Visual Recognition Meets Long-tail Data Distribution

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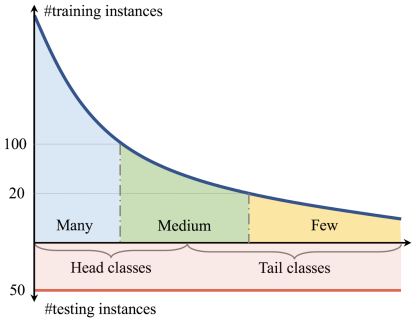
Outline

Outline

Problem Definition

Long-tail Classification

- Goal: Learn a mapping from input to label space. $y = \mathcal{M}(\mathbf{I}; \Theta)$
- Label space: $\mathcal{C} = \{c_1, \cdots, c_K\}$
- Model: feature extractor $f(\cdot)$ and classifier head $h(\cdot)$
  - Dot-product: $z_j = \mathbf{w}_j^\top \mathbf{x}$
  - Cosine Similarity: $z_j = s \cdot \frac{\mathbf{w}_j^\top \mathbf{x}}{||\mathbf{w}_j^\top|| ||\mathbf{x}||}$
- Train Data: Imbalanced $\mathcal{D}_{tr} = \{(\mathbf{x}_i, y_i)\}_{i=1}^N, \mathbf{x} = f(\mathbf{I}, \theta_f), \mathbf{z} = h(\mathbf{x}, \theta_h)$
- Evaluation: Balanced metric.



Long-tail data distribution

Outline

Tasks and Benchmarks

- Image Classification
  - Benchmarks: CIFAR-10/100, ImageNet-LT[1], iNaturalist[2], Places-LT[3]
  - Evaluation: F1-score, Mean Accuracy
- Object Detection/Instance Segmentation
  - Benchmarks: Visual Genome, LVIS v0.5/v1.0[4]
  - Evaluation: mAP
- Visual Relation Detection
  - Benchmarks: Visual Genome, Open Image V4/V6
  - Evaluation: Mean Recall

[1] Ziwei Liu et al. "Large-Scale Long-Tailed Recognition in an Open World". In: *CVPR*. 2019.

[2] Grant Van Horn et al. "The inaturalist species classification and detection dataset". In: *CVPR*. 2018.

[3] Ziwei Liu et al. "Large-Scale Long-Tailed Recognition in an Open World". In: *CVPR*. 2019.

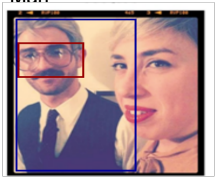
[4] Agrim Gupta, Piotr Dollar, and Ross Girshick. "LVIS: A Dataset for Large Vocabulary Instance Segmentation". In: *CVPR*. 2019.

Visual Relation Detection

Visual Relationship

- The interacting relationship between the entities(instances) that can be recognized by the visual clues.
- Triplets: (Subject entity,**Predicate**, Object entity)
- A structured, high-level visual information

Who were Glasses?
Man



(Man, Wear, Glasses)

Scene Graph

- A graph composed by the multiple visual relationships
- **Nodes: Entities(subject/object)**
- **Edges: Predicates**

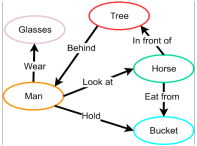


Illustration of SGG

Outline

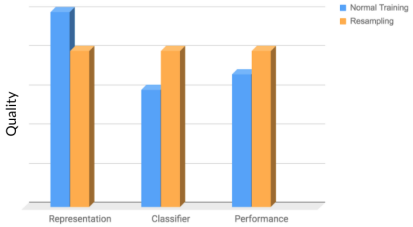
One-stage Learning Framework

Classification Performance = Representation Quality + Classifier Head Quality

One-stage Learning

Joint learn feature extractor $f(\cdot)$ and classifier head $h(\cdot)$

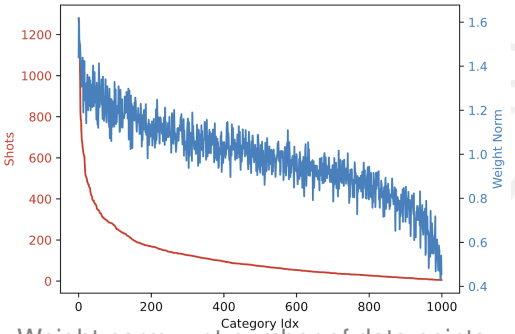
- With re-balance strategies/knowledge transfer ideas
- End-to-end training and the model is jointly optimized.



Classification Performance

Two-stage Framework

- Step-1: Joint learn feature extractor and classifier
- Step-2: Fix feature extractor and update classifier with class distribution prior
  - Non-parametric Logit Adjustment
  - Parametric Learned Classifier



Weight norm w.r.t number of data points.

Bound analysis

Non-parametric Logit Adjustment

- NCM(Nearest Centroid Mean)[a]
  - $\hat{z}_j = \lambda \cdot \frac{\mathbf{e}_j \cdot \mathbf{x}}{|\mathbf{e}_j||\mathbf{x}|}$
  - $\mathbf{e}_j$ is the mean feature of j-th categories in training set.
- τ-normalized[b]
  - $\hat{z}_j = \frac{\mathbf{w}_j^\top \mathbf{x}}{||\mathbf{w}_j||^\tau}$
- Logit Adjustment[c]
  - $\hat{z}_j = z_j - \lambda \log(\rho_j)$
  - ρ_j is the frequency of j-th categories.
- Deconfound[d](cls&det)
  - Cosine similarity classifier head. $\hat{z}_j = z_j - \lambda d(\mathbf{x}, \mathbf{e}) \mathbf{w}_j^\top \mathbf{e}$
  - $\mathbf{e}$ is mean feature of training data.

[a] Bingyi Kang et al. "Decoupling representation and classifier for long-tailed recognition". In: *ICLR* (2020).

[b] Bingyi Kang et al. "Decoupling representation and classifier for long-tailed recognition". In: *ICLR* (2020).

[c] Aditya Krishna Menon et al. "Long-tail learning via logit adjustment". In: *arXiv preprint* (2020).

[d] Kaihua Tang, Jianqiang Huang, and Hanwang Zhang. "Long-tailed classification by keeping the good and removing the bad momentum

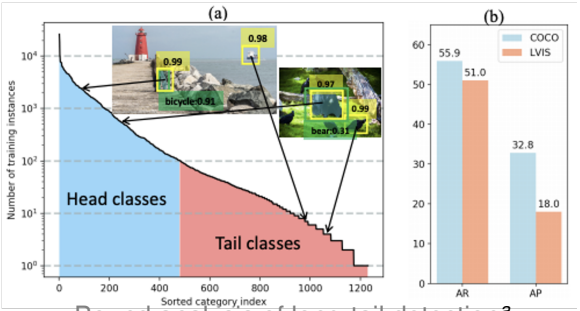
Parametric Learned Classifier(Proposed in Image Classification)

Parametric[a]

[a] Bingyi Kang et al. "Decoupling representation and classifier for long-tailed recognition". In: *ICLR* (2020).

- τ-normalized
  - $\hat{z}_j = \frac{\mathbf{w}_j^\top \mathbf{x}}{||\mathbf{w}_j||^\tau}$
- cRT(Classifier re-training)
  - $\hat{z}_j = \hat{\mathbf{w}}_j^\top \mathbf{x}$
  - ignore original classifier head.
- LWS
  - $\hat{z}_j = \alpha_j \cdot z_j$
  - α_j is class-wise learnable scale.

Parametric Learned Classifier(SimCal[5])



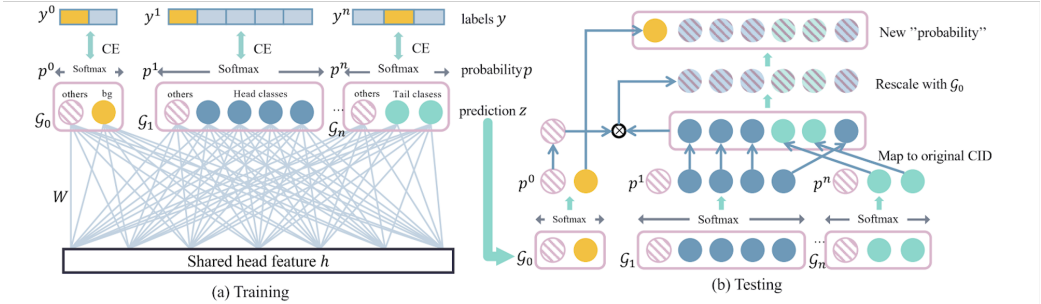
Bound analysis of long-tail detection[a]

- Like cRT[b]
- Introduce a bi-level balanced-sampling to create a batch:
  - First sample *n* categories uniformly.
  - Then sample images for each category
  - Only keep the proposals of sampled categories.

[a] Tao Wang et al. "The Devil is in Classification: A Simple Framework for Long-tail Instance Segmentation". In: *ECCV*. 2020.

[b] Bingyi Kang et al. "Decoupling representation and classifier for long-tailed recognition". In: *ICLR* (2020).

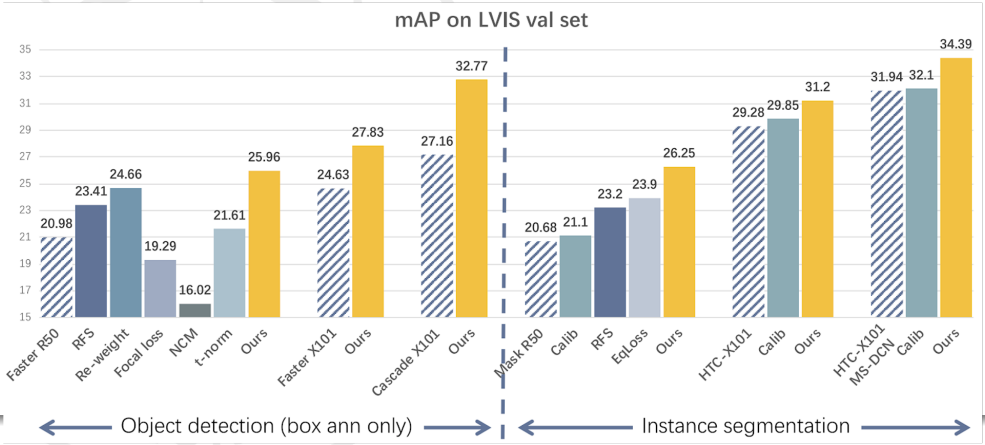
Parametric Learned Classifier(BalancedGroupSoftmax[6])



- Rely on the heuristic group split
- Too many hyper-parameters

[6] Yu Li et al. "Overcoming Classifier Imbalance for Long-Tail Object Detection With Balanced Group Softmax". In: *CVPR* 2020.

Parametric Learned Classifier(BalancedGroupSoftmax[7])



[7] Yu Li et al. "Overcoming Classifier Imbalance for Long-Tail Object Detection With Balanced Group Softmax". In: *CVPR* 2020.

Outline

Data: Re-sampling strategy[8]

$$p_j = \frac{n_j^q}{\sum_{i=1}^{C} n_i^q}, \quad q \in [0, 1]$$

- Instance-balanced re-sampling($q = 1$)
- Class-balanced re-sampling($q = 0$)
- Square-root re-sampling($q = 1/2$)
- Progressively-balanced re-sampling

$$p_j^{\mathrm{PB}}(t) = \left(1 - \frac{t}{T}\right) p_j^{\mathrm{IB}} + \frac{t}{T} p_j^{\mathrm{CB}}$$

  - t is the current epoch
  - T is the total epcoh
  - CB and IB are hyper-parameters.

[8] Bingyi Kang et al. "Decoupling representation and classifier for long-tailed recognition". In: *ICLR* (2020).

Loss: Re-weight

- Focal Loss[9]:

$$\mathcal{L}_{\text{focal}} := (1-\tilde{p})^{\gamma}\,\mathcal{L}_{CE} = -(1-\tilde{p})^{\gamma}\log(\tilde{p})$$

- Effective Number Re-weight[10]:

$$\mathcal{L}^{\text{CB}}_{\text{softmax}}(\mathbf{z}, y) = -\frac{1-\beta}{1-\beta^{n_y}}\log\left(\frac{\exp(z_y)}{\sum_{j=1}^{C}\exp(z_j)}\right)$$

- LDAM(Label-distribution-aware margin)[11]

$$\mathcal{L}_{\text{LDAM}} := -\log\frac{e^{z_j-\Delta_j}}{e^{z_j-\Delta_j}+\sum_{c}\neq j e^{z_c-\Delta_c}}$$

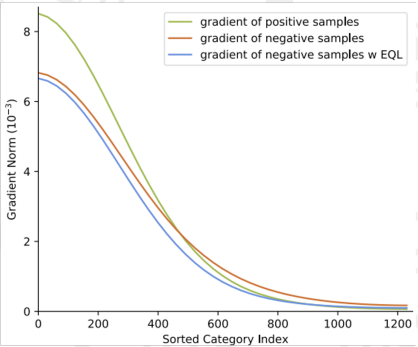
  - Δ_j is a class-aware margin, inversely proportional to number of j-th categories data.

[9] Tsung-Yi Lin et al. "Focal loss for dense object detection". In: *ICCV*. 2017.

[10] Yin Cui et al. "Class-balanced loss based on effective number of samples". In: *CVPR*. 2019.

[11] Kaidi Cao et al. "Learning Imbalanced Datasets with Label-Distribution-Aware Margin Loss". In: *NeurIPS*. 2019.

Loss: Re-weight



Gradient norm w.r.t data distribution

Equalization Loss[a]

[a] Jingru Tan et al. "Equalization Loss for Long-Tailed Object Recognition". In: *CVPR*. 2020.

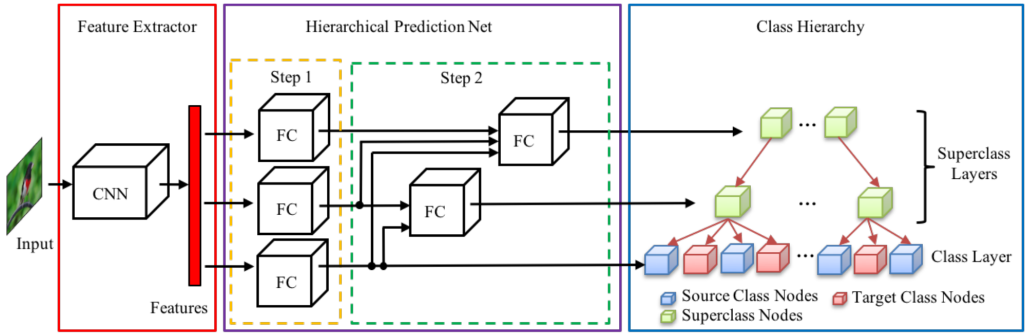
$$\mathcal{L}_{SEQL} = -\sum_{j=1}^{C} y_j \log\left(\tilde{p}_j\right) \tag{1}$$

$$\tilde{p}_j = \frac{e^{z_j}}{\sum_{k=1}^{C} \tilde{w}_k e^{z_k}} \tag{2}$$

$$\tilde{w}_k = 1 - \beta T_\lambda\left(f_k\right)\left(1 - y_k\right) \tag{3}$$

- β is a random variable with a probability of γ to be 1 and $1-\gamma$ to be 0

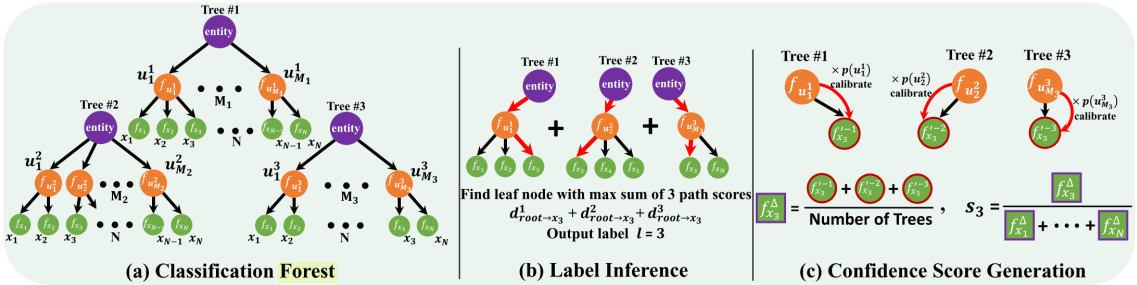
Category Hierarchy(Knowledge Transfer With Class Hierarchy)[12]



Overview of the framework

[12] Aoxue Li et al. "Large-Scale Few-Shot Learning: Knowledge Transfer With Class Hierarchy". In: *CVPR*. 2019.

Category Hierarchy(Forest R-CNN)[13]



Overview of the framework

[13] Jialian Wu et al. "Forest R-CNN: Large-vocabulary long-tailed object detection and instance segmentation". In: *ACM MM*. 2020.

Category Hierarchy(Taxonomic Classifier)[14]

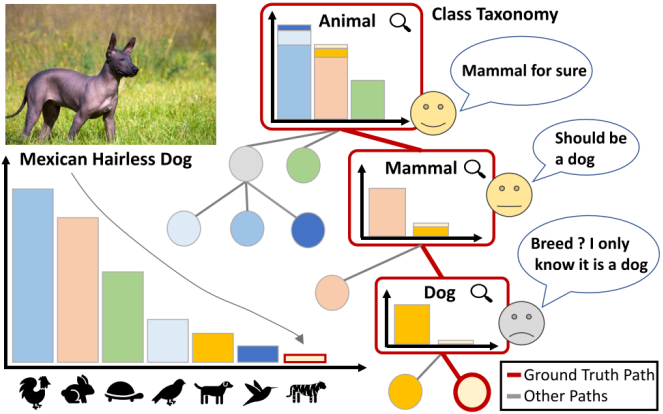
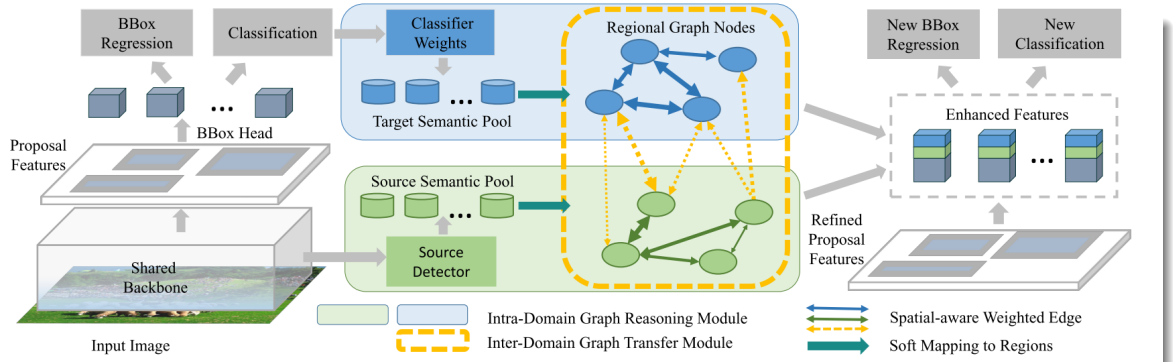


Illustration of the idea

[14] Tz-Ying Wu and Pedro Morgado. "Solving Long-tailed Recognition with Deep Realistic Taxonomic Classifier". In: *ECCV*. 2020.

Knowledge Transfer(Universal R-CNN)[15]



Overview of the framework

[15] Hang Xu et al. "Universal-RCNN: Universal Object Detector via Transferable Graph R-CNN.". In: *AAAI*. 2020.

Outline

Distribution Alignment: A Unified Framework for Long-tail Visual Recognition

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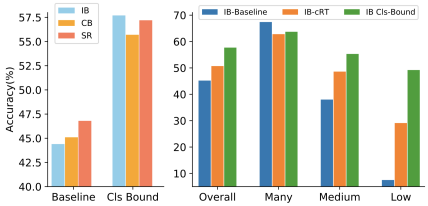
Empirical Study



Empirical Bound Experiment

- Training feature extractor with various strategies on ImageNet-LT dataset.
- Re-training the classifier only on ImageNet dataset.
- IB: instance-balanced; CB: class-balanced; SR: square-root

Conclusion

- Feature extractor learned with instance-balanced sampling can provide **sufficient** quality.
- **Bottleneck** is the classifier head.
- Previous works remain **sub-optimal**

Empirical Study

- The first stage produces a **strong feature representation** that can potentially lead to large performance gain and the **instance-based** sampling achieves better overall results
- The **biased decision boundary** in the feature space seems to be the **performance bottleneck** of the existing long-tail methods.

Outline

Our Method

Two-stage Learning Framework

1. Joint Learning Stage.
   Learn the feature extractor $f(\cdot)$ and original classifier head $h_o(\cdot)$ with **instance-balanced** strategy jointly on imbalanced $\mathcal{D}_{tr}$
2. Distribution Calibration Stage
   Freeze $f(\cdot)$ and **adjust the decision boundary** of the classifier head.
   - Adaptive Calibration Function.
   - Distribution Alignment with Generalized Re-weighting.

Our Method

Adaptive Calibration Function

- Original prediction: $\mathbf{z}^o = [z_1^o, \cdots, z_K^o]$ from $h_o(\cdot)$
- Reduce adverse impact from the limited data for tail.
- $s_j = \alpha_j \cdot z_j^o + \beta_j, \quad \forall j \in \mathcal{C}, \quad \alpha_j$ and β_j are the calibration parameters for each class, which will be learned from data
- Introduce a confidence score function $\sigma(\mathbf{x})$ to adaptively adjust the score.

$$\hat{z}_j = \sigma(\mathbf{x}) \cdot s_j + (1 - \sigma(\mathbf{x})) \cdot z_j^o \tag{4}$$

$$= (1 + \sigma(\mathbf{x})\alpha_j) \cdot z_j^o + \sigma(\mathbf{x}) \cdot \beta_j \tag{5}$$

- Prediction distribution after calibration.

$$p_m(y = j|\mathbf{x}) = \frac{\exp(\hat{z}_j)}{\sum_{k=1}^{C} \exp(\hat{z}_k)}. \tag{6}$$

Our Method

Alignment with Generalized Re-weighting

- Align the model prediction $p_m(\cdot)$ with a reference distribution $p_r(\cdot)$, by minimizing the expected KL-divergence

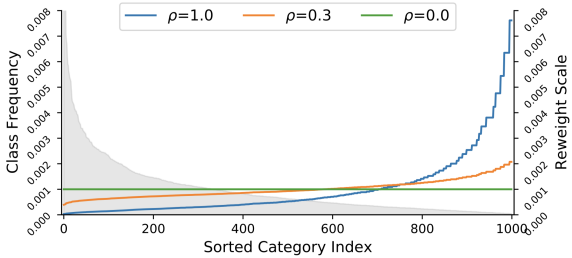
$$\mathcal{L} = \mathbb{E}_{\mathcal{D}_{tr}} \left[\mathcal{KL}(p_r(y|\mathbf{x}) || p_m(y|\mathbf{x})) \right] \tag{7}$$

$$\approx -\frac{1}{N} \sum_{i=1}^{N} \left[\sum_{y \in \mathcal{C}} p_r(y|\mathbf{x}_i) \log(p_m(y|\mathbf{x}_i)) \right] + C \tag{8}$$

- Reference distribution: $p_r(y = c|\mathbf{x}_i) = w_c \cdot \delta_c(y_i), \quad \forall c \in \mathcal{C}$, w_c is the class weight.
- Define empirical class frequencies $\mathbf{r} = [r_1, \cdots, r_K]$ on the training set.

$$w_c = \frac{(1/r_c)^\rho}{\sum_{k=1}^{K} (1/r_k)^\rho}, \quad \forall c \in \mathcal{C} \tag{9}$$

Connection with Previous Work



Method	Align Method			
	Type	Balance	Magnitude	Margin
Joint	-	-	-	-
LWS[6]	L	CB-RS	α_j	0
τ-Normalized[6]	H	CB-RS	$1/\|\|\mathbf{w}_j\|\|^\tau$	0
Logit Adjust[11]	H	-	1.0	$-\lambda \log(r_j)$
Deconfound*[14]	H	-	1.0	$-\lambda d(\mathbf{x}, \mathbf{e})\mathbf{w}_j^\top \mathbf{e}$
DisAlign	L	G-RW	$1 + \sigma(\mathbf{x})\alpha_j$	$\sigma(\mathbf{x})\beta_j$
DisAlign*	L	G-RW	$1 + \sigma(\mathbf{x})\alpha_j$	$\sigma(\mathbf{x})\beta_j$

Outline

Experiment on Classification

Method	Align Type	Top-1 Accuracy@R-50				Top-1 Accuracy@X-50			
		Average	Many	Medium	Few	Average	Many	Medium	Few
Baseline[6]	-	41.6	64.0	33.8	5.8	44.4	65.9	37.5	7.7
Baseline*	-	48.4	68.4	41.7	15.2	49.2	68.9	42.8	15.6
NCM[6]	Hand-Craft	44.3	53.1	42.3	26.5	47.3	56.6	45.3	28.1
τ-Norm[6]		46.7	56.6	44.2	27.4	49.4	59.1	46.9	30.7
Logit Adjust(post)[11]		50.4	-	-	-	-	-	-	-
Deconfound*[14]		-	-	-	-	51.8	62.7	48.8	31.6
cRT[6]	Learnable	47.3	58.8	44.0	26.1	49.6	61.8	46.2	27.4
cRT*[6]		-	-	-	-	49.7	60.4	46.8	29.3
LWS[6]		47.7	57.1	45.2	29.3	49.9	60.2	47.2	30.3
DisAlign		51.3	59.9	49.9	31.8	52.6	61.5	50.7	33.1
DisAlign*		**52.9**	61.3	52.2	31.4	**53.4**	62.7	52.1	31.4

Quantitative results on ImageNet-LT. $*$ denotes the model uses cosine classifier. **R-50** and **X-50** means the ResNet-50 and ResNeXt-50, respectively.

Experiment on Semantic Segmentation

Framework	Method	B	Mean IoU(%)				Mean Accuracy(%)			
			Average	Head	Body	Tail	Average	Head	Body	Tail
FCN[12]	Baseline	R-50	38.1	64.6	40.0	29.6	46.3	78.6	49.3	35.4
	DisAlign		40.1(+2.0)	65.0(+0.4)	42.8(+2.8)	31.3(+1.7)	51.4(+5.1)	78.6(+0.0)	56.1(+6.8)	40.6(+5.2)
	Baseline	R-101	41.4	67.0	43.3	33.2	50.2	80.6	52.9	40.1
	DisAlign		43.7(+2.3)	67.4(+0.4)	46.1(+2.8)	35.7(+2.5)	55.9(+5.7)	80.6(+0.0)	59.7(+6.8)	46.4(+6.3)
	Baseline	S-101	46.2	67.6	48.0	39.1	57.3	79.4	61.7	48.2
	DisAlign		46.9(+0.7)	67.7(+0.1)	48.2(+0.2)	40.3(+1.2)	60.1(+2.8)	79.7(+0.3)	64.2(+2.5)	51.9(+3.7)
DeepLabV3$^+$[2]	Baseline	R-50	44.9	67.7	48.3	36.4	55.0	80.1	60.8	44.1
	DisAlign		45.7(+0.8)	67.7(+0.0)	48.6(+0.3)	37.8(+1.4)	57.3(+2.3)	80.8(+0.7)	63.0(+2.2)	46.9(+2.8)
	Baseline	R-101	46.4	68.7	49.0	38.4	56.7	80.9	61.5	46.7
	DisAlign		47.1(+0.7)	68.7(+0.0)	49.4(+0.4)	39.6(+1.2)	59.5(+2.8)	81.4(+0.5)	64.2(+2.7)	50.3(+3.6)
	Baseline	S-101	47.3	69.0	49.7	39.7	58.1	80.8	63.4	48.2
	DisAlign		47.8(+0.5)	68.9(-0.1)	49.8(+0.1)	40.7(+1.0)	60.1(+2.0)	81.0(+0.2)	65.5(+2.1)	52.0(+3.8)

Performance of semantic segmentation on ADE-20K: All baseline models are trained with an image size of 512×512 and 160K iteration in total. **B** is backbone network(R-50, R-101, S-101 denote ResNet-50, ResNet-101 and ResNeSt-101, respectively).

Experiment on Detection/Instance Segmentation

Pre-Train	Method	BBox AP				Mask AP			
		AP_{bbox}	AP^r_{bbox}	AP^c_{bbox}	AP^f_{bbox}	AP_{mask}	AP^r_{mask}	AP^c_{mask}	AP^f_{mask}
ImageNet	Baseline	20.8	3.3	19.5	29.4	21.2	3.7	21.6	28.4
	Baseline*	22.8	10.2	21.1	30.1	23.8	11.5	23.7	28.9
	Focal Loss[9]	21.9	-	-	-	21.0	9.3	21.0	25.8
	SimCal[16]	22.6	13.7	20.6	28.7	23.4	16.4	22.5	27.2
	LST[5]	22.6	-	-	-	23.0	-	-	-
	RFS[4]	23.6	12.8	22.3	29.4	24.3	14.6	24.0	28.5
	EQL[13]	23.3	-	-	-	22.8	11.3	24.7	25.1
	DisAlign	23.9	7.5	25.0	29.1	24.3	8.5	26.3	28.1
	DisAlign*	**25.6**	13.7	25.6	30.5	**26.3**	14.9	27.6	29.2
COCO	Baseline	22.8	2.6	21.8	32.0	23.9	2.8	23.4	30.5
	Baseline*	25.0	10.2	23.9	32.3	25.3	11.0	25.5	30.7
	GroupSoftmax[8]	25.8	15.0	25.5	30.4	26.3	18.0	26.9	28.7
	DisAlign	25.5	8.2	26.3	32.4	25.7	9.4	27.6	29.7
	DisAlign*	**27.6**	14.8	27.9	32.4	**27.9**	16.2	29.3	30.8

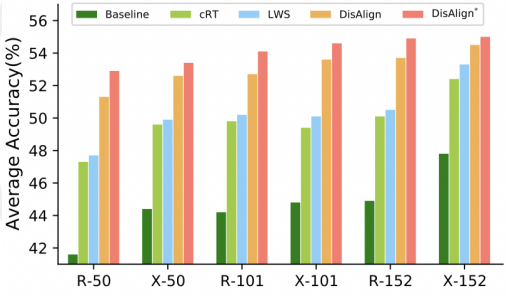
Comparison with the-state-of-art on LVIS with Mask-R-CNN-FPN(ResNet-50 backbone). All results are evaluated on the LVIS v0.5 validation set with the score threshold at 0.0001. ($*$ denotes cosine classifier for bbox classification.)

Ablation Study

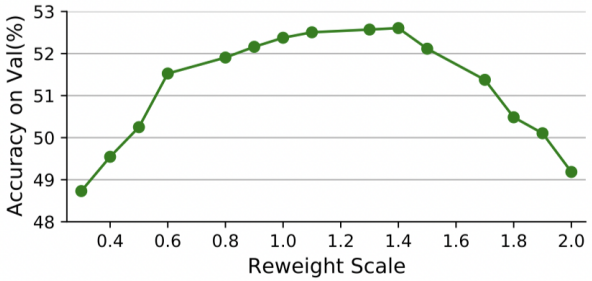
Backbone	Method	BBox AP				Mask AP			
		AP_{bbox}	AP^r_{bbox}	AP^c_{bbox}	AP^f_{bbox}	AP_{mask}	AP^r_{mask}	AP^c_{mask}	AP^f_{mask}
ResNet-50	Baseline*	26.5	8.7	25.0	36.0	23.5	8.1	22.4	31.5
	DisAlign*	30.5	17.9	30.1	36.5	27.0	15.7	27.0	31.9
ResNet-101	De-confound[14]	25.8	-	-	-	23.5	5.2	22.7	32.3
	De-confound TDE[14]	30.0	-	-	-	27.1	16.0	26.9	32.1
	Baseline*	28.9	11.8	27.7	37.8	25.6	10.5	24.9	33.0
	DisAlign*	32.7	20.5	32.8	38.1	28.9	18.0	29.3	33.3
ResNeXt-101	Baseline*	30.7	14.2	29.3	39.6	27.3	13.0	26.4	34.6
	DisAlign*	33.7	21.4	33.1	39.7	29.7	18.4	29.7	34.7

Results on LVIS v1.0 dataset with Cascade R-CNN. * denotes cosine classifier head.

Ablation Study



Different Backbone



Influence of the G-RW scale

Ablation Study

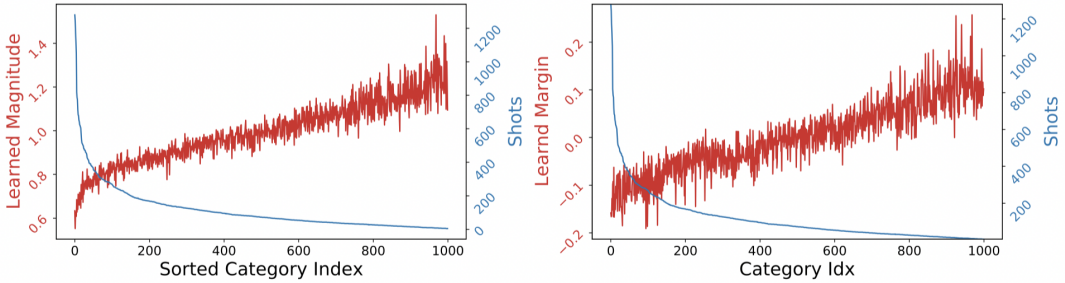


Figure 6: **Analysis of the Calibration.** We use model trained on ImageNet-LT with ResNeXt-50 for analysis.

Ablation Study

GR	MT	MG	Average	Many	Medium	Few
✗	✗	✗	41.6	64.0	33.8	5.8
✓	✓	✗	50.1	60.4	48.0	28.8
✓	✗	✓	49.9	63.9	46.9	21.2
✓	✓	✓	51.3	59.9	49.9	31.8

Ablation study of DisAlign. GR means the generalized reweight strategy. **MT** means the learnable magnitude parameter $(1+\sigma(\mathbf{x})\alpha)$ and **MG** is the learnable margin parameter $\sigma(\mathbf{x})\beta$.

Method	Calibration	G-RW	Top-1 Acc
Baseline*	-	-	49.2
cRT*	✗	✗	49.7
-	✗	✓	51.9
DisAlign*	✓	✓	53.4

Influence of Model Components. Backbone is ResNeXt-50, $*$ means cosine classifier.

Bipartite Graph Network with Adaptive Message Passing for Unbiased Scene Graph Generation

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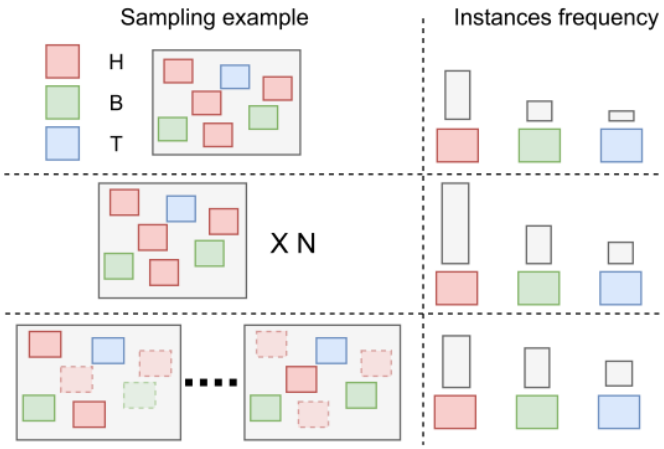
ShanghaiTech University
University of Chinese Academy of Sciences
KU Leuven

In Conference on Computer Vision and Pattern Recognition(CVPR) 2021

Bi-level Data-sampling



Bi-level Sampling

Future Direction

Future Direction

- Theoretical analysis of the optimization dynamics(feature extractor and classifier)
- Contrastive learning to alleviate the data imbalance
- Strong augmentation along with transformer structure
- Semi-supervised learning

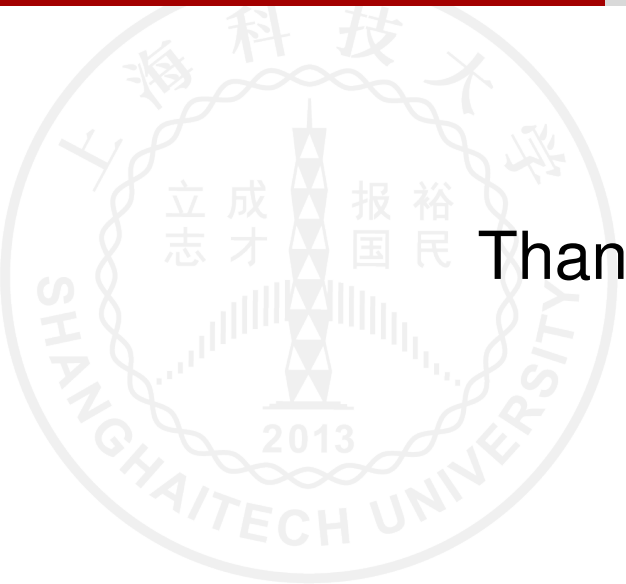
Take Home Message

Learning Framework

- **Two-stage** is more powerful.
- How to introduce **reference category distribution** is important.
- Distribution Alignment/Logit Adjustment/BalancedGroupSoftmax are effective.

Imbalance Strategy

- Sampling is more effective than re-weight in image classification
- Re-weight is more convenient than sampling in detection/instance segmentation
- Sampling and re-weight can be adopted jointly but suffer from overfitting.
- Knowledge transfer ideas are weak when using more powerful framework(Cascade R-CNN) or stronger backbones(X-101,S-101)
- **Strong augmentation** is significantly helpful in engineering.



Thanks!