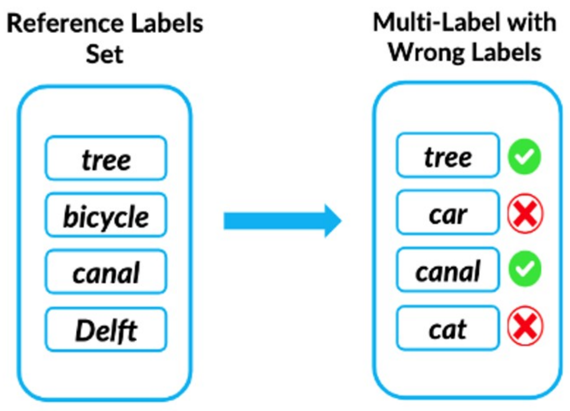
Multi-Label Gold Asymmetric Loss Correction with Single-Label Regulators (GALC-SLR)

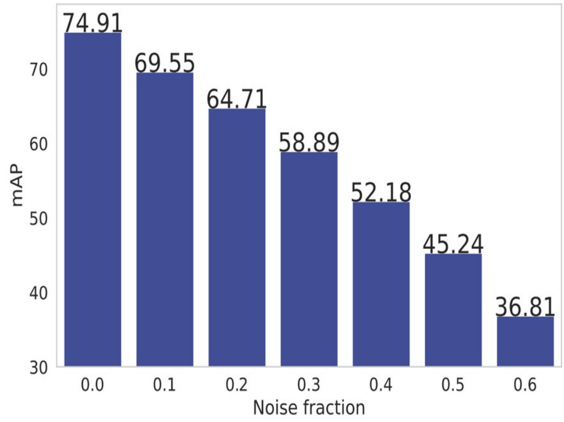
TUDelft

1 BACKGROUND

- **MLL – Multi Label-Learning**
Acquiring a fully labeled and reliable dataset is *time-consuming* and *expensive*
- **ASL[1] – Asymmetric Loss**
State-of-the-art results
- **GLC[2] – Gold Loss Correction**
Robust Single Label-Learning approach



Wrong label noise in multi-label classification

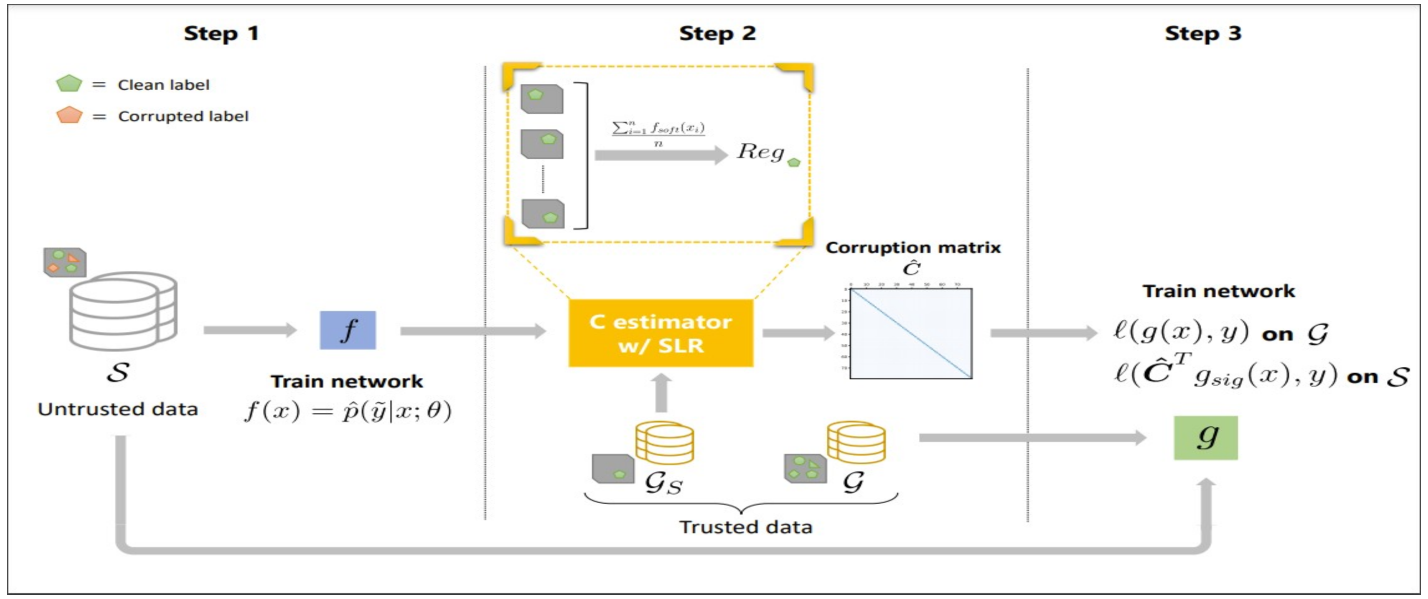


2 RESEARCH QUESTIONS

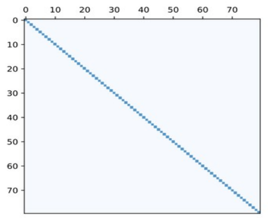
- What is the impact of wrong labels on the performance of a state-of-the-art multi-label classifier?
- How to accurately estimate the multi-label noise distribution using extra information from trusted data?
- How to train an accurate multi-label classifier with wrong label information?

3 METHOD – GALC-SLR

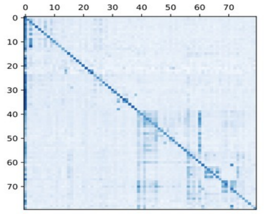
GALC-SLR combines an *asymmetric loss* approach with a *gold loss correction* approach to counter noisy labels.



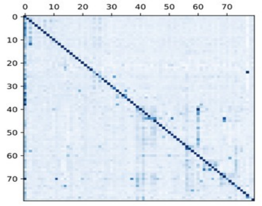
Training a classifier with asymmetric loss | Corruption matrix estimation using **single-label regulators** | Training a corrected classifier



True

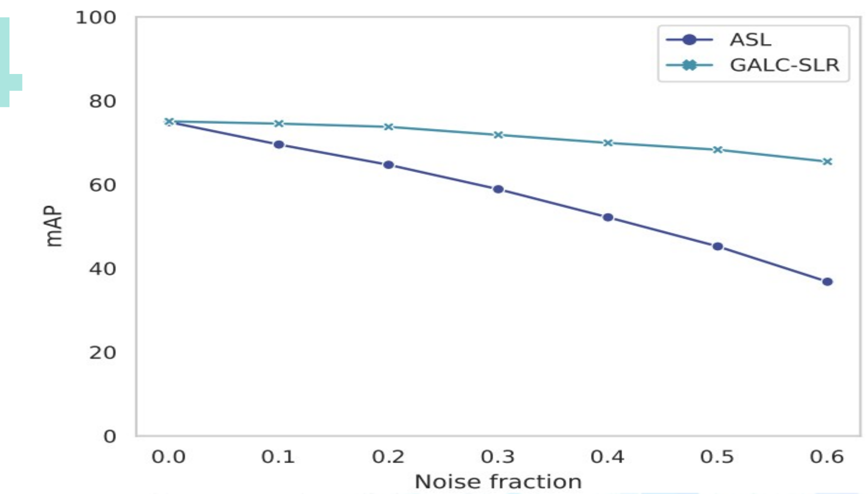


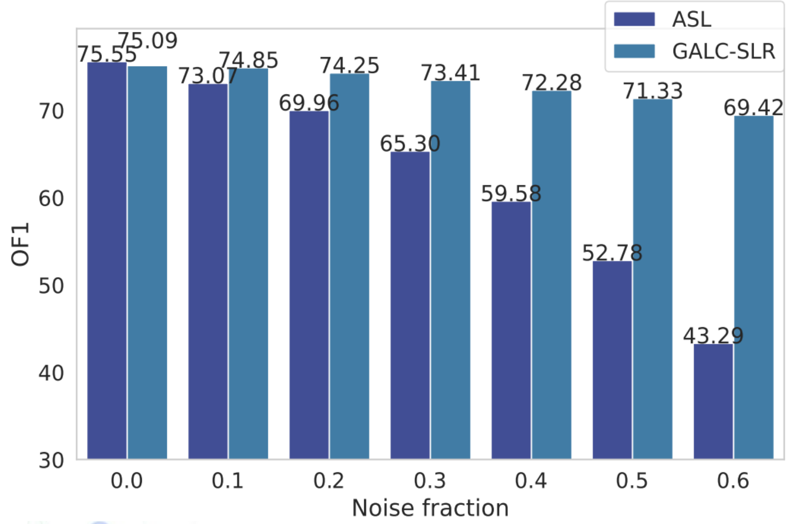
GLC

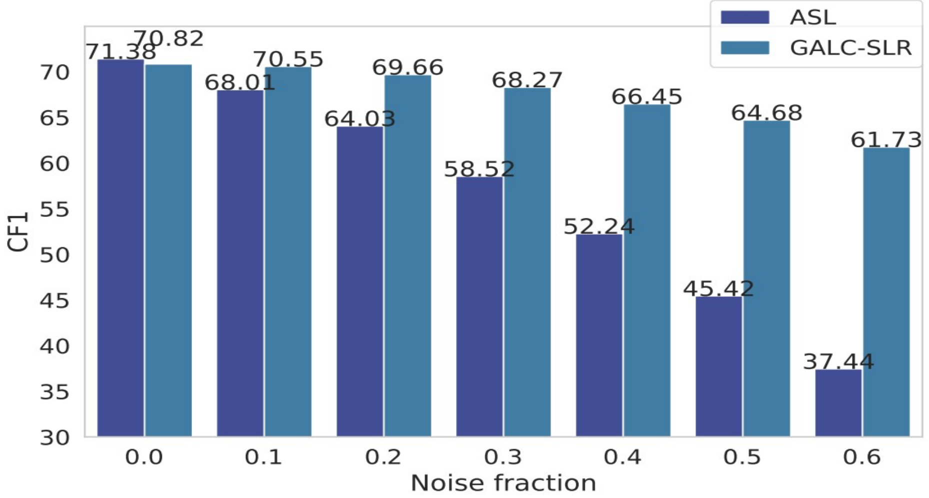


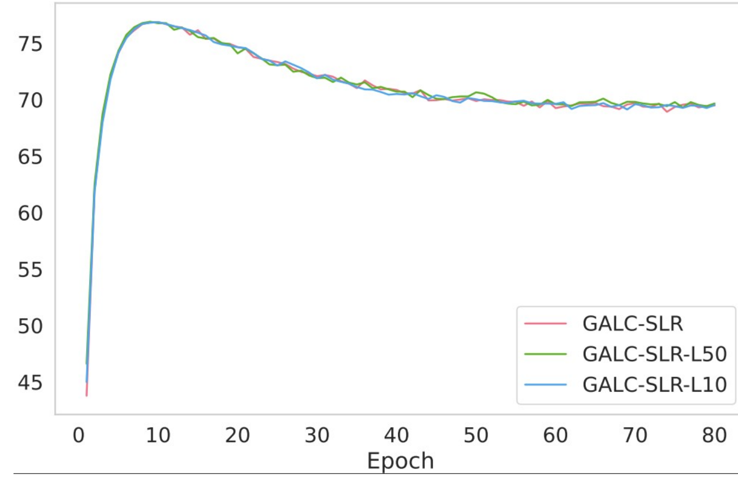
GALC-SLR

4 RESULTS









5 CONCLUSION

GALC-SLR improves the mean Average Precision (mAP) over ASL by **13.81%** *on average* and *up to* **28.67%**.

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[1] Baruch, Emanuel Ben et al. "Asymmetric Loss For Multi-Label Classification." ArXiv abs/2009.14119 (2020): n. pag.
[2] Hendrycks, Dan et al. "Using Trusted Data to Train Deep Networks on Labels Corrupted by Severe