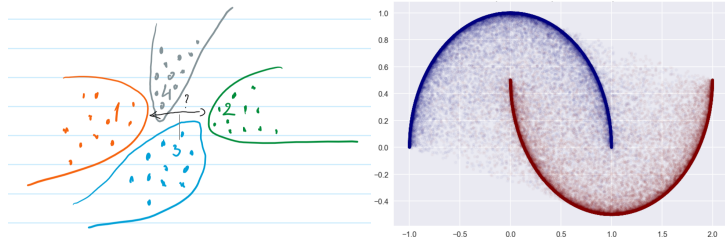


# Semi-supervised Learning Models, Group of Methods “MixUp”

# Outline

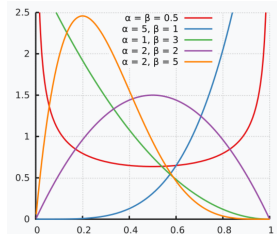
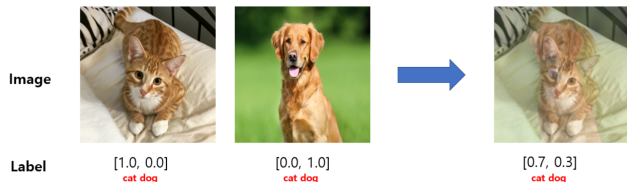
- MixUp (Zhang et al., ICLR 2018)
  - ▶ data augmentation method: train models on convex combination two inputs and two labels
- MixUp strategies for semi-supervised learning
  - ▶ ICT (Verma et al., IJCAI 2019)
  - ▶ MixMatch (Berthelot et al., NeurIPS 2019)
- MixUp strategies in NLP (Guo et al., 2019, Thulasidasan et al., NeurIPS 2019)
  - ▶ Word embeddings
  - ▶ Final vector representation

# MixUp: Intuition



- ML models rely and are overconfident on existing examples
- We need to fill in the gap between the points
- The paper bases on vicinal risk minimization (VRM) theory instead of empirical risk minimization (ERM)
  - ▶ train on augmented examples neighboring original examples

# MixUp: Data augmentation



- Convex combination of two examples

$$\lambda \sim \text{Beta}(\alpha, \alpha)$$

$$(x_i, y_i), (x_j, y_j) \sim \mathcal{D}_l$$

$$x_i' = \lambda x_i + (1 - \lambda)x_j$$

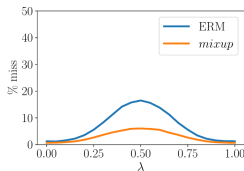
$$y_i' = \lambda y_i + (1 - \lambda)y_j$$

- Vicinal objective function

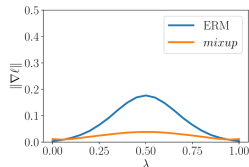
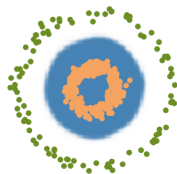
$$\mathcal{L}(\theta) = \ell(p(y|x_i'; \theta), y_i')$$

# MixUp: Benefits

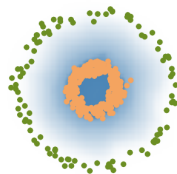
- Agnostic data augmentation: work on image, speech, text (with modification), tabular data, stabilizing GANs
- Generalize better to out-of-distribution examples
- Robustness to adversarial examples
- Smooth decision boundaries, reduce memorization and overfitting



ERM

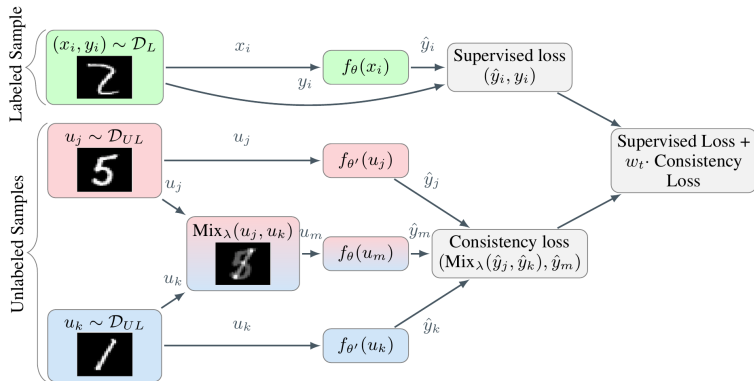


*mixup*



# MixUp strategies for semi-supervised learning: ICT (Verma et al., IJCAI 2019)

- Mixing unlabeled examples



# MixUp strategies for semi-supervised learning: MixMatch (Berthelot et al., NeurIPS 2019)

- Mixing both labeled and unlabeled examples as follows
  - ▶ Label predictions for unlabeled examples, averaging output distribution for  $K$  augmented unlabeled examples

$$y_{\text{ul}} = \frac{1}{K} \sum_{k=1}^K p(y|\hat{u}_{\text{ul}}; \theta)$$

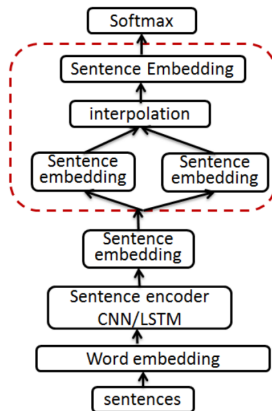
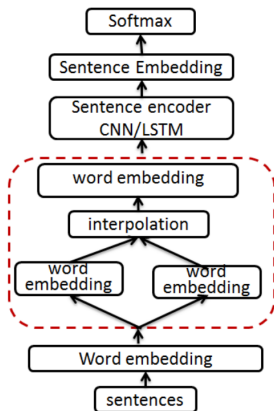
- ▶ Sharpening (temperature annealing) label predictions, forcing output distribution towards one-hot vector by adjusting temperature  $T \rightarrow 0$

$$y_{\text{ul},c} = \frac{y_{\text{ul},c}^{\frac{1}{T}}}{\sum_{c=1}^C y_{\text{ul},c}^{\frac{1}{T}}}$$

- ▶ MixUp all labeled and unlabeled examples
- Warning: during training, we pass  $K$  duplicated unlabeled images at the same time, so we need to adjust batchnorm updates to only take one set unlabeled images

# NLP MixUp Strategies

- Word embeddings
  - ▶ Mixing embeddings of aligned words between two sentences (padding sentences if one is shorter than the other)
- Final vector representation



# NLP MixUp Results

| RandomTune                         | Trec             | SST-1            | SST-2            | Subj             | MR               |
|------------------------------------|------------------|------------------|------------------|------------------|------------------|
| CNN- KIM Impl. (Kim, 2014b)        | 91.2             | 45.0             | 82.7             | 89.6             | 76.1             |
| CNN- HarvardNLP Impl. <sup>1</sup> | 88.2             | 42.2             | 83.5             | 89.2             | 75.9             |
| CNN - Our Impl.                    | 90.2±0.20        | 43.6±0.19        | 82.3±0.47        | 90.6±0.45        | 75.5±0.36        |
| CNN+wordMixup                      | 90.9±0.42        | 45.2±0.90        | 82.8±0.45        | <b>92.9±0.41</b> | <b>78.0±0.39</b> |
| CNN+senMixup                       | <b>92.1±0.31</b> | <b>45.2±0.22</b> | <b>83.0±0.35</b> | 92.7±0.38        | 77.9±0.76        |

| RandomTune                                | Trec             | SST-1            | SST-2            | Subj             | MR               |
|-------------------------------------------|------------------|------------------|------------------|------------------|------------------|
| LSTM-StanfordNLP Impl. (Tai et al., 2015) | N/A              | 46.4             | 84.9             | N/A              | N/A              |
| LSTM-AgrLearn Impl. (Guo et al., 2018a)   | N/A              | N/A              | N/A              | 90.2             | 76.2             |
| LSTM - Our Impl.                          | 86.5±0.61        | 45.9±0.58        | 84.4±0.35        | 90.9±0.42        | 77.2±0.75        |
| LSTM + wordMixup                          | <b>90.5±0.50</b> | 48.2±0.18        | 86.3±0.35        | <b>93.1±0.49</b> | <b>78.0±0.33</b> |
| LSTM + senMixup                           | 89.4±0.40        | <b>48.3±0.77</b> | <b>86.7±0.33</b> | 91.9±0.34        | 77.9±0.33        |

*Thank you !*