In this chapter, we'll discuss the unique responsibilities of an engineer when designing products for a broad base of users. Further, we evaluate how an organization, by embracing diversity, can design systems that work for everyone, and avoid perpetuating harm against our users.

In fact, understanding how to engineer products that empower and respect all our users is still something Google is learning to do. We have had many public failures in protecting our most vulnerable users, and so we are writing this chapter because the path forward to more equitable products begins with evaluating our own failures and encouraging growth.

Because of bias, Google has at times failed to represent users equitably within their products, with launches over the past several years that did not focus enough on underrepresented groups. Many users attribute our lack of awareness in these cases to the fact that our engineering population is mostly male, mostly White or Asian, and certainly not representative of all the communities that use our products. The lack of representation of such users in our workforce means that we often do not have the requisite diversity to understand how the use of our products can affect underrepresented or vulnerable users.

Google Misses the Mark on Racial Inclusion:

In 2015, software engineer Jacky Alciné pointed out that the image recognition algorithms in Google Photos were classifying his black friends as "gorillas." Google was slow to respond to these mistakes and incomplete in addressing them. This is an example of algorithmic bias in AI systems. The system's use of biased training data led it to make deeply offensive misclassifications involving people with darker skin tones. Google's initial response was slow and, instead of fully solving the problem, the company reportedly chose to block certain labels (like "gorilla," "chimpanzee," "monkey," etc.) from being used at all — rather than improving the model's fairness or accuracy for all skin tones. This case remains a prominent example in discussions of:

- Bias in AI datasets.
- The limitations of machine learning models trained on non-diverse data.

The ethical responsibility of tech companies to ensure inclusive, representative training data.

What caused such a monumental failure? Several things:

- Image recognition algorithms depend on being supplied a "proper" (often meaning "complete") dataset. The photo data fed into Google's image recognition algorithm was clearly incomplete. In short, the data did not represent the population.
- Google itself (and the tech industry in general) did not (and does not) have much black representation and that affects decisions subjective in the design of such algorithms and the collection of such datasets. The

unconscious bias of the organization itself likely led to a more representative product being left on the table.

As late as 2018, Google still had not adequately addressed the underlying problem.

In this example, our product was inadequately designed and executed, failing to properly consider all racial groups, **<u>and as a result, failed our users and caused Google bad press.</u>**

Other technology suffers from similar failures: autocomplete can return offensive or racist results. Google's Ad system could be manipulated to show racist or offensive ads. YouTube might not catch hate speech, though it is technically outlawed on that platform.

<u>"Build for everyone"</u> is a Google brand statement, but the truth is that we still have a long way to go before we can claim that we do. One way to address these problems is to help the software engineering organization itself look like the populations for whom we build products.

Understanding the Need for Diversity:

Google's target market for image recognition did not adequately include such underrepresented groups. Google's tests did not catch these mistakes; as a result, our users did, which both embarrassed Google and harmed our users.

As late as 2018, Google still had not adequately addressed the underlying problem.