Information Retrieval 1

IR-User Interaction

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Learning to rank

Evaluation

Document representation & matching

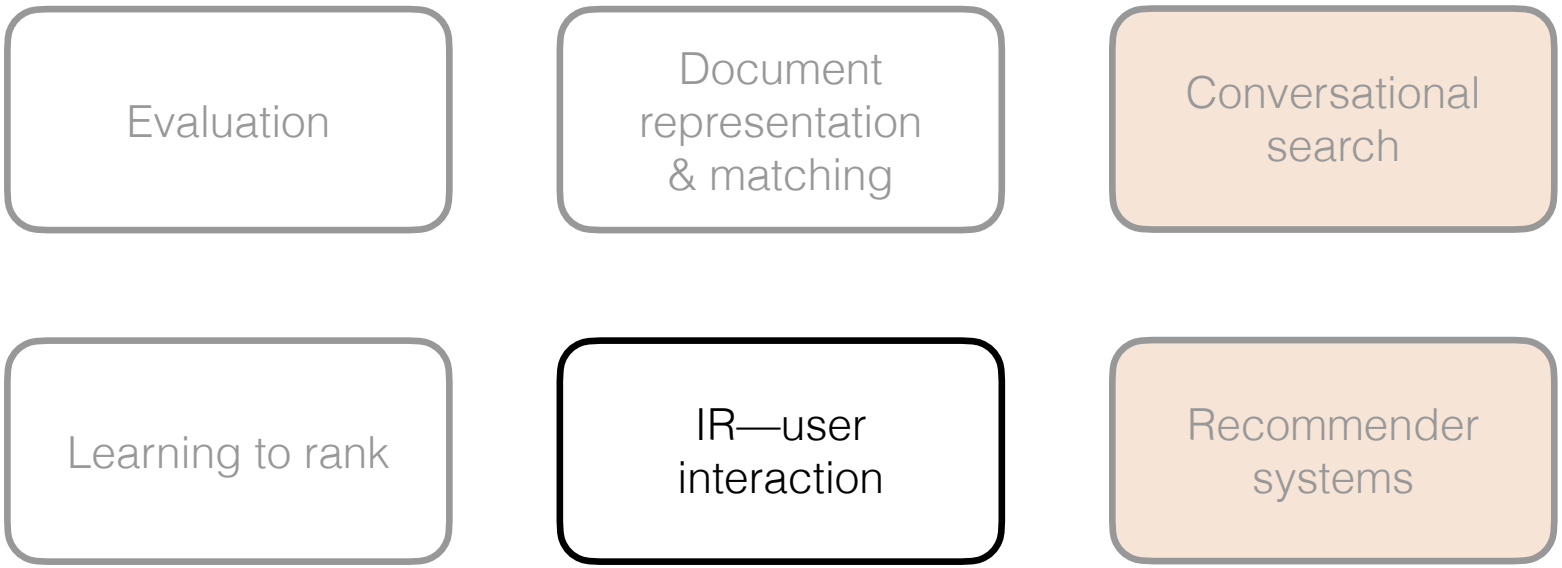
Conversational search

Learning to rank

IR—user interaction

Recommender systems

IR-User Interaction



User interactions

- Queries
- Interactions with a SERP (clicks, mousing, scrolling, etc.)
- Time between user actions
- Closing browser
- Interactions beyond search
- Etc.

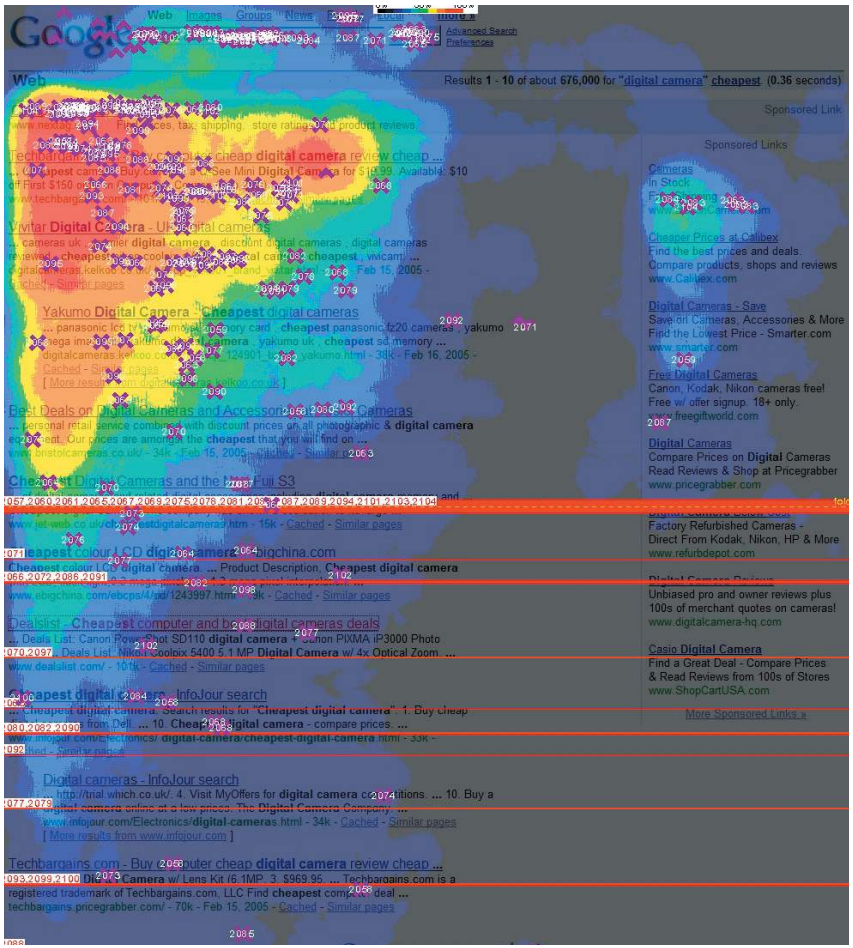
Why are user interactions important?

- Evaluate IR systems
- Improve IR systems

Models of user search interactions

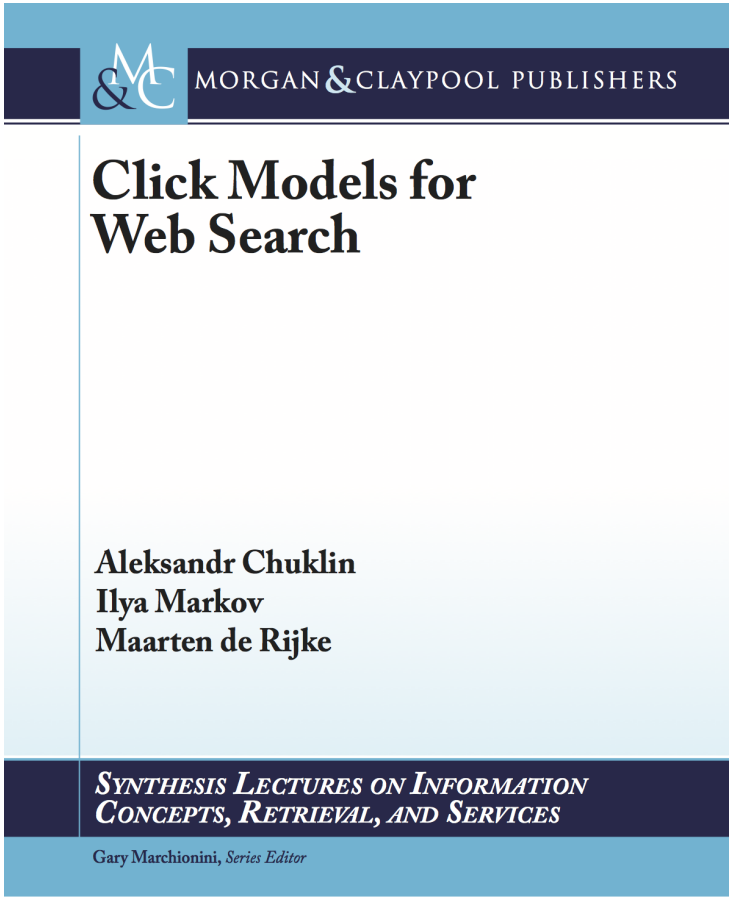
- Click models
- Models of mouse hovering
- Models of time between user actions

Position bias



Hotchkiss et al. "An In Depth Look at Interactions with Google using Eye Tracking Methodology"

Click models



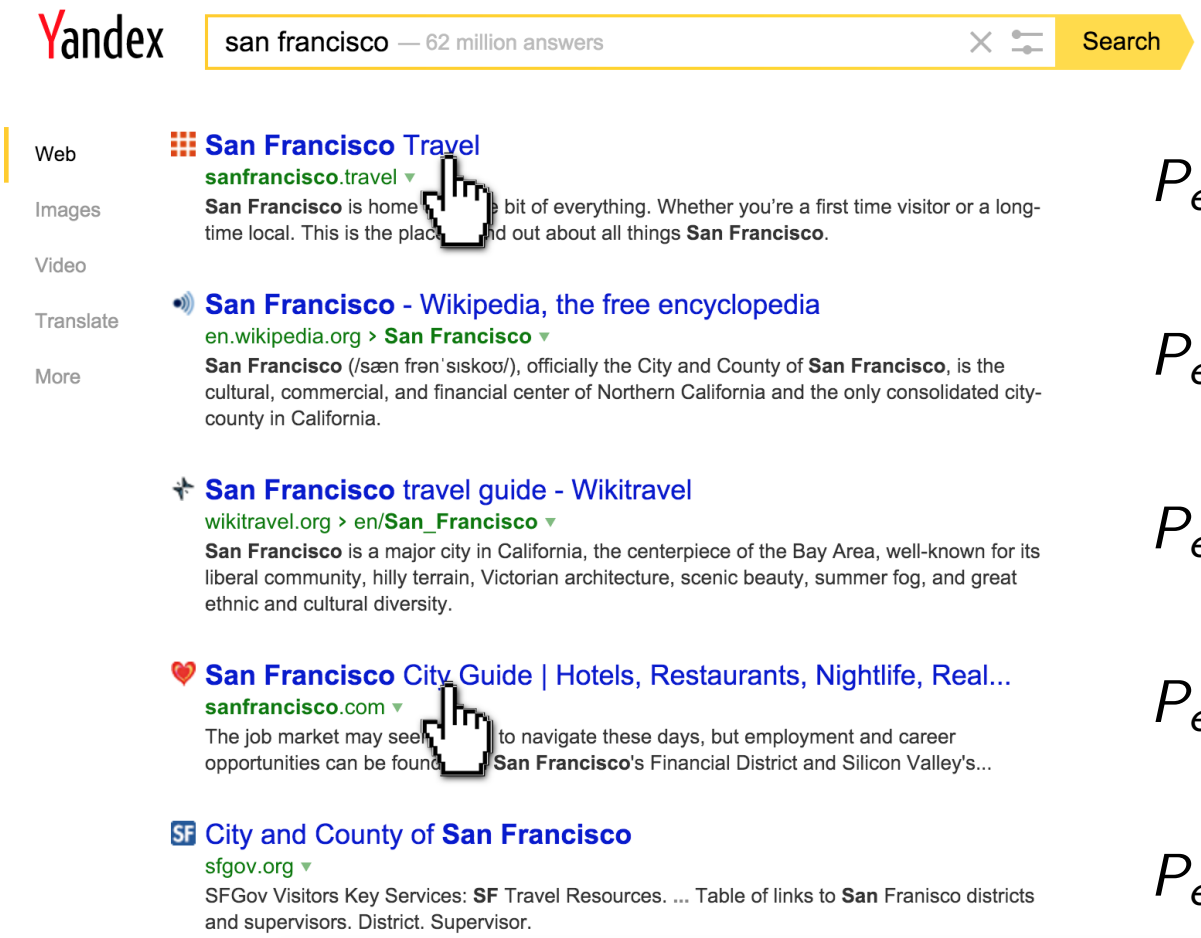
http://clickmodels.weebly.com/the-book.html

Outline

Basic click models

- Position-based model
- Cascade model

Position-based model



$P_{exam}(1),\ P_{attr}(qd_1)$

$P_{exam}(2),\ P_{attr}(qd_2)$

$P_{exam}(3),\ P_{attr}(qd_3)$

$P_{exam}(4),\ P_{attr}(qd_4)$

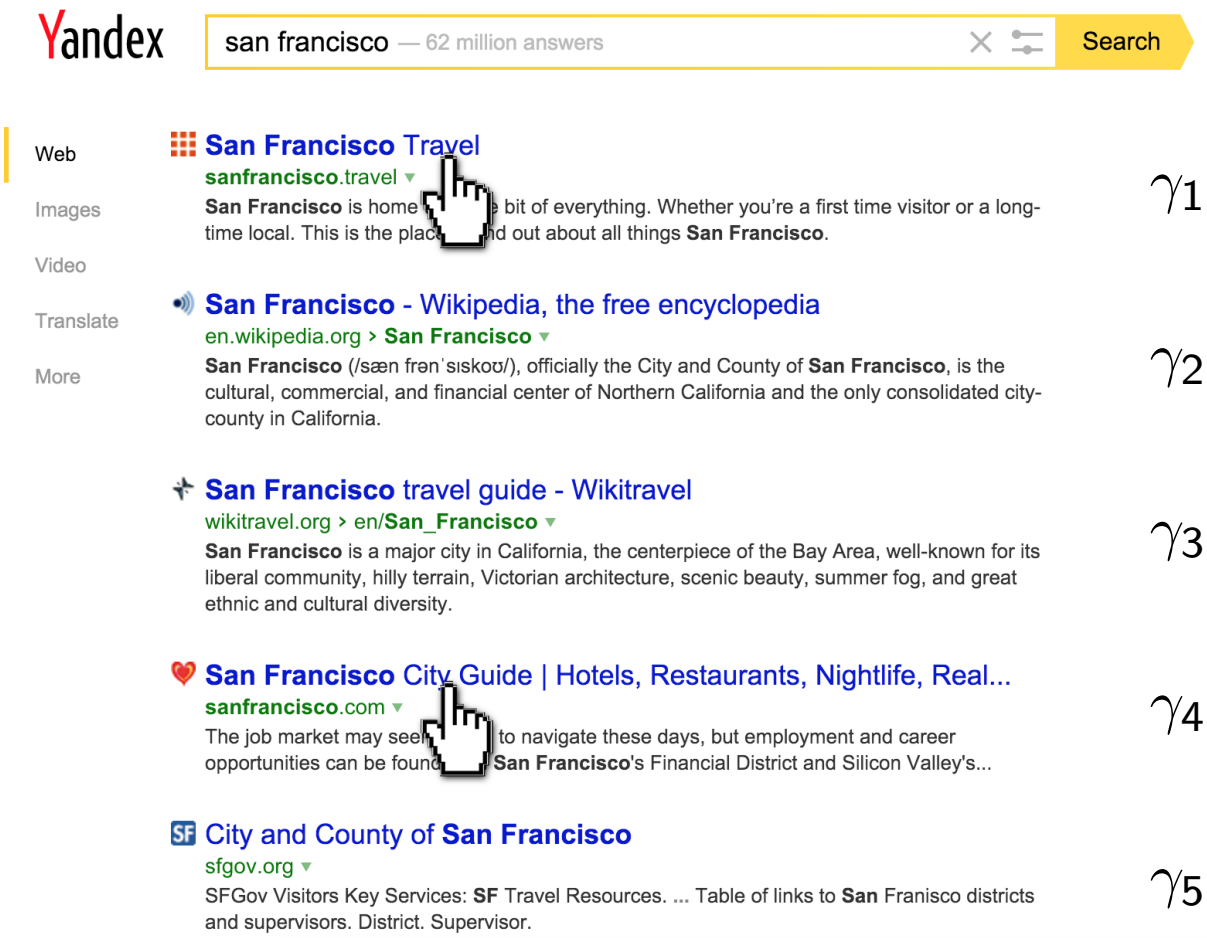
$P_{exam}(5),\ P_{attr}(qd_5)$

Position-based model: examination

- Terminology
  - Examination = reading a snippet
  - E_r – binary random variable denoting examination of a snippet at rank r
- Position-based model (PBM)
  - Examination depends on rank

$$P(E_r = 1) = \gamma_r$$

Position-based model



γ_1 , $P_{attr}(d_1 q)$

γ_2 , $P_{attr}(d_2 q)$

γ_3 , $P_{attr}(d_3 q)$

γ_4 , $P_{attr}(d_4 q)$

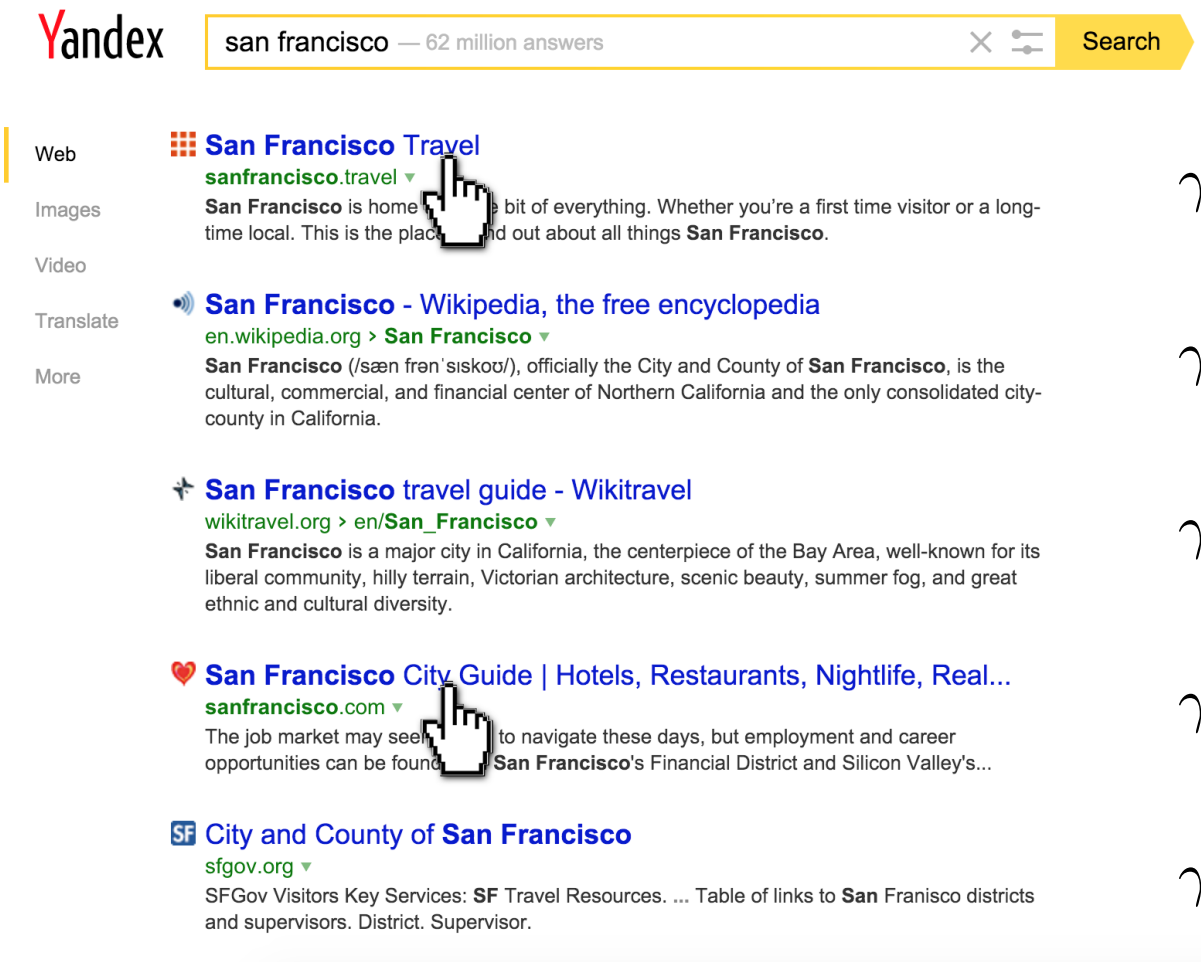
γ_5 , $P_{attr}(d_5 q)$

Position-based model: attractiveness

- Terminology
  - Attractiveness = a user wants to click on a document after examining (reading) its snippet
  - A_{qd} – binary random variable showing whether document d is attractive to a user, given query q
- Position-based model (PBM)
  - Attractiveness depends on a query-document pair

$$P(A_{qd} = 1) = \alpha_{qd}$$

Position-based model



γ_1 , α_{qd_1}

γ_2 , α_{qd_2}

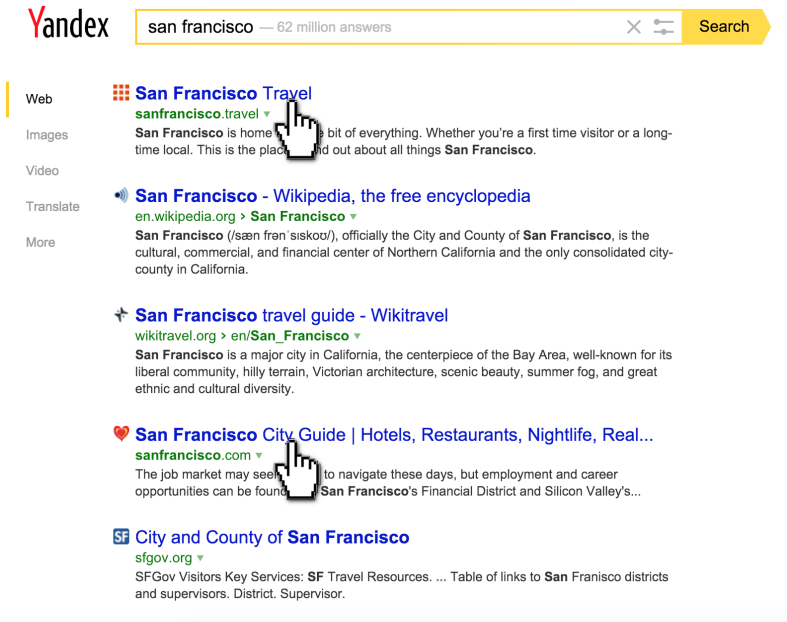
γ_3 , α_{qd_3}

γ_4 , α_{qd_4}

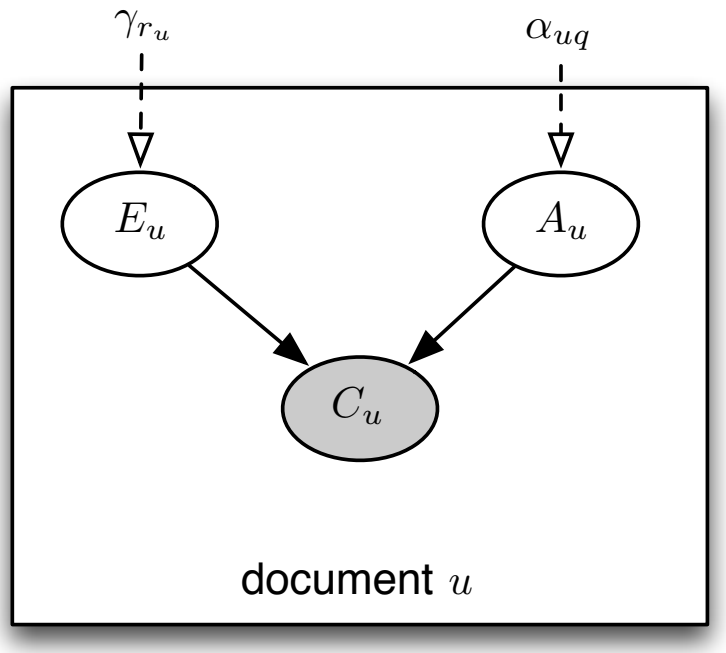
γ_5 , α_{qd_5}

Position-based model: summary

$$P(E_{r_d} = 1) = \gamma_{r_d}$$
$$P(A_{qd} = 1) = \alpha_{qd}$$
$$P(C_d = 1) = P(E_{r_d} = 1) \cdot P(A_{qd} = 1)$$



Position-based model: probabilistic graphical model

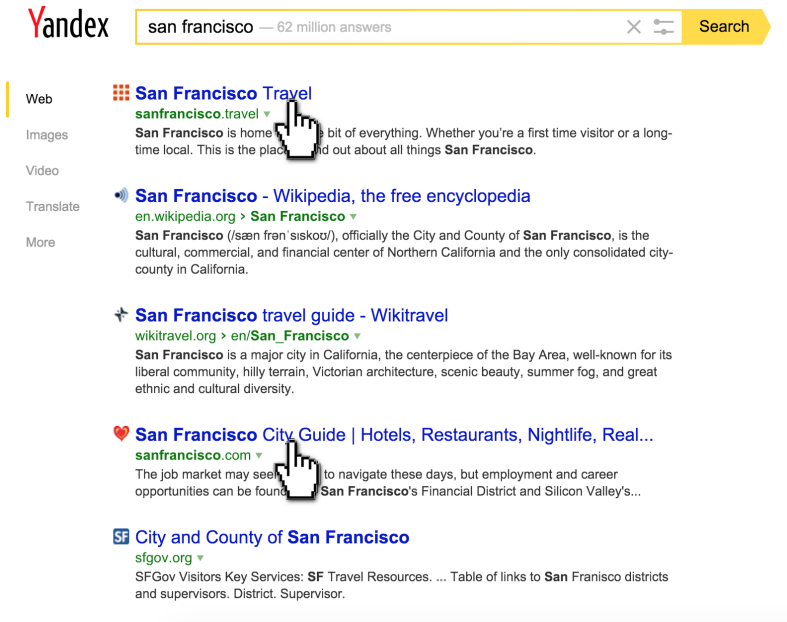


Position-based model

$$P(E_{r_d} = 1) = \gamma_{r_d}$$

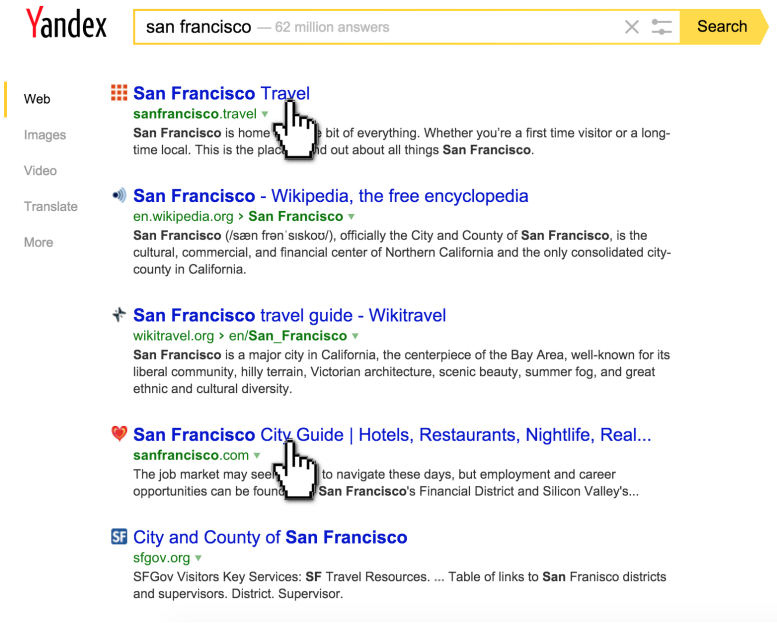
$$P(A_{qd} = 1) = \alpha_{qd}$$

$$P(C_d = 1) = P(E_{r_d} = 1) \cdot P(A_{qd} = 1)$$



Cascade model

1. Start from the first document
2. Examine documents one by one
3. If click, then stop
4. Otherwise, continue



Cascade model

$$E_r = 1 \text{ and } A_{d_r} = 1 \Leftrightarrow C_r = 1$$

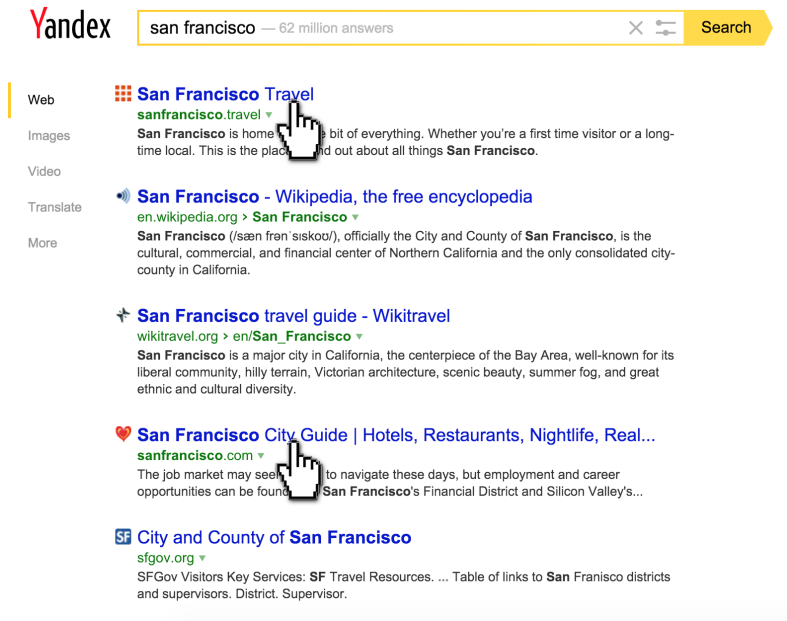
$$P(A_{d_r} = 1) = \alpha_{qd_r}$$

$$\underbrace{P(E_1 = 1) = 1}_{\text{start from first}}$$

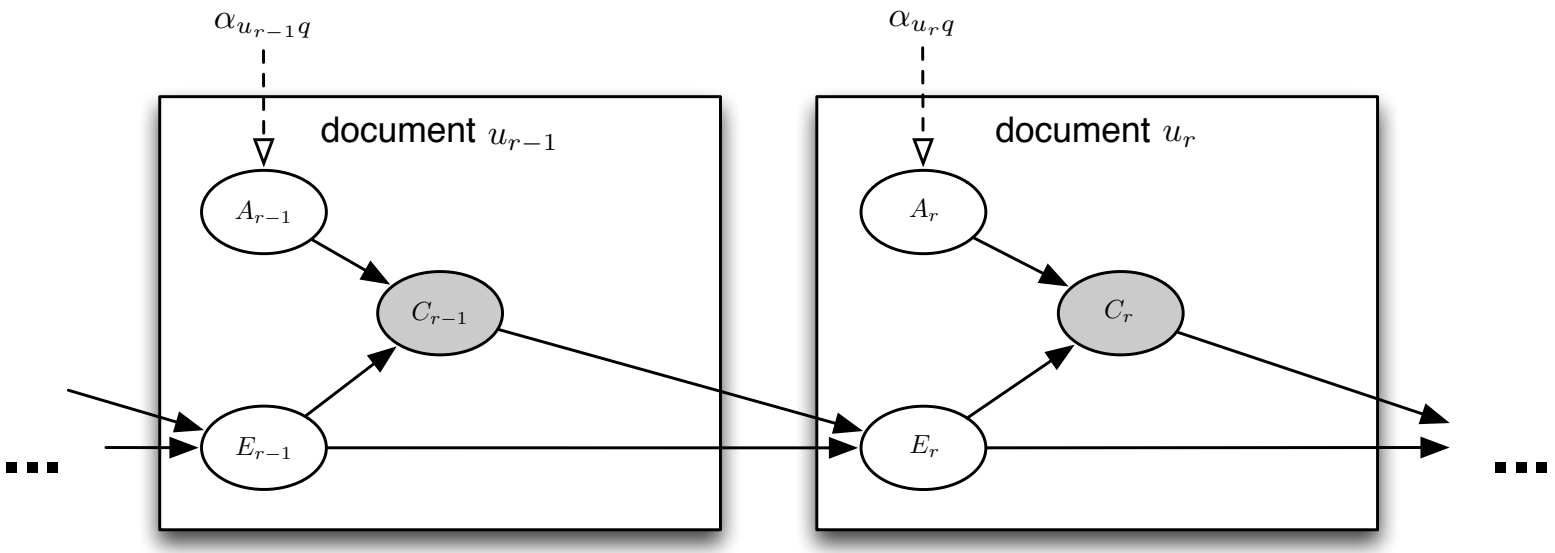
$$\underbrace{P(E_r = 1 \mid E_{r-1} = 0) = 0}_{\text{examine one by one}}$$

$$\underbrace{P(E_r = 1 \mid C_{r-1} = 1) = 0}_{\text{if click, then stop}}$$

$$\underbrace{P(E_r = 1 \mid E_{r-1} = 1, C_{r-1} = 0) = 1}_{\text{otherwise, continue}}$$



Cascade model: probabilistic graphical model



Basic click models summary

- Position-based model (PBM)
  - \+ examination and attractiveness
  - – examination of a document at rank r does not depend on examinations and clicks above r
- Cascade model (CM)
  - \+ cascade dependency of examination at r on examinations and clicks above r
  - – only one click is allowed

Outline

Parameter estimation

- Maximum likelihood estimation
- Expectation-maximization

Expectation maximization

1. Set parameters to some initial values
2. Repeat until convergence
   - E-step: derive the expectation of the likelihood function
   - M-step: maximize this expectation

Expectation maximization

$$Q(\theta_c) = \sum_{s \in \mathcal{S}} \mathbb{E}_{\mathbf{X}|\mathbf{C}^{(s)},\boldsymbol{\Psi}} \left[\log P\left(\mathbf{X}, \mathbf{C}^{(s)} \mid \boldsymbol{\Psi}\right) \right]$$

$$= \sum_{s \in \mathcal{S}} \mathbb{E}_{\mathbf{X}|\mathbf{C}^{(s)},\boldsymbol{\Psi}} \left[\sum_{c_i \in s} \left(\mathcal{I}\left(X_{c_i}^{(s)} = 1, \mathcal{P}(X_{c_i}^{(s)}) = \mathbf{p}\right) \log(\theta_c) + \mathcal{I}\left(X_{c_i}^{(s)} = 0, \mathcal{P}(X_{c_i}^{(s)}) = \mathbf{p}\right) \log(1 - \theta_c) \right) + \mathcal{Z} \right]$$

$$= \sum_{s \in \mathcal{S}} \sum_{c_i \in s} \left(P\left(X_{c_i}^{(s)} = 1, \mathcal{P}(X_{c_i}^{(s)}) = \mathbf{p} \mid \mathbf{C}^{(s)}, \boldsymbol{\Psi}\right) \log(\theta_c) + P\left(X_{c_i}^{(s)} = 0, \mathcal{P}(X_{c_i}^{(s)}) = \mathbf{p} \mid \mathbf{C}^{(s)}, \boldsymbol{\Psi}\right) \log(1 - \theta_c) \right) + \mathcal{Z}$$

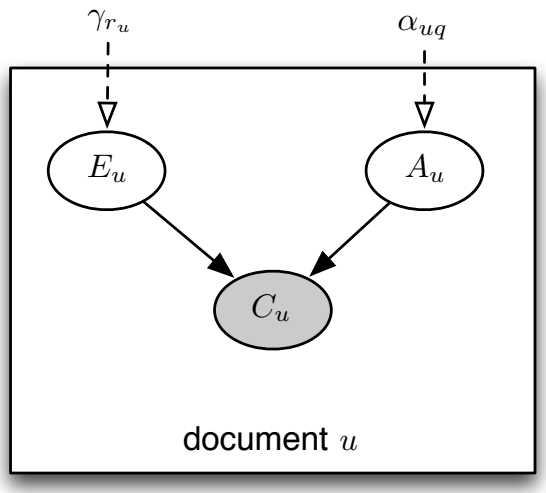
$$ESS(x) = \sum_{s \in \mathcal{S}} \sum_{c_i \in s} P\left(X_{c_i}^{(s)} = x, \mathcal{P}(X_{c_i}^{(s)}) = \mathbf{p} \mid \mathbf{C}^{(s)}, \boldsymbol{\Psi}\right)$$

$$\frac{\partial Q(\theta_c)}{\partial \theta_c} = \sum_{s \in \mathcal{S}} \sum_{c_i \in s} \left(\frac{P\left(X_{c_i}^{(s)} = 1, \mathcal{P}(X_{c_i}^{(s)}) = \mathbf{p} \mid \mathbf{C}^{(s)}, \boldsymbol{\Psi}\right)}{\theta_c} - \frac{P\left(X_{c_i}^{(s)} = 0, \mathcal{P}(X_{c_i}^{(s)}) = \mathbf{p} \mid \mathbf{C}^{(s)}, \boldsymbol{\Psi}\right)}{1 - \theta_c} \right) = 0$$

$$\theta_c^{(t+1)} = \frac{\sum_{s \in \mathcal{S}} \sum_{c_i \in s} P\left(X_{c_i}^{(s)} = 1, \mathcal{P}(X_{c_i}^{(s)}) = \mathbf{p} \mid \mathbf{C}^{(s)}, \boldsymbol{\Psi}\right)}{\sum_{s \in \mathcal{S}} \sum_{c_i \in s} \sum_{x=0}^{x=1} P\left(X_{c_i}^{(s)} = x, \mathcal{P}(X_{c_i}^{(s)}) = \mathbf{p} \mid \mathbf{C}^{(s)}, \boldsymbol{\Psi}\right)}$$

$$= \frac{\sum_{s \in \mathcal{S}} \sum_{c_i \in s} P\left(X_{c_i}^{(s)} = 1, \mathcal{P}(X_{c_i}^{(s)}) = \mathbf{p} \mid \mathbf{C}^{(s)}, \boldsymbol{\Psi}\right)}{\sum_{s \in \mathcal{S}} \sum_{c_i \in s} P\left(\mathcal{P}(X_{c_i}^{(s)}) = \mathbf{p} \mid \mathbf{C}^{(s)}, \boldsymbol{\Psi}\right)} = \frac{ESS^{(t)}(1)}{ESS^{(t)}(1) + ESS^{(t)}(0)}$$

EM for Position-Based Model



$$P(A_d = 1) = \alpha_{qd}$$
$$P(E_r = 1) = \gamma_r$$

EM update rules for PBM: attractiveness

$$\alpha_{qd}^{(t+1)} = \frac{1}{|\mathcal{S}_{qd}|} \sum_{s \in \mathcal{S}_{qd}} \left(c_d^{(s)} + (1 - c_d^{(s)}) \frac{(1 - \gamma_r^{(t)}) \alpha_{qd}^{(t)}}{1 - \gamma_r^{(t)} \alpha_{qd}^{(t)}} \right)$$

- t – iteration
- $\mathcal{S}_{qd}$ – search sessions initiated by query q and containing document u
- $c_d^{(s)}$ – observed click on document u in search session s

EM update rules for PBM: examination

$$\gamma_r^{(t+1)} = \frac{1}{|\mathcal{S}|} \sum_{s \in \mathcal{S}} \left(c_d^{(s)} + (1 - c_d^{(s)}) \frac{\gamma_r^{(t)} (1 - \alpha_{qd}^{(t)})}{1 - \gamma_r^{(t)} \alpha_{qd}^{(t)}} \right)$$

Outline

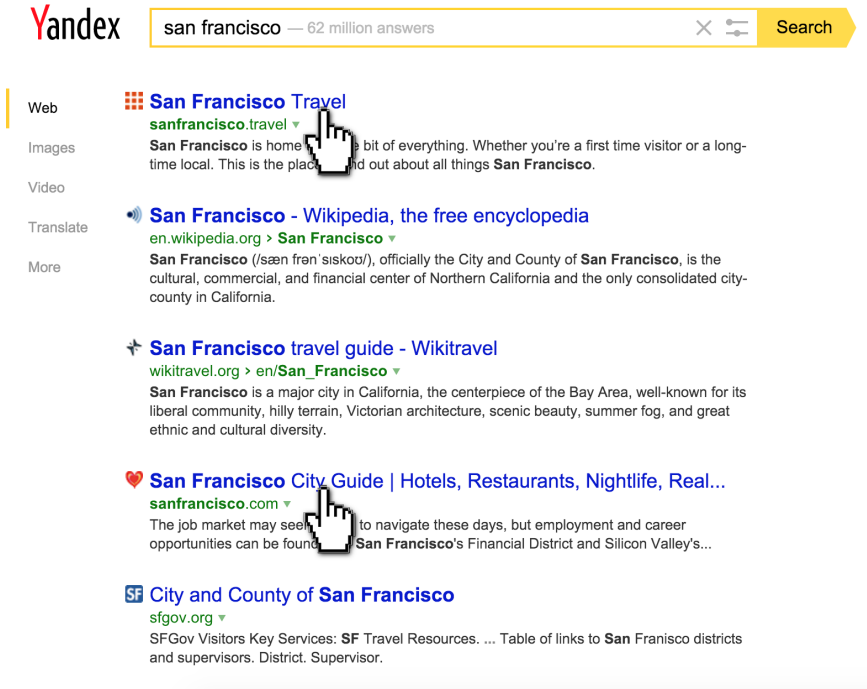
Click probabilities

- Full probability – probability that a user clicks on a document at rank r

$$P(C_r = 1)$$

- Conditional probability – probability that a user clicks on a document at rank r given previous clicks

$$P(C_r = 1 \mid C_1, \ldots, C_{r-1})$$



Applications of click models

Click model's output	Application
Full click probabilities	Model-based metrics
Conditional click probabilities	User simulation
Parameter values	Ranking

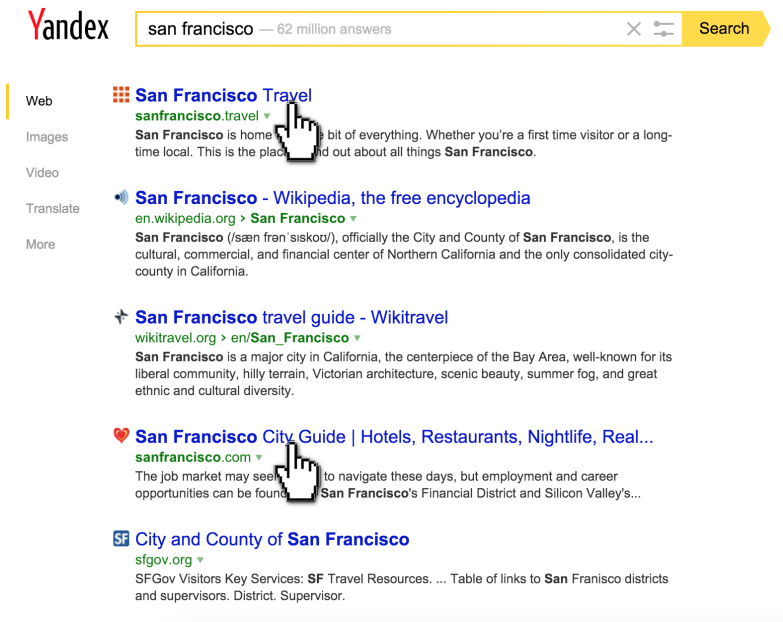
Model-based metrics

- Utility-based metrics

$$uMetric = \sum_{r=1}^{n} P(C_r = 1) \cdot U_r$$

- Effort-based metrics

$$eMetric = \sum_{r=1}^{n} P(S_r = 1) \cdot F_r$$



Expected reciprocal rank

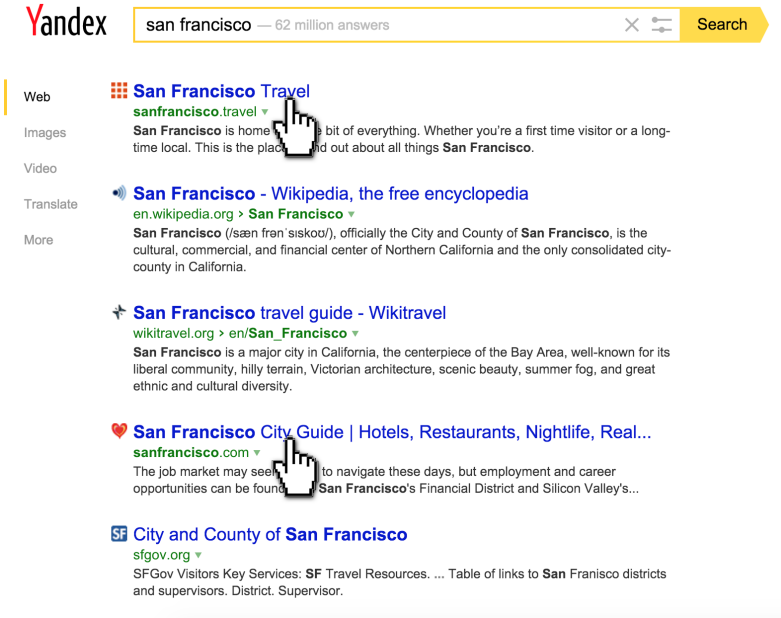
$$RR = \frac{1}{r}, \text{ where } S_r = 1$$

$$ERR = \sum_r \frac{1}{r} \cdot P(S_r = 1)$$

Dynamic Bayesian network model (DBN)

$$P(A_r = 1) = \alpha_{qd_r}$$
$$P(E_1 = 1) = 1$$
$$P(E_r = 1 \mid S_{r-1} = 1) = 0$$
$$P(E_r = 1 \mid S_{r-1} = 0) = \gamma$$
$$P(S_r = 1 \mid C_r = 0) = 0$$
$$P(S_r = 1 \mid C_r = 1) = \sigma_{qd_r}$$

$$P(S_r = 1) = ?$$



DBN: Satisfaction

$$
\begin{aligned}
P(S_r = 1) &= P(S_r = 1 \mid C_r = 1) \cdot P(C_r = 1) \\
&= \sigma_{qd_r} \cdot P(C_r = 1) \\
&= \sigma_{qd_r} \cdot \alpha_{qd_r} \cdot P(E_r = 1) \\
&= \sigma_{qd_r} \cdot \alpha_{qd_r} \cdot \prod_{i=1}^{r-1} \left(\gamma \cdot (1 - \sigma_{qd_i} \cdot \alpha_{qd_i})\right) \\
&= R_{qd_r} \cdot \prod_{i=1}^{r-1} \left(\gamma \cdot (1 - R_{qd_i})\right)
\end{aligned}
$$

Expected reciprocal rank

$$ERR = \sum_r \frac{1}{r} \cdot P(S_r = 1)$$

$$= \sum_r \frac{1}{r} \cdot R_{qd_r} \cdot \prod_{i=1}^{r-1} \left(\gamma \cdot (1 - R_{qd_i})\right)$$

Summary

- Interactions
  - Examples of interactions
  - Applications: evaluate and improve IR
- Interaction models
  - Basic click models: PBM, CM
  - Applications: ERR

Materials

- Aleksandr Chuklin, Ilya Markov, Maarten and de Rijke
  Click Models for Web Search
  Morgan & Claypool, 2015