1.

Question： Calculation of *Conditional Statistical Parity*. Is this to count all combinations of ages and genders? Or take their average?

Answer： We have to compute all the <*age, gender*> combination for this metric. Here, L=1 depends on the situation we would like to focus on. When L takes a single variable: for example, L refers to the qualification certificate, the CSP metric computes the proportion of predicted positive (Y’=1) to the qualified group (L=1); if L refers to age, which has no positive and negative concept, we check all ages and compute CSP for all age intervals. When L takes multiple variable: in our case age and gender, we compute CSP for all the combinations of age and gender.

2.

Question: Why does the test dataset have a larger sample size than the training dataset, and is this normal?

Answer： This is not normal and usually the training set is much larger. The training dataset and testing dataset is deliberately selected from the entire dataset <diabetic_preprocessed.csv>. This is because the true positive **readmit_30_days = 0** (89%) is extremely larger than its negative **readmit_30_days = 1** (11%), which could render almost all the prediction of **readmit_30_days** tends to be negative. Therefore, the training dataset is resampled to have balanced positive case and negative case, while the size of it is restricted by the size of **readmit_30_days = 1**.

If you really feel uncomfortable for that, you can select your test dataset from <diabetic_preprocessed_test.csv> to control the size of test dataset compared to the training dataset.

3.

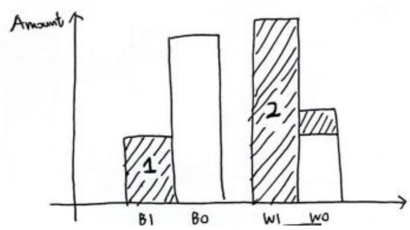
Question: Does it matter if the accuracy of the model is poor?

Answer： It doesn't matter. In this assignemnt, we're looking the model from the perspective of fairness evaluation. If the model is poor, the result of these metrics tends to be more different than a high accuracy model. This is because the model misclassification will have different degree of influences on different metrics.

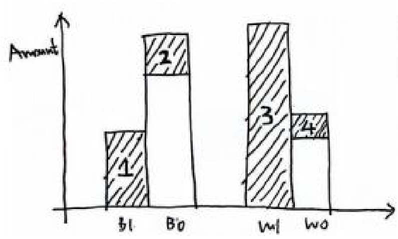
4.

Question: Does *Equalized Odds* includes *Equalized Opportunity*? What is the difference?

Answer： *Equalized Odds* actually involves *Equalized Opportunity*. In fact, *Equalized Opportunity* appears earlier than *Equalized Odds*. Later, people found that the *Equalized Opportunity* is not comprehensive enough, as it only considers the proportion of predicted positive (Y’=1) to the true positive (Y=1), ignoring the case of predicted positive (Y’=1) to the true negative (Y=0). Recall the graphs in slide <Concrete Examples>. For *Equalized Opportunity*, it considers *Area-1* and *Area-2*, which refers to the proportion of Y’=1 to Y=1. While for *Equalized Odds* that considers *Area-1* to *Area-4*, it extends the notion to further cover the case of both Y’=1 to Y=1 and Y’=1 to Y=0.



Equalized Opportunity



Equalized Odds

5.

Question: How to compare the fairness of *Equalized Odds* when Y takes both Y=1 and Y=0?

Answer：Take the average, the sum, or the other methods, just ensure that this make sense.

A=0: #1-Pr(Y'=1 | Y=1), #2-Pr(Y'=1 | Y=0)

A=1: #3-Pr(Y'=1 | Y=1), #4-Pr(Y'=1 | Y=0)

For example, for using the average, you can take A=0 the (#1+#2)/2, and take A=0 the (#3+#4)/2 to merge the information. For using the sum, you can take A=0 the #1+#2, and take A=0 the #3+#4. Or you can just separately compare #1 and #3, as well as #1 and #4.

6.

Question： Do we need to remove the <*unknown, invalid* or *missing*> values when checking whether the column is binary?

Answer： It would be appreciate to do so since these are meaningless values. The purpose of this part is to establish a better understanding of the dataset, so it will be fine as long as you can clearly describe the dataset.