A Statistical View of Ranking: Midway between Classification and Regression

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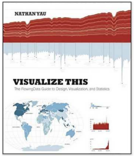
September 8, 2016

Ranking

- Aims to order a set of objects or instances reflecting their underlying utility, quality or relevance to queries



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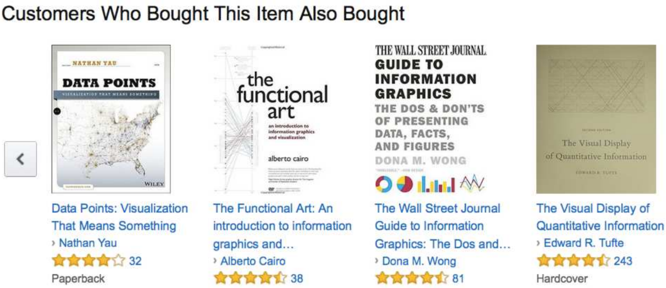

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Data for Ranking

$\boxed{\text{object}_1}$	positive
$\boxed{\text{object}_2}$	negative
$\vdots$	$\vdots$
$\boxed{\text{object}_{n-1}}$	positive
$\boxed{\text{object}_n}$	negative

How to order objects so that positive cases are generally ranked higher than negative cases?

Main Questions

- How to formulate ranking problems?
- What evaluation (or loss) criteria to use for ranking?
- What is the best ranking function given a criterion?
- How is it related to the underlying probability distribution for data?
- How to learn a ranking (or scoring) function from data?

Notation

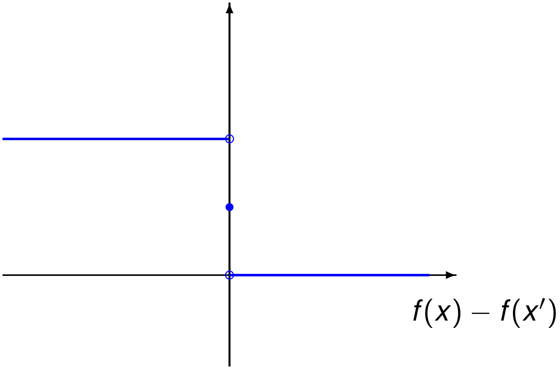
- $X \in \mathcal{X}$: an instance to rank
- $Y \in \mathcal{Y} = \{1, \cdots, k\}$: an ordinal response in multipartite ranking (bipartite ranking if $k = 2$, often with $\mathcal{Y} = \{\pm 1\}$)
- $g_{\pm}(x)$: pdfs of X given $Y = \pm 1$
- Training data: n pairs of (X, Y) from $\mathcal{X} \times \mathcal{Y}$
  e.g. $\{(x_i, +1)\}_{i=1}^{n_+} \cup \{(x'_j, -1)\}_{j=1}^{n_-}$ for bipartite ranking
- f: $\mathcal{X} \to \mathbb{R}$: a real-valued ranking function whose scores induce ordering over the input space

$$f(x) > f(x') \iff x \succ x'$$

Pairwise Ranking Loss

For a pair of "positive" x and "negative" x', define a loss of ranking function f as

$$\ell_0(f; x, x') = \mathbb{I}(f(x) - f(x') < 0) + \frac{1}{2}\mathbb{I}(f(x) - f(x') = 0)$$



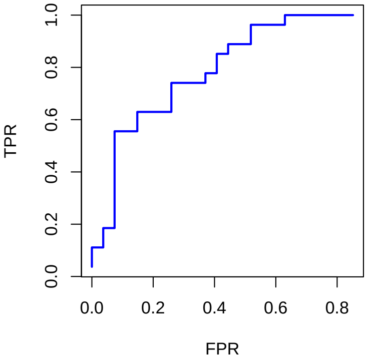
The loss is invariant under order-preserving transformation of f.

Bipartite Ranking

- Find f minimizing the empirical ranking error

$$R_{n_+,n_-}(f) = \frac{1}{n_+ n_-} \sum_{i=1}^{n_+} \sum_{j=1}^{n_-} \ell_0(f; x_i, x_j')$$

- Minimizing ranking error is equivalent to maximizing AUC (area under ROC curve) of f.
- Which f attains the smallest expected ranking error?



Likelihood Ratio Minimizes Ranking Risk

Clémençon et al. (2008), Uematsu and Lee (2011), and Gao and Zhou (2012)

Theorem

Define $f_0^*(x) = g_+(x)/g_-(x)$*, and let* $R_0(f) = E(\ell_0(f; X, X'))$ *denote the ranking risk of* f *under the bipartite ranking loss. Then for any ranking function* f*,*

$$R_0(f_0^*) \leq R_0(f).$$

Remark

Connection to posterior probability in classification:

$$P(Y = 1|X = x) = \frac{\pi_+ g_+(x)}{\pi_+ g_+(x) + \pi_- g_-(x)} = \frac{f_0^*(x)}{f_0^*(x) + (\pi_-/\pi_+)}$$

Classification, Ranking and Regression

Regression: $p_+(x) = P(Y = 1|X = x)$ or $\log \frac{p_+(x)}{1-p_+(x)}$

Ranking: order-preserving transformation of $p_+(x)$ or
likelihood ratio $g_+(x)/g_-(x)$

Classification: $\mathrm{sgn}(p_+(x) - \frac{1}{2})$

Convex Surrogate Loss for Bipartite Ranking

- Exponential loss
  in RankBoost (Freund et al. 2003):

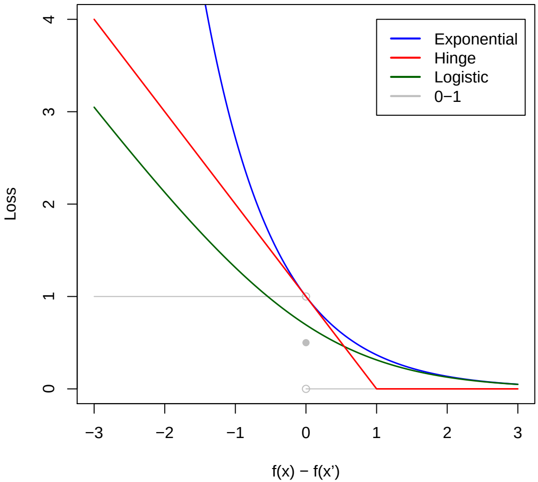
$$\ell(f; x, x') = \exp(-(f(x) - f(x')))$$

- Hinge loss
  in RankSVM (Joachims 2002) and AUCSVM
  (Rakotomamonjy 2004, Brefeld and Scheffer 2005):

$$\ell(f; x, x') = (1 - (f(x) - f(x')))_+$$

- Logistic loss (cross entropy)
  in RankNet (Burges et al. 2005):

$$\ell(f; x, x') = \log(1 + \exp(-(f(x) - f(x'))))$$



Bartlett et al. (2006), *Convexity, Classification, and Risk Bounds*

Is classification-calibration sufficient for ranking consistency?

Optimal Ranking Function Under Convex Loss

Theorem

Suppose that ℓ *is differentiable,* $\ell'(s) < 0$ *for all* $s \in \mathbb{R}$*, and* $\ell'(-s)/\ell'(s) = \exp(s/\alpha)$ *for some positive constant* α*.*
Let f^* *be the best ranking function* f *minimizing* $R_\ell(f) = E[\ell(f; X, X')]$*. Then*

$$f^*(x) = \alpha \log(g_+(x)/g_-(x)) \quad \text{up to a constant.}$$

Remark

- *For RankBoost,* $\ell(s) = e^{-s}$*, and* $\ell'(-s)/\ell'(s) = e^{2s}$*.*
  $f^*(x) = \frac{1}{2} \log(g_+(x)/g_-(x))$.
- *For RankNet,* $\ell(s) = \log(1 + e^{-s})$*, and* $\ell'(-s)/\ell'(s) = e^{s}$*.*
  $f^*(x) = \log(g_+(x)/g_-(x))$.

Ranking-Calibrated Loss

Theorem

Suppose that ℓ is convex, non-increasing, differentiable and $\ell'(0) < 0$. Then for almost every (x, z), $\frac{g_+(x)}{g_-(x)} > \frac{g_+(z)}{g_-(z)}$ implies $f^*(x) > f^*(z)$.

Remark

For RankSVM, $\ell(s) = (1 - s)_+$ with singularity at $s = 1$ could yield ties in ranking (leading to inconsistency) while $\ell(s) = (1 - s)_+^2$ is ranking-calibrated.

Toy Example: RankSVM

- $\mathcal{X} = \{x_1, x_2, x_3\}$ and $\frac{g_+(x_1)}{g_-(x_1)} < \frac{g_+(x_2)}{g_-(x_2)} < \frac{g_+(x_3)}{g_-(x_3)}$
- To identify f^* minimizing $E(1 - (f(X) - f(X')))_+$, let $s_1 = f(x_2) - f(x_1)$ and $s_2 = f(x_3) - f(x_2)$, and take the risk as a function of s_1 and s_2.
- Let $\Delta_{12} = \frac{g_-(x_1)}{g_+(x_1)} - \left(\frac{g_-(x_2)}{g_+(x_2)} + \frac{g_-(x_3)}{g_+(x_2)}\right)$ and $\Delta_{23} = \frac{g_+(x_3)}{g_-(x_3)} - \left(\frac{g_+(x_2)}{g_-(x_2)} + \frac{g_+(x_1)}{g_-(x_2)}\right)$.

  For f^*, the optimal increments s_1^* and s_2^* are:

  (i) if $\Delta_{12} > 0$ and $\Delta_{23} > 0$, $(s_1^*, s_2^*) = (1, 1)$
  (ii) if $\Delta_{23} < 0$ and $g_+(x_2) > g_-(x_2)$, $(s_1^*, s_2^*) = (1, 0)$
  (iii) if $\Delta_{12} < 0$ and $g_+(x_2) < g_-(x_2)$, $(s_1^*, s_2^*) = (0, 1)$

RankSVM Can Produce Ties

Theorem

Let $f^* = \arg\min_f E(1 - (f(X) - f(X')))_+$. Suppose that f^* is unique up to an additive constant.

(i) *For discrete $\mathcal{X}$, a version of f^* is integer-valued.*

(ii) *For continuous $\mathcal{X}$, there exists an integer-valued function whose risk is arbitrarily close to the minimum risk.*

Remark

- *Scores from RankSVM exhibit granularity.*
- *Ranking with the hinge loss is not consistent!*

Numerical Illustration

- Simulation setting:
  $X \sim N(1,1)$ and $X' \sim N(-1,1)$
  $\log(g_+(x)/g_-(x)) = 2x$ with 'Bayes' ranking error of
  $P(X < X') = \Phi(-\sqrt{2}) \approx 0.07865$

- Generate $\{(x_i, +1)\}_{i=1}^n \cup \{(x'_j, -1)\}_{j=1}^n$
  where n: sample size for each category

- Apply AUC maximizing SVM (Brefeld and Scheffer 2005) with a Gaussian kernel K

$$\min_{f \in \mathcal{H}_K} \quad C \sum_{i,j} \left(1 - (f(x_i) - f(x'_j))\right)_+ + \|f\|_K^2$$

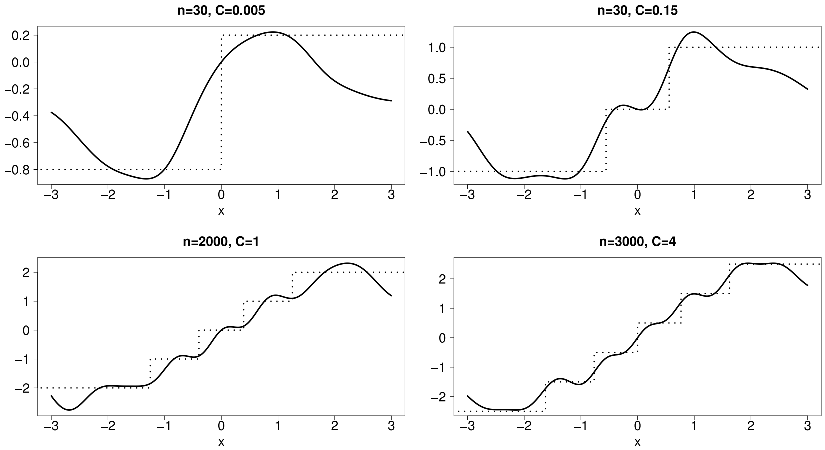


Figure: The solid lines are the estimated ranking functions, and the dotted lines are step functions with minimal risk.

Extension to Multipartite Ranking

- In general ($k \geq 2$), for a pair of (x, y) and (x', y') with $y > y'$, define a loss of ranking function f as

  $$\ell_0(f; x, x', y, y') = c_{y'y} I(f(x) < f(x')) + \frac{1}{2} c_{y'y} I(f(x) = f(x'))$$

  where $c_{y'y}$ is the cost of misranking a pair of y and y'.
  (Waegeman et al. 2008)

- Again, ℓ_0 is invariant under order-preserving transformations.

Optimal Ranking Function for Multipartite Ranking

Uematsu and Lee (2015)

Theorem

(i) When $k = 3$*, let* $f_0^*(x) = \dfrac{c_{12}P(Y = 2|x) + c_{13}P(Y = 3|x)}{c_{13}P(Y = 1|x) + c_{23}P(Y = 2|x)}$.
Then for any ranking function f*,*

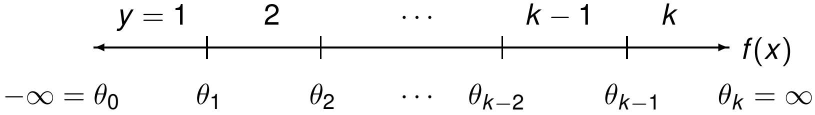
$$R_0(f_0^*; \mathbf{c}) \leq R_0(f; \mathbf{c}).$$

(ii) When $k > 3$ *and let* $f_0^*(x) = \dfrac{\sum_{i=2}^{k} c_{1i}P(Y = i|x)}{\sum_{j=1}^{k-1} c_{jK}P(Y = j|x)}$.
If $c_{1k}c_{ji} = c_{1i}c_{jk} - c_{1j}c_{ik}$ *for all* $1 < j < i < k$*, then for any ranking function* f*,*

$$R_0(f_0^*; \mathbf{c}) \leq R_0(f; \mathbf{c}).$$

Ordinal Regression

- Ordinal regression is commonly used to analyze data with ordinal responses in practice.



- A typical form of loss in ordinal regression for f with thresholds $\{\theta_j\}_{j=1}^{k-1}$:

$$\ell(f, \{\theta_j\}_{j=1}^{k-1}; x, y) = \ell(f(x) - \theta_{y-1}) + \ell(\theta_y - f(x)),$$

where $\theta_0 = -\infty$ and $\theta_k = \infty$.

Convex Loss in Ordinal Regression

- ORBoost (*Lin and Li* 2006):

$$\ell(s) = \exp(-s)$$

- Proportional Odds model, $\log \frac{P(Y \leq j|x)}{P(Y > j|x)} = f(x) - \theta_j$ (*McCullagh* 1980, *Rennie* 2006):

$$\ell(s) = \log(1 + \exp(-s))$$

- Support Vector Ordinal Regression (*Herbrich et al.* 2000):

$$\ell(s) = (1 - s)_+$$

Optimal Ranking Function with Ordinal Regression

Letting $p_j(x) = P(Y = j|X = x)$, when $k = 3$,

$$f_0^*(x) = \frac{c_{12}p_2(x) + c_{13}p_3(x)}{c_{13}p_1(x) + c_{23}p_2(x)}$$

- Ordinal Regression Boosting (ORBoost):

  $$f^*(x) = \frac{1}{2}\log\frac{p_2(x) + \exp(\theta_2^* - \theta_1^*)p_3(x)}{\exp(\theta_2^* - \theta_1^*)p_1(x) + p_2(x)} = \frac{1}{2}\log f_0^*(x)$$

  with $c_{12} = c_{23} = 1$ and $c_{13} = e^{\theta_2^* - \theta_1^*}$.

- Proportional Odds Model:
  $f^*(x)$ preserves the ordering of
  $r(x) = \dfrac{p_2(x) + p_3(x)}{p_1(x) + p_2(x)} = f_0^*(x)$ with $c_{12} = c_{23} = c_{13} = 1$.

- Support Vector Ordinal Regression (SVOR):
  $f^*(x)$ is a non-decreasing step function of $r(x)$.

Numerical Illustration

- Simulation setting:
  $X|Y = 1 \sim N(-2, 1)$, $X|Y = 2 \sim N(0, 1)$ and
  $X|Y = 3 \sim N(2, 1)$

- When $c_{12} = c_{23} = c_{13} = 1$,

$$f_0^*(x) = \frac{P(Y = 2|X = x) + P(Y = 3|X = x)}{P(Y = 1|X = x) + P(Y = 2|X = x)} = \frac{e^{2x} + e^2}{e^{-2x} + e^2}.$$

- Generate 500 observations in each category.

- Apply pairwise ranking risk minimization with exponential loss, proportional odds model, ORBoost and SVOR.

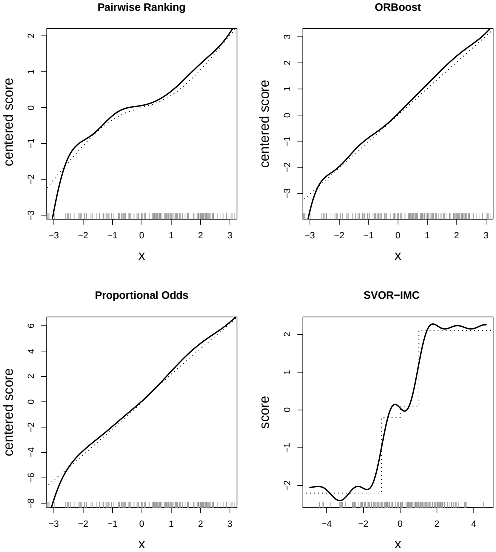


Figure: Theoretical ranking function (dotted line) and estimated ranking function (solid line) for pairwise ranking risk minimization with exponential loss, ORBoost, proportional odds model and SVOR with implicit constraints.

Application to Movie-Lens Data

- The data set consists of 100,000 ratings (on a scale of 1 to 5) for 1,682 movies by 943 users (GroupLens Research). `http://movielens.org/`
- Contains content information about the movies (release date and genres) and demographic information about the users (age, gender and occupation).
- Transform five categories into three categories:
  "Low" (1-3), "Middle" (4) and "High" (5)
  and check the analytical results in $k = 3$.

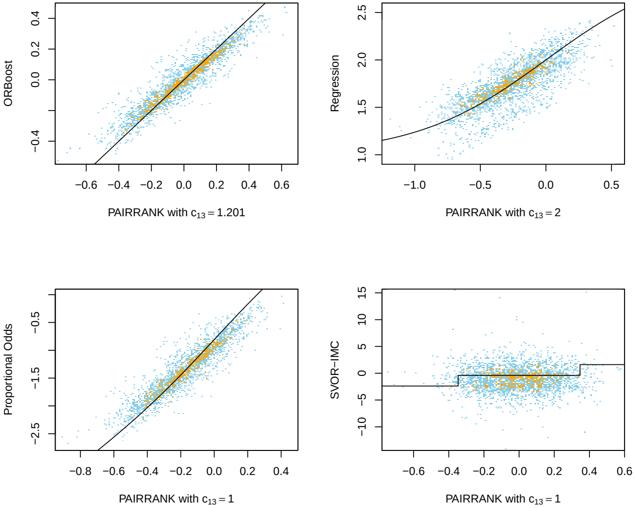


Figure: Scatter plots of ranking scores from ORBoost, regression, proportional odds model, and SVOR against pairwise ranking scores with matching cost c_{13} for MovieLens data with three categories. The solid lines indicate theoretical relation between ranking scores.

Concluding Remarks

- Provides a statistical view of ranking by identifying the optimal ranking function given loss criteria.
- Illustrates the connection between ranking and classification/ordinal regression in the framework of convex risk minimization.
- Ranking requires more information than classification.

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Acknowledgments

Kazuki Uematsu

DMS-12-09194
DMS-15-13566