

Classification

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Roadmap

- Combining rankings: taking advantage of multiple weak rankers
- Maximum margin ranking: support vector machines
- Reduction to classification: optimizing

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Ranking



About 75.800.000 results (0.58 seconds

Learning to rank - Wikipedia

https://en.wikipedia.org/wiki/Learnir Learning to rank or machine-learned rai supervised, semi-supervised or reinforc Applications · Feature vectors · Evaluati

Result ranking by machine le

https://nlp.stanford.edu/IR-book/htn Result ranking by machine learning. Th more than two variables. There are lots

[PDF] Ranking Methods in Mac

www.shivani-agarwal.net/Events/SD by S Agarwal - Cited by 1 - Related artic C.J.C. Burges, T. Shaked, E. Renshaw, A. using gradient descent, ICML 2005, S. / Generalization bounds for the area under 425, 2005.

Given input $x_1 \dots x_r$, return permutation of [r]. Permutation often parameterized by vector of scalars $y_1 \dots y_r$.

- Web search (Google used > 200 features)
- Movie rankings
- Dating

Kendall-τ

$$L(y',y) = \frac{2}{r(r-1)} \sum_{i} \sum_{j} \mathbb{1} \left[sign(y'_i - y'_j) \neq (y_i - y_j) \right]$$
 (1)

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Kendall-au

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 (1)

Normalized Discounted Cumulative Gain:

$$D(i) = \frac{1}{\lg(r - i + 2)} \text{if } i \in \{r - k + 1, \dots, r\}$$
 (2)

$$G(y', y) = \sum_{i} D(\pi(y')_{i}) y_{i}$$
(3)

(4)

Discount function: focus on top k elements in list

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Kendall-τ

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(4)

Gain function: weight examples based on whether they are in important part of list, defined by permutation π . For example, for r = 5, the vector y = (2, 1, 6, 1, 0.5) induces the permutation $\pi(y) = (4, 3, 5, 1, 2)$

Kendall- τ

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$$G(y', y) = \sum_{i} D(\pi(y')_{i}) y_{i}$$
(3)

$$L(y', y) = \sum_{i} \frac{1}{G(y, y)} \sum_{i} (D(\pi(y)_{i}) - D(\pi(y')_{i})) y_{i}$$
 (4)

(5)

Loss function focuses on how wrong top of list is

Examples as feature vectors

Every example has a feature vector f(x)

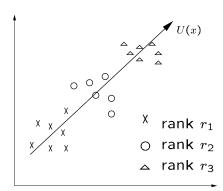
example	docID	query	cosine score	ω	judgment
Φ ₁	37	linux operating system	0.032	3	relevant
Φ_2	37	penguin logo	0.02	4	nonrelevant
Φ_3	238	operating system	0.043	2	relevant
Φ_4	238	runtime environment	0.004	2	nonrelevant
Φ_5	1741	kernel layer	0.022	3	relevant
Φ_6	2094	device driver	0.03	2	relevant
Φ_7	3191	device driver	0.027	5	nonrelevant

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Turning features to rank

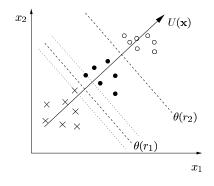
- Have a series of "levels" or ranks y = 1...
- We want to find a function to separate examples

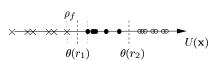
$$f(x) \equiv \langle w \cdot \phi(x) \rangle \tag{6}$$



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Maximizing the margin





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Recap

- Ranking is an important problem
- Different objective function
- Implementation similar to regression

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