

# Convex Calibrated Surrogates for Low-Rank Loss Matrices with Applications to Subset Ranking Losses

Harish G. Ramaswamy<sup>1</sup>, Shivani Agarwal<sup>1</sup> and Ambuj Tewari<sup>2</sup>



<sup>1</sup>Indian Institute of Science



<sup>2</sup>University of Michigan

# Calibrated Surrogates

## Binary Classification

$$\mathcal{Y} = \widehat{\mathcal{Y}} = \{\pm 1\}$$

$$\mathbf{L} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$

Minimize surrogate loss (e.g. hinge) over  $\mathbb{R}$ ; learn  $f : \mathcal{X} \rightarrow \mathbb{R}$

$$\xleftarrow{\hspace{1cm}} 0 \xrightarrow{\hspace{1cm}} \mathbb{R}$$

Final prediction in  $\{\pm 1\}$  :

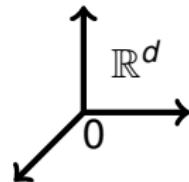
$$h(x) = \text{sign}(f(x))$$

## General Multiclass Problem

$$\mathcal{Y} = \{1, \dots, n\}; \widehat{\mathcal{Y}} = \{1, \dots, k\}$$

$$\mathbf{L} = \begin{bmatrix} 0 & 1 & 2 & 1 \\ 1 & 0 & 3 & 2 \\ 4 & 5 & 0 & 1 \end{bmatrix} \quad \begin{matrix} \text{(predictions)} \\ \text{(classes)} \end{matrix}$$

Minimize surrogate loss over  $\mathbb{R}^d$ ; learn  $f : \mathcal{X} \rightarrow \mathbb{R}^d$


$$\xleftarrow{\hspace{1cm}} 0 \xrightarrow{\hspace{1cm}} \mathbb{R}^d$$

Final prediction in  $\{1, \dots, k\}$  :

$$h(x) = \text{pred}(f(x))$$



# Application to Subset Ranking

Exponential sized loss matrices with low rank.

Loss matrix	Rank	Efficient predictor
NDCG	$r$	✓
Precision@q	$r$	✓
Expected Rank Utility	$r$	✓
Mean Average Precision	$\leq r^2$	X
Pairwise Disagreement	$\leq r^2$	X

$r$  = No. of docs. to be ranked

	$\sigma_1$	$\sigma_2$	$\dots$	$\hat{y}$	$\dots$	$\sigma_{r!}$
00...00						
00...01						
$\vdots$						
$y$						
$\vdots$						
11...11						

Poster Sat35  
Today