Statistical stopping criteria for automated screening in systematic reviews

Finn Müller-Hansen, Max Callaghan

20 October 2022

Researcher in the Loop process

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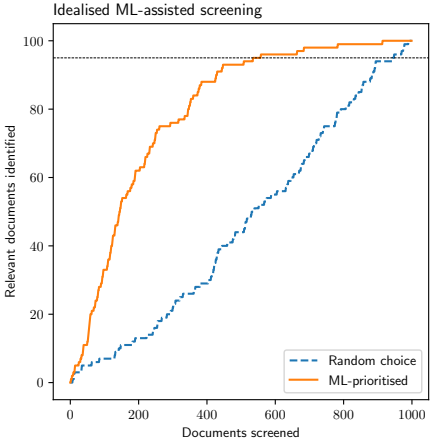

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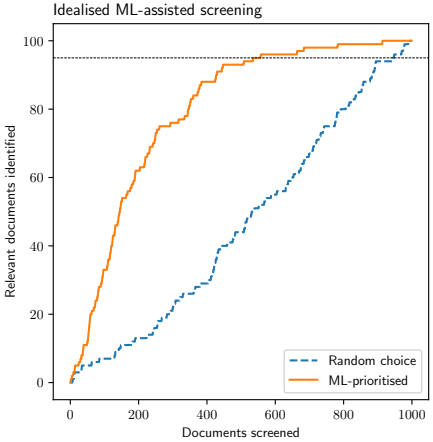

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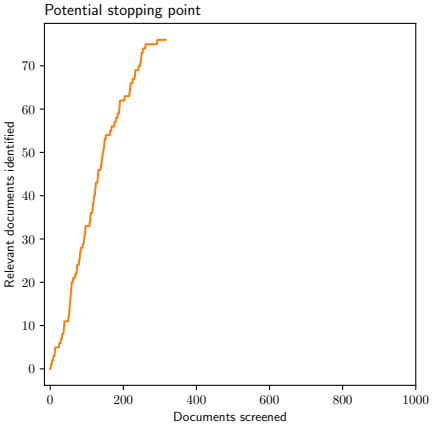

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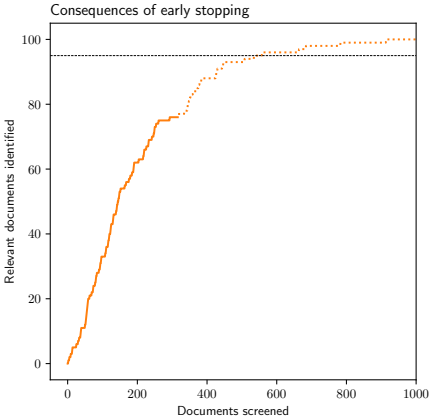
- Getting these wrong can mean missing our target



A stopping criterion

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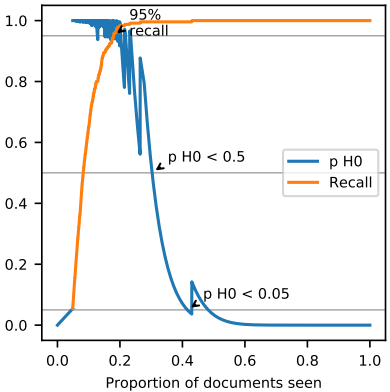

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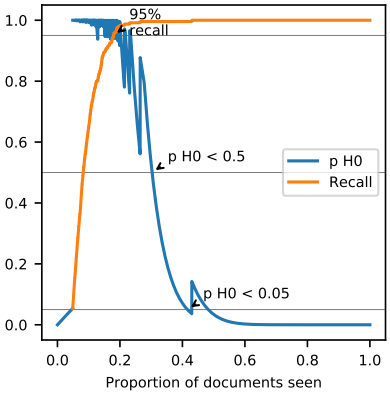

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Note, ML-prioritisation means documents are not drawn at random, which makes our test conservative as long as ML works as well as or better than random chance.

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)

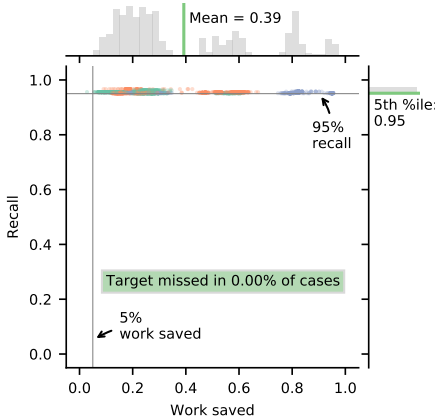

Figure: A priori knowledge

Results

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- Existing stopping criteria can result in catastrophic errors

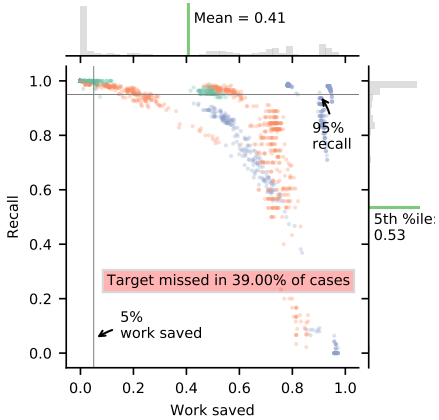

Figure: 50 consecutive irrelevant articles

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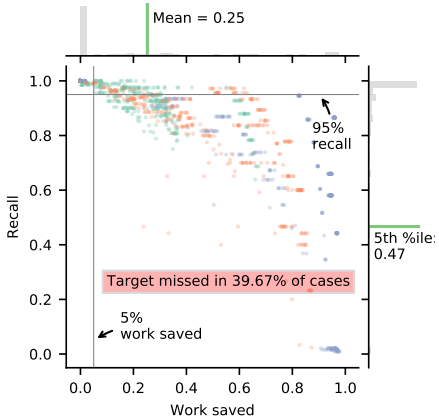

Figure: Estimating baseline inclusion rate

Results

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

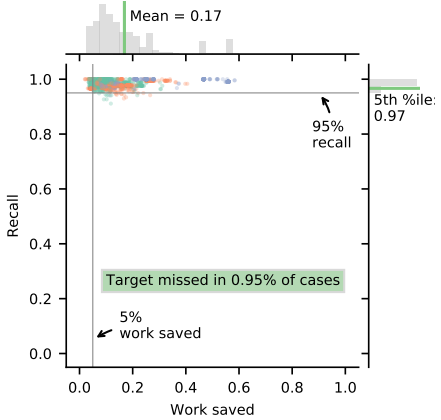


Figure: Our criterion

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!

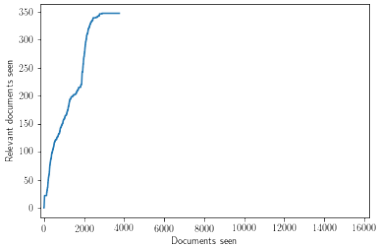
Contact: `mueller-hansen@mcc-berlin.net`, `callaghan@mcc-berlin.net`
Twitter: `https://twitter.com/MaxCallaghan5`

References

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.

Applications and extensions



- We have used the stopping criteria to generate massive savings (77%) in real projects

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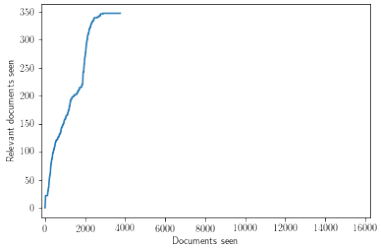

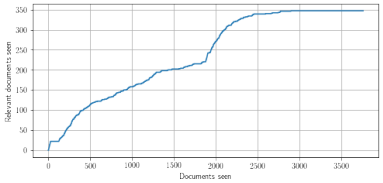

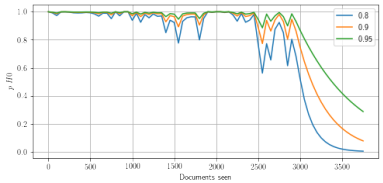

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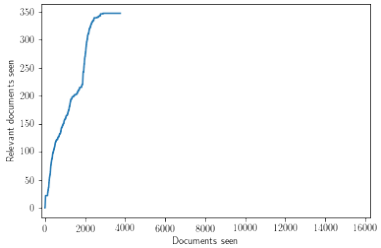
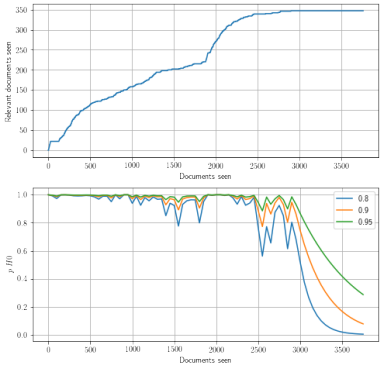
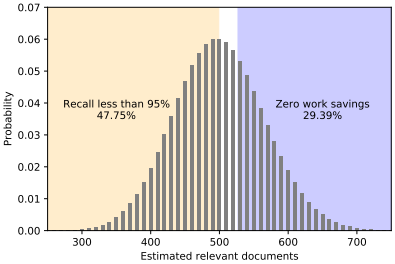




- We have used the stopping criteria to generate massive savings (77%) in real projects
- If rejecting our H_0 was less labour intensive we could have saved around 82%
- Using a biased urn could help create a more precise criterion

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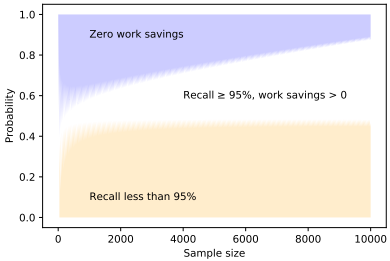
- Wrongness decreases with larger sample sizes, but bad outcomes remain most frequent.



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

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