Statistical stopping criteria for automated screening in systematic reviews

Max Callaghan, Finn Müller-Hansen

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Researcher in the Loop process

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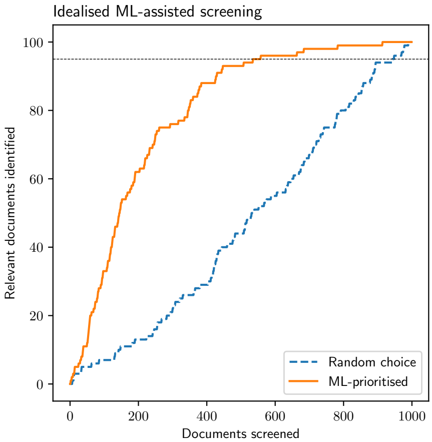

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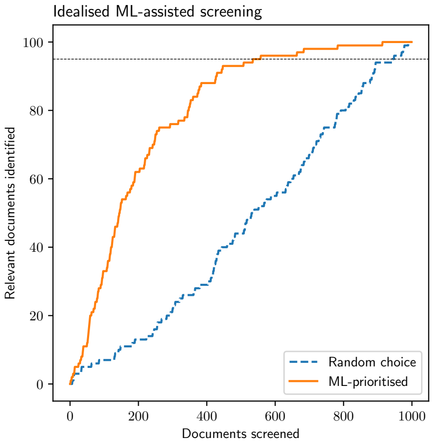

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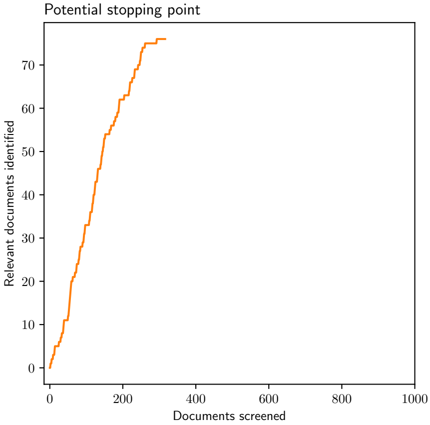

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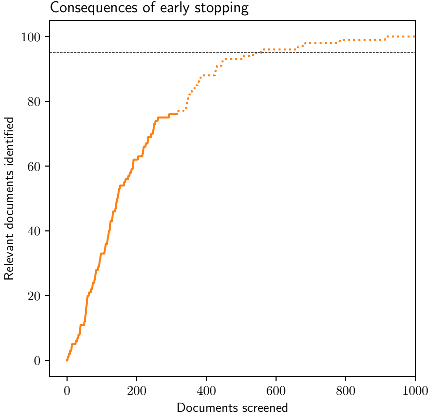
- Getting these wrong can mean missing our target



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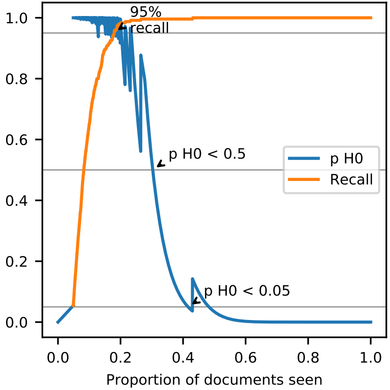

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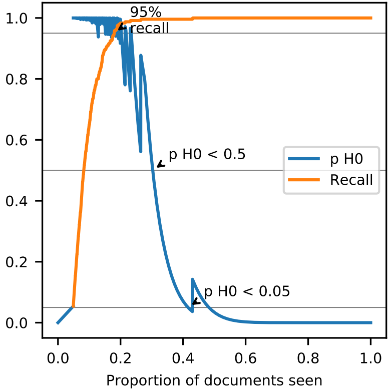

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Note, ML-prioritisation means documents are not drawn at random, which makes our test conservative as long as ML works as well as or better than random chance.

Results

We test our criteria against other commonly used criteria on 20 complete systematic review datasets

- *Potential* work savings (if we already knew when to stop) varied widely (higher for larger datasets - blue dots)

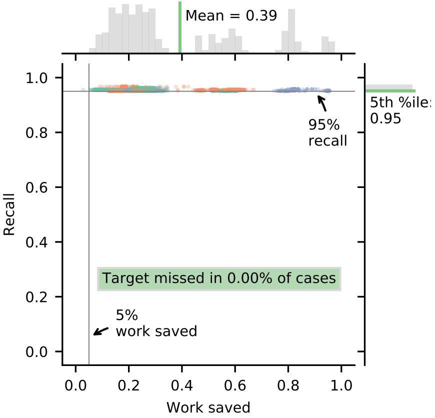

Figure: A priori knowledge

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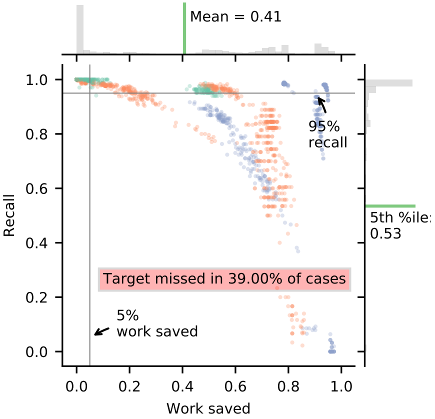

Figure: 50 consecutive irrelevant articles

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Figure: Estimating baseline inclusion rate

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- Our criteria generated work savings with reliably conservative performance wrt our recall target.

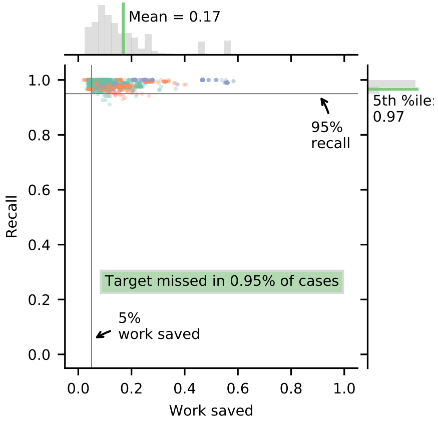
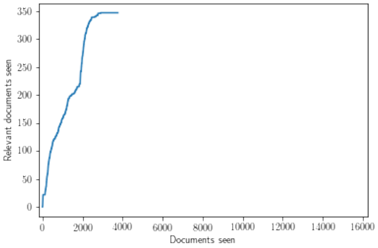


Figure: Our criterion

Applications and extensions



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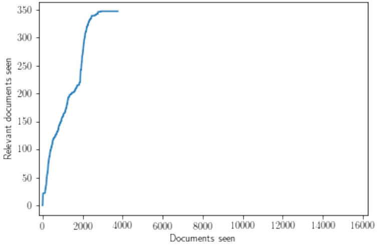

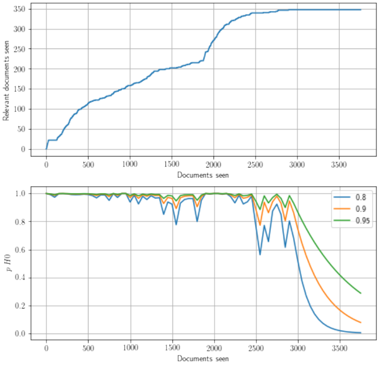

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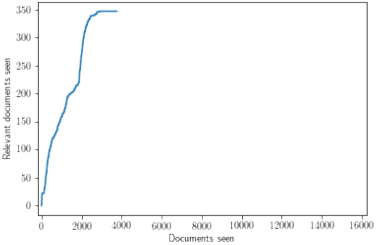
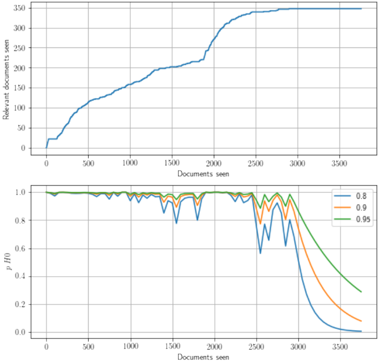
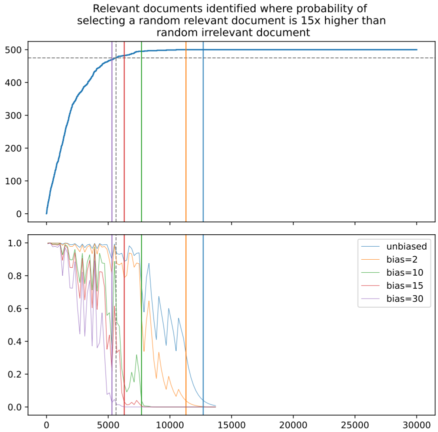




- We have used the stopping criteria to generate massive savings (77%) in real projects
- If rejecting our H_0 was less labour intensive we could have saved around 82%
- Using a biased urn could help create a more precise criterion

Biased urns



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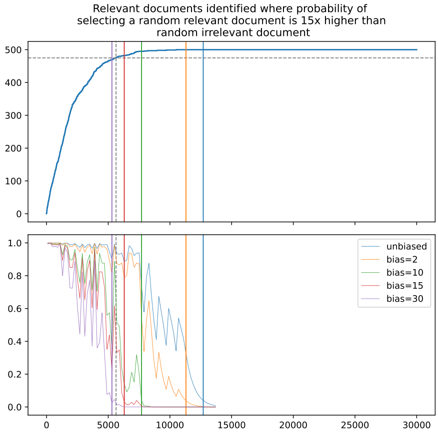

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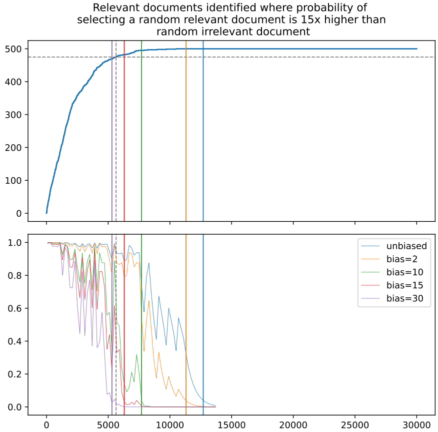

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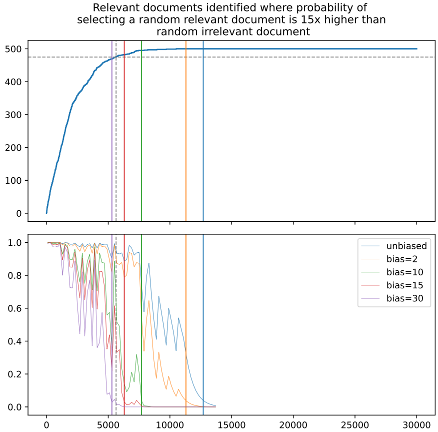

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- Using a non-central hypergeometric distribution (Fog, 2008), we can input a **bias** parameter indicating how much more likely we are to draw a random relevant than a random non-relevant document.
- Estimating this parameter is empirically non-trivial!

Realistic empirical evaluations for AI

To know when it is safe to use AI systems in future evidence synthesis projects, we need to evaluate them on past data ***under realistic conditions***

In living evidence applications:

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- How long can we trust classifier evaluations without labelling new data?
- How does topic model fit decay over time?
- How do we incorporate new topics?
- How frequently *would* LRs have been updated? Is this predictable?

Conclusion

We provide a stopping criteria that works on any model, with any tool:
https://github.com/mcallaghan/rapid-screening/blob/master/analysis/hyper_criteriaR.md.

Work savings in practice with large datasets are large!

Future work will identify how biased our urn is, in order to use a noncentral hypergeometric distribution, which should give a more precise, less conservative criterion.

Thanks!

Contact: mueller-hansen@mcc-berlin.net, callaghan@mcc-berlin.net

References

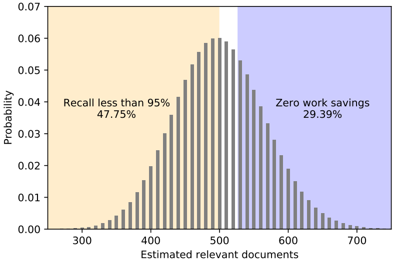
Fog, A. (2008). Calculation Methods for Wallenius' Noncentral Hypergeometric Distribution. *Communications in Statistics - Simulation and Computation*, 37(2):258–273.

O'Mara-Eves, A., Thomas, J., McNaught, J., Miwa, M., and Ananiadou, S. (2015). Using text mining for study identification in systematic reviews: A systematic review of current approaches. *Systematic Reviews*, 4(1):5.

van de Schoot, R., de Bruin, J., Schram, R., Zahedi, P., de Boer, J., Weijdema, F., Kramer, B., Huijts, M., Hoogerwerf, M., Ferdinands, G., Harkema, A., Willemsen, J., Ma, Y., Fang, Q., Hindriks, S., Tummers, L., and Oberski, D. L. (2021). An open source machine learning framework for efficient and transparent systematic reviews. *Nature Machine Intelligence*, 3(2):125–133.

Baseline Inclusion Rate

- If we try to estimate the baseline inclusion rate, we will get it wrong most of the time. Overestimating results in 0 work savings, while underestimating results in less than target recall.



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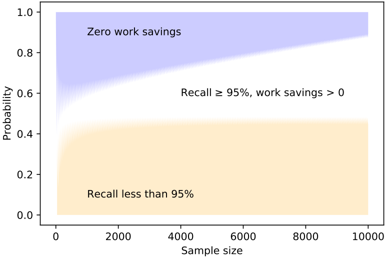
- Wrongness decreases with larger sample sizes, but bad outcomes remain most frequent.



Theory I

We form a null hypothesis that the target level of recall has not been achieved

$$H_0 : \tau < \tau_{tar} \tag{1}$$

To operationalise this, we come up with a hypothetical value of K which is the lowest value compatible with our null hypothesis

$$K_{tar} = \lfloor \frac{\rho_{seen}}{\tau_{tar}} - \rho_{AL} + 1 \rfloor \tag{2}$$

In other words, if there were K_{tar} or more relevant documents in the urn when sampling began, the ρ_{al} relevant we identified before sampling, and the k we drew from the urn would not be enough to meet our target recall level.

The cumulative distribution function gives us the probability of observing what we observed, if our null hypothesis were true

$$p = P(X \leq k), \text{ where } X \sim Hypergeometric(N, K_{tar}, n) \tag{3}$$