Implicit Rate-Constrained Optimization of Non-decomposable Objectives

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Problem setting

Optimize

- FNR at a fixed FPR
- Precision at a fixed Recall
- Precision at k
- Area under the ROC curve or area under the PR curve
- Fairness constraints

All these problems can be cast as:

$$\min_{\theta \in \mathbb{R}^p} f(\theta, \lambda) \quad \text{s.t.} \quad g(\theta, \lambda) = \mathbf{0}$$

where heta are the model parameters and λ are the thresholds that act on the model predictions.

f and g are replaced by smooth surrogates $ilde{f}$ and $ilde{g}$ for first-order optimization.

Most existing methods formulate Lagrangian based primal dual problem to solve these problems.

We propose ICO (implicit constrained optimization) where we directly express thresholds λ as function of model parameters heta using the Implicit Function Theorem.

$$\min_{ heta} ilde{f}\left(heta, ilde{h}(heta)
ight)$$

We can compute the derivative using the Implicit Function Theorem:

$$abla_ heta ilde{f}\left(heta, ilde{h}(heta)
ight) =
abla_ heta ilde{f}\left(heta, \lambda
ight) - rac{rac{\partial ilde{f}\left(heta, \lambda
ight)}{\partial \lambda}}{rac{\partial ilde{g}\left(heta, \lambda
ight)}{\partial \lambda}}
abla_ heta ilde{g}(heta, \lambda)$$

Updating model and thresholds

Model parameters are updated using

$$heta^{t+1} = OPT(heta^t,
abla_ heta ilde{f}\left(heta^t, ilde{h}(heta^t)
ight))$$

Using IFT, we approximate the new threshold as

$$egin{aligned} \lambda^{t+1} &= ilde{h}(heta^{t+1}) = ilde{h}(heta^t + \Delta heta) \ &pprox ilde{h}(heta^t) + \langle
abla_ heta ilde{h}(heta^t), \Delta heta
angle \ &= \lambda^t + \langle
abla_ heta ilde{h}(heta^t), \Delta heta
angle \end{aligned}$$

We use a correction step every au steps that sets the thresholds to satisfy the constraint exactly on k minibatches.

Minimizing FNR at a fixed FPR for CelebA: CE / TFCO[1] / ICO (proposed)

FPR	High-cheekbones	Heavy-makeup	Wearing-lipstick	Smiling	Black-hair	Blond-hair
1%	53.5/49.0/ 46.9	57.0/ 57.0/ 49.6	44.0/ 42.6/ 37.5	37.4/35.9/ 33.7	69.3/64.4/ 63.2	40.4/38.6/36.8
2%	44.8/40.9/ 39.8	45.6/41.2/ 38.9	32.7/30.4/26.7	29.4/27.8/26.1	56.4/ 52.0/ 50.5	28.9/25.6/ 24.2
5%	32.9/30.1/28.5	28.2/25.4/23.1	16.3/14.9/ 13.1	18.7/ 17.0/ 16.9	36.7/32.4/32.5	13.4/11.6/10.8
10%	22.9/ 20.4/ 19.7	15.1/13.6/12.4	6.6/ 5.9/ 4.7	11.7/ 10.7/ 10.2	23.0/ 19.2/ 18.6	6.5/ 4.9/ 4.7



Google Research

[1] https://github.com/google-research/tensorflow_constrained_optimization