Masked Contrastive Learning for Coarse-Labelled Dataset

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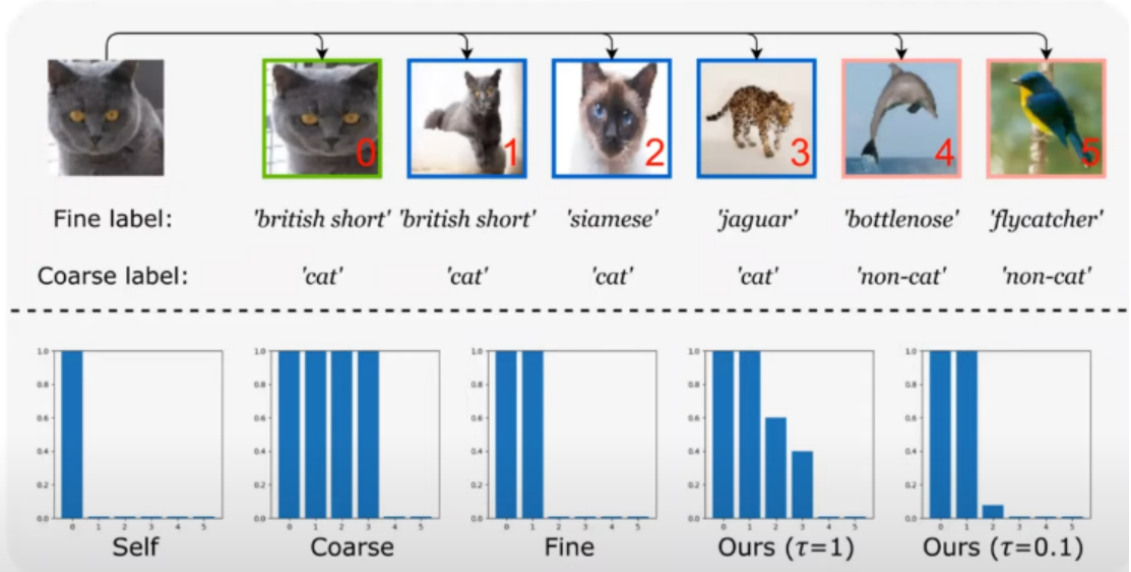
Feng, Chen, and Ioannis Patras. *"MaskCon: Masked Contrastive Learning for Coarse-Labelled Dataset."* Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2023.

Contents

Problem Statement

Many real-world datasets use coarse labels because fine-grained annotation is expensive and time-consuming.

- Deep learning performs well with fine-grained labels (e.g., classifying dog breeds like “Golden Retriever”).
- In contrast, coarse labels (e.g., just “dog”) are cheap and easier to get.
- MaskCon is proposed to bridge the gap: learn fine-grained representations only from coarse labels.



MaskCon Methodology

MaskCon is a contrastive learning method that works even when only coarse labels are available.

- Traditional contrastive loss pulls all positive pairs together, but this fails when fine-grained labels are missing.
- MaskCon uses coarse labels to form soft groupings and masks out irrelevant pairs.
- For a given anchor sample i, only samples j with the same coarse label contribute to similarity.

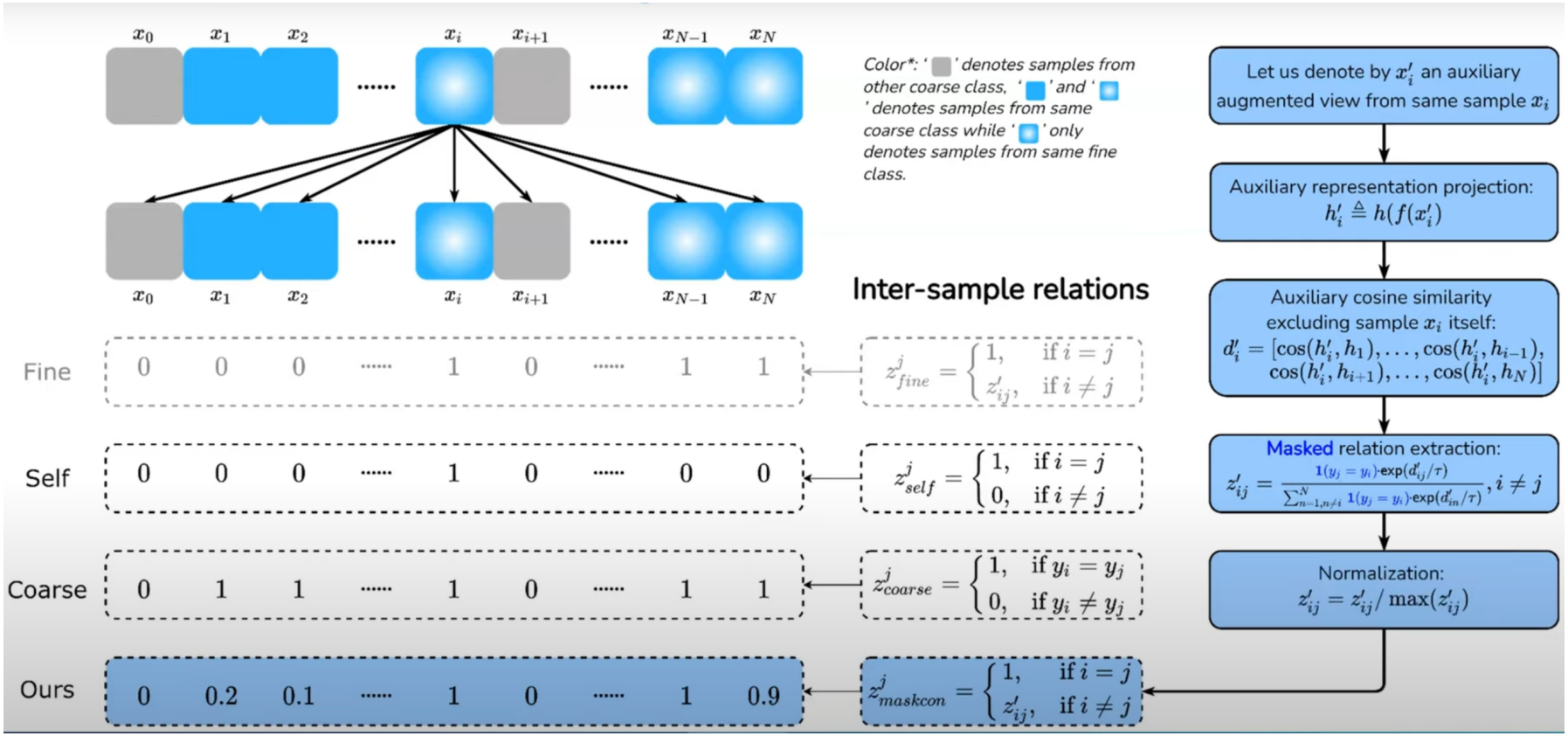
Masked Similarity and Final Loss

$$z'_{ij} = \frac{\mathbf{1}(y_i = y_j) \cdot \exp(\cos(h_i, h_j)/\tau)}{\sum_{n \neq i} \mathbf{1}(y_n = y_i) \cdot \exp(\cos(h_i, h_n)/\tau)}$$

where $\cos(h_i, h_j)$ is cosine similarity and τ is a temperature hyperparameter.

$$\mathcal{L} = w \cdot \mathcal{L}_{\text{MaskCon}} + (1 - w) \cdot \mathcal{L}_{\text{SelfCon}}$$

MaskCon Framework



The framework shows how MaskCon constructs soft similarity using coarse labels, cosine similarity, and masked contrastive loss.

Experimental Setup

Datasets Used

- **CIFAR-10 & CIFAR-100** (coarse labels)
- **ImageNet-1K** (coarse supervision)
- **Stanford Online Products (SOP)**
- **Stanford Cars 196**

Base Model

- **Backbone:** ResNet-18
- Modified: 3×3 conv, stride 1
- Max-pooling removed for CIFAR

Hyperparameters

- $w \in \{0,\ 0.2,\ 0.5,\ 0.8,\ 1.0\}$
- $\tau \in \{0,\ 0.01,\ 0.05,\ 0.1,\ 0.5,\ \infty\}$
- Best: $w = 1$, $\tau = 0.05$ or 0.1

Evaluation Metric

- **Recall@K**: retrieval accuracy
- 1 if any top-K result matches fine class
- Averaged over test samples

Paper Results: CIFARtoy Dataset

Method	CIFARtoy-goodsplit				CIFARtoy-badsplit			
	Recall@1	Recall@2	Recall@5	Recall@10	Recall@1	Recall@2	Recall@5	Recall@10
SelfCon	84.83	91.55	96.35	98.16	84.83	91.55	96.35	98.16
Grafit	86.61	92.33	97.01	98.38	89.96	94.36	97.61	98.10
SupCon	73.84	84.25	92.14	95.46	84.66	90.93	95.15	96.71
CoIns	86.15	92.76	97.21	98.46	90.55	94.94	97.73	98.71
SupCE	76.30	85.26	94.65	97.46	87.15	92.85	96.78	98.34
SupFINE	94.11	96.53	98.25	98.96	94.11	96.53	98.25	98.96
MaskCon (Ours)	**90.28** (13.98↑)	**94.04**	**97.33**	**98.53**	**91.56** (4.41↑)	**95.23**	**97.70**	**98.70**

Table 1. Results on CIFARtoy dataset.

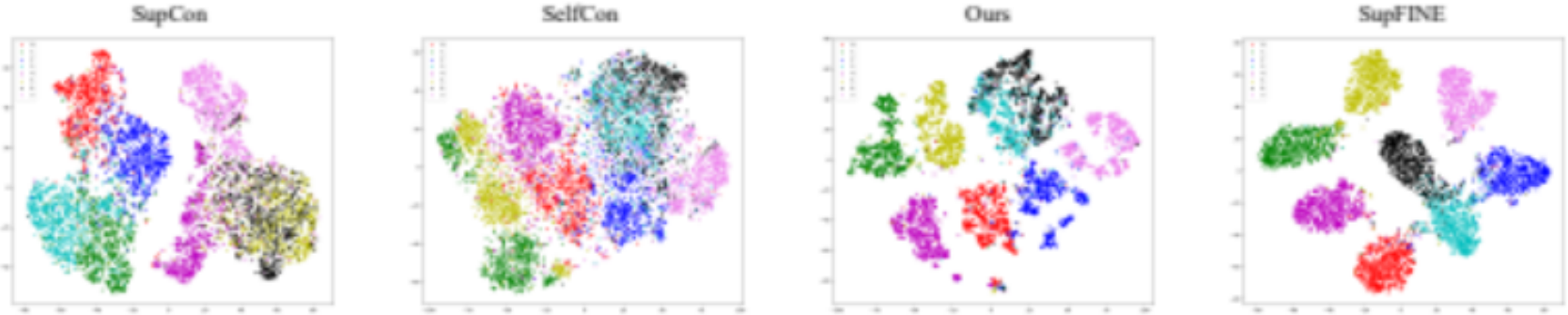
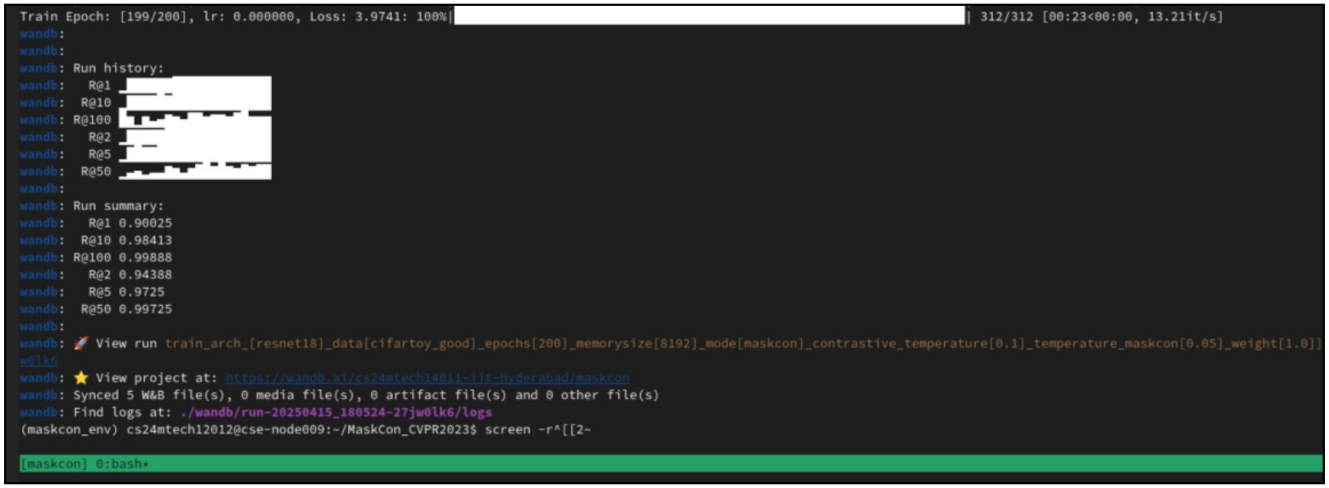


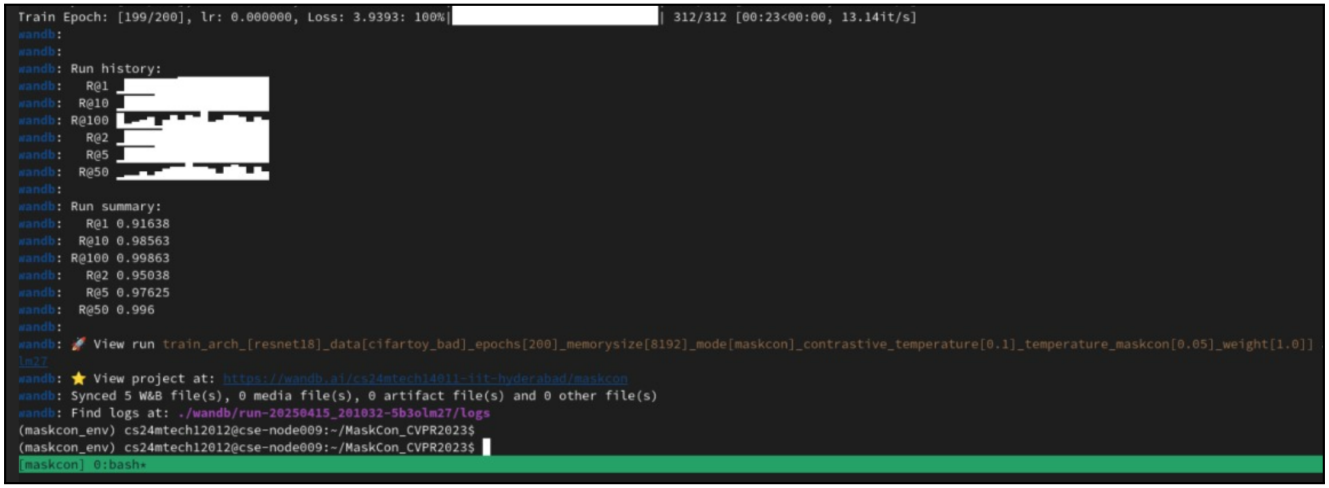
Figure 3. t-SNE visualization of learned representation on CIFARtoy dataset.

Reproduced Results: CIFARtoy Dataset

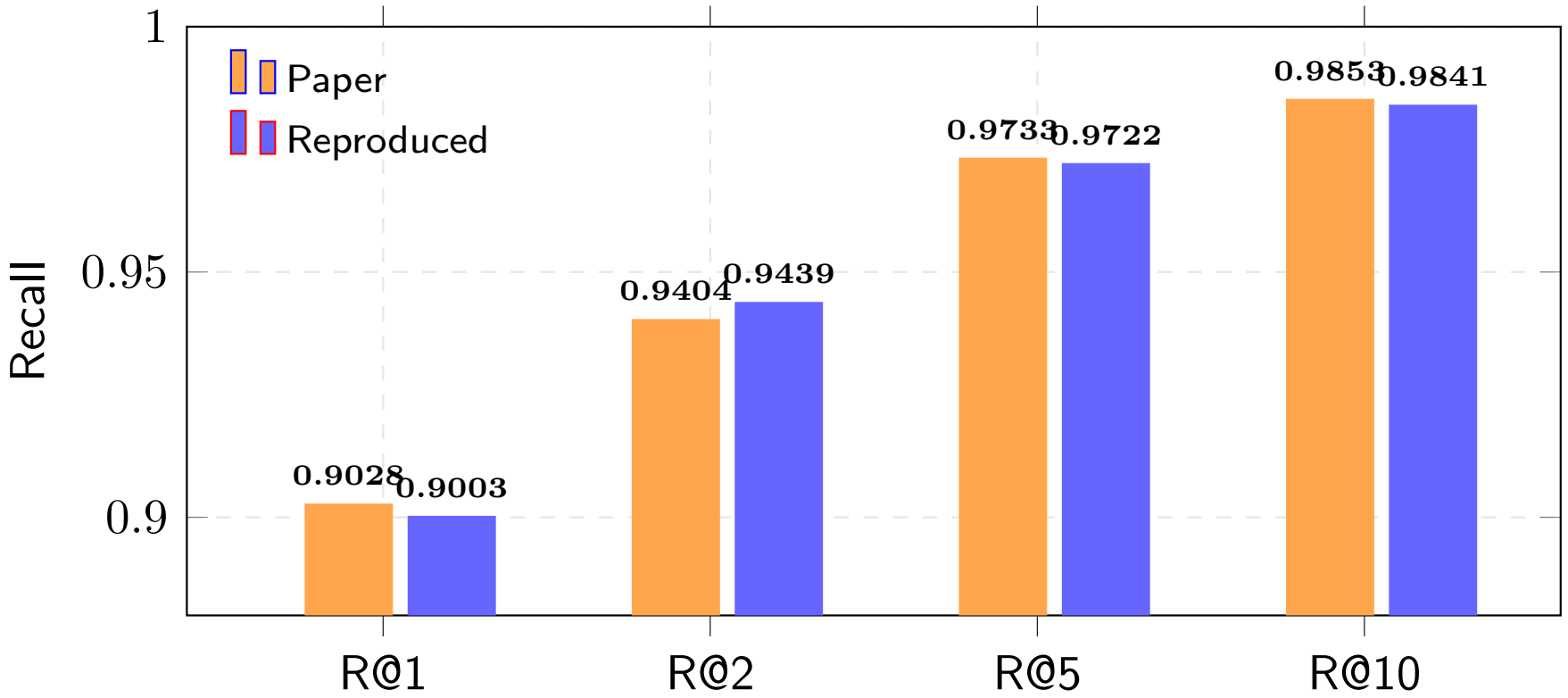
CIFARtoy-goodsplit



CIFARtoy-badsplit



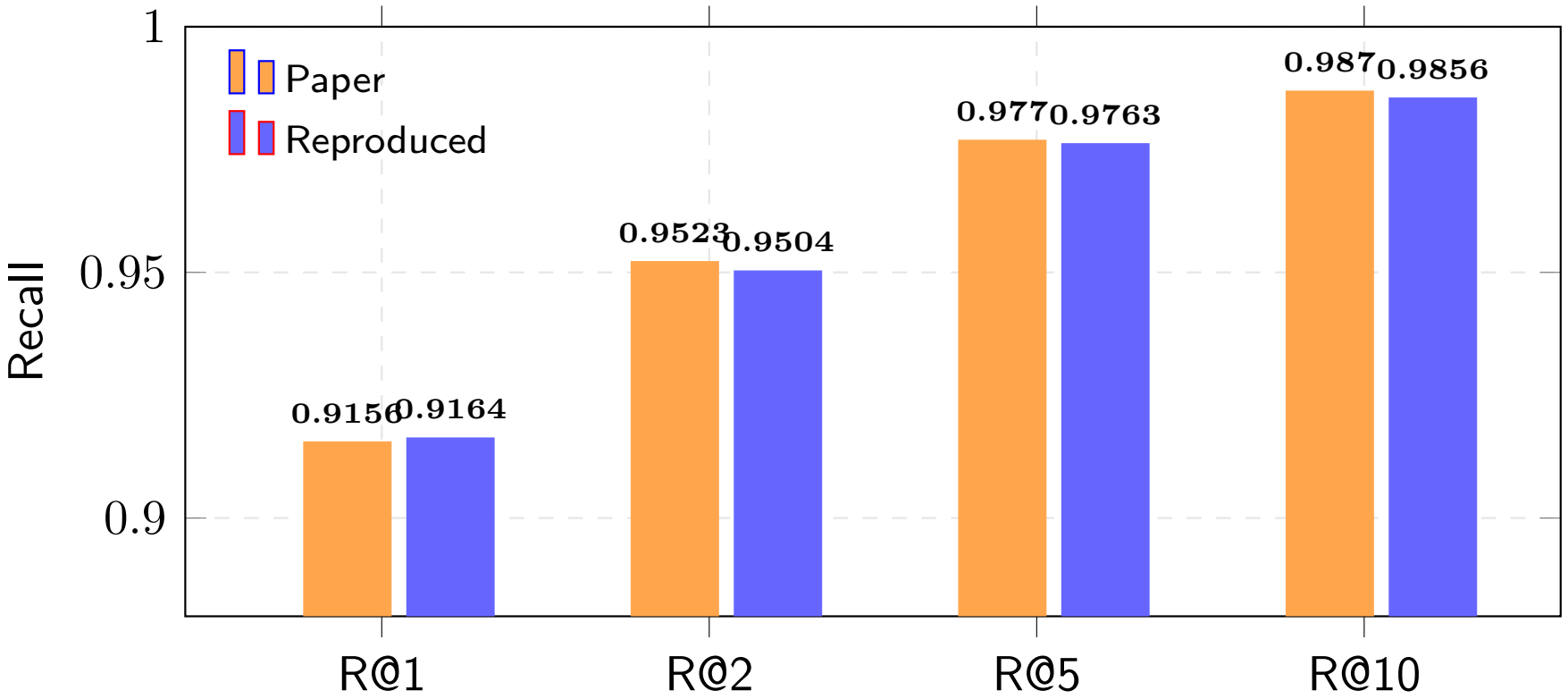
Comparison: MaskCon Paper vs Reproduced(Good Split



Setup

Epochs = 200, Temperature = 0.05, Weight $w_1 = 1.0$, Train size= 40k, Test size= 8k

Comparison: MaskCon Paper vs Reproduced (Bad Split)



Setup

Epochs $= 200$, Temperature $= 0.05$, Weight $w_1 = 1.0$, Train size$= 40$k, Test size$= 8$k

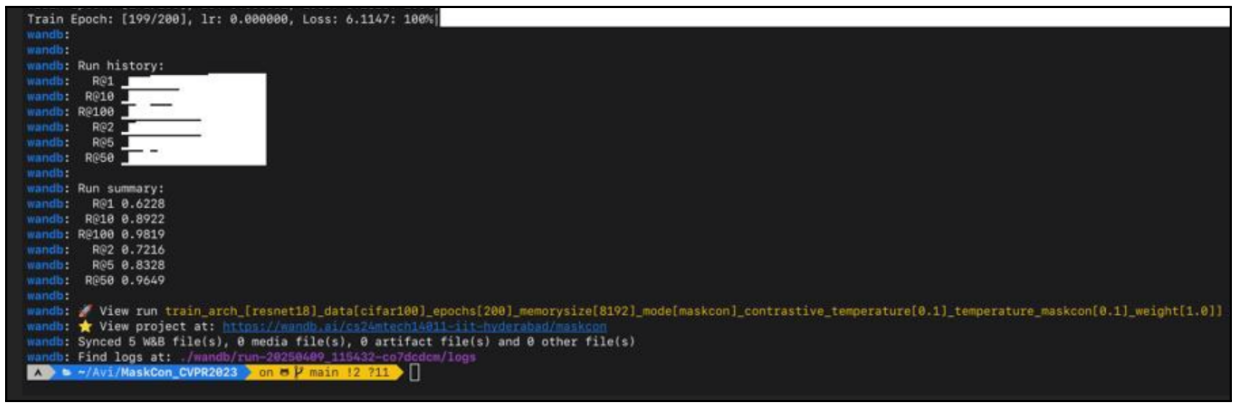
CIFAR100: Paper Results & Reproduced Results

Paper Results

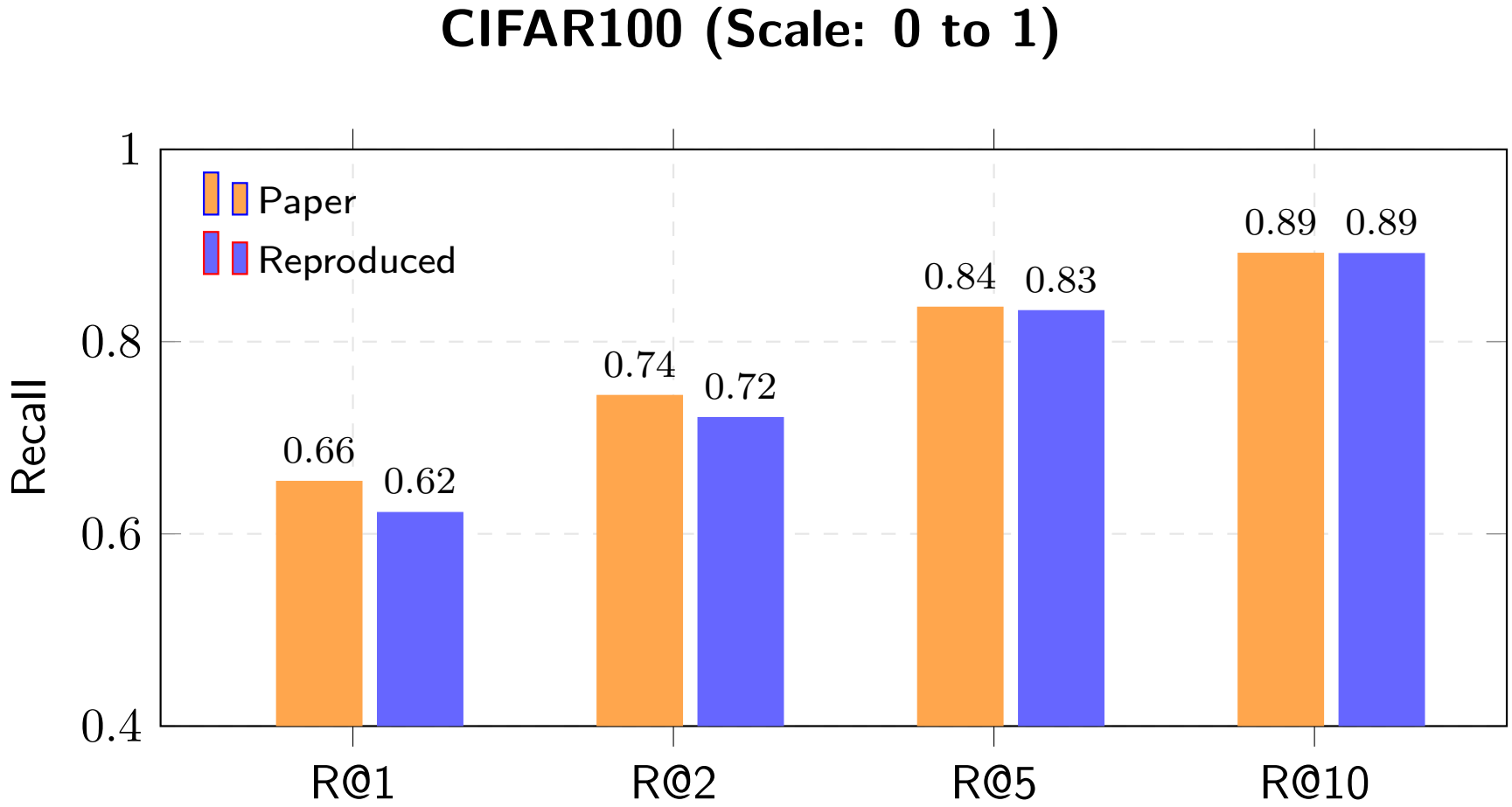
Method	Recall@1	Recall@2	Recall@5	Recall@10
SelfCon	40.50	51.83	66.23	76.66
Grafit	60.57	71.13	82.32	89.21
SupCon	58.65	70.04	82.18	89.09
CoIns	60.10	70.89	83.14	**89.52**
SupCE	47.25	61.24	77.78	87.01
SupFINE	71.13	80.03	87.61	91.59
MaskCon (Ours)	**65.52** (18.17↑)	**74.46**	**83.64**	89.25

Table 2. Results on CIFAR100 dataset.

Reproduced Results



Comparison: MaskCon Paper vs Reproduced



Setup

Epochs = 200, Temperature = 0.05, Weight $w_1 = 1.0$, Train size= 50k, Test size= 10k

Novelty: Proposed Methodology

Key Idea

Can we make the model learn better by leveraging the information associated with the binary vectors corresponding to every data point?

Caltech-UCSD Birds-200-2011

```
12 012.Yellow_headed_Blackbird
13 013.Bobolink
14 014.Indigo_Bunting
15 015.Lazuli_Bunting
16 016.Painted_Bunting
17 017.Cardinal
18 018.Spotted_Catbird
19 019.Gray_Catbird
20 020.Yellow_breasted_Chat
21 021.Eastern_Towhee
22 022.Chuck_will_Widow
23 023.Brandt_Cormorant
24 024.Red_faced_Cormorant
25 025.Pelagic_Cormorant
26 026.Bronzed_Cowbird
27 027.Shiny_Cowbird
28 028.Brown_Creeper
29 029.American_Crow
30 030.Fish_Crow
31 031.Black_billed_Cuckoo
```

```
48 048.European_Goldfinch
49 049.Boat_tailed_Grackle
50 050.Eared_Grebe
51 051.Horned_Grebe
52 052.Pied_billed_Grebe
53 053.Western_Grebe
54 054.Blue_Grosbeak
55 055.Evening_Grosbeak
56 056.Pine_Grosbeak
57 057.Rose_breasted_Grosbeak
58 058.Pigeon_Guillemot
59 059.California_Gull
60 060.Glaucous_winged_Gull
61 061.Heermann_Gull
62 062.Herring_Gull
63 063.Ivory_Gull
64 064.Ring_billed_Gull
65 065.Slaty_backed_Gull
66 066.Western_Gull
67 067.Anna_Hummingbird
```

Novelty: Caltech-UCSD Birds-200-2011 (CUB dataset)

- A collection of 11,788 images spanning 200 bird species.
- Each image is annotated with detailed attributes, including part locations and bounding boxes.
- Binary attributes for more precise identification and analysis.

```
143 has_eye_color::green
144 has_eye_color::pink
145 has_eye_color::orange
146 has_eye_color::black
147 has_eye_color::white
```

```
10 has_wing_color::blue
11 has_wing_color::brown
12 has_wing_color::iridescent
13 has_wing_color::purple
```

```
11788 294 0
11788 295 0
11788 296 0
11788 297 0
11788 298 0
11788 299 1
11788 300 0
11788 301 0
11788 302 0
11788 303 0
11788 304 0
11788 305 0
11788 306 1
11788 307 0
11788 308 1
11788 309 0
11788 310 0
11788 311 0
11788 312 1
```

312-dimensional binary vector for every data point.
Total Class = 200 bird species
Total images= 11,788
Fine labels Available

Novelty: Method

Our proposed method:

- Create vector representation for each image, given binary valued attributes.
- Find a similarity metric between each image attribute vector within the same coarse label.
- Obtain a probability distribution using softmax function.
- Take convex combination of the obtained probabilities with the vector Z'_{ij}.
- Use refined probabilities in the original MaskCon loss function to obtain fine labels.

Metrics to capture similarity:

- **Cosine similarity:** Dot product between similar species should be higher.
- **Hamming distance:** The difference between dissimilar data points is higher.
- **Euclidean distance:** Similar points have less distance between them.

Novelty: Adding the newly obtained information to the MaskCon loss

Augmenting Similarity into Loss

A convex combination of similarity measures Z'_{ij} and Z'_{ij_new} is used to augment the loss function:

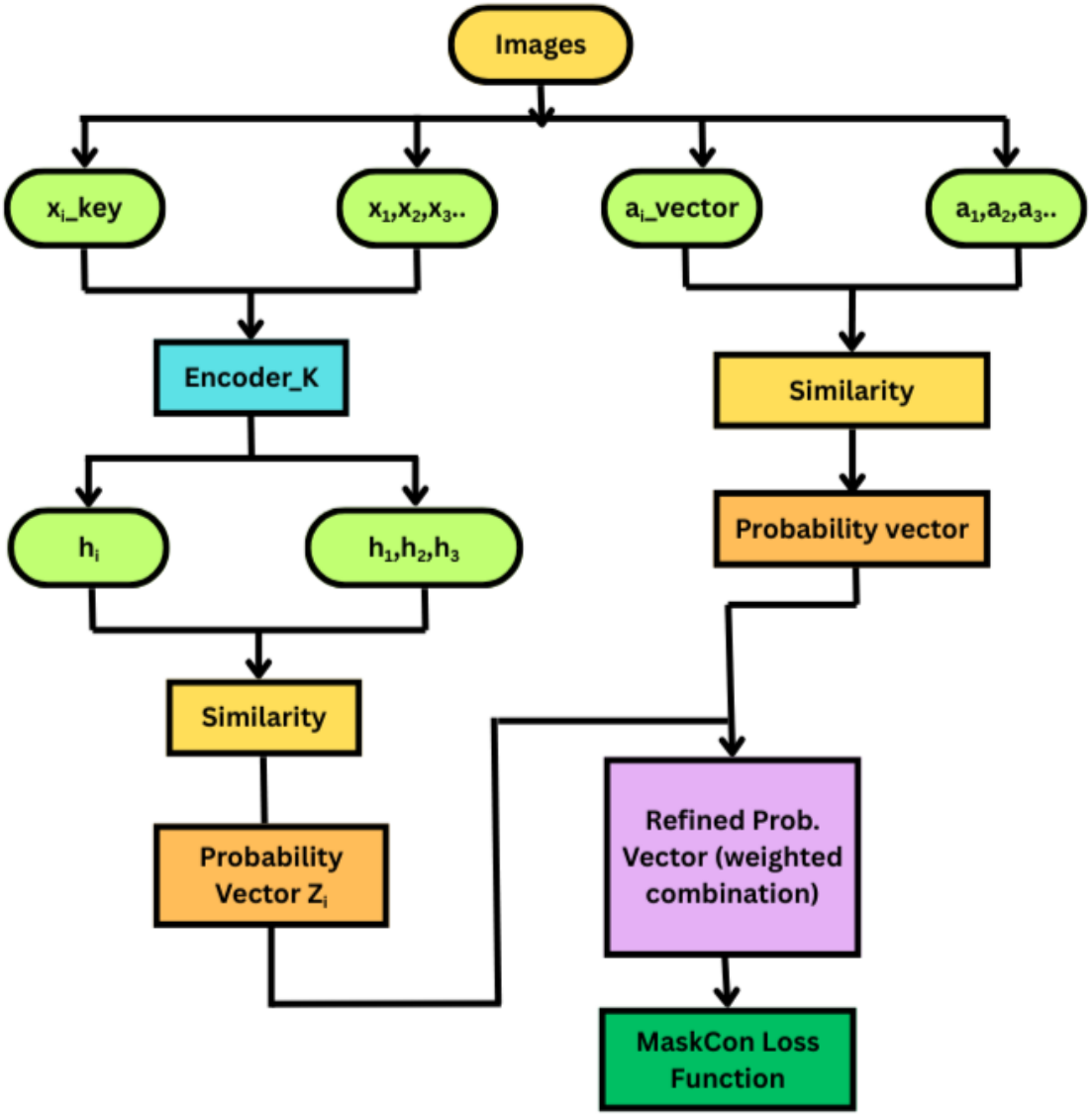
$$Z'_{ij\_final} = w \cdot Z'_{ij} + (1 - w) \cdot Z'_{ij\_new}, \quad 0 < w < 1$$

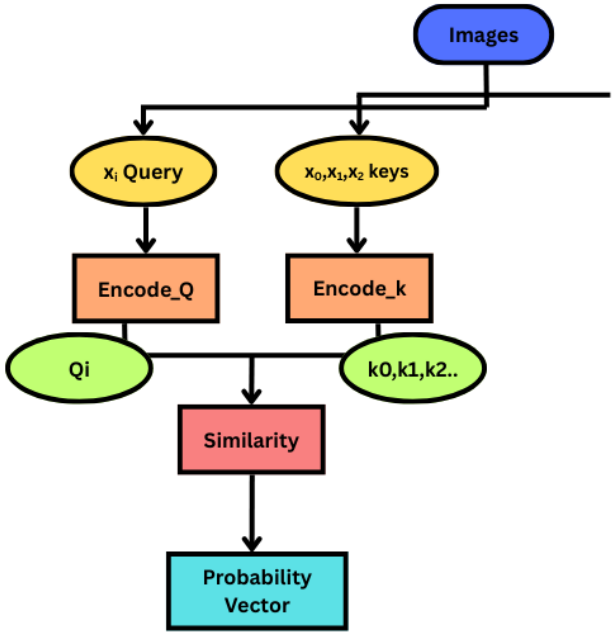
New loss: Replace Z'_{ij} with Z'_{ij_final} in the contrastive loss function.

Why adding information in the loss function is more intuitive?

To guide initial probabilities of Z_{ij} with Z_{ij}^{new}, which in turn helps the model better learn the similarities between data points that belong to the same coarse labels.

Novelty: End to End MaskCon with our Addition





Novelty: Results CUB Dataset (20 Classes)

MaskCon

$w_1 = 1.0,\ w_2 = 0.0$

Our Novelty

$w_1 = 0.5,\ w_2 = 0.5$

SupFINE

Supervised learning using the true fine labels

Common Setup

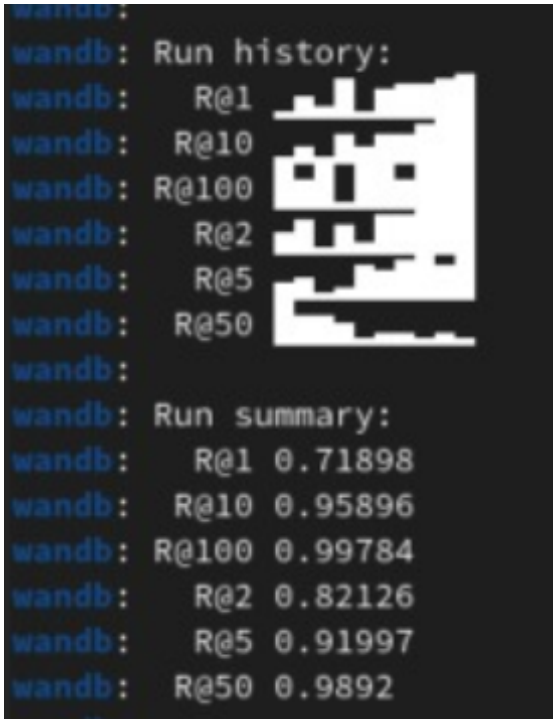
ResNet-50 , Temperature = 0.5, Epochs = 100, Weight=1.0 Train=600 , Test=515

Novelty: Results CUB Dataset (50 Classes)

MaskCon

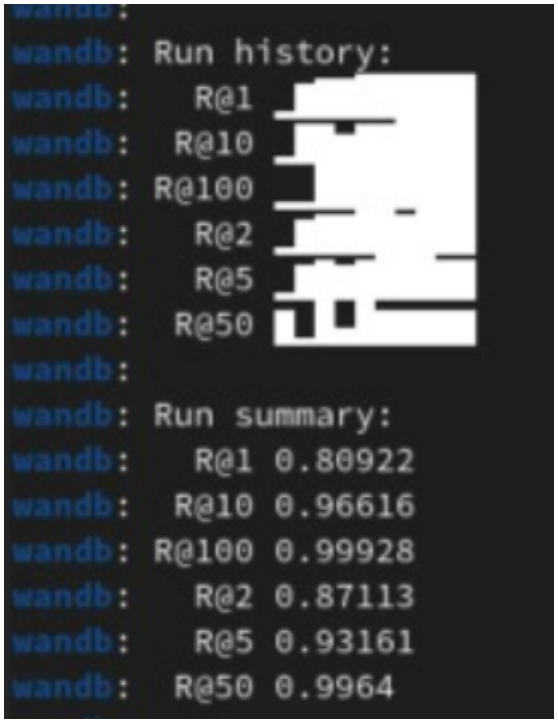
$w_1 = 1.0,\ w_2 = 0.0$

Our Novelty



$w_1 = 0.5,\ w_2 = 0.5$

SupFINE



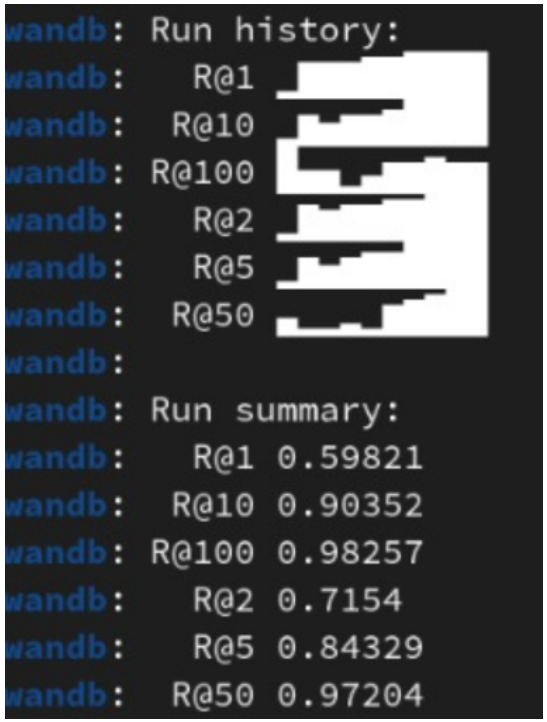
Supervised learning using the true fine labels

Common Setup

ResNet-50 , Temperature = 0.5, Epochs = 100, Weight=1.0 Train=1500 , Test=1389

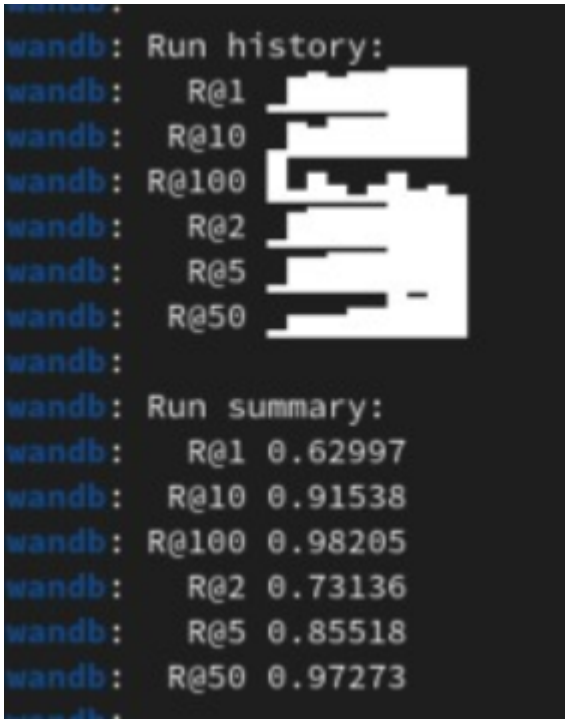
Novelty: Results CUB Dataset (200 Classes)

MaskCon



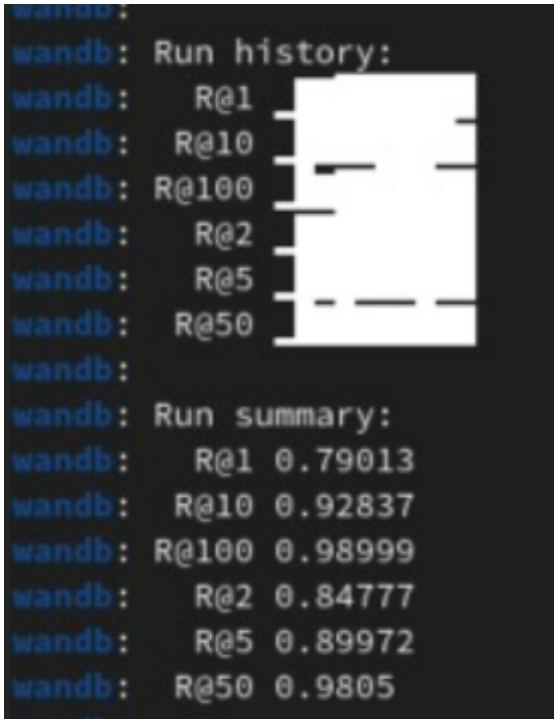
$w_1 = 1.0,\ w_2 = 0.0$

Our Novelty



$w_1 = 0.5,\ w_2 = 0.5$

SupFINE



Supervised learning using the true fine labels

Common Setup

ResNet-50 , Temperature = 0.5, Epochs = 100, Weight=1.0 Train=5994 , Test=5794

Novelty Results Across Class Settings

Classes	Method	Recall@1	Recall@2	Recall@5
20	MaskCon	0.8019	0.8835	0.9611
	Novelty	**0.8267**	**0.8935**	**0.9123**
	SupFINE	0.9068	0.9320	0.9553
50	MaskCon	0.6925	0.7926	0.9006
	Novelty	**0.7189**	**0.8212**	**0.9199**
	SupFINE	0.8092	0.8711	0.9316
200	MaskCon	0.5982	0.7154	0.8433
	Novelty	**0.6300**	**0.7314**	**0.8555**
	SupFINE	0.7901	0.8477	0.8997

Implementation Challenges

Challenges Faced During Implementation

- **Colab Limitations:**
  Training on 200-class datasets (e.g., CUB) was slow and often interrupted due to limited GPU runtime and memory.
- **Missing Coarse Labels:**
  Datasets like CUB and Cars196 lacked coarse labels. Manual grouping based on domain knowledge was required.
- **Long Training Time:**
  MaskCon's contrastive learning setup significantly increased training time for fine-grained classes.
- **Hyperparameter Sensitivity:**
  Model performance was sensitive to the choice of w and temperature τ, requiring repeated tuning.

Future Work

Planned Extensions and Improvements

- **Generalization to Other Datasets:**
  Extend MaskCon to other coarse-labeled or weakly supervised datasets like ImageNet-Coarse.
- **Automated Coarse Labeling:**
  Use clustering or external metadata to generate coarse labels automatically.
- **Improved Similarity Functions:**
  Explore learned or adaptive metrics beyond cosine, Hamming, and Euclidean.
- **Scalability Enhancements:**
  Support larger models and distributed training for higher-resolution, high-class datasets.

References

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Thank You

THANK YOU!