Introduction to Search Relevance Ranking- Session I

Tutorial Link: https://dlranking.github.io/dlrr/

Data source: https://huggingface.co/datasets/xglue

XGLUE: A New Benchmark Dataset for Cross-lingual Pre-training, Understanding and Generation)

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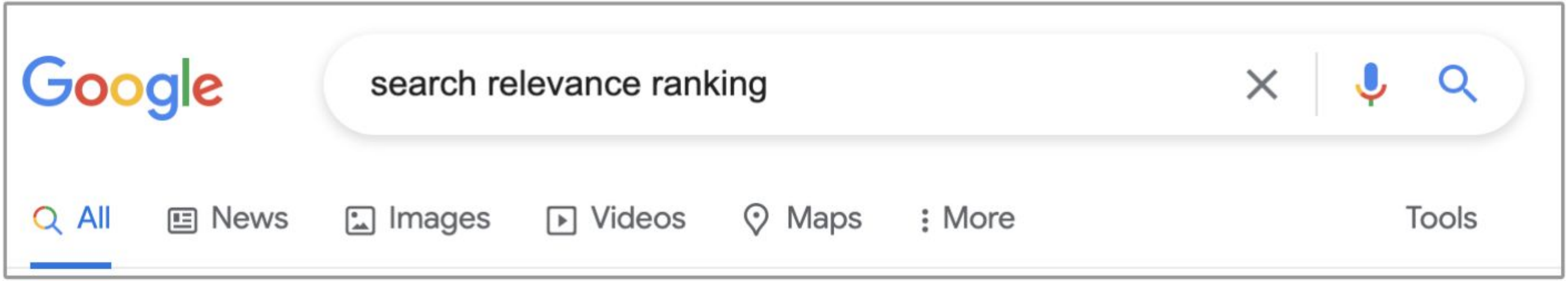
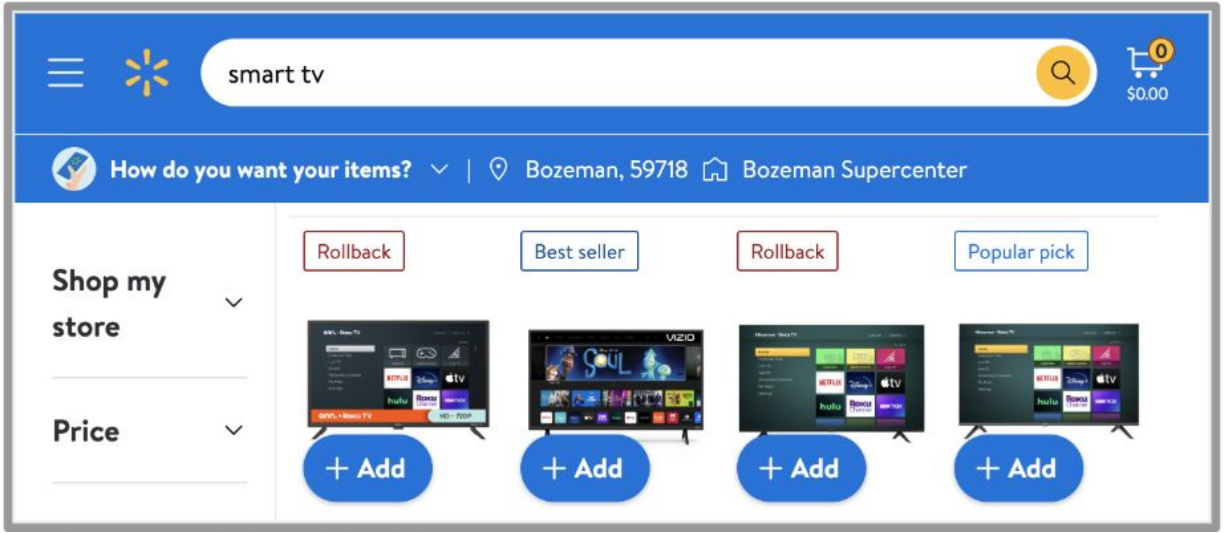
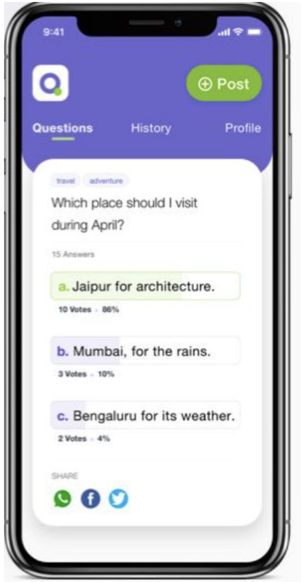
Agenda

- Overview of search relevance ranking
- Traditional IR models
- Machine Learning approaches
- Evaluation Metrics
- Data Set (xglue)
- Hands-on Session







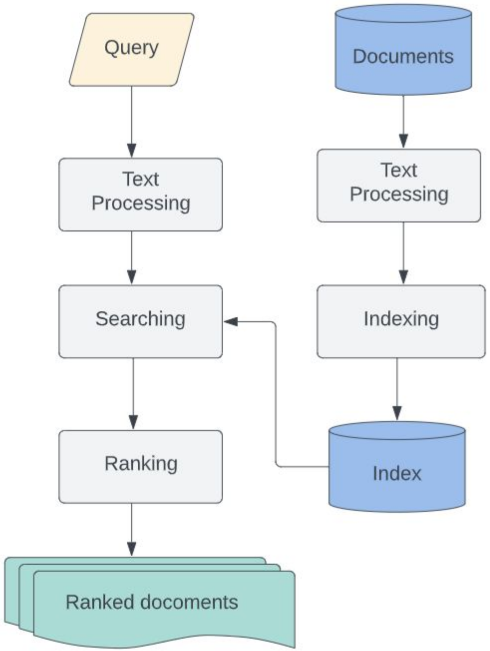
Applications

Information Retrieval System-IR system

Given a query (q) and a collections (d) of documents, relevance ranking algorithms /models determine how relevant each document is for the given query.

for each input x = (q, d) where q is a query and d is a document;

r= f(x) is relevance score function for each input.



IR Ranking Algorithms

IR Ranking Algorithms

Ranking model can be implemented by various approaches:

- Vector space Model
- Probabilistic Model: BM25
- Learn to Rank (machine learning approaches)

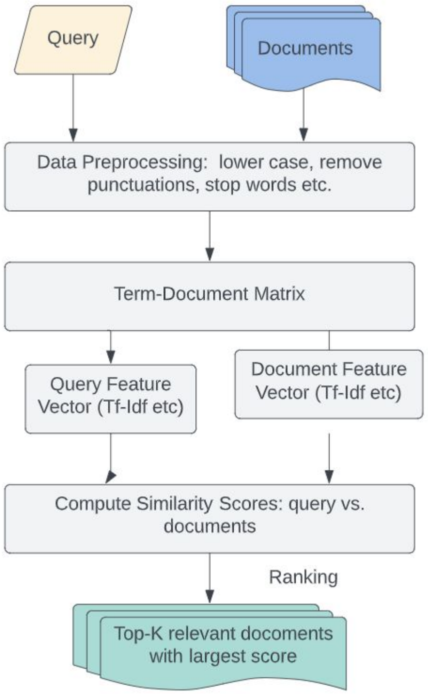
IR Ranking Algorithms -Vector space Model

1. **What is vector space model?**

   Compute a vector (e.g. using TF-IDF, Word2Vec, Doc2Vec, BERT etc) for each query and document, and then compute the relevance score ***f*(*x*) = *f*(*q*, *d*)** as the similarity distance between the vectors of ***q*** and ***d***.

2. **Similarity Metrics:**

   a. Cosine Similarity
   b. Jaccard distance
   c. Kullback-Leibler divergence
   d. Euclidean distance



IR Ranking Algorithms - Vector space Model

3. Algo: Given a set of points **D** (i.e. documents) in vector space **M** and a query point **q** $\in M$**,** find the closest point **D** to **Q (i.e.** queries).

Steps:

(1) Vectorize all documents – that gives **D**.
(2) Vectorize the query – that gives **Q**.
(3) Compute distance **d** between **Q** and **D**
(4) Sort documents in **D** in descending order- providing indices of most similar documents in D.
(5) Return top-k of D

IR Ranking Algorithms -Vector space Model

4. Example: (TF-IDF vector feature)

- TF= term frequency is the number of times a term occurs in a document
- IDF= inverse of the document frequency, given as : IDF= log(N/df), where df is the document frequency-number of documents containing a term

For instance: total number of documents =2 ; TF matrix and IDF matrix are given:

Terms/Docs	d1	d2	query
t1(machine)	1	0	1
t2(learning)	1	0	1
t3(models)	1	1	0
t4(and)	1	1	0
t4(applications)	0	1	0

DF	IDF
1	0.3
1	0.3
2	0
2	0
1	0.3

IR Ranking Algorithms - Vector space Model

TF-IDF Matrix			
Term/Docs	d1	d2	query
t1(machine)	0.3	0	0.3
t2(learning)	0.3	0	0.3
t3(models)	0	0	0
t4(and)	0	0	0
t4(applications)	0	0.3	0

IR Ranking Algorithms - BM25

BM25 (Best Match 25)

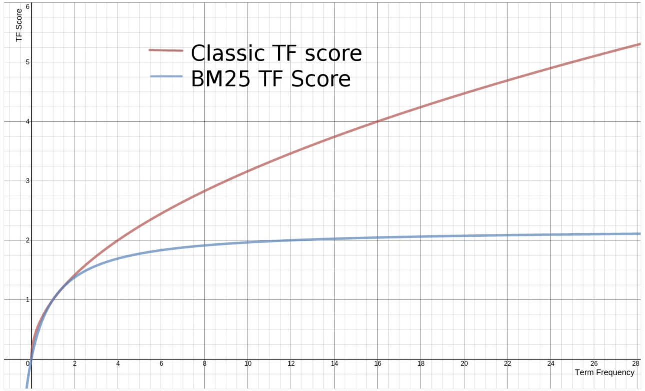
- Improves upon TF-IDF by treating relevance as a probability problem
- Formula:

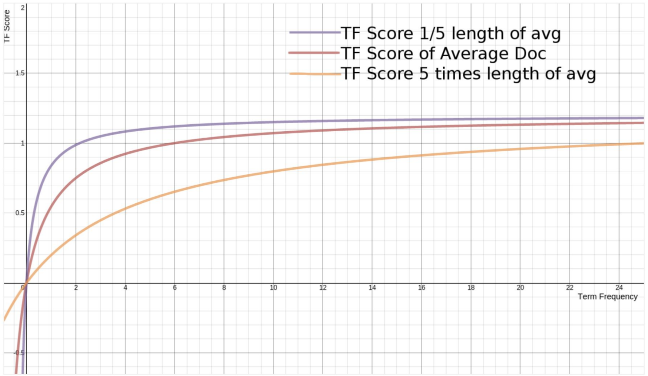
$$\text{BM25}(D, Q) = \sum_{i=1}^{n} IDF(q_i, D) \frac{f(q_i, D) \cdot (k_1 + 1)}{f(q_i) + k_1 \cdot (1 - b + b \cdot |D|/d_{avg}))}$$

- f(qi,D) is the number of times of query term qi occurs in Document
- |D| is the number of words in document D
- D_avg is the average number of words per document
- B and k1 are hyperparameters of BM25

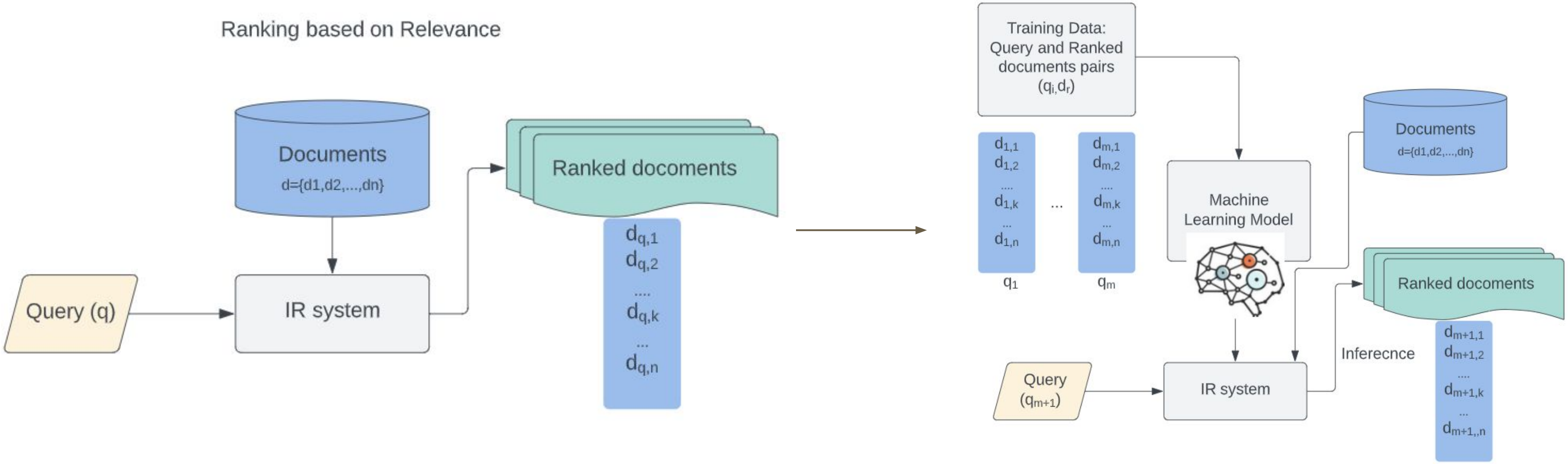
IR Ranking Algorithms - BM25

- f(qi,D) is “how many times does the ith query term occur in document D?”. The more times the query term(s) occur a document, the higher its score will be.
- k1 is a variable which helps determine TF(term frequency) saturation . The higher the value, the slower the saturation.
- |D|/d_avg : the more terms in the document that does not match input query, the lower the document's score should be.
- b (bound 0.0 ~ 1.0) : b is bigger, the effects of the document length compared to the average length are more amplified.





IR Ranking Algorithms - machine learning approaches

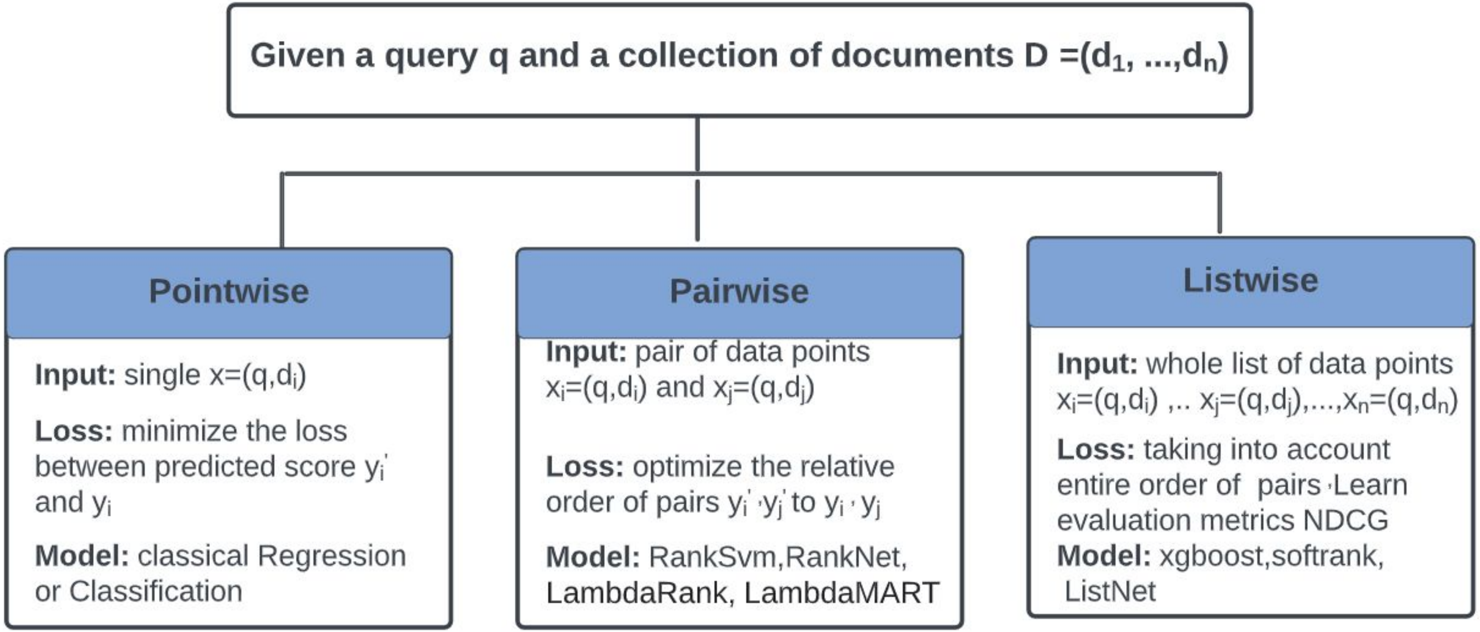


Traditional

Machine learning

Reference: A Short Introduction to Learning to Rank

IR Ranking Algorithms - machine learning approaches



Evaluation Metrics

Evaluation Metrics

- Binary assessments:
  - Precision: fraction of recommended docs that are relevant = P(relevant|recommended)
  - Recall: fraction of relevant docs that are recommended = P(recommended|relevant)

	Relevant	NonRelevant
Recommended	TP	FP
Not-Recommended	FN	TN

Precision = TP/(TP+FP) = # of recommendations are relevant/# of items are recommended

Recall = TP/(TP+FN) = # of recommendations are relevant/# of all possible relevant items

Evaluation Metrics

- Binary relevance
  - Precision@K (P@K)
  - Recall@K(R@K)
  - Mean Average Precision (MAP)

- Multiple levels of relevance
  - Normalized Discounted Cumulative Gain (NDCG)

Evaluation Metrics

Precision @k: precision evaluated only up to the k-th prediction

$$\text{Precision@}k = \frac{true\ positives\ @k}{(true\ positives\ @k) + (false\ positives\ @k)} = \frac{\#\,of\ recommended\ items\ @k\ that\ are\ relevant}{\#\,of\ recommended\ items\ @k}$$

k	DocID	PredictedRelevanceScore	GroudTruthRelevance (1/0)	Precision@k
1	3	0.93	1	1
2	6	0.86	0	0.5
3	1	0.76	1	0.67
4	36	0.65	1	0.75
5	42	0.43	0	0.6
6	64	0.21	1	0.67
7	25	0.13	0	0.57

$$\text{Precision@4} = \frac{\text{true positives @4}}{(\text{true positives @4}) + (\text{false positives @4})}$$

$$= \frac{3}{3+1}$$

$$= 0.75$$

Evaluation Metrics

Recall @k: Recall evaluated only up to the k-th prediction

$$\text{Recall@}k = \frac{true\ positives\ @k}{(true\ positives\ @k) + (false\ negatives\ @k)}$$

k	DocID	PredictedRelevance Score	GroudTruthRelevance (1/0)	Recall@k
1	3	0.93	1	0.25
2	6	0.86	0	0.25
3	1	0.76	1	0.5
4	36	0.65	1	0.75
5	42	0.43	0	0.75
6	64	0.21	1	1
7	25	0.13	0	1

$$\text{Recall@}4 = \frac{true\ positives\ @4}{(true\ positives\ @4) + (false\ negatives\ @4)}$$

$$= \frac{3}{3+1}$$

$$= 0.75$$

Ranking Performance Metrics

MAP(Mean Average Precision): Average Precision across multiple queries/rankings; or it is a simple average of AP over all examples in a validation set.It is a simple average of AP over all examples in a validation set.

k	GroudTruthRelevance1(1/0)	GroudTruthRelevance2(1/0)	Precision1@k	Precision2@k
1	1	1	1	1
2	0	0	0.5	0.5
3	1	1	0.67	0.67
4	1	1	0.75	0.75
5	0	1	0.6	0.8
6	1	1	0.67	0.83
7	0	0	0.57	0.71

$$AP_1 = \frac{1+0.5+0.67+0.75+0.6+0.67+0.57}{7}$$
$$= 0.68$$
$$AP_2 = \frac{1+0.5+0.67+0.75+0.8+0.83+0.71}{7}$$
$$= 0.75$$
$$MAP = \frac{0.68+0.75}{2}$$
$$= 0.715$$

- MAP is macro-averaging: each query counts equally
- MAP assumes user is interested in finding many relevant documents for each query

Ranking Performance Metrics

AP (average precision): measures how correct of a model's ranked prediction for a single data point

MAP(mean average precision): measures how correct a model's ranked predictions, on average, over a whole validation set. It is computed as mean of AP over all data points in validation set.

Ranking Performance Metrics

DCG: Discounted Cumulative Gain

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

where reli is the relevance of the document at index i, reli equals 1 if document i is relevant and 0 otherwise.

- One advantage of DCG over other metrics is that it also works if document relevances are a real number. In other words, when each document is not simply relevant/non-relevant , but has a relevance score instead.

- Uses graded relevance as a measure of usefulness, or gain, from examining a document

Two assumptions:

- Highly relevant documents are more useful than marginally relevant documents
- The lower the ranked position of a relevant document, the less useful it is for the user, since it is less likely to be examined

Ranking Performance Metrics

NDCG: Normalized Discounted Cumulative Gain

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

$$IDCG\ @k = \sum_{i=1}^{\substack{relevant\ documents\\at\ k}} \frac{2^{rel_i} - 1}{log_2(i+1)}$$

normalize the DCG score by the maximum DCG at each threshold k

.Where IDCG @k is the best possible value for DCG @k, i.e. the value of DCG for the best possible ranking of relevant documents at threshold k

Ranking Performance Metrics

k	GroudTruthRank		PreidctedRank1		PreidctedRank2	
	DocIDs	RelevanceScore	DocIDs	RelevanceScore1	DocIDs	RelevanceScore2
1	4	2	36	2	1	2
2	36	2	4	1	4	1
3	1	1	1	1	36	2
4	16	0	16	0	1	0

$$DCG = 2 + \frac{2}{\log_2 2} + \frac{1}{\log_2 3} + \frac{0}{\log_2 4} = 4.6309$$
$$DCG_1 = 2 + \frac{1}{\log_2 2} + \frac{1}{\log_2 3} + \frac{0}{\log_2 4} = 3.6309$$
$$DCG_2 = 2 + \frac{1}{\log_2 2} + \frac{2}{\log_2 3} + \frac{0}{\log_2 4} = 4.2619$$

$$MaxDGC = 4.6309$$
$$NDCG = 4.6309/4.6309 = 1$$
$$NDCG_1 = 3.6309/4.6309 = 0.7841$$
$$NDCG_2 = 4.2619/4.6309 = 0.9203$$

XGLUE dataset

XGLUE - QADSM dataset

QADSM: Microsoft Query-Ad Matching dataset

Dataset card   Files and versions   Community

Dataset Preview

Subset: qadsm

Split: train

query (string)	ad_title (string)	ad_description (string)	relevance_label (class label)
cruise portland maine	New England Cruises	Your New England Cruise Awaits! Holland America Line Official Site.	1 (Good)
transportation to cruise port miami	Holland America Line®	Explore Your World with Four Extraordinary Offers.	0 (Bad)
transportation to cruise port miami	Holland America Line®	Cruise to Your Own Private Island In the Caribbean. Learn More Now.	1 (Good)
galveston cruise parking	Caribbean Cruises	Sign Up for Offers and Explore the Caribbean with Holland America Line	0 (Bad)
cruise portland maine	Holland America Line®	Official Site - Sign Up for Special New England Cruise Offers Today.	1 (Good)
cruise portland maine	Premium Canada Cruises	Your Canada Cruise Awaits! Holland America Line Official Site.	0 (Bad)

XGLUE - QADSM dataset

Dataset size:

Train	train	(100,000, 4)
Validation	validation.en	(10,000, 4)
	validation.de	(10,000, 4)
	validation.fr	(10,000, 4)
test	test.en	(10,000, 4)
	test.de	(10,000, 4)
	test.fr	(10,000, 4)

Hands-on session

- Tutorial website: Link:
- Data Source : XGLUE: A New Benchmark Dataset for Cross-lingual Pre-training, Understanding and Generation

  Download: XGLUE (https://huggingface.co/datasets/xglue)

- Colab:
  - Vector Space Model:
  - BM25:

Thank you!