

# User Models, Metrics and Measures of Search: A Tutorial on the CWL Evaluation Framework

## ACM CHIIR UMMMS 2021

by

Leif Azzopardi, Alistair Moffat, Paul Thomas and Guido Zuccon



# **Section Two: What is C/W/L?**

Presenter: Alistair Moffat

# Measuring the usefulness of a ranking?

Let's suppose that a numeric **gain** can be attached to each document in the ranking, and that  $0 \leq r(i) \leq 1$  is the gain attached to the document at rank  $i$ .

A gain of **zero** means “useless”, and a gain of **one** means “fully useful”.

**How do we measure the usefulness of the ranking as a whole??**

# When one user looks at a ranking

First document

Second document

Third document

Fourth document

*[and then stops looking]*

# When a second user looks at the same ranking

First document

Second document

*[and then stops looking]*

# When a third user looks at the same ranking

First document

Second document

Third document

Fourth document

Fifth document

*[and then stops looking]*

# When a fourth user looks at the same ranking

First document

Second document

Third document

Fourth document

Fifth document

Sixth document

*[and then stops looking]*

# When a fifth user looks at the same ranking

First document

Second document

Third document

Fourth document

*[and then stops looking]*

# When a sixth user looks at the same ranking

First document

*[and then stops looking]*

# When a seventh user looks at the same ranking

First document

Second document

*[and then stops looking]*

# When an “average” user looks at the same ranking

**First document**

Second document

Third document

Fourth document

Fifth document

Sixth document

Seventh document

# When an “average” user looks at the same ranking

**First document**

Second document

Third document

Fourth document

Fifth document

Sixth document

Seventh document

$C(1)$ : probability of continuing from doc 1 to doc 2

$C(2)$ : probability of continuing from doc 2 to doc 3

$C(3)$ : probability of continuing from doc 3 to doc 4

$C(4)$ : probability of continuing from doc 4 to doc 5

$C(5)$ : probability of continuing from doc 5 to doc 6

$C(6)$ : probability of continuing from doc 6 to doc 7

# Huh? What is $C(i)$ ?

Define  $C(i)$  to be:

- the **conditional continuation probability** that a randomly selected user will proceed from document  $i$  in the ranking to document  $i+1$
- **given** that they have just looked at document  $i$ , and
- **assuming** that users always start at the top of the ranking at the first document (rank position 1).

# Huh? What is $C(i)$ ?

Clearly,  $0 \leq C(i) \leq 1$  for each depth  $i$  in the ranking.

And  $C(k+1)$  onward are immaterial if  $C(k)=0$  occurs for some  $k$ .

**What factors might affect  $C(i)$ ??**

# Huh? What is $C(i)$ ?

*Example:* suppose that users are modelled as **always** looking at the first five documents in the ranking, and **never** going beyond those five.

Then  $C(1)=C(2)=C(3)=C(4)=1.0$ , and  $C(5)=0.0$ .

If this pattern of behavior makes you think about the metric **precision at depth five**,  $P@5$ , your instincts are working well.

And if it doesn't, well, you'll find out why it should have in just a minute!

# Huh? What is $C(i)$ ?

*Example:* suppose that users are modelled as **always** continuing from depth  $i$  to depth  $i+1$  with some **constant probability**  $\phi$ , that is,  $C(i)=\phi$  for all  $i$ .

Now what? Now there will be non-zero “probability of being viewed” that can be calculated for every position in the ranking.

For each different function  $C(i)$  a **weight** can be derived and associated with the document at rank  $i$ .

# Huh? What are these “weights”?

We can compute the corresponding  $W(i)$  function for any  $C(i)$  function.

It captures the **fraction of all user attention associated with the document in the  $i$ 'th place of the ranking:**

$$W(i) = \frac{\prod_{j=1}^{i-1} C(j)}{\left( \sum_{k=1}^{\infty} \prod_{j=1}^{k-1} C(j) \right)}.$$

*Example:*  $C(1..4)=1.0$ ,  $C(5..)=0$ ; then  $W(1..5)=0.2$ ,  $W(6..)=0.0$ .

*Example:*  $C(i)=\phi$ ; then  $W(i)=(1-\phi)\phi^{(i-1)}$ .

# Huh? What are these “weights”?

Can now compute the **expected rate of gain** version of the “metric” defined by the values associated with the function  $C(i)$ :

$$M_{\text{ERG}}(r) = \sum_{i=1}^{\infty} W(i) \cdot r(i)$$

*Example:*  $C(1..4)=1.0$ ,  $C(5..)=0$ ; then  $W(1..5)=0.2$ ,  $W(6..)=0.0$ .

The corresponding metric is **Precision at Depth Five**,  $P@5$ .

# Huh? What are these “weights”?

$$M_{\text{ERG}}(r) = \sum_{i=1}^{\infty} W(i) \cdot r(i)$$

*Example:* if  $C(i)=\phi$ ; then  $W(i)=(1 - \phi)\phi^{(i-1)}$ .

The corresponding metric is **Rank-Biased Precision**. When  $\phi=0$ , the user is completely impatient, matching  $P@1$ . When  $\phi=0.5$ , the user is somewhat impatient, expected search depth is two.

When  $\phi=0.95$ , the user is relatively patient, and expected search depth = 20.

# ERG versus ETG metrics

Can also compute the **expected total gain**:

$$M_{\text{ETG}}(\mathbf{r}) = \sum_{i=1}^{\infty} \left( r(i) \times \prod_{j=1}^{i-1} C(j) \right)$$

This is the total “usefulness” derived by the average user when viewing the SERP in question.

# ERG versus ETG metrics

Simple algebra then gives the **expected viewing depth** (the average number of documents viewed by users) as  $1/W(1)$ .

ERG metrics measure systems based on the rate at which their users acquire “usefulness”, and have units of “rels/document”.

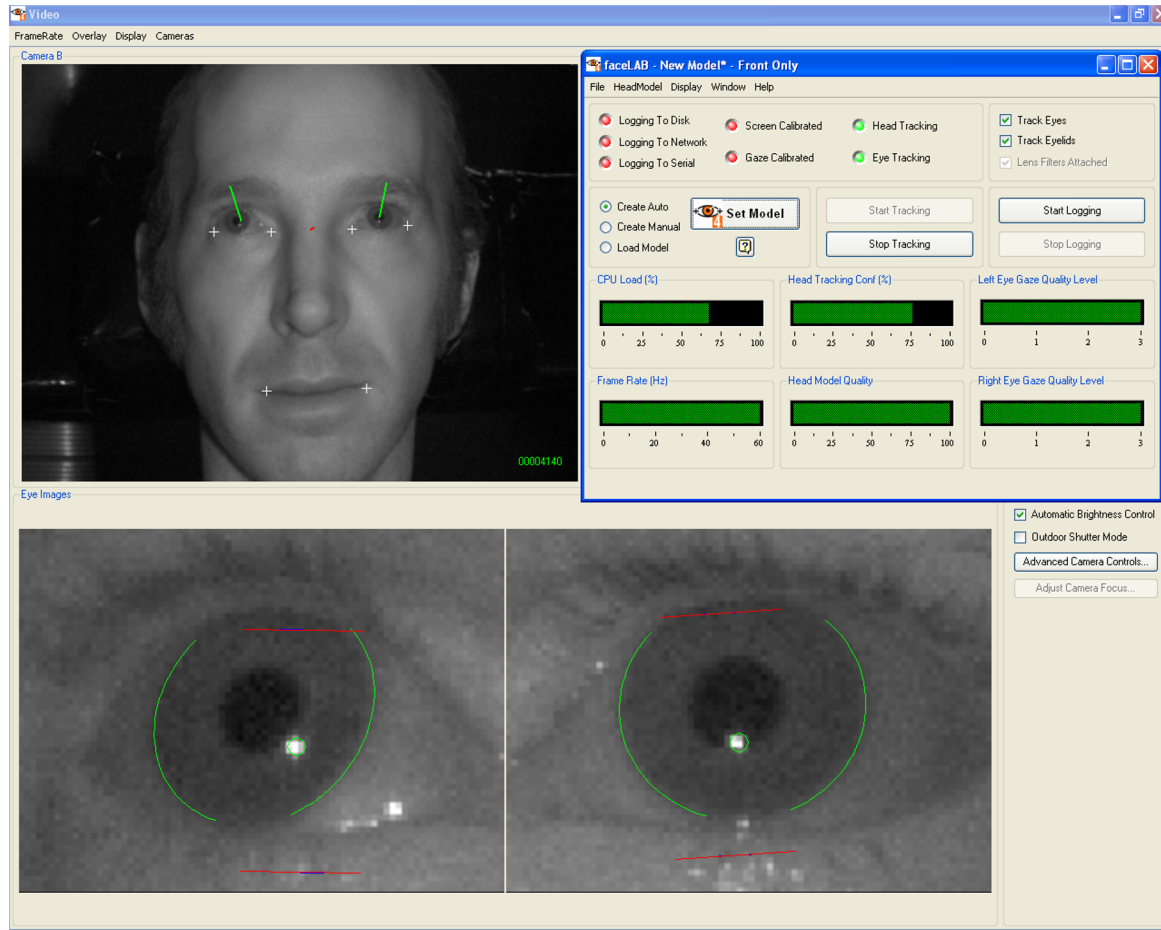
ETG metrics measure systems based on the total “usefulness” acquired by users, and have units of “rels”.

# What factors could/should/might affect $C(i)$ ?

Some “directional” hypotheses, assuming a user who searching for, and hoping to acquire, a total of  $T$  units of gain:

- When  $T$  is larger,  $C(i)$  is larger, AOTBE
- When  $i$  is larger,  $C(i)$  is larger, AOTBE
- As the relevance collected gets larger,  $C(i)$  gets smaller, AOTBE.

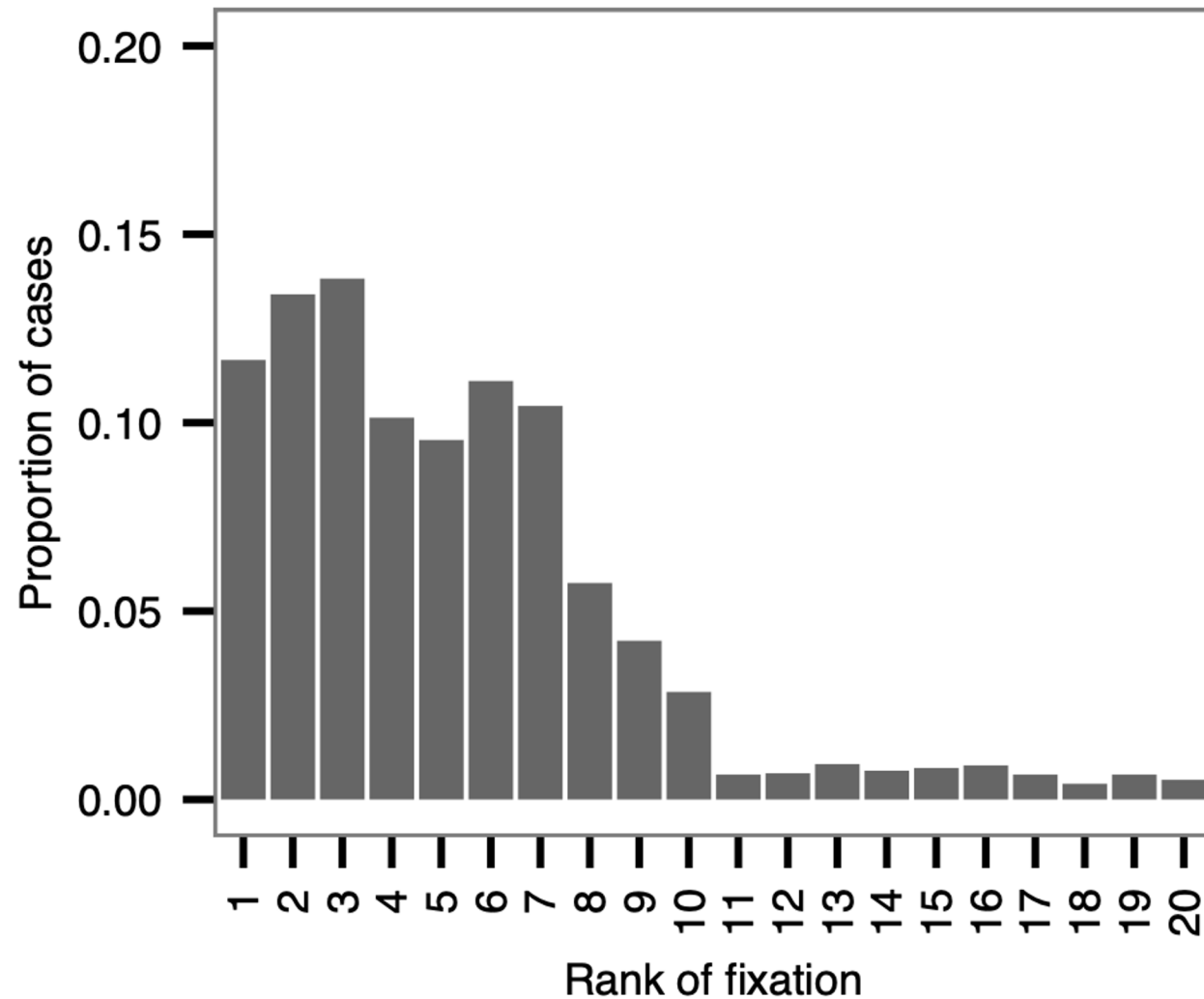
# Is there any evidence??



Source: Paul Thomas.

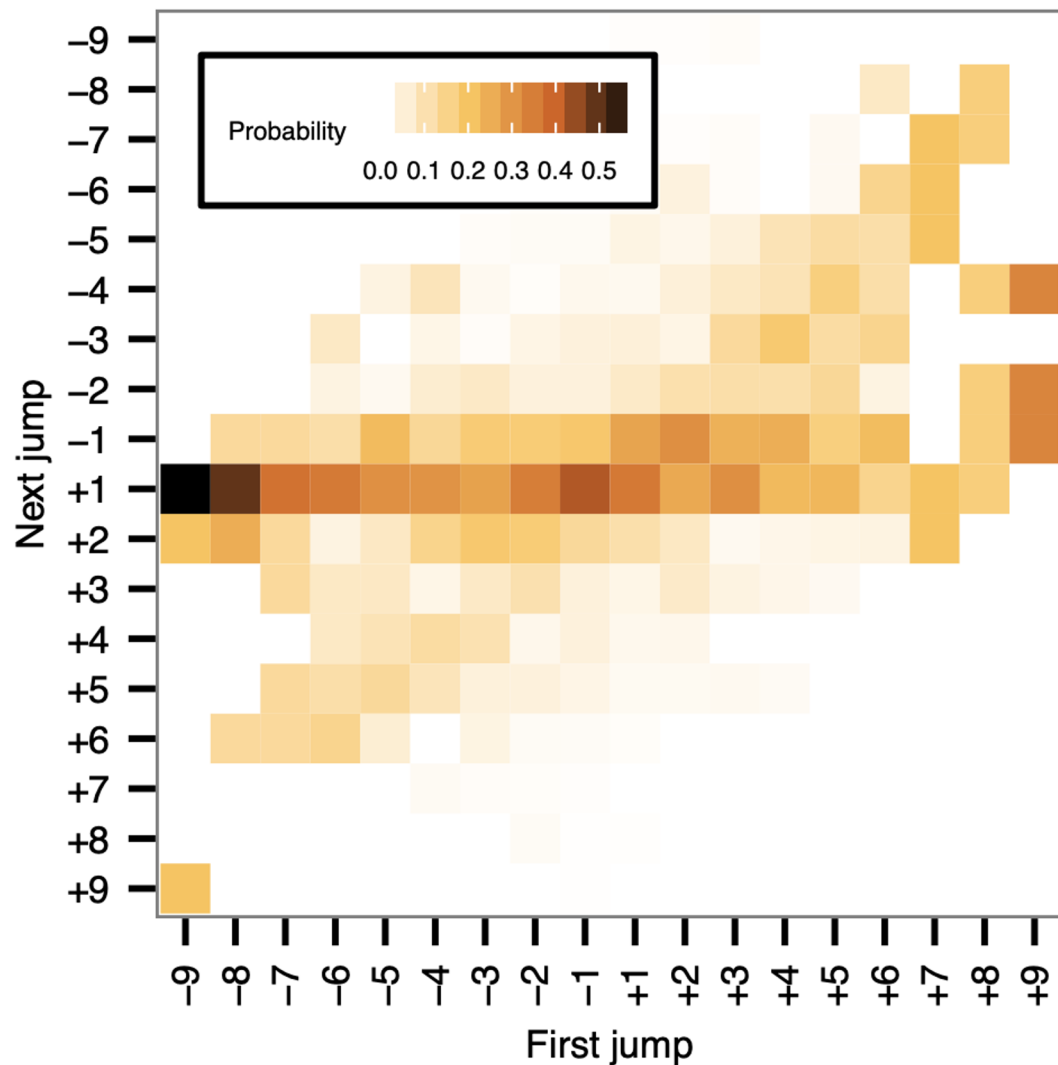


# Is there any evidence??



Graph: Thomas et al., AIRS 2013.

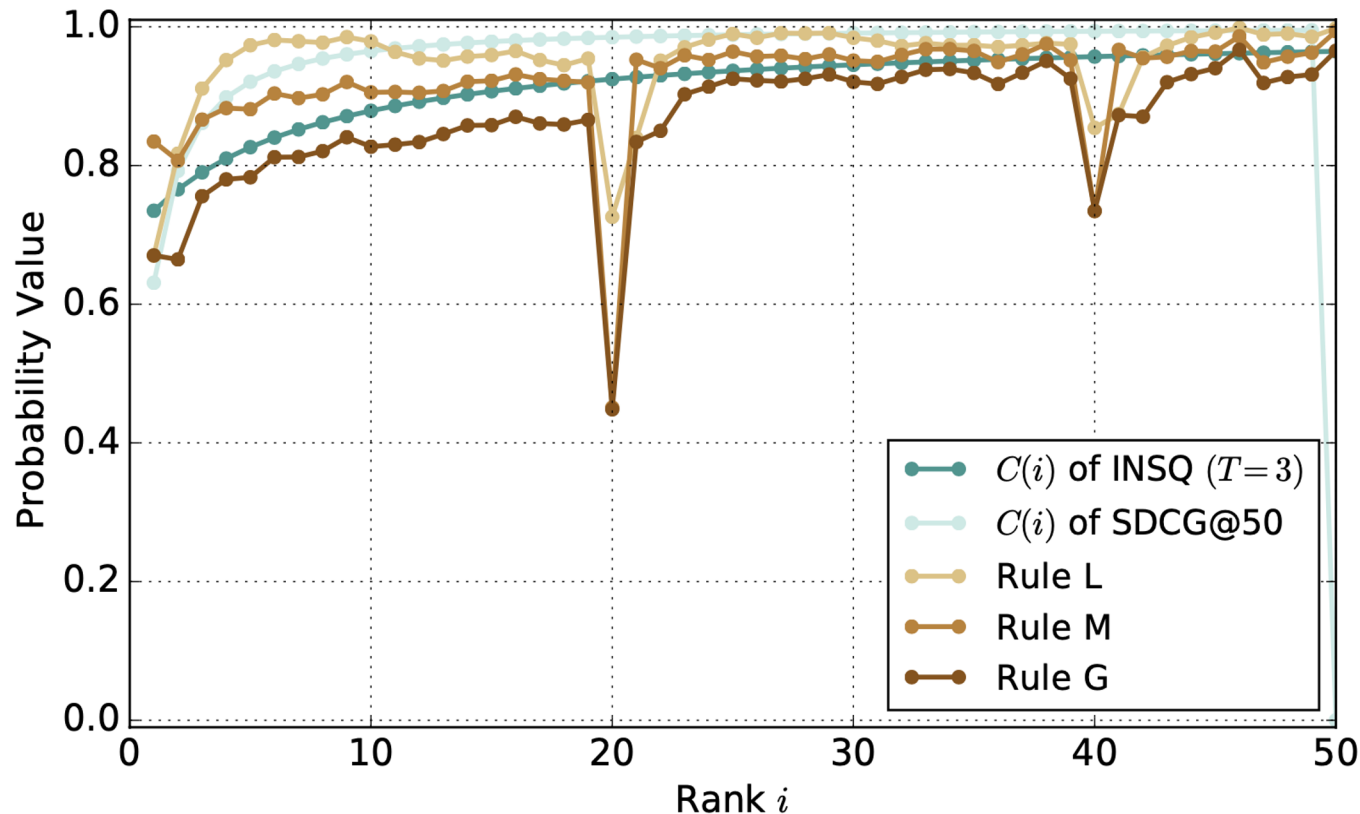
# Is there any evidence??



Graph: Thomas et al., AIRS 2013.

# Is there any evidence?

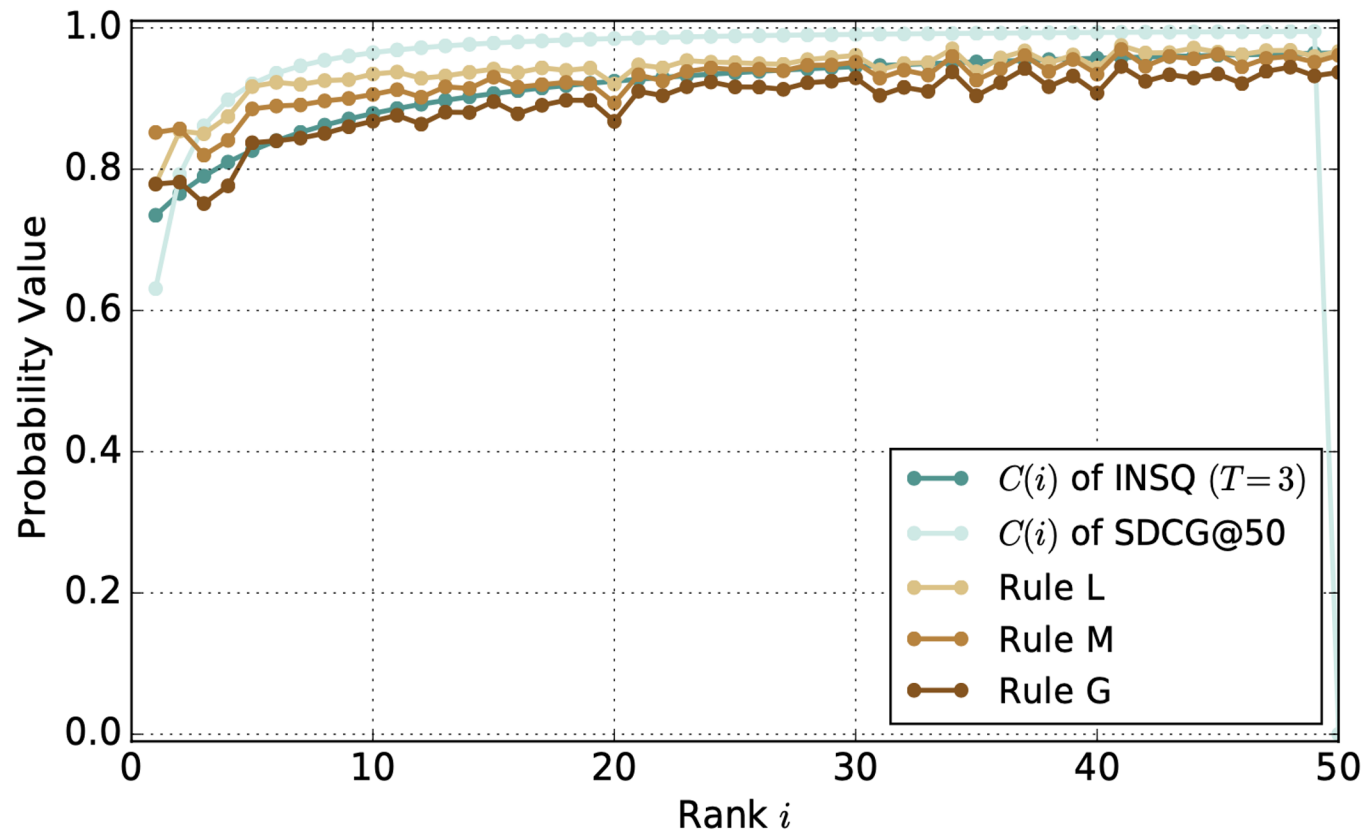
Inferred  $C(i)$  for job search users, web browser, pages of 20.



Graph: Wicaksono & Moffat, CIKM 2018, with thanks to Seek.com.

# Is there any evidence?

Inferred  $C(i)$  for job search users, phone app with continuous scroll.



Graph: Wicaksono & Moffat, CIKM 2018, with thanks to Seek.com.

# Formulating metrics (1)

Already covered in examples: if  $C(i)=1$  for  $1 \leq i < k$ , and  $C(k)=0$ , then the CWL metric is **P@k**.

And  $W(i)=1/k$  for  $1 \leq i \leq k$ , with  $W(i)=0$  for  $i > k$ .

The expected viewing depth is  $k$ .

That was an easy one, to get started.

## Formulating metrics (2)

Also already introduced: if  $C(i)=\phi$  for all  $i$ , then

- $W(1) = (1 - \phi)$ ,
- $W(i+1) = \phi W(i)$ , and
- expected viewing depth is  $1/(1 - \phi)$ .

Rank-biased precision assigns non-zero weight to every document in the ranking.

But unless  $\phi > 0.95$ , the actual weight assigned at ranks  $> 50$  is negligible.

## Formulating metrics (3)

What about a user who seeks one useful document, and stops if they find it?

Set  $C(i) = 1 - r(i)$ , and suppose that  $r(i)$  is binary, either zero or one. The metric is now **adaptive**, in that user behavior depends upon **what they have seen**. (Wow!)

Then  $W(i) = 1/d$ , where  $d$  is the rank of the first relevant document.

This is **Reciprocal Rank**!

(Could also have non-binary  $C(i) = 1 - r(i)$ , but does not equate to ERR.)

## Formulating metrics (4)

What about the metric defined by this function?

$$C(i) = \frac{\sum_{j=i+1}^{\infty} (r(j)/j)}{\sum_{j=i}^{\infty} (r(j)/j)}$$

The user is modeled as deciding what to do now (at rank  $i$ ) based on relevance values they have not yet seen (from ranks  $j > i$ ).

This is the definition of **Average Precision**. Yes!

## Formulating metrics (5)

Suppose the user starts their search with the hope of acquiring  $T$  units of “usefulness”. And suppose that by rank  $i$ , they have acquired  $R(i)$  units.

Define  $T(i) = T - R(i)$  as the “unmet requirement” at depth  $i$ . Then take

$$C(i) = \frac{(i + T + T(i) - 1)^2}{(i + T + T(i))^2}$$

This is the definition of a metric named **INST**.

# Formulating metrics (5) – Huh?

$$C(i) = \frac{(i + T + T(i) - 1)^2}{(i + T + T(i))^2}$$

INST has these properties (AOTBE):

- When T is larger, C(i) is larger – **goal sensitive**
- When i is larger, C(i) is larger – **sunk effort**
- As R(i) gets larger and T(i) gets smaller, C(i) gets smaller – **adaptive**.

# Formulating metrics (6)

You don't have to use any of those metrics!

If **you** have an understanding of **your** users and how they interact with **your** SERPs, you can define **your own**  $C(i)$  function, and use it to measure the effectiveness of **your** system as to strive to provide a better search experience.

# Hey, hang on! What about L?

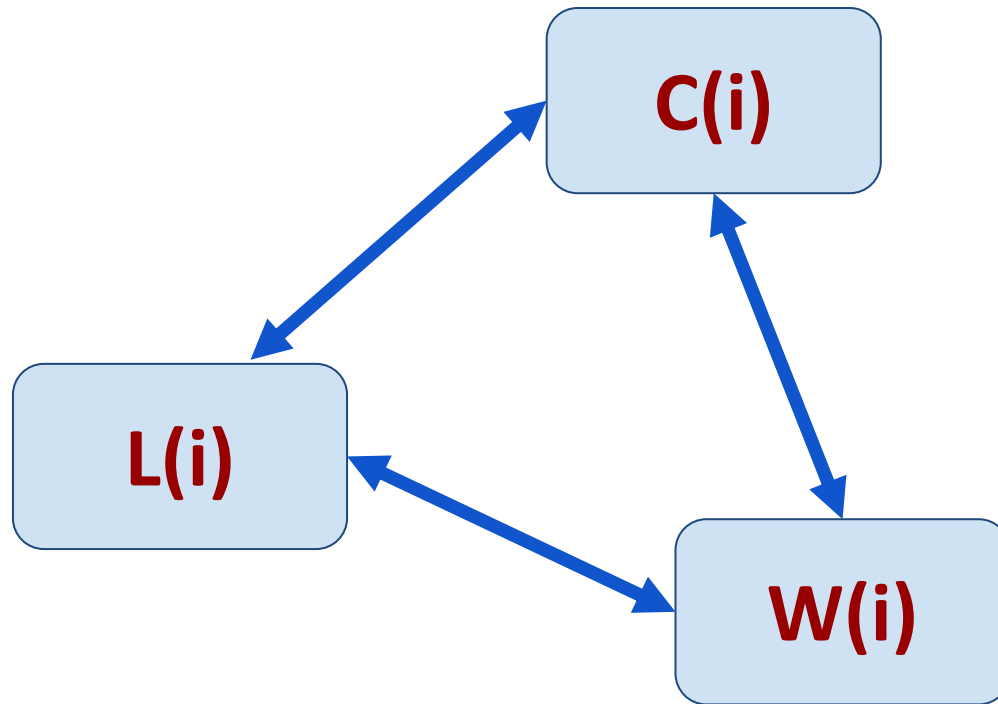
We have talked about  $C(i)$ . And about  $W(i)$ . What happened to  $L(i)$ ?

It is the “last” function, the probability that the document at rank  $i$  will be the last one inspected by the user.

It can be computed from either  $C(i)$  or from  $W(i)$ :

$$L(i) = \frac{W(i) - W(i + 1)}{W(1)}$$

# See, Double You, 'El!



# Something's missing: Residuals

To completely evaluate a metric, need relevance judgments.

What if full judgments are not available?

Compute a **residual** by calculating two scores:

- first, assuming all unjudged document have  $r(i)=0$
- then, assuming all unjudged documents have  $r(i)=1$

True score is between these extremes. The residual is the width of the interval.

If the residual is large, your experiment **may have a problem**.

## Summary of Section II

C/W/L metrics are constructed by hypothesizing behavior over a population of users.

The critical component is  $C(i)$ , the conditional continuation probability. But they can also be defined via  $W(i)$  and/or  $L(i)$ , each leads to the other two.

From any of C/W/L, ERG and ETG metrics are available, including ones that are goal sensitive and/or adaptive.

Residuals should be monitored, and not ignored.

## Summary of Section II

C/W/L metrics are constructed by hypothesizing a model over a population of users.

The critical component is  $C(i)$ , the continuation probability. But they can also be defined via  $W(i)$  and  $L(i)$ , each leads to the other two.

From any of C/W/L metrics are available, including ones that are goal sensitive and adaptive.

Residuals are monitored, and not ignored.

**C/W/L Spells "Cool"**

