Ashoka Horizons Achievers Program – Data Science, ML, AI

Homework Assignment Week 1

1. **The 'Aha!' Moment:**

   The idea that AI replaces tasks, not jobs, was a hard pill to swallow as it completely challenged my preconceived notions. After reading through Brynjolfsson & Mitchell's Workforce Implications article, I realised that AI has now undeniably become very good at repeatedly performing specific and well-defined tasks. However, a job is a messy, tangled bundle of tasks – most of which are poorly defined, highly implicit, social or contextually affected – and this is an area where AI still struggles. Thus, I concluded that while AI may automate some tasks, but not the entire role. As I went through the process of researching this topic, I think that AI can be best categorized in the role of an assistant, and certainly not a substitute for a real human doing a job. Many fear their job becoming obsolete (and I confess, I'm also guilty of this), but, as the article highlights, the workforce needs to evolve and shift from routine tasks to relational or creative ones. Irrespective of how advanced AI may get, a human always needs to be in the loop – AI can handle narrow, repetitive work whilst humans retain oversight and ethical judgement.

2. **Data is King (Or Is It?):**
   The use of data in the process of predictive maintenance in the Industrial Internet of Things (like UPS fleet management) is a stellar example of how having lots of data can be incredibly powerful. Companies like UPS equip vehicle parts with heat and vibration sensors that tracked usage patterns to predict any failures before they could happen. Naturally, these systems rely on millions of data points per second from varied sources (engines, GPS, etc), which offers the company with real-time and historical insights. Certainly, this data isn't pristine or "lab-quality" – but that's what makes the models what they are. The messy, noisy data provides the model with the variability factor (with regards to diversity of geographies and usage) that is essential for accurate predictive patterns. After all, the greater the scale, the greater the accuracy of the predictions. The sheer volume of data isn't just a neutral factor, but a boon as it results in massive cost savings, fewer breakdowns and improved logistics.

3. **Humanity in the Loop**
   In my opinion, one of the largest challenges that machine learning still faces is bias in algorithms due to imperfect training data. The problem is simple yet inescapable; in order for algorithms to function successfully, they need large amounts of data but oftentimes, this historical data reflects unavoidable societal biases. Not only will algorithms mimic this bias in their process outputs,

but it may also amplify them. As algorithms cannot recognize context or ethics, they blindly optimize results for accuracy – sometimes, at the cost of fair results. For example, a hiring algorithm might discriminate against women if trained on past data that favors male applicants for engineering roles. This can have real ethical impact, thus having a deep understanding of this issue is vital for all data scientists so that they can take responsibility for the actions of their models. Humans can address this issue by maintaining oversight and critically inspecting data sources, question assumptions and apply ethical reasoning that machines lack. While the scope for fairness-aware algorithms is limited due to the ongoing Moral Machine Dilemma, it certainly remains a viable option in the near future. In criminal justice risk assessments (like COMPAS), ML models used to predict recidivism were found to be biased against Black defendants. Humans must interpret and correct such outcomes by reevaluating data and assumptions.