Multi-Label Gold Asymmetric Loss Correction with Single-Label Regulators

1 BACKGROUND

- **MLL** – **M**ulti **L**abel-**L**earning

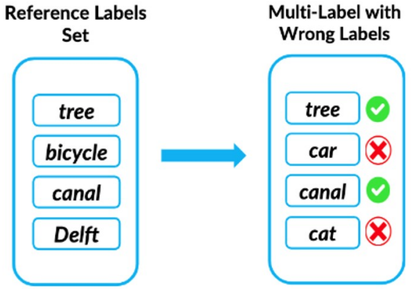
Acquiring a fully labeled and reliable dataset is time-consuming and expensive

- **ASL** – **As**ymmetric **L**oss

State of the Art results [1]

- **GLC** – **G**old **L**oss **C**orrection

Robust Single Label-Learning approach [2]



Wrong label noise in multi-label classification

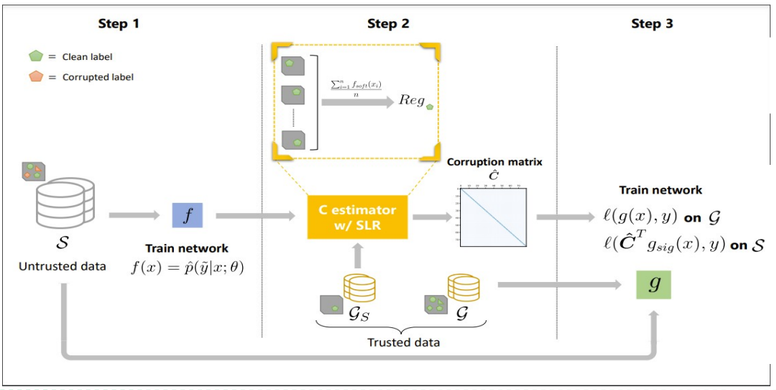
2 RESEARCH QUESTIONS

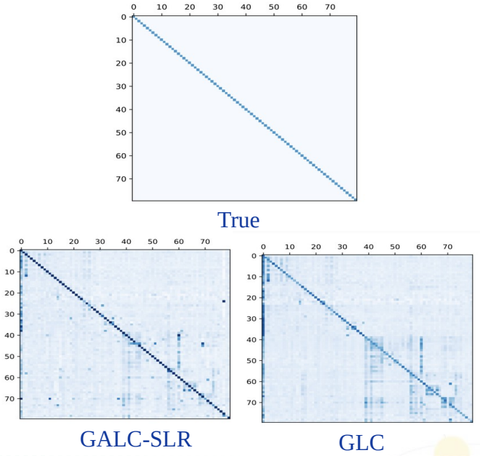
- What is the impact of wrong labels on the performance of a state-of-the-art multi-label classifier?
- How to accurately estimate the multi-label noise distribution using extra information from trusted data?
- How to cope with the class imbalance and label correlations, well-known issues in multi-label learning?
- How to train an accurate multi-label classifier with wrong label information?

3 METHOD – GALC-SLR

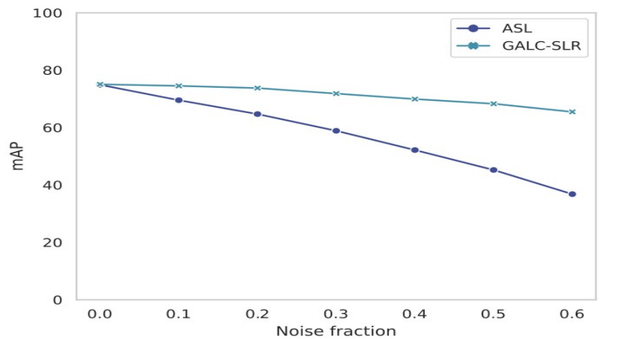
Extend GLC method in MLL for a better **noise estimation** and therefore, robustness against wrong label noise

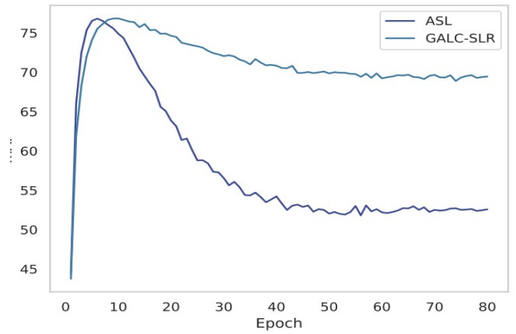
Extend GLC method in MLL for a better **noise estimation** and therefore, robustness against wrong label noise

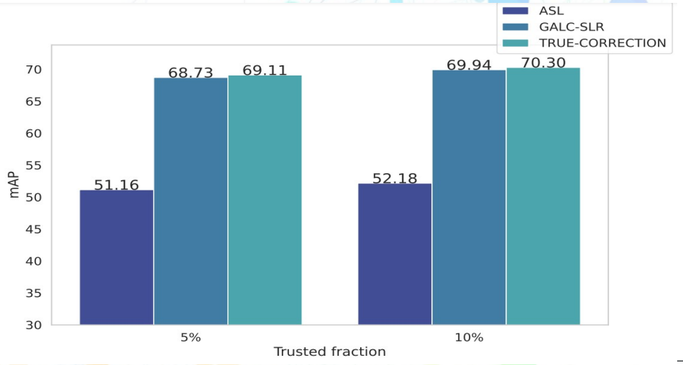


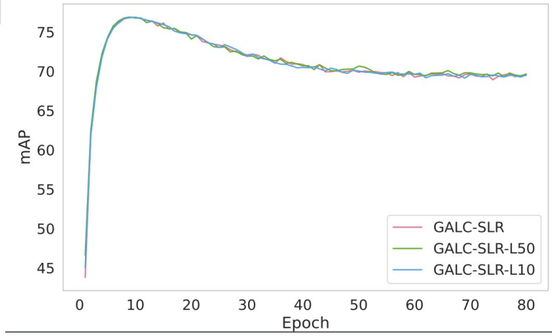


4 RESULTS









5 CONCLUSION

GALC-SLR proves to be **robust against wrong label noise**, while ASL's performance gets decreased

Cosmin Octavian Pene
c.o.pene@student.tudelft.nl

Professor: Lydia Y. Chen
Supervisors: Ammarsaad Ghiassi, Taraneh Younesian

[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