

Axiometrics: An Axiomatic Approach to Evaluation Metrics

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2015
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Let's be clear from the start:
I. Won't. Go. Overtime.



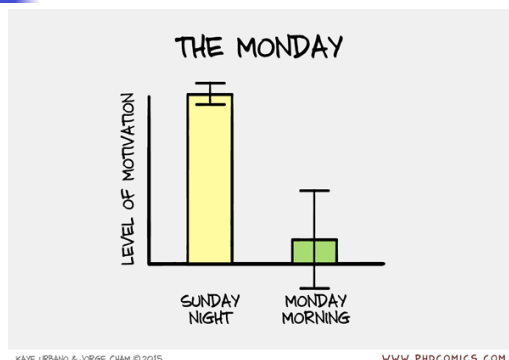
Aims – 1

- To present both:
 - basic material (what you find in books)
 - advanced material (recently published, even not yet published!)
- Links with Julio, Enrique, Evangelos
 - not (yet!) fully integrated
 - a bit disorganized...

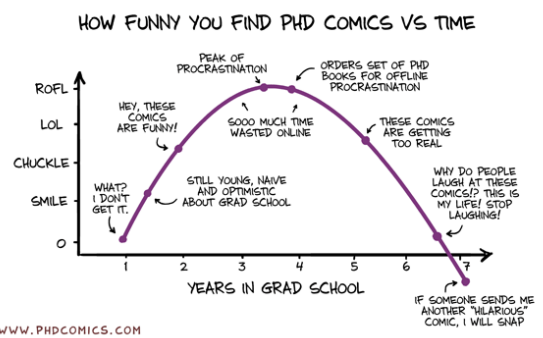
Aims – 2

- Intro to IR Evaluation
- Intro to IR Evaluation Measures / Metrics
- The Link between Measurement Theory and Metrics
 - Intro to Measurement Theory (Scales)
 - Metrics Analysis
 - The Axiometrics Framework (*)

The Monday effect...



You don't find it funny?!



Outline

- Evaluation [5']
- Measures / metrics [15']
- Measurement theory [15']
- Metrics analysis [5']
- Axiometrics framework [15']

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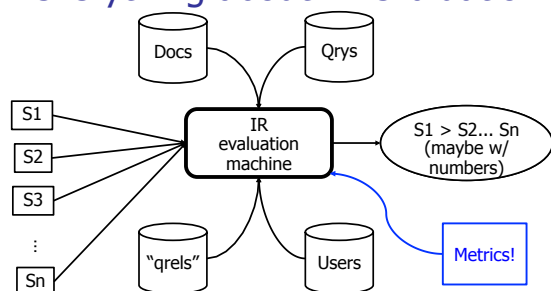
What is evaluation (in IR)?

- Eh...
- Ideally: a machine telling you how good an IR system is
- "Good": effective, capable to retrieve relevant (useful?!) documents
 - (efficiency is also studied, but focus is on effectiveness)

The importance of evaluation in IR

- Everybody agrees that evaluation is of paramount importance in IR
- One of the most evaluation-oriented disciplines in computer/information sciences
- We're busy doing a lot of evaluation since the 60s
 - So this talk is relevant. I do not know if it is useful :-)

A short history of nearly everything about IR evaluation



The importance of evaluation in IR

- Everybody agrees that evaluation is of paramount importance in IR
- One of the most evaluation-oriented disciplines in computer/information sciences
- We're busy doing a lot of evaluation since the 60s
- And we don't know (agree on) how to evaluate

(Other) Issues in IR evaluation

- Relevance
 - "Topicality"?
 - "Utility"?
 - ...
- Methodology
 - Test collection, benchmark ,TREC-like
 - User study (--> Diane)
 - Large log analysis
 - ...

Outline

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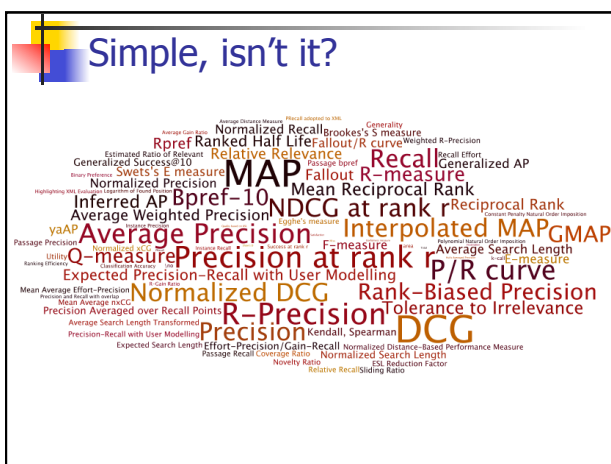
We go down the dark evaluation metrics rabbit hole



IR effectiveness metric

- (or, measure)
- ""A number telling us how effective an IR system is""
- Simple, isn't it?

Simple, isn't it?

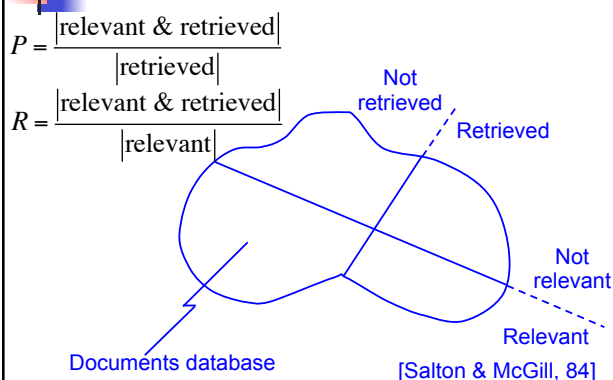


1	Precision	46	Discounted Cumulative Gain
2	Recall	47	Normalized DCG
3	Sweet's E measure	48	NDCG at rank k
4	Fallout	49	Average Weighted Precision
5	Normalized Recall	50	Weighted R-Precision
6	Normalized Precision	51	Average Distance Measure
7	P/R curve	52	Precision at recall to XM_L
8	Fallout/R curve	53	Precision and Recall with overlap
9	Brooker's S measure	54	Yno
10	Expected Search Length	55	area
11	ESL Reduction Factor	56	Success at rank r
12	Precision Averaged over Recall Points	57	Average Gain Ratio
13	Sliding Ratio	58	R-Gain Ratio
14	Coverage Ratio	59	Binary Preference
15	Novelty Ratio	60	Bpref-10
16	Relative Ratio	61	Q-measure
17	E-measure	62	R-measure
18	F-measure	63	Tolerance to Irrelevance
19	Utility	64	Estimated Ratio of Relevant
20	Average Precision	65	Eggh's measure
21	Mean Average Precision	66	Passage Recall
22	Interpolated MAP	67	Passage Precision
23	Precision at rank r	68	Passage boref
24	R-Precision	69	Kendall, Spearman
25	Generality	70	Normalized κG
26	Miss	71	Mean Average NCG
27	Shaw's D	72	Effort-Precision/Gain-Recall
28	PHS	73	Mean Average Effort-Precision
29	Satisfaction	74	Precision-Recall with User Modelling
30	Frustration	75	Geometric MAP
31	Total	76	Generalized AP
32	Usefulness measure	77	Inferred AP
33	Huff's Averaged Precision	78	Expected Precision-Recall with User Modelling
34	Average Search Length	79	Rpref
35	Quality based on ASL	80	Generalized Success@10
36	Normalized Distance-Based Performance Measure	81	k-call
37	Recall Effort	82	Highlighting XML Evaluation
38	Relative Relevance	83	Ranking Efficiency
39	Ranked Half Life	84	Rank-Based Precision
40	Reciprocal Rank	85	Average Search Length Transformed
41	Mean Reciprocal Rank	86	Logarithm of Fold Position
42	Instance Precision	87	Normalized Search Length
43	Instance Recall	88	Polynomial Natural Order Imposition
44	Classification Accuracy	89	Constant Probable Natural Order Imposition

A shorter list

- Precision, Recall
- Precision-Recall curve
- MAP (Mean Average Precision)
- P@n (Precision at n)
- NDCG (Normalized Discounted Cumulative Gain)
- MRR (Mean Reciprocal Rank)
- RBP (Rank Biased Precision)
- TBG (Time Based Gain)

Precision & Recall



P & R: probabilistic definition

- $P = p(\text{relevant} \mid \text{retrieved})$
- $R = p(\text{retrieved} \mid \text{relevant})$

Ranking!

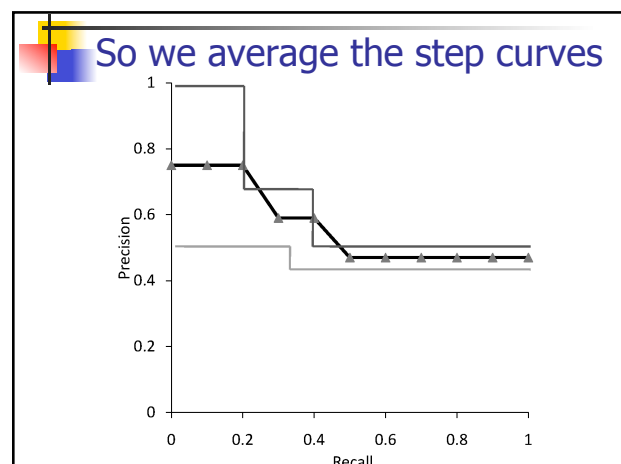
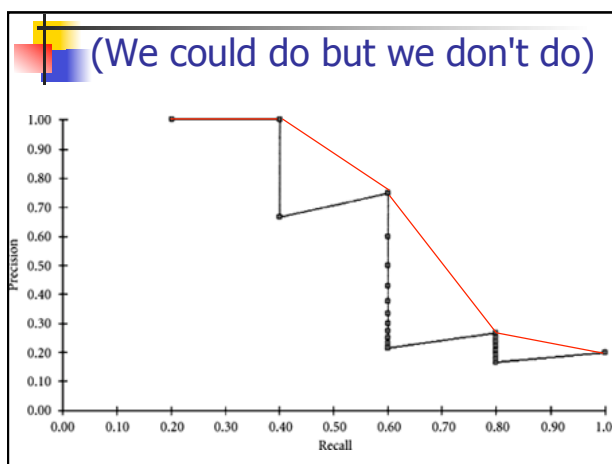
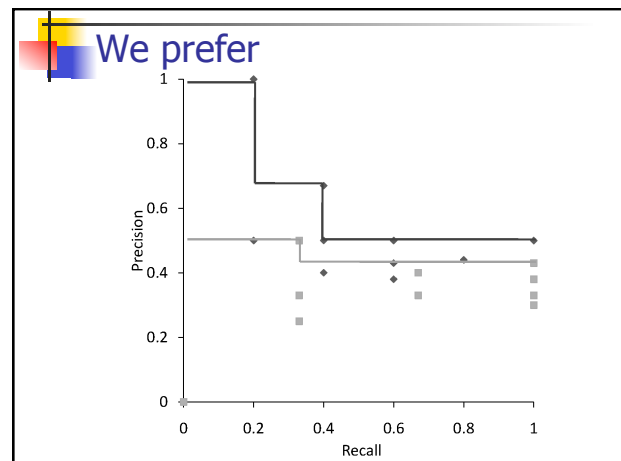
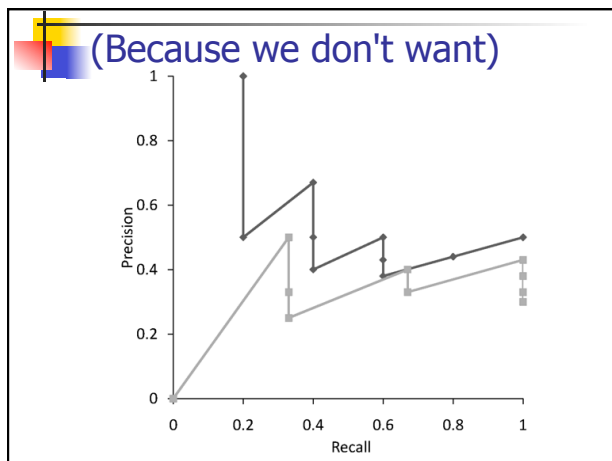
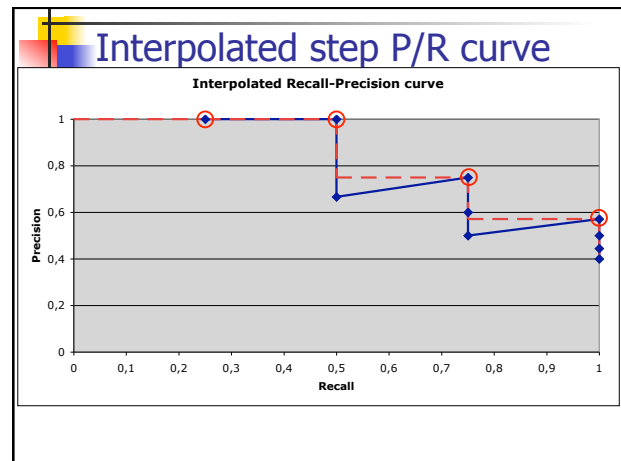
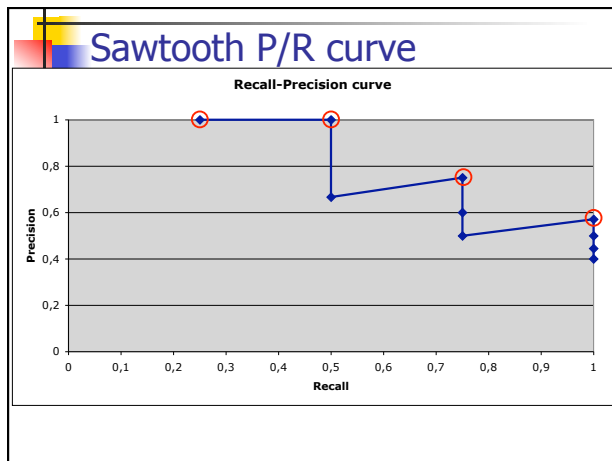
- But today all IR systems **rank** the documents
- Limitations of P&R
 - 2 numbers, not just one
 - Not affected by the rank of retrieved docs.
- Solutions: (too?) many.
 - Precision/Recall curve
 - MAP (Mean Average Precision)
 - ...
- Let us see some examples

Rank

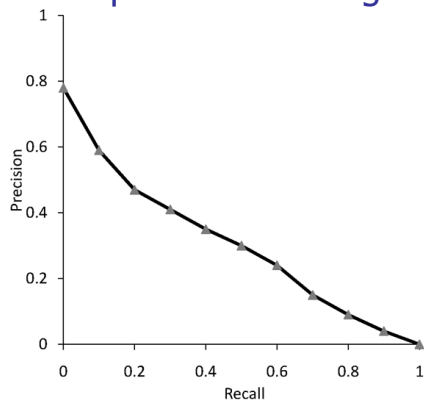
Rank	Rel?	R	P
1	1	0,25	1
2	1	0,5	1
3	0	0,5	0,67
4	1	0,75	0,75
5	0	0,75	0,6
6	0	0,75	0,5
7	1	1	0,57
8	0	1	0,5
9	0	1	0,44
10	0	1	0,4

Rank

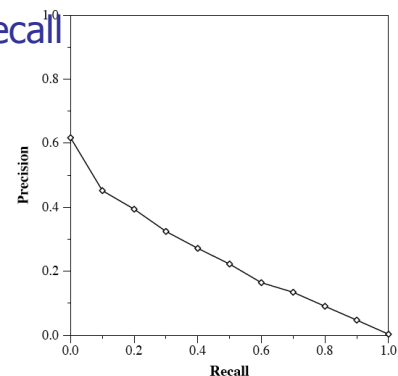
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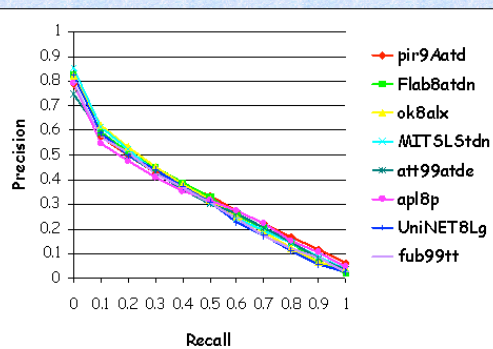
Over N queries and we get



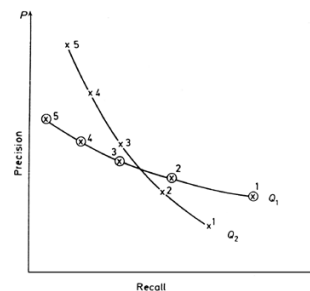
And of course on 11 levels of recall



We happily compare systems ?



Although often...



P/R curve --> MAP

- P/R curve
 - It is not a number
 - It can be transformed into a number by measuring **the area below the curve**
- --> **AP (Average Precision)**
- --> **MAP (Mean Average Precision)**
- Good property: top-heavyness

Rank	1	2	3	4	5	6	7	8	...
Rel	1	0	1	0	0	0	1	0	...

- User model?

P@n

- Simply count how many relevant documents are retrieved in the first n positions of the rank
- P@10 useful for classical Web search engines
- P@1 for "Feeling lucky"

Non binary relevance

- Some documents are "more relevant" than others
- Discounted Cumulative Gain (DCG, NDCG)
 - Different relevance --> different gain for the user
 - E.g., H --> 3, R --> 2, P --> 1, N --> 0
 - Sum of the gains while walking down the rank
 - Discounting more and more: late rank positions give less gain even if of equal relevance ("top-heaviness")

Example

Rank	Rel
1	H
2	P
3	N
4	R
5	H
6	R
7	N
8	P
9	N
10	P

Example

Rank	Rel	Gain
1	H	3
2	P	1
3	N	0
4	R	2
5	H	3
6	R	2
7	N	0
8	P	1
9	N	0
10	P	1

Example

Rank	Rel	Gain	CG
1	H	3	3
2	P	1	4
3	N	0	4
4	R	2	6
5	H	3	9
6	R	2	11
7	N	0	11
8	P	1	12
9	N	0	12
10	P	1	13

Example

Rank	Rel	Gain	CG	Discount
1	H	3	3	$\log(1)$ 1
2	P	1	4	$\log(2)$
3	N	0	4	$\log(3)$
4	R	2	6	$\log(4)$
5	H	3	9	$\log(5)$
6	R	2	11	$\log(6)$
7	N	0	11	$\log(7)$
8	P	1	12	$\log(8)$
9	N	0	12	$\log(9)$
10	P	1	13	$\log(10)$

Example

Rank	Rel	Gain	CG	Discount	DG
1	H	3	3	$\log(1)$ 1	$3/1=3$
2	P	1	4	$\log(2)$	$1/\log(2)=1$
3	N	0	4	$\log(3)$	$0/\log(3)=0$
4	R	2	6	$\log(4)$	$2/\log(4)=1$
5	H	3	9	$\log(5)$	$3/\log(5)=1.3$
6	R	2	11	$\log(6)$	$2/\log(6)=.8$
7	N	0	11	$\log(7)$	$0/\log(7)=0$
8	P	1	12	$\log(8)$	$1/\log(8)=.3$
9	N	0	12	$\log(9)$	$0/\log(9)=0$
10	P	1	13	$\log(10)$	$1/\log(10)=.3$

Example

Rank	Rel	Gain	CG	Discount	DG	DCG
1	H	3	3	$\log(1)$ 1	$3/1=3$	3.0
2	P	1	4	$\log(2)$	$1/\log(2)=1$	4.0
3	N	0	4	$\log(3)$	$0/\log(3)=0$	4.0
4	R	2	6	$\log(4)$	$2/\log(4)=1$	5.0
5	H	3	9	$\log(5)$	$3/\log(5)=1.3$	6.3
6	R	2	11	$\log(6)$	$2/\log(6)=.8$	7.1
7	N	0	11	$\log(7)$	$0/\log(7)=0$	7.1
8	P	1	12	$\log(8)$	$1/\log(8)=.3$	7.4
9	N	0	12	$\log(9)$	$0/\log(9)=0$	7.4
10	P	1	13	$\log(10)$	$1/\log(10)=.3$	7.7

Example

Rank	Rel	Gain	CG	Discount	DG	DCG	DCG Ideal
1	H	3	3	$\log(1)$ 1	$3/1=3$	3.0	(H) 3.0
2	P	1	4	$\log(2)$	$1/\log(2)=1$	4.0	(H) 6.0
3	N	0	4	$\log(3)$	$0/\log(3)=0$	4.0	(R) 7.3
4	R	2	6	$\log(4)$	$2/\log(4)=1$	5.0	(R) 8.3
5	H	3	9	$\log(5)$	$3/\log(5)=1.3$	6.3	(P) 8.7
6	R	2	11	$\log(6)$	$2/\log(6)=.8$	7.1	(P) 9.1
7	N	0	11	$\log(7)$	$0/\log(7)=0$	7.1	(P) 9.4
8	P	1	12	$\log(8)$	$1/\log(8)=.3$	7.4	(N) 9.4
9	N	0	12	$\log(9)$	$0/\log(9)=0$	7.4	(N) 9.4
10	P	1	13	$\log(10)$	$1/\log(10)=.3$	7.7	(N) 9.4

Example

Rank	Rel	Gain	CG	Discount	DG	DCG	DCG Ideal	NDCG
1	H	3	3	$\log(1)$ 1	$3/1=3$	3.0	(H) 3.0	1.00
2	P	1	4	$\log(2)$	$1/\log(2)=1$	4.0	(H) 6.0	0.67
3	N	0	4	$\log(3)$	$0/\log(3)=0$	4.0	(R) 7.3	0.55
4	R	2	6	$\log(4)$	$2/\log(4)=1$	5.0	(R) 8.3	0.61
5	H	3	9	$\log(5)$	$3/\log(5)=1.3$	6.3	(P) 8.7	0.72
6	R	2	11	$\log(6)$	$2/\log(6)=.8$	7.1	(P) 9.1	0.78
7	N	0	11	$\log(7)$	$0/\log(7)=0$	7.1	(P) 9.4	0.75
8	P	1	12	$\log(8)$	$1/\log(8)=.3$	7.4	(N) 9.4	0.78
9	N	0	12	$\log(9)$	$0/\log(9)=0$	7.4	(N) 9.4	0.78
10	P	1	13	$\log(10)$	$1/\log(10)=.3$	7.7	(N) 9.4	0.82

Example

Rank	Rel	Gain	CG	Discount	DG	DCG	DCG Ideal	NDCG
1	H	3	3	$\log(1)$ 1	$3/1=3$	3.0	(H) 3.0	1.00
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8	P	1	12	$\log(8)$	$1/\log(8)=.3$	7.4	(N) 9.4	0.78
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A shorter list

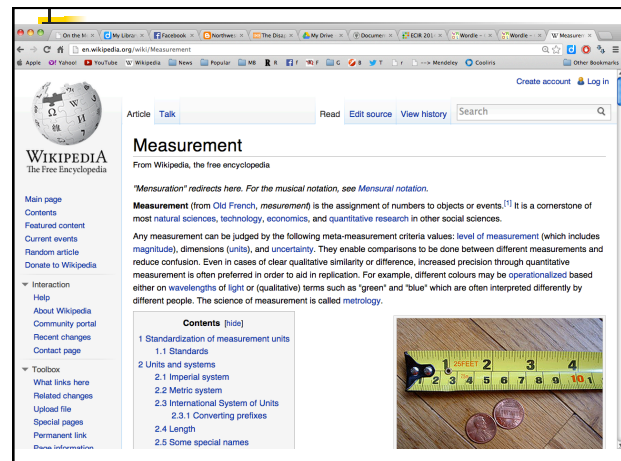
- Precision, Recall
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... even continuous relevance

- Dynamometer, Hand force grip, even physiological data
- IR System showing a "relevance bar" close to each document
 - "estimation of the amount of relevance"
- Magnitude estimation (paper @ last SIGIR)
- ...

Measurement

- Definition: A process aimed at determining a relationship between a physical quantity and a unit of measurement
- Typically, one assigns numbers to objects/events
- Studied in Measurement Theory
 - Reasonably settled



SCIENCE

Vol. 103, No. 2684

Friday, June 7, 1946

On the Theory of Scales of Measurement

S. S. Stevens

Director, Psycho-Acoustic Laboratory, Harvard University

FOR SEVEN YEARS A COMMITTEE of the British Association for the Advancement of Science debated the problem of measurement. Appointed in 1932 to represent Section A (Mathematical and Physical Sciences) and Section J (Psychology), the committee was instructed to consider and report upon the possibility of "quantitative estimates of sensory events"—meaning simply: Is it possible to measure human sensation? Deliberation led only to disagreement, mainly about what is meant by the term measurement. An interim report in 1938

by the formal (mathematical) properties of the scales. Furthermore—and this is of great concern to several of the sciences—the statistical manipulations that can legitimately be applied to empirical data depend upon the type of scale against which the data are ordered.

A CLASSIFICATION OF SCALES OF MEASUREMENT

Paraphrasing N. R. Campbell (Final Report, p. 340), we may say that measurement, in the broadest sense, is defined as the assignment of numerals to objects or events according to rules. The fact that

Measurement Theory

- One important concept: which numbers can I select when measuring? What properties do they have?
- Which **measurement scale**?
 - (or "level")
 - E.g., to measure length:
 - Meters
 - Inches
 - "Longer than" (?)



Measurement scales

- Standard set of scales:
 1. Nominal
 2. Ordinal
 3. Interval
 4. Ratio
- (other proposals exist)

Perhaps not so well settled...

QUANTITATIVE METHODS IN PSYCHOLOGY

Measurement Scales and Statistics: A Clash of Paradigms

Joel Michell
University of Sydney
Sydney, New South Wales, Australia

(1986)

The "permissible statistics" controversy stems from a clash of different theories or paradigms of measurement. Three theories are identified: the representational, the operational, and the classical. In each case the relation between measurement scales and statistical procedures is explored. The representational theory implies a relation between measurement scales and statistics, though not the one mentioned by Stevens or his followers. The operational and classical theories, for different reasons, imply no relation between measurement scales and statistics, contradicting Stevens's prescriptions. A resolution of this issue depends on a critical evaluation of these different theories.

And indeed

- Nicholas Chrisman
- 1998
- Proposes 10 scales, not just 4

Rethinking Levels of Measurement for Cartography
Nicholas R. Chrisman

ABSTRACT: Several measurement levels (nominal, ordinal, interval and ratio) have become a familiar part of cartography and GIS. These levels have been accepted unquestioned from publications in social sciences dating from the 1940s and 1950s. The Stevens taxonomy has been used to provide appropriate guidelines for statistical treatment in each scale of measurement. This paper reviews the process by which these levels became a part of cartography, as well as subsequent literature that cartographers have all too ignored over the intervening four decades. The paper concludes that the four levels of measurement are not adequate to cover the circumstances of cartography, and that the ordinal level alone does not provide a sufficient guide to problems of statistical treatment. A broader framework for measurement must be considered, including the relationships of current the Stevens taxonomy to new approaches to general measurement of an object. An informed use of each does not depend on numbers alone, but on the whole "measurement framework," the system of objects, relationships and actions implied by a given system of representation.

How Measurement Levels Reached Cartography
The approach to measurement in certain social sciences (including geography) is still strongly influenced by Stevens (1946) paper "Seven Levels of Measurement." Stevens' work is an excellent foundation for textbooks in spatial analysis (Upton 1981) and in cartography (Brettner et al. 1993; Muehrcke and Muehrcke 1978; Dunn 1995). In fact, there has been continued development of the theory of measurement (Kitchin and Sabo 1995), although no measurement in cartography and GIS were mentioned in 1946. This phenomenon is interesting because it is followed by an assumption of a new set of ideas, and resistance to further progress. It also is important because the measurement concepts are as fundamental for measurement as the Stevens taxonomy. This paper will review the process leading up to this paper and how it diffused into cartographic theory.

History of Theories of Measurement
"Idealist" school of measurement has its roots in Aristotle's metaphysics and common-sense notions to include the physical sciences.

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Cartography and Geographic Information Systems, Vol. 22, No. 4, 1995, pp. 227-242

Anyway "Good Old Fashioned" Measurement scales

- Nominal
- Ordinal
- Interval
- Ratio

4. Ratio scale


- I'm twice taller than him
- He is twice richer than me
 - (Both "how much" & "how many")
- I'm twice older than you
 - Years, months (*12), days, ...
- Zero
 - Age starts from zero!
- But not
 - Today is twice as hot as yesterday?

3. Interval scale

- Today is twice as hot as yesterday?
- In the last two days we had the same increase of 5°C in temperature
 - The difference between today and yesterday temperature is the same as ...
- Dates are another example
 - Difference: OK (2014 – 2012 = 2006 – 2004)
 - Ratio: KO (2000 is not 2 * 1000)
 - (ratios of differences: OK)

2. Ordinal scale

- A measure is not an amount but a **rank**
- It is a form of measurement!
- Ex: Lines ranked according to their length
- It does **not** mean that:
 - the first is twice as long than the second
 - the length difference between the 1st and the 2nd is the same as the 2nd and the 3rd



1. Nominal scale

- Qualitative
- Categories
- Names, gender, nationality, ...
- Can be Dichotomous or Non-dichotomous
- No assumptions on ratios, distances, ranks.

Legit operations

- Given a scale, only some operations make sense
 - Arithmetic: $+$, $-$, $*$, $/$
 - Statistic: Mean, median, mode, ...
- Ex:
 - Average height, weight, ...: OK
 - Average gender: KO

Legit relational/math operations

	$=, \neq$	$>, <$	$+, -$	\times, \div
Nominal	✓	✗	✗	✗
Ordinal	✓	✓	✗	✗
Interval	✓	✓	✓	✗
Ratio	✓	✓	✓	✓

Permissible transformations

	$a \cdot x$	$a \cdot x + b$	Monotonic	1-to-1
Nominal	✓	✓	✓	✓
Ordinal	✓	✓	✓	✗
Interval	✓	✓	✗	✗
Ratio	✓	✗	✗	✗

Meaning

- If you transform the measure, are you still measuring the same thing?
 - Nationality
 - Rank
 - Temperature
 - Money

Examples

- Nominal scale for nationality
 - Greek = 1
 - Italian = 2
 - Spanish = 3
 - Japanese = 4
 - ...
 - $3 - 1 = 4 - 2$ Uh?!?
- Whereas interval scale for temperature $^{\circ}\text{C}$
 - $30^{\circ} - 10^{\circ} = 40^{\circ} - 20^{\circ}$: ok

Legit statistics

	Mode	Median	Mean	
			Arithmetic	Geometric, Harmonic
Nominal	✓	✗	✗	✗
Ordinal	✓	✓	✗	✗
Interval	✓	✓	✓	✗
Ratio	✓	✓	✓	✓

Examples

- Nationality, mode, ok
- Mean rank? Uh?!
 - (think of ranking ten students...)
- Mean temperature, ok

Adv in Health Sci Educ
DOI 10.1007/s10459-010-9222-y

METHODOLOGIST'S CORNER

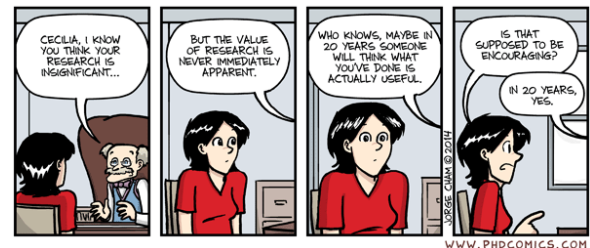
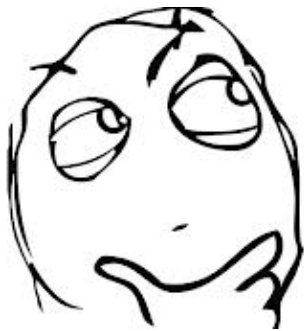
Likert scales, levels of measurement and the "laws" of statistics

Geoff Norman

Received: 22 January 2010 / Accepted: 22 January 2010
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Abstract Reviewers of research reports frequently criticize the choice of statistical methods. While some of these criticisms are well-founded, frequently the use of various parametric methods such as analysis of variance, regression, correlation are faulted because: (a) the sample size is too small, (b) the data may not be normally distributed, or (c) The data are from Likert scales, which are ordinal, so parametric statistics cannot be used. In this paper, I dissect these arguments, and show that many studies, dating back to the 1930s consistently show that parametric statistics are robust with respect to violations of these assumptions. Hence, challenges like those above are unfounded, and parametric methods can be utilized without concern for "getting the wrong answer".

Why are you telling me this?



Why are you telling me this?

- Two reasons
 - 1. Measurement theory and scales can be used to directly analyze IR metrics
 - 2. Because IR can be seen as a measurement. Of relevance --> Language to define axioms on metrics
- Let's see 1. first

Outline

- Evaluation [5']
- Measures / metrics [15']
- Measurement theory [15']
- Metrics analysis [5']
- Axiometrics framework [15']

MRR (Mean Reciprocal Rank)

- Take the rank of the 1st relevant doc.
 - Take the reciprocal (...)
- $$RR = \frac{1}{rank(i)}$$
- Then take the mean (...) over some topics

$$MRR = \frac{1}{|Q|} \sum_{q \in Q} \frac{1}{rank(i_q)}$$

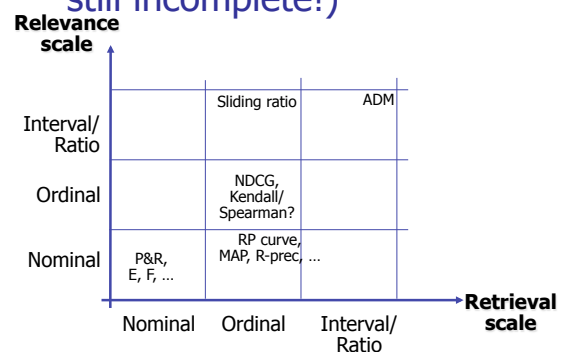
MRR?!

- It is used
- In many papers
- Even in some TREC tracks
- When analyzed with "measurement theory glasses", is is not "measurement theory proof"
- A **reciprocal** is taken on an **ordinal** scale...
- ... then it is **averaged**...

Even worse than that... NDCG

- H,R,P,N --> 3, 2, 1, 0 ?
 - Linear, most common
- H,R,P,N --> 100, 10, 1, 0 ?! (or 4, 2, 1, 0)
 - Exponential, sometimes used, actually
- H,R,P,N --> 100, 99, 90, 0 ??
 - "Crazy", never heard of... why?
- Arbitrary choice!
- By transforming relevance levels into gains, we transform an 2. Ordinal scale --> 4. Ratio scale!
- And we also discount
 - Dividing by log(rank)...
 - All metrics that can be modeled as gain/discount...

Classification (more principled, still incomplete!)



To summarize, but not to conclude

- 100+ metrics
- Measurement theory seems a useful tool
 - Metric classification
 - Some arbitrary choices
 - Some metrics are not "Measurement theory proof"
- Metric **engineering** seems more an **art** (artisan) than a **science**...
- A more principled approach?

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Now, similarity...

Psychological Review

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VOLUME 84 NUMBER 4 JULY 1977

Features of Similarity

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The metric and dimensional assumptions that underlie the geometric representation of similarity are questioned on both theoretical and empirical grounds. A new set-theoretical approach to similarity is developed in which objects are represented as collections of features, and similarity is described as a feature-matching process. Specifically, a set of qualitative assumptions is shown to

Similarity comparison

- And we can compare similarities
- For example,

$$\text{sim}_{q,d}(\alpha, \sigma) < \text{sim}_{q,d}(\alpha, \sigma')$$
- means that on the query q and the document d , and given the human relevance judgment α , system σ is worse than σ' (i.e., less similar to α)

Similarity --> Metric

- On the basis of the notion of similarity, we can define an IR effectiveness metric
- The more σ is similar to α , the higher the metric value

So, to summarize (but not to conclude!)

- Measurement** theory, Measurement scales, IR as relevance measurement
 - $\sigma(q,d), \sigma(q,D), \sigma(Q,D), \alpha(q,d), \alpha(q,D), \alpha(Q,D)$
- Similarity**

$$\text{sim}_{q,d}(\alpha, \sigma) < \text{sim}_{q,d}(\alpha, \sigma')$$
- Metric**

$$\text{metric}_{Q,D}(\alpha, \sigma)$$

Generality: Across different measurement scales

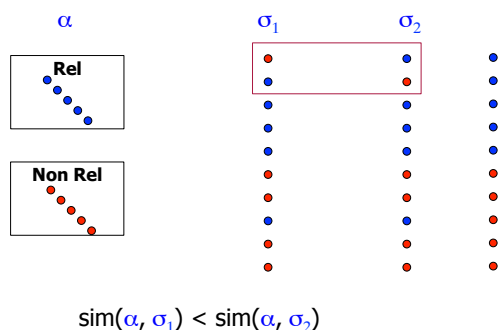
- We can compute the similarity of two relevance judgments when they are on the same scale
- ...but more than that...
- ... also when they are on different scales, in some cases
 - E.g., the classical ad-hoc retrieval
 - scale(σ) = [[ordinal]]
 - scale(α) = [[nominal]] (binary relevance. Ordinal)

Same scales: binary IR

α	σ_1	σ_2
Rel	Ret	Ret
Non Rel	Non Ret	Non Ret

$\text{sim}(\alpha, \sigma_1) > \text{sim}(\alpha, \sigma_2)$

Different scales: ad hoc IR



Ok, but we want Axioms!

Some details...

- I do not trust our axioms too much yet...
- ... preliminary work...
- Actually:
 - I think axioms are correct and consistent
 - I don't know if they are complete
- Stating axioms is also useful to "test the framework"
 - Measurement theory is an effective language to state them!

A First Axiom

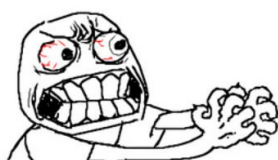
Axiom 3 (Similarity of two systems). *Let q be a query, d a document, α a human relevance measurement and σ and σ' two system relevance measurements such that*

$$\sigma(q, d) = \sigma'(q, d). \quad (1)$$

Then

$$\text{sim}_{q,d}(\alpha, \sigma) = \text{sim}_{q,d}(\alpha, \sigma'). \quad (2)$$

Come on you're kidding!



- All this and then such a stupid axiom????

Ok, ok. Second Axiom

Axiom 6 (Overestimated documents). *Let q be a query, d and d' two documents, α a human relevance measurement and σ a system relevance measurement such that*

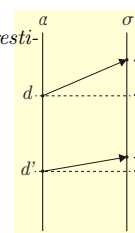
$$\alpha(d) > \alpha(d'),$$

$$\text{sim}_{q,d}(\alpha, \sigma) < \text{sim}_{q,d'}(\alpha, \sigma)$$

and (6) and (8) hold (i.e., both d and d' are overestimated), then

$$\text{metric}_{q,d}(\alpha, \sigma) < \text{metric}_{q,d'}(\alpha, \sigma).$$

- (d is more relevant, sim on d is lower, then metric value on d has to be lower)
- d is both "more wrong" and "more visible" to the user



Ok, ok. Third Axiom

Axiom 8 (System relevance). *Let q be a query, d and d' two documents, α a human relevance measurement and σ a system relevance measurement such that $\text{sim}_{q,d}(\alpha, \sigma) = \text{sim}_{q,d'}(\alpha, \sigma)$, $\sigma(d) > \sigma(d')$, and*

$$\alpha(d) \geq \alpha(d'). \quad (10)$$

Then

$$d \sqsupset_{\text{metric}(\alpha, \sigma)} d'.$$

(document d affects the metric value more than d')

Meaning?

- Corollary:
- By taking $\text{scale}(\sigma) = [[\text{Rank}]]$ we derive that:
 - Early rank positions affect a metric value more than later rank positions
 - IR metrics should be **"top-heavy"**
- Previous Axiom 8 states a more abstract/general principle, independent of the scales

Now, a last Axiom

Axiom 9 (User relevance). *Let q be a query, d and d' two documents, α a human relevance measurement and σ a system relevance measurement such that: $\text{sim}_{q,d}(\alpha, \sigma) = \text{sim}_{q,d'}(\alpha, \sigma)$, $\alpha(d) > \alpha(d')$, and*

$$\sigma(d) \geq \sigma(d'). \quad (11)$$

Then

$$d \sqsupset_{\text{metric}(\alpha, \sigma)} d'.$$

(document d affects the metric value more than d')

Meaning?

- A metric should weigh more, and be more affected, by more relevant documents
- "α top heavyness", "human top heavyness"
 - Perhaps less intuitive than previous axiom,
 - but it does indeed seem natural in the framework
 - by symmetry (treat α as σ)
 - To evaluate a nonrelevant document as nonrelevant is an easy job (the vast majority of documents in a collection are nonrelevant)

Meaning?

- Consequence: linear gain values of 3, 2, 1, 0 in NDCG (for H, R, P, N) can be questioned
 - Exponential 100, 10, 1, 0 (or 4, 2, 1, 0) might be better
 - (already proposed in the original paper, but not much used...)
 - And "crazy" 100, 99, 90, 0 is wrong!

A theorem

Theorem 2 (Unbalanced query). *Let Q be a query set, $q \notin Q$ a query, D a document set, α a human relevance measurement and σ and σ' two system relevance measurements such that*

$$\text{metric}_{Q,D}(\alpha, \sigma) > \text{metric}_{Q,D}(\alpha, \sigma')$$

and

$$\text{metric}_{Q \cup \{q\}, D}(\alpha, \sigma) \leq \text{metric}_{Q \cup \{q\}, D}(\alpha, \sigma').$$

Then

$$\text{metric}_{q,D}(\alpha, \sigma) < \text{metric}_{q,D}(\alpha, \sigma').$$

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Then

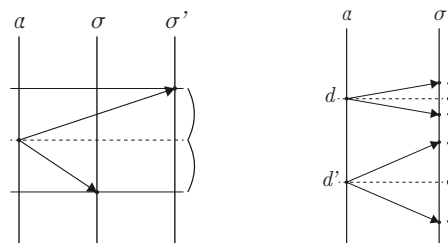
$$\text{metric}_{q,D}(\alpha, \sigma) < \text{metric}_{q,D}(\alpha, \sigma').$$

on the query set Q and the document collection D , and given the human relevance judgment α , σ is more effective than σ'

we add a new query q and then σ becomes less effective than σ'

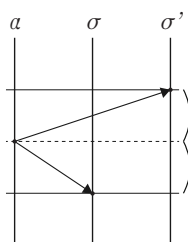
σ is less effective than σ' also on the new query q

When we can't say anything (i.e., we can't state an axiom)

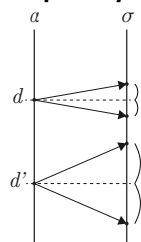


Why we can't say anything

"P-oriented"
"R-oriented"



"Top-heavy"



Hopefully you got the point

- By relying on **measurement theory**,
- one can define **relevance measurement**,
- that in turn allows to define **similarity** between (human and system) measurements,
- that in turn allows to define **Axioms** and **Theorems** on **metrics**
- that seem somehow interesting
 - not (always) trivial, more general, even inspiring
 - ...

Outline + wrap-up

- Evaluation [5']
 - Yes, it's complex!
- Measures / metrics [15']
 - Oh dear, so many metrics?
- Measurement theory [15']
 - Maybe a useful tool...
- Metrics analysis [5']
 - Are we doing it wrong?!
- Axiometrics framework [15']
 - Attempt to shift focus from metric A vs. B to metric properties

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