# **Chapter IR:V**

### V. Evaluation

- Laboratory Experiments
- □ Measuring Performance
- □ Set Retrieval Effectiveness
- □ Ranked Retrieval Effectiveness
- □ Training and Testing
- Logging

## **Experiment Scope**

#### Interactive retrieval:

- Processing a query depending on other queries (of the user).
- The user has a goal or a task that requires many queries and exploration.
- Dependent variables are result quality, human factors, context, user interface and experience, and the retrieval system's supporting facilities.
- Experiments typically require user studies
- Measurement of retrieval performance depends on the setup

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### Ad hoc retrieval:

- Processing a query independently from other queries (of the user).
- → Amenable to laboratory environments
- Canonical measurement of retrieval performance
- Reproducibility and scalability

"ad hoc" (Latin: "for this") means "concerned with a particular end or purpose" and "formed or used for specific or immediate problems or needs" [Merriam Webster]

## **Experimental Setup**

## A laboratory experiment for ad hoc retrieval requires three items:

### 1. A document collection (corpus)

- □ A representative sample of documents from the domain of interest.
- ☐ If representativeness is difficult to achieve, the larger the sample, the better.

## 2. A set of information needs (topics)

- □ Formalized, written descriptions of users' tasks, goals, or gaps of knowledge.
- □ Alternatively, declarative descriptions of desired search results.
- □ Often accompanied by specific queries the users (would) have used.

## 3. A set of relevance judgments (ground truth)

- □ Pairs of topics and documents, where each document has been manually assessed with respect to its relevance to the associated topic.
- □ Ideally, the users who supplied topics also judge, in practice third parties do so.
- □ Judgments may be given in binary form, or on a Likert scale.

Every retrieval system has parameters. Parameter optimization must use an experimental setup (training, validation) different from that used for evaluation (test).

- This setup is sometimes referred to as an experiment under the Cranfield paradigm, in reference to Cyril Cleverdon's series of projects at the Cranfield University in the 1960s, which first used this evaluation methodology. [codalism.com 1] [codalism.com 2]
- In linguistics, a corpus (plural corpora) or text corpus is a large and structured set of texts.
   They are used to carry out statistical analysis and hypothesis testing, checking occurrences or validating linguistic rules within a specific language territory.

The term has been adopted in various other branches of the human language technologies.

□ The evaluation corpus split between training, validation, and test set should be used in conjunction with *k*-fold cross-validation, since the variance of performance results is often high.

[Fuhr 2017]

Experimental Setup: Document Collections / Corpora

For ad hoc retrieval, the <u>Text Retrieval Conference (TREC)</u> has organized evaluation tracks since 1992, inviting scientists to compete.

### Key document collections used:

Collection	Documents	Size	Words/Doc.	Topics	Words/Query	Jdgmts/Query
CACM	3,204	2.2 MB	64	64	13.0	16
AP	242,918	0.7 GB	474	100	4.3	220
GOV2	25 million	426.0 GB	1073	150	3.1	180
ClueWeb09	1 billion	25.0 TB	459	200	2.5	821
ClueWeb12	733 million	27.3 TB	448	200	3.6	793
ClueWeb22B	200 million	11.7 TB	_	_	_	_

- □ CACM: titles and abstracts from Communications of the ACM 1958–1979
- □ AP: newswire documents from Associated Press 1988–1990
- □ GOV2: crawl of .gov domains early 2004
- □ ClueWeb: web crawls from 2009, 2012, and 2022 (not in use, yet)

Reusing experimental setups renders previous approaches comparable.

- □ TREC is organized by the United States National Institute of Standards and Technology (NIST). The conference has been key to popularize laboratory evaluation of retrieval systems; every year, evaluation tracks on many different retrieval-related tasks are organized.
- □ At TREC, usually 50 topics are provided per edition of a shared task. The ones from previous years can be used for training.
- □ Ad hoc retrieval has been studied in the <u>ad hoc tracks</u>, the <u>terabyte tracks</u>, and the web tracks.
- □ Several initiatives similar to TREC have formed, namely CLEF, NTCIR, and FIRE.

Experimental Setup: Topics

```
<topic number="794" type="single">
<query> pet therapy </query>
```

### <description>

How are pets or animals used in therapy for humans and what are the benefits?

</description>

#### <narrative>

Relevant documents must include details of how pet or animal-assisted therapy is or has been used. Relevant details include information about pet therapy programs, descriptions of the circumstances in which pet therapy is used, the benefits of this type of therapy, the degree of success of this therapy, and any laws or regulations governing it.

</narrative>

- The description element is a longer version of the query, clarifying it, since the short query itself may be ambiguous.
- ☐ The narrative field is optional. It usually describes the criteria for relevance and is used by assessors to carry out relevance judgments.
- Another topic type are faceted topics:

```
<topic number="265" type="faceted">
    <query>F5 tornado</query>
    <description>What were the ten worst tornadoes in the USA?</description>
    <subtopic number="1" type="inf">What were the ten worst tornadoes in the USA?</subtopic>
    <subtopic number="2" type="inf">Where is tornado alley?</subtopic>
    <subtopic number="3" type="inf">What damage can an F5 tornado do?</subtopic>
    <subtopic number="4" type="inf">Find information on tornado shelters.</subtopic>
    <subtopic number="5" type="nav">What wind speed defines an F5 tornado?</subtopic>
</topic>
</topic></topic>
```

Experimental Setup: Relevance Judgments

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### <description>

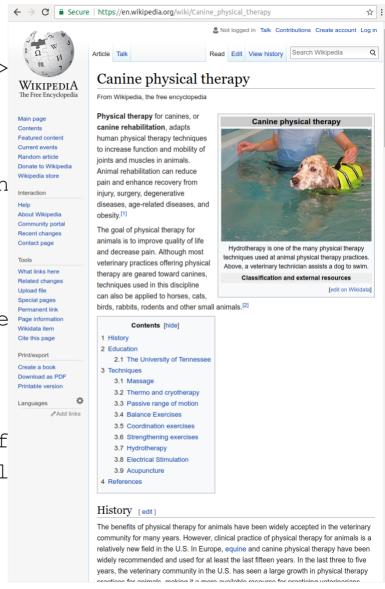
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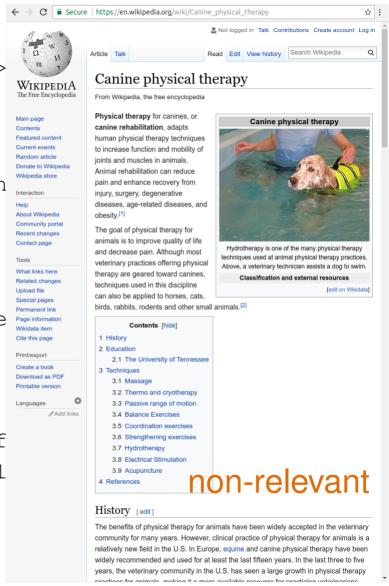
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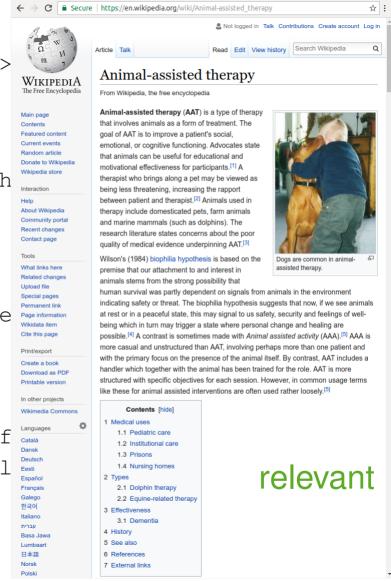
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Experimental Setup: Relevance Judgments

A relevance judgment requires the manual assessment of whether a document returned by a retrieval system for a given query is relevant for a given topic.

## Assessment depth

- □ Assessment does not scale with the number of documents retrieved by retrieval systems.
- □ A sampling strategy called pooling is used.

### Assessment scale

- Binary scale: relevant and non-relevant
- $\square$  *n*-point Likert scale of degrees of relevance: from non-relevant (0) to highly relevant ( $n \le 5$ )

### Assessor selection and instruction

- ☐ The people who had the information needs underlying the topics, if available.
- □ Volunteer assessors who receive training and exhaustive topics.

# Assessor reliability

- □ Assessors make errors, which affects the objectivity of the results.
- □ Multiple assessments can be used to verify the reliability of assessors and assessments.

□ At TREC, assessors are recruited from retired NIST staff:



**Experimental Setup: Pooling** 

Pooling is a sampling strategy for documents retrieved by to-be-evaluated retrieval systems for a given set of topics.

## For each topic:

- 1. Collect the top-k results returned by each retrieval system (variant).
- 2. Merge the results, omitting duplicates, obtaining a "pool" of documents.
- 3. Present the pool of documents in random order to assessors.

### Caveats:

- Only documents "considered" relevant enough by one of the participating retrieval system are analyzed.
- All documents ranked below the pooling depth are deemed non-relevant by default, regardless the truth.
- New retrieval systems that are evaluated later may retrieve many unjudged documents; probably requiring new judgments from different assessors.

## **Assessor Reliability**

The degree of agreement between assessors and the degree of consistency of the same assessor are quantified using assessor reliability measures. Lack of agreement or consistency indicate flawed setups or insufficient training.

Assessor reliability is measured whenever ambiguous or subjective decisions have to be made. Relevance is a subjective notion.

## Several alternative approaches have been proposed:

- Joint probability of agreement
   Percentage of times the raters agree. Here, agreement by chance is not taken into account.
- □ Kappa Statistics
  Improvement over joint probability, taking into account agreement by chance.
- Correlation coefficient
   Pairwise correlation among assessors on ordered scales. Full rankings are required.

Assessor Reliability: Kappa Statistics

Given the judgments of two annotators on a given topic, a kappa statistic measures their agreement as follows:

$$\kappa = \frac{p_o - p_e}{1 - p_e} \;,$$

where  $p_o$  denotes the proportion of agreement observed, and  $p_e$  the expected proportion of agreement by chance.

## Properties:

- $\kappa \in (-\infty,1]$ , where 1 indicates perfect agreement, 0 random agreement, and  $\kappa < 0$  has no meaningful interpretation [Kvålseth 2015]
- $\Box$  At  $p_e = 1$ ,  $\kappa$  is undefined.
- $\Box$   $p_o p_e$  denotes the agreement attained above chance
- $\Box$  1  $p_e$  denotes the agreement attainable above chance

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Suppose A and B are two annotators asked to make n binary relevance judgments. Then a simple kappa statistic can be computed as follows:

		В		$\sum$
		yes	no	
Α	yes	a	b	c
	no	d	e	$\int$
$\sum$		g	h	n

$$p_o=rac{a+e}{n}$$
  $p_e=P( extsf{yes})^2+P( extsf{no})^2$   $P( extsf{yes})=rac{c+g}{2n},\quad P( extsf{no})=rac{f+h}{2n}$ 

Assessor Reliability: Kappa Statistics

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Suppose A and B are two annotators who made the following n=400 binary relevance judgments. The simple kappa statistic then yields:

		В		$\sum$
		yes	no	
Α	yes	300	20	320
	no	10	70	80
$\sum$		310	90	400

$$p_o = \frac{300 + 70}{400}$$
 
$$p_e = P(\text{yes})^2 + P(\text{no})^2$$
 
$$P(\text{yes}) = \frac{320 + 310}{2 \cdot 400}, \quad P(\text{no}) = \frac{80 + 90}{2 \cdot 400}$$

$$\kappa = 0.776$$

- $\Box$  Well-known kappa statistics include Cohen's  $\kappa$ , Scott's  $\pi$ , and Fleiss'  $\kappa$ .
- $\Box$  Scott's  $\pi$  is the one exemplified.
- $\Box$  Fleiss'  $\kappa$  is a generalization of Scott's  $\pi$  to arbitrary numbers of annotators and categories. It also does not presume that all cases have been annotated by the same group of people.
- Presuming that annotators A and B work independently, the probability  $P(yes)^2$  (and similarly  $P(no)^2$ ) denotes the probability of both voting yes (no) by chance. Another way of computing  $p_e$  is to sum the multiplication of the rater-specific probabilities of each rater voting yes (no).
- $\square$  Some assign the following interpretations to  $\kappa$  values measured (disputed):

$\kappa$	Agreement
< 0	poor
0.01 - 0.20	slight
0.21 - 0.40	fair
0.41 - 0.60	moderate
0.61 - 0.80	substantial
0.81 - 1.00	almost perfect

[Wikipedia]

 $\Box$  Within TREC evaluations, typically a "substantial" agreement ( $\kappa \approx [0.67, 0.8]$ ) is achieved.

[Manning 2008]