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Towards (Automatic) Quality Control of Life Science Articles. Between Censorship and Good Research Practice

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Session 071 Infodemic Management:
Strategies for Combatting Health Mis/Dis/Malinformation
July 26th 2022

ZB MED Information Centre for Life Sciences

Outline

1. *Status quo* on mis-information at ZB MED holdings
2. Quality control at ZB MED: Providing information on
   - Good scientific practice
   - Automated classification of mis-information

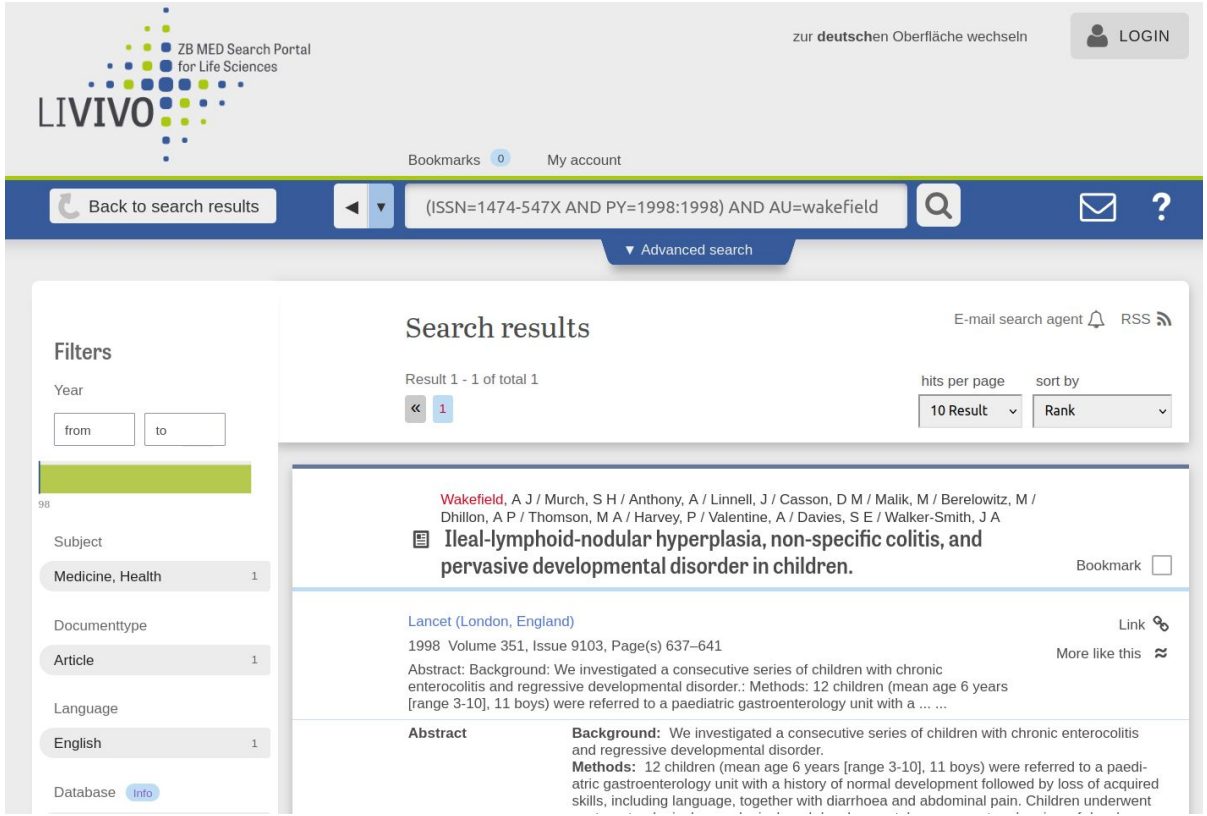
Status quo: ZB MED Discovery system LIVIVO

- Aggregating 50 databases (*MEDLINE, AGRICOLA, BASE*, library catalogues…)
- >70 M items
- No quality filtering

https://www.livivo.de/

Status quo: Mis-information is widespread

- Mis-information in LIVIVO
- Scientific literature portals are affected (*Holone 2016*)
- Mis-information is everywhere in public spaces, but also in (Life) Sciences
  - Homeopathy *(EU 2021a)*
  - WHO: One of the ten greatest health hazards worldwide: Vaccination refusal (measles…) *(WHO 2019)*



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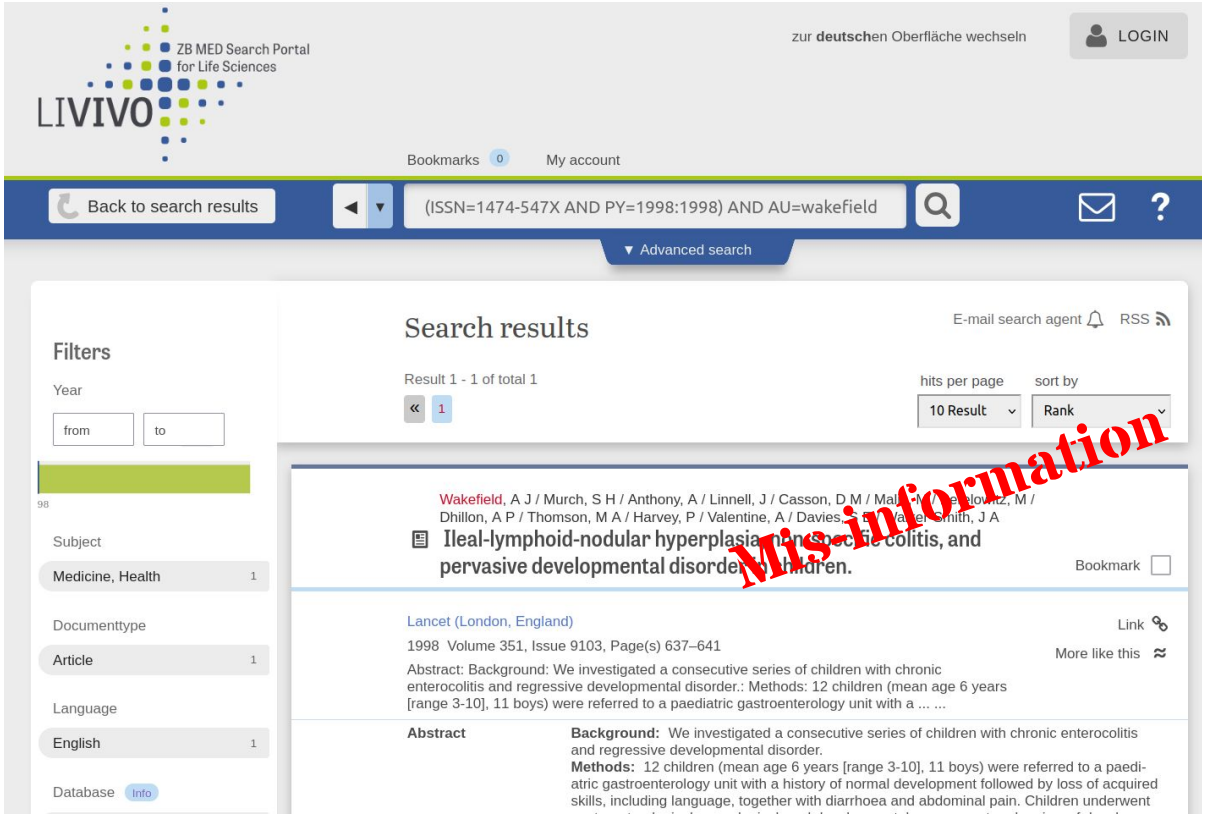

Status quo: Mis-information cannot be completely filtered out

- Technical difficulties
- Often part of correct context *(Gensing 2020)*
- Complex character: intended disinformation, retracted incorrect information, simplified popular information…
- Difficult distinction: new / unpopular / critical work and mis-information
- Particular research question is unknown

→ No censorship of suspicious items but provision of information

→ Strengthening information literacy *(CILIP 2018)*

What to do?

Solution

Quality control at *ZB MED*: Providing information on

- Good scientific practice
- Automated classification of mis-information

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Quality control at *ZB MED*: Providing information on

- **Good scientific practice**
- Automated classification of mis-information

Solution Part 1: Aspects of good scientific practice

- *German National Research Alliance (DFG)*:
  „Guidelines for Safeguarding Good Research Practice. Code of Conduct" *(DFG 2019)*
- 19 Guidelines
- Guideline No. 7:

  "**If researchers** have made their findings publicly available and subsequently **become aware of inconsistencies or errors** in them**, they make the necessary corrections.** [...]

  The origin of the data, organisms, materials and software used in the research process **is disclosed** and the reuse of data is clearly indicated; **original sources are cited**. " *(DFG 2019)*

Solution Part 1: Aspects of good scientific practice

Quality features:

- Peer-review?
- Scientific references?
- Already cited?
- Has it been retracted?

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  → Reference data: *Crossref* database

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https://www.crossref.org

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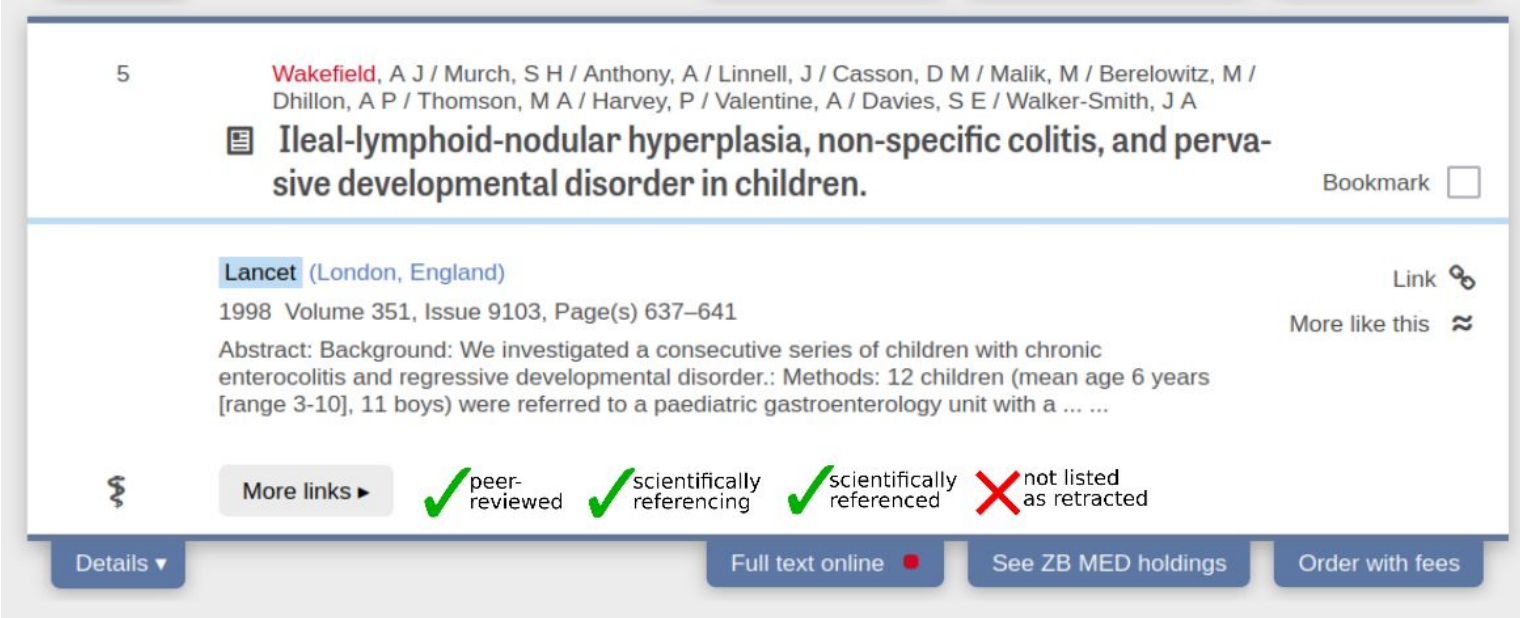
- → *Retraction Watch* database

https://www.crossref.org
https://retractionwatch.com

Solution Part 1: Aspects of good scientific practice

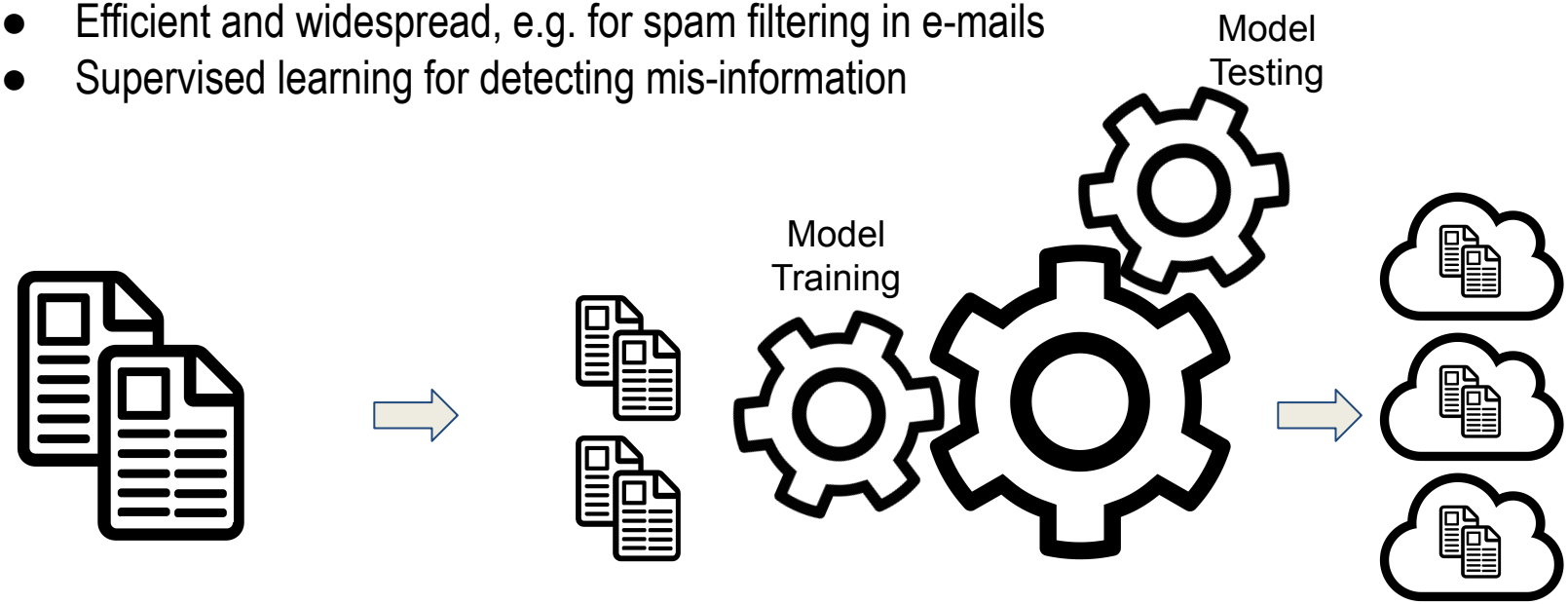


Solution

1. Quality control at *ZB MED*: Providing information on
   - Good scientific practice
   - **Automated classification of mis-information**

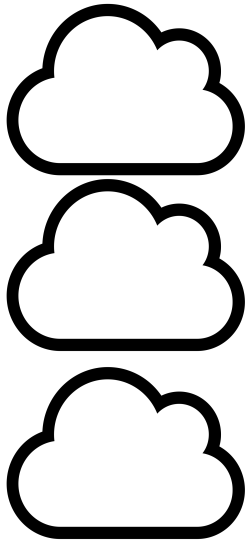
Solution Part 2 : Automated classification

- Efficient and widespread, e.g. for spam filtering in e-mails
- Supervised learning for detecting mis-information



Solution Part 2: Automated classification

- Classification for supervised learning approach is required
- Basic (e.g.):
  - Scientific information
  - Mis-information
- More differentiated (e.g.):
  - Scientific information
  - Mis-information
  - Popular information



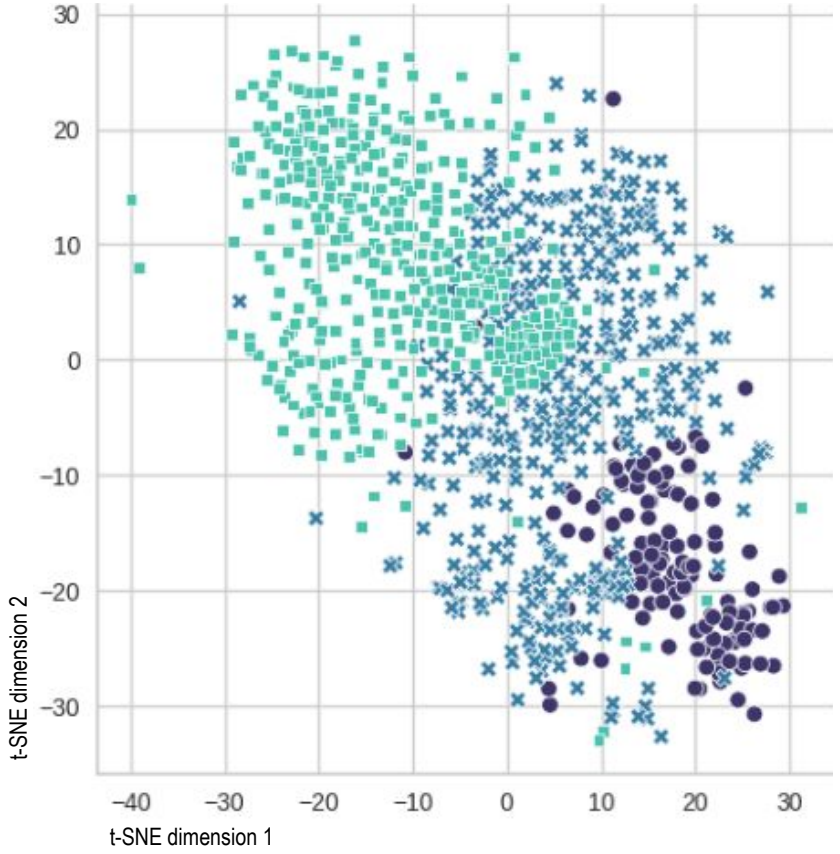
Solution Part 2: Automated classification

- Data set for training and testing
- Full texts for all classes
- Preprocessing to avoid overfitting *(Oshikawa/Qian/Wang 2020)*
- Reuse of data sets from Life Sciences
  - PUBHEALTH *(Kotonya/Toni 2020)*
  - Health&Well Being (HWB) Fake News Dataset *(Singh/Deepak/Anoop 2020)*
- Data set within classification:
  - Scientific texts: PubMed Central…
  - Popular science texts: MedlinePlus, Medhelp, Wikipedia, PUBHEALTH, HWB…
  - Mis-Information: Signs of the times, PUBHEALTH, HWB…

Solution Part 2: Machine Learning classification

Unsupervised clustering of the German test data set with Doc2Vec (t-SNE projection)

- Specialized texts
- Popular-science texts
- Mis-informative texts



Solution Part 2: Automated classification

Result representation

- Display of all similarity values,
  without harmonization, e.g. by using a bar chart
- Always risk of wrong classification
- Explainability of the workflow *(EU 2021b)*

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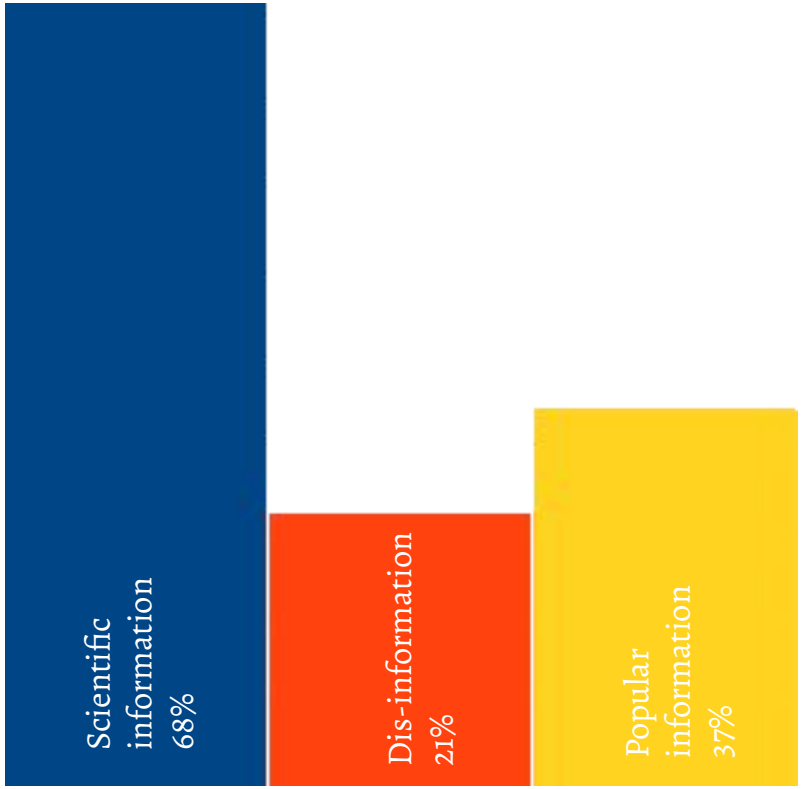
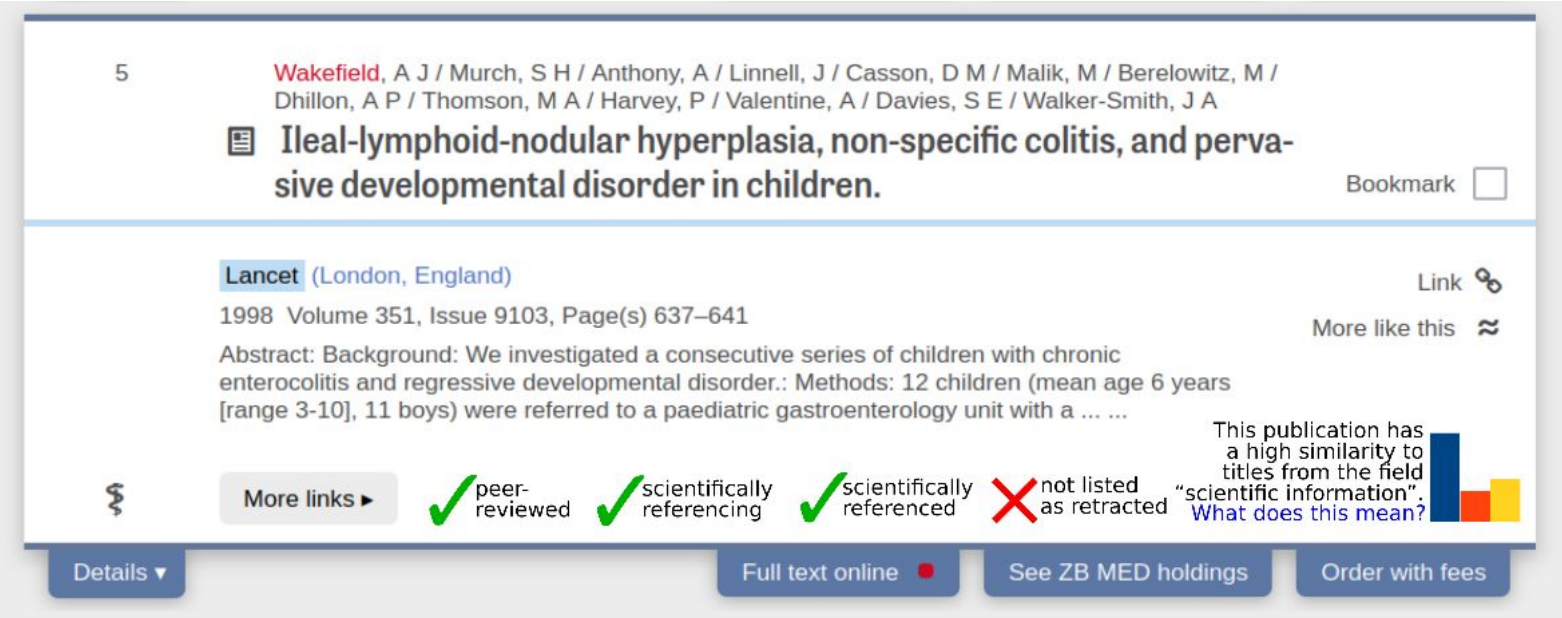
This publication has a high similarity to titles from the field “scientific information”.

What does this mean?



Solution Part 2: Automated classification



Solution Part 2: Automated classification

Potential

- Powerful capacity for classifying full texts in the future

Challenges

- Careful selection of dataset for training
- Overfitting in training
- Risk of wrong classification by the machine learning model
- In use: Lack of full texts for publications in library holdings
- Results presentation of all similarity values
- Risk of loss of confidence in machine learning

Summary

- Mis-information widespread - also in science
- Data literacy is better than censorship
- Provision on information compliance to good scientific practice, such as:
  - Peer-review status
  - References to scientific literature
  - Cited by scientific literature
  - Retraction status
- Machine learning can be used for automated classification, but:
  - Risk of overfitting and wrong classification
  - Recommendation: Display similarity values to all classes
  - Explainability: Transparent machine learning workflow

Acknowledgements to:

YOU!

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References:

- Crossref, online: https://www.crossref.org/ (2022-07-15).
- Chartered Institute of Library Information Professionals (CILIP) (2018). **Definitions of Information Literacy 2018**, https://infolit.org.uk/ILdefinitionCILIP2018.pdf (2022-07-16).
- DFG (2019). **Guidelines for Safeguarding Good Research Practice,** doi: **10.5281/zenodo.6472827, online:** https://www.dfg.de/en/research_funding/principles_dfg_funding/good_scientific_practice/ (2022-07-15).
- European Commission, Directorate-General for Communications Networks, Content and Technology (2021a). **European Commission Guidance on Strengthening the Code of Practice on Disinformation.** https://eur-lex.europa.eu/legal-content/en/TXT/?uri=CELEX%3A52021DC0262.
- European Commission (2021b). **Proposal for a Regulation of the European Parliament and of the council laying down harmonised rules on artificial intelligence artifical intelligence act and amending certain union legislative acts.** 2021/0106 (COD).
- Gensing, Patrick (2020). **Fakten gegen Fake News oder Der Kampf um die Demokratie**. Schriftenreihe Band 10500.Bonn: Bundeszentrale für politische Bildung.
- Holone, Harald (2016). T**he filter bubble and its effect on online personal health information**. In: Croatian Medical Journal 57.3. doi: 10.3325/cmj.2016.57.298, p. 298–301.
- Kotonya, Neema und Francesca Toni (Okt. 2020). E**xplainable Automated Fact-Checking for Public Health Claims**. In: arXiv:2010.09926 [cs]. arXiv: 2010.09926.
- LIVIVO, online: www.livivo.de (2022-07-15).
- Oshikawa, Ray, Jing Qian und William Yang Wang (2020). **A Survey on Natural Language Processing for Fake News Detection.** In: arXiv:1811.00770 [cs]. arXiv: 1811.00770.
- Retraction Watch, online: https://retractionwatch.com/ (2022-07-15).
- Singh, Iknoor, P. Deepak und K. Anoop (2020). **On the Coherence of Fake News Articles**. In: ECML PKDD 2020 Workshops. Ed. by Irena Koprinska et al. Vol. 1323. Cham, p. 591–607.
- WHO (2019). online: **Ten threats to global health in 2019** https://www.who.int/news-room/spotlight/ten-threats-to-global-health-in-2019 (2022-07-15).
- ZB MED, online: www.zbmed.de (2022-07-15).

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