

Outline

Morning program

Preliminaries

Modeling user behavior

Semantic matching

Learning to rank

Afternoon program

Entities

Generating responses

Recommender systems

Industry insights

Q & A

Understanding user behavior is the key



The ability to accurately predict the behavior of a particular user allows search engines to construct optimal result pages

User behavioral signals



Actions

(e.g., click, first/last click, long click, satisfied click, repeated click)

Times between actions

(e.g., time between clicks, time to first/last click)

Yandex ✕ ↔ Search

Web **Amsterdam** - Wikipedia, the free encyclopedia
en.wikipedia.org > **Amsterdam** ▾
Amsterdam (/ˈæmstərdæm, ˈæmstərˈdæm/; Dutch: [ɑmstərˈdɑm]) is the capital and most populous municipality of the Kingdom of the Netherlands. Its status as the capital is mandated by the Constitution of the Netherlands, although it is not the seat of t...

Images

Video

Translate **Amsterdam travel guide** - Wikitravel
wikitravel.org > **Amsterdam** ▾
Amsterdam is the capital of the Netherlands. With more than one million inhabitants in its urban area, it is the country's largest city and its financial, cultural, and creative centre. **Amsterdam** derives its name from the city's origin as "Dam" ...

More **Your guide to visit, enjoy, live, work & invest in Amsterdam**
iamsterdam.com > **en** ▾
 Welcome to I **amsterdam.com**. We would like to ask a few questions about your experience on our website. This will only take a few minutes of your time.

Amsterdam 2016: Best of Amsterdam, The Netherlands Tourism
tripadvisor.com > **Tourism-g188590-Amsterdam_North...** ▾
Amsterdam Tourism: TripAdvisor has 865,752 reviews of **Amsterdam** Hotels, Attractions, and Restaurants making it your best ... **Amsterdam** Tourism: Best of **Amsterdam**.

Interpretation is difficult

Biases in user behavior — (statistically significant) differences between probability distributions of user behavioral signal observed in different contexts

Clicks are biased towards:

- ▶ higher ranked results (**position bias**)
- ▶ visually salient results (**attention bias**)
- ▶ previously unseen results (**novelty bias**)

CLICK
M O D E L S

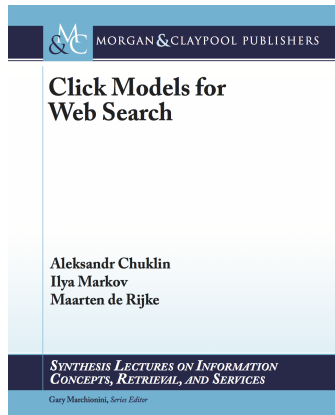
account for biases in clicks

Click dwell times are biased

Times to first/last/satisfied clicks are biased

Applications of user behavior models

- ▶ Understand users
- ▶ Simulate users
- ▶ Features for ranking
- ▶ Evaluate search



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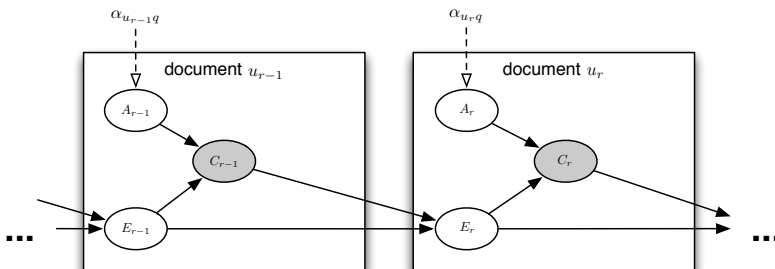
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Recommender systems

Industry insights

Q & A

Traditional click models

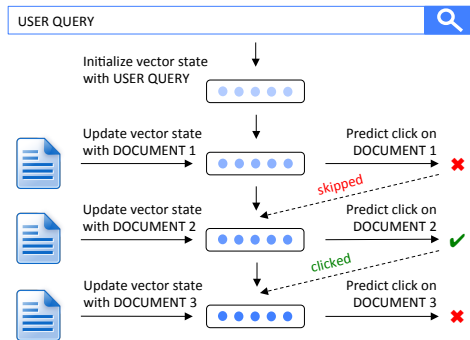


Graphical representation of the cascade click model.

Pros: Based on the **probabilistic graphical model** (PGM) framework

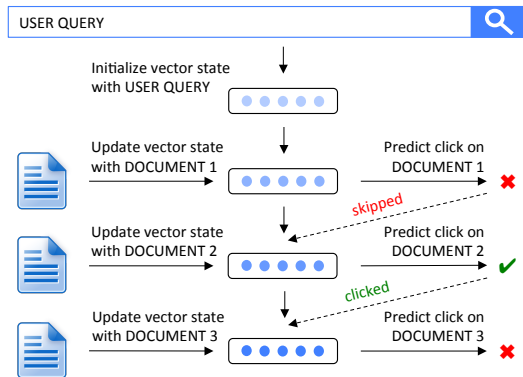
Cons: Structure of the underlying PGM has to be set manually

Neural click modeling framework



A neural click model for web search [Borisov et al., 2016].

Learns patterns of user behavior directly from click-through data

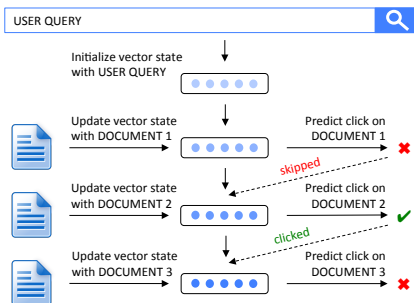
Distributed representations (s_0, s_1, s_2, \dots)

We model user browsing behavior as a sequence of vector states (s_0, s_1, s_2, \dots) that describes the information consumed by the user as it evolves during a query session.

Mappings I , U and Function F

$$\mathbf{s}_0 = \mathcal{I}(q)$$

$$\mathbf{s}_{r+1} = \mathcal{U}(\mathbf{s}_r, i_r, d_{r+1})$$



$$P(C_{r+1} = 1 \mid q, i_1, \dots, i_r, d_1, \dots, d_{r+1}) = \mathcal{F}(\mathbf{s}_{r+1})$$

q — user query

d_r — document at rank r

i_r — user interaction
with document at rank r

Neural click modeling framework \rightarrow $\text{NCM}_{\substack{\{\text{RNN, LSTM}\} \\ \{\text{QD, QD+Q, QD+Q+D}\}}}$

Representations of q , d_r and i_r

Use three sets: QD, QD+Q, QD+Q+D

Parameterization of \mathcal{I} , \mathcal{U} and \mathcal{F}

\mathcal{I} Feed-forward neural network

\mathcal{U} Recurrent neural network (RNN, LSTM)

\mathcal{F} Feed-forward neural network

(with one output unit and the sigmoid activation function)

Training

Stochastic gradient descent

(with AdaDelta update rules and gradient clipping)

Experimental setup

Dataset

Yandex Relevance Prediction dataset¹
(146,278,823 query sessions)

Tasks and evaluation metrics

Click prediction task (log-likelihood, perplexity)
Relevance prediction task (NDCG)

Baselines

Dynamic Bayesian network (DBN), Dependent click model (DCM)
Click chain model (CCM), User browsing model (UBM)

Results on click prediction task

Click model	Perplexity	Log-likelihood
DBN	1.3510	-0.2824
DCM	1.3627	-0.3613
CCM	1.3692	-0.3560
UBM	1.3431	-0.2646
NCM ^{RNN} _{QD}	1.3379	-0.2564
NCM ^{LSTM} _{QD}	1.3362	-0.2547
NCM ^{LSTM} _{QD+Q}	1.3355	-0.2545
NCM ^{LSTM} _{QD+Q+D}	1.3318	-0.2526

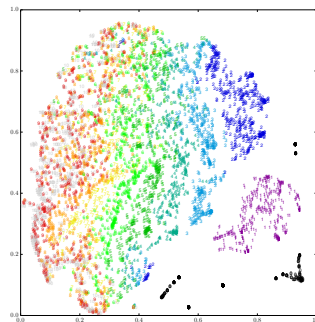
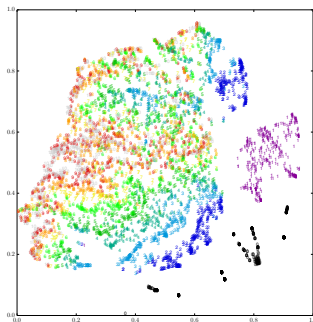
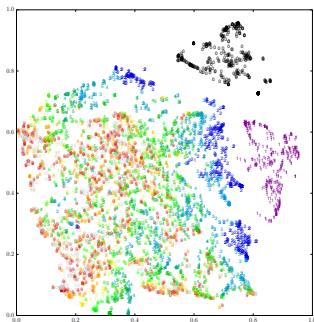
Differences between all pairs of click models are statistically significant ($p < 0.001$)

Results on relevance prediction task

Click model	NDCG			
	@1	@3	@5	@10
DBN	0.717	0.725	0.764	0.833
DCM	0.736	0.746	0.780	0.844
CCM	0.741	0.752	0.785	0.846
UBM	0.724	0.737	0.773	0.838
$\text{NCM}_{\text{QD}}^{\text{RNN}}$	0.762	0.759	0.791	0.851
$\text{NCM}_{\text{QD}}^{\text{LSTM}}$	0.756	0.759	0.789	0.850
$\text{NCM}_{\text{QD}+\text{Q}}^{\text{LSTM}}$	0.775	0.773	0.799	0.857
$\text{NCM}_{\text{QD}+\text{Q}+\text{D}}^{\text{LSTM}}$	0.755	0.755	0.787	0.847

Improvements of $\text{NCM}_{\text{QD}}^{\text{RNN}}$, $\text{NCM}_{\text{QD}}^{\text{LSTM}}$ and $\text{NCM}_{\text{QD}+\text{Q}}^{\text{LSTM}}$ over baseline click models are statistically significant ($p < 0.05$)

Analysis



Learns regularities in user browsing behavior that

1. have been manually encoded in existing click models, such as **ranks** and **distances to previous clicks** (large clusters on t-SNE projections of vector states s_r)
2. can not be manually encoded in traditional click models (small clusters on t-SNE projections of vector states s_r)

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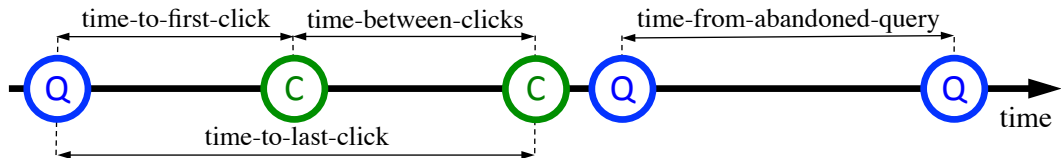
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Q & A

Times between user actions



- ▶ **time-to-first-click** (reflects quality of result presentation)
- ▶ **time-between-clicks** (proxy for click dwell time)
- ▶ **time-to-last-click** (reflects quality of search engine results)
- ▶ **time-from-abandoned-query** (reflects quality of search engine results in query sessions with no clicks)

How to interpret times between user actions

Average

$$\hat{t} = \frac{1}{N} \sum_{i=1}^N \tau_i$$

Uncertainty: $\frac{1}{2}(3 + 600)$ vs. $\frac{1}{7}(30 + 28 + 45 + 23 + 100 + 23 + 58)$

How to interpret times between user actions

Average

$$\hat{t} = \frac{1}{N} \sum_{i=1}^N \tau_i$$

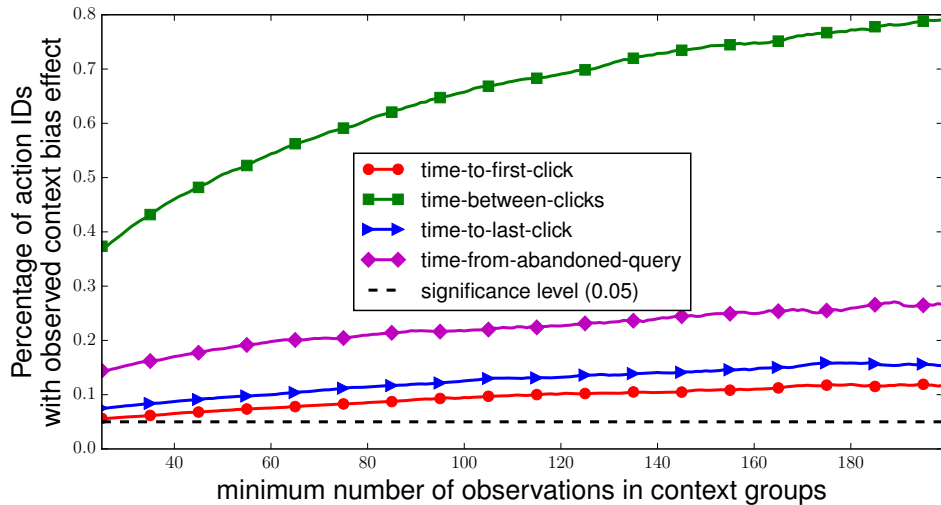
Uncertainty: $\frac{1}{2}(3 + 600)$ vs. $\frac{1}{7}(30 + 28 + 45 + 23 + 100 + 23 + 58)$

Fit distribution (e.g., exponential, gamma, Weibull)

$$\hat{\theta} = \arg \max_{\theta} \prod_{i=1}^N f(\tau_i | \theta)$$

Context bias: $f_{\text{high expectation}}(\tau = 15 | \theta_1)$ vs. $f_{\text{low expectation}}(\tau = 10 | \theta_2)$

Detected context bias effect



Context-aware time modeling (naive)

$$Time(action, context) \sim Gamma(\mathbf{k}(\textcolor{red}{act}, \textcolor{blue}{ctx}), \boldsymbol{\theta}(\textcolor{red}{act}, \textcolor{blue}{ctx}))$$

Context-aware time modeling

$$\begin{aligned} \textit{Time}(\textit{action}, \textit{context}) \sim & \textit{Gamma}(\\ & \textcolor{red}{a}_k(\textit{ctx}) \cdot \textcolor{blue}{k}(\textit{act}) + \textcolor{red}{b}_k(\textit{ctx}), \\ & \textcolor{red}{a}_\theta(\textit{ctx}) \cdot \textcolor{blue}{\theta}(\textit{act}) + \textcolor{red}{b}_\theta(\textit{ctx}) \end{aligned}$$

Parameter estimation

$$\begin{aligned} \text{Time}(\text{action}, \text{context}) \sim \text{Gamma}(\hspace{10em} \\ \textcolor{red}{a}_k(\text{ctx}) \cdot \textcolor{blue}{k}(\text{act}) + \textcolor{red}{b}_k(\text{ctx}), \\ \textcolor{red}{a}_\theta(\text{ctx}) \cdot \textcolor{blue}{\theta}(\text{act}) + \textcolor{red}{b}_\theta(\text{ctx})) \end{aligned}$$

1. Fix **context-independent** parameters
2. Optimize **context-dependent** parameters using *neural networks*
3. Fix **context-dependent** parameters
4. Optimize **context-independent** using *gradient descent*
5. Repeat until convergence

Parameter estimation

- ▶ We do not know the form of **context-dependent** parameters
⇒ neural networks
- ▶ We know the form of **context-independent** parameters (Gamma distribution)
⇒ direct optimization

Dataset

3 months of log data from Yandex search engine

Time between actions	Max time	# Observations
Time-to-first-click	1 min	30,747,733
Time-between-clicks	5 min	6,317,834
Time-to-last-click	5 min	30,446,973
Time-from-abandoned-query	1 min	11,523,351

Evaluation tasks

Task1. Predict time between clicks

- ▶ Log-likelihood
- ▶ Root mean squared error (MSE)

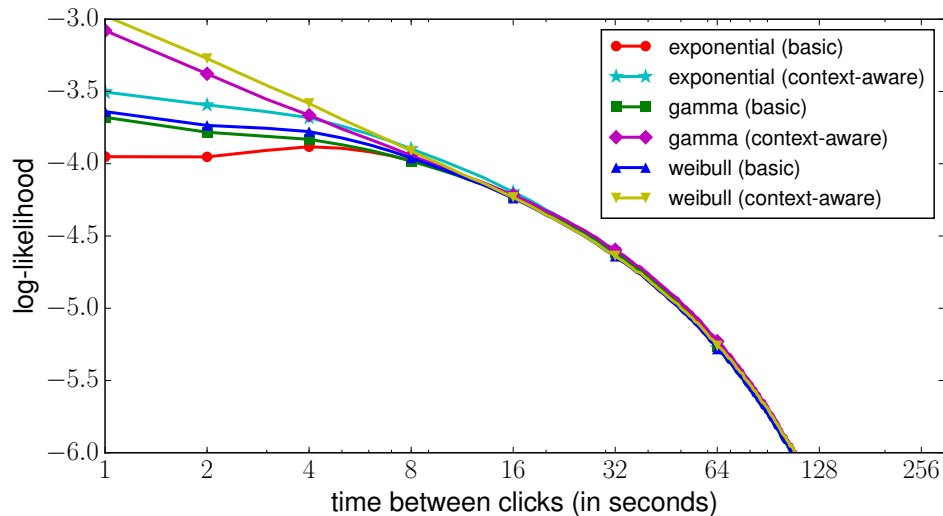
Task2. Rank results based on time between clicks

- ▶ $n\text{DCG}@ \{1, 3, 5, 10\}$

Task 1. Predicting time

Time model	Distribution	Log-likelihood	RMSE
Basic	exponential	-4.9219	60.73
	gamma	-4.9105	60.76
	Weibull	-4.9077	60.76
Context-aware	exponential	-4.8787	58.93
	gamma	-4.8556	58.98
	Weibull	-4.8504	58.94

Results on time prediction task (time-between-clicks)



Task 2. Ranking results

Time model	Distribution	NDCG			
		@1	@3	@5	@10
Average	—	0.651	0.693	0.728	0.812
Context-aware	exponential	0.668	0.710	0.743	0.820
	gamma	0.675	0.715	0.748	0.822
	Weibull	0.671	0.709	0.745	0.821

Summary

- ▶ Remove **context bias** from time between actions
- ▶ Predict user search interactions better (**Task 1**)
- ▶ Use the **context-independent** component for better document ranking (**Task 2**)

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Entities

Generating responses

Recommender systems

Industry insights

Q & A

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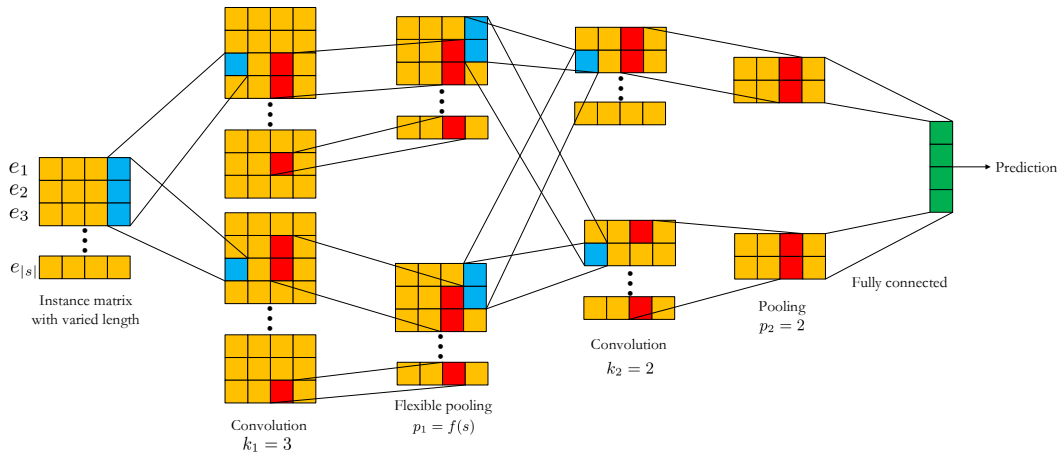
In **web search** we work (mostly) with **query sessions** and **search sessions**

In **sponsored search** we need to consider **longer user histories**

Recurrent Neural Networks (RNNs) can be used not only **to account for biases**, but also to **infer user interests** and **behavioral patterns** from **very long sequences of user actions**

Sequential Click Prediction for Sponsored Search with Recurrent Neural Networks [Zhang et al., 2014]

Web search vs. sponsored search



A Convolutional Click Prediction Model [Liu et al., 2015]

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Take aways and future work

Neural Networks — an alternative to **probabilistic graphical models** (PGMs) that allows to learn patterns of user behavior directly from the data

Understanding and modelling user behavior with PGMs — is a mature field
We expect many ideas to be transfered from **PGM** to **neural** framework

Future user behavior models

- ▶ will learn patterns of user behavior directly from the data
- ▶ will take very long user history into account
- ▶ will extract signals from images, videos, user voice and background sounds
- ▶ will improve our understanding of humankind