Introduction into Natural Language Processing

Lectures: Anton Alekseev, Steklov Mathematical Institute at St Petersburg
NRU ITMO, St Petersburg, 2019

Logistics of the course

‘Who are you to _____ lecture me?’

Lectures

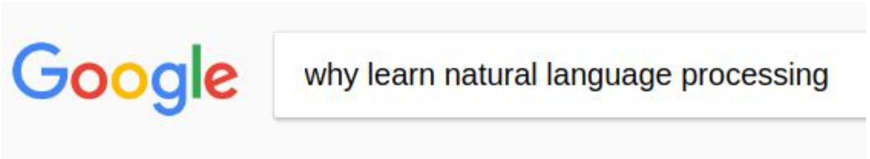
Anton Alekseev, researcher at Steklov Mathematical Institute
ex-Yandex, ex-SofitLabs (chatbots), ex-nativeroll.tv (ML in video ads)

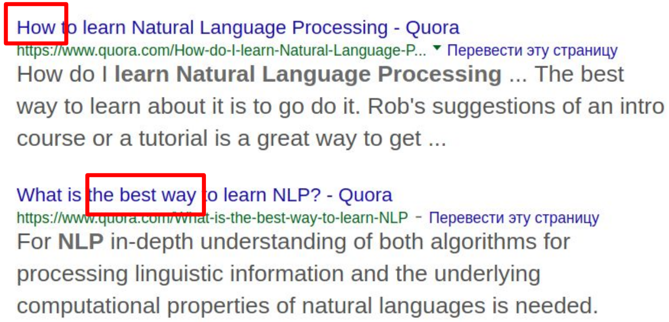
Seminars, labs and tests

Ksenia Buraya, PhD student at NRU ITMO, developer at VK

Questions regarding lectures and the course in general:
anton.m.alexeyev+itmo@gmail.com

Why know anything about NLProc?





Google doesn't even…
(could be so due to personalization though)

- NLProc is fun
- We communicate with intelligent machines, they communicate with us
- Web Data ~ Collective Intelligence
- NLP engineers are paid, like, money
- etc

Course features

Fast-paced introductory course on NLProcessing

- practice-oriented
- statistical approaches are always preferred
- mostly based on lecturer’s hands-on experience
- memes

An Incomplete List of NLProcessing Tasks

Language modeling
Part-of-speech tagging
Named entity recognition
Text (topic) classification
Keyword extraction
Spelling checking
Syntax parsing
Dependency parsing
Machine translation
Stemming
Lemmatization
Distributional semantics
Text generation
Text clustering

Wikification
QA systems, dialogue systems
Plagiarism detection
Morpheme analysis
Grammar check
Hyphenation
Relation extraction
Entity linking
Sentiment analysis
Topic modeling
Text summarization
Semantic role labeling
Information retrieval
Speech Recognition / Synthesis

Stuff NOT covered in the course

1. We are not focused JUST on neural networks

    Deep Learning for NLP requires one more course (which may be based on this one)

    A Primer on Neural Network Models for Natural Language Processing, Yoav Goldberg
    Natural Language Processing with Deep Learning, Christopher Manning

2. Oldschool classic theories and methods from early CompLing

3. *With this simple trick you can write your own chatbot in just 2 weeks*

4. A few important yet complex/esoteric tasks
    (e.g., text summarization, coreference resolution, QA-systems, ...)
    a. one can't fit everything into NLP 101;
    b. these are problems the average engineer doesn't solve every day.

Used/Recommended materials

1. **Introduction to Information Retrieval**,
   Chr. Manning, Pr. Raghavan and H. Schütze. Cambridge University Press. 2008.
2. **Foundations of Statistical Natural Language Processing**,
   Chr. Manning, H. Schütze, MIT Press. Cambridge, MA: May 1999.
3. **Speech and Language Processing**
   Daniel Jurafsky, James H. Martin
4. **Прикладная и КОМПЬЮТЕРНАЯ ЛИНГВИСТИКА.** Николаев И.С., Митренина О.В., Ландо Т.М. (ред.). Изд.2 Прикладная и компьютерная лингвистика URSS. 2017. 320 с.
5. LxMLS 2015 tutorials, lectures, code
6. HPLabs @ CSCenter NLP Course (Al. Ulanov), Autumn 2013
7. Certain papers and reviews + personal experience
8. *Wikipedia* (pics, formulae, pseudocode :))

Other useful sources

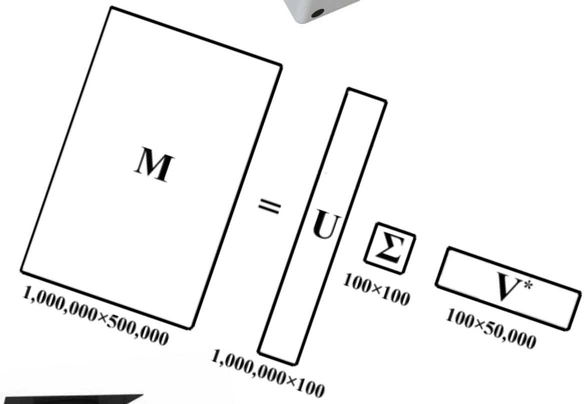
1. Coursera (Chr. Manning - D.Jurafsky, M. Collins, D. Radev), Stepik (П. Браславский)
2. http://ods.ai/ - Russian-speaking data scientists community
3. http://nlpub.org/ - NLProc wiki in Russian

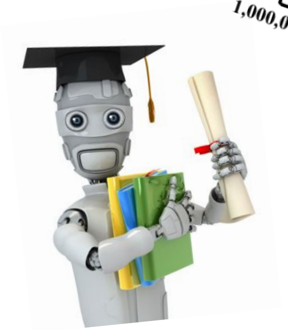
Quick check

1. NLProcessing courses (MOOCs count)?
2. Statistics courses?
3. ML courses?
4. Information theory?
5. Your own ML projects?
6. Ever used scikit-learn?
7. Which NN framework is your favourite one?

Prerequisites

1. Probability theory basics
2. Linear algebra basics
3. Algorithms
4. Machine learning basics
   (or a huge interest towards it)
5. The skill to hand in **homeworks on time**
6. Python basics





Scores

Cumulative:

1. Tests
2. Labs (homeworks)
3. Final exam

Previous course session: 0.15 - **0.65** - 0.2

scores will be a little different this year as tests and labs are going to be different

Any questions?

Introduction into NLP

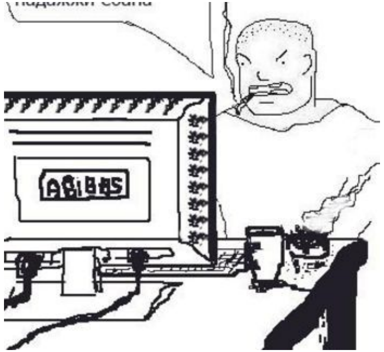
things i **have to** tell you, because other teachers usually do
minimum minimorum

Natural language

- CompLing vs NLP

- Linguistics studies language
  - *Phonetics*
  - Morphology
  - Syntax
  - Semantics
  - *Pragmatics*

    (arguable division)



- What’s so hard?

  aaaaa how do i represent words and characters as numbers, there are too many words, it is hard to obtain a representative sample, polysemy! word order, all sorts and flavors of ambiguities, no word for some senses in some

Roots, bloody roots

- Can’t skip this: Alexander Markov Sr., 1913, “Eugene Onegin”, experimenting: Markov chains for consonants/vowels distribution

- Established opinion: CompLing was born in 1950s
  thanks to the machine translation task (both in the USA and the USSR)
  Georgetown experiment
  60+ sentences, 6 rules
  1954, IBM + Georgetown University, ”the task will be solved in 3-5 years” **:)**

  Vyelyichyina ugla opryedyelyayetsya otnoshyenyiyem dlyini dugi k radyiusu.
  Magnitude of angle is determined by the relation of length of arc to radius.

  Myezhdunarodnoye ponyimanyiye yavlyayetsya vazhnim faktorom v ryeshyenyiyi polyityichyeskix voprosov.
  International understanding constitutes an important factor in decision of political questions.

https://en.wikipedia.org/wiki/Georgetown%E2%80%93IBM_experiment
http://rvb.ru/soft/articles/eonegin_1913.htm

Must know

- **ELIZA**: virtual assistant, rogerian psychotherapist parody,
  based on keywords extraction, pattern matching and slot filling
  MIT AI lab, Joseph Weizenbaum, 1966

  See wiki: https://en.wikipedia.org/wiki/ELIZA_effect

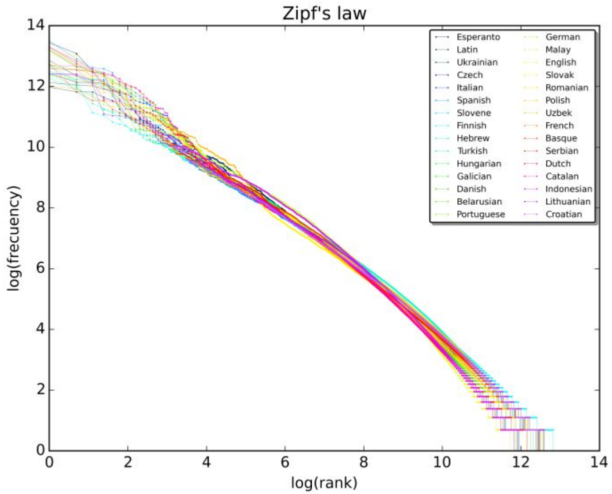
  young woman: You are not very aggressive but I think you don't want me to notice that.
  eliza: What makes you think *I am not very aggressive*?
  young woman: You don't argue with me.
  eliza: Why do you think *I don't argue with you*?
  young woman: You are afraid of me.
  eliza: Does it please you to believe *I am afraid of you*?

https://web.stanford.edu/group/SHR/4-2/text/dialogues.html

Zipf law [1949]: rank * freq ~ const

(Jean-Baptiste Estoup (1868–1950), Felix Auerbach (1856–1933), George Kingsley Zipf (1902–1950))

Russian Wikipedia words frequencies, sorted (starting with the third one)



First 10 million words in 30 national wikipedia texts (Oct. 2015) (log-log scale!).

Must know: progress

50-e: first attempts, Information Theory, Formal Grammars

60-70-e: ‘Syntactic Structures’, AI, bayesian models, first corpora

80-e: structured models (speech!), first distributional semantics approaches, data-driven research

90-e: models evaluation tracks, applications for wide range of users

2000-e: web! data! machine learning, unsupervised approaches

2010-e: Deep Learning feast, tons of applications in various fields

Introduction into Information Retrieval

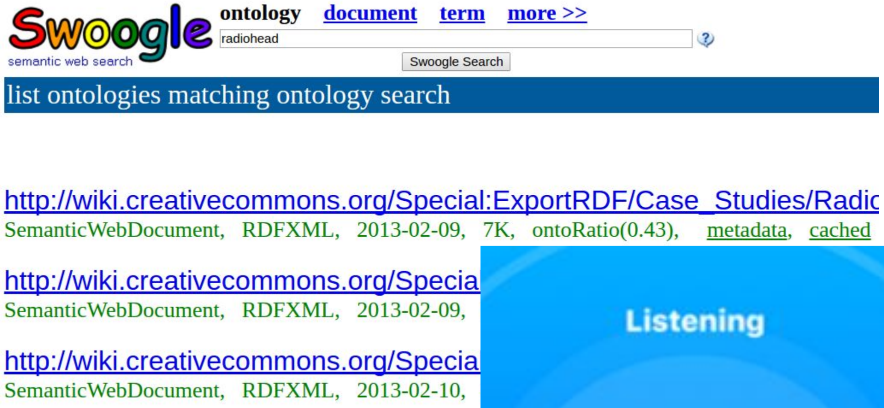
Lectures: Anton Alekseev, Steklov Mathematical Institute in St Petersburg
NRU ITMO, St Petersburg, 2018

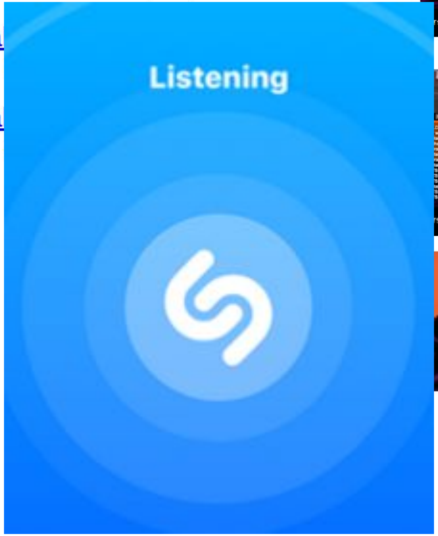
Why do we even discuss this?

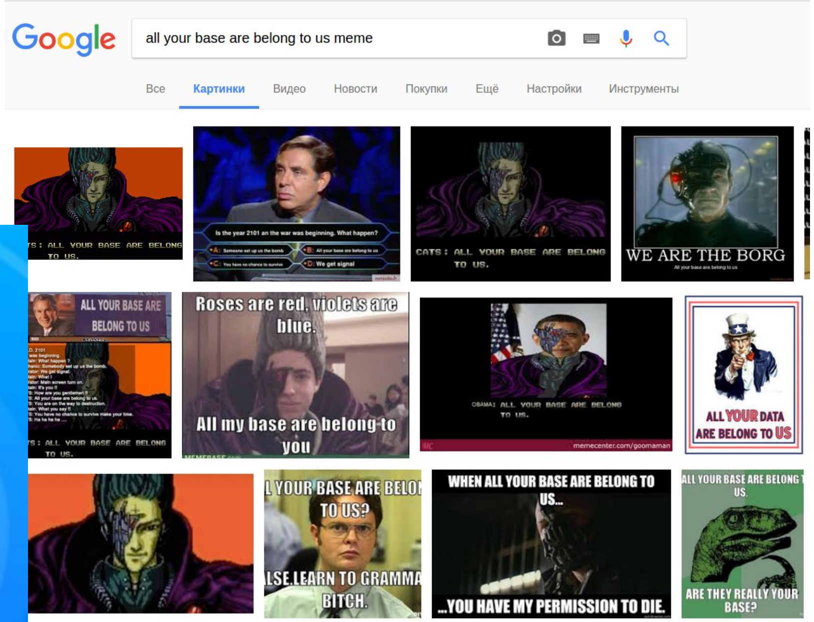
Information retrieval (even **text retrieval**) is not a part of NLP, however

- intersection is large,
- classical IR tricks are widely used in NLP,
- a good and hopefully inspiring practical start for the NLP course,
- other lecturers do this ¯_(ツ)_/¯ (yeah, cargo cult!)

ad-hoc-retrieval - text is not the only option







...but this course is focused on text processing

ad-hoc search task clumsy definition

D - a set of documents (that is, texts + possibly some metadata)
T - a set of terms (words)
Q - a set of queries, also a sequence of terms

We believe there exists a fuction **Rel: Q x D -> R** that can provide all pairs of queries and documents with an estimate of relevance (a measure to what extent the user's information need (represented as a query) is satisfied by the document)

The goal is to find best-matching documents (in terms of **Rel**). On the fly.

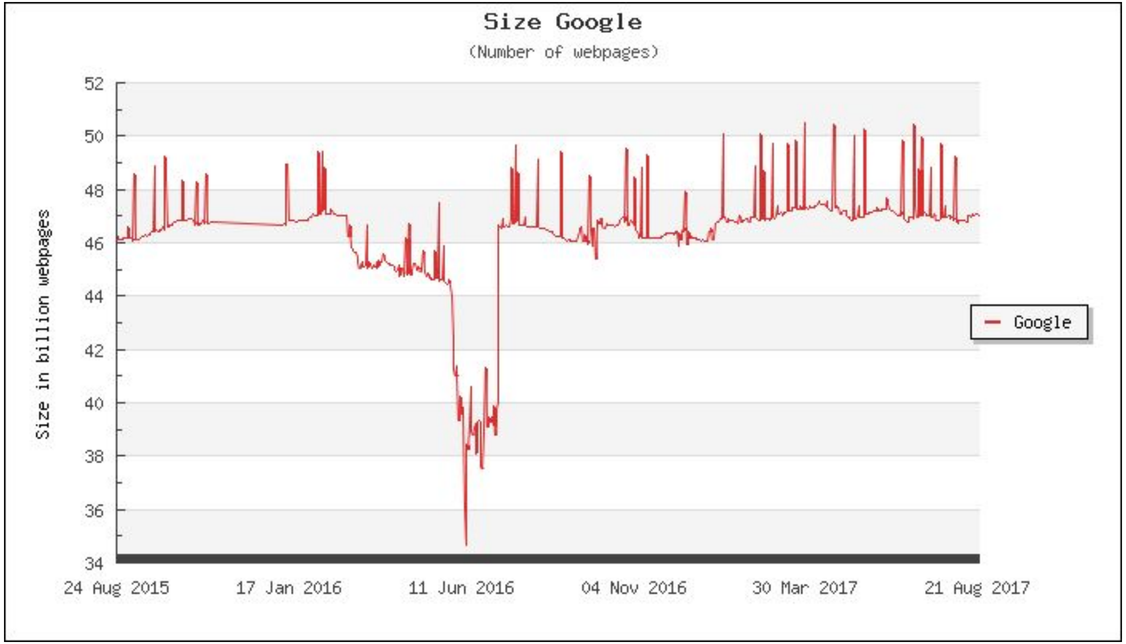
Cunning plan

1. “Download the Internet”
2. Invent Rel
3. Scan the database for every query and compute Rel for every query-document pair
4. ???????
5. PROFIT!

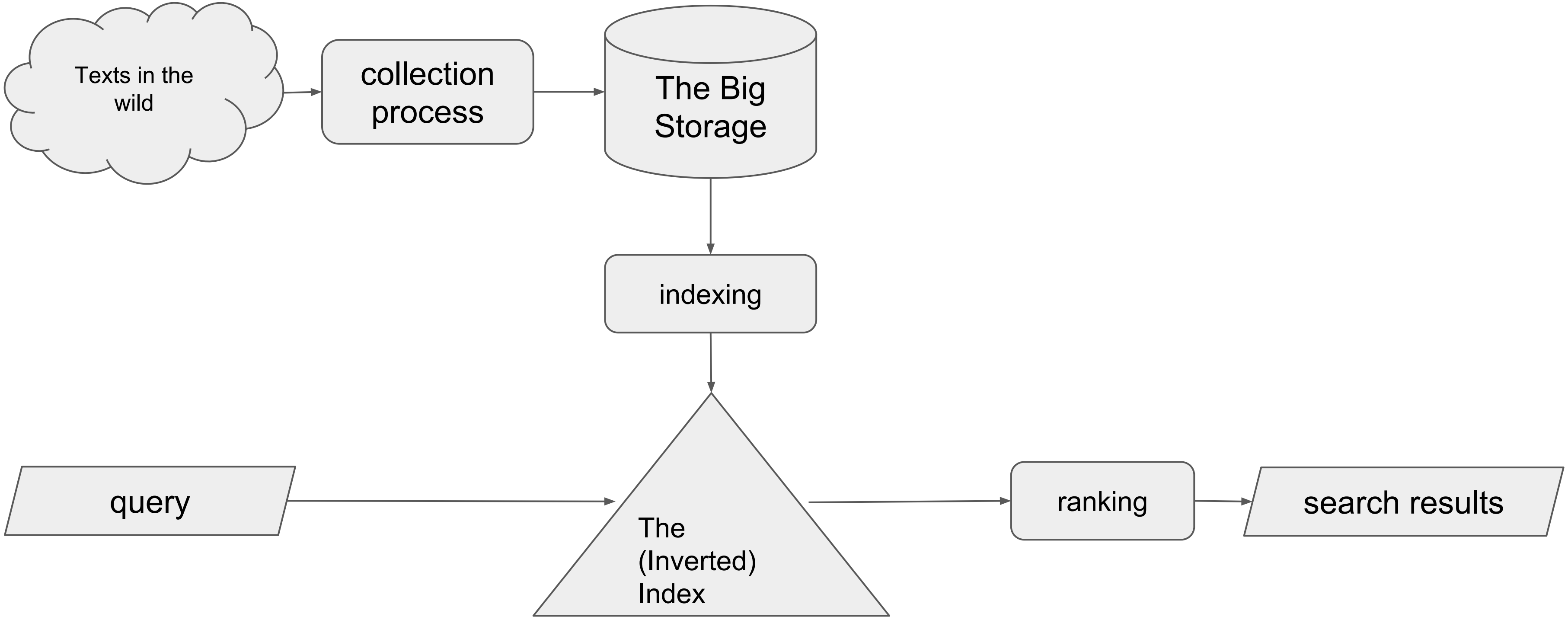
GENIUS!

Well, no.

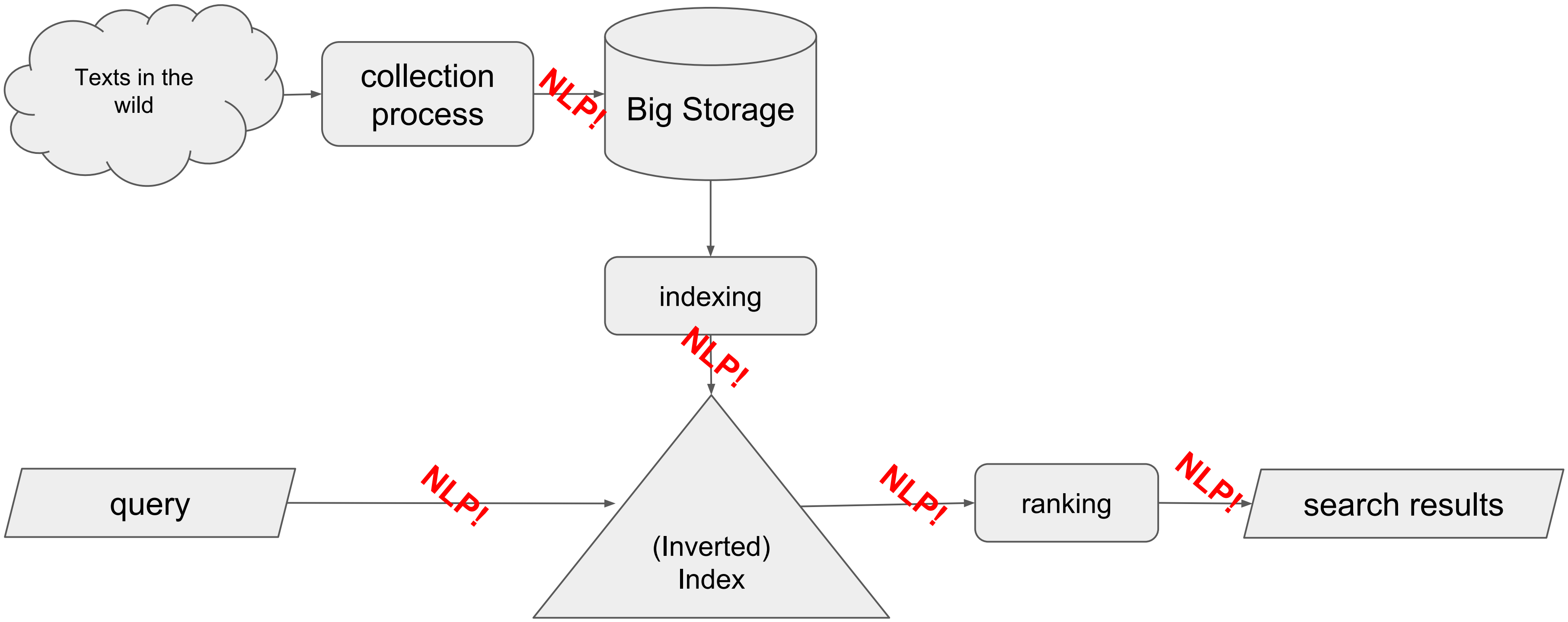
(you should be terrified: Google would have to perform a full scan for 45+ billion records per query!)



How it is usually done



How it is usually done



Information retrieval stages

1. Collecting and cleaning data
2. Preparing documents
3. Document indexing
4. Query processing
5. Documents retrieval by query
6. Document ranking
7. Search results preparation

Also: (8) personalization, (9) query suggestions, ...

Documents preparation

Initially we have ‘dirty’ texts

«На** **берегу ** **пустынных волн**»</p>**

на берег**у** пустын**ных** волн

«Russian language!»

lemmatization (base forms)

на берег пустынный волна

(или: **на** берег пустын волн)

stemming (stripping suffixes, etc.)

берег пустынный волна

not even a word

Data preparation: stemming

Morphing words so that all possible forms of the word would turn into a single item, stem. Can be solved as a language-independent task.

- Usually when we say ‘stemming’ we mean cutting words (removing suffixes, prefixes, etc.) so that only the **common part of all forms of the target word remains**

Procrustes knew a few things about stemming // «The Labyrinth. Theseus’ Labours» (USSR, 1971)

Classics: Porter stemmer

The firs paper on stemming

Lovins, Julie Beth (1968). Development of a Stemming Algorithm. Mechanical Translation and Computational Linguistics

More widely spread and well-known is this one

C.J. van Rijsbergen, S.E. Robertson and M.F. Porter, 1980. New models in probabilistic information retrieval. London: British Library. (British Library Research and Development Report, no. 5587).

M.F. Porter, 1980, An algorithm for suffix stripping, Program, 14(3) pp 130−137.

Позже разработал фреймворк для разработки стеммеров -- Snowball.

The *rules* for removing a suffix will be given in the form

(condition) S1 -> S2

The 'condition' part may also contain the following:

*S - the stem ends with S (and similarly for the other letters).
v - the stem contains a vowel.
*d - the stem ends with a double consonant (e.g. -TT, -SS).
*o - the stem ends cvc, where the second c is not W, X or Y (e.g. -WIL, -HOP).

IZ	-> IZE	siz(ed)	-> size
(*d and not (*L or *S or *Z))	-> single letter	hopp(ing)	-> hop

http://snowball.tartarus.org/algorithms/porter/stemmer.html

Porter stemmer usage example

>>> from **nltk**.stem.porter import
>>> stemmer = PorterStemmer()
>>> words = "hello,dear,students,!,who,cares,about,linguistics,?".split(",")
>>> words =
"hello,dear,student**s**,!,who,car**es**,about,linguist**ics**,?,let**'s**,evalu**ate**,all,the,corpora,!".split
(",")

>>> " ".join([stemmer.stem(w) for w in words])
"hello dear student ! who care about linguist ? let' evalu all the corpora !"

>>> stemmer.stem("corpuses")
'corpus'

Preparing documents: lemmatization

- conversion to infinitive forms of words

Usually: dictionary-based approach + morphological tricks!

“World languages”: **nltk, spacy, pattern,** ...

Russian: **mystem 3.1 / pymorphy2**

Bird, Steven, Edward Loper and Ewan Klein (2009), Natural Language Processing with Python. O’Reilly Media Inc.
Korobov M.: Morphological Analyzer and Generator for Russian and Ukrainian Languages // Analysis of Images, Social Networks and Texts, pp 320-332 (2015).
I.Segalovich,Yandex. A fast morphological algorithm with unknown word guessing induced by a dictionary for a web search engine

Yandex MyStem Demo

./mystem.exe -e utf-8 -i --format json -d --weight
варкалось. хливкие шорьки

```
[
{"text":"варкалось","analysis":[
{
"Wt":0.6584257483,
"Lex":"варкаться",
"gr":"V,несов,нп=прош,ед,изъяв,сред",
"Qual":"bastard"
}]},
{"text":"хливкие","analysis":[
{"wt":0.9958436489,"lex":"хливкий","gr":"A=вин,мн,полн,неод","qual":"bastard"},
{"wt":0.9958436489,"lex":"хливкий","gr":"A=им,мн,полн","qual":"bastard"}]},
{"text":"шорьки","analysis":[
{"wt":0.3092010319,"lex":"шорька","gr":"S,жен,неод=вин,мн","qual":"bastard"},
{"wt":0.3092010319,"lex":"шорька","gr":"S,жен,неод=род,ед","qual":"bastard"},
{"wt":0.3092010319,"lex":"шорька","gr":"S,жен,неод=им,мн","qual":"bastard"}]}
]
```

Yandex MyStem Demo: morph. ambiguity

$ ./.local/bin/mystem

мама мыла раму

мама{мама}мыла{мыло|мыть}раму{рама|рам}

NOUN (soap)

VERB (wash) past tense

$ ./.local/bin/mystem -d

мама мыла раму

мама{мама}мыла{мыть}раму{рама}

Enabling disambiguagion

VERB (wash) past tense

Information retrieval stages

1. Collecting and cleaning data
2. Preparing documents
3. Document indexing
4. Query processing
5. Documents retrieval by query
6. Document ranking
7. Search results preparation

Also: (8) personalization, (9) query suggestions, ...

Indexing (for boolean search)

So one does not simply scan the web

The minimal entity in search are **terms** -- so let us first learn how to retrieve documents containing certain terms and term combinations, that is, "boolean retrieval"

Information need = "would love to read wiki page on manul or maine coon"
Boolean query = "wiki" AND ("maine coon" OR "manul")

http://images.mentalfloss.com/sites/default/files/styles/mf_image_3x2/public/mainecoonhed.png?itok=pLmeE_3q&resize=1100x740

http://osledah.ru/img/manul.gif

Indexing (for boolean search)

“wiki” AND (“manul” OR “maine coon”)

Long bit vectors + bitmasking for search!

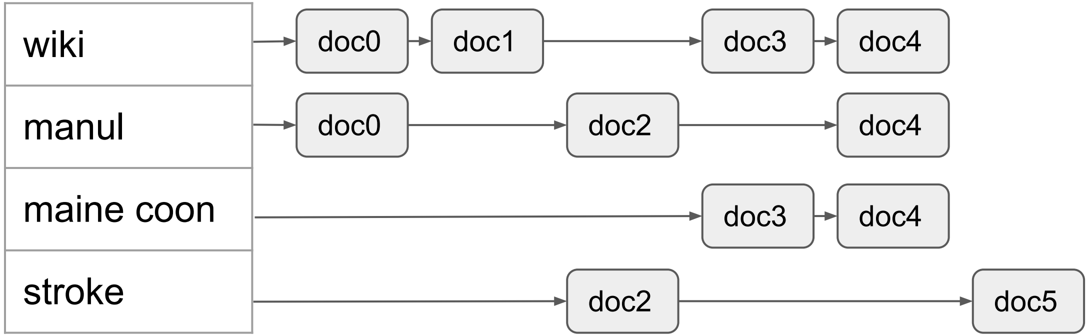
Is this an acceptable solution?

	wiki	manul	maine coon	stroke
doc0	1	1	0	0
doc1	1	0	0	0
doc2	0	1	0	1
doc3	1	0	1	0
doc4	1	1	1	1

Indexing (for boolean search)

“wiki” AND (“maine coon” OR “manul”)

	wiki	manul	m.coon	stroke
doc0	1	1	0	0
doc1	1	0	0	0
doc2	0	1	0	1
doc3	1	0	1	0
doc4	1	1	1	1
doc5	0	0	0	1



A dictionary, with linked lists of document metainformation records (position in text, true word form, frequency of the term in concern in the document etc.) **ordered by document IDs**

How would you solve this retrieval problem algorithmically?

Inverted indices

AND: intersection of sorted lists
OR: union of sorted lists

Dictionary can be stored in memory, lists can be stored on disk

Multiple natural tricks for performance and quality boost:

- store lists compressed and unpack on the fly when reading
- store IDs diffs, not IDs themselves
- add forward-links once in a while (skip-lists)
- store positions of terms in the doc
  (allows to use distances between terms from query)

Information retrieval stages

1. Collecting and cleaning data
2. Preparing documents
3. Document indexing
4. Query processing
5. Documents retrieval by query
6. Document ranking
7. Search results preparation

Also: (8) personalization, (9) query suggestions, ...

Query preprocessing

Preparing the query the way we did with the document -- and we have the boolean retrieval system all set and ready

Also a good idea in practice

- add extra similar and relevant terms (**query expansion**)
- classification of query intention to understand which index to use (there may be many specific ones)

However, there are many more tricks, which are out of scope of this course

Information retrieval stages

1. Collecting and cleaning data
2. Preparing documents
3. Document indexing
4. Query processing
5. Documents retrieval by query
6. Document ranking
7. Search results preparation

Also: (8) personalization, (9) query suggestions, ...

Ranking is the brain of the search engine

Why is that hard?

jaguar

jaguar напиток

jaguar

jaguar xf

Jaguar в Санкт-Петербурге - отзывы, фото, телефоны,...
maps.yandex.ru › jaguar
Jaguar в Санкт-Петербурге - отзывы, фото, телефоны, адреса с рейтингом, отзывами и фотографиями. Адреса, телефоны, часы работы, схема проезда.

jaguar — смотрите картинки
yandex.ru/images › jaguar

Jaguar — подержанные и новые авто в **Санкт-Петербурге**
Запчасти Объявления Отзывы Каталог Дилеры
auto.ru › Jaguar
Большая база объявлений о продаже автомобилей **Jaguar**. Полная информация об автомобилях — фотографии, отзывы, характеристики и цены.

an animal, a vehicle, a drink

Why so hard?

One have to solve multiple problems simultaneously

1. Matching document and query
2. Document quality
3. Matching user’s interests and behavioral patterns*
4. Search results diversification
   (one of the “Jaguar case” solutions)
5. ...

Ranking: the task

The goal is to sort search results so that the most relevant would be at the top of the list

Can be treated as a task of finding the relevance function

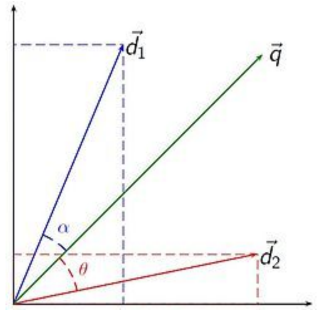
Rel: Q x D -> R

Classics: Vector Space Model (VSM)

Every text and every query is represented as a vector of the same fixed number of dimensions, then documents vector representations are sorted by the distance/closeness to the query vector

$$d_j = (w_{1,j}, w_{2,j}, \dots, w_{t,j})$$

$$q = (w_{1,q}, w_{2,q}, \dots, w_{n,q})$$



Example:

$$\cos\theta = \frac{\mathbf{d_2} \cdot \mathbf{q}}{\|\mathbf{d_2}\| \, \|\mathbf{q}\|}$$

$$\mathrm{sim}(d_j, q) = \frac{\mathbf{d_j} \cdot \mathbf{q}}{\|\mathbf{d_j}\| \, \|\mathbf{q}\|} = \frac{\sum_{i=1}^{N} w_{i,j} w_{i,q}}{\sqrt{\sum_{i=1}^{N} w_{i,j}^2} \sqrt{\sum_{i=1}^{N} w_{i,q}^2}}$$

How to build vectors: counters

Query / document:
“На берегу пустынных волн...”

абакан	абырвалг	азкабан	аксакал	аксолоть	аксон	берег	волна	заноза	...
0	0	0	0	0	0	1	1	0	...

(tip: *never ever forget to try this way of representing texts, may work surprisingly well, sometimes way better than all those trendy things everyone loves*)

How to build vectors: tf-idf

Are there many docs with this word in the collection?
(the smaller the number of documents the better)

$$\mathrm{tfidf}(t, d, D) = \mathrm{tf}(t, d) \cdot \mathrm{idf}(t, D)$$

Is the word met frequently in the document?
(more is "better")

$$\mathrm{tf}(t,d) = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}}$$

$$\mathrm{idf}(t, D) = \log \frac{N}{|\{d \in D : t \in d\}|}$$

Variants of term frequency (TF) weight

weighting scheme	TF weight
binary	$0, 1$
raw count	$f_{t,d}$
term frequency	$f_{t,d} \Big/ \sum_{t' \in d} f_{t',d}$
log normalization	$1 + \log(f_{t,d})$
double normalization 0.5	$0.5 + 0.5 \cdot \frac{f_{t,d}}{\max_{\{t' \in d\}} f_{t',d}}$
double normalization K	$K + (1-K) \frac{f_{t,d}}{\max_{\{t' \in d\}} f_{t',d}}$

Variants of inverse document frequency (IDF) weight

weighting scheme	IDF weight ($n_t = \|\{d \in D : t \in d\}\|$)
unary	1
inverse document frequency	$\log \frac{N}{n_t} = -\log \frac{n_t}{N}$
inverse document frequency smooth	$\log \left(1 + \frac{N}{n_t}\right)$
inverse document frequency max	$\log \left(\frac{\max_{\{t' \in d\}} n_{t'}}{1 + n_t}\right)$
probabilistic inverse document frequency	$\log \frac{N - n_t}{n_t}$

Explaining tf-idf with ‘theory’

TF-IDF(q,d) — мера релевантности документа d запросу q

n_{dw} (term frequency) — число вхождений слова w в текст d;
N_w (document frequency) — число документов, содержащих w;
N — число документов в коллекции D;

N_w/N — оценка вероятности встретить слово w в документе;
$(N_w/N)^{n_{dw}}$ — оценка вероятности встретить его n_{dw} раз;
$P(q,d) = \prod_{w \in q} (N_w/N)^{n_{dw}}$ — оценка вероятности встретить в документе d слова запроса $q = \{w_1, \dots, w_k\}$ *чисто случайно*;

Оценка релевантности запроса q документу d:

$$-\log P(q,d) = \sum_{w \in q} \underbrace{n_{dw}}_{\mathrm{TF}(w,d)} \underbrace{\log(N/N_w)}_{\mathrm{IDF}(w)} \to \max.$$

$\mathrm{TF}(w,d) = n_{dw}$ — term frequency;
$\mathrm{IDF}(w) = \log(N/N_w)$ — inverted document frequency.

К. В. Воронцов (voron@forecsys.ru) Ранжирование 6 / 21

Probability to see the term **w** in ANY document

Probability to see the term **w** in a document **the number of times** it actually shows up in a document (n_{dw})

Probability to see query **q** terms in a document **ACCIDENTALLY**

Relevance: the larger, **the less the ‘randomness’ of query terms** occurence in the document

BM is for Best Match

The famous **Okapi BM25** — a family of IDF-like functions that were popular in early web search engines

Q — query
D — document
avgdl — average document length

The rest — tuneable parameters

$$\text{score}(D, Q) = \sum_{i=1}^{n} \text{IDF}(q_i) \cdot \frac{f(q_i, D) \cdot (k_1 + 1)}{f(q_i, D) + k_1 \cdot \left(1 - b + b \cdot \frac{|D|}{\text{avgdl}}\right)},$$

Machine learning, of course

Learning to Rank!

Rel(d,q): D x Q => R

- **Elementwise** approach:
  We have relevance scores defined in train set; fitting to them

- **Pairwise** approach
  Rel(d, q) < Rel(d', q), fitting the function given pairs

- **Listwise** approach
  Lists of documents {$\mathbf{d}_i$}, sorted by relevance for **q**

Information retrieval stages

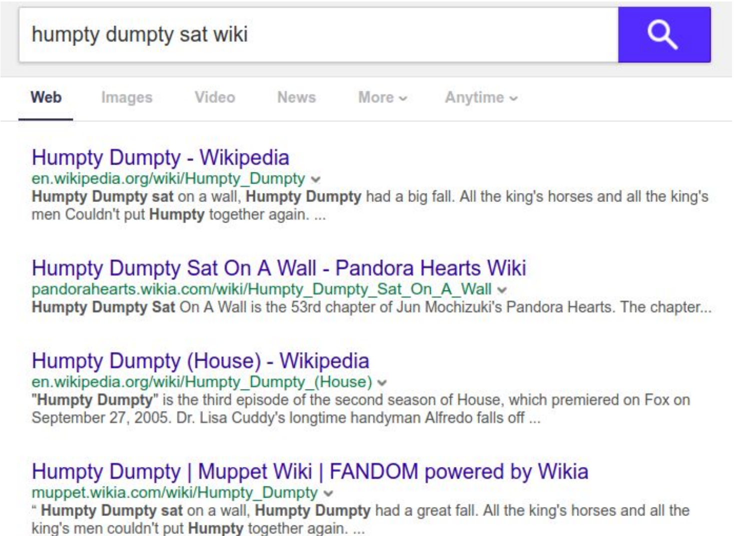
1. Collecting and cleaning data
2. Preparing documents
3. Document indexing
4. Query processing
5. Documents retrieval by query
6. Document ranking
7. Search results preparation

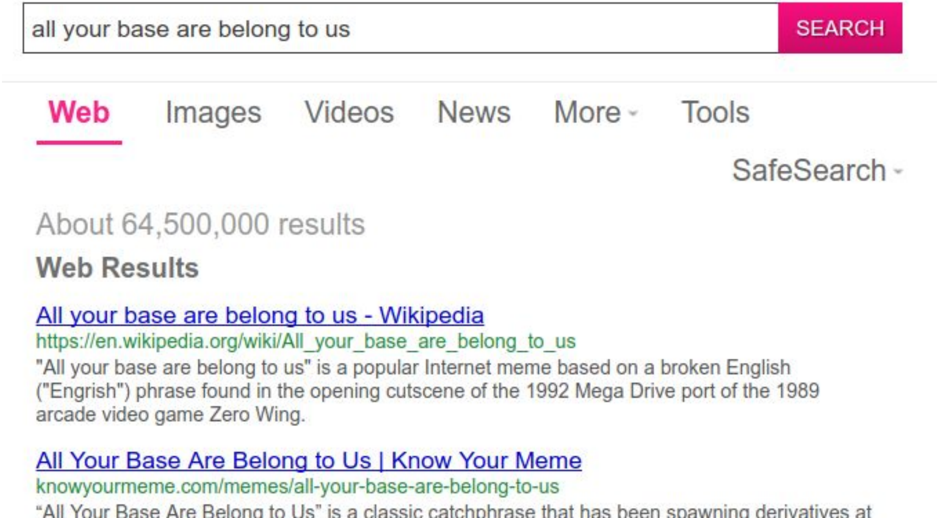
Also: (8) personalization, (9) query suggestions, ...

Search results preparation

Search results representation for the user is terribly important

Snippets preparation is a separate NLP task, similar to automatic text summarization problem





Standard datasets

- **The Cranfield collection**
  (kinda ancient, 1400 texts on aeronautics, judgements on relevance 0/1)

- **TREC**
  (text retrieval conference; various tasks and datasets; new challenges every year)

- **CLEF**
  (cross language evaluation forum; tasks for various languages)

How to build your own IR engine

Lots of open source software providing IR-out-of-box.

Python

- Scrapy, requests/urllib + BeautifulSoup
- Pylucene, Xapian

Java

- Crawling: Nutch, StormCrawler, …
- Retrieval: **Lucene** (Java library), ElasticSearch (incl. Lucene), Solr

Software for doing IR

Solr
elasticsearch
APACHE HBASE
STORMCRAWLER
Apache nutch
scrapinghub
LUCENE.net
SEARCH ENGINE LIBRARY
Lucene
Open Source Search Server
Sphinx
hadoop

...the list is not even close to being a complete one

Conferences and schools

- International **ACM SIGIR**
  Conference on Research and Development in Information Retrieval
- **ECIR**
- WWW (and the like)
- Schools: ESSIR, RuSSIR

- Many more:
  http://www.wikicfp.com/cfp/call?conference=information%20retrieval

Other tasks in web search

- Query correction/augmentation
- Query expansion: morphology, semantics
- Search/suggestions personalization
- Dealing with queries semantic ambiguity
- Fact extraction
- Smart suggestions
- Queries classification
- Document clustering
- Duplicate detection
- Virus / spam detection
- Events detection
- ...

Final remarks on IR's impact on NLP

- It is mainly thanks to IR community's efforts that evaluation of data processing algorithms became a common practice (esp. in NLP)

- IR != NLP, but IR + NLP = <3
  interconnections & common tricks

- Web search is probably the most successful case of applying NLP in production (tthough the number grows)

Overview

1. Text search nuts and bolts
2. Stemming and lemmatization
3. Boolean retrieval
4. Vector Space Model
5. **Cosine similarity**
6. **TF-IDF**
7. A few popular ranking quality evaluation metrics

Introduction into Information Retrieval

Anton Alekseev
anton.m.alexeyev+itmo@gmail.com

Thanks for useful comments go to: Denis Kiryanov

BTW

please create some channel for us all to communicate, e.g. in Telegram

Extra: ranking quality evaluation

$$DCG(ranking\ for\ query\ q) = \sum_{j=1}^{N_q} \frac{rel_j}{log_2 j + 1}$$

$$nDCG(...) = \frac{DCG(ranking\ for\ query\ q)}{DCG(ideal\ ranking\ for\ query\ q)}$$

$$\mathrm{MAP} = \frac{\sum_{q=1}^{Q} \mathrm{AveP(q)}}{Q}$$

$$pfound = \sum_{i=1}^{n} pLook[i] * p\mathrm{Re}l[i]$$

$$pLook[i] = pLook[i-1] * (1 - p\mathrm{Re}l[i-1]) * (1 - pBreak)$$

http://romip.ru/russir2009/slides/yandex/lecture.pdf
http://romip.ru/romip2009/15_yandex.pdf

Discounted cumulative gain (DCG)
(penalty for highly relevant results being put to the bottom of the ranked list)

nDCG (normalized ...)
(normalizing DCG (perfect ranking in the denominator); known to correlate well with human judgements)

Precision@K (-> MAP@k)
(count of ‘true relevant’ items found in predicted TOP-k; MAP - averaging for all ranked lists)

pFound
modeling the user viewing search results page from top to bottom, and sometimes leaving it; **pRel** - relevance probability estimate