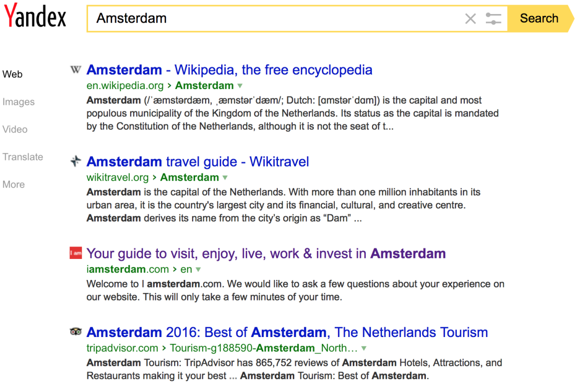
Outline

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)

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 MODELS

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

Outline

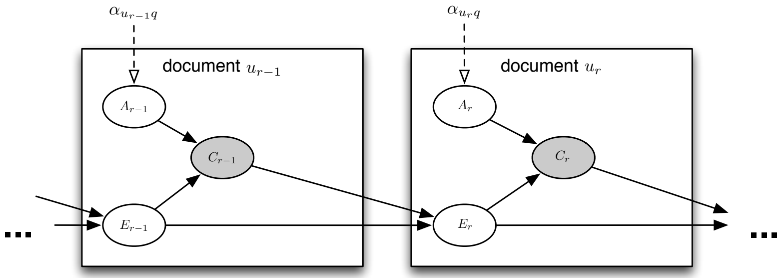
Morning program

- Preliminaries
- Text matching I
- Text matching II

Afternoon program

- Learning to rank
- Modeling user behavior
  - Neural click model
  - Context-aware time model
- Generating responses
- Outlook
- Wrap up

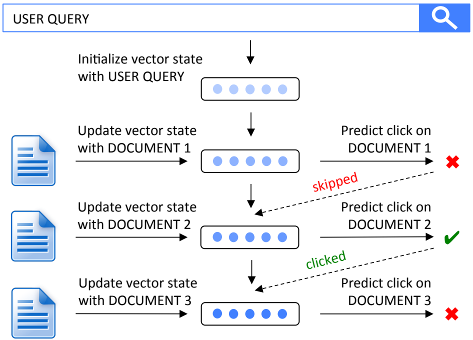
Traditional click models



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

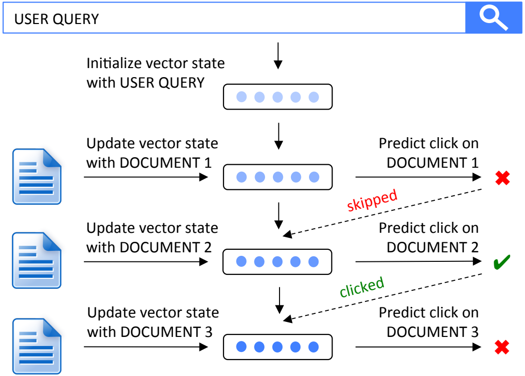
Neural click modeling framework



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

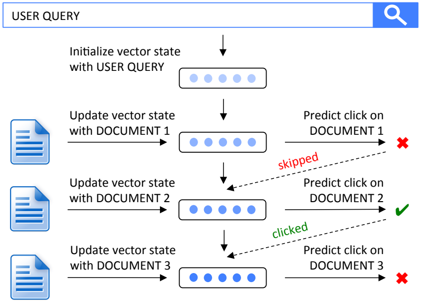
Learns patterns of user behavior directly from click-through data

Distributed representations $(\mathbf{s}_0, \mathbf{s}_1, \mathbf{s}_2, \ldots)$



We model user browsing behavior as a sequence of vector states $(\mathbf{s}_0, \mathbf{s}_1, \mathbf{s}_2, \ldots)$ that describes the information consumed by the user as it evolves during a query session.

Mappings I, U and Function F



$$\mathbf{s}_0 = \mathcal{I}(q)$$
$$\mathbf{s}_{r+1} = \mathcal{U}(\mathbf{s}_r, i_r, d_{r+1})$$

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

q — user query

d_r — document at rank r

i_r — user interaction with document at rank r

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

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 dataset[1]
($146,278,823$ 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
$\text{NCM}^{\text{RNN}}_{\text{QD}}$	1.3379	-0.2564
$\text{NCM}^{\text{LSTM}}_{\text{QD}}$	1.3362	-0.2547
$\text{NCM}^{\text{LSTM}}_{\text{QD+Q}}$	1.3355	-0.2545
$\text{NCM}^{\text{LSTM}}_{\text{QD+Q+D}}$	1.3318	-0.2526

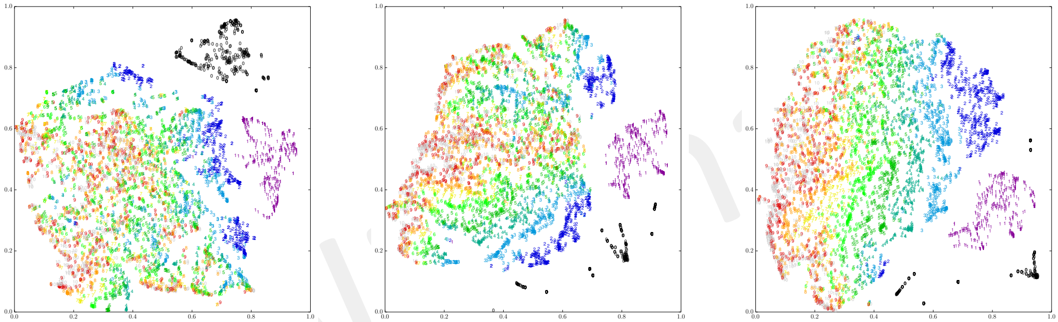
Differences between all pairs of click models are statistically significant $(p < 0.001)$

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
$\text{NCM}^{\text{RNN}}_{\text{QD}}$	0.762	0.759	0.791	0.851
$\text{NCM}^{\text{LSTM}}_{\text{QD}}$	0.756	0.759	0.789	0.850
$\text{NCM}^{\text{LSTM}}_{\text{QD+Q}}$	0.775	0.773	0.799	0.857
$\text{NCM}^{\text{LSTM}}_{\text{QD+Q+D}}$	0.755	0.755	0.787	0.847

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

Analysis

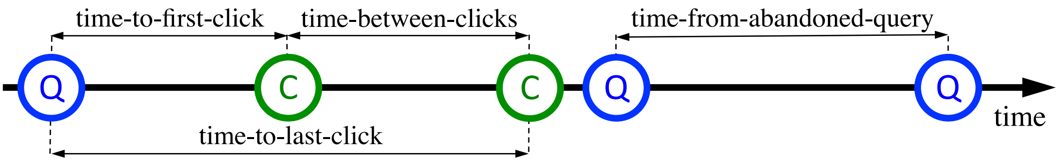


Learns regularities in user browsing behavior that

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 $\mathbf{s}_r$)
2. can not be manually encoded in traditional click models (small clusters on t-SNE projections of vector states $\mathbf{s}_r$)

Outline

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

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

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

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

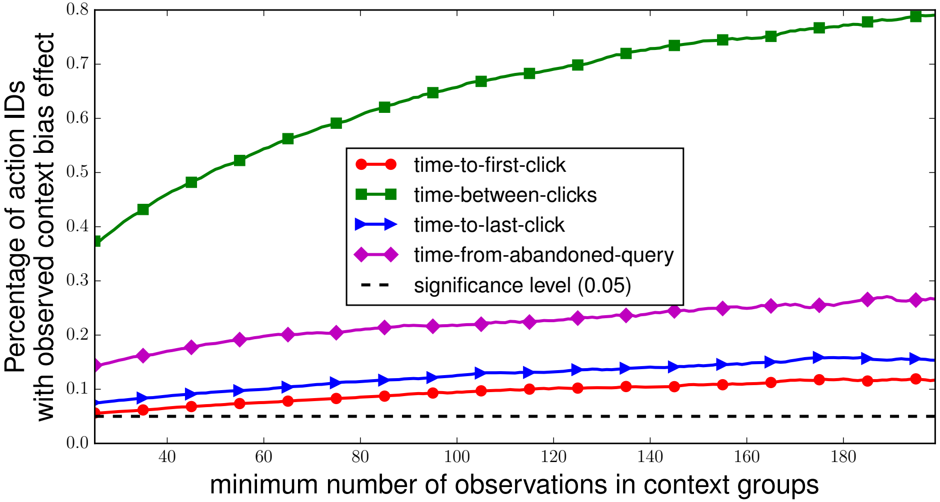
Uncertainty: $\frac{1}{2}(3 + 600)$ vs. $\frac{1}{7}(30 + 28 + 45 + 23 + 100 + 23 + 58)$

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

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

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

Detected context bias effect



Context-aware time modeling (naive)

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

Context-aware time modeling

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

Parameter estimation

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

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
  $\Longrightarrow$ neural networks

- We know the form of context-independent parameters (Gamma distribution)
  $\Longrightarrow$ 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)

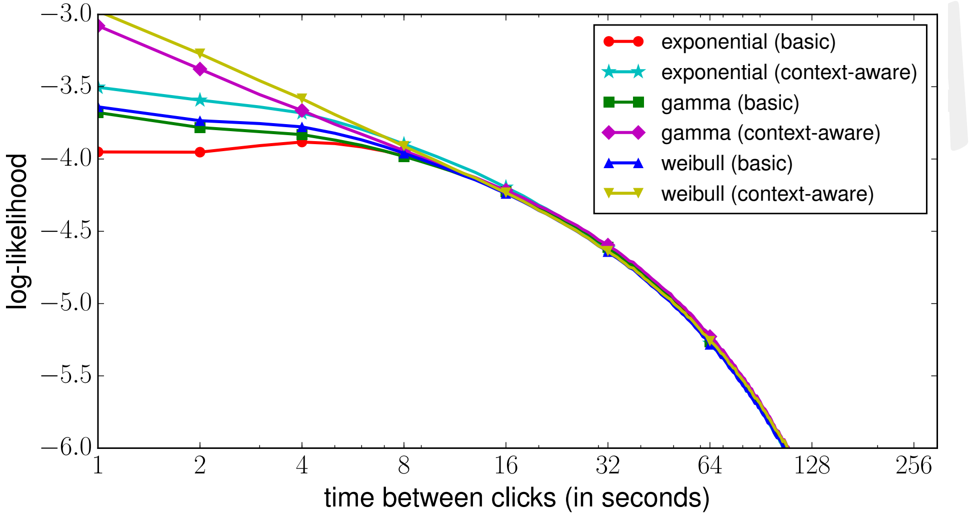
Task2. Rank results based on time between clicks

- nDCG@$\{1, 3, 5, 10\}$

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

		NDCG			
Time model	Distribution	@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**)

Future work

Neural Networks — an alternative to probabilistic graphical models (PGMs) that allows 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.

By 2027 (50th anniversary of SIGIR), 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