Highlight Note

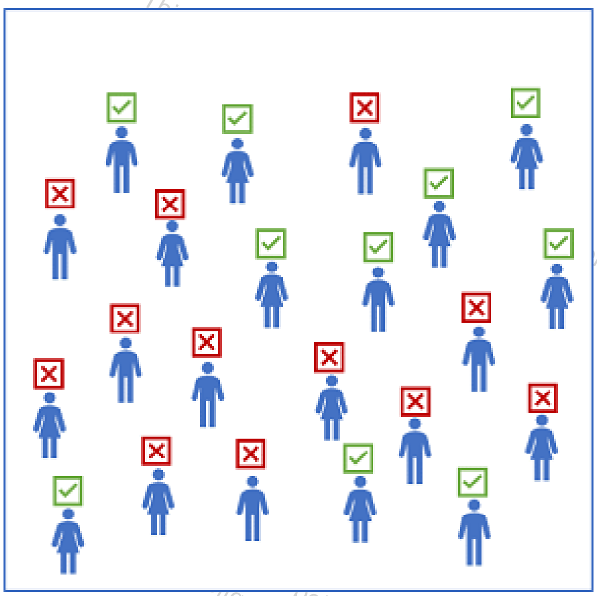
Evaluating Model Fairness

When we consider the concept of *fairness* in relation to predictions made by machine learning models, it helps to be clear about what we mean by “fair”.

For example, suppose a classification model is used to predict the probability of a successful loan repayment, and therefore influences whether or not the loan is approved. It's likely that the model will be trained using features that reflect characteristics of the applicant, such as:

- Age
- Employment status
- Income
- Savings
- Current debt

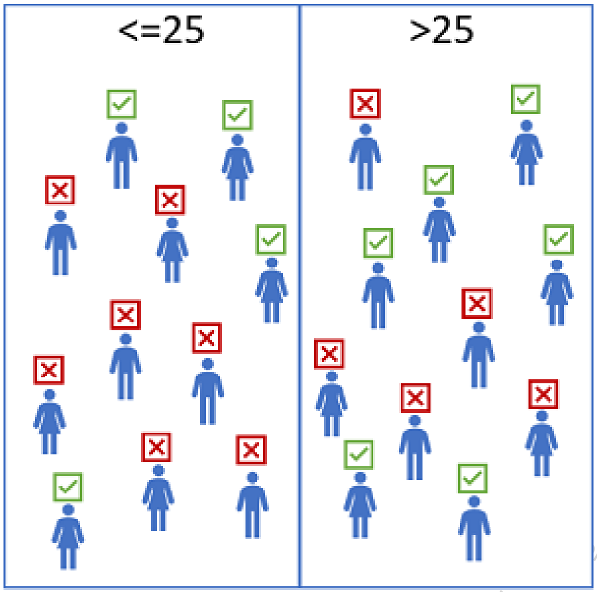
These features are used to train a binary classification model that predicts whether an applicant will repay a loan.



Suppose the model predicts that around 45% of applicants will successfully repay their loans. However, on reviewing loan approval records, you begin to suspect that that fewer loans are approved for applicants aged 25 or younger than for applicants who are over 25. How can you be sure the model is *fair* to applicants in both age groups?

Measuring disparity in predictions

One way to start evaluating the fairness of a model is to compare *predictions* for each group within a *sensitive feature*. For the loan approval model, *Age* is a sensitive feature that we care about, so we could split the data into subsets for each age group and compare the *selection rate* (the proportion of positive predictions) for each group.



Let's say we find that the model predicts that 36% of applicants aged 25 or younger will repay a loan, but it predicts successful repayments for 54% of applicants aged over 25. There's a disparity in predictions of 18%.

At first glance, this comparison seems to confirm that there's bias in the model that discriminates against younger applicants. However, when you consider the population as a whole, it may be that younger people generally earn less than people more established in their careers, have lower levels of savings and assets, and have a higher rate of defaulting on loans.

The important point to consider here is that just because we want to ensure fairness in regard to age, it doesn't necessarily follow that age is <u>not</u> a factor in loan repayment probability. It's possible that in general, younger people really are less likely to repay a loan than older people. To get the full picture, we need to look a little deeper into the predictive performance of the model for each subset of the population.

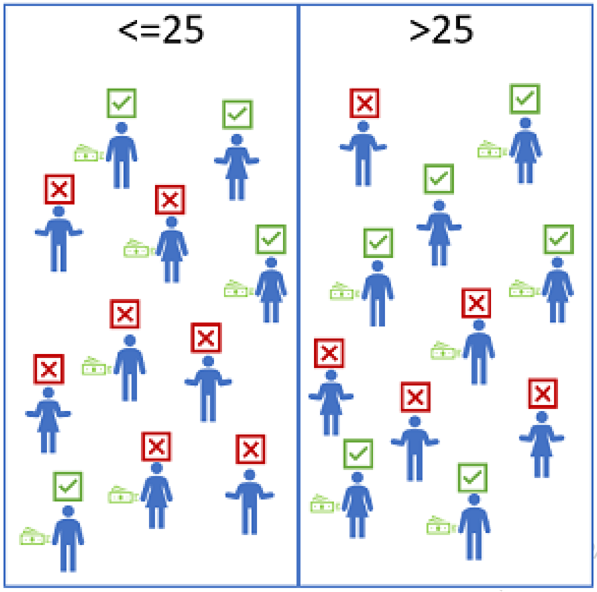
Measuring disparity in prediction performance

When you train a machine learning model using a supervised technique, like regression or classification, you use metrics achieved against hold-out validation data to evaluate the overall predictive performance of the model. For example, you might evaluate a classification model based on *accuracy*, *precision*, or *recall*.

To evaluate the fairness of a model, you can apply the same predictive performance metric to subsets of the data, based on the sensitive features on which your population is grouped, and measure the disparity in those metrics across the subgroups.

For example, suppose the loan approval model exhibits an overall *recall* metric of 0.67 - in other words, it correctly identifies 67% of cases where the applicant repaid the loan. The question is whether or not the model provides a similar rate of correct predictions for different age groups.

To find out, we group the data based on the sensitive feature (*Age*) and measure the predictive performance metric (*recall*) for those groups. Then we can compare the metric scores to determine the disparity between them.



Let's say that we find that the recall for validation cases where the applicant is 25 or younger is 0.50, and recall for cases where the applicant is over 25 is 0.83. In other words, the model correctly identified 50% of the people in the 25 or younger age group who successfully repaid a loan (and therefore misclassified 50% of them as loan defaulters), but found 83% of loan repayers in the older age group (misclassifying only 17% of them). The disparity in prediction performance between the groups is 33%, with the model predicting significantly more false negatives for the younger age group.