



Università degli Studi di Padova



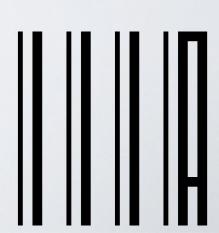
Evaluation of Quantum Computing for IR and RS

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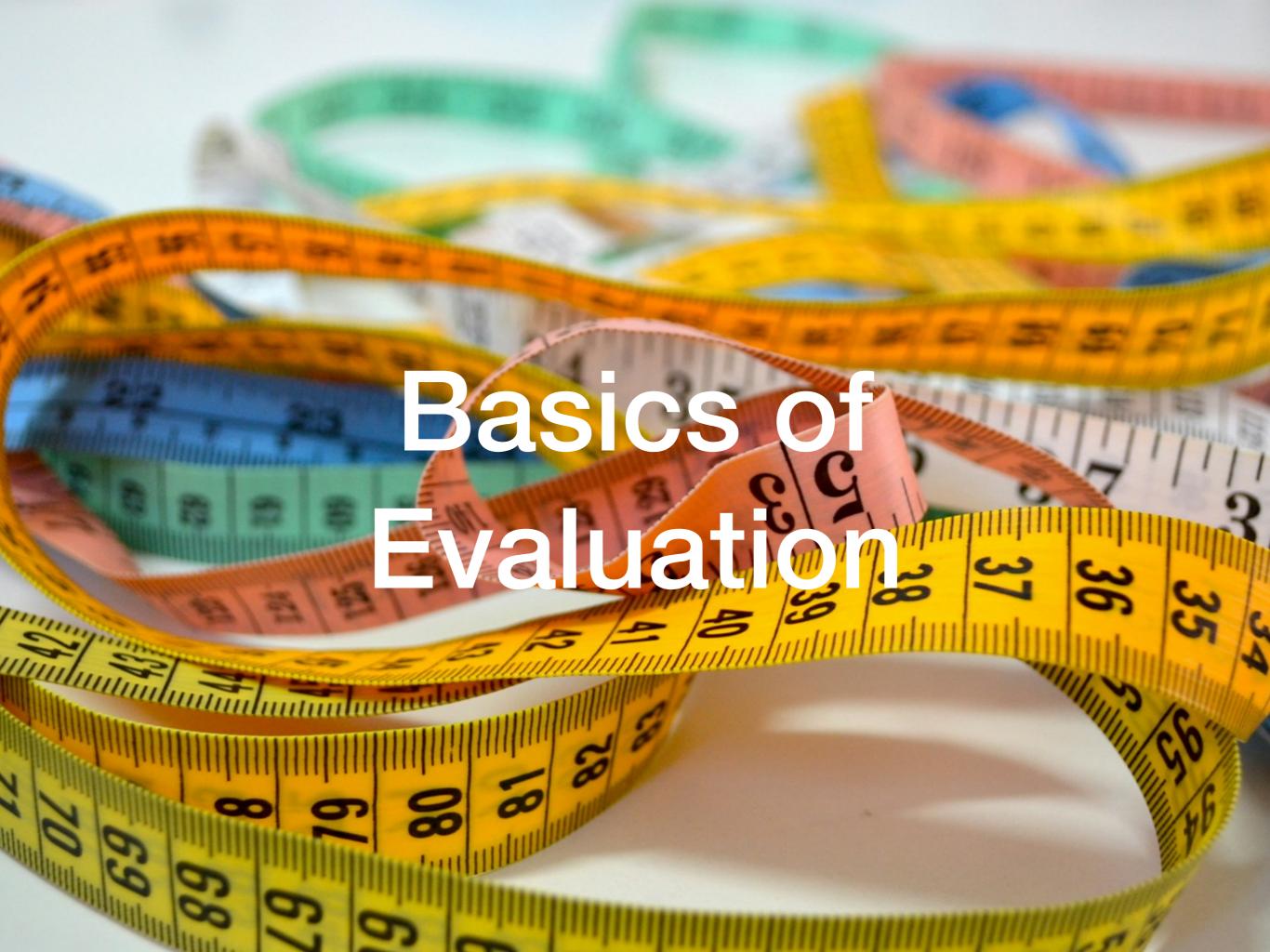


Outline



Basics of Evaluation

QuantumCLEF

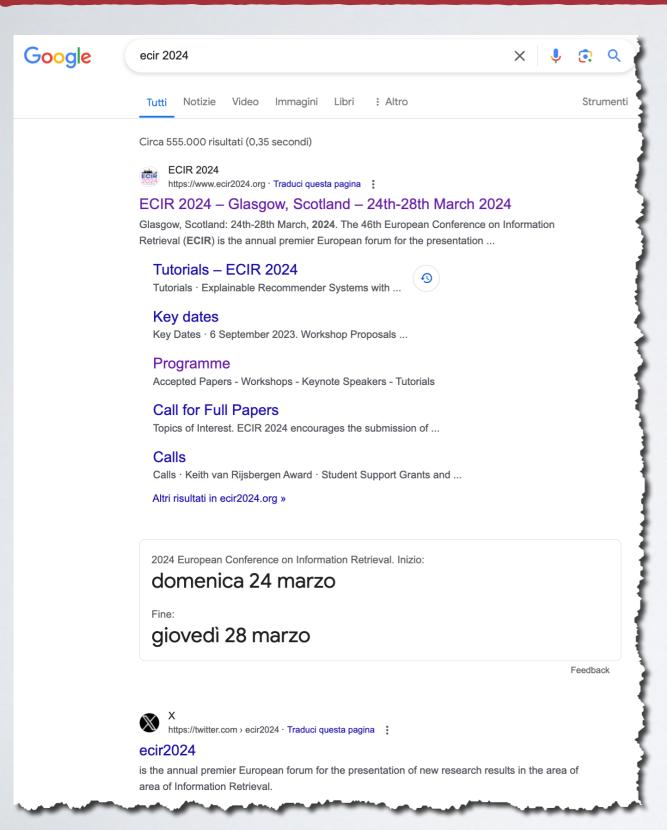


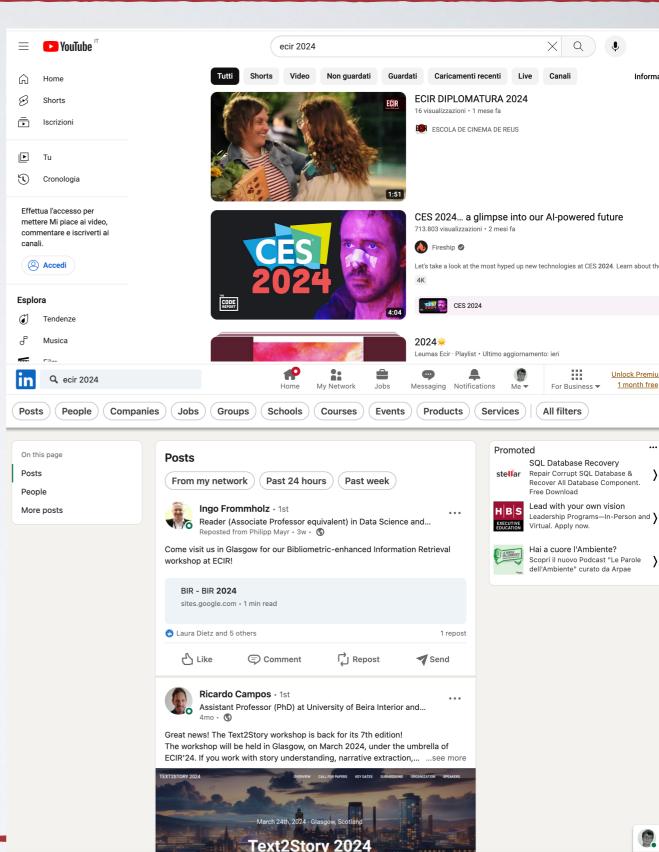


Our Goal

© Nico



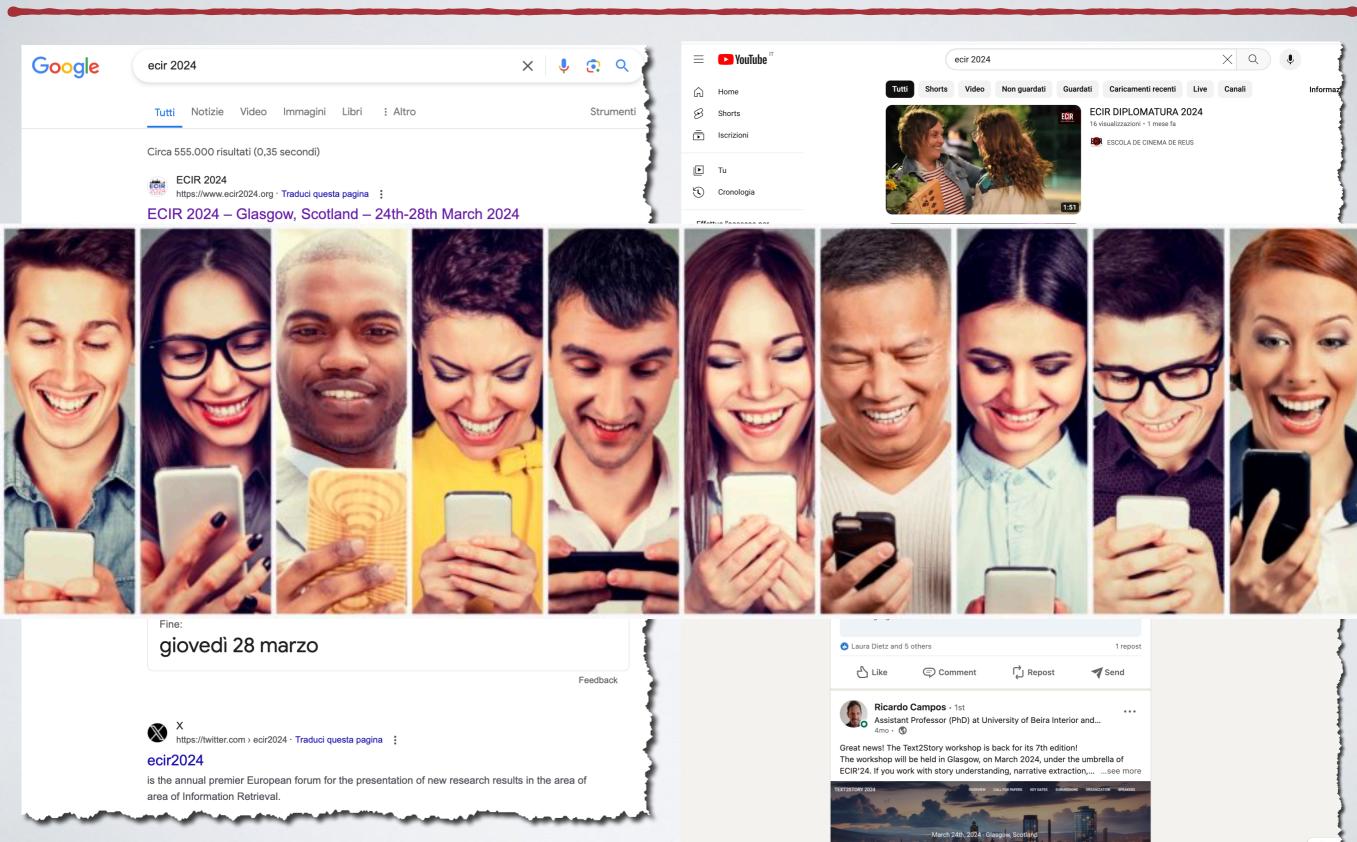






Our Goal





Text2Story 2024



Why Evaluation?





"To measure is to know"

"If you cannot measure it, you cannot improve it"

Lord William Thompson, first Baron Kelvin (1824-1907)



What to Evaluate?



Efficiency



Effectiveness



VS



Critical Issues in Evaluation



- It must be scientifically valid
 - valid methodology, measures, and statistics
 - large-scale enough to be statistically valid
 - must be "repeatable" if possible

- It must be realistic for the applications that will be using the information retrieval systems
 - task and use cases

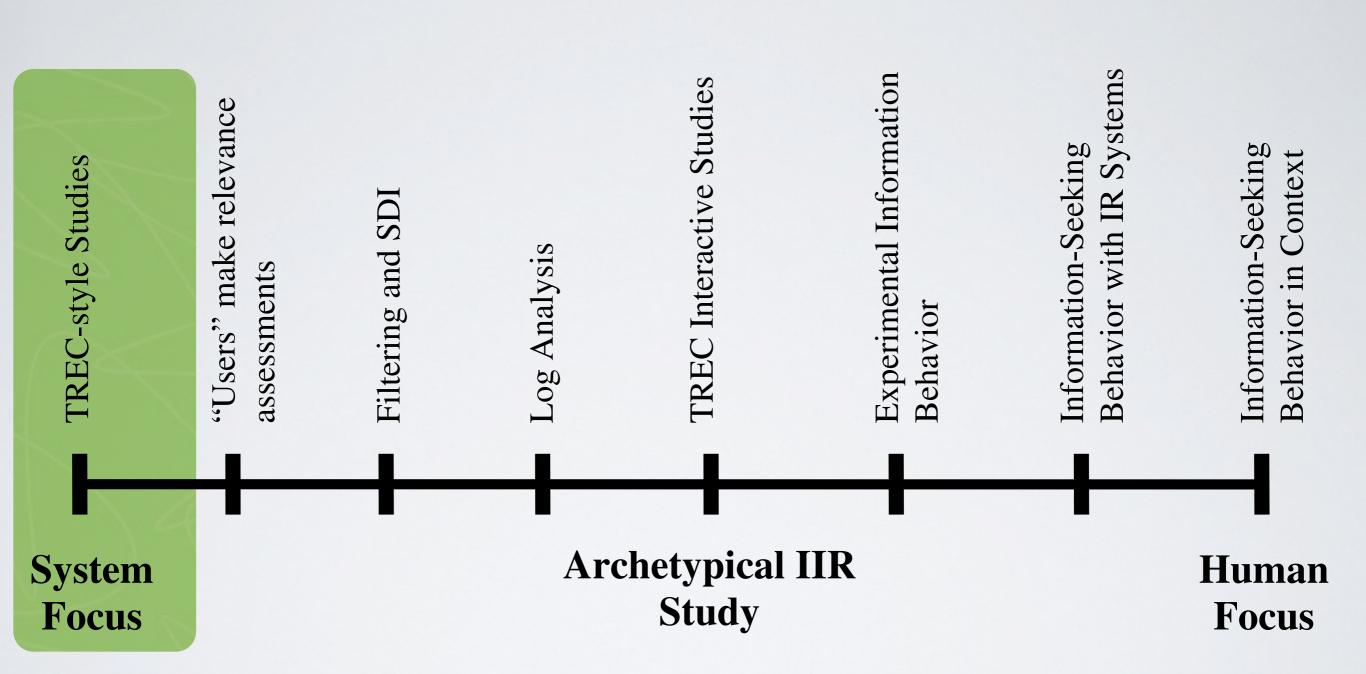
It must be understandable to your audience/client

Harman, D. K. (2011). Information Retrieval Evaluation. Morgan & Claypool Publishers, USA.



Evaluation Spectrum





Kelly, D. (2009). Methods for evaluating interactive information retrieval systems with users. Foundations and Trends in Information Retrieval (FnTIR), 3(1-2), 1-224.

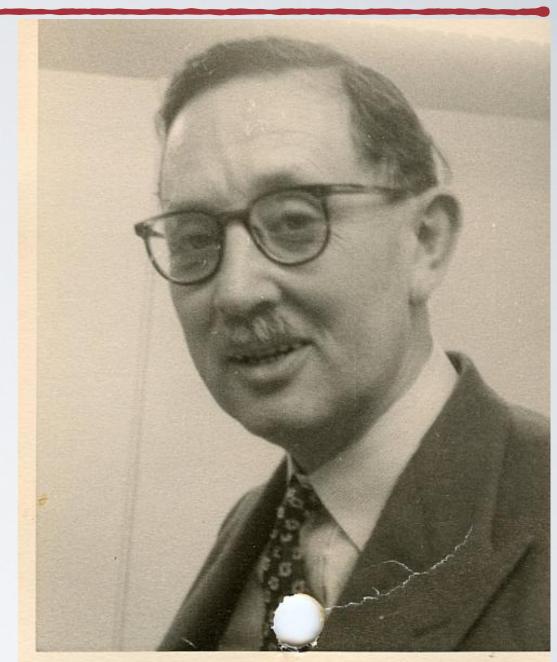


How Does Experimental Evaluation Work



- Cranfield Paradigm by Cyril W. Cleverdon
 - Dates back to mid 1960s
- Makes use of experimental collections
 - documents (corpora)
 - **topics**, which are a surrogate for information needs
 - relevance judgments (binary or graded) also called relevance assessment or ground-truth (or qrels)





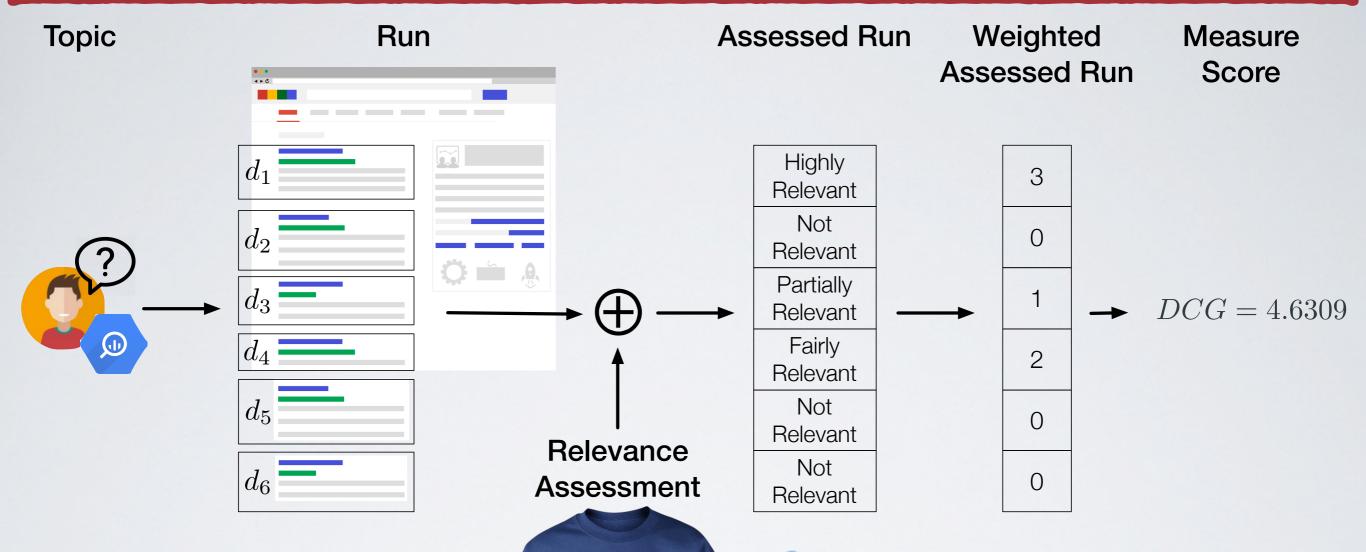
Cyril W. Cleverdon

Cleverdon, C. W. (1962). Report on the Testing and Analysis of an Investigation into the Comparative Efficiency of Indexing Systems. Aslib Cranfield Research Project, College of Aeronautics, Cranfield, UK. Cleverdon, C. W. (1997). The Cranfield Tests on Index Languages Devices. In Spärck Jones, K. and Willett, P., editors, Readings in Information Retrieval, pages 47–60. Morgan Kaufmann Publisher, Inc., San Francisco, CA, USA.



Evaluation with Test Collections in a Nutshell





- Since we use set of topics, we can average the performance of a system over them
- We can compare two systems A and B run on the same test collection by comparing their average performance or, much better, by using statistical significance tests

Sanderson, M. (2010). Test Collection Based Evaluation of Information Retrieval Systems. Foundations and Trends in Information Retrieval (FnTIR), 4(4):247–375.

KEEP CALM

Assessor



A Taxonomy of Evaluation Measures

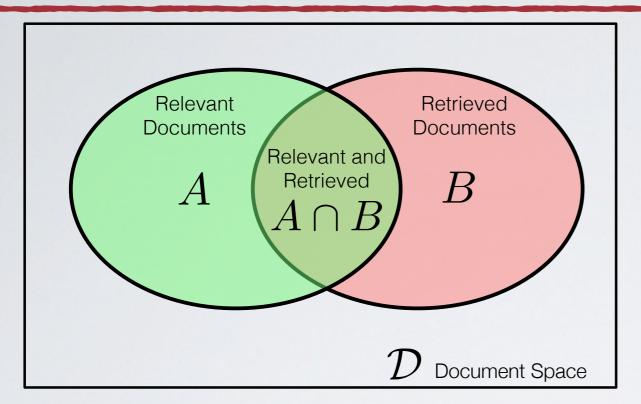


	Set-Based Retrieval	Rank-Based Retrieval
Binary Relevance	Precision (P) Recall (R) F-measure (F)	Precision at Document Cut-off (P@k) Recall at Document Cut-off (R@k) R-Precision (Rprec) Average Precision (AP) Rank-Biased Precision (RBP)
Multi-graded Relevance	Not widely agreed generalizations of Precision and Recall	Discounted Cumulated Gain (DCG)



Set-based Measures: Precision, Recall and F-measure





$$P = \frac{|A \cap B|}{|B|} \qquad R = \frac{|A \cap B|}{|A|}$$

$$F = \frac{2}{\frac{1}{P} + \frac{1}{R}} = 2\frac{P \cdot R}{P + R}$$

- Precision is the the proportion of retrieved documents that are actually relevant
- Recall is the the proportion of relevant documents actually retrieved
- Together, Precision and Recall measure retrieval effectiveness, meant as the ability of a system
 to retrieve relevant documents while at the same time holding back non-relevant ones
 - maximizing Precision and Recall corresponds to optimal retrieval in the sense of the **Probability Ranking Principle**, i.e. ordering documents by their decreasing probability of being relevant, and creates a tight link between retrieval models and evaluation
- F-measure is the harmonic mean of Precision and Recall, summarising them into a single score

van Rijsbergen, C. J. (1974). Foundations of Evaluation. *Journal of Documentation*, 30(4):365–373. van Rijsbergen, C. J. (1981). Retrieval effectiveness. In Spärck Jones, K., editor, *Information Retrieval Experiment*, pages 32–43. Butterworths, London, United Kingdom.



Rank-based Measures: Average Precision



$$AP = \frac{1}{RB} \sum_{k \in \mathcal{R}} P(k) = \frac{1}{RB} \sum_{n=1}^{N} \left(\frac{1}{n} \sum_{m=1}^{n} r_m \right) r_n =$$

$$= \frac{rr}{RB} \cdot \frac{1}{rr} \sum_{k \in \mathcal{R}} P(k)$$
Recall arithmetic mean of $P(k)$

where

- ullet is the set of the rank positions of the relevant retrieved documents
- $oldsymbol{r} r = |\mathcal{R}|$ is the total number of relevant retrieved documents
- ullet N is the total number of retrieved documents, i.e. the length of the run



Chris Buckley

- The Mean Average Precision (MAP) is the mean of AP over a set of topics
 - Differently from the other measures, this mean has its own name since it is the most widely used single number to summarise the whole performance of a system

Buckley, C. and Voorhees, E. M. (2005). Retrieval System Evaluation. In Harman, D. K. and Voorhees, E. M., editors, *TREC. Experiment and Evaluation in Information Retrieval*, pages 53–78. MIT Press, Cambridge (MA), USA.



Rank-based Measures: Discounted Cumulated Gain



$$DCG(k) = \begin{cases} \sum_{n=1}^{k} r_n & \text{if } k < b \\ DCG(k-1) + \frac{r_k}{\log_b(k)} & \text{if } k >= b \end{cases} = \sum_{n=1}^{k} \frac{r_n}{\max(1, \log_b(n))}$$

- ullet where the base of the logarithm b indicates the patience of the user in scanning the result list
 - $lackbox{0}{\hspace{0.1cm}} b=2$ is an impatient user
 - $lackbox{0}{\hspace{0.1cm}} b=10$ is a patient user
- DCG naturally handles multi-graded relevance
- DCG does not depend on the recall base
- DCG is not bounded in [0, 1]

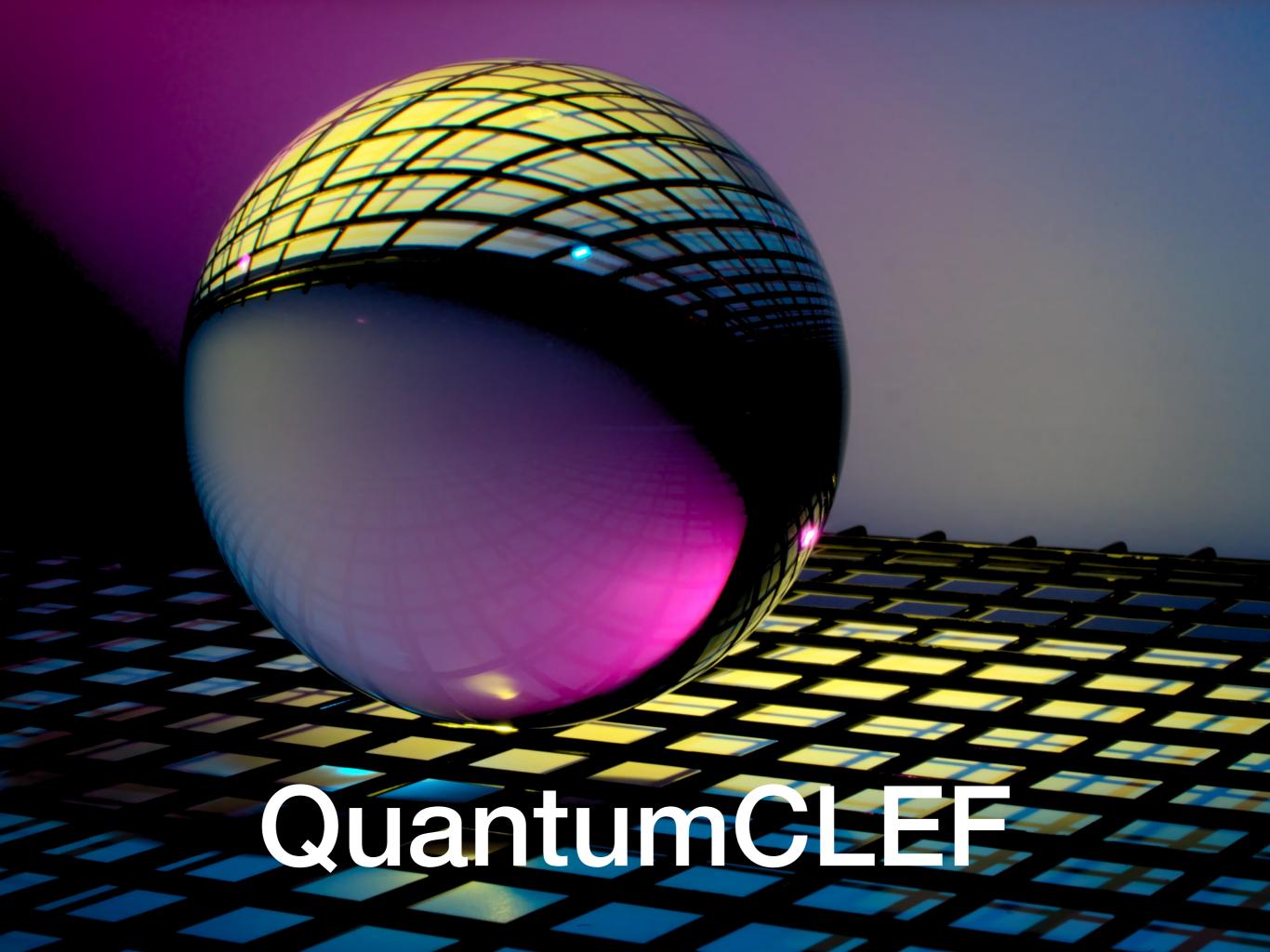


Kalervo Järvelin



Jaana Kekäläinen

Järvelin, K. and Kekäläinen, J. (2002). Cumulated Gain-Based Evaluation of IR Techniques. ACM Transactions on Information Systems (TOIS), 20(4):422-446

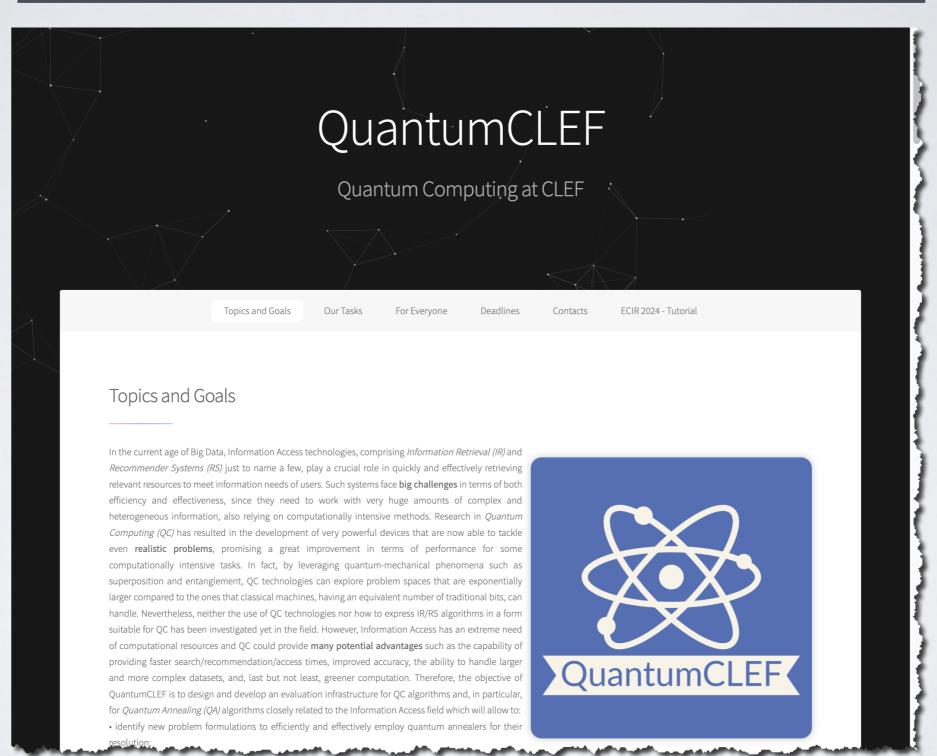




QuantumCLEF



https://qclef.dei.unipd.it/





Task 1: Feature Selection



- Task 1A IR: Select the most relevant features in the considered datasets to train a LambdaMART
 - A baseline is computed using Recursive Feature Elimination (RFE) with the Logistic Regression classifier
 - Datasets: MQ2007/LETOR and iSTELLA (challenging because of number of features)
 - Measure: nDCG@10
- Task 1B RS: The task is to select the subset of features that will produce the best recommendation quality when used for an Item-Based KNN recommendation model
 - A baseline is computed using features selected by a bayesian search optimizing the model recommendation effectiveness

Feature Selection

Subset of Features

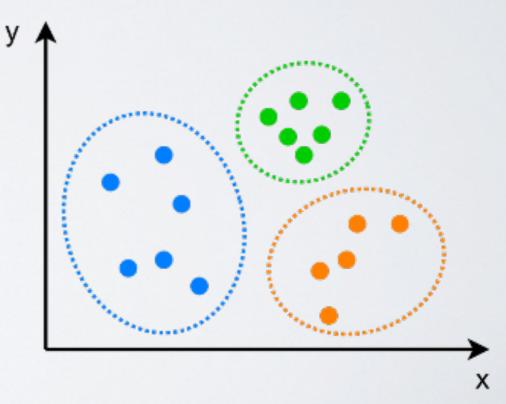
- Datasets: 150_ICM and 500_ICM (music recommendation)
- Measure: nDCG@10



Task 2: Clustering



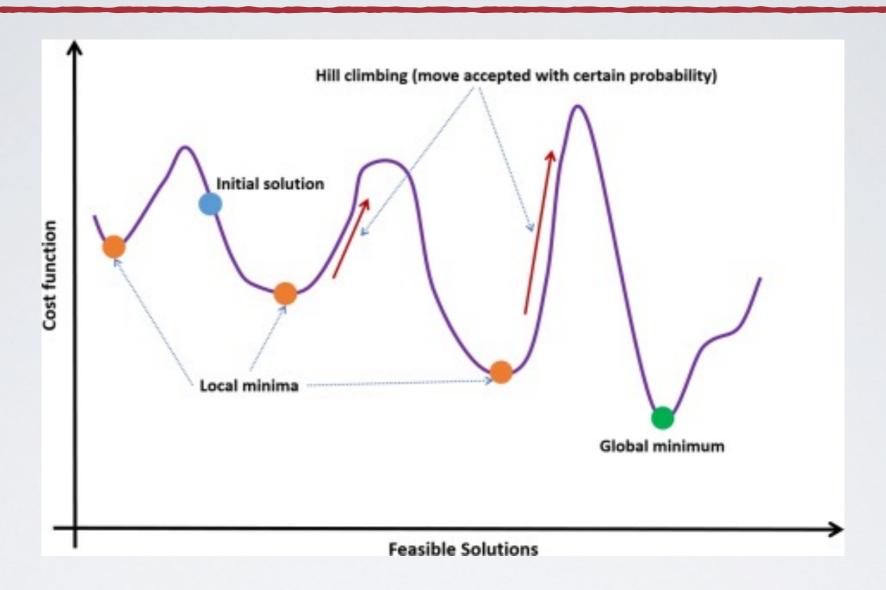
- Use QA to cluster different documents in the form of embeddings to ease processing of large collections
 - Obtain a list of representative centroids of the given dataset of embeddings
 - Search will be restricted to the clusters that are most likely to contain relevant documents, thereby reducing the search space and improving retrieval speed
- Dataset: ANTIQUE dataset
- Measure:
 - the Davies-Bouldin Index will be used to measure the overall cluster quality
 - the nDCG@10 will be used to measure the overall retrieval quality





Simulated Annealing



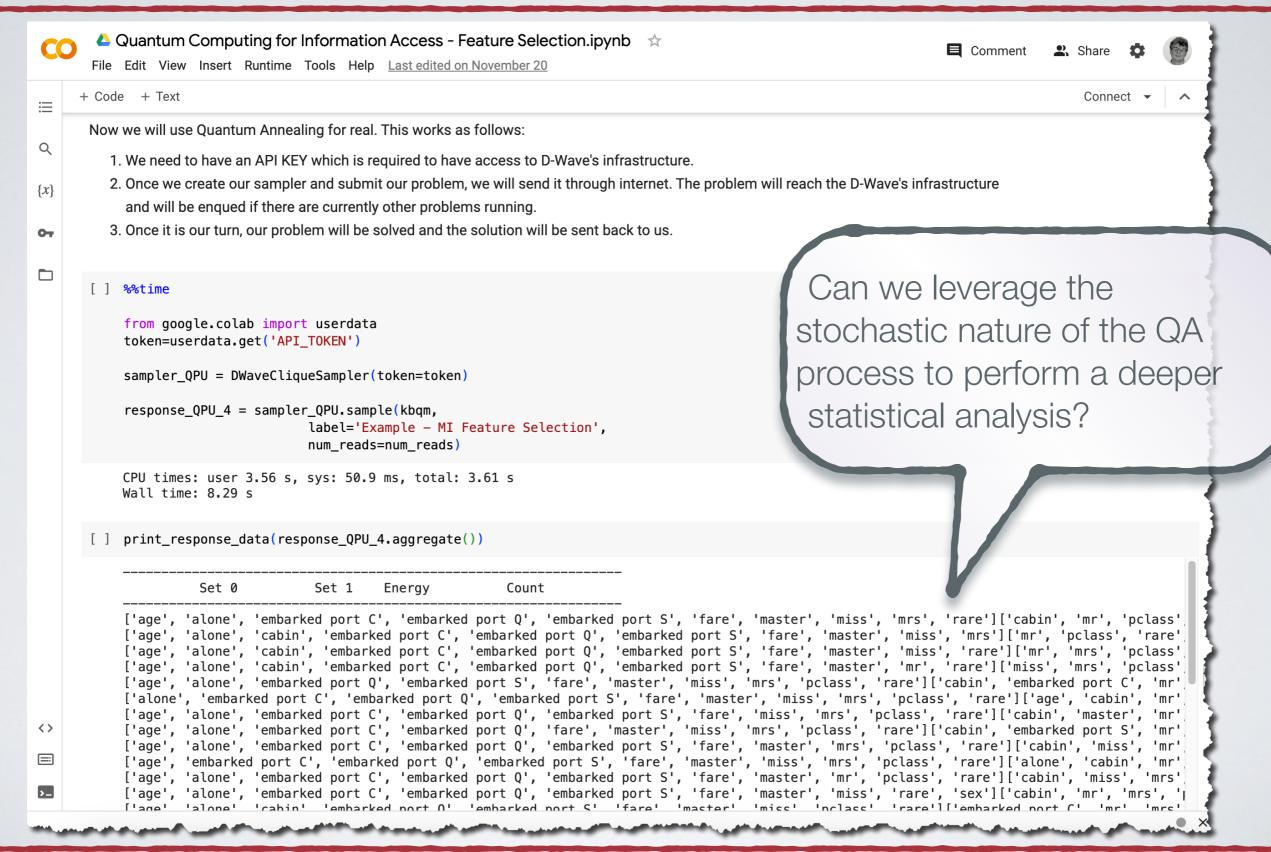


 For both tasks (Feature Selection and Clustering), the QA approach will be compared against a SA approach, using the same QUBO formulation



Effectiveness Challenges



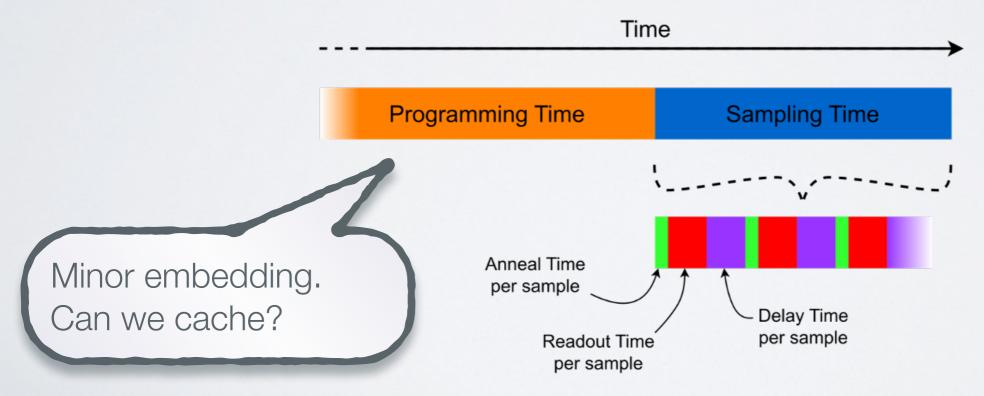




Efficiency Challenges



- There is not a standard way to measure the efficiency of Quantum Annealers
- There are several steps in the Annealing phase, each requiring a different amount of time based also on the used quantum annealer



Resch Resch, S. and Karpuzcu, U. R. (2022). Benchmarking Quantum Computers and the Impact of Quantum Noise. ACM Computing Surveys (CSUR), 54(7):142:1–142:35.



QuantumCLEF Infrastructure



