Information retrieval

Evaluation of retrieval systems and learn to rank

Clovis Galiez

Laboratoire Jean Kuntzmann, Statistiques pour les sciences du Vivant et de l'Homme

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Objectives of the course

- Acquire a culture in information retrieval
- Master the basics concepts allowing to understand:
  - what is at stake in novel IR methods
  - what are the technical limits

This will allow you to have the basics tools to analyze current limitations or lacks, and imagine novel solutions.

Today's outline

- Guided correction of the hands-on
- Evaluation of IR systems
- Learning to search
- Wrap-up

Evaluation of IR systems

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Can be seen as a partial function $g : \mathcal{Q} \times \mathcal{D} \to \mathbb{R}$ associating to a couple query-document its quantification of *correctness*, *relevance* or *truth*.
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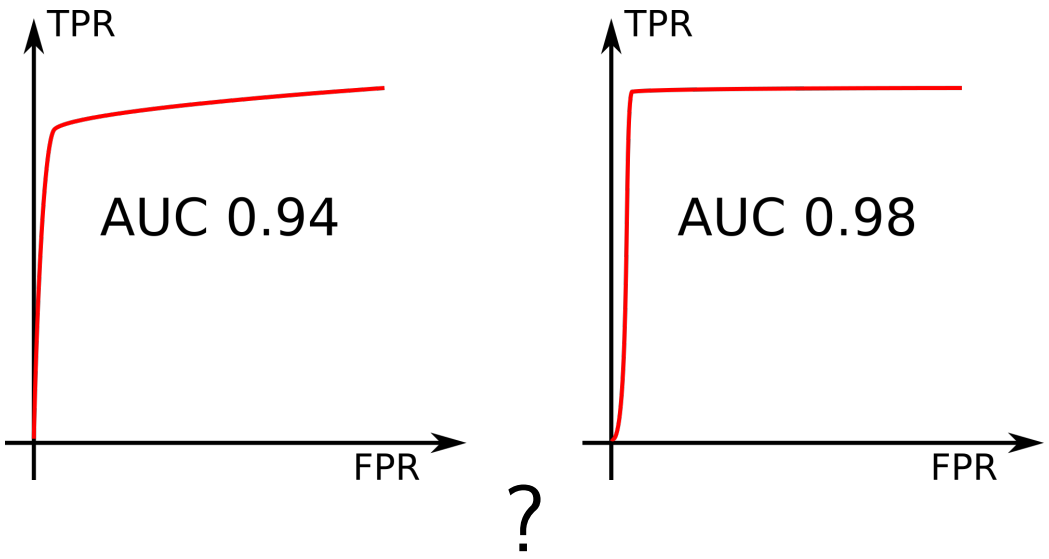
What can be an indicator?
We distinguish the special case of $\text{dom}(g) = \{0, 1\}$.

Indicators for binary gold standards[1]

Standard indicators: FP, FP, FN, TN.

Use the right summary indicator (e.g. AUC-ROC/AUC-ROC5).



[1] To be used for assessing correctness for instance.

Indicators for rank gold standards[2]

Ranking functions $f_1, f_2 : \mathcal{Q} \times \mathcal{D} \to \mathbb{R}_+^*$. How can we say that f_1 is better than f_2?

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Indicators for rank gold standards[2]

Ranking functions $f_1, f_2 : \mathcal{Q} \times \mathcal{D} \to \mathbb{R}_+^*$. How can we say that f_1 is better than f_2?
Given a gold standard $g : \mathcal{Q} \times \mathcal{D} \to \mathbb{R}_+^*$, one can measure the cumulative gain:

$$\mathsf{CG}_n(q, f) = \sum_{k:\mathsf{ord}_n(q,f)} g(q, k)$$

where $\mathsf{ord}_n(q, f)$ are the n first elements of $\mathcal{D}$ when sorting by $f(q, \_)$.

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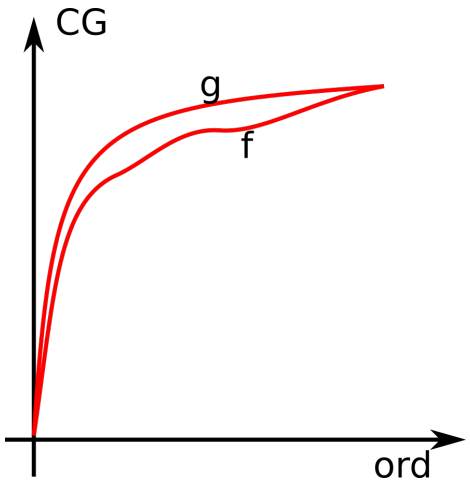
The normalized cumulative gain is:

$$\mathsf{NCG}_n(q, f) = \frac{\mathsf{CG}_n(q,f)}{\mathsf{CG}_n(q,g)}$$



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Indicators for ranking, stressing first results

In the same spirit of the difference AUC/AUC5, one can stress more the first results, by weighting the relevance by a *discount*[3] function:

$$\mathsf{DCG}(q, f) = \sum_{k:\mathsf{ord}_{N_q}(q,f)} \frac{g(q,k)}{\log(i+1)}$$

where N_Q is $\mathsf{card}\{d|(q, d) \in \mathsf{dom}(g)\}$ and i is the index in the summation.

The NDCG is defined as:

$$\mathsf{NDCG}(q, f) = \frac{\mathsf{DCG}_{N_Q}(q,f)}{\mathsf{DCG}_{N_Q}(q,g)}$$

[3] One can choose different discount functions, but $\frac{1}{\log i}$ has nice theoretical foundations [Wang et al. JMLR 13] and is good in practice.

Comparing ranking strategies

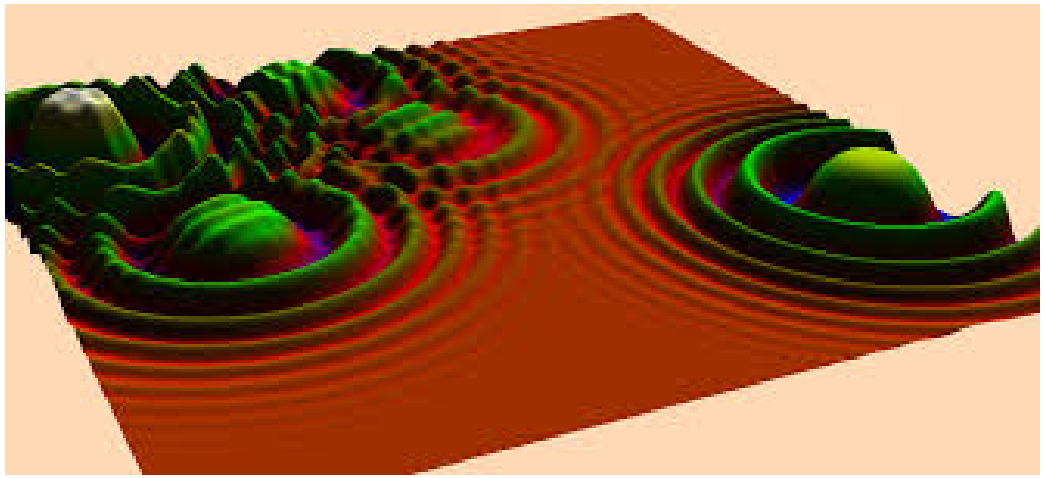
Ranking functions $f_1, f_2 : \mathcal{Q} \times \mathcal{D} \to \mathbb{R}_+^*$. How can we say that f_1 is better than f_2?
Can use the expected NDCG(q, f_i) summary statistic:

$$\rho_i = \frac{1}{Q} \sum_q \text{NDCG}(q, f_i)$$

As usual, averaging can hide bad performance when the gold standard is dominated by high performance on many similar queries.

Learning the parameters

Having a gold standard not only allows evaluation, but also optimization of the parameters.



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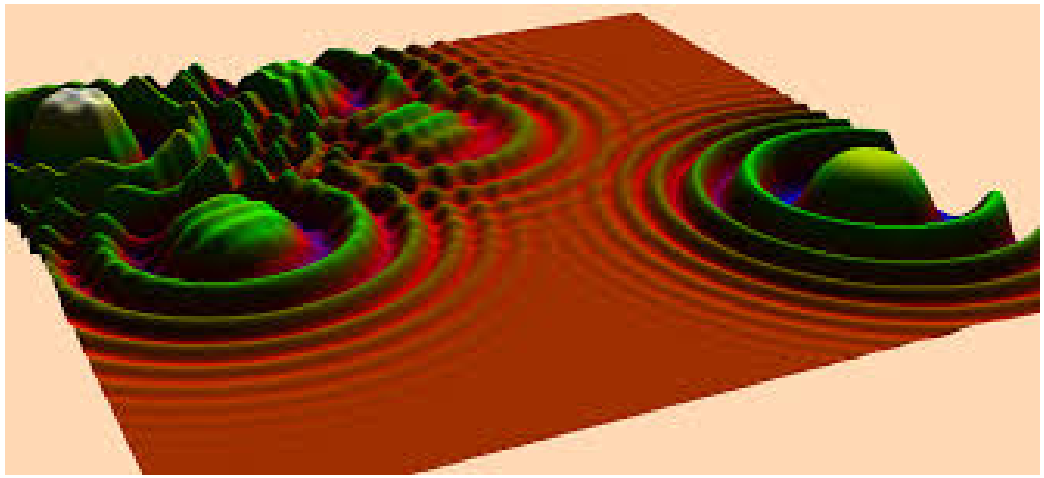

What parameters are we talking about?

Some parameters to tune

At the semantics level:

- Tokenization (parameters in *phrase as tokens* cf. patent in 1st tutorial session)

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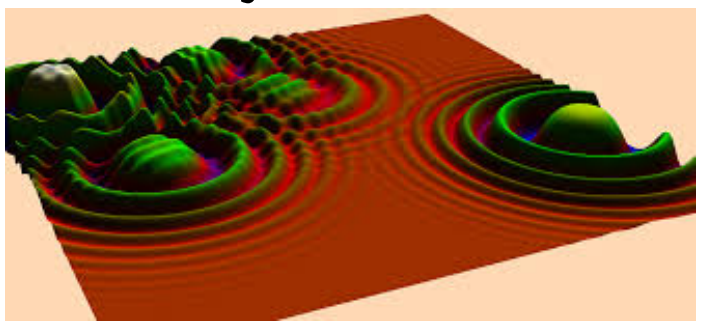
But also...

...the **trade-off** between the semantic scores (e.g. tf-idf vector model, text importance score) and the authority ranking score.

Optimize the objective function by tuning the parameters

$$\text{obj} : \mathbb{R}^p \to \mathbb{R}$$



This is an optimization problem:

$$\arg\max_{\mathbb{R}^p} \text{obj}$$

One can therefore use optimization strategies to maximize performance indicators by tuning p parameters.

Why not going further?

Why learning only few parameters?

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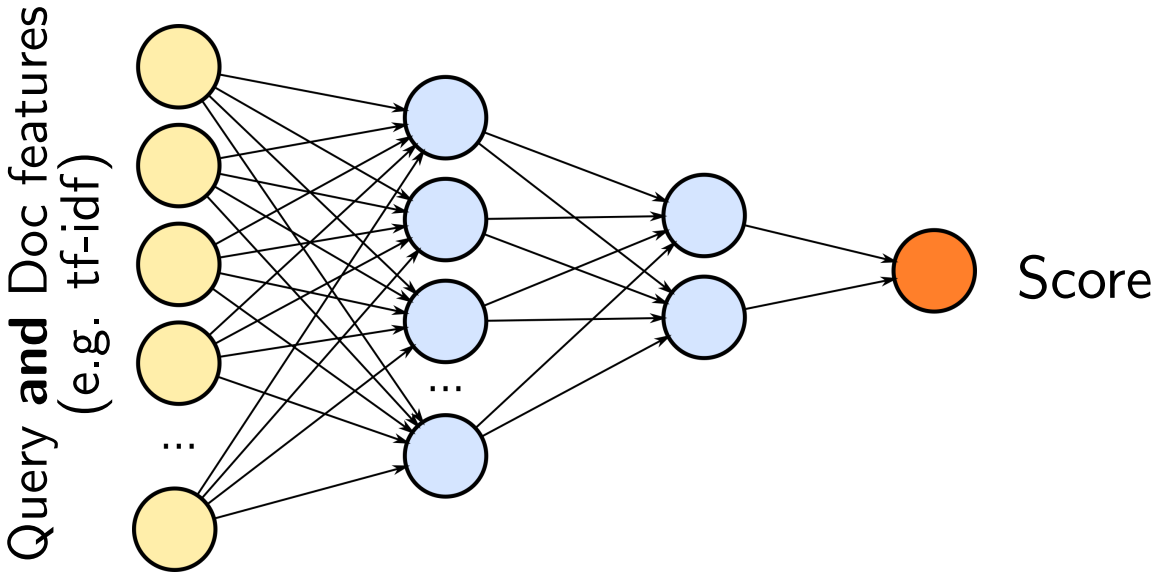
Why learning only few parameters? Why not learning directly:



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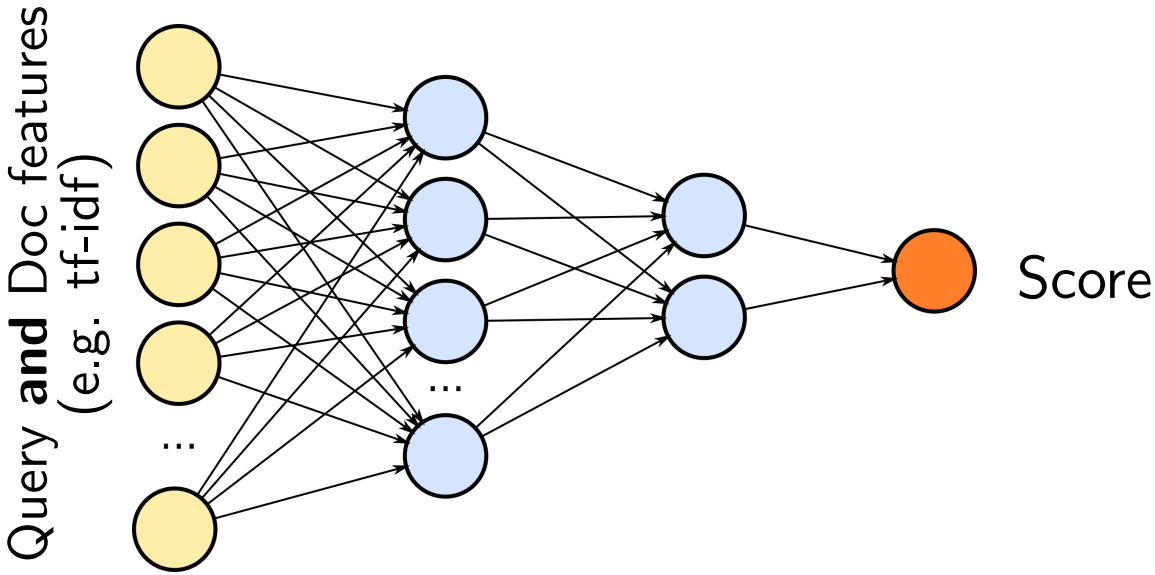

Issue

Curse of dimensionality, training set limitation, overtraining.

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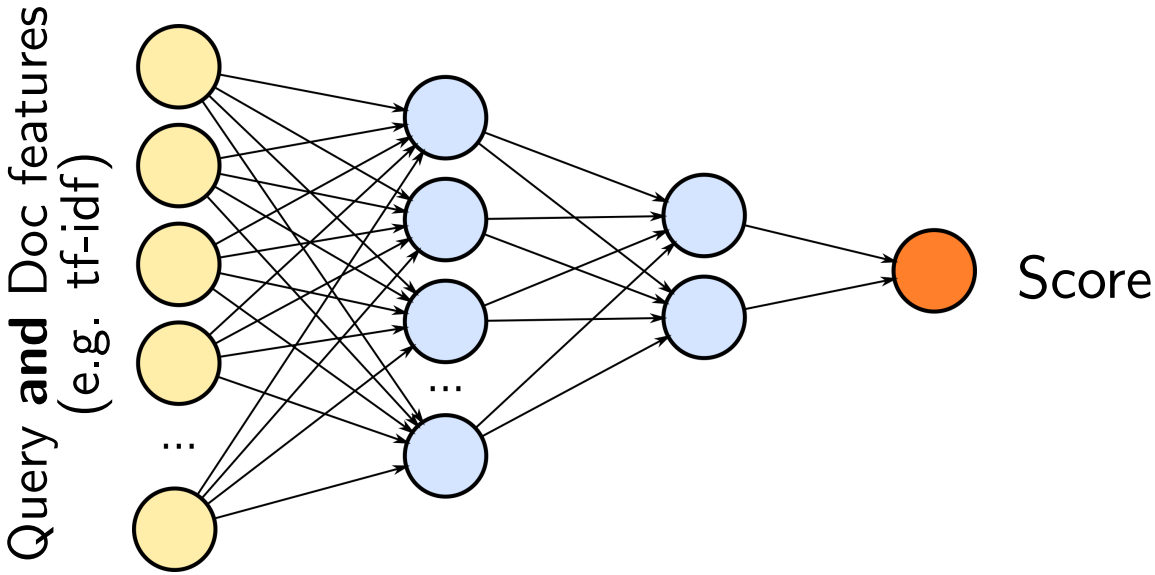

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Way out

Decrease the number of features or/and **expand the training set**.

Increasing the training set

If you own a popular search engine, imagine a simple way of increasing your training set.

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Click-through strategy: $g : (q, d) \mapsto$ nb of clicks on d

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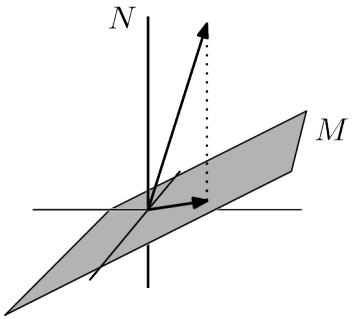

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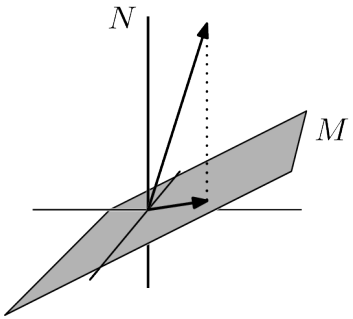
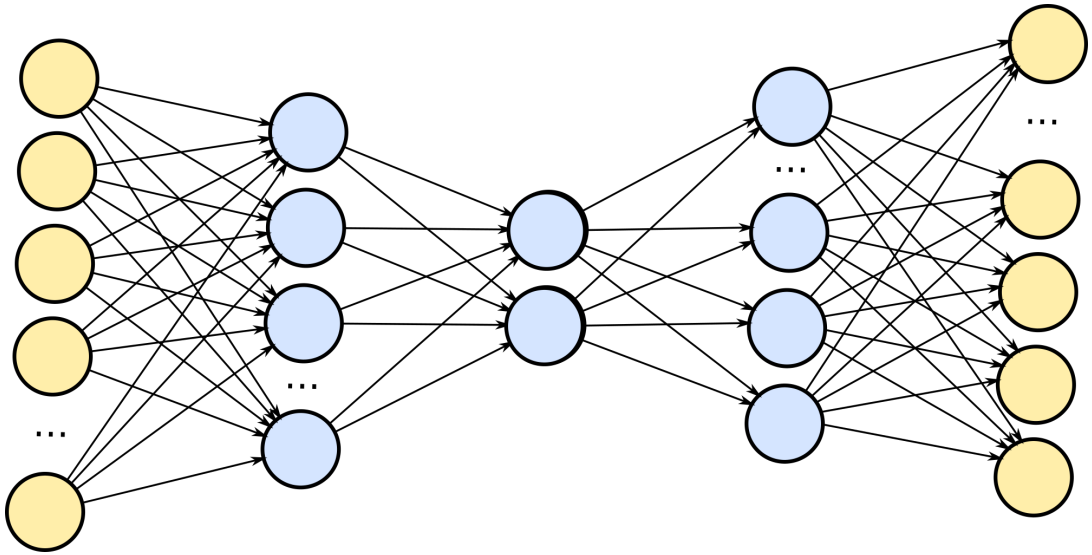
What dimensionality reduction technique have we seen before?



Note that for reducing the dimension we do not lack of data! The Internet is big enough :)

$\rightarrow$ More powerful techniques such as autoencoders.

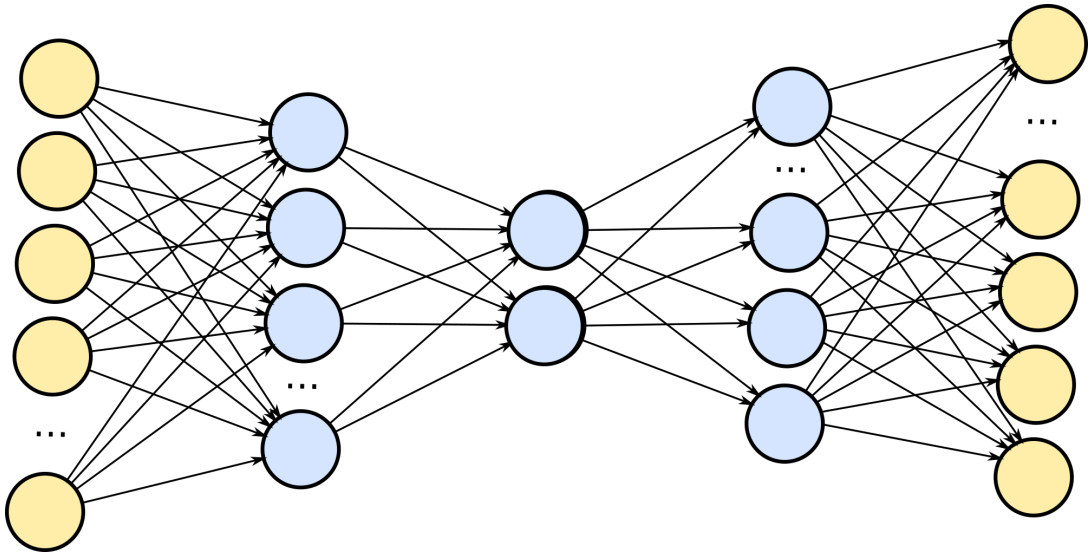
Autoencoders



If you were an autoencoder...

If you were an autoencoder with **few** intermediate neurons, how would you encode a document?

Autoencoders



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If one wants to minimize the loss between the input and the output, a neuron of the intermediate layer represents a topic, or a concept.

Wrap-up I

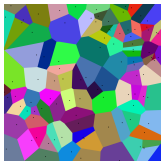
WIKIPEDIA
The Free Encyclopedia

Main page
Contents

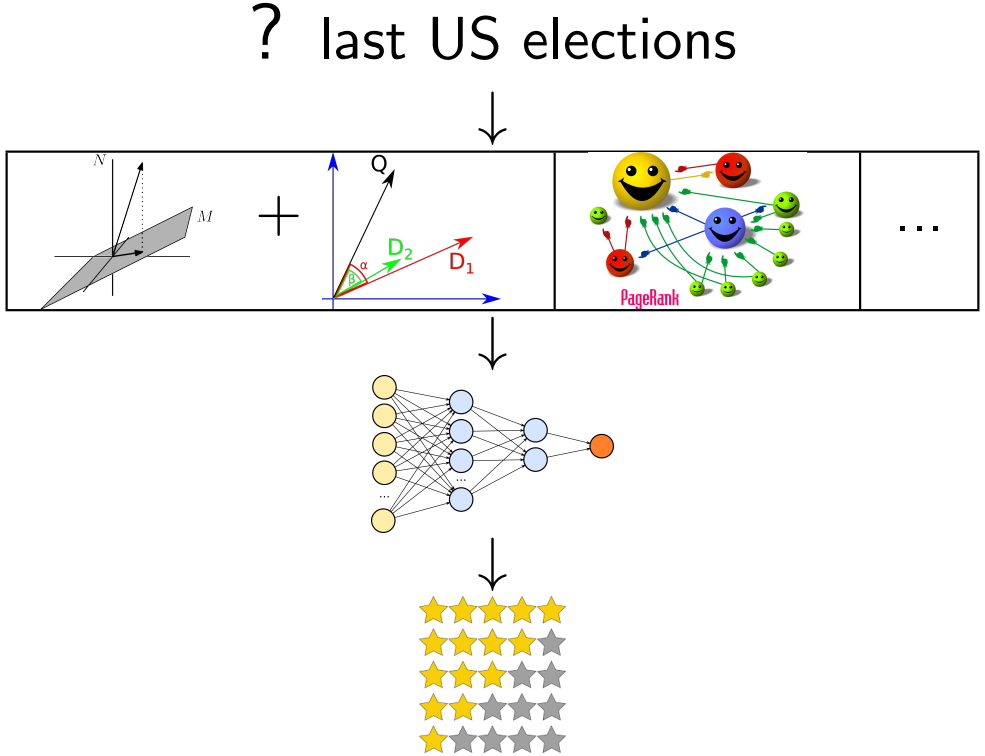
Information retrieval

From Wikipedia, the free encyclopedia

Information retrieval (**IR**) is the activity of obtaining information system resources relevant to an information need from a collection of information resources. Searches can be based on full-text



Wrap-up II



Hope you enjoyed.

Find the material on `http://clovisg.github.io`

Extras