



Building AI to Unlearn Bias in Recruiting

How to use AI and machine learning to ensure diversity in the workforce

By the creators of AllyO, the end-to-end AI recruiter



Bias is a problem we need to address

Our society is struggling with bias and its negative impacts on our workforce.

154%

A study by the Ascend Foundation showed that white men and women in major Silicon Valley firms were 154% more likely to become executives than other races.

35%

A Mckinsey diversity study concluded that companies in the top quartile of diversity performance generate 35% more financial returns than the median.

While we have made significant progress in uncovering and unlearning causes of bias, our progress in unbiasing society is potentially at risk due to advancements in AI technology. An AI-led future is evident — and it is our collective responsibility to get it right.

What's causing bias today?

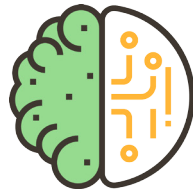
Humans drive and make most of the decisions in our current recruiting processes. A person's judgments can often be based on a small number of anecdotal data points (e.g., if three similar applicants perform well in a Sales Executive interview, we might subconsciously start screening for traits common to them). Decision makers' judgment calls may also vary based on their cultural, social and educational backgrounds, leading to low consistency across individuals. Furthermore, we aren't always self-aware of all the filters we are applying to make judgments. This is commonly referred to as unconscious bias.

We aren't always self-aware of all the filters we are applying to make judgments.

As automation increases over time, humans become involved in fewer points of decision making. While this reduces inconsistency and task completion errors, the actual risk of bias might not reduce much since most of the automated tasks were quite objective to begin with. As long as humans are making subjective decisions without checks and balances, bias will exist in the system.

Can AI reduce bias?

The new era of AI-led automation is replacing humans' subjective decision making and is now evaluating large amounts of data that were not earlier methodically factored in.



The advantage of using machines is that judgments are based on holistic correlations on a statistically significant sample — leading to high consistency and better outcomes. However, we need to be aware of the following points:

1

Without explicit external guidance, machines will use every factor for its face value. This means that while they aren't mathematically biased, socially they could be using factors that we deem inappropriate.

2

Training for the same outcomes that humans would have made doesn't really take out bias (as the premise would be that the original decisions had no bias in them).

3

Most of these systems are GIGO: Garbage In Garbage Out. This means that if incorrect data — or more likely insufficient data — is fed in, the models can be wrongly trained or overtrained and thus would not be much good at making sound judgments.

4

The current implementation of AI in the form of machine learning / deep learning feels like a black box. It is often difficult to dissect these learning systems and understand how decisions are being engendered within them. Their internal guts and flows don't always translate to real world notions.

Bias challenges in current recruiting solutions

Let's take some examples of bias challenges in AI recruiting technology that are currently available today:

Personality/skill based assessment

There are a ton of assessment systems that profile your current high and low performing employees to determine the right qualities of a new hire. While the smarter version of these systems don't take into account a subject's personal information, how does one make sure that the qualities that are taken into account aren't directly correlated to more frowned upon qualities? How do we know that the company's performance would actually improve if we hired more of the same type of "high-performing" people?

Automated resume screening for job matching

Given that resumes don't really have a standard template, they are often bashed for being insufficient and inconsistent in representing candidate skills and qualities. There are also known predilections on how different genders speak about their skills in resumes. Yet resume parsing technology often does not account for these factors when scoring candidates.

Video assessment

There are video interviewing tools out there that automatically screen for certain qualities, like the number of times a candidate says 'please' or the number of times they smile. They also give hiring managers the ability to view the videos before inviting someone for an interview. How do we make sure that this doesn't lead to unconscious screening for gender or race?

How do we make sure that giving hiring managers the ability to view candidates' videos before inviting someone for an interview doesn't lead to unconscious screening for gender or race?

How to implement AI to unlearn bias in recruiting

Here are our recommendations on how to implement AI correctly so that it can unlearn bias in recruiting:



Clean up the input data: make sure that it's appropriate and devoid of bias-causing factors.

Machine Learning systems have algorithms that are sensitive to input and training data, and as such are GIGO (Garbage in → Garbage out). Thus, it is foundational to ensure that the input data is indeed appropriate and devoid of bias-causing factors, e.g., PII and EEO data like gender, race, name, military status, etc.



Ensure Visibility: Really understand what the system is producing on a continuous basis.

Consider the following before buying/deploying an AI recruiting system:

- Ensure that the system can share how the input parameters are related to outcomes (e.g., correlation strengths)
- Keep a control data set that is separate from the training set: when an algorithm goes through changes or self-improvement, it must provide visibility to change in the control set.
- Ensure that the system doesn't produce outcomes based on any and all correlations - Understand patterns of which correlations matter and whether there is a logical explanation (causality). Understand where the human outcome is different from the machine and learn from the differences. Separate causality from correlations.



Test & Control: Show that system actively discourages conscious bias — choose factors that matter and provide continuous feedback.

- Once the system is tuned, create a control set that has different types of parameters — these can be automatically or manually constructed
- Test the algorithm against that set and see where the response is different from what would have been expected
- The system should allow giving feedback — weigh this parameter higher or lower. This can help it tune for the specific use case and industry.
- Compare what those outcomes would be for the control set if human recruiters go through the steps independently. This can train the system better and also help human recruiters uncover their own biases!

Compare what the outcomes would be for the control set if human recruiters go through the steps independently — this can train the system better and help human recruiters uncover their own biases!



Leave room for the unknown: Establish a process for external input.

- Setup a process where people can add in complaints.
- Ultimately, bias elimination will take time — it's an evolution that our society is advancing to uncover and unlearn. A system, just like a human, doesn't know what it doesn't know. So there should always be room for feedback that can go back into it as training data.
- The control set should grow with unique, complicated cases that the system couldn't handle. Every time a data point appears that wasn't covered well within the algorithm, we should add that to the control set to check.

Just like how we train humans to uncover and reduce bias — we should also “teach” AI systems by providing quality untainted training data, and build them to provide the visibility and control we need to solve the challenge of bias in recruiting.



www.allyo.com



hello@allyo.com