Robust Multi-Label Active Learning for missing labels

CSE 3000 02-07-2021

1. Background

Multi-Label Learning

- Extention of multi-class classification where an instance can belong to multiple classes simultaneously
- Closer to real world applications, since most images have more than 1 label
- Asymetric Loss [1] (ASL), current state-of -art for MLL.

Active Learning

- Special case of machine learning that identifies informative samples
- Makes use of an oracle to help label these samples
- Needs less data compared to normal supervised learning

Missing Labels

- Not all correct labels are present in the dataset
- Due to annotation cost being expensive, most Multi-Label datastes are not fully labeled

Correct Labels	MLL with missing labels
Person	Person
Sports Ball	???????
Tennis Racket	Tennis Racket

- **Figure 1:** Example of missing labels in MLL. Image from MSCOCO dataset [2]

2. Question

How can one determine the missing labels using Active Learning?

3. Method

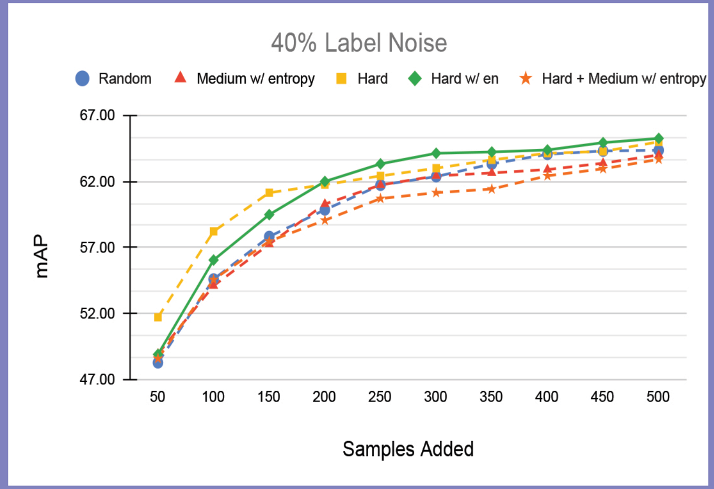
Proposed Method:

- Combine the ASL model with Active Learning
  - Use informativeness measures that exploit the number of missing labels per sample
- Relabelling cost of sample then defined as nr. of labels relabelled.

Measures:

- **Hard Sampling**: Pick the samples with the highest ratio of missing to given labels
- **Medium Sampling**: Pick samples where the ratio of missing to given labels is the closest to 1
- **Hard + Medium**: First 10% of samples picked with Hard sampling and rest with Medium Sampling
- **Random**: Pick a sample randomly
- **Entropy / Uncertainty**: Used to model the uncertainty of the model regarding a sample
  - Combined with other measures to include samples model finds informative

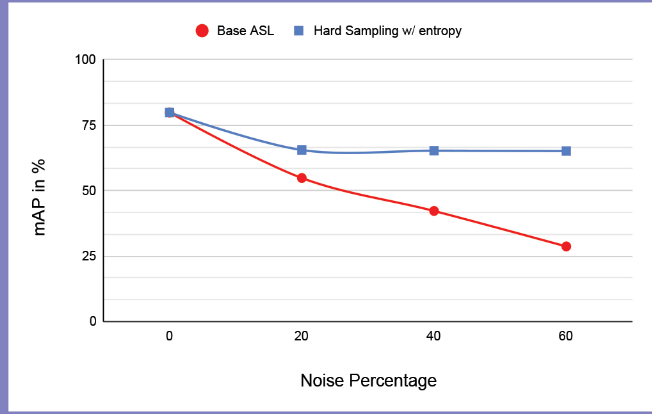
4. Results



- **Figure 2:** The mAP per 50 added samples on 40% label noise on the MSCOCO dataset [2]. Some measures ommited to increase readability. Hard sampling with entropy has highest final mAP.

Measure	% increase per label	mAP at 16.000
Random	0.002239	64.36
Medium	0.0018	61.84
Medium w/ entropy	0.001899	63.38
Hard	0.001879	64.13
Hard w/ entropy	0.002086	64.93
Hard + Medium	0.001792	63.08
Hard + Medium w/ entropy	0.001888	62.42

- **Figure 3:** Cost evaluation of the measures. Second column represents the percentage increase of relabelling 1 label. Third column compares the mAP of the measures at a fixed relabelling cost.



- **Figure 4:** A comparison between the proposed method and ASL on various degrees of noise. Increases the mAP of ASL by 10%, 20% and 30% for 20%, 40% and 60%.

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5. Conclusion

- As can be clearly seen in Figure 4, the proposed method proves to be much more robust against missing labels than ASL.
- For sampling startegies:
  - Since Hard sampling with entropy has overall best performance, it is the suggested measure.
  - If cost is a big factor, Random samping preferred below 50% label noise, while Medium samping above 50%.

References

[1] E. Ben-Baruch, T. Ridnik, N. Zamir, A. Noy, I. Friedman,M. Protter, L. Zelnik-Manor. (2020). Asymmetric Loss For Multi-Label Classification
[2] Lin, T.-Y., Maire, M., Belongie, S., Bourdev, L., Gir-shick, R., Hays, J., Perona, P., Ra- manan, D., Zitnick, C.L. Dollar, P. (2014). Microsoft COCO: Common Objects in Context

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