Creation Cost Minimization

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Problem 1

• Minimize Creation Cost, discrete user preference set *W*:

Given a dataset D, a user preference set W, a cover percentage τ , a positive integer k and a creation cost function C, CCM introduces a new product p such that the cover ratio

$$cp(p,k) = \frac{|\{w | \forall w \in W, p \ is \ in \ TopK(w)\}|}{|W|} > \tau$$

and the creation cost C(p) is minimized.

Problem 2

• Minimize Creation Cost, user distribution θ :

Given a dataset D, a user preference distribution θ , a cover percentage τ , a positive integer k and a creation cost function C, CCM introduces a new product p such that the cover ratio

$$cp(p,k) = \frac{|\{w | \forall w \in \theta, p \text{ is in } TopK(w)\}|}{|\theta|} > \tau$$

and the creation cost C(p) is minimized.

For this week: reading 2 papers

- **kSPR**: [Tang et al., 2017] Tang, B., Mouratidis, K., and Yiu, M. L. (2017). Determining the impact regions of competing options in preference space. In Proceedings of the 2017 ACM International Conference on Management of Data, pages 805–820. ACM.
- **TopRR**: [Tang et al., 2019] Tang, B., Mouratidis, K., Yiu, M. L., and Chen, Z. (2019). Creating top ranking options in the continuous option and preference space. Proceedings of the VLDB Endowment, 12(9):xxx-yyy.

kSPR

kSPR-Problem Definition

• The k-Shortlist Preference Region problem (kSPR) takes as input a dataset D,

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a focal record p=(p_1,p_2,\cdots,p_d), and an integer k.
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It reports all the regions in preference space where if the weight vector lies, p ranks among the top-k records.

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A straight forward solution is to find  \cup C_i  For all C_i that C_i = h_{i,1}^- \cap h_{i,2}^- \cap \cdots \cap h_{i,|D|-k}^-, h_{i,j}^- is the half-space of S(r_{i,j}) < S(p) and S(r) = w \cdot r
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kSPR-Problem Definition

A straight forward solution is to find $\cup C_i$ For all C_i that $C_i = h_{i,1}^- \cap h_{i,2}^- \cap \cdots \cap h_{i,|D|-k}^-,$ $h_{i,i}^-$ is the half-space of $S(r_{i,i}) < S(p)$ and $S(r) = w \cdot r$

在一个半空间内表明p比一个r分数高, 只要p在至少|D|-k个半空间内它必能排前k(D包含p)

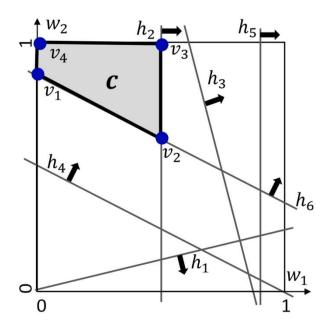
而这|D|-k个半空间是从|D|-1个半空间组合, 只要将所有结果取并集就是最后结果, 时间复杂度为组合数

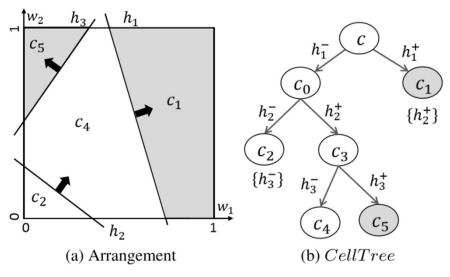
kSPR-CTA• Cell c is defined as

• Cell c is defined as $h_1^- \cap h_2^- \cap h_3^- \cap h_4^+ \cap h_5^- \cap h_6^+$

- 剪枝:
 - 数halfspaces数
 - 利用option之间的domination关系

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TopRR: problem definition

• Given a dataset D, a positive integer k, and a preference region $wR \subset W$,

compute the maximal region oR in option space where a new option o should lie, so that it is a top-ranking option.

TopRR: Notation

Notation	Description
\mathcal{D}	Option dataset
p_{i}	An (existing) option in \mathcal{D}
\mathcal{W}	Continuous preference space
w	A weight vector in \mathcal{W}
wR	Region in preference space
O	Continuous option space
0	New option to be placed in \mathcal{O}
οR	Region in option space (output of TopRR)
$S_{\mathbf{w}}(\mathbf{p}_i)$	The score of p_i according to w (equal to $p_i \cdot w$)
TopK(w)	k -th highest score in \mathcal{D} according to w
oH(w)	Impact halfspace for w (Definition 2)
$wHP(\pmb{p}_i, \pmb{p}_j)$	Hyperplane for $S_{\mathbf{w}}(\mathbf{p}_i) = S_{\mathbf{w}}(\mathbf{p}_j)$ in preference space
$wH(p_i, p_j)$	Halfspace for $S_{\mathbf{w}}(\mathbf{p}_i) \geq S_{\mathbf{w}}(\mathbf{p}_j)$ in preference space

Impact halfspace:

$$oH(w) = \{o \in \mathcal{O}: S_w(o) \geq TopK(w)\}$$

where $\boldsymbol{\mathcal{O}}$ is the option region and $S_w(o)$ is the score of o respect to w

For example,

$$w = (0.4, 0.6), TopK(w) = 0.5,$$

then $oH(w) = \{(x, y) | 0.4x + 0.6y \ge 0.5, x \in [0, 1], y \in [0, 1]\}$

w的impact halfspace里的所有options都是能在w这个权重下排前k的,也就是说所有w的impact halfspace的交集就是我们TopRR问题下要的能满足在任意w下都能排前k的region

LEMMA 1. Let \mathbf{p} and \mathbf{p}' be two options, and wR_i be a convex polytope in preference space. Let also \mathcal{V} be the vertex set that defines wR_i , i.e., the set of the polytope's extreme vertices. If it holds that $S_{\mathbf{v}}(\mathbf{p}) \geq S_{\mathbf{v}}(\mathbf{p}')$ for every vertex $\mathbf{v} \in \mathcal{V}$, then $S_{\mathbf{w}}(\mathbf{p}) \geq S_{\mathbf{w}}(\mathbf{p}')$ also holds for every weight vector $\mathbf{w} \in \mathsf{wR}_i$.

PROOF. Consider a weight vector $w \in wR_i$. Since wR_i is a convex polytope, w can be expressed as:

$$w = \sum_{v \in \mathcal{V}} \lambda_v v \tag{1}$$

for some positive λ_{ν} coefficients, where $\sum_{\nu \in \mathcal{V}} \lambda_{\nu} = 1$.

Since $S_{\nu}(\mathbf{p}) \geq S_{\nu}(\mathbf{p}')$ for each vertex $\nu \in \mathcal{V}$, it follows that $\lambda_{\nu}S_{\nu}(\mathbf{p}) \geq \lambda_{\nu}S_{\nu}(\mathbf{p}')$ too. By summing across all $\nu \in \mathcal{V}$, we get:

$$\sum_{\nu \in \mathcal{V}} \lambda_{\nu} S_{\nu}(\mathbf{p}) \geq \sum_{\nu \in \mathcal{V}} \lambda_{\nu} S_{\nu}(\mathbf{p}')$$

$$\Rightarrow \sum_{\nu \in \mathcal{V}} \lambda_{\nu}(\nu \cdot \mathbf{p}) \geq \sum_{\nu \in \mathcal{V}} \lambda_{\nu}(\nu \cdot \mathbf{p}')$$

$$\Rightarrow \mathbf{p} \cdot \sum_{\nu \in \mathcal{V}} \lambda_{\nu} \nu \geq \mathbf{p}' \cdot \sum_{\nu \in \mathcal{V}} \lambda_{\nu} \nu \qquad \triangleright \text{applying Equation (1)}$$

$$\Rightarrow \mathbf{p} \cdot \mathbf{w} \geq \mathbf{p}' \cdot \mathbf{w}$$

Thus, $\forall w \in \mathsf{wR}_i$, it holds that $S_w(p) \geq S_w(p')$. \square

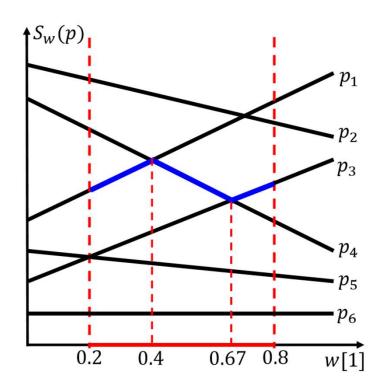
• **kipr**, rank-k invarian preference region:

A region wRi in preference space is a rank-k invariant preference region (**kIPR**) if the top-k result for every weight vector

 $w \in wR_i$

- (i) comprises the same k options, and
- (ii) the top-k-th option is always the same.

As shown in the figure, region [0.2, 0.8] and [0.2, 0.67] are not kIPR but region [0.67, 0.8] is.



LEMMA 2: The TopRR solution for a kIPR convex polytope wR_i is option region

$$oR_i = \bigcap_{v \in V} oH(v)$$

Theorem: Given the partitioning of wR into kIPRs, let V_{all} be the set of all vertices that define those kIPRs. The TopRR solution for wR is option region

$$oR_i = \bigcap_{v \in V_{all}} oH(v)$$

TAS, test-and-split:

- (i) Testing whether a region is kIPR
- (ii) Splitting a non kIPR region
- (iii) Recursively repeat (i) and (ii) until all regions are split as kIPR

(iv) Find the result oR by

$$oR_i = \bigcap_{v \in V_{all}} oH(v)$$

where V_{all} is the set of all vertices that define those kIPRs.