Learning Fairness from an Adversary

June 18, 2015

The Adversarial Approach

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- In an adversarial setting you also have a second model $A(\phi)$ and instead you solve the problem

$$\min_{\theta} \max_{\phi} L(\theta, \phi),$$

where the adversary opposes you (the model) by trying to maximize the loss function.

Generative Adversarial Networks

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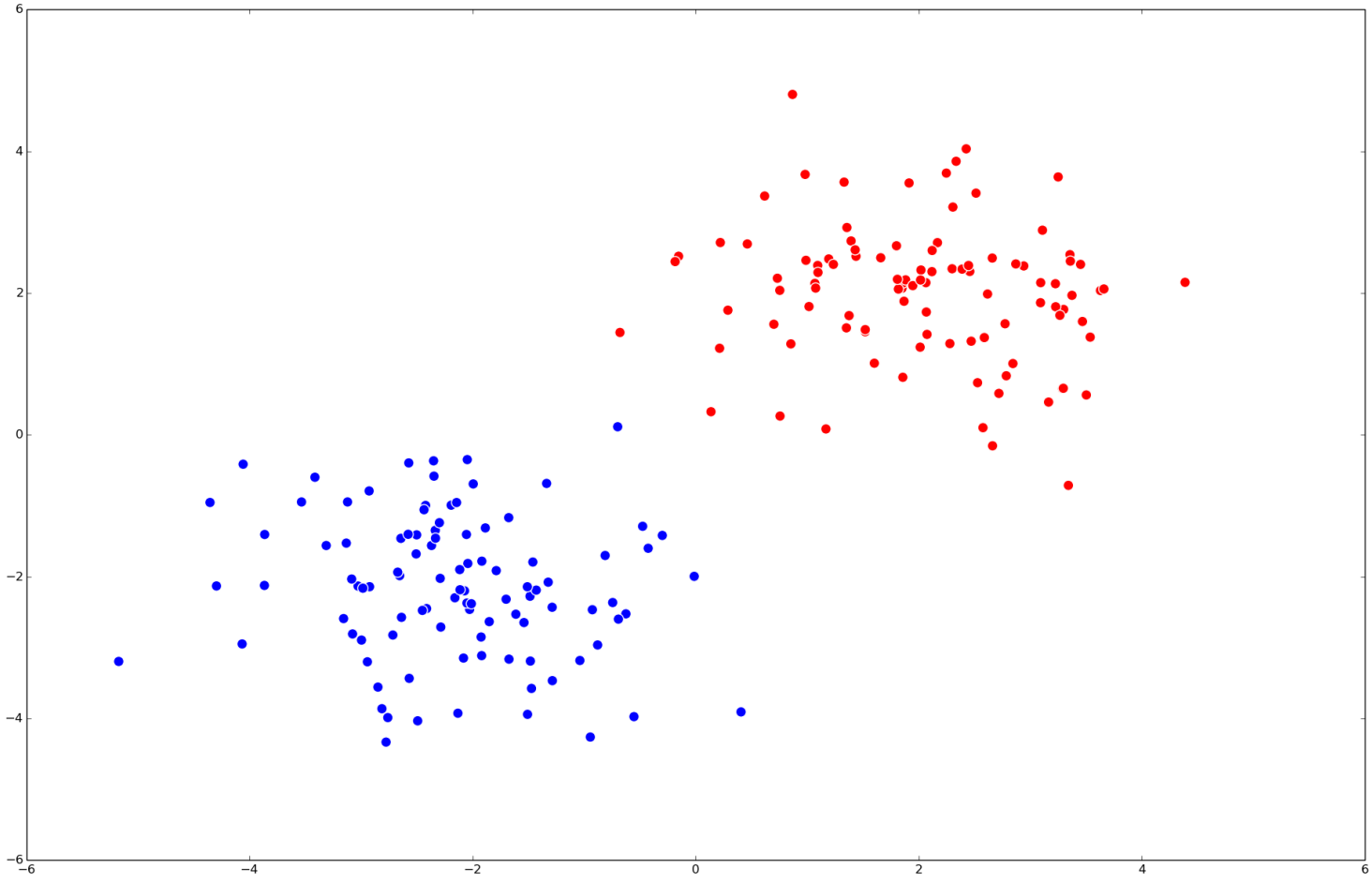
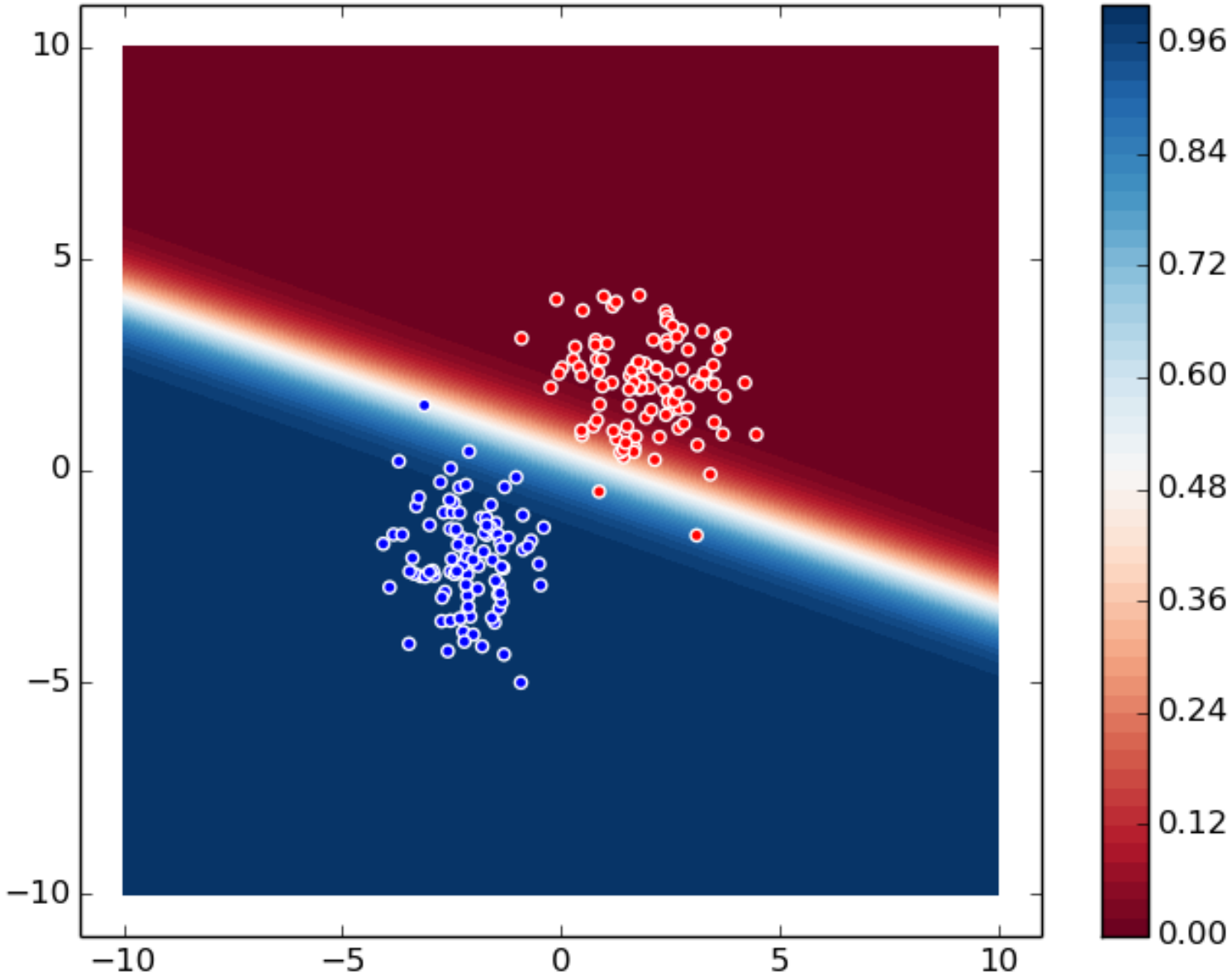
- Once you have done this, if you can sample from S, you can sample from T.
- In this case the adversary is a classifier that tries to predict whether a sample is from T or $f(S)$

An Example

In our example we will try to make the red (source) data look like the blue (target) data, and the adversary will be a logistic regressor.



Example Cont'd



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- But not everyone was happy: in 2011 the European Court of Justice ruled that "the use of sex as a factor in the calculation of premiums and benefits for the purposes of insurance and related financial services shall not result in differences in individuals' premiums and benefits".
- So we ask the question: how can we make machine learning algorithms whose decisions are *independent* of a given protected variable, like gender?

A Fair Classifier

Given features X, a binary protected variable D and binary targets Y, a *fair classifer* for Y with respect to D is a mapping $f : X \to [0, 1]$ where $f(x) = P_f(Y = 1|x)$ such that

$$P_f(Y = 1|D = 1) = P_f(Y = 1|D = 0).$$

We measure this using the *discrimination*:

$$|P_f(Y = 1|D = 1) - P_f(Y = 1|D = 0)|,$$

which is empirically estimated by

$$\left| \frac{1}{\#i : d_i = 1} \sum_{i:d_i=1} f(x_i) - \frac{1}{\#i : d_i = 0} \sum_{i:d_i=0} f(x_i) \right|.$$

Fair Representations Make a Fair Classifier

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- The intermediate representations are clusters $Z \in \{0 \dots m\}$ and each input x is mapped to a probability distribution over the clusters, so that cluster assignment is 'fair' that is

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  for each $k \in \{0 \dots m\}$.
- The classifier then makes decisions like:

$$P(Y = 1|x) = \sum_k P(Y = 1|Z = k)P(Z = k|x),$$

  and it follows that the classifier will be fair so long as the cluster assignment is fair.

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- In both methods, there is a tradeoff between fairness and accuracy controlled by weighting parameters.

Experiments

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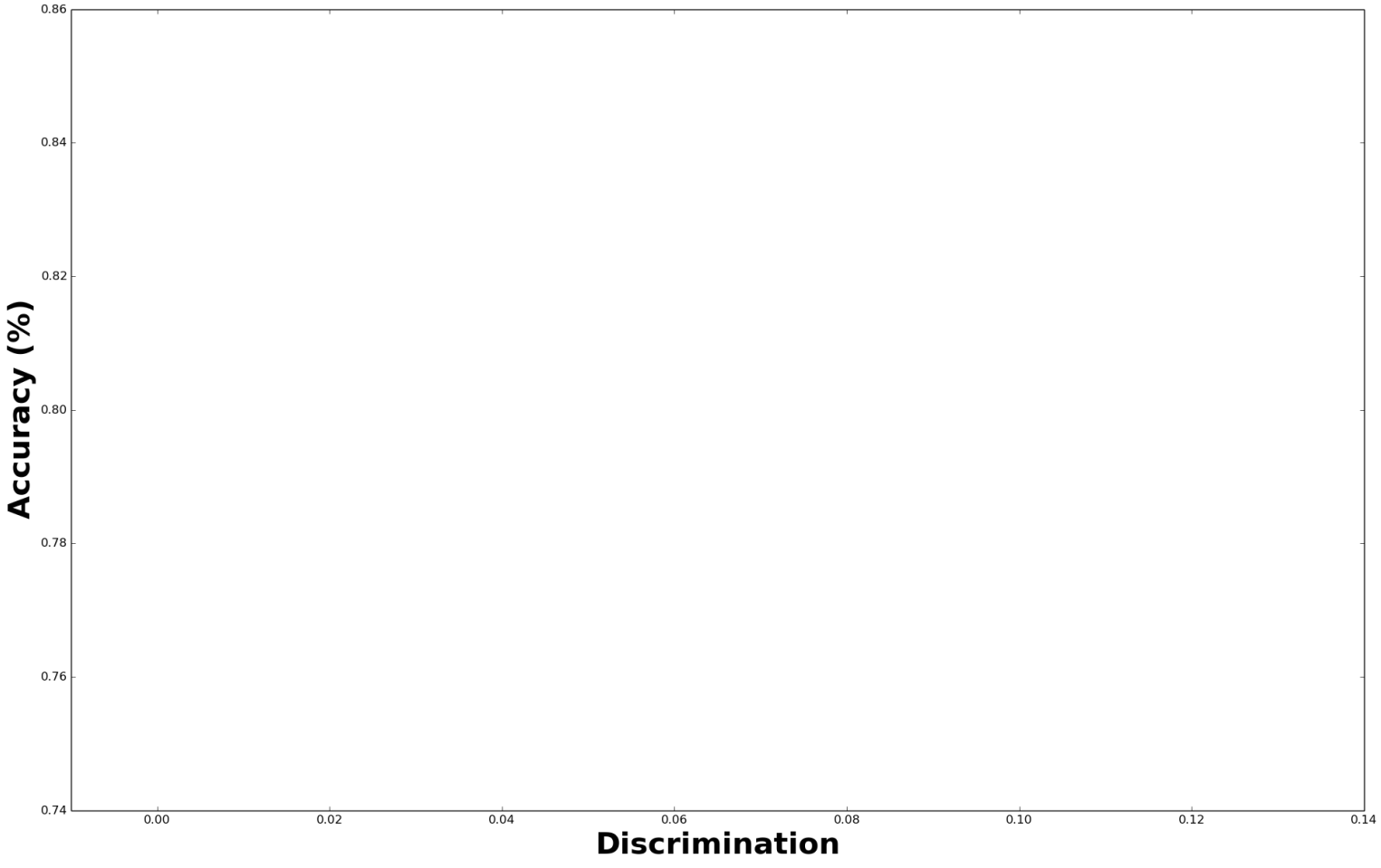
- The task is to predict whether a person's salary is above or below $\$50K$ and the protected variable is sex.
- The data set has around $50K$ entries and 100 features.

Results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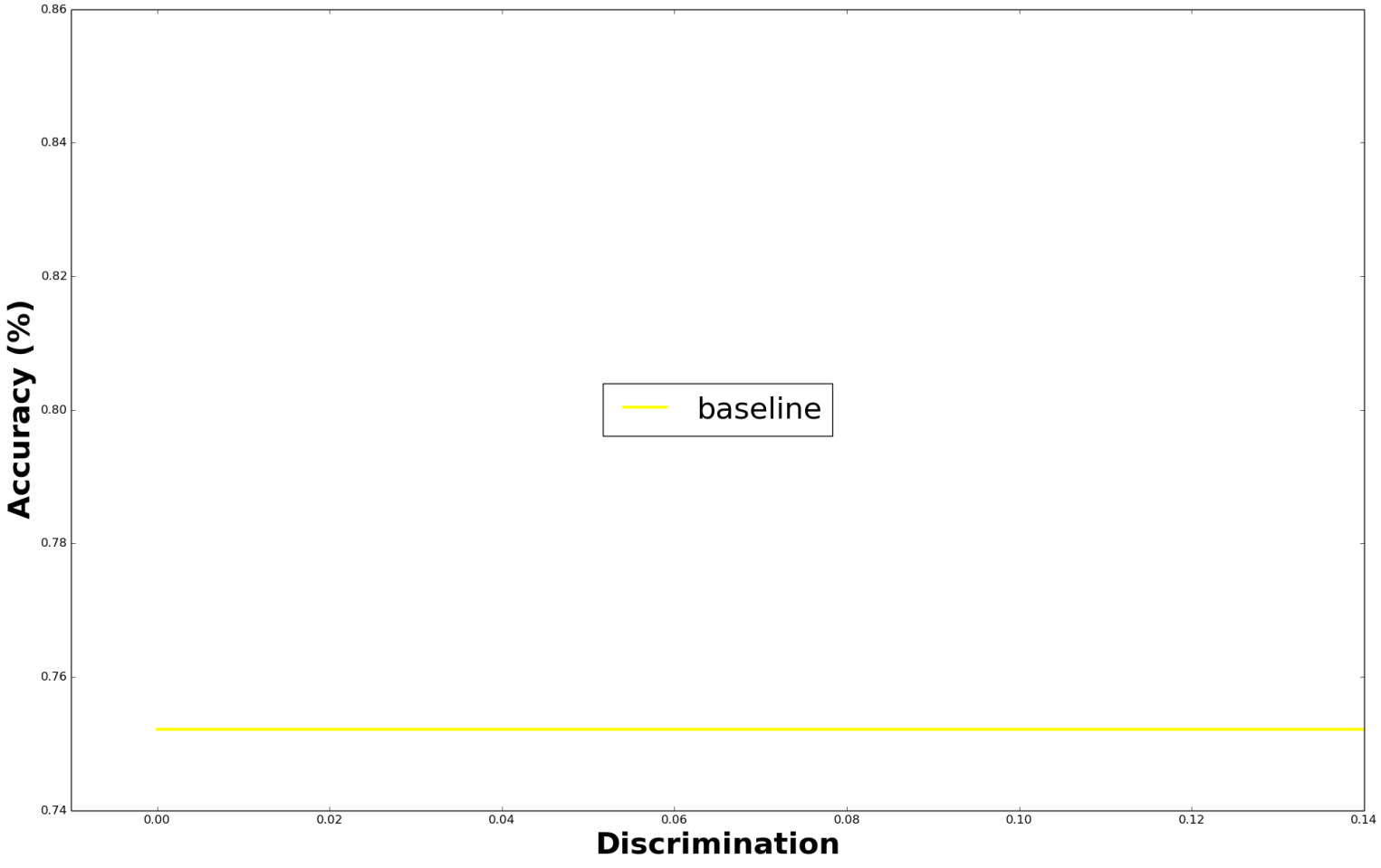
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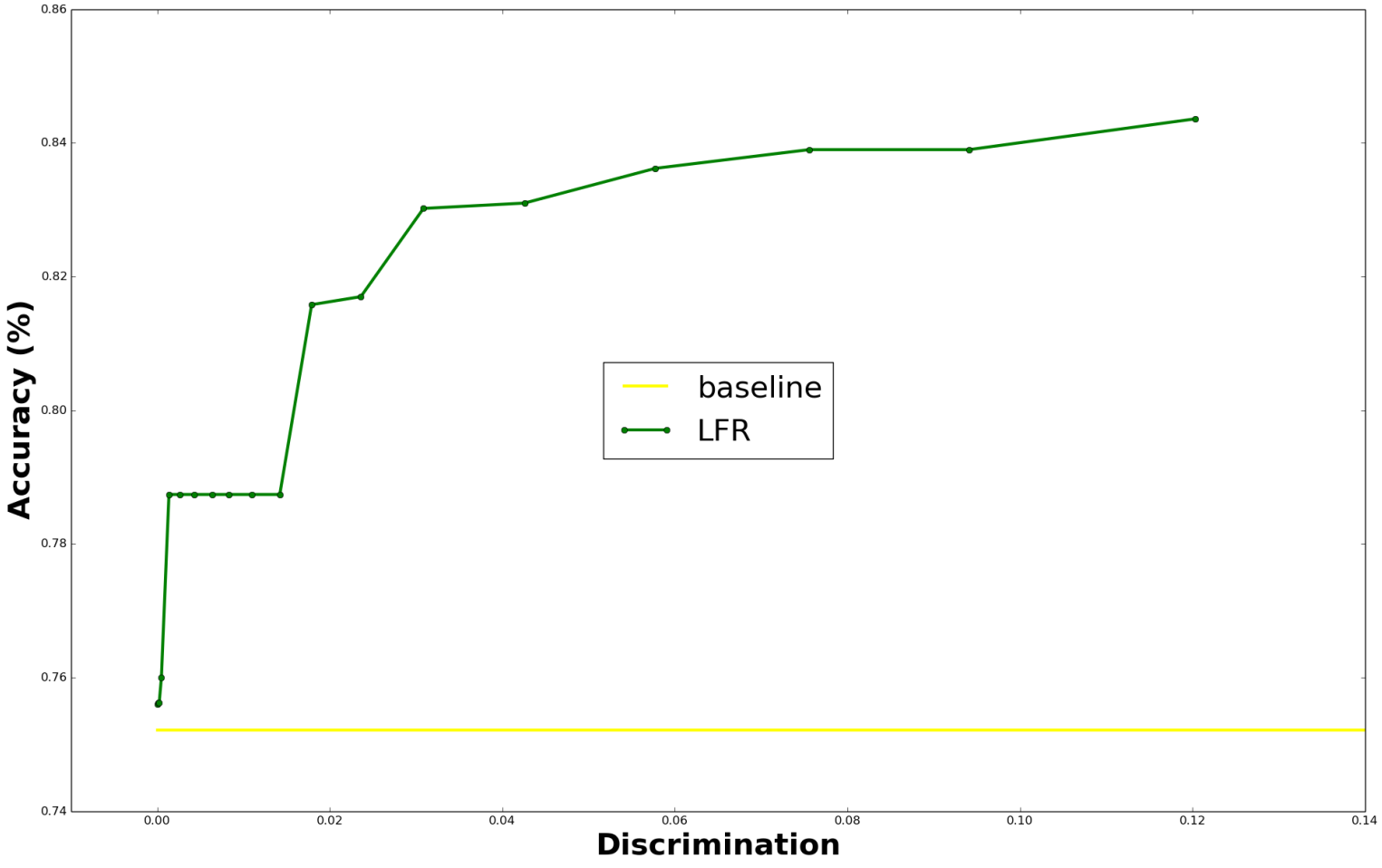
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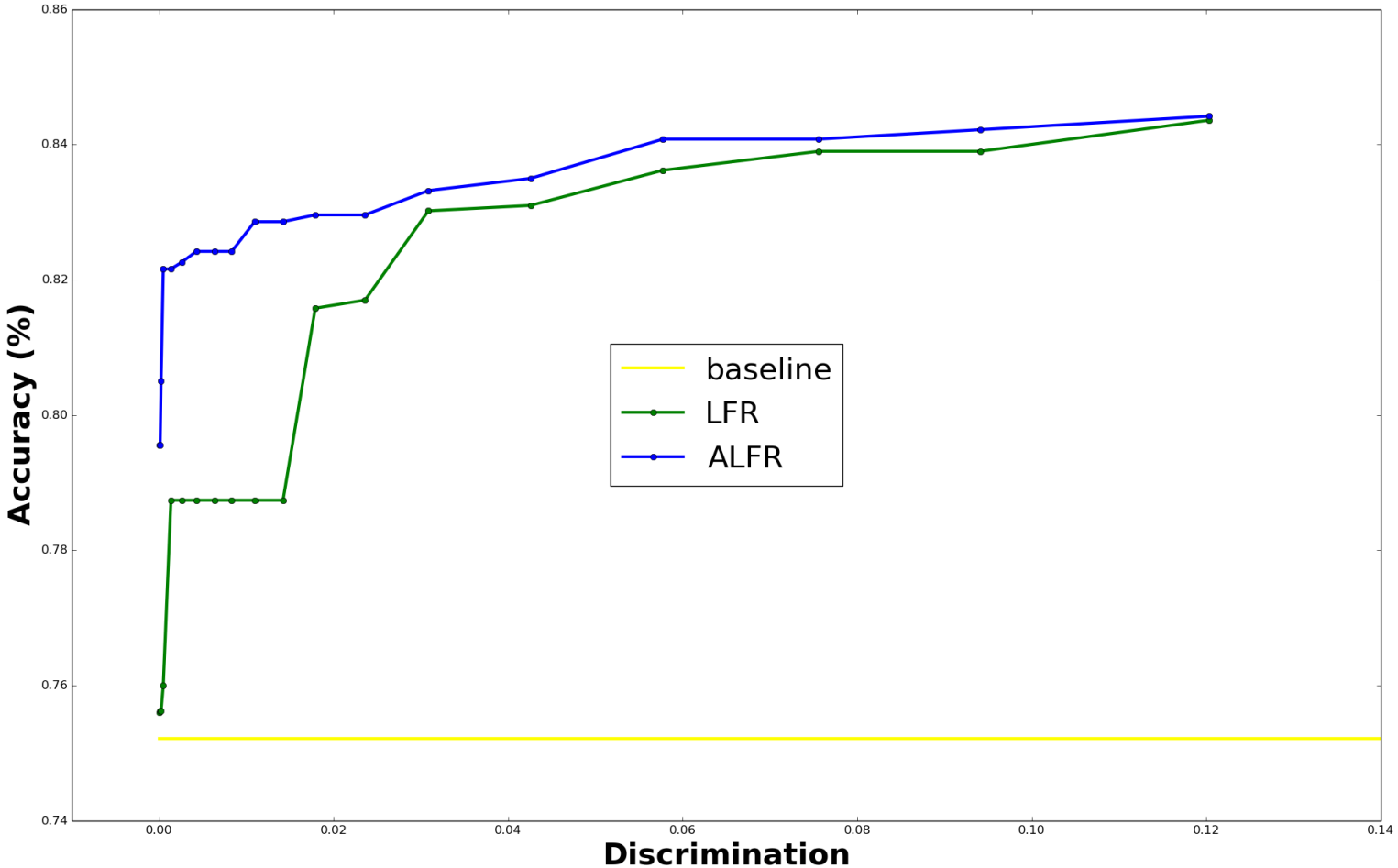
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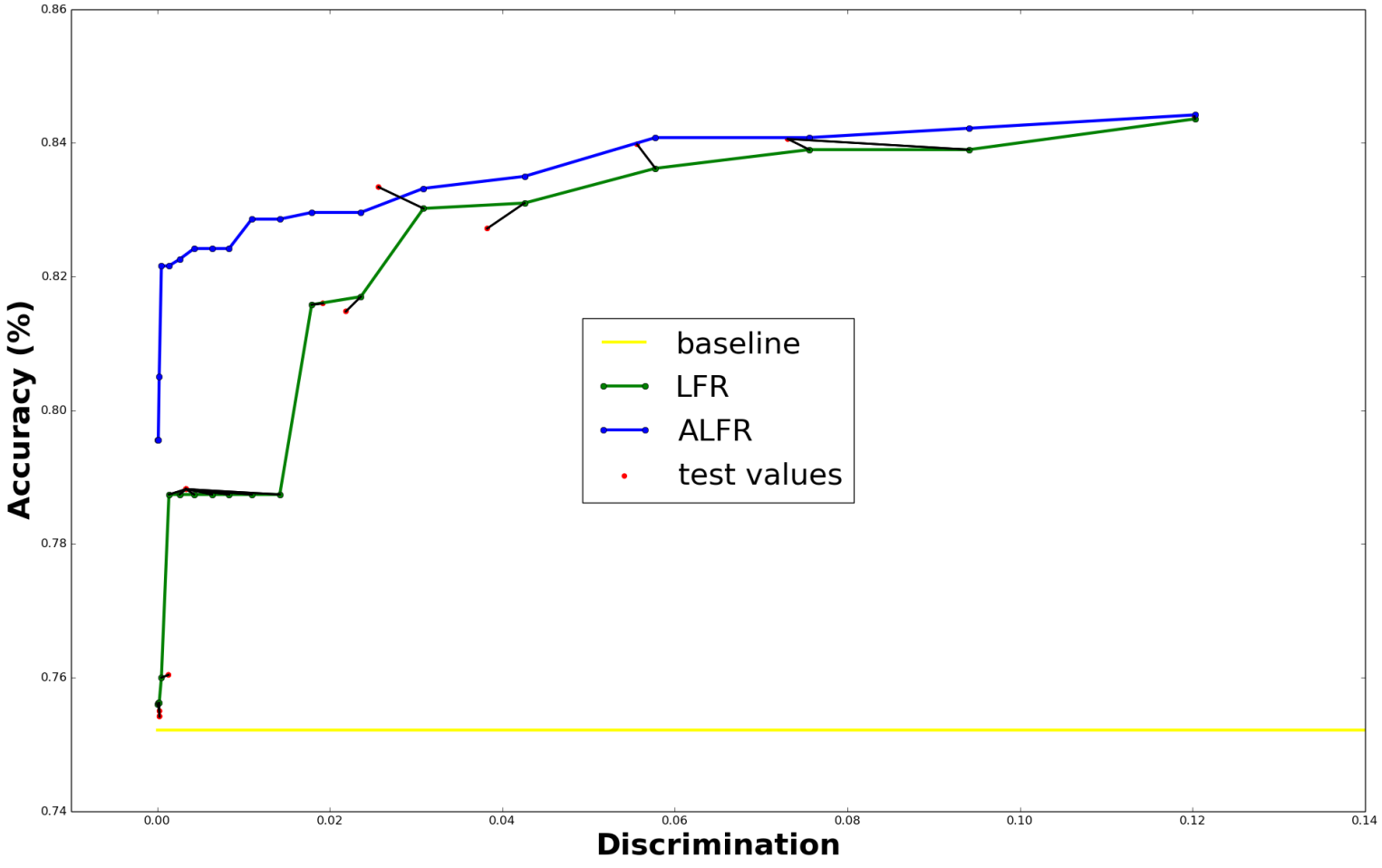
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test values

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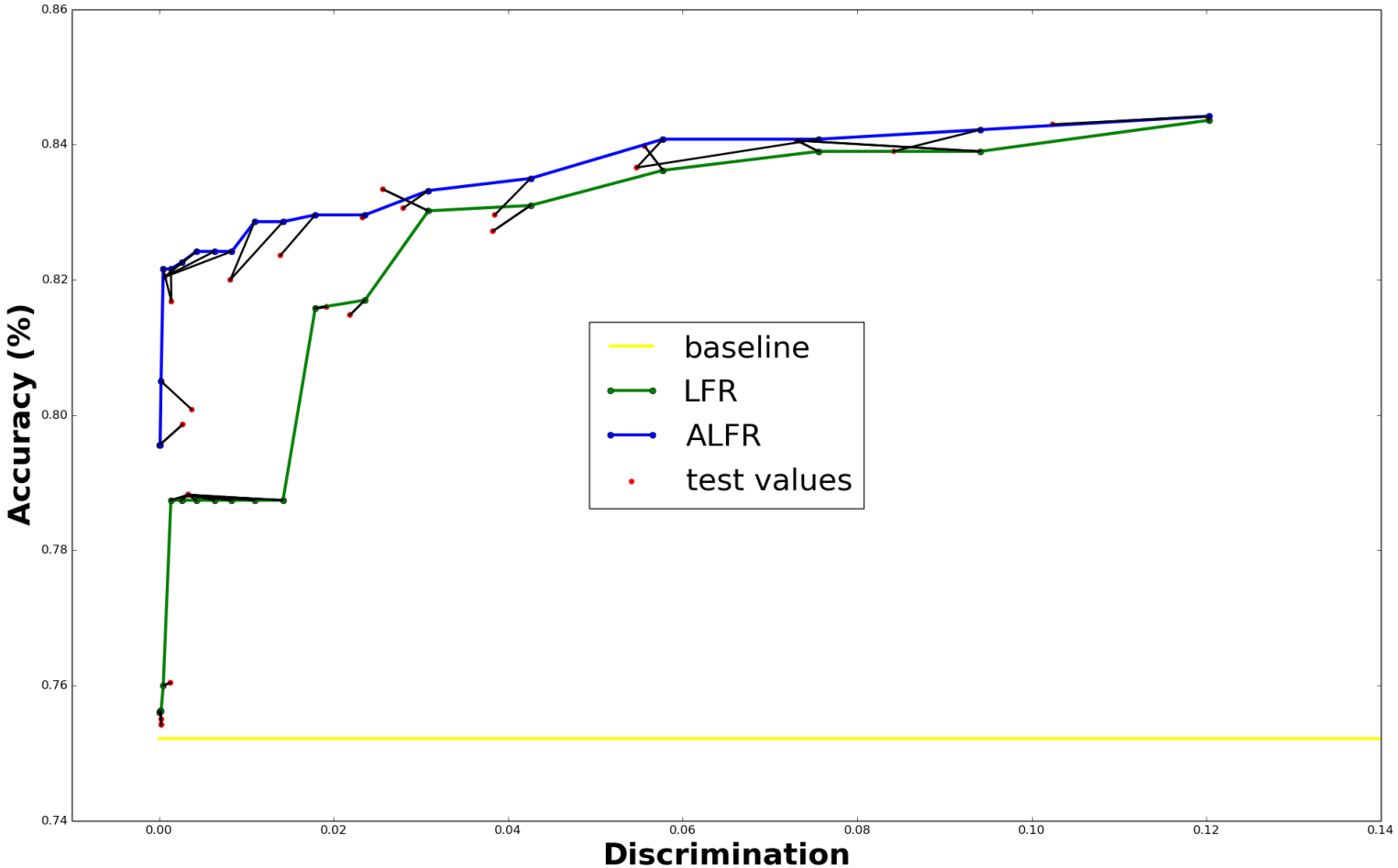
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