

Learning to pivot

Machine Learning in High Energy Physics

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Pivoted classifier¹ f is a classifier which output does not depend on nuisance parameters Z :

$$\forall s : \forall z, z' : P(f(X) = s \mid Z = z) = P(f(X) = s \mid Z = z')$$

Examples:

- legal reasons;
- differences between simulation and real data;
- unobservable nuisance parameters.

¹One can also consider a regressor or any other method that is based on likelihood maximization. This presentation is based on <https://arxiv.org/abs/1611.01046>

Ideally, classifier should be regularized:

$$\mathcal{L}_{\text{pivot}}(f) = \mathcal{L}(f) + \text{dependency-measure}(f, Z) \rightarrow \min$$

How dependencies can be measured?

One way to measure dependency is as predictability of nuisance given output of f :

$$\text{dependency-measure}(f, Z) = -\min_r \mathcal{L}_{\text{adv}}(r, f(X), Z);$$

$$\mathcal{L}_{\text{adv}}(r, f(X), Z) = \mathbb{E}_{X,Z} \log P_r(Z \mid f(X)).$$

The final loss function:

$$L_{\text{pivoted}} = -\frac{1}{N} \sum_{i=1}^N \log P_f(y_i | x_i) + \frac{1}{N} \sum_{i=1}^N \log P_r(z_i | f(x_i)) \rightarrow \min$$

The training procedure is similar to GAN:

- train adversary r ;
- make one step for classifier f with fixed r .

Sometimes it is desirable to make a classifier independent from nuisance within each class.

$$\forall y : \forall s : \forall z, z' : P(f(X) = s \mid Z = z, Y = y) = P(f(X) = s \mid Z = z', Y = y)$$