# Optimal ranking of online search requests for long-term revenue maximization



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# **Search engines**

- Major role in the Internet economy
- most popular way to reach web pages
- > 20 billion requests per month from US home and work computers only

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For a given (set of) keyword(s), a search engine returns a ranked list of links: the organic results.

Organic results are supposed to be based on relevance only

Is this true?

Each engine has its own formula to measure (or estimate) relevance. May depend on user (IP address), location, etc.

CORV Shop by -	specialized s v	All Categories									
Refine your search for specialized s work venge 52											
Categories	All Listings	Auction Buy It Now	,	Sort: Best I	Match 🔹 View: 🖪 🔹	•					
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More refinements	T		<b>\$6,400.00</b> or Best Offer	From United States							
Recently viewed items	G										



### How are items ranked? Relevance vs expected revenue?



#### video justin trudeau boxing

Web News V

Videos Images

Shopping More \* Search tools

About 993,000 results (0.31 seconds)

#### Justin Trudeau vs. Patrick Brazeau Boxing Match p1 ... www.youtube.com/watch?v=tb-sgWJyWgA -



Mar 31, 2012 - Uploaded by ClReport ca Skinny Indian? What part of Brazeau is skinny? Secondly please 1200 take a good look at Patrick Brazeau, if he is ...

#### Justin Trudeau -- Patrick Brazeau Charity Boxing Match ...



www.youtube.com/watch?v=XuSpZ3\_5pTc ▼ Apr 1, 2012 - Uploaded by FactPointVideo Justin Trudeau -- Patrick Brazeau Charity Boxing Match --English ... they were under. Llowe watching the ...

#### Trudeau vs Brazeau BOXING FOR CANCER (Full fight ...



https://www.youtube.com/watch?v=fYfWiZMhaLE Apr 1, 2012 - Uploaded by Reasoning Conspiracy ... link http://www.sunnewsnetwork.ca/video/1540728713001 Watch the ... Patrick Brazeau and Justin ...

#### Meet Justin Trudeau: The Tattooed, Boxing New Canadian ...



www.nbcnews.com/.../video/meet-justin-trudeau--the-t... 16 hours ago Meet Justin Trudeau: The Tattooed, Boxing New Canadian Prime Minister ... Stunning Video Shows Qantas ...





www.youtube.com/watch?v=go7nf6xwfyA ▼ Mar 31, 2012 - Uploaded by LP - Mma Nouvelles Justin Trudeau vs Patrick Brazeau Le combat de boxe .... Justin ▶1997 Trudeau - Patrick Brazeau Charity Boxing ...

#### Justin Trudeau Boxing Match Weigh In With Senator Patrick ...



www.youtube.com/watch?v=M0e9D2rBN9w ▼ Mar 28, 2012 - Uploaded by althiaraj Liberal MP Justin Trudeau meets his competitor Conservative Senator Patrick Brazeau for a weigh in before ...

#### Justin Trudeau Boxing - YouTube



www.youtube.com/watch?v=JLQWA35er3g Aug 6, 2015 - Uploaded by Alex Guibord



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More - Search tools

About 11,400 results (0.18 seconds)

News

#### Video: Evo Morales caught kneeing player in groin during ...



Web

www.telegraph.co.uk > ... > South America > Bolivia Oct 5, 2010 Evo Morales, the Bolivian president, has been caught on camera kneeing an opposing player in the groin ...



#### Bolivian president Morales plays football for UN - YouTube



www.youtube.com/watch?v=uHIT3T9b86I Sep 27, 2013 - Uploaded by AFP news agency President of Bolivia Evo Morales during a soccer match at a park near the UN on the sidelines of the 68th ...

#### Bolivian President kicks man in bollocks (in football match ...



https://www.youtube.com/watch?v=6XkbNUlx5Bo Cct 6, 2010 - Uploaded by TrashTVChannel Bolivian president Evo Morales caught on camera knee-ing opponent (Daniel Gustavo Cartagenam) in the ...

#### Ahmadinejad plays football with Bolivian President Evo ...



www.youtube.com/watch?v=ragki2EPqxw Cct 27, 2010 - Uploaded by sherlock72 During a visit of Bolivian President Evo Morales to Iran , he bit6 played a friendly football game with Iranian ...

#### Bolivian president Morales plays football for UN - Video ...



www.dailymotion.com/video/x158t77\_bolivian-presid... Sep 27, 2013

President of Bolivia Evo Morales during a soccer match at a park near the UN on the sidelines of the 68th ...

#### Bolivia: Watch Evo Morales play against ex-Real Madrid ...



https://www.youtube.com/watch?v=v9oz0vvD2U4 Oct 8, 2014 - Uploaded by Ruptly TV Video ID: 20141008-057 M/S Evo Morales and former Real Madrid ... Bollvian President Evo Morales ...

#### Bolivian President Morales plays in friendly football match ...



www.youtube.com/watch?v=PUxWijVVGLOI Jul 31, 2015 - Uploaded by AP Archive Bolivian President Evo Morales walking onto pitch in Cadiz stadium 2... Bolivian President Morales plays ...



#### barack obama basketball video - Google Search



Books

Web Images Videos News Maps

About 11.000.000 results

Any country Country: Canada

Any time

Past hour Past 24 hours Past week Past month Past year

All results Verbatim

.....



Barack Obama playing Basketball Game. AMAZING FOOTAGE

https://www.youtube.com/watch?v=0OIDdGQQ0L8

#### Images for barack obama basketball video



Barack Obama's basketball fail - YouTube https://www.youtube.com/watch?v=gmTfKPx1Cug 1 Apr 2013 - 1 min - Uploaded by The Telegraph

https://www.google.ca/search?q=barack+obama+basketball+video&ie=utf-8&coe=utf-8&gws\_rd=cr&ei=jBpBVqaLL8jGesPTjYgL[2015-11-09 17:11:24]



#### putin judo video

Web Videos Images News Maps More - Search tools

About 54,600 results (0.24 seconds)

All YouTube:

#### 'Judo Knight' Putin shows off martial arts skills in wrestling ... https://www.youtube.com/watch?v=0lxMgli8LuM



Dec 23, 2010 - Uploaded by RT Prime Minister Vladimir Putin has taken another step to boost his charisma by ... Bodyguard face-off video ...

#### Putin's Judo - YouTube



https://www.youtube.com/watch?v=dYtDQ\_t-\_HQ Apr 5, 2012 - Uploaded by strawisinthesack Vladimir Putin has a black belt in the martial art and has competed at a high ... One day....a dream face off ...

#### Let's Learn Judo with Vladimir Putin (2008) - YouTube



https://www.youtube.com/watch?v=f62myM2iPjE Nov 7, 2012 - Uploaded by Putinery ... Russian President Vladimir Putin shares his favourite judo moves... Let's Learn Judo with Vladimir ...

#### Putin may join Russian Olympic judo team - YouTube



https://www.youtube.com/watch?v=2c3wzbtyikw Dec 20, 2009 - Uploaded by RT The Russian Judo Olympic team may have a new member. ... >334 Russia's Got Talent: Extra video of Putin ...

#### Putin practices judo - No comment - YouTube



https://www.youtube.com/watch?v=V5z5UAtCxgE Dec 21, 2009 - Uploaded by No Comment TV http://www.euronews.com/nocomment/ Vladimir Putin announcing be could help the Russian Judo Team if ...

#### Putin Judo - YouTube



https://www.youtube.com/watch?v=IdXwu2MXR\_s Jun 14, 2006 - Uploaded by timourkh

Russian President Vladimir Putin has a black belt in Judo.

#### Putin & Co to teach you judo - YouTube



https://www.youtube.com/watch?v=C7yjCaCQPO8 Oct 7, 2008 - Uploaded by RT

### Do search engines return biased results?

Comparison between Google, Bing, and Blekko (Wright, 2012):

- Microsoft content is 26 times more likely to be displayed on the first page of Bing than on any of the two other search engines
- Google content appears 17 times more often on the first page of a Google search than on the other search engines

Search engines do favor their own content

### Do search engines return biased results?



Percentage of Google or Bing search results with **own content not ranked similarly** by any rival search engine (Wright, 2012).

## Search Neutrality (relevance only)

Some say search engines should be considered as a public utility.

Idea of search neutrality: All content having equivalent relevance should have the same chance of being displayed. Content of higher relevance should never be displayed in worst position.

More fair, better for users and for economy, encourages quality, etc.

What is the precise definition of "relevance"? Not addressed here ...

Debate: Should neutrality be imposed by law? Pros and cons.

Regulatory intervention: The European Commission, is progressing toward an antitrust settlement deal with Google.

"Google must be even-handed. It must hold all services, including its own, to exactly the same standards, using exactly the same crawling, indexing, ranking, display, and penalty algorithms."

# In general: trade-off in the rankings

From the viewpoint of the SE: Tradeoff between

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relevance (long term profit)
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versus

expected revenue (short term profit)

Better relevance brings more customers in the long term because it builds reputation.

What if the provider wants to optimize its long-term profit?

### Simple model of search requests

**Request:** random vector  $Y = (M, R_1, G_1, \ldots, R_M, G_M)$  where M = number of pages (or items) that match the request,  $M \le m_0$ ;  $R_i \in [0, 1]$ : measure of relevance of item *i*;  $G_i \in [0, K]$ : expected revenue (direct or indirect) from item *i*. has a prob. distribution over  $\Omega \subseteq \mathbb{N} \times ([0, 1] \times [0, K])^{m_0}$ . Can be discrete or continuous.

 $y = (m, r_1, g_1, \dots, r_m, g_m)$  denotes a realization of Y.

 $c_{i,j}(y) = \mathbb{P}[\text{click page } i \text{ if in position } j] = \text{click-through rate (CTR)}.$ Assumed  $\nearrow$  in  $r_i$  and  $\searrow$  in j. Example:  $c_{i,j}(y) = \theta_j \psi(r_i)$ 

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Assumed  $\nearrow$  in  $r_i$  and  $\searrow$  in  $j$ . Example:  $c_{i,j}(y) = \theta_j \psi(r_i)$ 

**Decision** (ranking) for any request y: Permutation  $\pi = (\pi(1), \ldots, \pi(m))$  of the m matching pages.  $j = \pi(i) = \text{position of } i$ .

Local relevance and local revenue for y and  $\pi$ :

$$r(\pi, y) = \sum_{i=1}^{m} c_{i,\pi(i)}(y)r_i,$$
  $g(\pi, y) = \sum_{i=1}^{m} c_{i,\pi(i)}(y)g_i.$ 

### **Deterministic stationary ranking policy** $\mu$ It assigns a permutation $\pi = \mu(y) \in \Pi_m$ to each $y \in \Omega$ .

Long-term expected relevance per request (reputation of the provider) and expected revenue per request (from the organic links), for given  $\mu$ :

$$r = r(\mu) = \mathbb{E}_Y[r(\mu(Y), Y)],$$
  
$$g = g(\mu) = \mathbb{E}_Y[g(\mu(Y), Y)].$$

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**Objective:** Maximize long-term utility function  $\varphi(r, g)$ . Assumption:  $\varphi$  is strictly increasing in both r and g.

Example: expected revenue per unit of time

$$arphi(r,g) = \lambda(r)(eta+g)$$
, where

 $\lambda(r) = \text{arrival rate of requests, strictly increasing in } r;$   $\beta = \mathbb{E}[\text{revenue per request}] \text{ from non-organic links (ads on root page);}$  $g = \mathbb{E}[\text{revenue per request}] \text{ from organic links.}$ 

# Deterministic stationary ranking policy $\mu$

It assigns a permutation  $\pi = \mu(y) \in \Pi_m$  to each  $y \in \Omega$ . Q: Is this the most general type of policy?

Long-term expected relevance per request (reputation of the provider) and expected revenue per request (from the organic links), for given  $\mu$ :

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### Randomized stationary ranking policy $\tilde{\mu}$

$$\tilde{\mu}(y) = \{q(\pi, y) : \pi \in \Pi_m\}$$

is a probability distribution, for each  $y = (m, r_1, g_1, \ldots, r_m, g_m) \in \Omega$ .

Expected relevance

$$r = r(\tilde{\mu}) = \mathbb{E}_{Y}\left[\sum_{\pi} q(\pi, Y) \sum_{i=1}^{M} c_{i,\pi(i)}(Y) R_{i}\right]$$

Expected revenue

$$g = g(\tilde{\mu}) = \mathbb{E}_Y \left[ \sum_{\pi} q(\pi, Y) \sum_{i=1}^M c_{i,\pi(i)}(Y) G_i \right]$$

### Randomized stationary ranking policy $\tilde{\mu}$

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is a probability distribution, for each  $y = (m, r_1, g_1, \dots, r_m, g_m) \in \Omega$ . Let  $z_{i,j}(y) = \mathbb{P}[\pi(i) = j]$  under  $\tilde{\mu}$ .

Expected relevance

$$r = r(\tilde{\mu}) = \mathbb{E}_{Y}\left[\sum_{\pi} q(\pi, Y) \sum_{i=1}^{M} c_{i,\pi(i)}(Y) R_{i}\right] = \mathbb{E}_{Y}\left[\sum_{i=1}^{M} \sum_{j=1}^{M} z_{i,j}(Y) c_{i,j}(Y) R_{i}\right]$$

Expected revenue

$$g = g(\tilde{\mu}) = \mathbb{E}_{Y}\left[\sum_{\pi} q(\pi, Y) \sum_{i=1}^{M} c_{i,\pi(i)}(Y) G_{i}\right] = \mathbb{E}_{Y}\left[\sum_{i=1}^{M} \sum_{j=1}^{M} z_{i,j}(Y) c_{i,j}(Y) G_{i}\right]$$

In terms of (r, g), we can redefine (simpler)  $\tilde{\mu}(y) = \mathbf{Z}(y) = \{z_{i,j}(y) \ge 0 : 1 \le i, j \le m\}$  (doubly stochastic matrix). **Q**: Here we have a stochastic dynamic programming problem, but the rewards are not additive! Usual DP techniques do not apply.

How can we compute an optimal policy?

Seems very hard in general!

# **Optimization problem**

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$$\begin{array}{lll} \max_{\substack{\tilde{\mu}\in\tilde{\mathcal{U}}\\ \tilde{\mu}\in\tilde{\mathcal{U}}}} & \varphi(r,g) = \lambda(r)(\beta+g) \\ \text{bject to} \\ r & = & \mathbb{E}_{Y}\left[\sum_{i=1}^{M}\sum_{j=1}^{M}z_{i,j}(Y)c_{i,j}(Y)R_{i}\right] \\ g & = & \mathbb{E}_{Y}\left[\sum_{i=1}^{M}\sum_{j=1}^{M}z_{i,j}(Y)c_{i,j}(Y)G_{i}\right] \\ \tilde{\mu}(y) & = & \mathbf{Z}(y) = \{z_{i,j}(y) : 1 \le i,j \le m\} \quad \text{ for all } y \in \Omega. \end{array}$$

### **Optimization problem**

$$\max_{\substack{\tilde{\mu}\in\tilde{\mathcal{U}}\\ \tilde{\mu}\in\tilde{\mathcal{U}}}} \varphi(r,g) = \lambda(r)(\beta+g)$$
  
subject to  
$$r = \mathbb{E}_{Y} \left[ \sum_{i=1}^{M} \sum_{j=1}^{M} z_{i,j}(Y)c_{i,j}(Y)R_{i} \right]$$
$$g = \mathbb{E}_{Y} \left[ \sum_{i=1}^{M} \sum_{j=1}^{M} z_{i,j}(Y)c_{i,j}(Y)G_{i} \right]$$
$$\tilde{\mu}(y) = \mathbf{Z}(y) = \{z_{i,j}(y) : 1 \le i,j \le m\} \text{ for all } y \in \Omega.$$

To each  $\tilde{\mu}$  corresponds  $(r, g) = (r(\tilde{\mu}), g(\tilde{\mu}))$ . **Proposition:** The set  $C = \{(r(\tilde{\mu}), g(\tilde{\mu})) : \tilde{\mu} \in \tilde{U}\}$  is convex.

Optimal value:  $\varphi^* = \max_{(r,g) \in \mathcal{C}} \varphi(r,g) = \varphi(r^*,g^*)$  (optimal pair). Idea: find  $(r^*,g^*)$  and recover an optimal policy from it.





r



### Optimization

$$\nabla \varphi(r^*,g^*)'(r-r^*,g-g^*) = \varphi_r(r^*,g^*)(r-r^*) + \varphi_g(r^*,g^*)(g-g^*) = 0.$$

Let  $\rho^* = \varphi_g(r^*, g^*) / \varphi_r(r^*, g^*) =$  slope of gradient. Optimal value =  $\max_{(r,g) \in \mathcal{C}} \varphi(r, g)$ .

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Optimal "solution" satisfies  $(r^*, g^*) = \arg \max_{(r,g) \in \mathcal{C}} (r + \rho^* g)$ .

The optimal  $(r^*, g^*)$  is unique if the contour lines of  $\varphi$  are strictly convex. True for example if  $\varphi(r, g) = r^{\alpha}(\beta + g)$  where  $\alpha > 0$ .

The arg max for the linear function is unique if and only if green line  $\varphi_r(r^*, g^*)(r - r^*) + \varphi_g(r^*, g^*)(g - g^*) = 0$  touches C at a single point.



r

### One more assumption

Standard assumption: click-through rate has separable form:

 $c_{i,j}(y) = \theta_j \, \psi(r_i),$ 

where  $1 \ge \theta_1 \ge \theta_2 \ge \cdots \ge \theta_{m_0} > 0$  (ranking effect) and  $\psi : [0, 1] \rightarrow [0, 1]$  increasing.

Let  $\tilde{R}_i := \psi(R_i)R_i$ ,  $\tilde{G}_i := \psi(R_i)G_i$ , and similarly for  $\tilde{r}_i$  and  $\tilde{g}_i$ . Then

$$r = \mathbb{E}_{Y} \left[ \sum_{i=1}^{M} \sum_{j=1}^{M} z_{i,j}(Y) \theta_{j} \tilde{R}_{i} \right] \quad \text{and} \\ g = \mathbb{E}_{Y} \left[ \sum_{i=1}^{M} \sum_{j=1}^{M} z_{i,j}(Y) \theta_{j} \tilde{G}_{i} \right].$$

# **Optimality conditions, discrete case**

**Definition.** A linear ordering policy with ratio  $\rho$  (LO- $\rho$  policy) is a (randomized) policy that ranks the pages *i* by decreasing order of their score  $\tilde{r}_i + \rho \tilde{g}_i$  with probability 1, for some  $\rho > 0$ , except perhaps when  $\theta_{i'} = \theta_i$  where the order does not matter.

**Theorem.** Suppose Y has a discrete distribution, with  $p(y) = \mathbb{P}[Y = y]$ . Then any optimal randomized policy must be an LO- $\rho^*$  policy.

Idea of proof: by an interchange argument. If for some y with p(y) > 0, page i at position j has lower score  $\tilde{r}_i + \rho^* \tilde{g}_i$  than the page at position j' > j with probability  $\delta > 0$ , we can gain by exchanging those pages, so this is cannot be optimal.

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One can find  $\rho^*$  via a linear search on  $\rho$  (various methods for that). For each  $\rho$ , one may evaluate the LO- $\rho$  policy either exactly or by simulation.

Just finding  $\rho^*$  appears sufficient to determine an optimal policy

### Nice!

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### Nice! Right?

What if two or more pages have the same score  $\tilde{R}_i + \rho^* \tilde{G}_i$ ? Can we rank them arbitrarily? What if two or more pages have the same score  $\tilde{R}_i + \rho^* \tilde{G}_i$ ? Can we rank them arbitrarily?

The answer is NO.

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The answer is **NO**.

Specifying  $\rho^*$  is not enough to uniquely characterize an optimal policy when equality can occur with positive probability.

![](_page_37_Figure_0.jpeg)

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### Counter-example.

Single request 
$$Y = y = (m, r_1, g_1, r_2, g_2) = (2, 1, 0, 1/5, 2).$$
  
 $\psi(r_i) = 1, (\theta_1, \theta_2) = (1, 1/2), \varphi(r, g) = r(1 + g).$   
For each request,  $\mathbb{P}[\text{ranking } (1, 2)] = p = 1 - \mathbb{P}[\text{ranking } (2, 1)].$ 

One finds that  $\varphi(r,g) = (7+4p)(3-p)/10$ , maximized at  $p^* = 5/8$ . This gives  $r^* = 19/20$ ,  $g^* = 11/8$ ,  $\varphi(r^*, g^*) = 361/160$ . p = 0 gives  $\varphi(r,g) = 336/160$  and p = 1 gives  $\varphi(r,g) = \varphi^* = 352/160$ .

No optimal deterministic policy here!

![](_page_39_Figure_0.jpeg)

**Definition.** A randomized policy  $\tilde{\mu}$  is called an LO- $\rho$  policy if for almost all Y,  $\tilde{\mu}$  sorts the pages by decreasing order of  $\tilde{R}_i + \rho \tilde{G}_i$ , except perhaps at positions j and j' where  $\theta_j = \theta_{j'}$ , at which the order can be arbitrary.

**Theorem** (necessary conditions). Any optimal policy must be an LO- $\rho$  policy with  $\rho = \rho^*$ .

### **Continuous distribution for** Y

Assumption A. For any  $\rho \ge 0$  and j > i > 0,  $\mathbb{P}[M \ge j \text{ and } \tilde{R}_i + \rho \tilde{G}_i = \tilde{R}_j + \rho \tilde{G}_j] = 0.$ 

**Theorem** (sufficient condition). Under Assumption A, for any  $\rho \ge 0$ , a deterministic LO- $\rho$  policy sorts the pages for Y uniquely with probability 1. For  $\rho = \rho^*$ , this policy is optimal.

Idea: With probability 1, there is no equality.

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Idea: With probability 1, there is no equality.

In this case, it suffices to find  $\rho^*$ , which is a root of

$$ho = \tilde{h}(
ho) := h(r,g) := rac{arphi_g(r,g)}{arphi_r(r,g)} = rac{\lambda(r)}{(eta+g)\lambda'(r)}.$$

Can be computed by a root-finding technique.

**Proposition.** (i) If h(r,g) is bounded over  $[0,1] \times [0,K]$ , then the fixed-point equation  $\tilde{h}(\rho) = \rho$  has at least one solution in  $[0,\infty)$ . (ii) If the derivative  $\tilde{h}'(\rho) < 1$  for all  $\rho > 0$ , then the solution is unique.

### Proposition.

Suppose  $\varphi(r,g) = \lambda(r)(\beta + g)$ . Then  $h(r,g) = \lambda(r)/(\beta + g)\lambda'(r)$  and (i) If  $\lambda(r)/\lambda'(r)$  is bounded for  $r \in [0,1]$  and  $g(\rho(0)) > 0$ , then the fixed point equation has at least one solution in  $[0,\infty)$ . (ii) If  $\lambda(r)/\lambda'(r)$  is also non-decreasing in r, then the solution is unique.

Often,  $\rho \mapsto \tilde{h}(\rho)$  is a contraction mapping. It is then rather simple and efficient to compute a fixed point iteratively.

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In this continuous case, computing an optimal deterministic policy is relatively easy. It suffices to find the root  $\rho^*$  and use the LO- $\rho^*$  policy, which combines optimally relevance and profit.

## What to do for the discrete case?

Often, only a randomized policy can be optimal. But such a policy is very hard to compute and use in general! Not good!

### Much simpler and better solution:

Select a small  $\epsilon > 0$  (e.g.,  $\epsilon = 10^{-10}$ ) and whenever some items *i* have equal scores, add a random perturbation, uniform over  $(-\epsilon, \epsilon)$ , to each  $G_i$ .

Under this perturbed distribution of Y, the probability of equal scores becomes 0 and one can compute the optimal  $\rho^*(\epsilon)$ , which gives the optimal policy w.p.1.

**Proposition.** Let  $\varphi^*$  be the optimal value (average gain per unit of time) and  $\varphi^{**}$  the value when applying the optimal policy for the perturbed model (with an artificial perturbation), both for the original model. Then

$$0 \leq \varphi^* - \varphi^{**}(\epsilon) \leq \lambda(r^*(\epsilon))(\theta_1 + \cdots + \theta_{m_0})\epsilon.$$

### Application to previous example

![](_page_46_Figure_1.jpeg)

$\epsilon$	$p^*(\epsilon)$	$ ho^*(\epsilon)$	$r^*(\epsilon)$	$g^*(\epsilon)$	$\varphi^*(\epsilon)$	$\varphi^{**}(\epsilon)$
0.0	0.625	0.4	0.95	1.375	2.25625	2.25625
0.001	0.62491	0.39995	0.94996	1.37521	2.25636	2.25615
0.01	0.62411	0.39950	0.94964	1.37006	2.25736	2.25539
0.1	0.61705	0.39537	0.94682	1.39476	2.26741	2.24869
0.5	0.59771	0.38137	0.93908	1.46240	2.31240	2.23031

 $\varphi^* = \varphi^*(0) = optimal value.$  $\varphi^*(\epsilon) = optimal value of perturbed problem.$  $\varphi^* * (\epsilon) = value using optimal policy of perturbed problem.$ 

# Conclusion

Even if our original model can be very large and an optimal policy can be complicated (and randomized), we found that for the continuous model, the optimal policy has a simple structure, with a single parameter  $\rho$  that can be optimized via simulation.

In real-life situations in which our model assumptions may not be satisfied completely, it makes sense to adopt the same form of policy and optimize  $\rho$  by simulation. This is a viable strategy that should be often close to optimal.

Other possible approach (future work): a model that uses discounting for both relevance and gains.

Model can be refined in several possible directions.

## More details

P. L'Ecuyer, P. Maille, N. Stier-Moses, and B. Tuffin. Revenue-Maximizing Rankings for Online Platforms with Quality-Sensitive Consumers.

**GERAD** Report

On my web page.

Also at https://hal.inria.fr/hal-00953790.