

# Deep Learning Powered In-Session Contextual Ranking using Clickthrough Data

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#### Problem

- 1.  $Q_1, Q_2, ..., Q_m$  are the history queries in one session.
- 2.  $u_{i1}, u_{i2}, ..., u_{in}$  are the URLs in one impression page for query  $Q_n$ , it contains sat and unsat clicks.
- 3. Q is the current query.
- 4.  $u_1, u_2, ..., u_n$  are the URLs in the impression page for query Q based on the current ranking algorithm. **Goal**: re-rank the  $u_1, u_2, ..., u_n$  based on some signals (i.e. topic, domain) derived from the in-session clickthrough data.

# An Example

Table 1 shows two queries (2<sup>nd</sup> and 6<sup>th</sup> queries) in one session from real log data. The difference between query 2 and query 6 is query specification by adding the term of "wiki" in query 6. In query 2, the corresponding Wikipedia page was clicked as a unsatisfied click (**red** color in the table), and in this case it is good to demote the Wikipedia page from the first position of the 6<sup>th</sup> query since it was examined as a unsatisfied page in query 2, while, in reality, the wikia page in the second position of the query 6 is a satisfied click (**green** color in the table) from users' log. Thus, it is better to promote the position of wikia page in the ranking result.

Query 2: the dangerous days of daniel x	Query 6: the dangerous days of daniel x Altreda wiki
http://en.wikipedia.org/wiki/The_Dangerous_Days_of_Daniel_X	http://en.wikipedia.org/wiki/The_Dangerous_Days_of_Daniel_X
http://www.amazon.com/The-Dangerous-Days-Daniel-X/dp/0316119709	http://fanon.wikia.com/wiki/The_Dangerous_Days_of_Daniel_X
http://www.goodreads.com/book/show/2235597.The_Dangerous_Days_of_Daniel_X	http://www.amazon.com/The-Dangerous-Days-Daniel-X/dp/0316119709
http://www.daniel-x.co.uk/books/dangerous-days/	http://danielx.wikia.com/wiki/The_Dangerous_Days_of_Daniel_X_(novel)
http://www.freebooknotes.com/summaries-analysis/the-dangerous-days-of-daniel-x/	http://danielx.wikia.com/wiki/Daniel_X
http://www.jamespatterson.com/books_danielX.php#.VCR0vOfUe1A	http://www.goodreads.com/series/49946-daniel-x
http://jamespatterson.com/books_daniel_x.php#.VCR01efUe1A	http://en.wikipedia.org/wiki/Daniel_X:_Watch_the_Skies
http://books.google.com/books/about/The_Dangerous_Days_of_Daniel_X.html?id=2UBONTvr_BEC	http://www.jamespatterson.com/books_danielX.php

Table 1. Two queries from the current ranker

# Our Approach

- 1. Correlate users' clicks with their satisfaction and derive a set of fine-grained features (i.e. URL-level discriminative features, Click-Based features) to explore the relations between in-session history queries, clicked URLs and current query, URLs.
- 2. Employ the semantic deep learning models (i.e. XCode, DSSM, CDSSM) to measure the similarity for the semantic features.
- 3. Incorporate these features into the ranking model, to re-rank the results.

# Step 1. Fine-grained Features

Features	Level	Description	Category
Semantic Features	URL-URL	The similarity between the URLs of previous queries	sat
	UKL-UKL	and URLs of current query	unsat
	Ouani IIDI	The similarity between the previous queries and	sat
	Query-URL	URLs of current query	unsat
	Weighted URL-URL	The weighted similarity between the URLs of previous queries and URLs of current query	sat
			unsat
Click-Based Features	URL Level	The domain and history click statistics of current URL in the previous queries	history click
			domain click
	lmanyaasian Laval	The cat/upoat statistics of in cassion biotomy greation	clicked URL
	Impression Level	The sat/unsat statistics of in-session history queries	clicked count

- **Semantic features** measure the similarity between previous queries, clicked URLs to the current query, URLs from a semantic level. All of them are URL-level and can distinguish one URL from another.
- Click-Based features encode the user interaction behaviors and content preferences in web search, e.g.
   unsatisfied/satisfied click count, domain unsatisfied/satisfied click count etc.

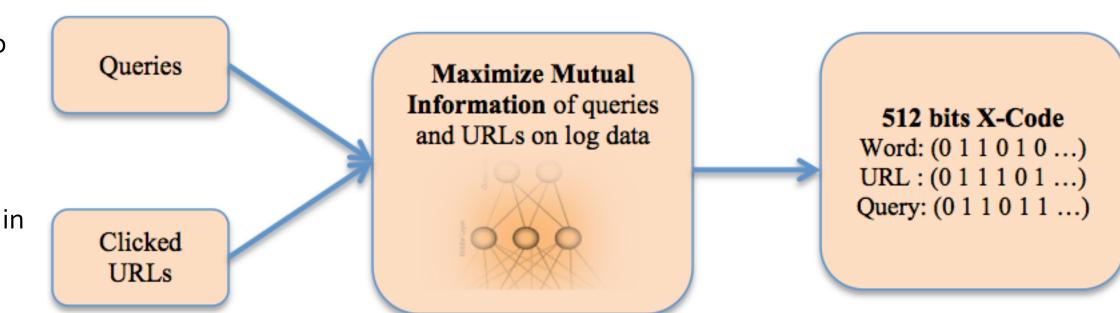
# Acknowledgements

- 1. The first author would thank the support and funding from Microsoft Research.
- 2. JS was supported by DARPA Grant FA8750-13-2-0039.

# Step 2. Semantic Features Calculation

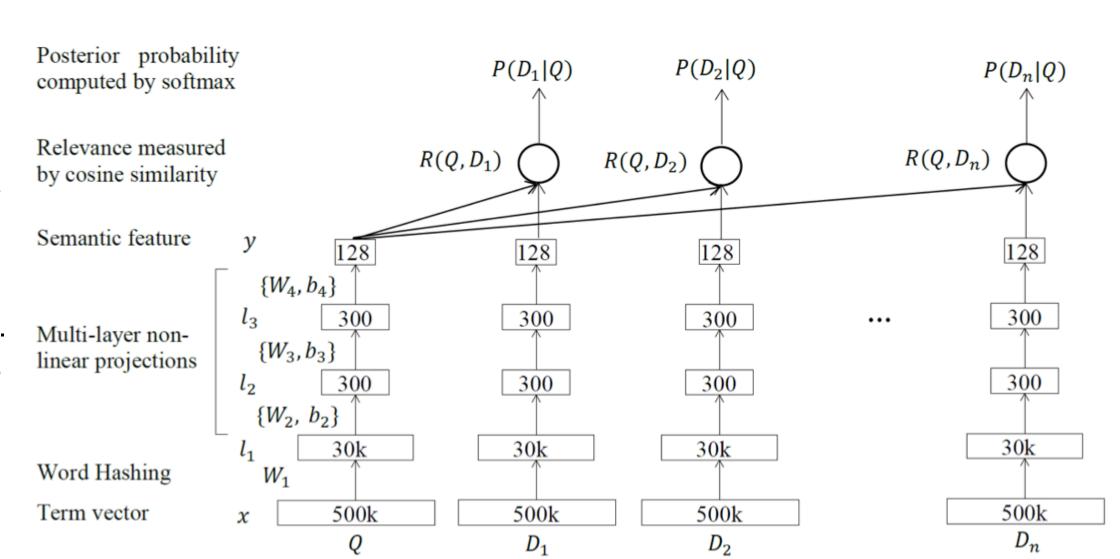
### Model 1 XCode

- Map every word, query, URL into an intent space.
- Each URL, query and word has a unique 512-bit XCode.
- Measure the semantic similarity in this intent space.



#### Model 2 DSSM

- Representation: use deep neural networks to extract abstract semantic representations.
- Learning: maximize the similarity between the query and the documents.
- Scalability: use sub-word unit (i.e. letter-ngram) as raw input feature to handle a unlimited vocabulary (word hashing).



#### Model 3 Convolutional DSSM

- Difference between CDSSM and DSSM
  - 1. Sliding window: capture the contextual feature for a word.

    Convolutional layer, project each word within a context.
  - 2. Convolutional layer: project each word within a context window to a local contextual feature vector.
  - 3. Max pooling layer: extract the most salient local features to form a fixed-length global contextual feature vector.
- Semantic layer: yAffine projection matrix:  $W_s$ Max pooling layer: vMax pooling operation

  Max pooling operation

  Convolutional layer:  $h_t$ Convolution matrix:  $W_c$ Word hashing layer:  $f_t$ Word sequence:  $x_t$  < > >  $w_1$   $w_2$  ...  $w_T$  < > >
- Both DSSM and CDSSM provides a way to encode how well contextual information is matched at the semantic level.
  - Map queries/titles/brokenURLs to a common low dimensional semantic space using DNN

CDSSM / DSSM Double Model Training		
Training Data	Source Model	Target Model
<query, title=""></query,>	Query Model	Title Model
<query, brokenurl=""></query,>	Query Model	BrokenURL Model

Model	Distance	Range	<b>Semantics</b>
XCode	Hamming Distance	[0, 512]	o is the most similar, 512 is the least similar
DSSM	Cosine Distance	[-1, 1]	1 is the most similar, -1 is the least similar
CDSSM	Cosine Distance	[-1, 1]	1 is the most similar, -1 is the least similar

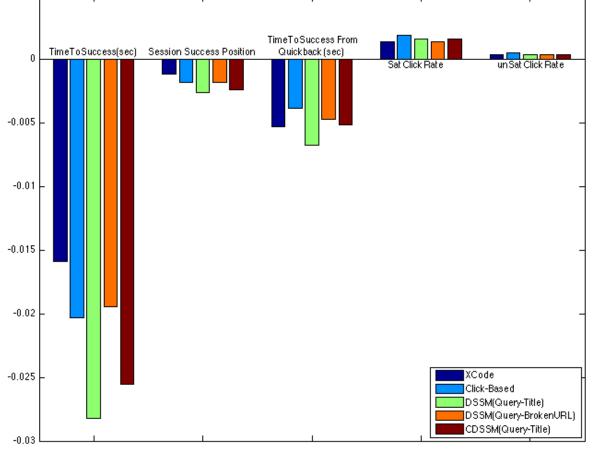
## Click-Based Features

	Level	Category	<b>Semantics</b>	Features
	URL Level	History Click	How many sat/unsat clicks for the current URL in the previous queries in the same session	clickcount_url_total clickcount_url_sat clickcount_url_unsat
	OKL LEVEI	Domain Click	the previous queries in the same session	domain_click_total domain_click_sat domain_click_unsat
	Clicked URL	sat_click_urls unsat_click_urls		
Impression Level	Clicked Count	Some statistics information from in-session history queries	sat_click_count unsat_click_count	

# Step 3. Performance Evaluation

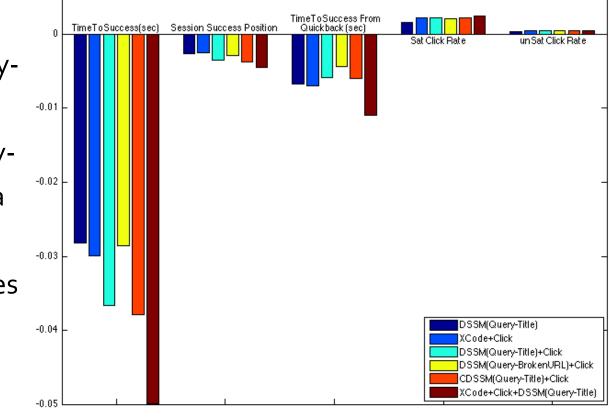
#### Individual Features

- Conduct large-scale analysis on real clickthrough log data, 15 days raw data, around 2TB.
- Measure the performance using the mean average precision (MAP) of the re-ranked lists.
- For Semantic features, DSSM (Query-Title) is the best group.
- The Click-Based features is better than
   XCode features, and easy to be flighted.



#### **Combined Features**

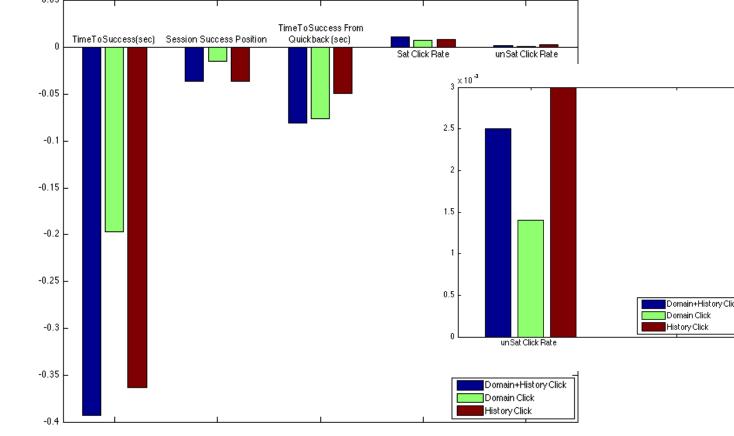
- Combined features is better than any individual group of features.
- For two groups of features, CDSSM (Query-Title) + Click-Based is the best.
- The Combination of XCode + DSSM(Query-Title) + Click-Based features can gain extra improvement.
- Semantic features and Click-Based features can provide different context information to the web search task.



#### Click-Based Features

Conduct a depth analysis for the domain clicks features and history clicks features:

- Domain Click features can effectively decrease the unsat clicks.
- History Click features can improve the TimeToSuccess, SessionSuccessPosition.



# Revisit the Example

Since the Wikipedia domain has 5 unsatisfied clicks in the query 2, the new ranker will demote the Wikipedia page, and promotes the wikia page in the query 6. And this wikia page is a satisfied click at the query 6, perfectly meeting the user's needs.

Query 6: the dangerous days of daniel x Altreda wiki	Query 6: the dangerous days of daniel x Altreda wiki
http://en.wikipedia.org/wiki/The_Dangerous_Days_of_Daniel_X	http://fanon.wikia.com/wiki/The_Dangerous_Days_of_Daniel_X
http://fanon.wikia.com/wiki/The_Dangerous_Days_of_Daniel_X	http://en.wikipedia.org/wiki/The_Dangerous_Days_of_Daniel_X
http://www.amazon.com/The-Dangerous-Days-Daniel-X/dp/0316119709	http://danielx.wikia.com/wiki/The_Dangerous_Days_of_Daniel_X_(novel)
http://danielx.wikia.com/wiki/The_Dangerous_Days_of_Daniel_X_(novel)	http://www.goodreads.com/series/49946-daniel-x
http://danielx.wikia.com/wiki/Daniel_X	http://danielx.wikia.com/wiki/Daniel_X
http://www.goodreads.com/series/49946-daniel-x	http://www.amazon.com/The-Dangerous-Days-Daniel-X/dp/0316119709
http://en.wikipedia.org/wiki/Daniel_X:_Watch_the_Skies	http://www.jamespatterson.com/books_danielX.php
http://www.jamespatterson.com/books_danielX.php	http://en.wikipedia.org/wiki/Daniel_X:_Watch_the_Skies

Table 2. The new ranking results, the left is based on baseline ranker, the right is from the new ranker.

#### Discussion

- In the Individual features, it shows DSSM model is slight better than CDSSM, while we expect CDSSM would provide better performance. Some potential reasons follow:
  - DSSM was trained a very large dataset, while CDSSM can only be trained on a small dataset with a up-bounded size (i.e. 1M queries); the size of training dataset might affect the prediction ability of the model.
  - Due to time constraint, not all parameters of CDSSM in the experiment were optimally tuned.
- All the experiments were conducted offline over real clicked log data, we are going to verify the gain in the online settings.