modified simulation I tried to include a feedback loop and survey data about talent and capital as mentioned in the critique section. I used the European Social Survey (ESS) dataset to derive measures for talent and capital [European Social Survey European Research Infrastructure (ESS ERIC), 2024]. German respondents were filtered from the ESS data in order to keep the conditions for a simulation as consistent as possible.

Talent

For the talent index the following variables were standardised and averaged:

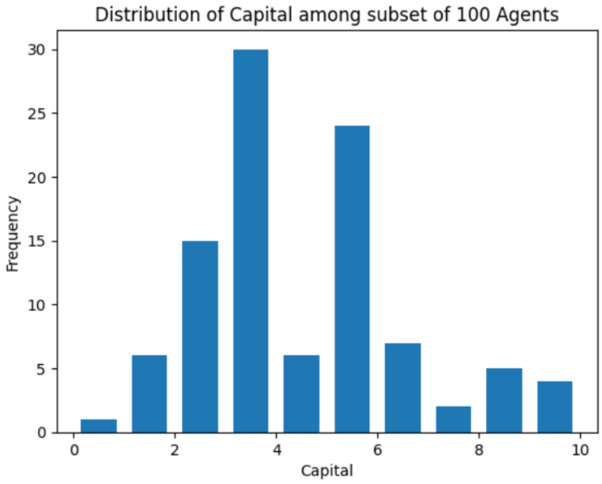
- atncrse: "During the last twelve months, have you taken any course or attended any lecture or conference to improve your knowledge or skills for work?"
- ipcrtiva: "Important to think new ideas and being creative"
- ipshabta: "Important to show abilities and be admired"

The index indirectly takes into account the third point of criticism, namely that talent is not a time-independent construct. The first variable, whether one has attended a course in the last year, also considers the development of the agents' talent.



Capital

Capital was proxied by the parents' level of education, as there was no variable for wealth. It is assumed that the parents' level of education has an influence on the agent's starting capital. The created capital variable from the ESS has a range between 0 and 10. In the authors' original simulation, all agents receive the same starting capital of 10 units.



Socio Economic Status

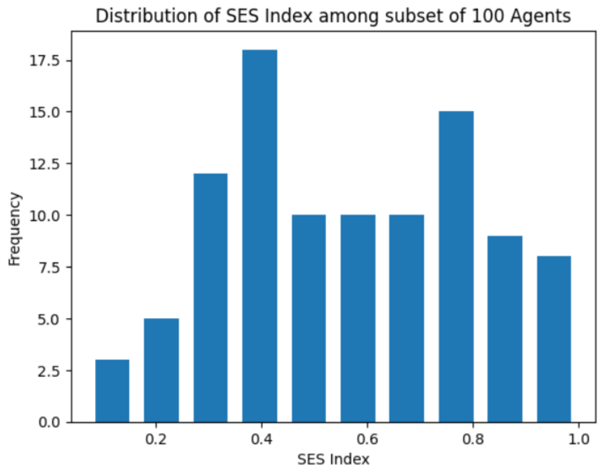
Socio-economic status was defined as an index of education and income and has a range between 0 and 1

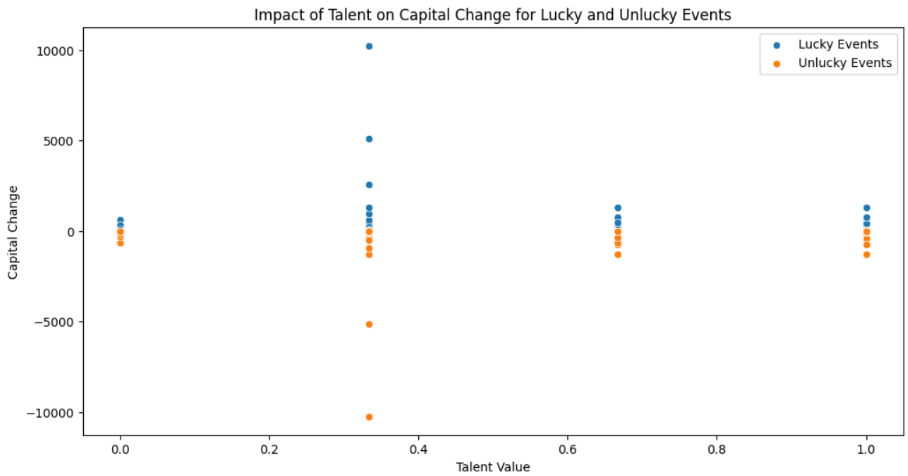
The feedback loop is implemented as probabilistic check to simulate the chance of an agent successfully taking advantage of a lucky event, depending on the capital, socio economic status and the talent index. As capital is a dynamic variable, past successes in an agent's career are taken into account. The probability is defined as capital + ses_index + talent_index divided by 3.

The results diagram of the modified simulation emphasises once again that the results are a product of the model architecture. Event points always have an effect on success, happy events have a positive effect and negative events have a negative effect because they have been defined in that way. However, it also shows that moderate talent of 0.3 can lead to greater changes in success than higher talent.

References

[European Social Survey European Research Infrastructure (ESS ERIC), 2024] European Social Survey European Research Infrastructure (ESS ERIC) (2024). Ess11 - integrated file, edition 1.0.





[KontraK, 2015] KontraK (2015). Erfolg ist kein glück.

[PLUCHINO et al., 2018] PLUCHINO, A., BIONDO, A. E., and RAPISARDA, A. (2018). Talent versus luck: The role of randomness in success and failure. *Advances in Complex Systems*, 21(03n04):1850014.