When in Doubt Throw It Out: Building on Confident Learning for Vulnerability Detection

Artifacts Available
Artifacts Evaluated Reusable
Artifacts Evaluated Functional

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What Confident learning is all about

IF dataset not so good → use model to re-label it

- IF Score(x,1) < Confid(Score(x,1)) → label(x,0)
- and so on for 0

BUT

For vulnerabilities, model aren’t good either…

- Wen et al. ICSE’23 → Best precision < 55%
- Croft et al. ICSE’23 → Wrong labels > 28%

Our Idea: when in doubt throw them out

- Relabelling is too risky → too many wrong elements
- Drop elements we are not sure → they are confusing the model

Confidence level = weighted average of the predicted vulns

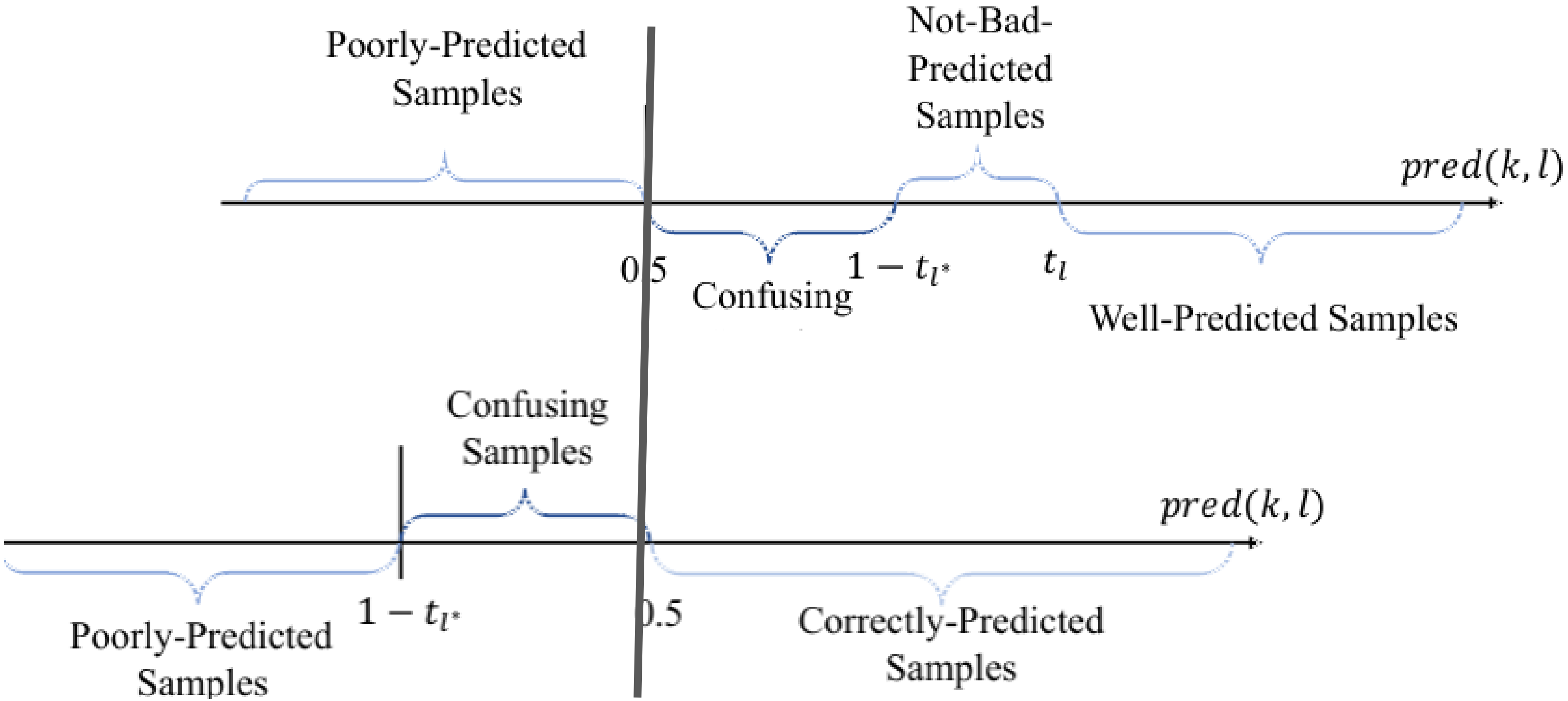
$$t_\ell = \frac{1}{\sum_k label(k,\ell)} \sum_k pred(k,\ell) \cdot label(k,\ell)$$

Well predicted → $pred(k,\ell) > t_\ell > \frac{1}{2}$

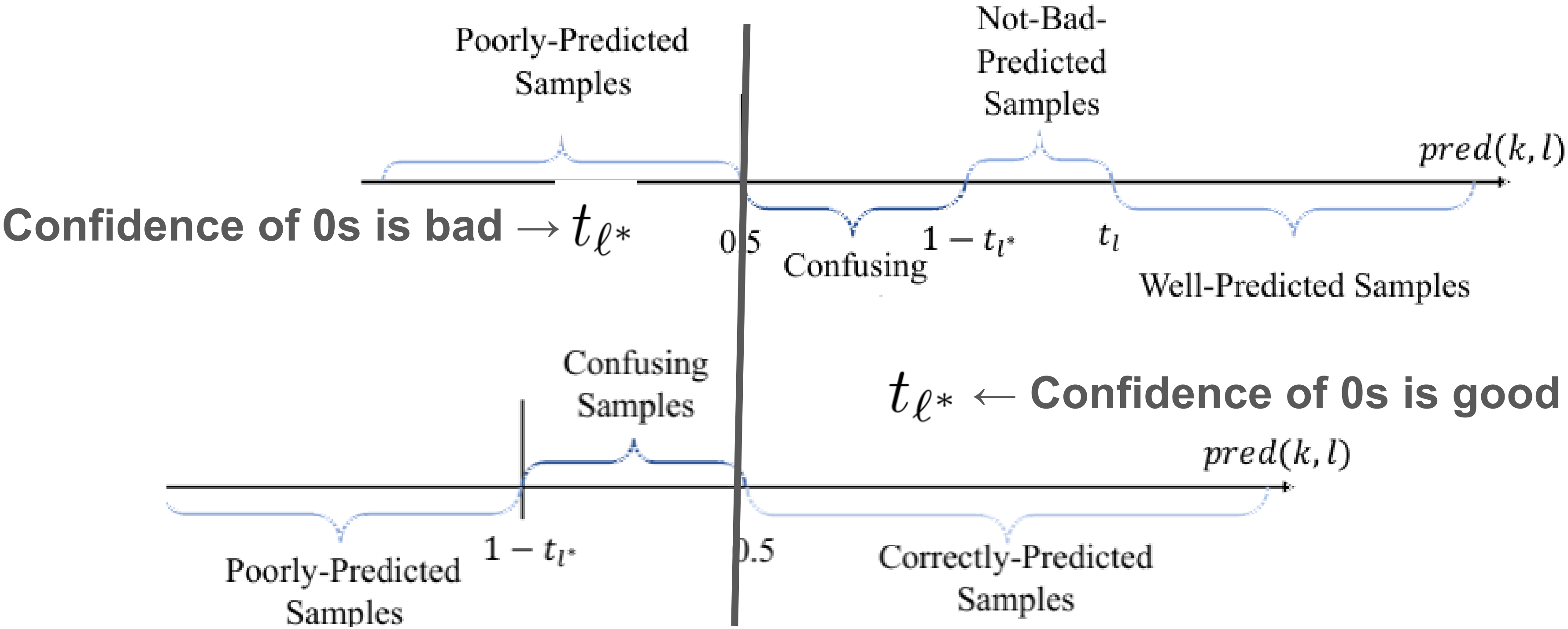
Poorly predicted → $pred(k,\ell) \leq \frac{1}{2}$

The rest → the one confusing the models

Two possible conditions



Two possible conditions → confidence of 0s



And it works….

Running vulnerability dataset with 8K samples (50-50) on a BERT Model

	Data kept	Precision	Recall
Original Dataset	100%	63%	48%
Invert Mislabelled	100%	60%	70%
Remove Mislabelled	72%	59%	77%
Remove Confusing 0	89%	60%	75%
Remove Confusing 1	99%	59%	77%

DROP 1% of datapoints and Recall increases
Without big change on Precision

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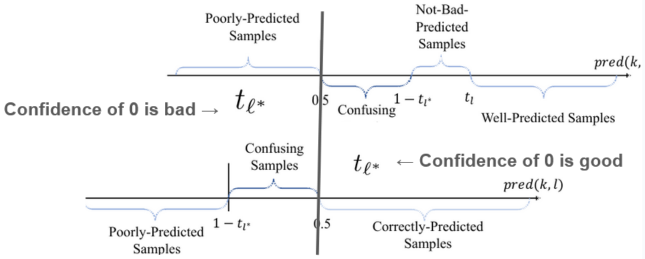

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