

Some Biases in Data Science

Allan Hanbury



COMPLEXITY
SCIENCE
HUB
VIENNA

```
graph LR; Data[Data] --> Algorithm[Algorithm]; Algorithm --> Results[Results];
```

Data

Algorithm

Results

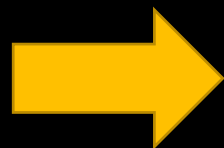
BIASED



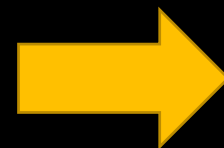
Creation



Data



Algorithm



Results

BUSINESS NEWS

OCTOBER 10, 2018 / 5:12 AM / 7 MONTHS AGO

Amazon scraps secret AI recruiting tool that showed bias against women

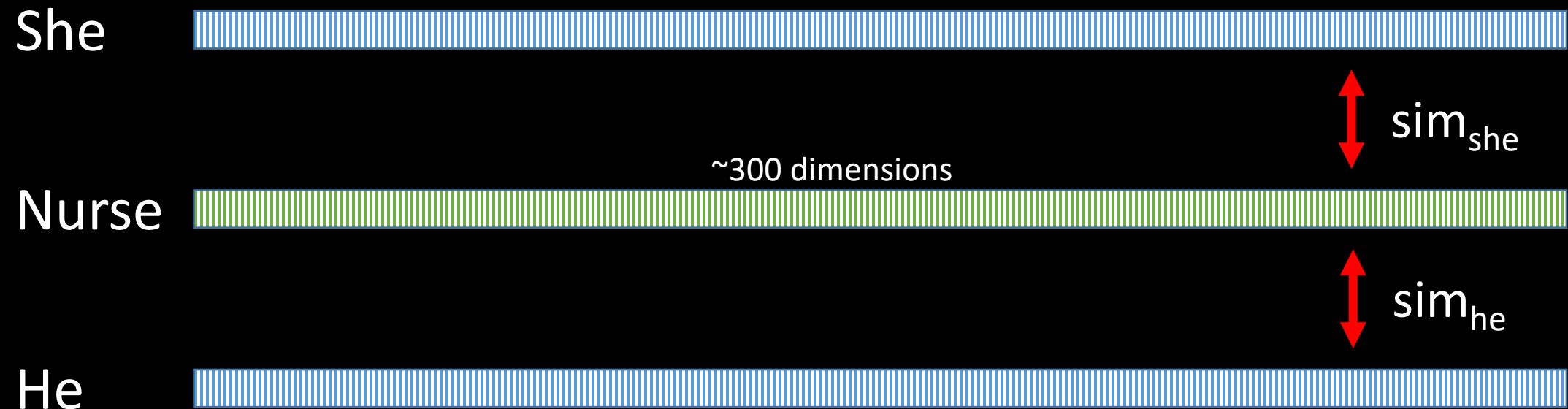
Jeffrey Dastin

8 MIN READ



SAN FRANCISCO (Reuters) - Amazon.com Inc's ([AMZN.O](#)) machine-learning specialists uncovered a big problem: their new recruiting engine did not like women.

Word Embedding



$$\text{sim}_{\text{she}} > \text{sim}_{\text{he}}$$

Creating Word Embedding

Source Text

Training Samples

The quick brown fox jumps over the lazy dog. →	(the, quick) (the, brown)
The quick brown fox jumps over the lazy dog. →	(quick, the) (quick, brown) (quick, fox)
The quick brown fox jumps over the lazy dog. →	(brown, the) (brown, quick) (brown, fox) (brown, jumps)
The quick brown fox jumps over the lazy dog. →	(fox, quick) (fox, brown) (fox, jumps) (fox, over)

She	is	a	nurse	in	a	clinic
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(nurse, she)



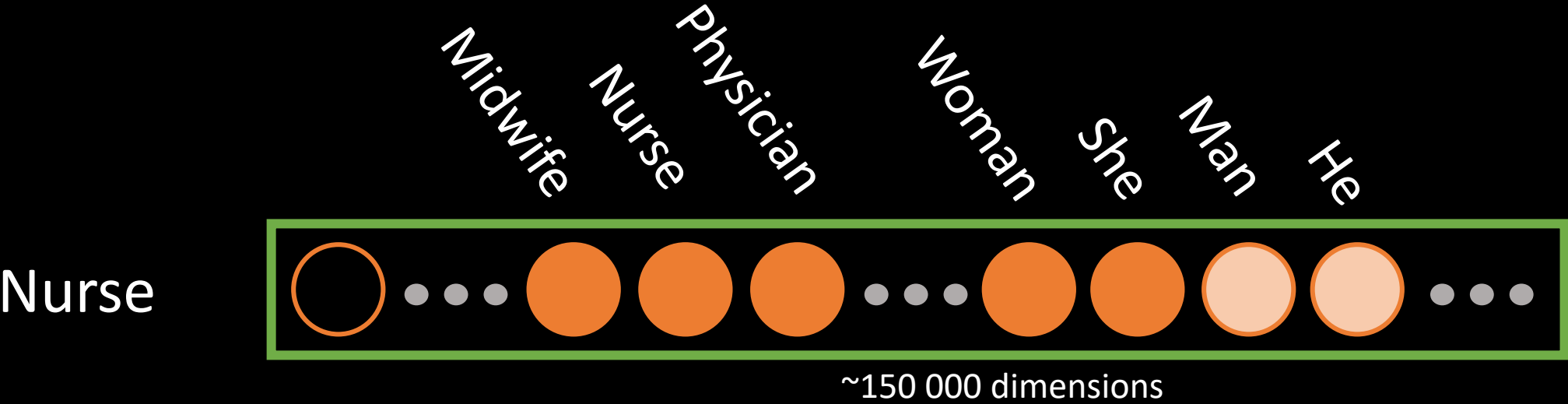
The vector for “nurse”
contains an element
of “she”-ness

(she, nurse)



The vector for “she”
contains an element
of “nurse”-ness

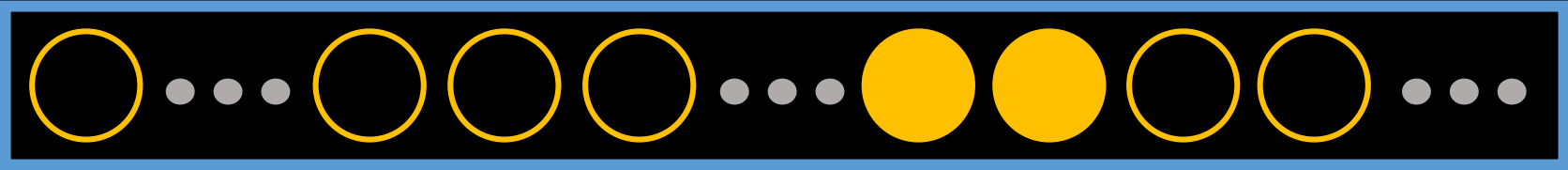
Explicit Word Embedding Vectors



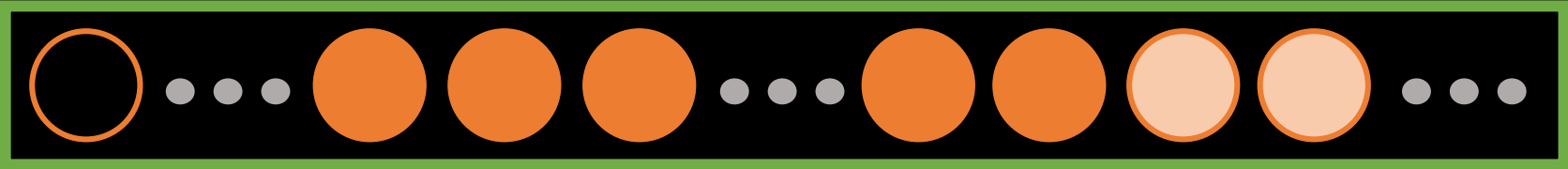
Explicit Word Embedding Vectors

Midwife Nurse Physician Woman She Man He

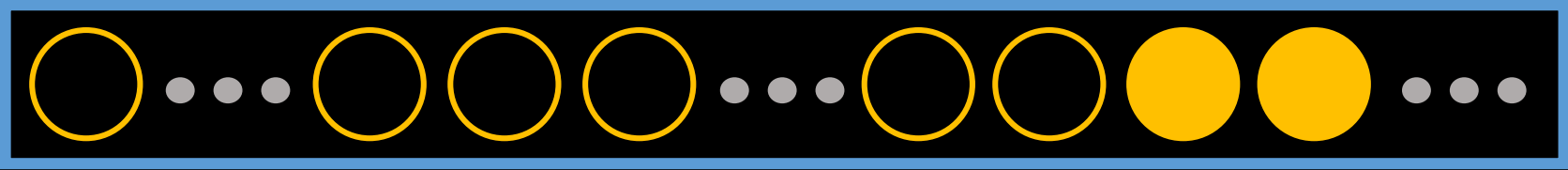
“Female”



Nurse

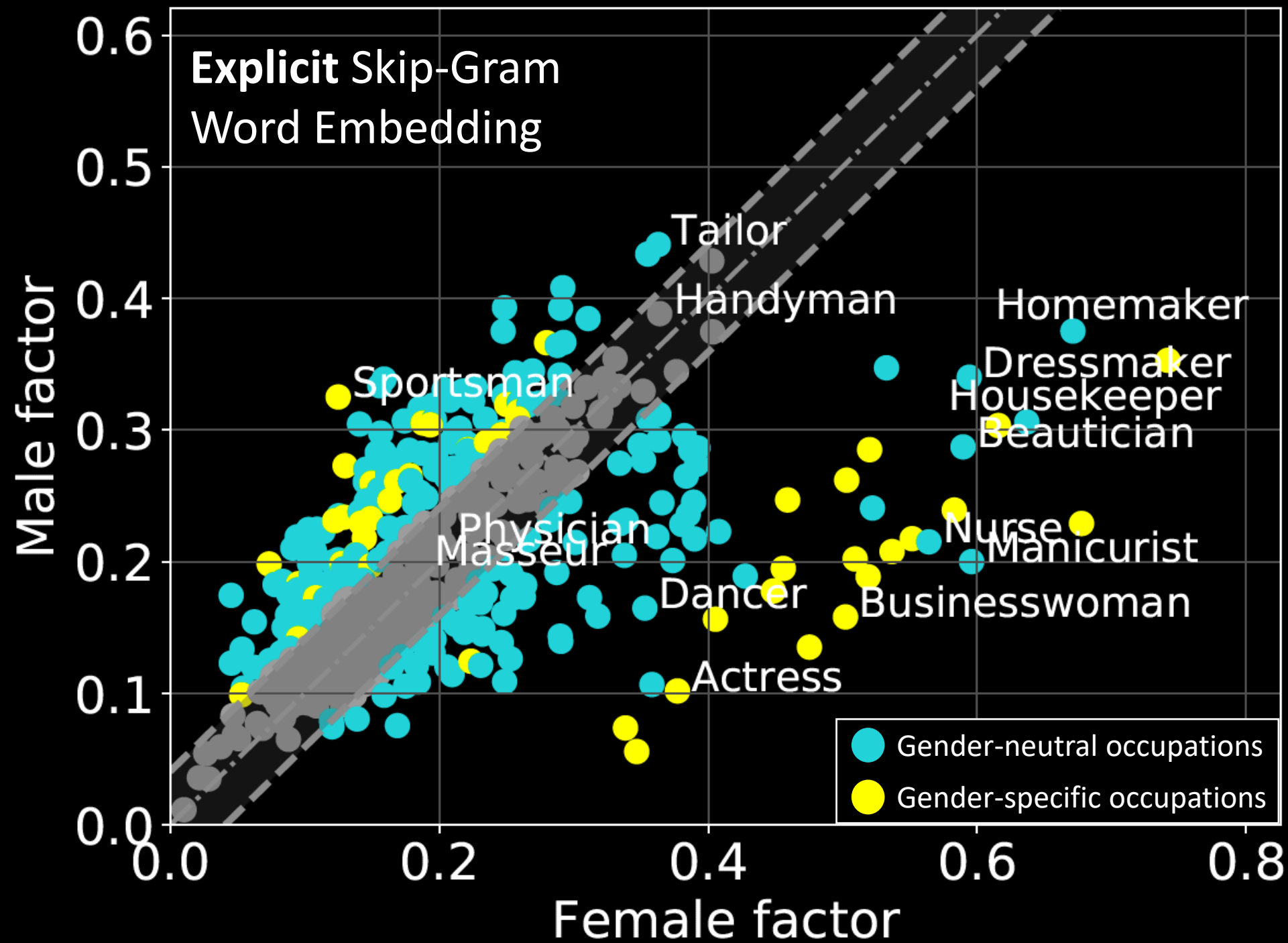


“Male”



$\text{sim}_{\text{female}}$

sim_{male}



Correlation to Bias in the Real World

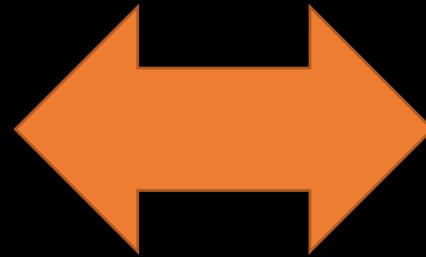
US Labour Statistics

1. Secretary	95%
2. Hairdresser	92%
3. Receptionist	90%
4. Nurse	90%
5. Housekeeper	89%
6. Cleaner	89%
7. Assistant	85%
8. Librarian	84%



Word Embedding Female Factor

1. Nanny	0.74
2. Midwife	0.68
3. Housekeeper	0.64
4. Manicurist	0.60
5. Dressmaker	0.59
6. Beautician	0.59
7. Maid	0.58
8. Nurse	0.56



Spearman ρ
correlation

Spearman ρ correlation coefficient between Wikipedia embedding and US labour data

Standard Skip-Gram
Word Embedding

0.53

Explicit Skip-Gram
Word Embedding

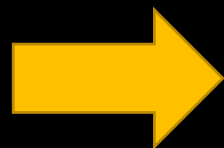
0.64



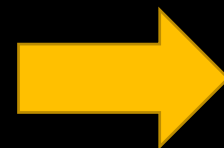
Creation



Data



Algorithm

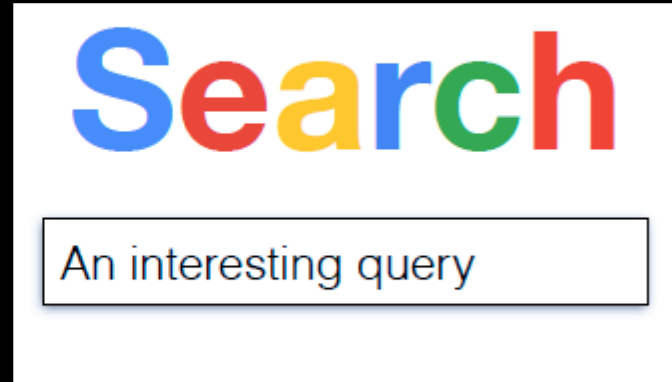


Results

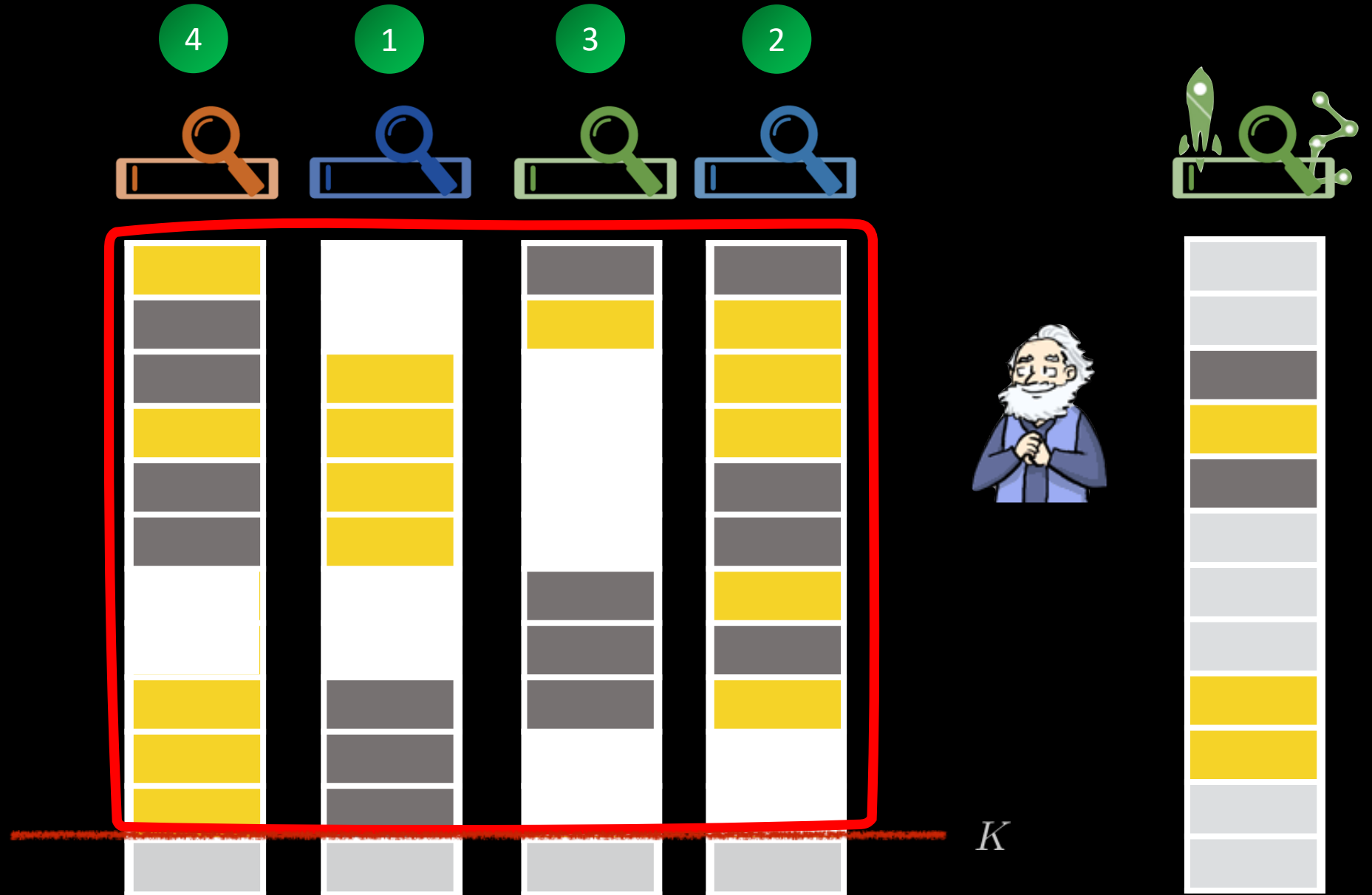
BIASED



Search



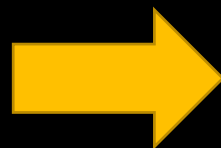
Pooling



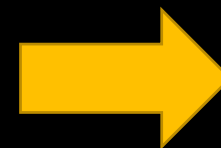


Input

Data

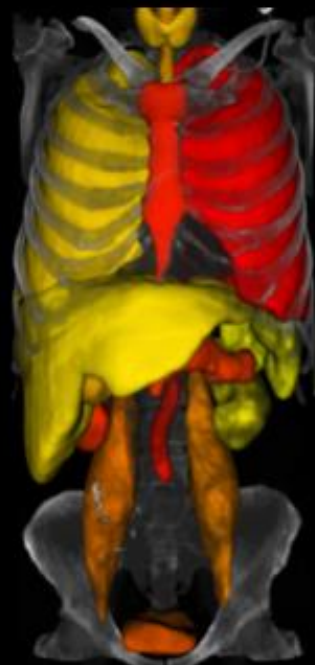
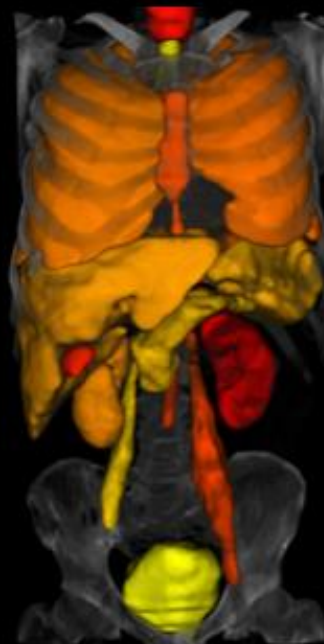
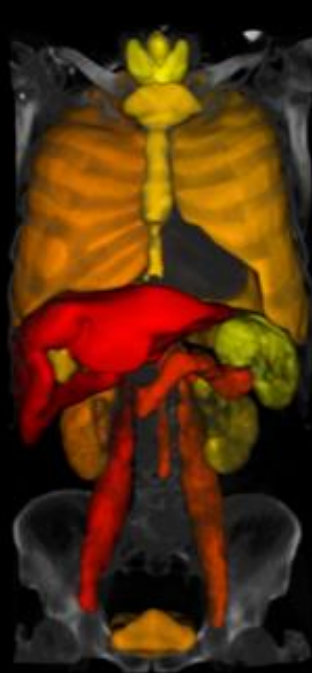


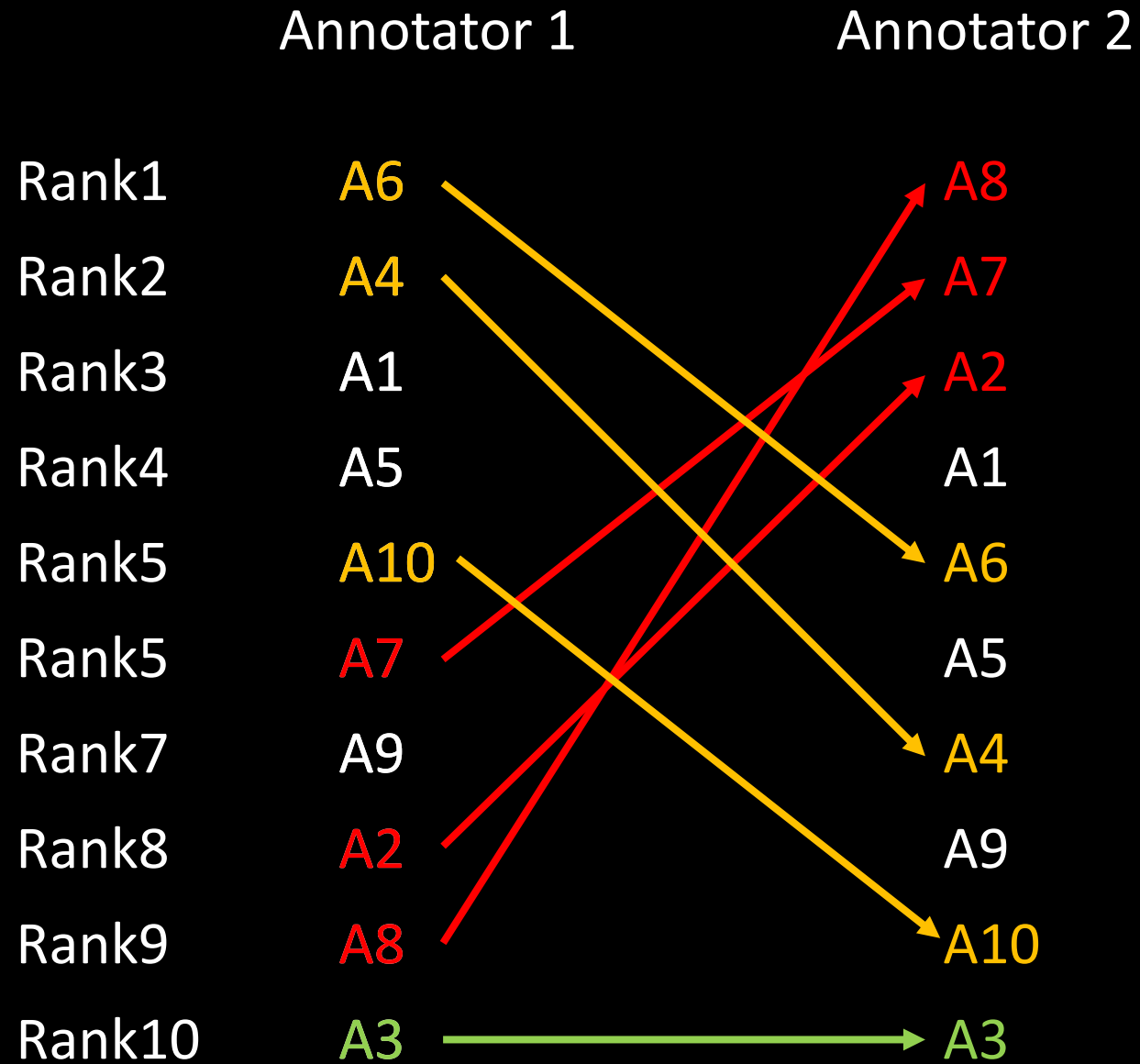
Algorithm



Results

“Unpaid assessors largely disagree with paid assessors with respect to relevance labels [...] These differences have a noticeable impact on system ranking.”



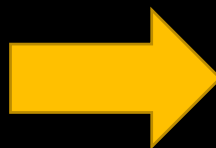
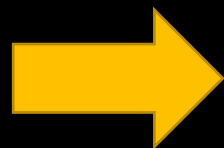
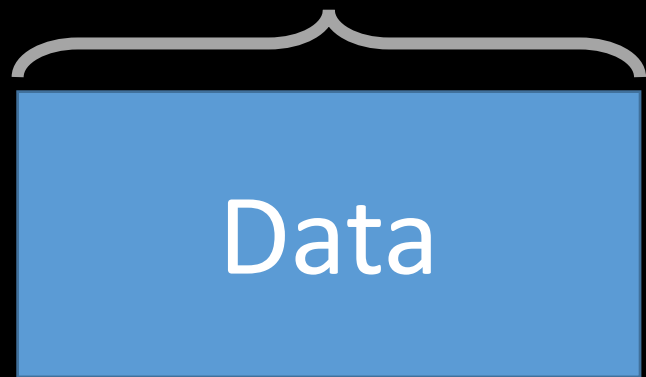




Creation



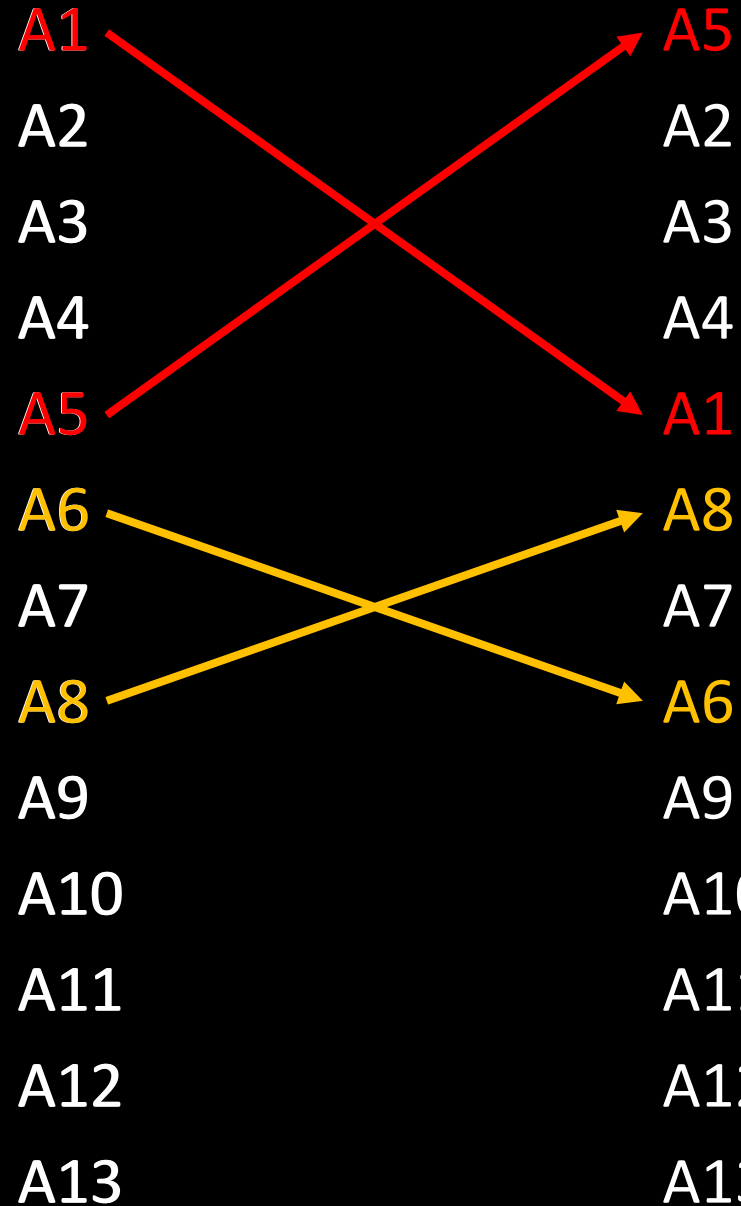
Input



Experiment Design

Aggregation
with mean

Aggregation
with median

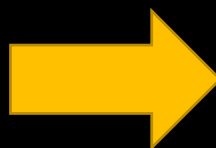
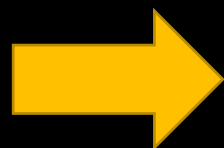
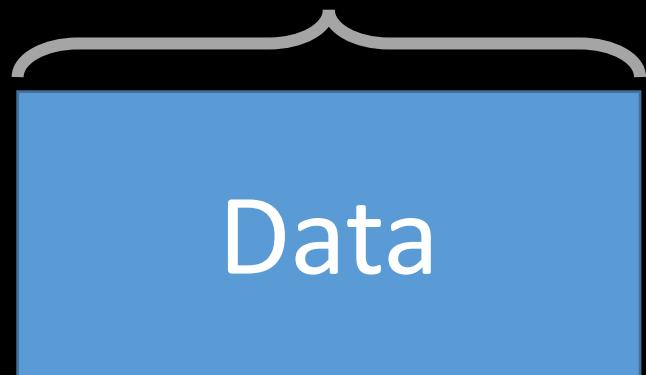




Creation



Input



Experiment Design



Reporting

“Half of the relevant information
is not reported”

Parameter name	Coverage [%]
Challenge name ^a	100
Challenge website ^a	99
Organizing institutions and contact person ^a	97
Life cycle type ^a	100
Challenge venue or platform	99
Challenge schedule ^a	81
Ethical approval ^a	32
Data usage agreement	60
Interaction level policy ^a	62
Organizer participation policy ^a	6
Training data policy ^a	16
Pre-evaluation method	5

“In 66% of all tasks, there was no description of how the reference annotation was performed.”

Closing Questions

1. How can the reliability of published results be improved?
2. What is bias and who defines it?

Acknowledgements

Linda Andersson, Alexandros Bampoulidis, Tobias Fink, Georg Heiler, Sebastian Hofstätter, Florian Kromp, Aldo Lipani, Mihai Lupu, João Palotti, Florina Piroi, Navid Rekabsaz, Abdel Aziz Taha, Markus Zlabinger



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