Re-ranking Web Documents Based on Personal Preferences

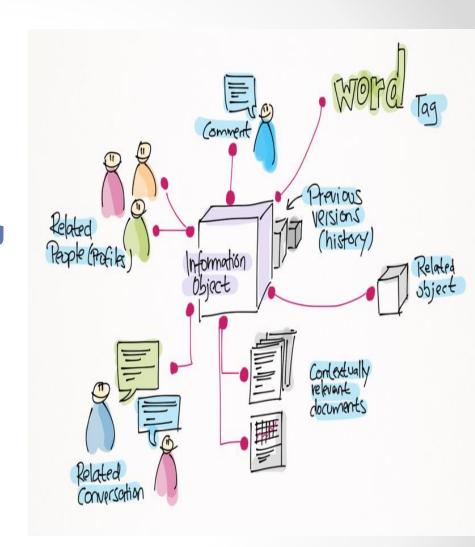
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Personalisation... Why??

- Each Individual is unique.
- Search Engines should rerank its results based on his profile so that his specific requirements can be met



- Personalisation works using Individualisation and Contextualisation
- Individualisation means creating each User's Individual Profile using his Long-Term History
- Contextualisation means Identifying relation between sessions using **\$hort-Term** History



Dataset... Fully Anonymized

- Dataset was provided by Yandex (Almost 16 GB of train data and 400 MB of test Data)
- Search Data for 30 days from a large city was collected.
- To allay privacy concerns the user data is fully anonymized.
- Only meaningless numeric IDs of users, queries, query terms, sessions, URLs and their domains are released.
- Training was done on data of first 27 days and testing on last
 3 days.

Data Format

The log represents a stream of user actions, with each line representing a session metadata, a query action, or a click action. Each line contains tab-separated values according to the following format:

Session metadata (TypeOfRecord = M):

SessionID TypeOfRecord Day USERID

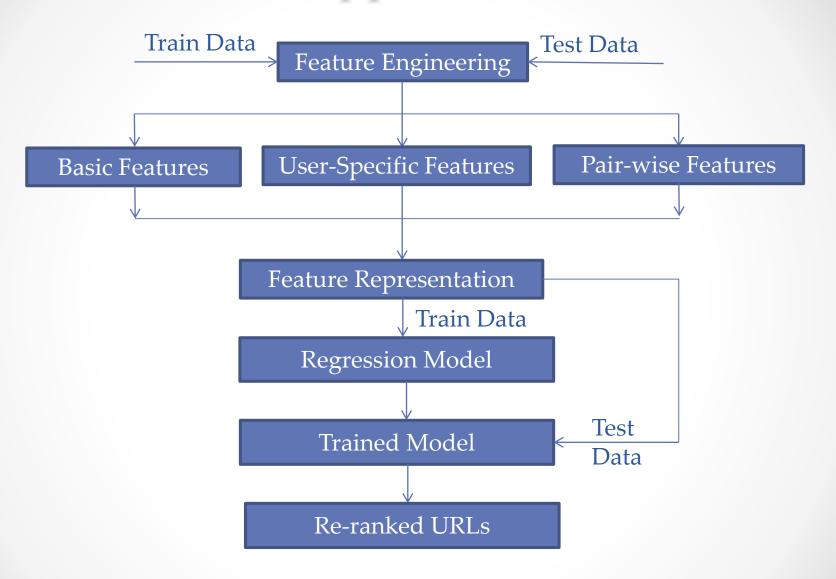
Query action (TypeOfRecord = Q or T):

SessionID TimePassed TypeOfRecord SERPID QueryID ListOfTerms ListOfURLsAndDomains

Click action (TypeOfRecord = C):

SessionID TimePassed TypeOfRecord SERPID URLID

Approach



Feature Engineering

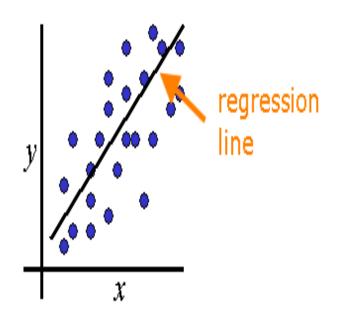
- Initially each URL is labelled with a relevance label of:
 - O (irrelevant): no clicks or click less than 50 time units
 - 1 (relevant): clicks with 50 to 399 time units
 - 2 (highly relevant): dwell time grater than 400 units
- Basic Features used include URL-query instance such as original position of URL for query, URLId, DomainId of URLs, TermIds of query and various joint features such as URLId X position, URLId X QueryId, DomainId X TermId etc.

Feature Engineering

- User Specific Features include for each user, dividing each URL in 5 categories based on relevance labels and whether URL was previously displayed or skipped to the User.
- Pairwise Features include for each query checking the relative position of a pair of URL
 - f(URLi, URLj) = 1 if URLi occurs at better position than URLj
 - f(URLi, URLj) = -1 if URLj occurs at better position than URLi

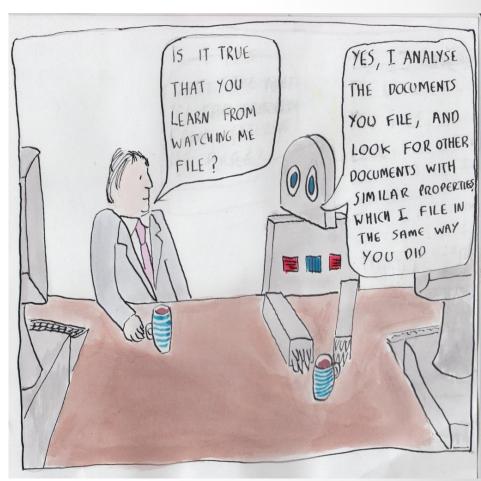
Logistic Regression

- Simple Logistic Regression Model was used.
- URL with positive relevance was labelled 1. Rest labelled -1.
- Relevance Labels assigned to each URL w.r.t to each User were used as Weight.
- Out of Core learning Algorithms are used as they can work with huge Data in hours.



Vowpal Wabbit for Logistic Regression

- Fast Machine Learning tool.
- Works on huge data in a parallel manner.
- · RAM efficient.
- Fast Convergence to a Good Predictor.
- Handles TBs of Data in Matter of Hours.



Machine Learning

Evaluation and Results

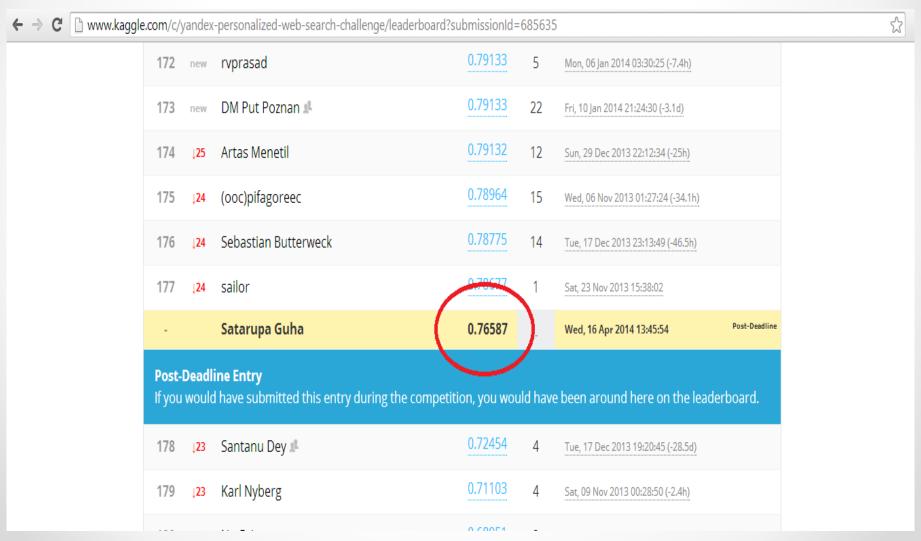
- We used NDCG (Normalized Discounted Cumulative Gain)for evaluation of our results.
- Calculated using the ranking of URLs for each query, and then averaged over queries.

$$DCG@10 = \sum_{i=1}^{10} \frac{2^{rel_{i-1}}}{\log_2(i+1)}$$

where rel_i , i=1,2,...10 is the relevance list that contain 10 URL's relevance values. IDCG@10 is the maximum possible (ideal) DCG for a given set of queries, documents, and relevance value. Then, NDCG@10 is given by

$$NDCG@10 = \frac{DCG@10}{IDCG@10}$$

- Uploaded the final Result file online on Kaggle Portal for Evaluation.
- Our Team (Satarupa Guha) Got NDCG Score 0.76857
- Team who secured first Position got 0.80725



Thank You!!!