Multi-AL: Robust Active learning for Multi-label Classifier On wrong label noise

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Multi-Label with

Wrong Labels

tree

car

canal

cat

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1. Background

Research Question

Data acquisition for multi-label purposes is expensive and data is often corrupted¹

Active Learning identifies possibly mislabelled instances and identifies the most **informative** instances to train a high-accuracy classifier, with as little queries as possible.

ASL³ is a current state-of-the-art multi-label classifier build using a Deep Neural Network (DNN) Architecture.

2. Method

Multi-AL consists of two measures; mislabelling measure and an informativeness measure and uses ASL³ as base classifier

- Mislabelling measure: Calculate mislabelling likelihood using conflicting label pairings and output probability of the neural network.
- **Safe mode:** A portion of instances with a sufficiently low mislabelling 2. value are used without querying the expert
- Informative measure: Identify informative instances to relabel on 3. either:
 - The **amount of conflicting information** present in features a. (CBIM) from [2] but now multi-label and using a DNN as classifier, (used as baseline)
 - The classifier's uncertainty (Entropy). b.

Both identified safe instances and already relabelled instances are used during the training phase.



How could one benefit from active learning to identify informative examples to relabel by the expert?

Figure 1: Multi-Label Data with Wrong Labels



Figure 3: Accuracy barebone ASL compared to Multi-AL for different noise levels

References

conflicting label pairings

Predicted

Labels

bicycle

car

pizza

knife

[1] T.-Y. Lin et al. Microsoft coco: Common objects in context, 2015.

[2] M.-R. Bouguelia et al. Stream-based active learning in the presence of label noise, ICPRAM, pp. 25-34, 2015

[3] E. Ben-Baruch, Asymmetric loss for multi-label classification, 2020

3. Evaluation

How well does Multi-AL compare to current state-of-the-art classifier ASL and other sampling approaches?

Instances are sampled from subset of **MS COCO¹** consisting of 23k instances total.

100 instances used to train initial classifier

Query 50 instances each iteration



Figure 4: Validation Accuracy according to number of gueried instances for 40 % random label noise

4. Conclusion

Safe mode increases the accuracy significantly when applied to 20 and 40% noise for any sampling method

Multi-AL outperforms default ASL for all levels of noise on average by 28% even though only a fraction of the instances are used during training