Statistical stopping criteria for automated screening in systematic reviews

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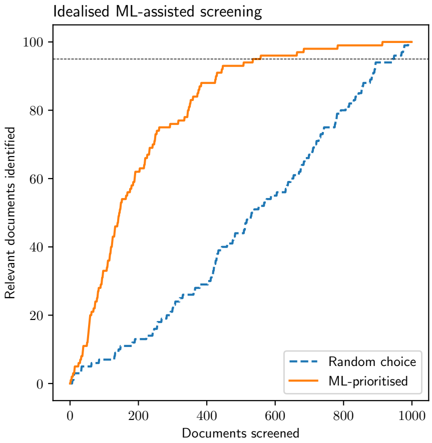

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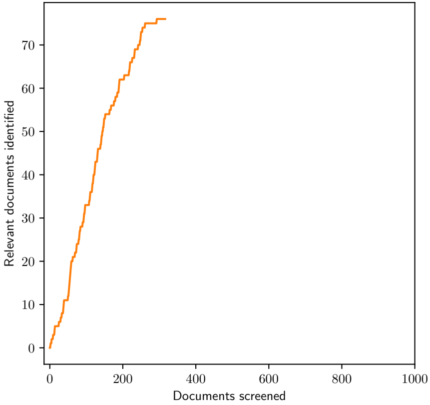
- BUT, given we do not know *a priori* the true number of relevant documents, we need criteria when to stop screening.

Potential stopping point



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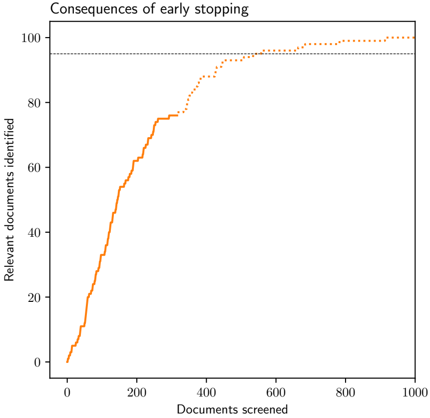
- Stopping too early can lead to huge biases in reviews.



A statistical stopping criterion

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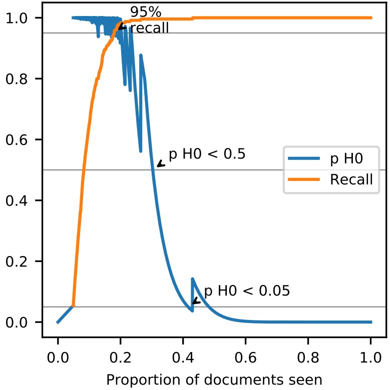

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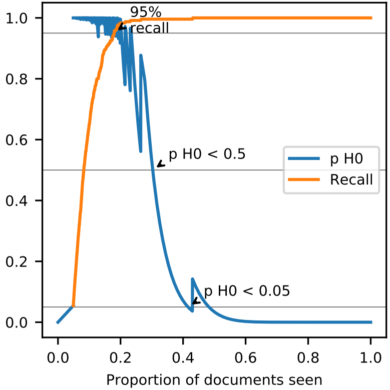

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Note: ML-prioritisation means documents are not drawn at random, which makes our test conservative.

Results

We run simulations on 20 complete systematic review datasets to test our criterion.

- *Theoretically achievable* work savings in the datasets varies widely (higher for larger datasets - blue dots)

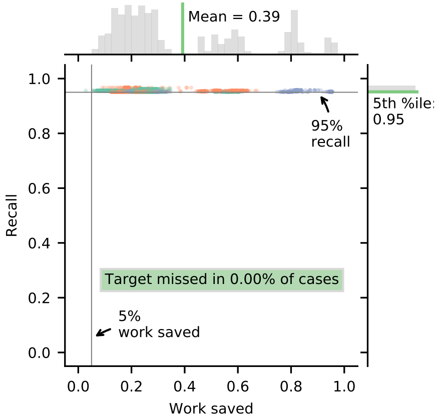

Figure: A priori knowledge

Results

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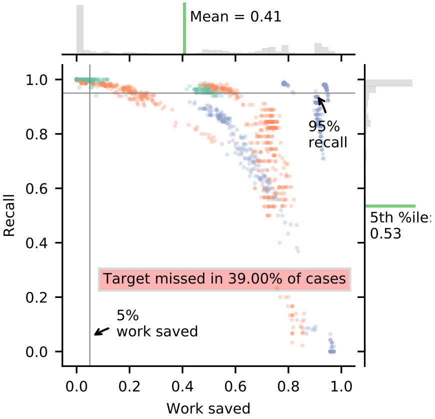

Figure: 50 consecutive irrelevant articles

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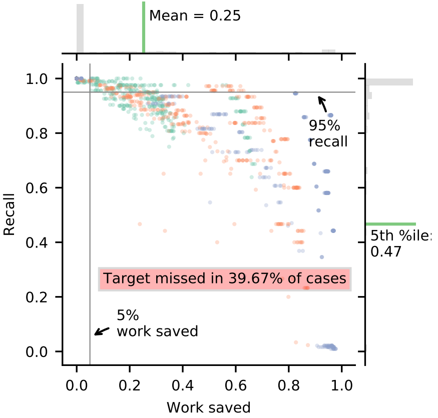

Figure: Estimating baseline inclusion rate

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- *Theoretically achievable* work savings in the datasets varies widely (higher for larger datasets - blue dots)
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- Our criterion generated work savings with reliably conservative performance wrt our recall target.

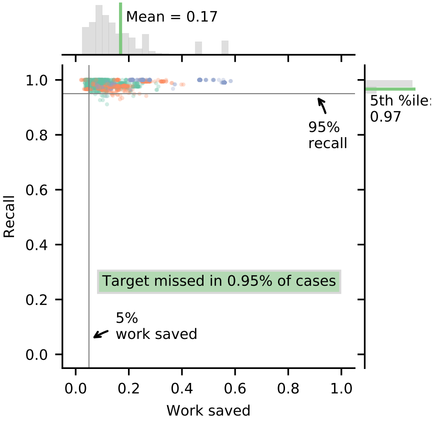

Figure: Our criterion

Conclusion

We provide a stopping criterion that works on any model and can be included in any tool: `https://github.com/mcallaghan/rapid-screening/blob/master/analysis/hyper_criteriaR.md`.

In practice, we see huge work savings for large datasets!

Future work: use noncentral hypergeometric distribution to generate a less conservative test and save more work.

Thanks!

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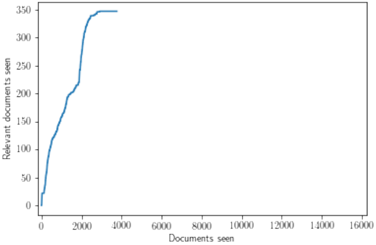
Twitter: https://twitter.com/MaxCallaghan5

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 criterion to generate massive savings (77%) in real projects

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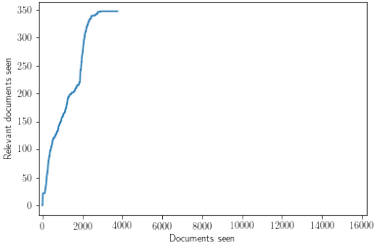

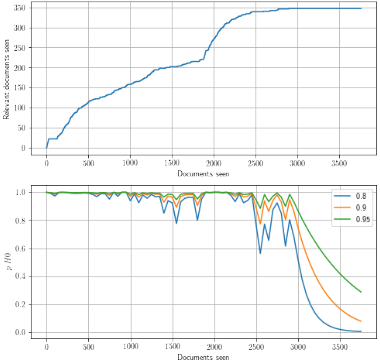

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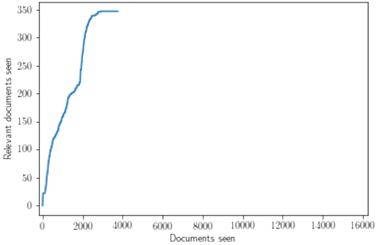
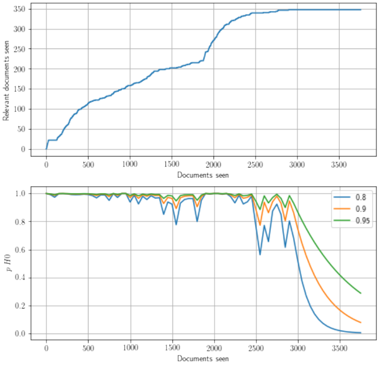
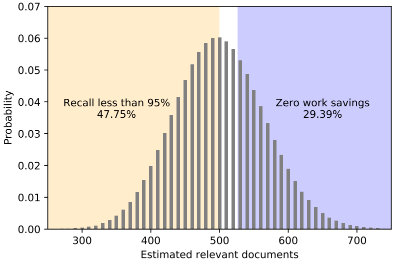




- We have used the stopping criterion to generate massive savings (77%) in real projects
- If rejecting our H_0 was less labour intensive we could have saved around 82%
- Using a biased urn could help create a more precise criterion

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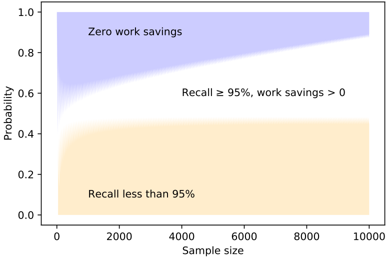
- Wrongness decreases with larger sample sizes, but bad outcomes remain most frequent.



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

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