# Learning Socially Optimal Information Systems from Egoistic Users

#### Karthik Raman Thorsten Joachims

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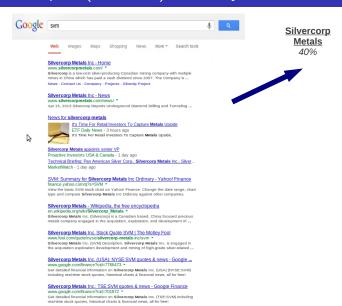
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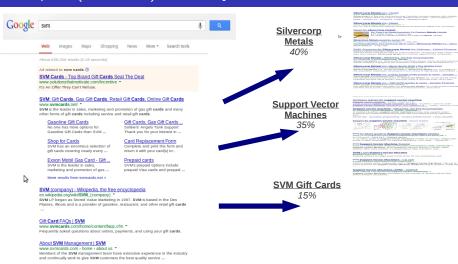
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40%

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Machines

35%

Silvers are a Material Long Library



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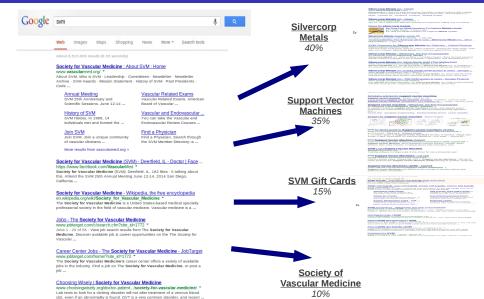
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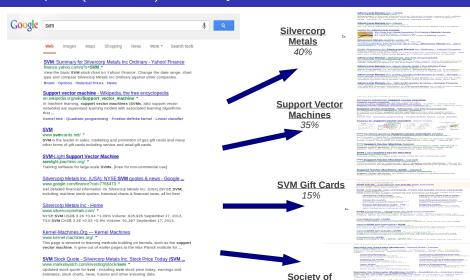
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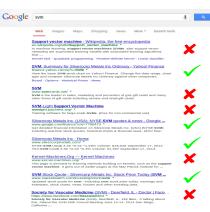
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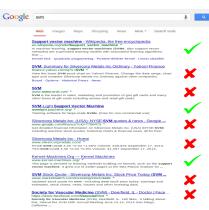
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User Interest	Pref Ranking
Company	$a_1, a_2, a_3, \dots$
ML	
Gift Cards	
Social Opt	



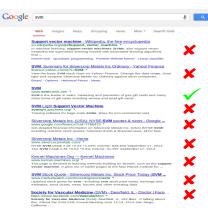
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User Interest	Pref Ranking
Company	$a_1, a_2, a_3, \dots$
ML	$b_1, b_2, b_3, \ldots$
Gift Cards	
Social Opt	



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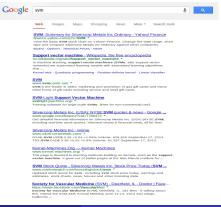
User Interest	Pref Ranking
Company	$a_1, a_2, a_3, \dots$
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Gift Cards	$c_1, c_2, c_3, \ldots$
Social Opt	$a_1, b_1, c_1, \dots$

 Even if social optimal is presented, users may indicate preferences for other rankings.



#### Related work

 [CG98, ZCL03, CK06]: Address Extrinsic Diversity. ☐ Do not use learning. [YJ08, SMO10, RJS11]: Use learning for diversity. ☐ Require relevance labels for all user-document pairs. [RKJ08]: Uses online learning: Array of (decoupled) MA Bandits. □ Learns very slowly. Does not generalize across queries. • [SRG13]: Couples the arms together. Does not generalize across queries. Hard-coded notion of diversity. [YG12]: Generalizes across queries. Requires cardinal utilities. • [RSJ12]: Learns from user preferences. Requires all users directly optimize social utility U.

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- KEY: Treat user feedback as preferences.



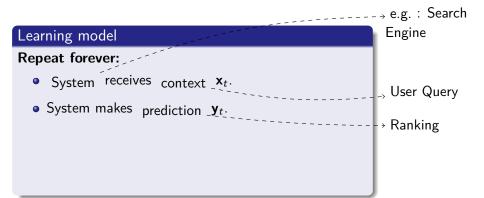
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- KEY: Treat user feedback as preferences.
- How do we learn from such preferential feedback?



#### Learning model

#### Repeat forever:

- System receives context  $\mathbf{x}_t$ .
- System makes prediction  $\mathbf{y}_t$ .



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- System receives context  $\mathbf{x}_t$ .
- System makes prediction  $\underline{\mathbf{y}}_{t}$ .
- Regret = Regret +  $U(\mathbf{x}_t, \mathbf{y}_t^*) U(\mathbf{x}_t, \mathbf{y}_t)$

 $\rightarrow$  e.g. : Search

Engine

\_, User Query

→ Ranking

Social utility

#### Learning model

## Repeat forever:

- System receives context  $\mathbf{x}_t$ .
- System makes prediction  $y_t$ .
- $\bullet \ \mathsf{Regret} = \mathsf{Regret} + \ \mathit{U}(\mathbf{x}_t, \mathbf{y}_t^*) \mathit{U}(\mathbf{x}_t, \mathbf{y}_t)$
- System gets (preference) feedback:  $U_i(\mathbf{x}_t, \overline{\mathbf{y}}_t) \geq_{\alpha, \delta} U_i(\mathbf{x}_t, \mathbf{y}_t)$

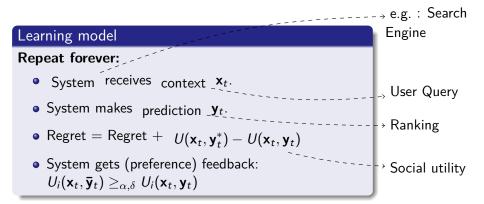
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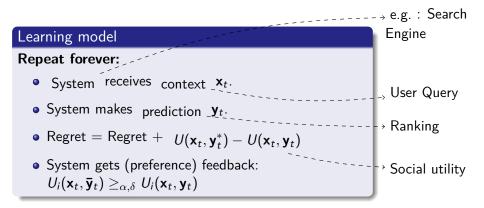
\_ User Query

 $\rightarrow$  Ranking

Social utility



Feedback received in terms of personal utilities  $U_i$ . But regret is in terms of social utility U.

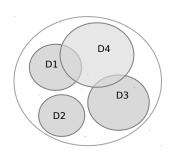


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How does we model utilities?

### Modeling User Utility: Submodularity

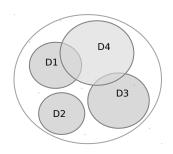
- Assume personal utilities are submodular.
- **Diminishing returns:** Marginal benefit of additional document on ML diminishes if 10 docs already shown *vs* only 1 previous doc.



- Computing ranking ≈ Submodular maximization
- Use simple, efficient greedy algorithm.
- Approximation guarantee of  $\frac{1}{2}$  (under partition matroid constraint).

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- Computing ranking ≈ Submodular maximization
- Use simple, efficient greedy algorithm.
- Approximation guarantee of  $\frac{1}{2}$  (under partition matroid constraint).
- How does this lead to diversity?

Posn	Doc	machine	learning	metal	silver
1					
2					
3					
4					
MAX	of Col				

Doc	Marginal Benefit
$d_1$	
$d_2$	
<b>d</b> <sub>3</sub>	
$d_4$	
$d_5$	
$d_6$	
d <sub>7</sub>	
d <sub>8</sub>	

Doc	Words	
$d_1$	ma:3 le:3	
$d_2$	ma:5 le:2	
$d_3$	ma:2 le:5	
$d_4$	ma:2 le:3	
$d_5$	me:3 si:5	
$d_6$	me:6 si:2	
$d_7$	me:4 si:2 ma:1	
d <sub>8</sub>	me:3 si:1 ma:1	

W	/ord	Weight
ma	chine	5
lea	rning	7
m	etal	4
si	lver	6

Posn	Doc	machine	learning	metal	silver
1					
2					
3					
4					
MAX	of Col				

Doc	Marginal Benefit		
$d_1$	3*5 + 3*7	36	
$d_2$			
<b>d</b> <sub>3</sub>			
$d_4$			
$d_5$			
$d_6$			
$d_7$			
d <sub>8</sub>			

Doc	Words	
$d_1$	ma:3 le:3	
$d_2$	ma:5 le:2	
$d_3$	ma:2 le:5	
$d_4$	ma:2 le:3	
$d_5$	me:3 si:5	
$d_6$	me:6 si:2	
$d_7$	me:4 si:2 ma:1	
d <sub>8</sub>	me:3 si:1 ma:1	

Word	Weight
machine	5
learning	7
metal	4
silver	6

Posn	Doc	machine	learning	metal	silver
1					
2					
3					
4					
MAX	of Col				

Doc	Marginal Benefit	
$d_1$	3*5 + 3*7	36
$d_2$	5*5 + 2*7	39
<b>d</b> <sub>3</sub>	2*5 + 5*7	45
$d_4$	2*5 + 3*7	31
$d_5$	3*4 + 5*6	42
$d_6$	6*4 + 2*6	36
d <sub>7</sub>	1*5 + 4*4 + 2*6	33
d <sub>8</sub>	1*5 + 3*4 + 1*6	23

Doc	Words
$d_1$	ma:3 le:3
$d_2$	ma:5 le:2
<b>d</b> <sub>3</sub>	ma:2 le:5
d <sub>4</sub>	ma:2 le:3
$d_5$	me:3 si:5
$d_6$	me:6 si:2
$d_7$	me:4 si:2 ma:1
<i>d</i> <sub>8</sub>	me:3 si:1 ma:1

Word	Weight
machine	5
learning	7
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silver	6

Posn	Doc	machine	learning	metal	silver
1	<b>d</b> <sub>3</sub>	2	5	0	0
2					
3					
4					
MAX of Col		2	5	0	0

Doc	Marginal Benef	it
$d_1$	3*5 + 3*7	36
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ma:3 le:3	
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me:3 si:5	
me:6 si:2	
me:4 si:2 ma:1	
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Posn	Doc	machine	learning	metal	silver
1	<b>d</b> <sub>3</sub>	2	5	0	0
2					
3					
4					
MAX of Col		2	5	0	0

Doc	Marginal Benefit		
$d_1$	(3-2)*5	5	
$d_2$	(5-2)*5	15	
<b>d</b> <sub>3</sub>	-	-	
$d_4$	0	0	
$d_5$	3*4 + 5*6	42	
$d_6$	6*4 + 2*6	36	
d <sub>7</sub>	4*4 + 2*6	28	
d <sub>8</sub>	3*4 + 1*6	18	

Doc	Words	
$d_1$	ma:3 le:3	
$d_2$	ma:5 le:2	
<b>d</b> <sub>3</sub>	ma:2 le:5	
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<b>d</b> 8	me:3 si:1 ma:1	

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Posn	Doc	machine	learning	metal	silver
1	<b>d</b> <sub>3</sub>	2	5	0	0
2	$d_5$	0	0	3	5
3					
4					
MAX of Col		2	5	3	5

Doc	Marginal Benefit		
$d_1$	(3-2)*5	5	
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<b>d</b> <sub>3</sub>	-	-	
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1	<b>d</b> <sub>3</sub>	2	5	0	0
2	$d_5$	0	0	3	5
3	<b>d</b> <sub>2</sub>	5	2	0	0
4					
MAX of Col		5	5	3	5

Doc	Marginal Benefit		
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<b>d</b> <sub>3</sub>	-	-	
$d_4$	0	0	
$d_5$	-	-	
$d_6$	(6-3)*4	12	
d <sub>7</sub>	(4-3)*4	4	
d <sub>8</sub>	0	0	

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2	$d_5$	0	0	3	5
3	$d_2$	5	2	0	0
4	<b>d</b> 6	0	0	6	2
MAX	of Col	5	5	6	5

Doc	Marginal Benefit		
$d_1$	0	0	
$d_2$	-	-	
<b>d</b> <sub>3</sub>	-	-	
$d_4$	0	0	
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### More General Submodular Utility

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   Yes.
- Given ranking/set  $\mathbf{y} = (d_{i_1}, \dots, d_{i_n})$ , aggregate features as:

$$\phi_F^j(\mathbf{x},\mathbf{y}) = F(\gamma_1 \phi^j(\mathbf{x},d_{i_1}), \gamma_2 \phi^j(\mathbf{x},d_{i_2}), \dots, \gamma_n \phi^j(\mathbf{x},d_{i_n}))$$

- $\triangleright \phi^j(\mathbf{x}, d_i)$  is  $j^{th}$  feature of  $d_i$ .
- $\triangleright$  *F* is a submodular function (modeling decision).
- $\ \ \ \ \ \gamma_1 \geq \gamma_2 \geq \ldots \geq \gamma_n \geq 0$  are position-discount factors

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- $\ \ \ \ \gamma_1 \ge \gamma_2 \ge ... \ge \gamma_n \ge 0$  are position-discount factors
- Utility modeled as linear in aggregate features:  $U(\mathbf{x}, \mathbf{y}) = \mathbf{w}_*^T \phi_F(\mathbf{x}, \mathbf{y})$ 
  - Submodular aggregation leads to diversity.

- **1** Initialize weight vector  $\mathbf{w}_1 \leftarrow \mathbf{0}$ .
- ② Given context  $\mathbf{x}_t$  compute  $\mathbf{y}_t \leftarrow \operatorname{argmax}_{\mathbf{y}} \mathbf{w}_t^{\top} \phi(\mathbf{x}_t, \mathbf{y})$ .
- **3** Observe user clicks  $\mathcal{D}$ .
- **1** Construct preference feedback  $\bar{\mathbf{y}}_t \leftarrow PrefFeedback(\mathbf{y}_t, \mathcal{D})$ .
- **6** Clip:  $\mathbf{w}_{t+1}^j \leftarrow \max(\mathbf{\bar{w}}_{t+1}^j, 0)$
- Repeat from step 2.

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- ② Given context  $\mathbf{x}_t$  compute  $\mathbf{y}_t \leftarrow \operatorname{argmax}_{\mathbf{y}} \mathbf{w}_t^{\top} \phi(\mathbf{x}_t, \mathbf{y})$ .  $\triangleright$  Using greedy algorithm.
- **3** Observe user clicks  $\mathcal{D}$ .
- **①** Construct preference feedback  $\bar{\mathbf{y}}_t \leftarrow PrefFeedback(\mathbf{y}_t, \mathcal{D})$ .
- $\textbf{0} \ \mathsf{Clip:} \ \mathbf{w}_{t+1}^j \leftarrow \mathsf{max}(\mathbf{\bar{w}}_{t+1}^j, \mathbf{0})$
- Repeat from step 2.

- **1** Initialize weight vector  $\mathbf{w}_1 \leftarrow \mathbf{0}$ .
- ② Given context  $\mathbf{x}_t$  compute  $\mathbf{y}_t \leftarrow \operatorname{argmax}_{\mathbf{y}} \mathbf{w}_t^{\top} \phi(\mathbf{x}_t, \mathbf{y})$ .  $\triangleright$  Using greedy algorithm.
- $\odot$  Observe user clicks  $\mathcal{D}$ .
- **②** Construct preference feedback  $\bar{\mathbf{y}}_t \leftarrow PrefFeedback(\mathbf{y}_t, \mathcal{D})$ . ▷ Pairwise feedback.
- **6** Clip:  $\mathbf{w}_{t+1}^j \leftarrow \max(\mathbf{\bar{w}}_{t+1}^j, 0)$
- Repeat from step 2.

- **1** Initialize weight vector  $\mathbf{w}_1 \leftarrow \mathbf{0}$ .
- ② Given context  $\mathbf{x}_t$  compute  $\mathbf{y}_t \leftarrow \operatorname{argmax}_{\mathbf{y}} \mathbf{w}_t^{\top} \phi(\mathbf{x}_t, \mathbf{y})$ .  $\triangleright$  Using greedy algorithm.
- $\odot$  Observe user clicks  $\mathcal{D}$ .
- Construct preference feedback  $\bar{\mathbf{y}}_t \leftarrow PrefFeedback(\mathbf{y}_t, \mathcal{D})$ .
  - ▶ Pairwise feedback.
- - Perceptron update.
- $\bullet \quad \mathsf{Clip}: \mathbf{w}_{t+1}^j \leftarrow \mathsf{max}(\bar{\mathbf{w}}_{t+1}^j, 0)$ 
  - To ensure submodularity.
- Repeat from step 2.

### Regret Bound

#### **Definition**

User feedback is **expected**  $\alpha_i, \delta_i$ -informative if  $\bar{\xi}_t \in \Re$  is chosen s.t. :

$$\mathbf{E}_{\mathbf{\bar{y}}_t}[U_i(\mathbf{x}_t,\mathbf{\bar{y}}_t)] \geq (1+\delta_i)U_i(\mathbf{x}_t,\mathbf{y}_t) + \alpha_i\left(U_i(\mathbf{x}_t,\mathbf{y}_t^{*,i}) - U_i(\mathbf{x}_t,\mathbf{y}_t)\right) - \bar{\xi}_t.$$

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#### Theorem

For any  $\mathbf{w}_* \in \mathbf{R}^m$  and  $\|\phi(\mathbf{x}, \mathbf{y})\|_{\ell_2} \leq R$  the average regret of the SoPer-R algorithm can be upper bounded as:

$$REG_T \leq \frac{1}{\eta T} \sum_{t=0}^{T-1} \mathbf{E}_i[p_i \bar{\xi_t}] + \frac{R \|\mathbf{w}_*\|}{2\eta} + \frac{\sqrt{15}R \|\mathbf{w}_*\|}{\eta \sqrt{2T}}.$$

with: 
$$\delta_i \geq \left(\Gamma_F \cdot \frac{1-p_i}{p_i}\right)$$
,  $\eta = \min_i p_i \alpha_i$ .

### Regret Bound: Analysis

#### Theorem

Average regret of the SoPer-R algorithm can be upper bounded as:

$$REG_T \leq \frac{1}{\eta T} \sum_{t=0}^{T-1} \mathbf{E}_i[p_i \bar{\xi_t}] + \frac{R \|\mathbf{w}_*\|}{2\eta} + \frac{\sqrt{15}R \|\mathbf{w}_*\|}{\eta \sqrt{2T}}.$$

with: 
$$\delta_i \geq \left(\Gamma_F \cdot \frac{1-p_i}{p_i}\right)$$
,  $\eta = \min_i p_i \alpha_i$ .

- Does not depend on number of dimensions.
  - ▷ Only on feature ball radius R.
- Decays gracefully with noisy feedback (the  $\alpha_i$ s and  $\eta$ ).
- Need not converge to optimal.
  - ▶ Partly due to NP-hardness of submodular maximization.

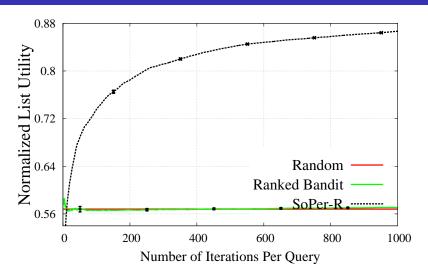
### Social Perceptron for Sets

- **SoPer-S** Algorithm for predicting diverse sets.
- See paper for more details.

### **Experimental Setup**

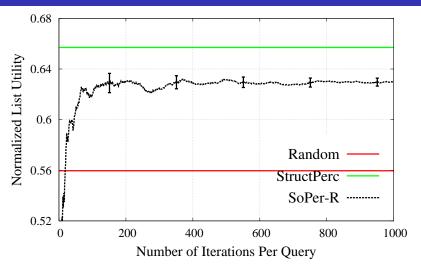
- Used standard TREC 6-8 Interactive search-diversification dataset:
  - ▶ Each query has 7-56 user types.
- Setup as in previous work [BJYB11, RJS11].
- Simulated user behavior:
  - ▶ Users scan rankings top to bottom.
  - ▷ Click on first document relevant to them (with small error chance).
- Utility function: Normalized DCG-coverage function (i.e.  $F(x_1, ..., x_n) = \max_i \gamma_i x_i$ ) upto rank 5.

# Learning to Diversify: Single Query



• Improved learning for single-query diversification.

# Learning to Diversify: Cross-Query



- StructPerc is (rough) skyline: Uses optimal for training.
- First method to learn cross-query diversity from implicit feedback.

#### Robustness

User Fncn	SoPer-R Function		Rand
	MAX SQRT		
MAX	.630 ±.007	.620 ±.006	.557 ±.006
SQRT	.656 ±.007	.654 ±.007	$.610  \pm .007$

• Robust to difference between submodular functions used in *User's* utility and *Algorithm's* utility.

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Robust to difference between submodular functions used in *User's* utility and *Algorithm's* utility.

Random	No Noise	Noise
.557 ±.006	.630 ±.007	.631 ±.007

• Works even if user feedback is noisy

#### Conclusions

- Proposed online-learning algorithms for aggregating conflicting user preferences of a diverse population.
  - ▶ Utilizes the coactive learning model.
- Modeled user utilities as submodular.
- Provided regret bounds for algorithms.
- Works well empirically and is robust.

# THANKS









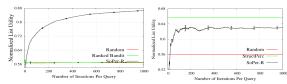
# **QUESTIONS?**

Feedback SORATCHION PROGRESS, Darlot A. Date do

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#### Poster #15





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### Experimental Setup Details

- TREC 6-8 Interactive diversification dataset:
  - ▷ Contains 17 queries. Each has 7-56 user types. Binary relevance labels.
  - ▶ Similar results observed for WEB diversification dataset.
- Setup details:
  - $\triangleright$  Re-ranking documents relevant to  $\ge 1$  user.
  - ho Probability of user type  $\propto$  # of documents relevant to user.
- DCG-position discounting:  $\gamma_i = \frac{1}{\log_2{(1+i)}}$ .

### Regret Bound

#### Definition

User feedback is **expected**  $\alpha_i, \delta_i$ -**informative** for user with personal utility function  $U_i$ , if  $\bar{\xi}_t \in \Re$  is chosen s.t. for some given  $\alpha_i \in [0,1]$  and  $\delta_i > 0$ :

$$\mathbf{E}_{\mathbf{\bar{y}}_t}[U_i(\mathbf{x}_t,\mathbf{\bar{y}}_t)] \geq (1+\delta_i)U_i(\mathbf{x}_t,\mathbf{y}_t) + \alpha_i\left(U_i(\mathbf{x}_t,\mathbf{y}_t^{*,i}) - U_i(\mathbf{x}_t,\mathbf{y}_t)\right) - \bar{\xi}_t.$$

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For any  $\mathbf{w}_* \in \mathbf{R}^m$  and  $\|\phi(\mathbf{x}, \mathbf{y})\|_{\ell_2} \leq R$  the average regret of the SoPer-R algorithm can be upper bounded as:

$$REG_T \leq \frac{1}{\eta T} \sum_{t=0}^{T-1} \mathbf{E}_i[p_i \bar{\xi_t}] + \frac{\beta R \|\mathbf{w}_*\|}{\eta} + \frac{\sqrt{2}\sqrt{4 - \beta^2} R \|\mathbf{w}_*\|}{\eta \sqrt{T}}.$$

$$\textit{with: } \delta_i \geq \Big( \Gamma_F \cdot \frac{1-p_i}{p_i} \Big), \ \eta = \min_i \ p_i \alpha_i \ \textit{and} \ \beta = \big( 1-\beta_{\textit{gr}} \big) = \frac{1}{2}.$$