Performance Evaluation of IR Systems

CS 7263 Information Retrieval
Lecture 05

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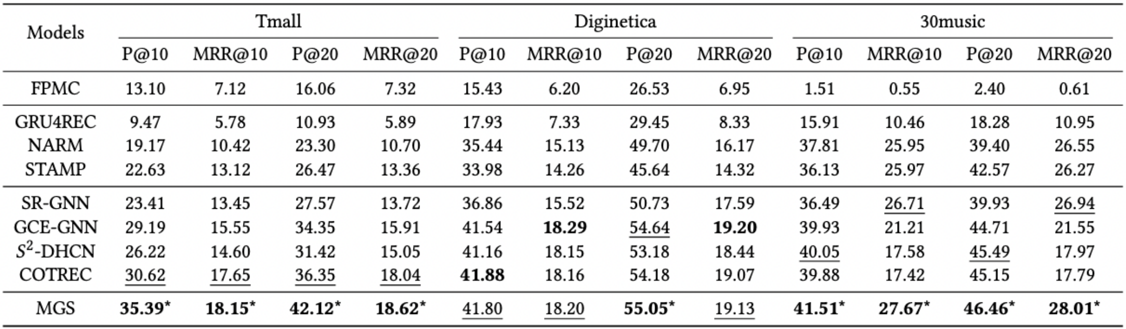
Example – Result Table 1

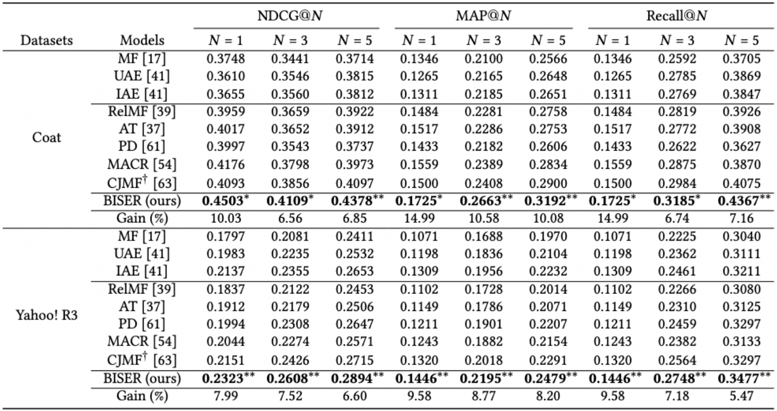


Models	Tmall				Diginetica				30music			
	P@10	MRR@10	P@20	MRR@20	P@10	MRR@10	P@20	MRR@20	P@10	MRR@10	P@20	MRR@20
FPMC	13.10	7.12	16.06	7.32	15.43	6.20	26.53	6.95	1.51	0.55	2.40	0.61
GRU4REC	9.47	5.78	10.93	5.89	17.93	7.33	29.45	8.33	15.91	10.46	18.28	10.95
NARM	19.17	10.42	23.30	10.70	35.44	15.13	49.70	16.17	37.81	25.95	39.40	26.55
STAMP	22.63	13.12	26.47	13.36	33.98	14.26	45.64	14.32	36.13	25.97	42.57	26.27
SR-GNN	23.41	13.45	27.57	13.72	36.86	15.52	50.73	17.59	36.49	26.71	39.93	26.94
GCE-GNN	29.19	15.55	34.35	15.91	41.54	**18.29**	54.64	**19.20**	39.93	21.21	44.71	21.55
S^2-DHCN	26.22	14.60	31.42	15.05	41.16	18.15	53.18	18.44	40.05	17.58	45.49	17.97
COTREC	30.62	17.65	36.35	18.04	**41.88**	18.16	54.18	19.07	39.88	17.42	45.15	17.79
MGS	**35.39***	**18.15***	**42.12***	**18.62***	41.80	18.20	**55.05***	19.13	**41.51***	**27.67***	**46.46***	**28.01***

Evaluation metrics: P@n, MRR

[1] table from SIGIR '22 "An Attribute-Driven Mirror Graph Network for Session-based Recommendation"

Example – Result Table 2



Datasets	Models	NDCG@N			MAP@N			Recall@N		
		$N = 1$	$N = 3$	$N = 5$	$N = 1$	$N = 3$	$N = 5$	$N = 1$	$N = 3$	$N = 5$
Coat	MF [17]	0.3748	0.3441	0.3714	0.1346	0.2100	0.2566	0.1346	0.2592	0.3705
	UAE [41]	0.3610	0.3546	0.3815	0.1265	0.2165	0.2648	0.1265	0.2785	0.3869
	IAE [41]	0.3655	0.3560	0.3812	0.1311	0.2185	0.2651	0.1311	0.2769	0.3847
	RelMF [39]	0.3959	0.3659	0.3922	0.1484	0.2281	0.2758	0.1484	0.2819	0.3926
	AT [37]	0.4017	0.3652	0.3912	0.1517	0.2286	0.2753	0.1517	0.2772	0.3908
	PD [61]	0.3997	0.3543	0.3737	0.1433	0.2182	0.2606	0.1433	0.2622	0.3627
	MACR [54]	0.4176	0.3798	0.3973	0.1559	0.2389	0.2834	0.1559	0.2875	0.3870
	CJMF† [63]	0.4093	0.3856	0.4097	0.1500	0.2408	0.2900	0.1500	0.2984	0.4075
	BISER (ours)	**0.4503***	**0.4109***	**0.4378****	**0.1725***	**0.2663****	**0.3192****	**0.1725***	**0.3185***	**0.4367****
	Gain (%)	10.03	6.56	6.85	14.99	10.58	10.08	14.99	6.74	7.16
Yahoo! R3	MF [17]	0.1797	0.2081	0.2411	0.1071	0.1688	0.1970	0.1071	0.2225	0.3040
	UAE [41]	0.1983	0.2235	0.2532	0.1198	0.1836	0.2104	0.1198	0.2362	0.3111
	IAE [41]	0.2137	0.2355	0.2653	0.1309	0.1956	0.2232	0.1309	0.2461	0.3211
	RelMF [39]	0.1837	0.2122	0.2453	0.1102	0.1728	0.2014	0.1102	0.2266	0.3080
	AT [37]	0.1912	0.2179	0.2506	0.1149	0.1786	0.2071	0.1149	0.2310	0.3125
	PD [61]	0.1994	0.2308	0.2647	0.1211	0.1901	0.2207	0.1211	0.2459	0.3297
	MACR [54]	0.2044	0.2274	0.2571	0.1243	0.1882	0.2154	0.1243	0.2382	0.3133
	CJMF† [63]	0.2151	0.2426	0.2715	0.1320	0.2018	0.2291	0.1320	0.2564	0.3297
	BISER (ours)	**0.2323****	**0.2608****	**0.2894****	**0.1446****	**0.2195****	**0.2479****	**0.1446****	**0.2748****	**0.3477****
	Gain (%)	7.99	7.52	6.60	9.58	8.77	8.20	9.58	7.18	5.47

Evaluation metrics: NDCG, MAP, Recall

[1] Table from SIGIR '22 "Bilateral Self-unbiased Learning from Biased Implicit Feedback"

Example – Result Table 3

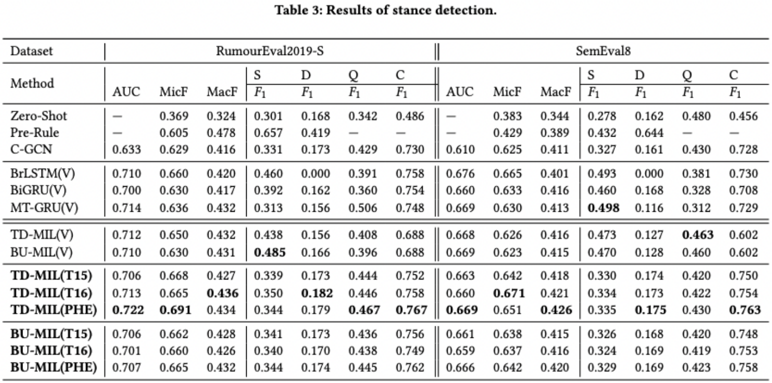


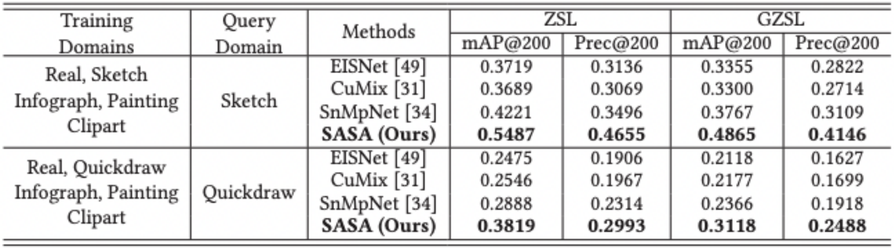
Table 3: Results of stance detection.

Dataset	RumourEval2019-S							SemEval8						
Method				S	D	Q	C				S	D	Q	C
	AUC	MicF	MacF	F_1	F_1	F_1	F_1	AUC	MicF	MacF	F_1	F_1	F_1	F_1
Zero-Shot	–	0.369	0.324	0.301	0.168	0.342	0.486	–	0.383	0.344	0.278	0.162	0.480	0.456
Pre-Rule	–	0.605	0.478	0.657	0.419	–	–	–	0.429	0.389	0.432	0.644	–	–
C-GCN	0.633	0.629	0.416	0.331	0.173	0.429	0.730	0.610	0.625	0.411	0.327	0.161	0.430	0.728
BrLSTM(V)	0.710	0.660	0.420	0.460	0.000	0.391	0.758	0.676	0.665	0.401	0.493	0.000	0.381	0.730
BiGRU(V)	0.700	0.630	0.417	0.392	0.162	0.360	0.754	0.660	0.633	0.416	0.460	0.168	0.328	0.708
MT-GRU(V)	0.714	0.636	0.432	0.313	0.156	0.506	0.748	0.669	0.630	0.413	**0.498**	0.116	0.312	0.729
TD-MIL(V)	0.712	0.650	0.432	0.438	0.156	0.408	0.688	0.668	0.626	0.416	0.473	0.127	**0.463**	0.602
BU-MIL(V)	0.710	0.630	0.431	**0.485**	0.166	0.396	0.688	0.669	0.623	0.415	0.470	0.128	0.460	0.602
TD-MIL(T15)	0.706	0.668	0.427	0.339	0.173	0.444	0.752	0.663	0.642	0.418	0.330	0.174	0.420	0.750
TD-MIL(T16)	0.713	0.665	**0.436**	0.350	**0.182**	0.446	0.758	0.660	**0.671**	0.421	0.334	0.173	0.422	0.754
TD-MIL(PHE)	**0.722**	**0.691**	0.434	0.344	0.179	**0.467**	**0.767**	**0.669**	0.651	**0.426**	0.335	**0.175**	0.430	**0.763**
BU-MIL(T15)	0.706	0.662	0.428	0.341	0.173	0.436	0.756	0.661	0.638	0.415	0.326	0.168	0.420	0.748
BU-MIL(T16)	0.701	0.660	0.426	0.340	0.170	0.438	0.749	0.659	0.637	0.416	0.324	0.169	0.419	0.753
BU-MIL(PHE)	0.707	0.665	0.432	0.344	0.174	0.445	0.762	0.666	0.642	0.420	0.329	0.169	0.423	0.758

Evaluation metrics: AUC, MicF, MacF, F1

[1] Table from SIGIR '22 "A Weakly Supervised Propagation Model for Rumor Verification..."

Example – Result Table 4

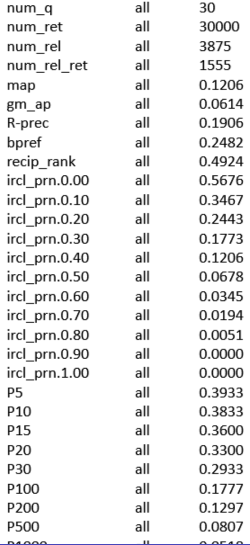


Training Domains	Query Domain	Methods	ZSL		GZSL	
			mAP@200	Prec@200	mAP@200	Prec@200
Real, Sketch Infograph, Painting Clipart	Sketch	EISNet [49]	0.3719	0.3136	0.3355	0.2822
		CuMix [31]	0.3689	0.3069	0.3300	0.2714
		SnMpNet [34]	0.4221	0.3496	0.3767	0.3109
		SASA (Ours)	**0.5487**	**0.4655**	**0.4865**	**0.4146**
Real, Quickdraw Infograph, Painting Clipart	Quickdraw	EISNet [49]	0.2475	0.1906	0.2118	0.1627
		CuMix [31]	0.2546	0.1967	0.2177	0.1699
		SnMpNet [34]	0.2888	0.2314	0.2366	0.1918
		SASA (Ours)	**0.3819**	**0.2993**	**0.3118**	**0.2488**

Evaluation metrics: mAP, Prec

[1] Table from SIGIR '22 "Structure-Aware Semantic-Aligned Network..."

TREC_EVAL Example Results



```
num_q           all     30
num_ret         all     30000
num_rel         all     3875
num_rel_ret     all     1555
map             all     0.1206
gm_ap           all     0.0614
R-prec          all     0.1906
bpref           all     0.2482
recip_rank      all     0.4924
ircl_prn.0.00   all     0.5676
ircl_prn.0.10   all     0.3467
ircl_prn.0.20   all     0.2443
ircl_prn.0.30   all     0.1773
ircl_prn.0.40   all     0.1206
ircl_prn.0.50   all     0.0678
ircl_prn.0.60   all     0.0345
ircl_prn.0.70   all     0.0194
ircl_prn.0.80   all     0.0051
ircl_prn.0.90   all     0.0000
ircl_prn.1.00   all     0.0000
P5              all     0.3933
P10             all     0.3833
P15             all     0.3600
P20             all     0.3300
P30             all     0.2933
P100            all     0.1777
P200            all     0.1297
P500            all     0.0807
P1000           all     0.0518
```

- **map**: mean average precision
- **gm_ap**: geometric mean average precision
- **R-prec**: R-precision
- **bpref**: preference-based IR measure
- **recip_rank**: reciprocal rank
- **ircl_prn**: interpolated recall – precision average at r recall
- **p@k**: precision at k

1. **What do we evaluate?**

2. Evaluation Metrics
   - Binary assessment
   - Rank-based measures
   - Diagnostic Tools
   - Beyond Binary Relevance: NDCG

3. Test Collections and Benchmarking

IR Evaluation

- How do we compare these search engines? How do we evaluate the IR systems behind?
  - How are the results relevant to the user query?
  - How fast does it search?
  - How fast does it index (update contents)?
  - Is the result presented effectively?
- In this lecture, we will mainly focus on the retrieval effectiveness
  - How good an IR system retrieve **relevant** items to the user's information need.

IR Evaluation (Cont.)

- Note: **user need** is translated into a **query**
- Relevance is assessed relative to the user need, not the query
- E.g.,
  - Query: *"pool cleaner"*
  - Information need: [*My swimming pool bottom is becoming black and needs to be cleaned*]
- Assess whether the retrieved documents address the underlying need, not whether it has these words

Difficulties in Evaluating IR Systems

- **Relevancy** of items difficult to assess
- Relevancy is not typically binary but continuous.
- Relevancy is subjective and depends on the user's information need.
    - It depends on the user's judgment based on his/her background, knowledge, and experience.
    - It relates to user's current need.
    - It depends on human perception, which is not always consistent.
    - It changes over time.

Precision and Recall

- The relevance of a document to a query is **subjective**.
- We need precise definition of "relevance" and quantitative evaluation metrics.
- How can we evaluate the retrieval performance?
  - Manual vs. Automatic

rank	model A	model B
1	87641	1851596
2	57182758	8722556
3	6165392	13769
4	157692	2910525
5	878262	37619
6	4718	995166

Table: Two ranked list of documents, Which are better?

1. What do we evaluate?
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Human Judgment for Evaluating IR Systems

- Given a corpus of documents and a set of queries for this corpus,
- Have one or more human assessors judge the relevance of each document to each query.
- Relevance is typically assessed on a **binary scale** (relevant or not relevant) or on a **graded scale** (e.g., 0-3).
- It requires a lot of human effort to assess the relevance of documents to queries.

Confusion Matrix – Binary Assessment

- Confusion matrix is a table that shows the performance of a supervised learning model.
  - Each row represents the ground truth class assignments,
  - while each column represents the predicted classes, or vice versa.

	Retrieved	Non Retrieved
Relevant	True Positive (TP)	False Negative (FN)
Not Relevant	False Positive (FP)	True Negative (TN)

Precision and Recall

- Precision is the fraction of retrieved documents that were relevant.
$$prec. = \frac{|\text{retrieved and relevant}|}{|\text{retrieved}|} = \frac{TP}{TP + FP}$$

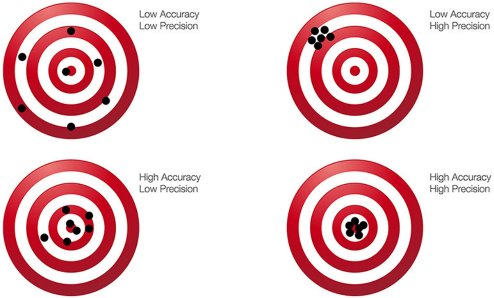
- Recall is the fraction of relevant documents retrieved by the system.
$$recall = \frac{|\text{retrieved and relevant}|}{|\text{relevant}|} = \frac{TP}{TP + FN}$$

Accuracy

- Accuracy is the fraction of all documents that were correctly retrieved.

$$\begin{aligned} accuracy &= \frac{|\text{retrieved and relevant}| + |\text{not retrieved and not relevant}|}{|\text{all documents}|} \\ &= \frac{TP + TN}{TP + TN + FP + FN} \end{aligned}$$

Precision vs Accuracy



- Precision is how close/dispersed the measurements are **to each other**.
- Accuracy is how close or far off a given set of measurements are **to their true value**.

Precision and Recall with Ranked Lists

- Suppose the total number of relevant documents is 10
- Green's are TPs; predicted "relevant" and that is correct
- Red's are FPs; predicted "relevant" and that is incorrect
- The values in the table are the document ids.

rank	model A	model B
1	87641	1851596
2	57182758	8722556
3	6165392	13769
4	157692	2910525
5	878262	37619
6	4718	995166

What are the precision and recall of the models?

F-score

- **F-Measure** combines both recall and precision, so systems that favor are penalized for whichever is lower.

$$F_\beta = (1+\beta^2) \cdot \frac{\mathit{precision} \cdot \mathit{recall}}{(\beta^2 \cdot \mathit{precision}) + \mathit{recall}}$$

- Commonly used F-Measure is the F1 score, where $\beta = 1$, which is the **harmonic mean** of precision and recall.

$$F_1 = 2 \cdot \frac{\mathit{precision} \cdot \mathit{recall}}{\mathit{precision} + \mathit{recall}} = \frac{2}{\frac{1}{\mathit{precision}} + \frac{1}{\mathit{recall}}}$$

What are the F1 scores of the model A and B?

1. **What do we evaluate?**

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3. **Test Collections and Benchmarking**

Rank-based Measures

Precision/Recall/F-1 are set-based measures. Now, we will discuss rank-based measures

- Binary relevance
  - precision@K (P@K)
  - Mean Average Precision (MAP)
  - Mean Reciprocal Rank (MRR)
- Multiple levels of relevance
  - Normalized Discounted Cumulative Gain (NDCG)

P@K: Precision at K

- **Precision at K** corresponds to the number of relevant results among the top K retrieved documents
  1. set a rank threshold k
  2. compute the percentage of relevant in top k
  3. ignore documents ranked lower than k
- Model A: $P@5 = 2/5 = .4$
- Model B: $P@5 = 2/5 = .4$

rank	model A	model B
1	87641	1851596
2	57182758	8722556
3	6165392	13769
4	157692	2910525
5	878262	37619
6	4718	995166

What are the shortcomings of precisionK measure?

AP: Average Precision

- It is desirable to also consider the order (i.e., the positions of the relevant documents) in which the returned documents are presented.
- Average precision computes the average value of **precision at K scores**.

$$AP(\vec{r}, n) = \frac{1}{R} \sum_{k:\vec{r}_k=1} P@K(\vec{r}, k)$$

Average Precision – Example

rank	model A	P@K	AP
1	87641		
2	57182758		
3	6165392		
4	157692		
5	878262		
6	4718		
7	957174		
8	5827561		

- Suppose $\vec{r} = (0, 1, 1, 0, 0, 0, 1, 0)$
- Consider the rank of each relevant documents: $k_{\vec{r}_k=1} = (2, 3, 7)$

Average Precision – Example (Cont.)

rank	model A	P@K	AP
1	87641	0/1	0
2	57182758	1/2	(1/2) / 1
3	6165392	2/3	(1/2+2/3) / 2
4	157692	2/4	same as above
5	878262	2/5	same as above
6	4718	2/6	same as above
7	957174	3/7	(1/2+2/3+3/7) / 3
8	5827561	3/8	same as above

- Compute the $P@K$ for each k: $P@k = (1/2, 2/3, 3/7)$
- Average Precision at $k = 7$:

$$AP(\vec{r}, 7) = \frac{1}{3} \cdot \left(\frac{1}{2} + \frac{2}{3} + \frac{3}{7} \right) \approx 0.53$$

What would be the precision at K from a perfect system?

MAP: Mean Average Precision – Example

- Related metric is **Mean Average Precision (MAP)**, which is the mean of Average Precision across multiple queries/rankings.
- E.g.,
  - $AP(\vec{r}(q_1), 10) = (1.0 + 0.67 + 0.5 + 0.44 + 0.5)/5 = 0.62$
  - $AP(\vec{r}(q_2), 10) = (0.5 + 0.4 + 0.43)/3 = 0.44$

$$MAP((q_1, q_2), 10) = \frac{1}{2} \cdot (0.62 + 0.44) = 0.53$$

Mean Average Precision (Cont.)

- If a relevant document never gets retrieved, we assume the precision corresponding to that relevant doc to be zero.
- MAP is macro-averaging: each query counts equally.
- **Good for web search**?
  - MAP assumes user is interested in finding many relevant documents for each query.
  - MAP requires many relevance judgments in text collection.

R-Precision

- **R-precision** is the precision@R where R is the number of relevant documents to the given query.
- R is used as the cutoff, which varies from query to query
  - Suppose there are 20 documents (i.e., $R = 20$) to “apple store” in a corpus.
  - If your ranking system retrieved 5 relevant documents in the top 20 list, then R-precision is $5/20 = 0.25$.
- *R-precision requires knowing all documents that are relevant to a query.*

MRR: Mean Reciprocal Rank

- MRR considers the rank position (k) of the first relevant document – Could be the clicked website of the web search results.
- Reciprocal Rank:

$$RR = \frac{1}{k}$$

- MRR is the mean RR across multiple queries.

1. **What do we evaluate?**

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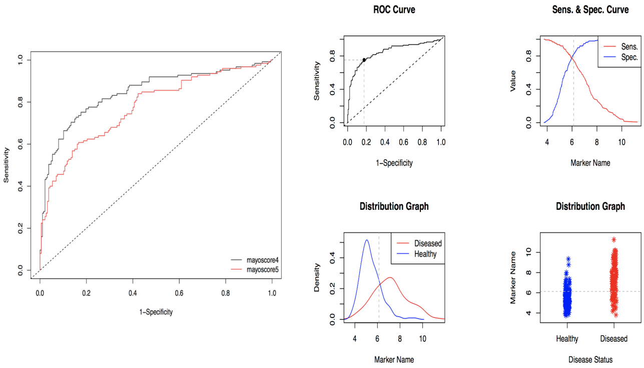
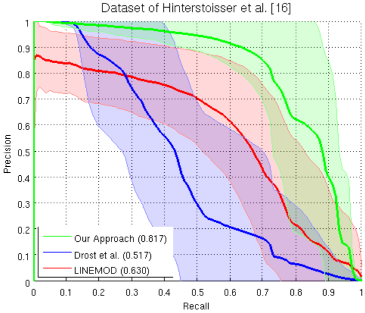
Diagnostic Tools



- In this lecture, we will discuss two diagnostic tools: ROC Curve and Precision-Recall Curve
- The area under the curve can be used to directly compare the models.

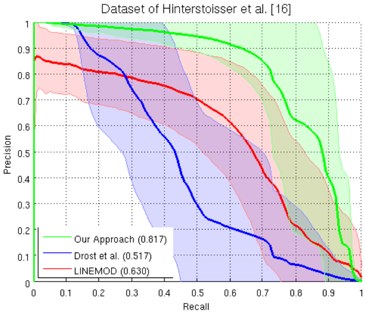
[a] image from: http://www.biosoft.hacettepe.edu.tr/easyROC/

Precision-Recall Curves



- **Precision-Recall curves** illustrate the trade-off between **precision** and **recall** for every possible *discrimination threshold cut-off*.
- *What happen, if you classifier predicts everything positive? Or, vice versa?*

Precision-Recall Curves (Cont.)

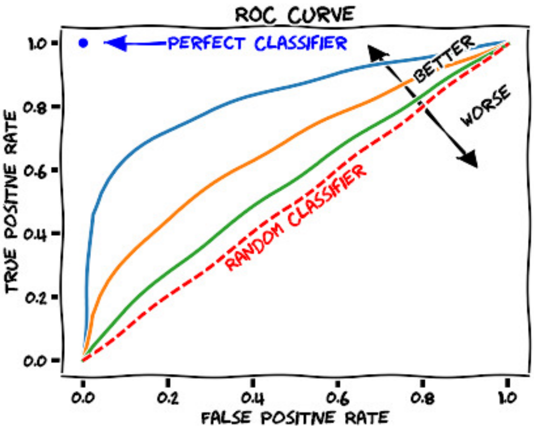


- Precision-Recall is plotting the precision against recall
  - $precision = TP/(TP + FP)$
  - $recall = TP/(TP + FN)$

Computing Recall/Precision Points

1. For a given query, produce a ranked list of documents.
2. Adjust the *discrimination threshold* to produce a set of retrieved documents.
3. Evaluate the retrieved documents against the ground truth.
4. For each threshold, compute the precision and recall.
5. Plot the precision and recall values to produce the Precision-Recall curve.

ROC Curves



ROC (Receiver Operating Characteristic) curves illustrate the *relationships between correct predictions* and *wrong predictions on the* **positive** *class.*

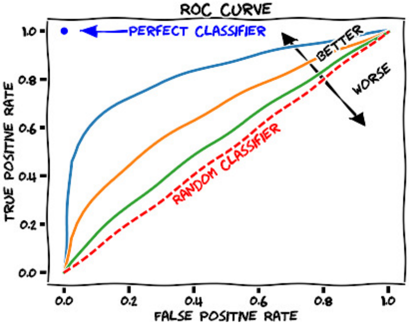
ROC Curves (Cont.)

- ROC Curves plot the **True Positive Rate** (TPR) against **False Positive Rate** (FPR).
- True Positive Rate (also called *recall*, *sensitivity*, *hit rate*).

$$TPR = \frac{TP}{P} = \frac{TP}{TP + FN}$$

- False Positive Rate (also called *fall-out*)

$$FPR = \frac{FP}{N} = \frac{FP}{FP + TN}$$



Prec.-Recall Curve vs. ROC

- **Precision-Recall curves** focus on the **positive class** and are more informative when the classes are imbalanced.
- **ROC curves** consider both classes and are useful when the classes are balanced (i.e., the # of positive and negative samples are roughly equal).
- A high area under the curve (AUC or AUPRC) indicates the model maintains a good balance between precision and recall.
- Both curves provides complementary insights and may be reported together, especially in research.

1. **What do we evaluate?**

2. **Evaluation Metrics**
   - Binary assessment
   - Rank-based measures
   - Diagnostic Tools
   - Beyond Binary Relevance: NDCG

3. **Test Collections and Benchmarking**

Normalized Discounted Cumulative Gain (NDCG)

Normalized Discounted Cumulative Gain

Assumptions:

- Graded relevance (beyond binary): For example, in 0-3 relevance scale, we have 0-irrelevant, 1-marginally relevant, 2-fairly relevant, 3-highly relevant.
- The relevant documents ranked lower are less useful for the user, since it is less likely to be examined.

Normalized Discounted Cumulative Gain (NDCG)

Normalized Discounted Cumulative Gain

- Graded relevance is used as a measure of usefulness, or **gain**
- Gain is **accumulated** starting at the top of the ranking and may be reduced, or discounted, at lower ranks
- Typical **discount** is $1/\log(rank)$
- DCG (Discounted Cumulative Gain) is the total gain accumulated at a particular rank p:

$$DCG_p = rel_1 + \sum_{i=2}^{p} \frac{rel_i}{\log_2 i}$$

DCG Example

- 10 ranked documents judged on 0–3 relevance scale:
  (3, 2, 3, 0, 0, 1, 2, 2, 3, 0)
- Discounted gain:
  $(3, 2/1, 3/1.59, 0, 0, 1/2.59, 2/2.81, 2/3, 3/3.17, 0)$
  $= (3, 2, 1.89, 0, 0, 0.39, 0.71, 0.67, 0.95, 0)$
- Discounted Cumulative Gain:
  $(3, 5, 6.89, 6.89, 6.89, 7.28, 7.99, 8.66, 9.61, 9.61 (= DCG_{10}))$

NDCG for summarizing rankings

Normalized Discounted Cumulative Gain

- Normalize DCG at rank n
  - DCG at rank n by the DCG value at rank n of the ideal ranking
- The ideal ranking would first return the documents with the highest relevance level, then the next highest relevance level, etc
- Normalization is useful for contrasting queries with varying numbers of relevant results
- **NDCG** is now quite popular in evaluating Web search

NDCG Example

Suppose we have four documents: d_1, d_2, d_3, d_4 and the relevance judgment.

i	Ground Truth	Ranking Model A	Ranking Model B
1	$d_4(r_1 = 2)$	$d_3(r_2 = 2)$	$d_3(r_2 = 2)$
2	$d_3(r_2 = 2)$	$d_4(r_1 = 2)$	$d_2(r_3 = 1)$
3	$d_2(r_3 = 1)$	$d_2(r_3 = 1)$	$d_4(r_1 = 2)$
4	$d_1(r_4 = 0)$	$d_1(r_4 = 0)$	$d_1(r_4 = 0)$

NDCG Example (Cont.)

i	Ground Truth	Ranking Model A	Ranking Model B
1	$d_4(r_1 = 2)$	$d_3(r_2 = 2)$	$d_3(r_2 = 2)$
2	$d_3(r_2 = 2)$	$d_4(r_1 = 2)$	$d_2(r_3 = 1)$
3	$d_2(r_3 = 1)$	$d_2(r_3 = 1)$	$d_4(r_1 = 2)$
4	$d_1(r_4 = 0)$	$d_1(r_4 = 0)$	$d_1(r_4 = 0)$

- Ground Truth:

$$DCG_{gt} = 2 + \left(\frac{2}{\log_2 2} + \frac{1}{\log_2 3} + \frac{0}{\log_2 4}\right) = 4.631$$

NDCG Example (Cont.)

i	Ground Truth	Ranking Model A	Ranking Model B
1	$d_4(r_1 = 2)$	$d_3(r_2 = 2)$	$d_3(r_2 = 2)$
2	$d_3(r_2 = 2)$	$d_4(r_1 = 2)$	$d_2(r_3 = 1)$
3	$d_2(r_3 = 1)$	$d_2(r_3 = 1)$	$d_4(r_1 = 2)$
4	$d_1(r_4 = 0)$	$d_1(r_4 = 0)$	$d_1(r_4 = 0)$

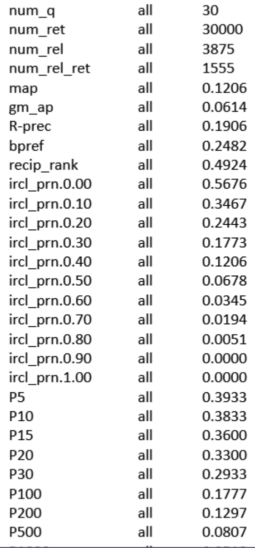
- Model A

$$DCG_A = 2 + \left(\frac{2}{\log_2 2} + \frac{1}{\log_2 3} + \frac{0}{\log_2 4} \right) = 4.631, \quad nDCG_A = 4.631/4.631 = 1.000$$

- Model B

$$DCG_B = 2 + \left(\frac{1}{\log_2 2} + \frac{2}{\log_2 3} + \frac{0}{\log_2 4} \right) = 4.262, \quad nDCG_B = 4.262/4.631 = 0.920$$

TREC_EVAL Example Results



```
num_q           all     30
num_ret         all     30000
num_rel         all     3875
num_rel_ret     all     1555
map             all     0.1206
gm_ap           all     0.0614
R-prec          all     0.1906
bpref           all     0.2482
recip_rank      all     0.4924
ircl_prn.0.00   all     0.5676
ircl_prn.0.10   all     0.3467
ircl_prn.0.20   all     0.2443
ircl_prn.0.30   all     0.1773
ircl_prn.0.40   all     0.1206
ircl_prn.0.50   all     0.0678
ircl_prn.0.60   all     0.0345
ircl_prn.0.70   all     0.0194
ircl_prn.0.80   all     0.0051
ircl_prn.0.90   all     0.0000
ircl_prn.1.00   all     0.0000
P5              all     0.3933
P10             all     0.3833
P15             all     0.3600
P20             all     0.3300
P30             all     0.2933
P100            all     0.1777
P200            all     0.1297
P500            all     0.0807
```

- **map**: mean average precision
- **gm_ap**: geometric mean average precision
- **R-prec**: R-precision
- **bpref**: binary preference
- **recip_rank**: reciprocal rank
- **ircl_prn**: interpolated recall – precision average at r recall
- **p@k**: precision at k

1. What do we evaluate?

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3. **Test Collections and Benchmarking**

User-based vs. Laboratory Evaluation

User-based Evaluation

- Assessment is performed by real users; hence it is expensive and time-consuming.
- One-off: The system is evaluated once.
- It is difficult to eliminate the influence of the user on the evaluation (i.e., biases).
- The results are often inconsistent between raters and over time.
- Humans judgmentare not always representative of the population.

User-based vs. Laboratory Evaluation

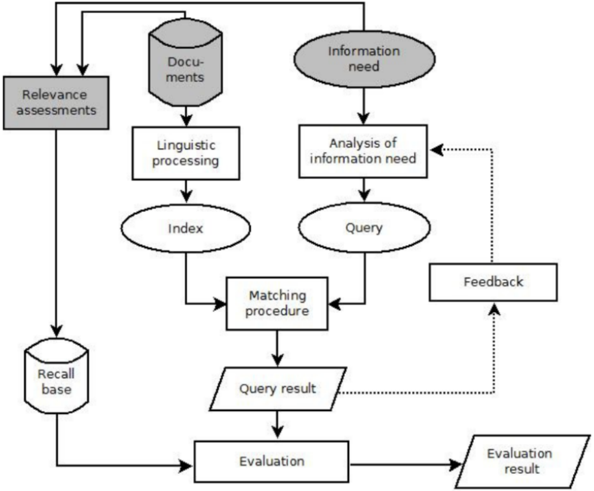
Laboratory-based Evaluation

- Evaluation is performed in a controlled environment.
- Automated evaluation is possible; hence it is not expensive.
- It is faster and easier to evaluate and to replicate.
- However, it is difficult to build a fair test collection that is representative of the real world.

Test Collections

- To compare the performances of the IR systems
- Test collection is **a laboratory environment** that does not change in which we test and compare retrieval models
- It is wrong to report results on a test collection which were obtained by tuning the model parameters to maximize performance on the test collection.
- You should *tune* your model on one or more development test collections and obtain results from the test collection.

Schematic of Test Collection



Experimental Setup for Test Collections

1. Performance of a retrieval model is evaluated on a **test collection** consisting of:
    - A set of document
    - A set of queries
    - Relevance judgments: An assessment of either **Relevant** or **Non-relevant** for each query and each document
2. Performance data is valid only for the test collection used, and cannot be generalized to other collections.

TREC (Text REtrieval Conference)

- Run by the U.S. National Institute for Standards and Technology (NIST) in Maryland
- Has been a major driver of IR research and source of test collections from 1992 onward.
- Several language-specific conferences have been created internationally to follow its approach

TREC-style Conferences

name	focus	started	recent topics
TREC	English (mainly)	1992	conversational assistance, deep learning, health misinformation, news, podcast, precision medicine
NTCIR	East Asian languages	1999	financial tweets, government data, Wikipedia, ad hoc web search
CLEF	European languages, cross-language IR	2000	math QA, biomedical QA, multimedia retrieval, text translation (scientific to simple text)
FIRE	Indian and South Asian languages	2008	hate speech detection, AI for legal assistant, sentiment analysis, fake news detection, causality-driven ad hoc IR

TREC – the Precision Medicine (PM) Track

2021 TREC-PM Objective

TREC-PM focuses on **identifying high-quality evidence for a specific cancer treatment**. Each case will describe the patient's disease (type of cancer), the relevant genetic variants (which genes are mutated), and the proposed treatment. Participants of the track will be challenged with retrieving biomedical articles providing strong evidence for/against the treatment in the specific population.

Document Collections

- The MEDLINE baseline will be used for the scientific abstracts, which is a repository for biomedical and life science journal articles.

Document Collection Example

- NLM produces a baseline set of MEDLINE/PubMed citation records in XML format.

```
<?xml version="1.0"?>
 <!DOCTYPE article PUBLIC "-//NLM//DTD Journal Archiving and Interchange
   DTD v2.3 20070202//EN" "archivearticle.dtd">
 <article xmlns:xlink="http://www.w3.org/1999/xlink" article-type="review-article">
   <?properties open_access?>
   <front>
     <journal-meta>
       <journal-id journal-id-type="nlm-ta">Crit Care</journal-id>
       <journal-title>Critical Care</journal-title>
       <issn pub-type="ppub">1364-8535</issn>
       <issn pub-type="epub">1466-609X</issn>
       <publisher>
         <publisher-name>BioMed Central</publisher-name>
         <publisher-loc>London</publisher-loc>
       </publisher>
     </journal-meta>
     ...
```

Topics

The topics for the track consist of synthetic patient cases consist of the disease, genetic variants, and the proposed treatment.

	Patient 1	**Patient 2**
Disease:	melanoma	melanoma
Variant:	BRAF (V600E)	BRAF (V600E)
Treatment:	Dabrafenib	Cobimetinib

Topics in XML format: topic2020.xml

Relevance Judgments

- Binary (*relevant* vs. *non-relevant*) in the simplest case
  - More nuanced relevance levels also used (e.g., 0-3 scale)
- **Any Issues?**
  - Human judges often disagree
  - We expect to pay human experts (doctors, medical coders, etc.)

```
1 0 1065003 1
1 0 1065013 1
1 0 1065027 1
1 0 1065055 0
1 0 1065094 2
1 0 107740 0
1 0 1079876 0
1 0 1160567 1
1 0 1160569 1
1 0 117132 0
1 0 1175863 1
1 0 1175871 0
1 0 1175911 0
1 0 1180426 0
```

Pooling technique and Why?

- In most collections, it is not feasible to assess the relevance of each document for each query;
  - For example, 10,000 predicted documents for 50 topics from 100 participating systems. Assuming that judging each document takes 5 mins, then it will take up to 475 years to evaluate!!
- Hence, pooling technique is used on a large scale IR evaluation tasks.

Typical Pooling Sequence

1. The documents and queries are created.
2. Multiple IR systems are run on the queries.
3. Each system returns top-ranking m documents, which are collected into a pool.
4. The resulting pool of documents is assessed in random order, typically by multiple judges.
5. When judges disagree, they meet and discuss the document until they reach consensus.

Summary

- Question?