Introducing The NTCIR-17 FairWeb-1 Task

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Version 20220925

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“You are serving as a general chair of an IR conference. You want to hire diverse IR researchers as organisers.”

Diversity dimensions:

- Different career stage (include junior researchers, not just famous researchers)
- Different genders
- Different countries

etc.

Screenshot taken on 14th July, 2022

information retrieval researchers

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2,460,000,000 Results Any time

An information retrieval system not only occupies an important position in the network information platform, but also plays an important role in information acquisition, query processing, and wireless sensor networks. It is a procedure to help researchers **extract documents from data sets as document retrieval tools**.

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Publish Year: 2019

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Research on information retrieval model based on ontology

jwcn-eurasipjournals.springeropen.com/articles/10.1186/s13638-019-1354-z

Was this helpful?

People also ask

What is information retrieval?

What is information retrieval in engineering engineering?

What is the purpose of the information retrieval community study?

When was the first information retrieval system invented?

Information retrieval

Information retrieval (IR) in computing and information science is the process of obtaining information system resources that are relevant to an information need from a collection of those resources. ...

Related people

Susan Dumais | C. J. van Rijsbergen | Ricardo Baeza-Yates | Gerard Salton | Calvin Mooers

Data: Wikipedia

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h-index > 100

h-index > 80

We only get famous and high h-index people…

Screenshot taken on 14th July, 2022

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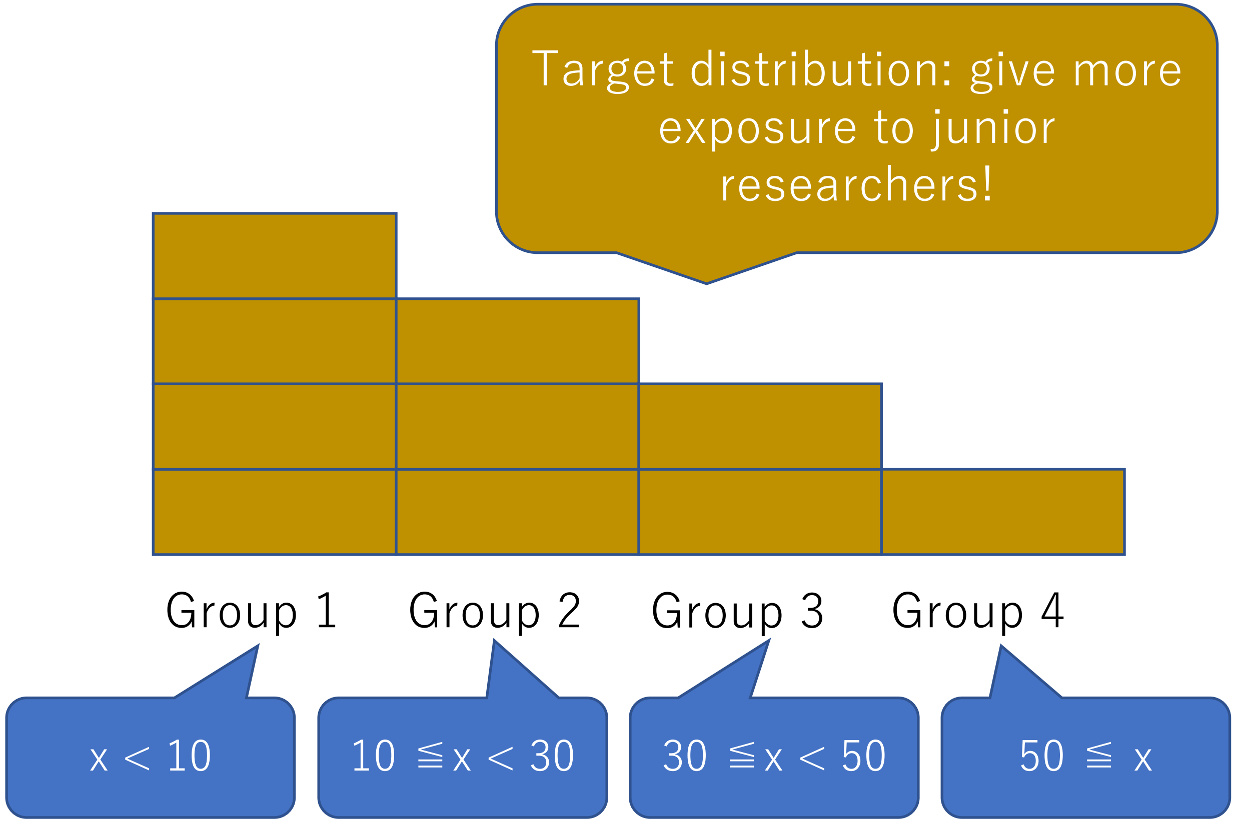
Feedback

Explore more

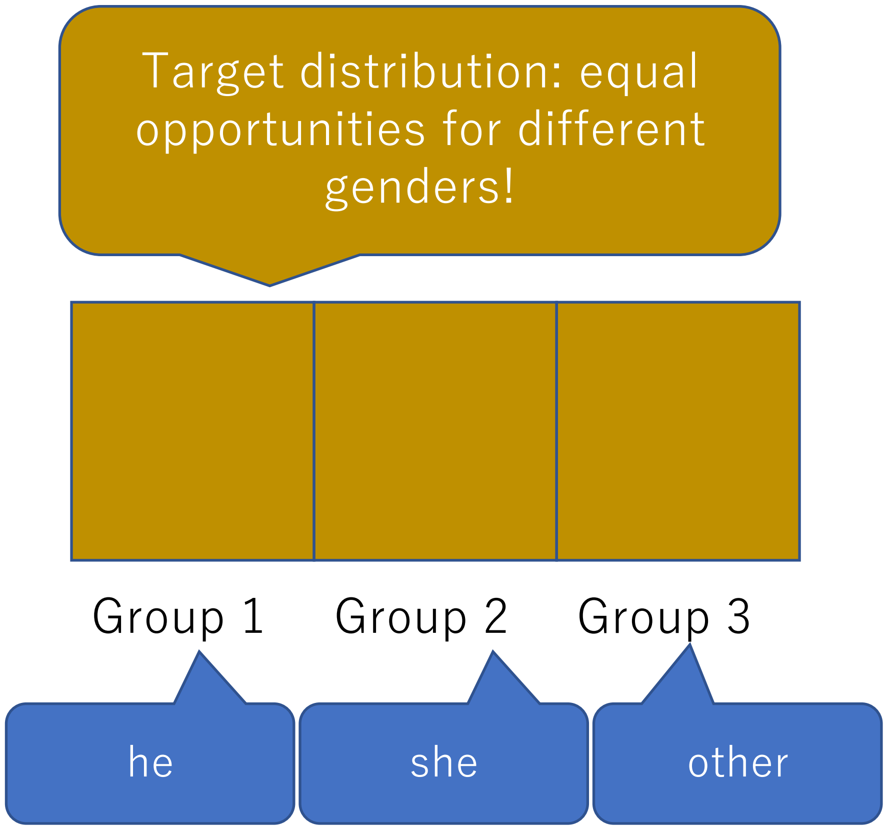
Poor gender balance…

Let's consider group fairness

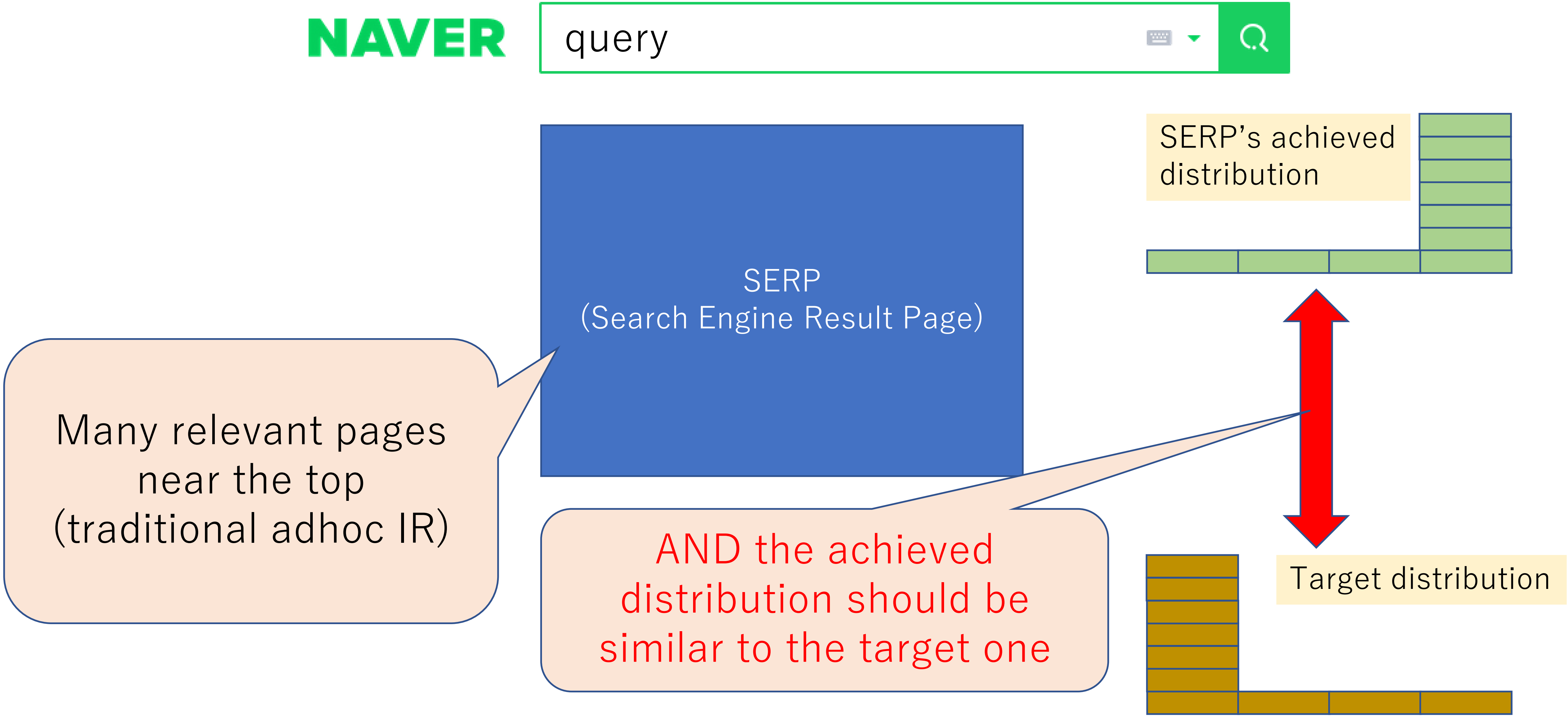
Attribute set: HINDEX



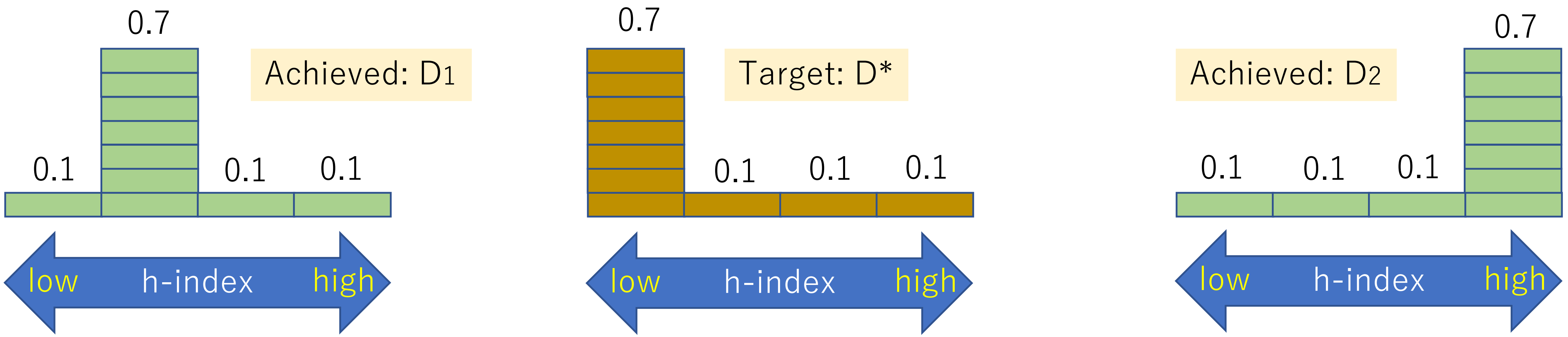
Attribute set: GENDER



Web search that considers group fairness



Handling ordinal groups properly



If divergences for nominal groups (e.g. Jensen-Shannon Divergence) is used…

JSD = 0.3651

JSD = 0.3651

Divergences for ordinal groups can tell the difference

NMD = 0.2000

Closer to target

RNOD = 0.5477

Closer to target

NMD = 0.6000

RNOD = 0.6000

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Input/Output

INPUT

- Search topic: describes an information need about entities that satisfy a certain condition
- One or more attribute set and a target distribution (probability mass function) for each of them

OUTPUT

- Run: a SERP for each topic (TREC format). Expected to contain relevant documents near top ranks AND to be group-fair wrt each attribute set

Task workflow

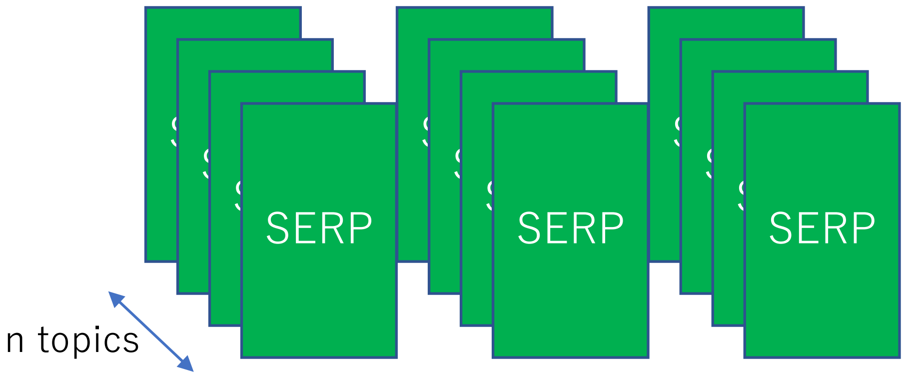
Annotators

Organisers

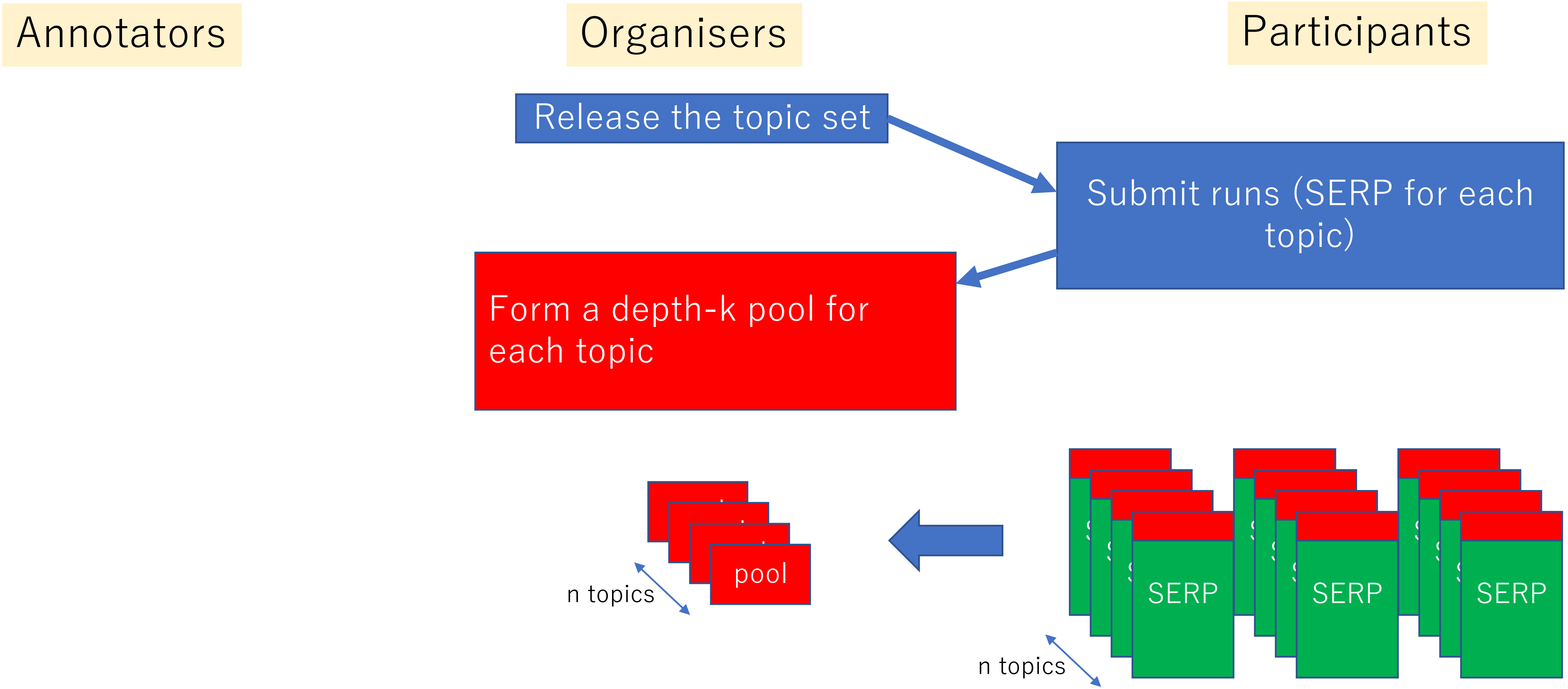
Participants

Release the topic set

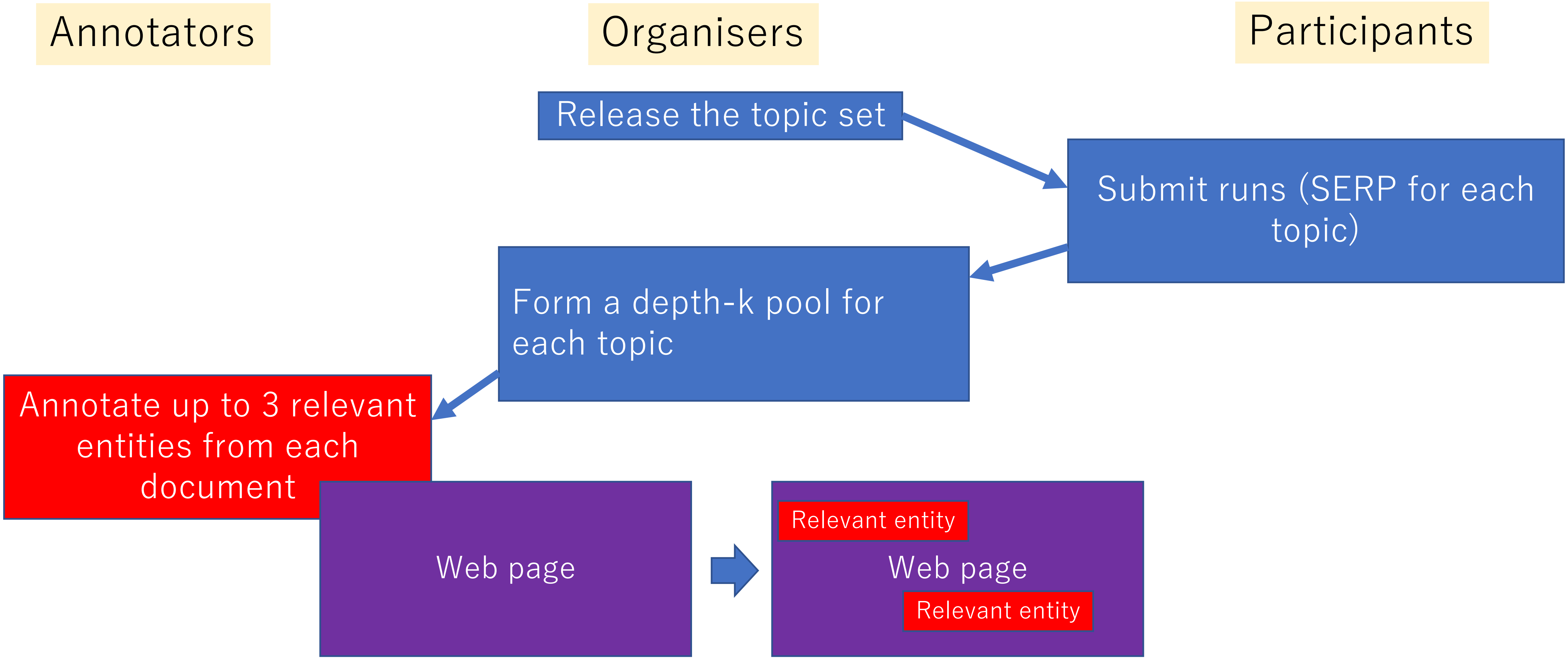
Submit runs (SERP for each topic)



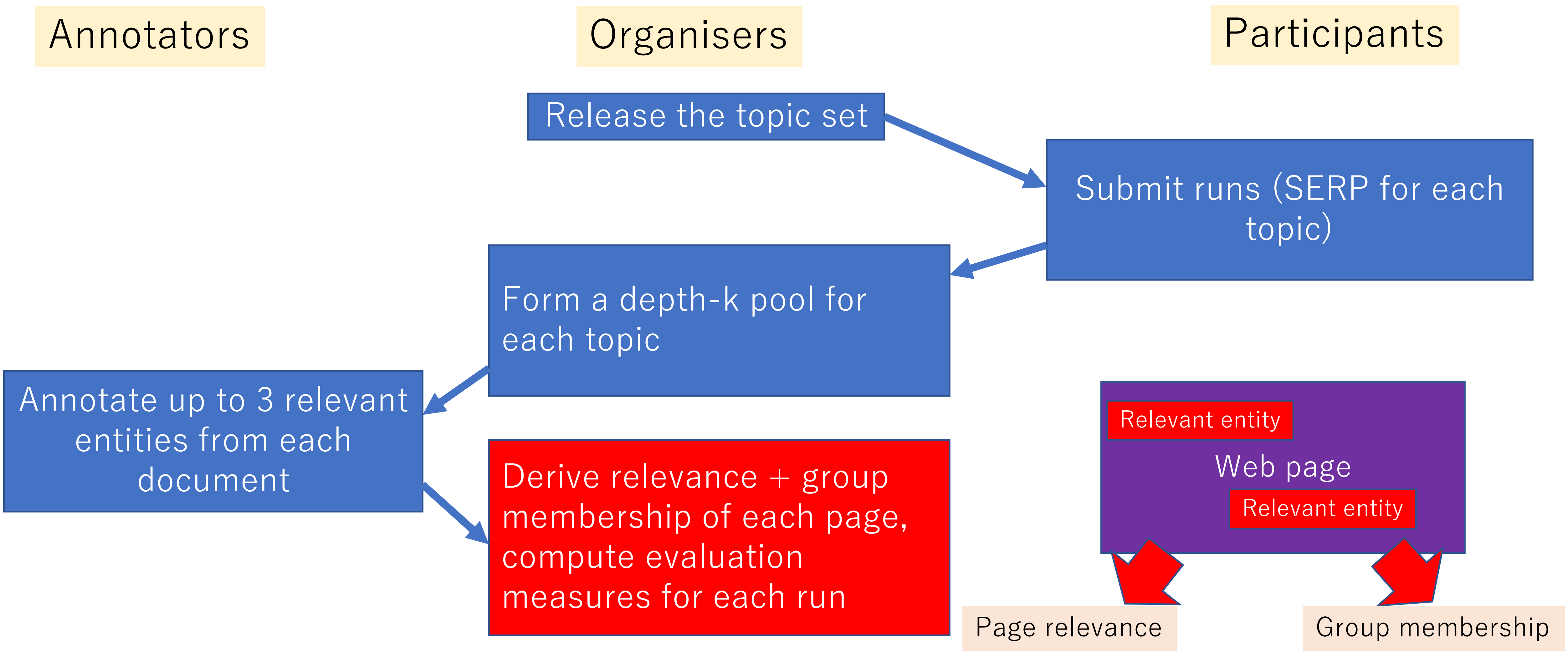
Task workflow



Task workflow



Task workflow



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Entities

"something that exists apart from other things, having its own independent existence"

https://dictionary.cambridge.org/dictionary/english/entity

Four entity types considered at FairWeb-1:

R: researchers

M: movies

T: Twitter accounts

Y: YouTube contents

Relevant entities and topics

Relevant entity: entities that satisfy the condition specified in the topic description.

Four topic types with examples:

R: information retrieval researchers

M: Daniel Craig 007 movies

T: Twitter accounts that provide info on COVID

Y: Coldplay covers on YouTube

The underlined parts indicate the topic type

Attribute sets for each topic type

- R topic: HINDEX (ordinal, 4 groups)
  GENDER (nominal, 3 groups)
- M topic: REVIEWS (ordinal, 4 groups)
  ORIGIN (nominal, 8 groups)
- T topic: FOLLOWERS (ordinal, 4 groups)
- Y topic: SUBSCS (ordinal, 4 groups)

Attribute sets for each topic type

- R topic: HINDEX (ordinal, 4 groups)
  GENDER (nominal, 3 groups)
- M pic: REVIEWS (ordinal, 4 groups)
  ORIGIN (nominal, 8 groups)

pic: FOLLOWERS (ordinal, 4 g

(ordinal, 4 g

Google scholar h-index
$x < 10$
$10 \leqq x < 30$
$30 \leqq x < 50$
$50 \leqq x$

Gender label (he/she/other) based solely on what pronoun is used in the official researcher bio

Note that this is just an approximation and simplification of true gender

Attribute sets for each topic type

- R topic: HINDEX (ordinal, 4 groups)
  GENDER (nominal, 3 groups)
- M topic: REVIEWS (ordinal, 4 groups)
  ORIGIN (nominal, 8 groups)
- pic: FOLLOWERS (ordinal, 4 gr
  (ordinal, 4 g

#reviews on IMDb page
$x < 100$
$100 \leqq x < 10K$
$10K \leqq x < 1M$
$1M \leqq x$

Countries of origin on IMDb page mapped to 8 geographic regions (one movie may cover multiple countries)

e.g. a UK-Japan movie => Asia, Europe

Africa
America
Antarctica
Asia
Caribbean
Europe
Middle East
Oceania

Attribute sets for each topic type

- R topic: HINDEX (ordinal, 4
  GENDER (nominal,
- M topic: REVIEWS (ordinal, 4 gro
  ORIGIN (nominal, 8 group
- T topic: FOLLOWERS (ordinal, 4 groups)
- Y topic: SUBSCS (ordinal, 4 groups)

#followers of twitter account
(same grouping as REVIEWS)

#subscribers of the creator
(same grouping as REVIEWS)

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Relevant entity schema

R
(ResearcherName, BioURL, he/she/other, GoogleScholarURL, h-index)

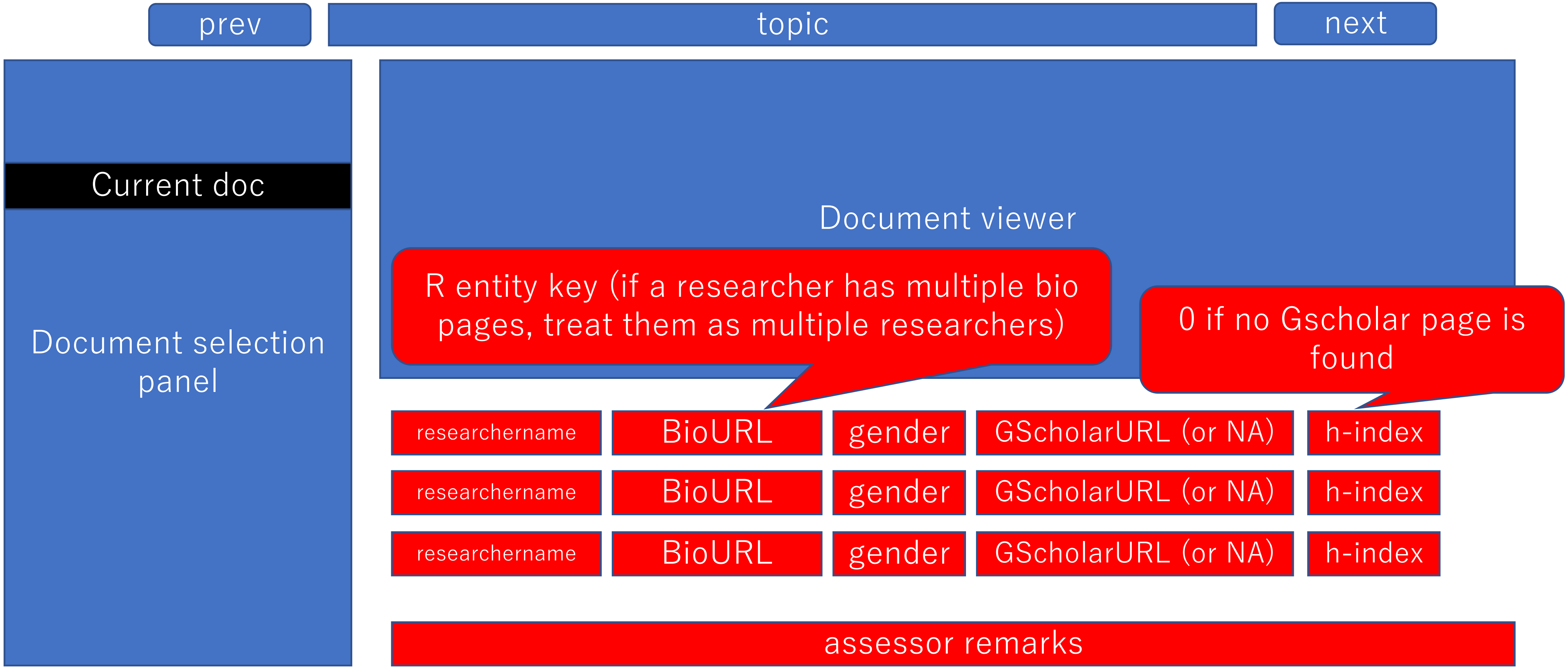
M
(MovieName, IMDbURL, #reviews, countries)

T
(TwitterAccountURL, #followers)

Y
(YouTubeContentURL, #subscribers)

Annotators will use their favourite search engines to locate BioURLs, GSholarURLs, and IMDbURLs.

Annotation interface (R topic)



Backend records: <topicID, docID, ResearcherName, BioURL, he/she/other, GScholarURL, h-index>

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Deriving page relevance

If 2 annotators each find 3 nonoverlapping relevant entities

d: page

E(d): set of relevant entities extracted from d ($|E(d)| \leqq 6$)

$r(e) \in \{1,2\}$: relevance level of $e \in E(d)$

Page relevance level $g(d) \in \{0,1,2\}$ defined as follows

Max relevance level G=2

$$g(d) = \begin{cases} 0 & (E(d) = \emptyset); \\ \max_{e \in E(d)} r(e) & (\text{otherwise}). \end{cases}$$

Page relevance level = max entity relevance level within page

Deriving page group membership

Group 1

$C = \{C_1, \cdots C_{|C|}\}$: attribute set

$F(e, C_i)$: flag that maps e to exactly one group

Hard group membership for entities

A researcher whose h-index=5 (C=HINDEX):

$F(e, C_1)=1$, $F(e, C_2) = F(e, C_3) = F(e, C_4) = 0$

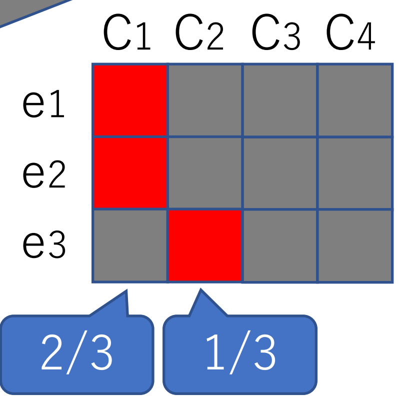
Ad researcher whose bio says ”he” (C=GENDER):

$F(e, C_1)=1$, $F(e, C_2) = F(e, C_3) = 0$

Uniform for nonrelevant page

Group membership probabilities of d:

$$P(d, C_i) = \begin{cases} 1/|C| & (E(d) = \emptyset); \\ \frac{|\sum_{e \in E(d)} F(e, C_i)|}{|\sum_i \sum_{e \in E(d)} F(e, C_i)|} & (\text{otherwise}). \end{cases}$$



Deriving page group membership

C = $\{C_1, \cdots C_{|C|}\}$: attribute set (geo regions)

ORIGIN(e) ($\subseteq$ C): set of geo regions for movie e $\in$ E(d)

(m = |ORIGIN(e)| ($\geqq$1))

Soft group membership for movie entities

$$G(e, C_i) = \begin{cases} 1/m & (C_i \in ORIGIN(e)); \\ 0 & (\text{otherwise}). \end{cases}$$

$$P(d, C_i) = \begin{cases} 1/|C| & (E(d) = \emptyset); \\ \frac{|\sum_{e \in E(d)} G(e, C_i)|}{|\sum_i \sum_{e \in E(d)} G(e, C_i)|} & (\text{otherwise}). \end{cases}$$

Uniform for nonrelevant page

	C1	C2	C3	C4
e1	0.5		0.5	
e2	1			
e3		0.5	0.5	

1.5/3 0.5/3 1.0/3

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GFR (Group Fairness and Relevance)

https://arxiv.org/pdf/2204.00280.pdf

L: SERP

d L@k : doc at rank k in L

Probability that users will be satisfied with doc at k

Page relevance level

$$p^{\mathrm{sat}}_{L@k} = \frac{2^{g(d_{L@k})} - 1}{2^G}$$

0, ¼, ¾ in our task

Probability that users will reach k and finally get satisfied

$$Decay_{L@k} = \begin{cases} p^{\mathrm{sat}}_{L@1} & k = 1 \\ p^{\mathrm{sat}}_{L@k} \prod_{j=1}^{k-1}(1 - p^{\mathrm{sat}}_{L@j}) & \text{otherwise.} \end{cases}$$

$$GFR(L) = \sum_{k=1}^{|L|} \underbrace{Decay_{L@k} \left(w_0 Utility_{L@k}\right.}_{\text{Relevance measures like ERR}} \left. + \sum_{m=1}^{M} w_m DistrSim^{m}_{L@k} \right)$$

Similarity between achieved distribution@k and target

Decay: probability that the users will abandon the SERP at rank k

ERR (Expected Reciprocal Rank) user model

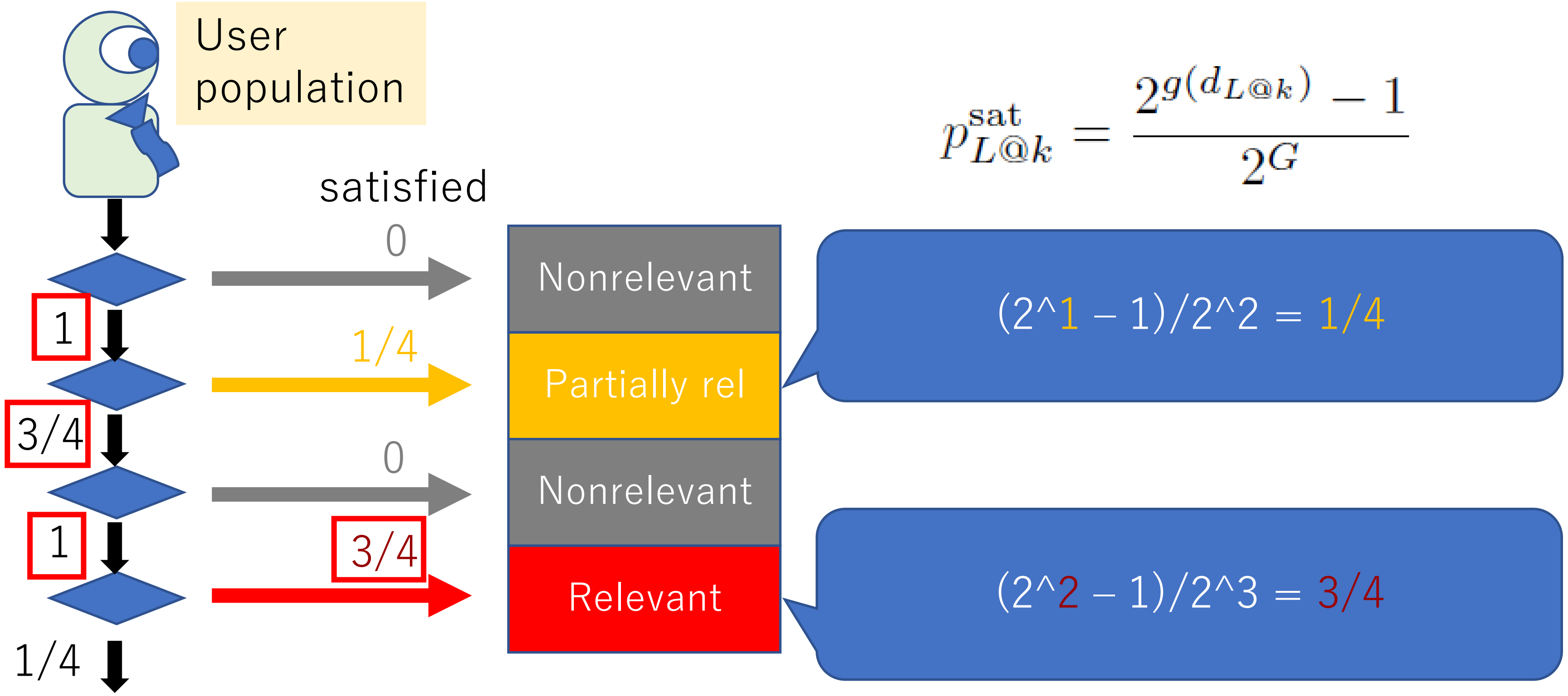
$$p^{\mathrm{sat}}_{L@k} = \frac{2^{g(d_{L@k})} - 1}{2^{G}}$$

Decay L@1 = 0

Decay L@2 = 1 * (1/4) = 1/4

Decay L@3 = 1 * (3/4) * 0 = 0

Decay L@4 = 1 * (3/4) * 1 * (3/4)
= 8/16



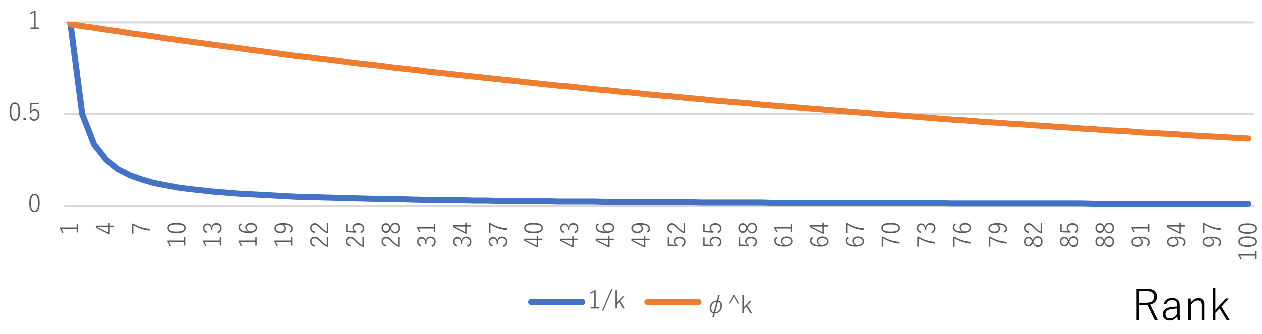
Utility: how useful was the top k of the SERP?

$$Utility^{\mathrm{ERR}}_{L@k} = 1/k$$

$$Utility^{\mathrm{iRBU}}_{L@k} = \phi^k$$

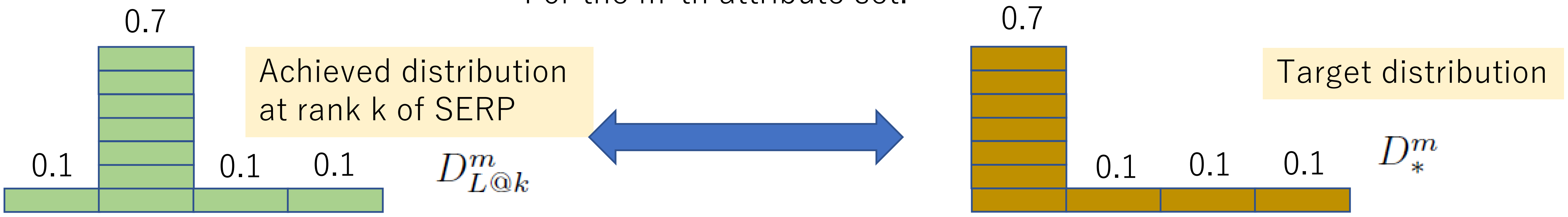
(Φ =0.99)

	Nonrelevant	
1/2 = 0.50	Partially rel	0.99^2 = 0.98
	Nonrelevant	
1/4 = 0.25	Relevant	0.99^4 = 0.96



DistrSim: Similarity between achieved distribution@k and target

For the m-th attribute set:



Similarity: larger=better

$$DistrSim^m_{L@k}(D^m_{L@k} \parallel D^m_*) = 1 - Divergence^m_{L@k}(D^m_{L@k} \parallel D^m_*)$$

- For attribute sets containing nominal groups:

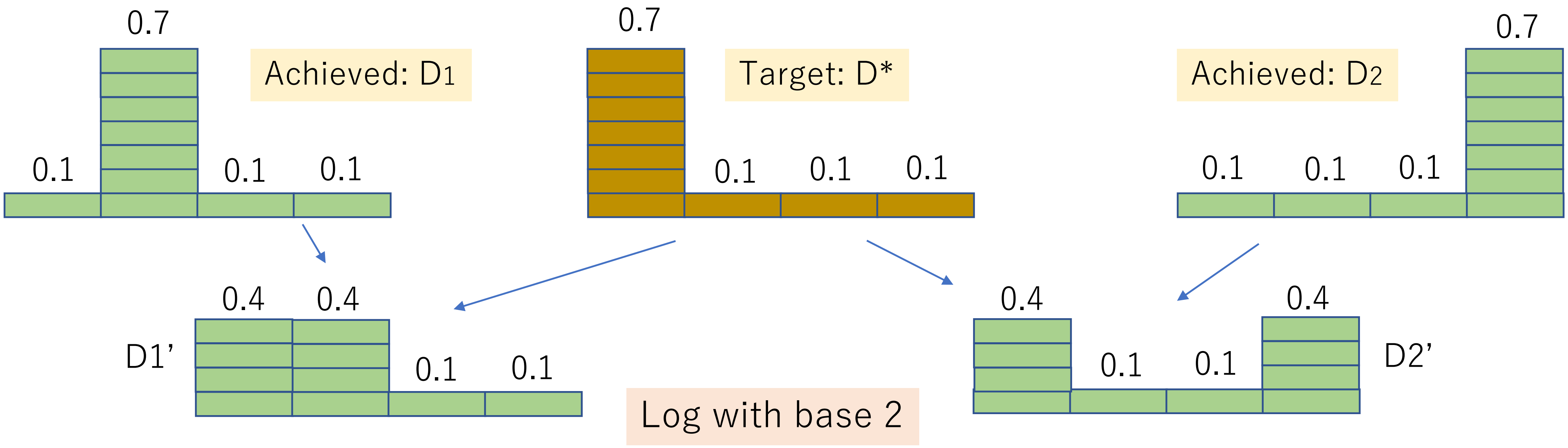
Divegence= JSD (Jensen-Shannon Divergence)

- For attribute sets containing ordinal groups:

Divegence= NMD (Normalised Match Distance) or
RNOD (Root Normalised Order-aware Divergence)

See Sakai's CIKM2021LQ workshop paper: http://ceur-ws.org/Vol-3052/paper21.pdf

JSD etc. are not suitable for ordinal groups

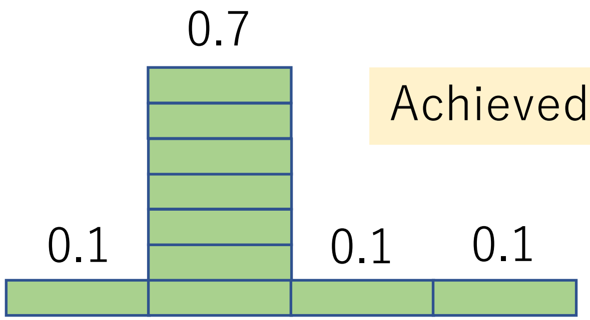


$KLD(D_1||D_1') =$
$0.1\log(0.1/0.4) + 0.7\log(0.7/0.4) = 0.3651$
$KLD(D^*||D_1') =$
$0.7\log(0.7/0.4) + 0.1\log(0.1/0.4) = 0.3651$
$JSD = (0.3651+0.3651)/2 = 0.3651$

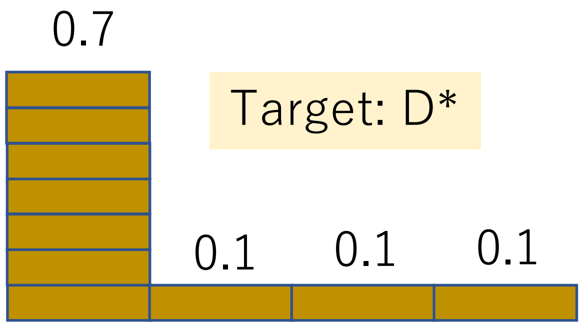
$KLD(D_2||D_2') =$
$0.1\log(0.1/0.4) + 0.7\log(0.7/0.4) = 0.3651$
$KLD(D^*||D_2') =$
$0.7\log(0.7/0.4) + 0.1\log(0.1/0.4) = 0.3651$
$JSD = (0.3651+0.3651)/2 = 0.3651$

D_1 (not too bad) and D_2 (terrible) considered equivalent aka Earth Mover's Distance

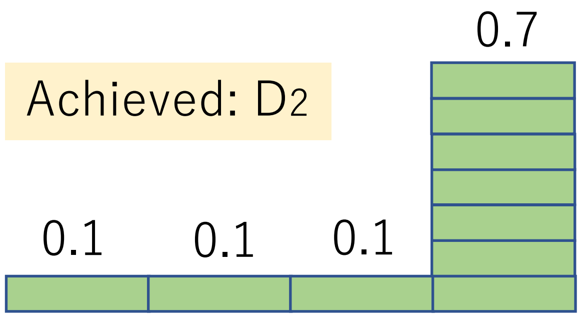
NMD (Normalised Match Distance)



Achieved: D1



Target: D*



Achieved: D2

Cumulative:

(0.1, 0.8, 0.9, 1.0)

Cumulative:

(0.7, 0.8, 0.9, 1.0)

Cumulative:

(0.1, 0.2, 0.3, 1.0)

NMD =
(|0.1-0.7| + |0.8-0.8| +
|0.9-0.9| + |1.0-1.0|)/3
= 0.6/3
= 0.2000

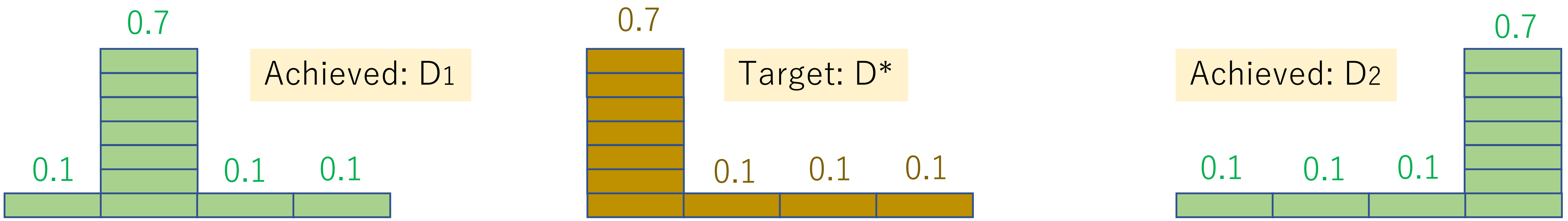
Closer to the target!

NMD =
(|0.1-0.7| + |0.2-0.8| +
|0.3-0.9| + |1.0-1.0|)/3
=(0.6+0.6+0.6)/3
= 0.6000

For computing RNOD

DW (Distance-Weighted sum of squares)

$$DW_i = \sum_{j=1}^{|C|} |i-j|(P_j - P_j^*)^2$$



DW1 = j=2 j=3 j=4
1*(0.7-0.1)^2 + 2*(0.1-0.1)^2 + 3*(0.1-0.1)^2
= 0.36

DW2 = j=1 j=3 j=4
1*(0.1-0.7)^2 + 1*(0.1-0.1)^2 + 2*(0.1-0.1)^2
= 0.36

DW3 = j=1 j=2 j=4
2*(0.1-0.7)^2 + 1*(0.7-0.1)^2+ 1*(0.1-0.1)^2
= 1.08

DW4 = j=1 j=2 j=3
3*(0.1-0.7)^2 + 2*(0.7-0.1)^2 + 1*(0.1-0.1)^2
= 1.80

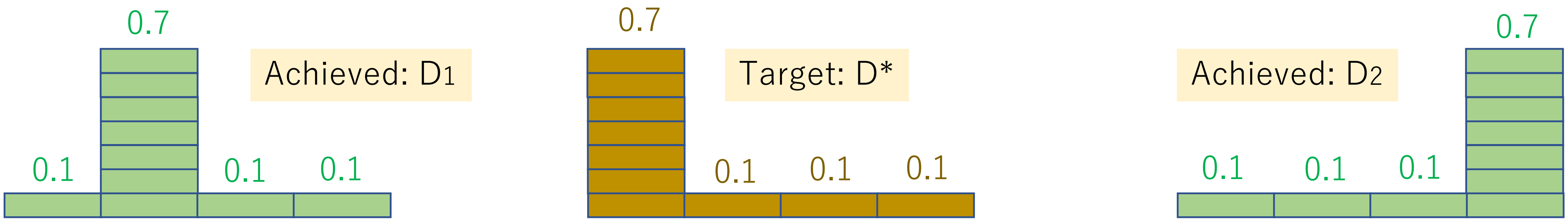
DW1 = j=2 j=3 j=4
1*(0.1-0.1)^2 + 2*(0.1-0.1)^2 + 3*(0.7-0.1)^2
= 1.08

DW2 = j=1 j=3 j=4
1*(0.1-0.7)^2 + 1*(0.1-0.1)^2 + 2*(0.7-0.1)^2
= 1.08

DW3 = j=1 j=2 j=4
2*(0.1-0.7)^2 + 1*(0.1-0.1)^2 + 1*(0.7-0.1)^2
= 1.08

DW4 = j=1 j=2 j=3
3*(0.1-0.7)^2 + 2*(0.1-0.1)^2 + 1*(0.1-0.1)^2
= 1.08

RNOD (Root Normalised Order-aware Divergence)



DW (0.36, 0.36, 1.08, 1.08)

DW (1.08, 1.08, 1.08, 1.08)

$$OD(D \parallel D^*) = \frac{\sum_{i \text{ s.t. } C_i \in C^*} DW_i}{|C^*|}$$

OD =
(0.36+0.36+1.08+1.80)/4
= 0.90

RNOD =
SQRT(0.90/3)
= 0.5477

Closer to the target!

$$RNOD(D \parallel D^*) = \sqrt{\frac{OD(D \parallel D^*)}{|C| - 1}}$$

OD =
(1.08+1.08+1.08+1.08)/4
=1.08

RNOD =
SQRT(1.08/3)
= 0.6000

Evaluating intersectional group fairness

- R topics

relevance

HINDEX (ordinal)

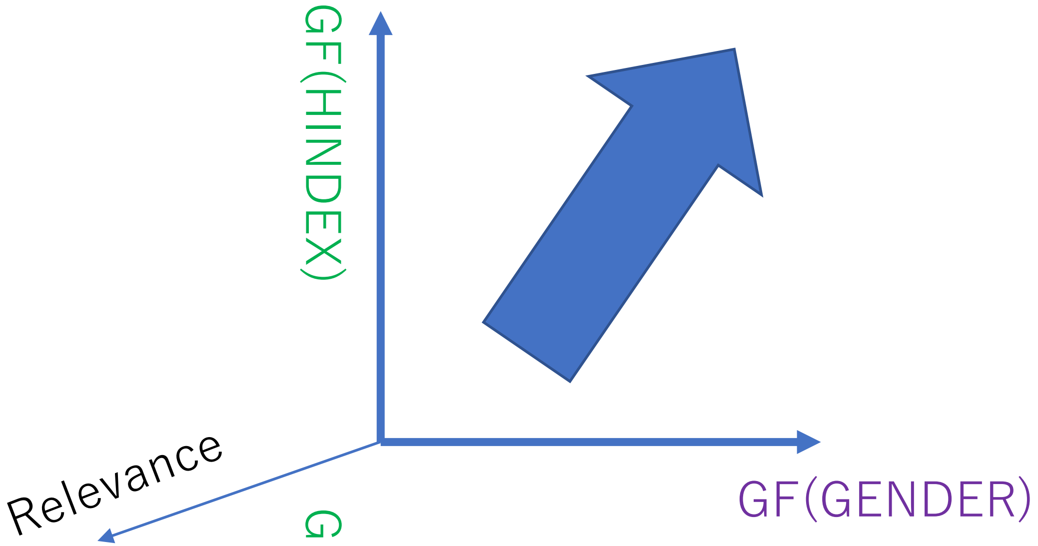
GENDER (nominal)

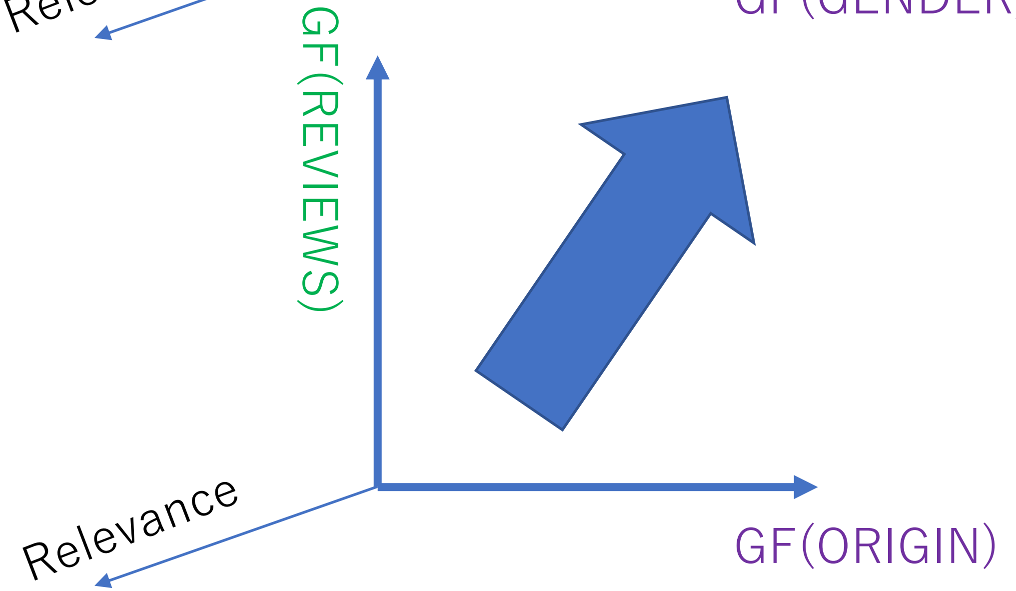
- M topics

relevance

REVIEWS (ordinal)

ORIGIN (nominal)





How is GFR different from the single-ranking measure used at TREC 2022?

https://fair-trec.github.io/docs/Fair_Ranking_2022_Participant_Instructions.pdf

Main diffs:

- Decay: TREC uses nDCG decay (relevance-unaware); we use ERR decay (relevance-aware)
- Divergence: TREC uses JSD; we use JSD for nominal groups but NMD and RNOD for ordinal groups
- Combining relevance and group fairness: TREC multiplies the two; we average relevance (ERR or iRBU score) and one or two GF scores (and also look at the relationship across components, e.g. ERR vs GF(HINDEX) vs GF(GENDER)).

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Summary

- Participants are expected to returns SERPs that are relevant and group-fair!
- The FairWeb-1 task treats ordinal groups as ordinal, and considers intersectional group fairness between ordinal groups and nominal groups.
- Ensuring fairness is researchers' one big responsibility! Please participate!

Timeline (tentative)

October 7, 2022:	Release of 1st CFP with sample topics and evaluation protocol
December 16, 2022:	Pilot relevance assessments for the sample topics and a few pilot runs released; topic set size determined
Dec 19-Feb 28, 2023:	Topic development
March 1, 2023:	Topics released; task registrations due
May 12, 2023:	Run submissions due
May 15-July 31, 2023:	Entity annotations; runs evaluated
August 1, 2023:	Evaluation results and draft overview released
September 1, 2023:	Draft participant papers due
November 1, 2023:	Camera ready papers due
December 2023:	NTCIR-17@NII, Tokyo, Japan

On the history of NTCIR (open access book, 2020)

https://link.springer.com/content/pdf/10.1007/978-981-15-5554-1.pdf