Noisy Label Refinement with Semantically Reliable Synthetic Images

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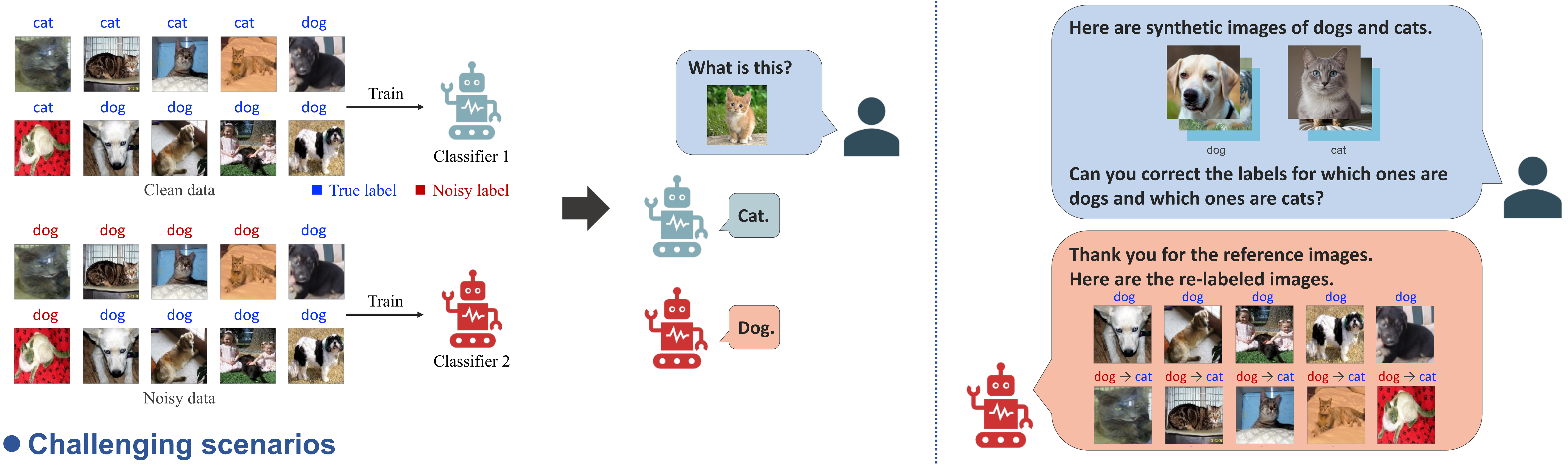
Paper | Code

Introduction

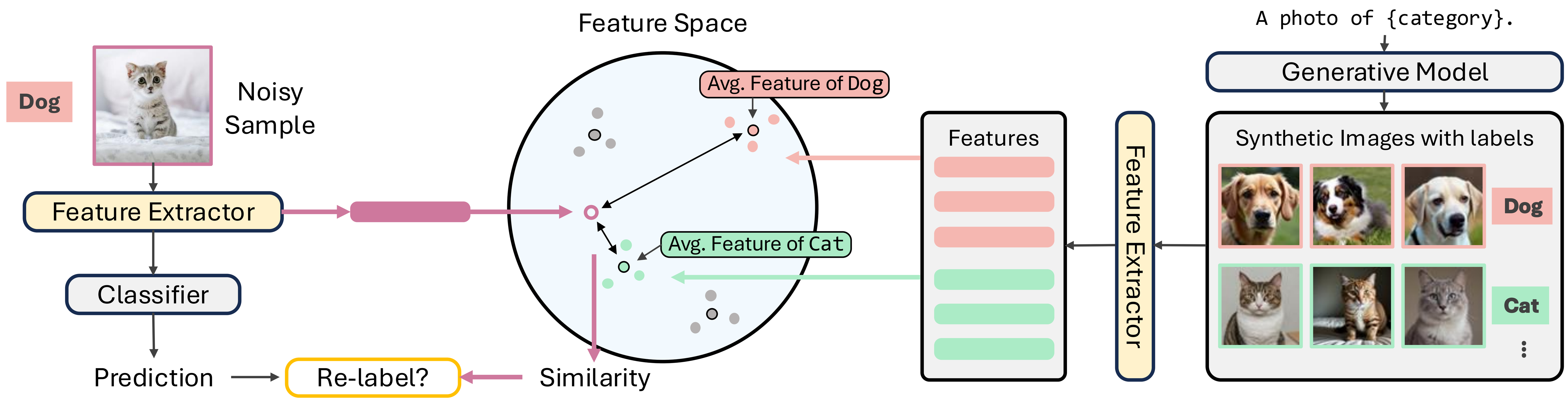


- **Challenging scenarios**
  - High proportion of label noise
  - Noise is systematic, not random

  → **Reference-guided information is needed**

- **Proposal:** Leverage synthetic images as stable anchors to identify and correct mislabeled samples

Approach



- **Preprocessing**
  - Synthetic image generation
  - Model training with noisy supervision
  - Synthetic prototype construction
- **Label refinement**
  - **Feature extraction:** Extract features of real images
  - **Score computation:** Combine feature similarity and classifier confidence
  - **Re-labeling:** Update the label if the highest score exceeds a threshold

Experiments

Settings

- **Datasets:** CIFAR datasets
  - **Training set:** 500 images / category
  - **Test set:** 100 images / category
- **Synthetic dataset**
  - **Model:** SDXL-Turbo
  - **CIFAR-SD:** 100 images / category
- **Noise types**
  - Feature-dependent noise: PMD noise [1]
  - Hybrid noise
    - PMD noise + Uniform noise (PMD + U)
    - PMD noise + Asymmetric noise (PMD + A)
- **Classifier:** ResNet-34 trained from scratch

Main results

- **Standard:** Baseline accuracy obtained by training on noisy labels
- **Re-labeled data:** Fine-tune the classifier with the updated labels
- **Method combination:** Apply refined labels to PLC [1] and LRA-diffusion [2]

	CIFAR-10				
Methods	35% PMD	70% PMD	35% PMD + 30% U	35% PMD + 60% U	35% PMD + 30% A
Standard	80.81	40.32	77.12	67.92	77.40
Re-labeled data (Ours)	82.46 (+1.65)	54.10 (+13.78)	79.76 (+2.64)	72.38 (+4.46)	78.97 (+1.57)
PLC	82.87	38.65	77.98	61.87	78.52
PLC + Ours	83.26 (+0.39)	54.01 (+15.36)	81.38 (+3.40)	72.57 (+10.70)	80.49 (+1.97)
LRA-diffusion (SimCLR)	89.29	40.87	88.83	83.67	86.89
LRA-diffusion (SimCLR) + Ours	88.87 (-0.42)	60.78 (+19.91)	88.41 (-0.42)	85.31 (+1.64)	87.95 (+1.06)
LRA-diffusion (CLIP)	96.91	41.78	96.61	88.66	94.35
LRA-diffusion (CLIP) + Ours	**96.93** (+0.02)	**71.59** (+29.81)	**96.68** (+0.07)	**94.94** (+6.28)	**96.78** (+2.43)

	CIFAR-100				
Methods	35% PMD	70% PMD	35% PMD + 30% U	35% PMD + 60% U	35% PMD + 30% A
Standard	59.28	44.43	55.98	43.50	52.23
Re-labeled data (Ours)	61.45 (+2.17)	47.15 (+2.72)	59.35 (+3.37)	44.91 (+1.41)	61.39 (+9.16)
PLC	60.06	45.03	57.67	38.92	59.34
PLC + Ours	59.59 (-0.47)	46.13 (+1.10)	59.43 (+1.76)	43.25 (+4.33)	60.08 (+0.74)
LRA-diffusion (SimCLR)	54.95	48.00	55.23	47.47	53.99
LRA-diffusion (SimCLR) + Ours	56.18 (+1.23)	49.34 (+1.34)	54.67 (-0.56)	48.54 (+1.07)	55.45 (+1.46)
LRA-diffusion (CLIP)	75.91	56.15	74.69	63.08	69.97
LRA-diffusion (CLIP) + Ours	**77.01** (+1.10)	**66.88** (+10.73)	**76.10** (+1.41)	**66.27** (+3.19)	**74.42** (+4.45)

References

[1] Learning with Feature-Dependent Label Noise: A Progressive Approach. Zhang et al., ICLR2021.
[2] Label-Retrieval-Augmented Diffusion Models for Learning from Noisy Labels. Chen et al., NeurIPS2023.