

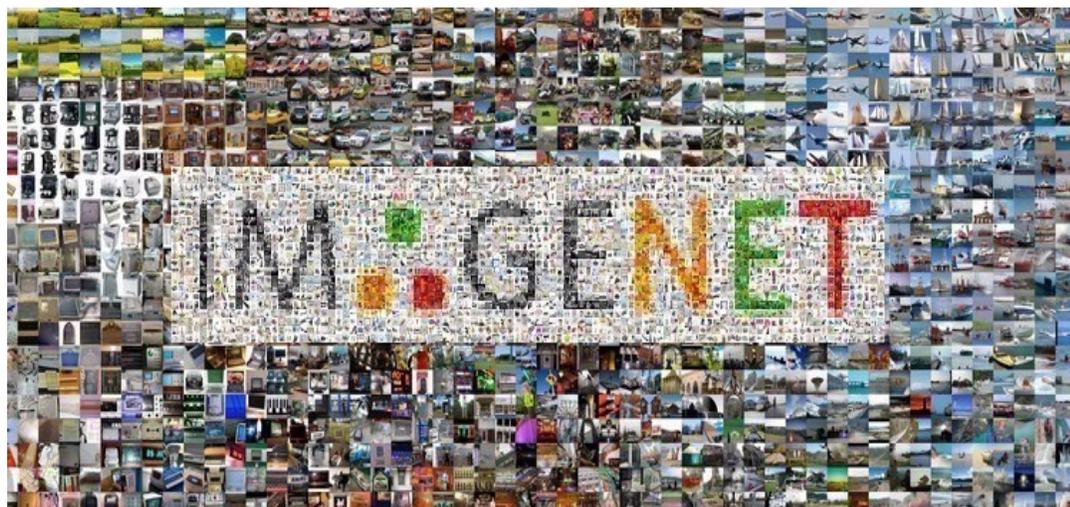
Combating Label Noise in Deep Learning using Abstention

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A Practical Challenge for Deep Learning

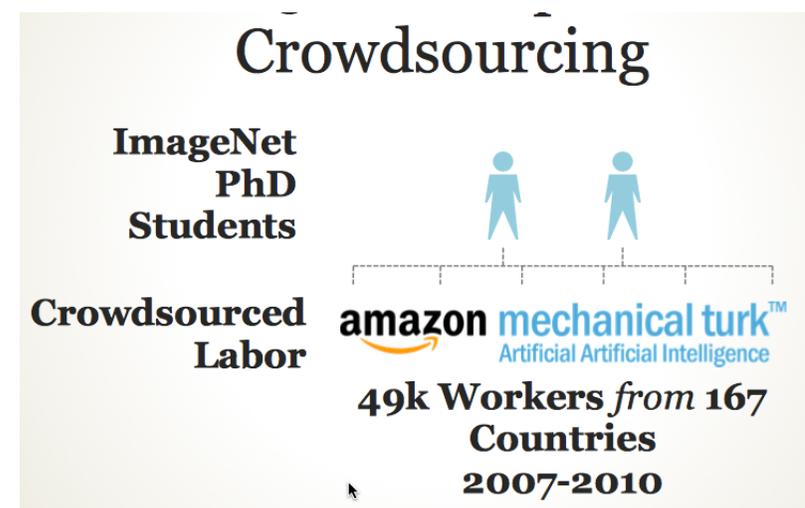
State-of-the-art models require *large amounts of clean, annotated data*.

Annotation is labor intensive!



ImageNet: 15 million labeled images; over 20,000 classes

The data that transformed AI research—and possibly the world (D. Gershgorin, quartz, magazine, 2017)

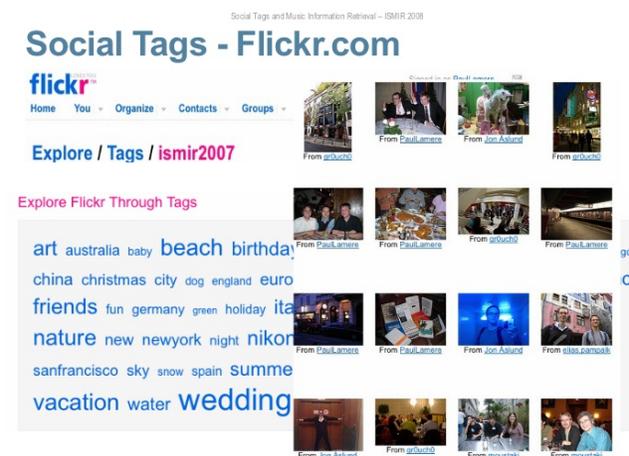


Slide from Fei-Fei Li and Jia Deng

- 49k workers
- 167 countries
- 2.5 years to complete!

Approaches to large-scale labeling

- Crowdsource at scale – labor intensive, but relatively cheap
- Use weak labels from queries, user tags and pre-trained classifiers



Approaches to large-scale labeling

- Crowdsourcing at scale – labor intensive, but

Both approaches can lead to significant labeling errors!

- Use weak labels from queries, user tags and pre-trained classifiers

amazon



Slide credit: S
Guo et al '2018

- Label noise is an inconsistent mapping from features X to labels Y



Dog



Dog



Dog



The Deep Abstaining Classifier (DAC)

Approach: Use learning difficulty on incorrectly labeled or confusing samples to defer on learning -- “*abstain*” -- till correct mapping is learned.

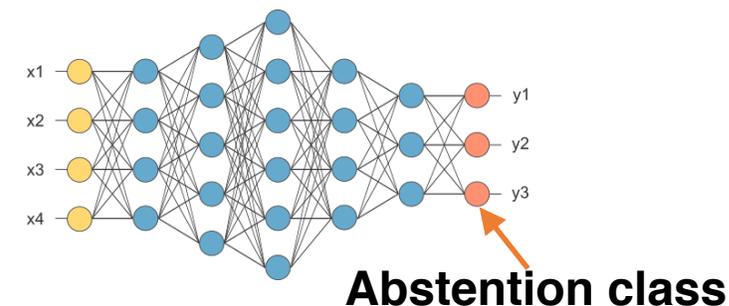
Training a Deep Abstaining Classifier

$$\mathcal{L}(x) = (1 - p(x)_{k+1}) \left(- \sum_{i=1}^k t(x)_i \log \frac{p(x)_i}{1 - p(x)_{k+1}} \right) + \alpha \log \frac{1}{1 - p(x)_{k+1}}$$



Cross entropy as usual

Training a Deep Abstaining Classifier

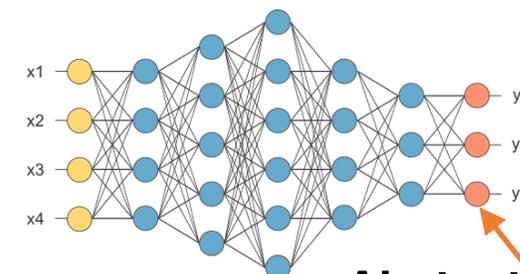


$$\mathcal{L}(x) = (1 - p(x)_{k+1}) \left(- \sum_{i=1}^k t(x)_i \log \frac{p(x)_i}{1 - p(x)_{k+1}} \right) + \alpha \log \frac{1}{1 - p(x)_{k+1}}$$

Encourages abstention

Cross entropy over actual classes

Training a Deep Abstaining Classifier



$$\mathcal{L}(x) = (1 - p(x)_{k+1}) \left(- \sum_{i=1}^k t(x)_i \log \frac{p(x)_i}{1 - p(x)_{k+1}} \right) + \alpha \log \frac{1}{1 - p(x)_{k+1}}$$

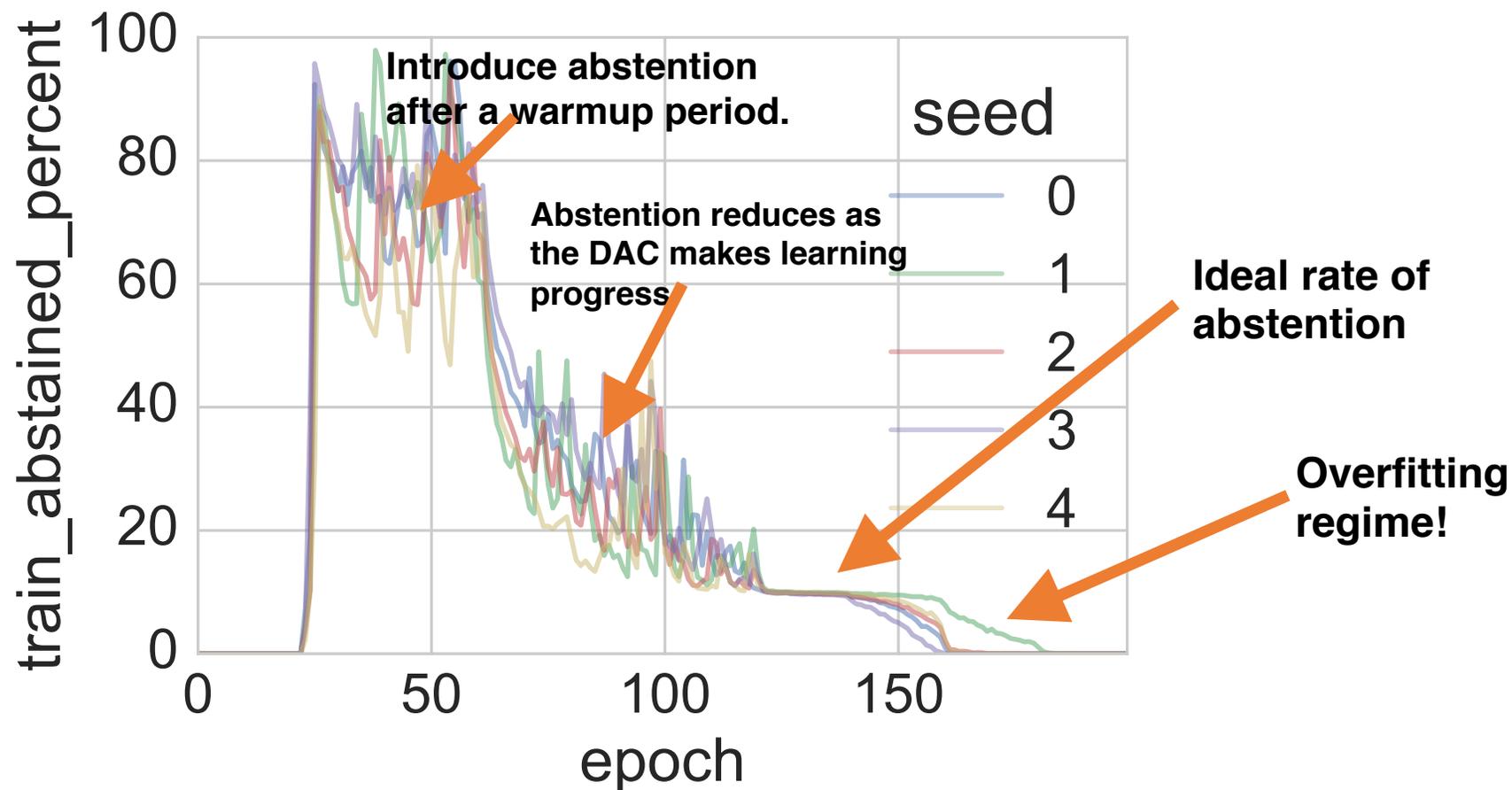
Encourages abstention

Cross entropy over actual classes

Penalizes abstention

Automatically tuned during learning.

Abstention Dynamics

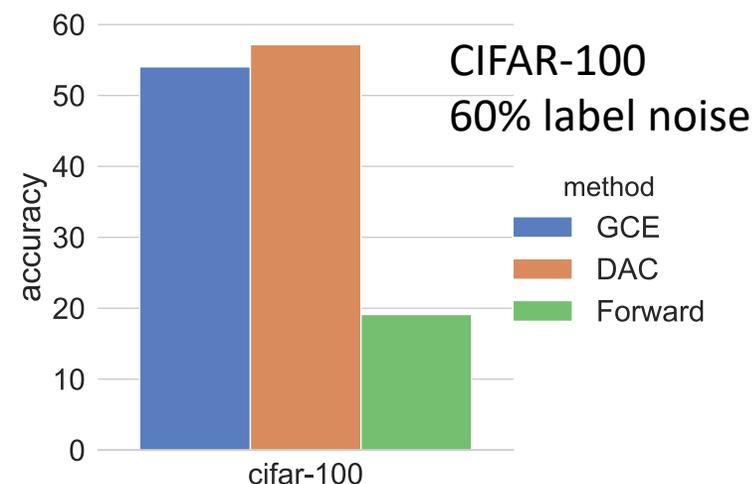
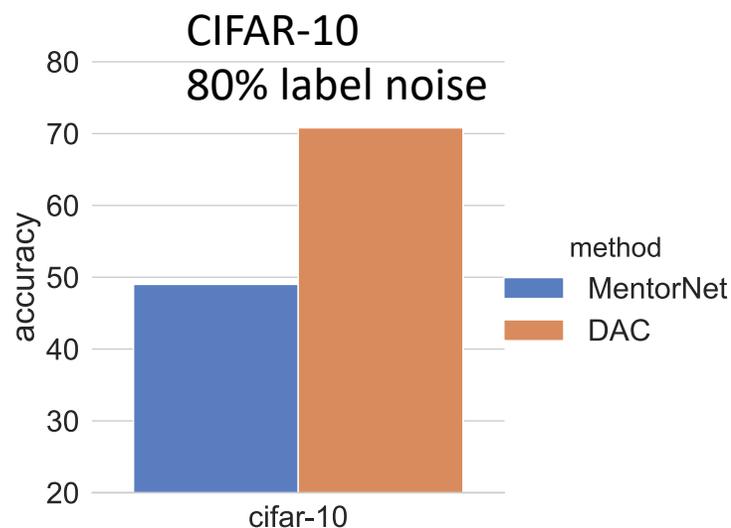
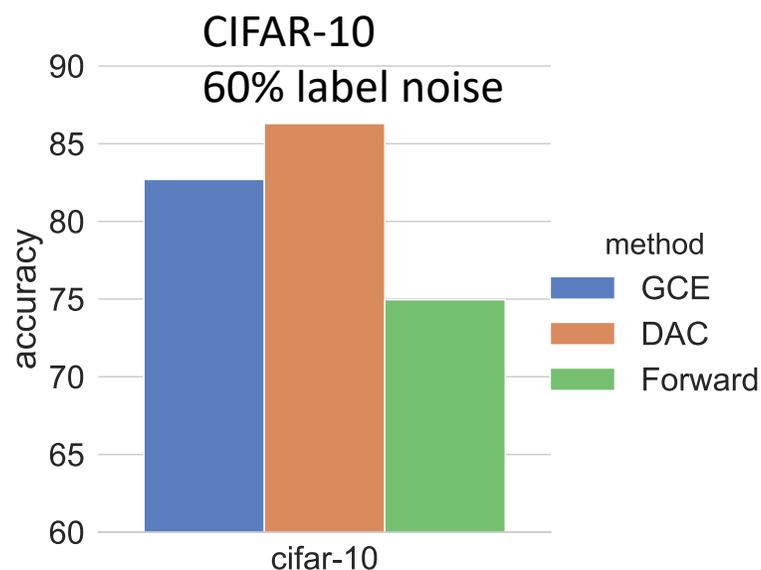


Abstained percent on training set vs epoch with **10% label noise**.

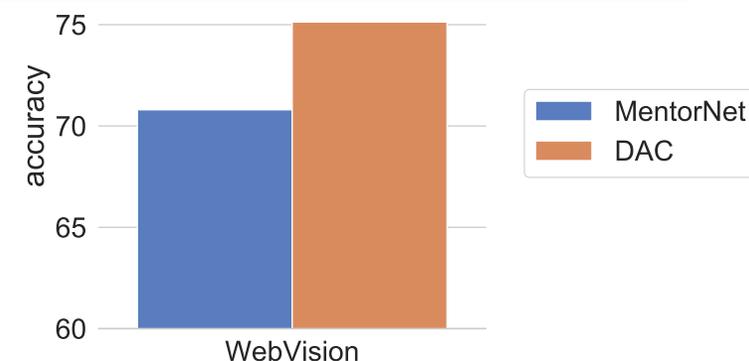
The DAC gives state-of-art results in label-noise experiments.

Training protocol:

- Use DAC to identify and eliminate label noise.
- Retrain on cleaner set.

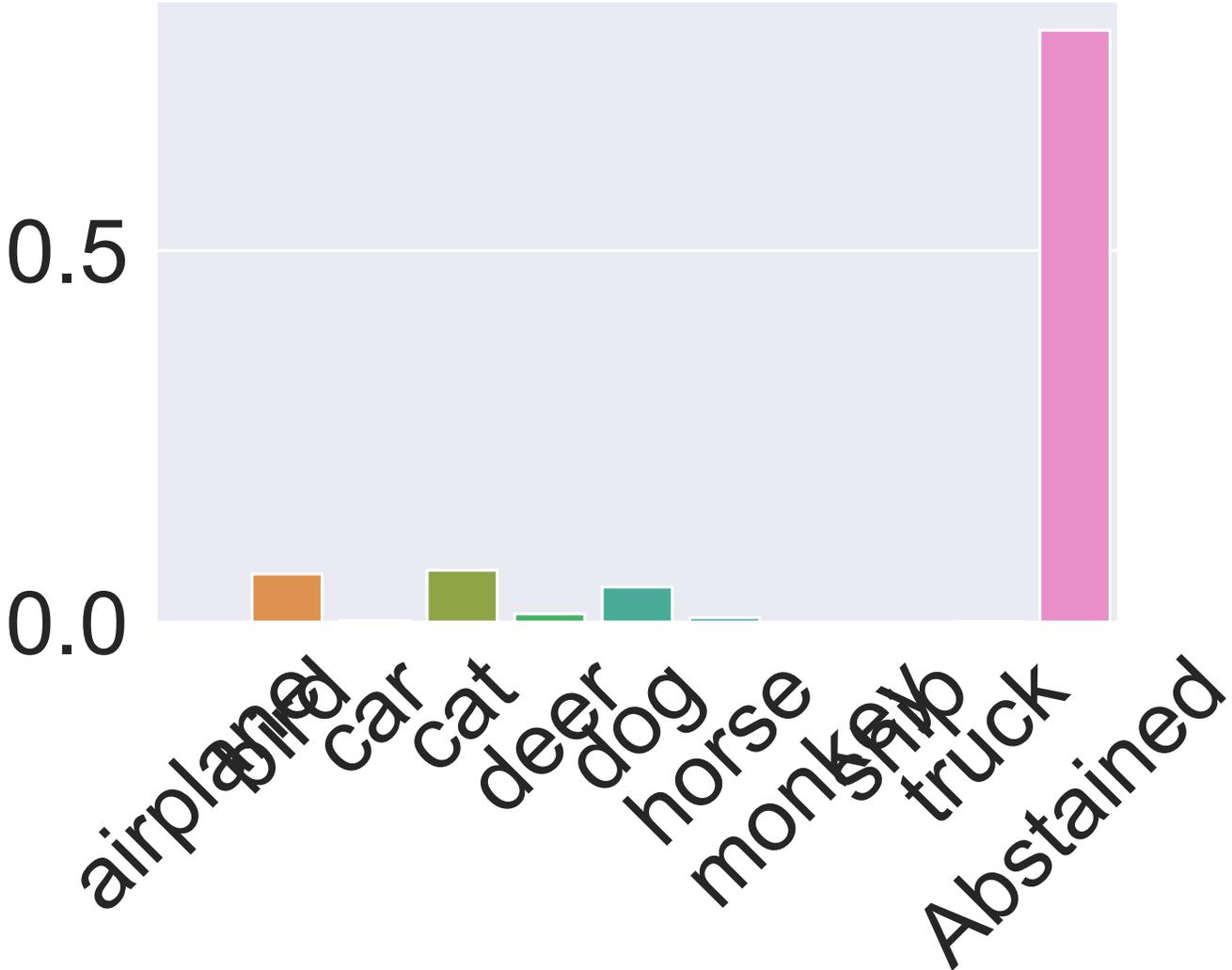


**WebVision: Real-world noisy dataset.
~2.4M images. ~35-40% label noise**



GCE: Generalized Cross-Entropy Loss (Zhang et al NIPS '18); Forward (Patrini et al, CVPR '17); MentorNet (Li et al, ICML '18)

Random Monkeys: DAC Predictions on Monkey Images

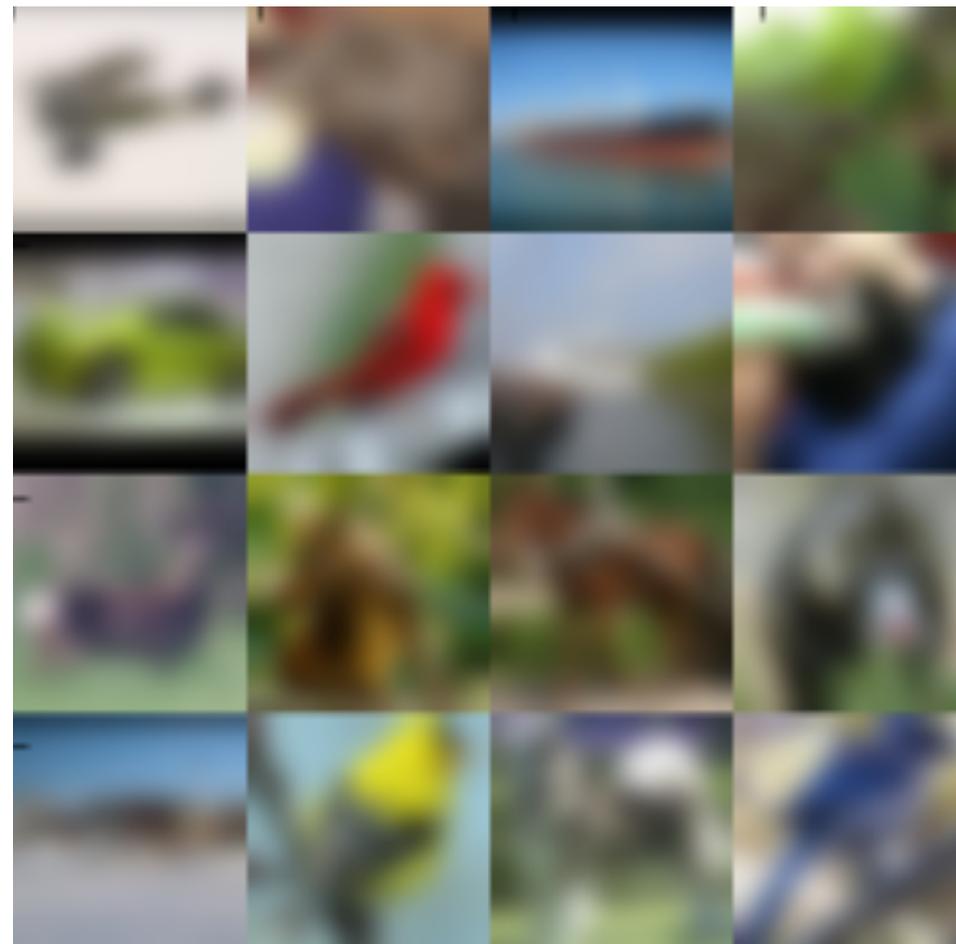


The DAC abstains on most of the monkeys in the test set!

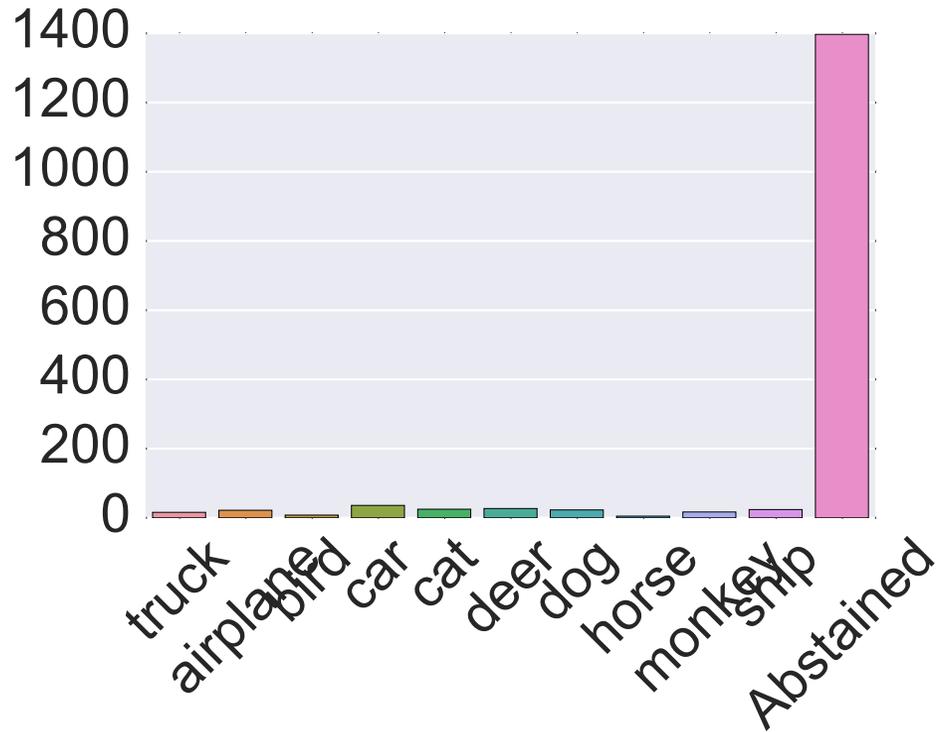
Image Blurring

Blur a subset (20%)
of the images in the
training set and
randomize labels

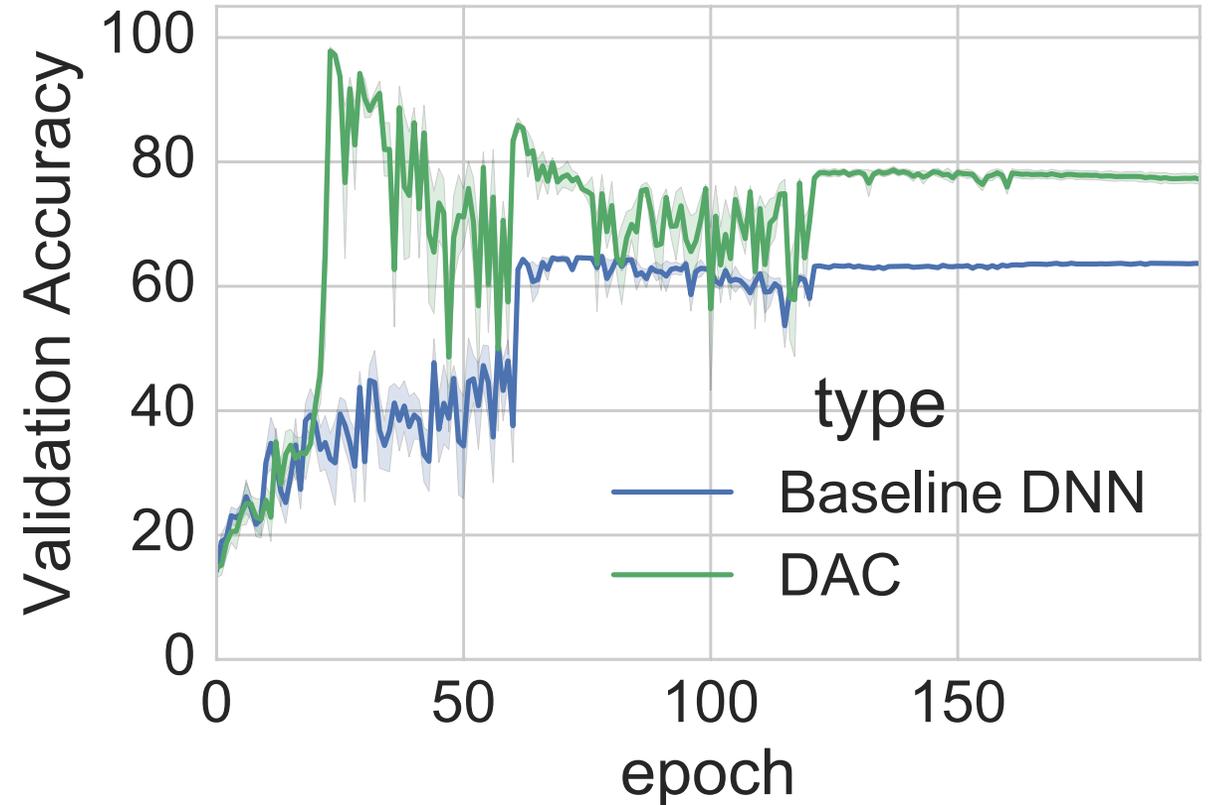
Will the DAC learn to
abstain on blurred
images in the test
set?



DAC Behavior on Blurred Images



DAC abstains on most of the blurred images in the test set



For DAC, validation accuracy is calculated on non-abstained samples.

Conclusions

Code available at <https://github.com/thulas/dac-label-noise>

- **Abstention training is an effective way to clean label noise in a deep learning pipeline.**
- Abstention can also be used as a *representation learner* for label noise.
 - Especially useful for interpretability in “don’t-know” decision situations.

Code available at <https://github.com/thulas/dac-label-noise>

Joint work with.....



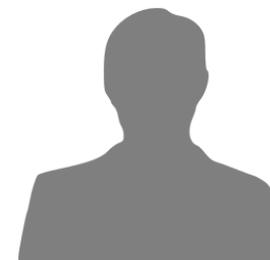
**Tanmoy
Bhattacharya**
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National Lab



Jeff Bilmes
University of
Washington



**Gopinath
Chennupati**
Los Alamos
National Lab



**Jamal Mohd-
Yusof**
Los Alamos
National Lab

Poster:

Tue Jun 11th
06:30 -- 09:00
PM @ Pacific
Ballroom #9

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