Thanks Brandon! I’m Shan and will talk about ‘efficiency and correctness’ of algorithmic decision making. I’ll talk about both positive and negative sides which include *[SLIDE 23]*

For positive side:

Firstly, *[SLIDE 24]*

* As Brandon said before, human always emotional when making decisions
  + Decisions can be a final decision
  + OR, decisions that affect factors of algorithms
* These factors are decided or implemented by us, developers or anyone who take charge of the algorithm

In other words, we made algorithms, they just do what we ask them to do, and algorithms are the reflection of our decisions. However, they won’t make silly mistakes or unpredictable mistakes as people. Algorithms are only as unbiased as the data they draw on.

Secondly, *[SLIDE 25-1]*

* For example, algorithms are the basis for granting loans and setting insurance premiums, as well as for the detection of tax evasion, money laundering, drug trafficking, smuggling, and terrorist activities. Moreover, they steer the answers to our information quests, the advertisements fed to us, the recommendations offered to us, etc.

So due to the size and complexity of these data sets, algorithmic decision making can help unlock value from all this data in a way that humans cannot.

*[SLIDE 25-2]*

* Organizations can be slow to make decisions. Perhaps the people responsible are overloaded with work, they’re agonizing over the decisions assigned to them, or there are too many decision-makers involved in one approval step. Such scenarios create bottlenecks in business processes that can impede productivity and profitability.

For negative side:

Firstly, *[SLIDE 26]*

* As I demonstrated before, algorithms always correct. There are things that can’t be measured with numbers, or at least not measured well, like how much a teacher engages their students, or helps them with family or personal problems. This can mean using proxies, or that some potentially important factors aren’t considered at all. This point also leads to another issue, who make the rule and who to blame, which related to accountability. And Jeremy will discuss more about it after I finished my part.

Secondly, *[SLIDE 27]*

* For example, if a university uses a machine learning algorithm to assess applications for admission, it will be trained on historical data containing the biases – conscious or unconscious – of earlier admissions processes. The university may have decided to use an algorithm to eliminate bias, but it could end up entrenching it instead.
* For the sake of illustration, let us consider model construction for admission decisions concerning university education. Apart from the issue that the target variable (fit for education) is a subjective affair, the process of labelling applicants with one of its possible values may be influenced by prejudice, say against women. So, from the very start, some of the training data points may carry wrong labels. Furthermore, the dataset to be used for training may be biased against specific groups that society wants to protect from discrimination. Along, say, lines of race or gender, records contain more errors, less details, or simply suffer from underrepresentation in the sample as a whole. Unavoidably, skewed data will produce a skewed model later on.

A bit conclusion of ‘Efficiency and correctness’ of algorithmic decision making, which is “Algorithms always correct and mostly they just the reflection of human decisions”