**INTRODUCTION**

- **Motivation**
  - Standard Supervised Learning Setting
  - Assume: training data $= \{(x_i, y_i)\}_{i=1}^{N}$
  - However, in practical setting, $y_i \neq \hat{y}_i$
    - High cost and time consuming
    - Expert knowledge
    - Unattainable at scale
  - Learning with Noisy Label
    - Suffered from poor generalization on test data

**SELFIE (SELectively refurbItSh unClean samples)**

- Hybrid approach of loss correction and sample selection
- Introduce the concept of *refurbishable samples* $\mathcal{R}$ that can be corrected with high precision
- Correct the losses of *refurbishable samples* $\mathcal{R}$ and combine them with the losses of "clean samples" $\mathcal{C}$ to propagate backward

**Update Equation**

- Let $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$, $\mathcal{M} = \{(x_i, \hat{y}_i)\}_{i=1}^{N}$; noisy label
- Standard update equation
  $$\theta_{t+1} = \theta_t - \alpha\frac{1}{N} \sum_{i=1}^{N} L(x_i, y_i)$$
- Modified update equation
  $$\theta_{t+1} = \theta_t - \alpha\frac{1}{N} \sum_{i=1}^{N} \left( L(x_i, y_i) + \mathcal{R}(x_i) \right)$$

**Select Clean samples $\mathcal{C}$ and refurbishable samples $\mathcal{R}$**

- Clean samples $\mathcal{C}$ from the mini-batch $\mathcal{M}$
  - We adopt the widely used loss-based selection
  - $\mathcal{C} = \{(100 - \text{noise rate})\% \text{ of low-loss samples in } \mathcal{M}\}$
- Refurbishable samples $\mathcal{R}$ from the mini-batch $\mathcal{M}$
  - Before the network fully fits the noisy labels, the label predictions of mislabeled samples $\mathcal{R}$ changes inconsistently
  - $R_{\epsilon}(x_i) \neq \hat{y}_i$; noisy labeling
  - $R_{\epsilon}(x_i) = \epsilon\%$ predicted label for previous $\epsilon$ times

**Advantage of SELFIE**

- Minimize the false correction during the training
- Only the samples in $\mathcal{R}$ are connected with high precision
- Explode all training samples at the end of training
- As the training progresses, more samples become refurbishable

**Noise Type**

- **Syntethic Noise**
  - Injected the two widely used synthetic noise $\mathcal{E}_p$
    - Pair noise
  - Symmetric noise
    - CIFAR-10, CIFAR-100, and Tiny-ImageNet were used
  - Robust Deep Learning
    - Built ANIMAL-10N dataset with real-world noise
    - Caved 5 pairs of confusing animals (total #: 60,000 images)
      - (cat, lynx), (jaguar, cheetah), (hamster, guinea pig), ...

**OUR METHODOLOGY**

**Sample Selection (Recent Direction)**

- Select clean *(easy)* samples $\mathcal{C}$ for parameter updates (SGD step)
  - E.g., Select $\{(100 - \text{noise rate})\% \text{ of low-loss samples as clean}\}$
  - Achieve a much better performance on heavily noisy data
- However, use only partial exploration of the entire training data
- Ignore useful hard samples classified as unclean

**EVALUATION**

**Performance on Synthetic Noise**

- Trained DenseNet ($L=25$, $k=12$) and VGG-19 with varying noise rates
  - Absolute error reduction by up to $6.9\%$ (DenseNet) and $6.5\%$ (Symmetric)

**Performance on Robust Noise**

- Trained DenseNet ($L=25$, $k=12$) and VGG-19
  - Absolute error reduction by up to $8.7\%$ (DenseNet) and $2.4\%$ (VGG)

---

**SELFIE: Refurbishing Unclean Samples for Robust Deep Learning**

Hwanjun Song†, Minseok Kim†, Jae-Gil Lee‡*

† Graduate school of Knowledge Service Engineering, KAIST
‡ Corresponding Author