TUE-PM-320

Two-way Multi-Label Loss

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JUNE 18-22, 2023

CVPR

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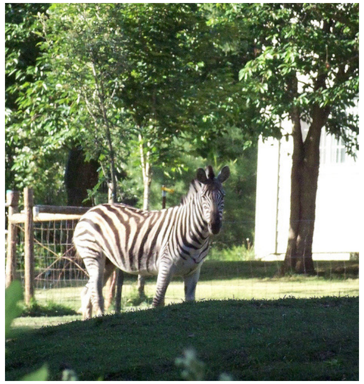
Image Classification

- Real images frequently contain multiple targets.
- It poses **multi-label classification**, in comparison to a standard single-label one, e.g., ImageNet.

☑ zebra
☑ giraffe
☑ car
☑ truck



☑ zebra

Task: **Multi-label classification** Single-label classification

Gap between Softmax and Multi-Label

- Although softmax loss works quite well in single-label scenario, it is rarely applied to multi-label learning.
  - There is a gap between the softmax loss and multi-label classification.

☑ zebra
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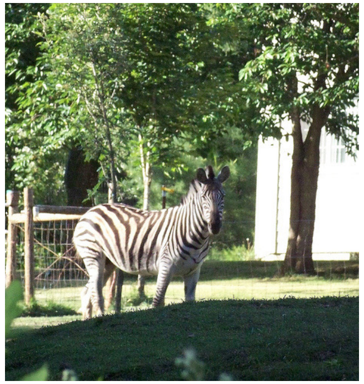

☑ zebra

	Multi-label classification		Single-label classification
Task:	**Multi-label classification**	← ?	Single-label classification
Loss:	BCE loss bunch of single-class classification		Softmax loss good at dealing with multiple classes

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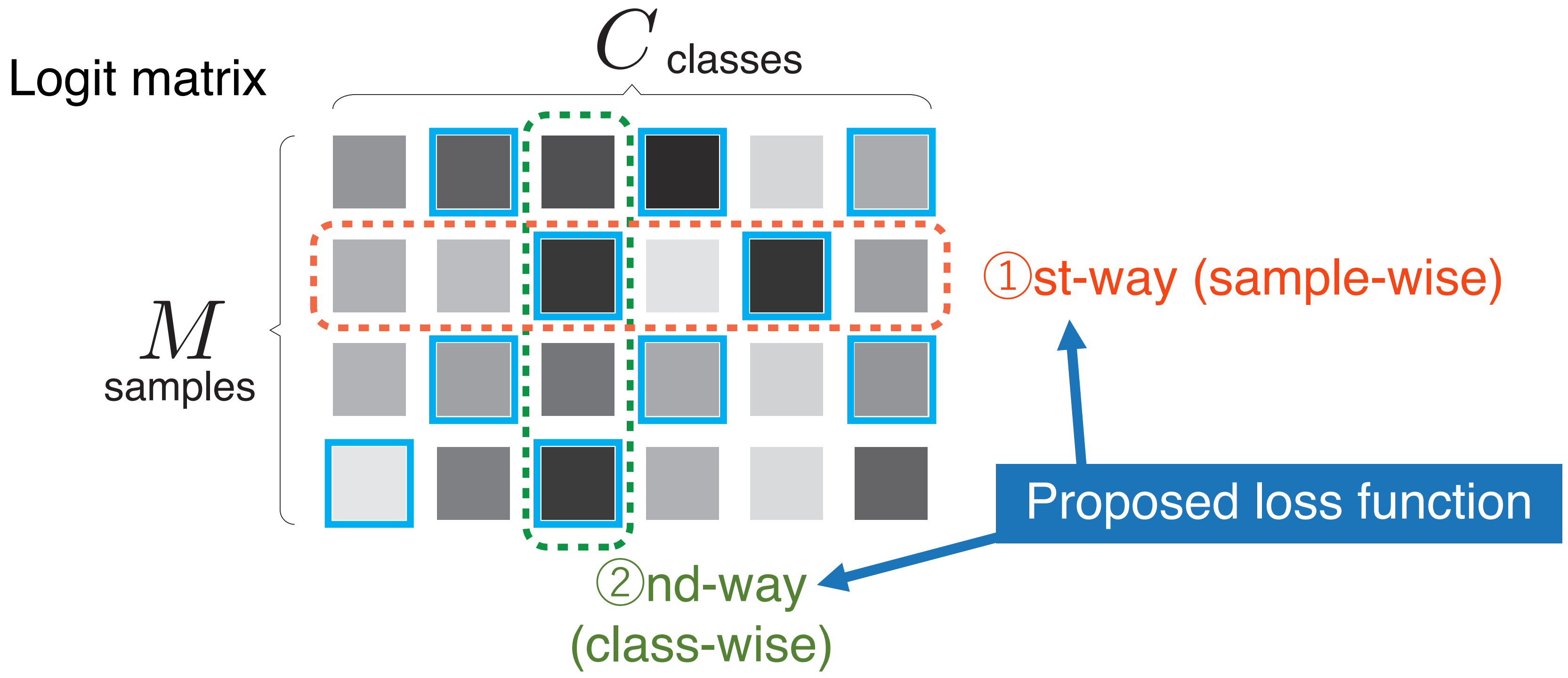
Contributions

- We propose a softmax-based multi-label loss function and a novel two-way approach to apply it for learning models.

- The method inherits favorable properties of softmax loss and enhance discriminative power of feature representation from two aspects.



Revisit: Softmax Loss

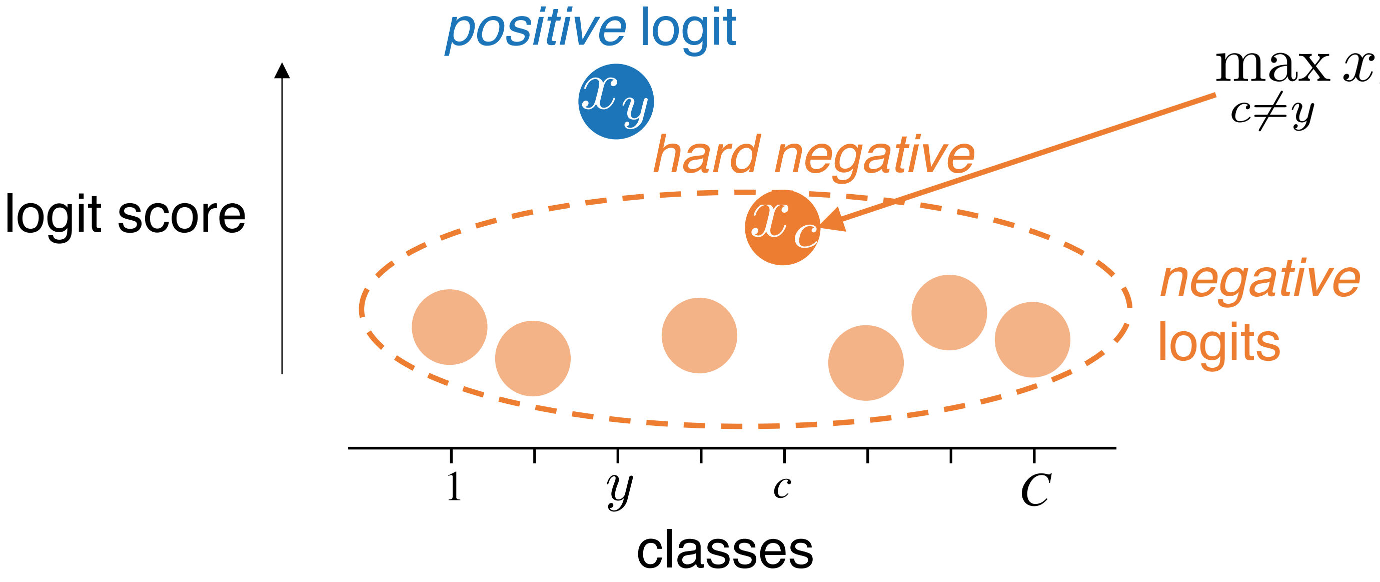
- Measure discrepancy between single ground-truth logit and others.

$$\ell_{\mathrm{sm}} = -\boldsymbol{p}_y \log \boldsymbol{q}(\boldsymbol{x}) = -\log \frac{e^{x_y}}{\sum_c e^{x_c}} = \mathsf{softplus}\left[\underline{\log\left\{\sum_{c\neq y} e^{x_c}\right\}} - x_y\right]$$

The other logits are well aggregated by **log-sum-exp**.

$$\max_{c\neq y} x_c \approx \log \sum_{c\neq y} e^{x_c}$$

- Find hard negatives.



Softmax Loss in Multi-Label Setting

- A straight-forward extension to multiple labels.
  - Average of single softmax losses over given labels.

$$\ell_{\mathrm{sm}} = -\boldsymbol{p} \log \boldsymbol{q}(\boldsymbol{x}) = \frac{1}{m} \sum_{p=1}^{m} -\log \frac{e^{x_{y_p}}}{\sum_c e^{x_c}}$$

- Positive logits *unfavorably* conflict with each other.

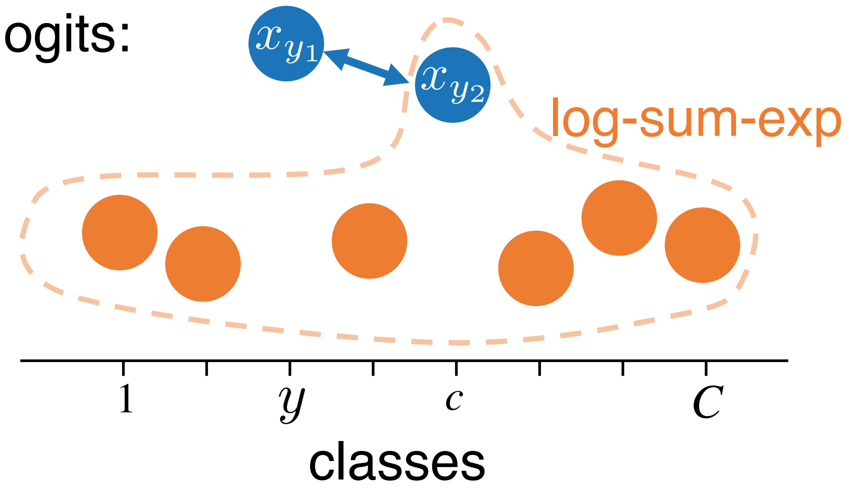
softmax:

positive for y_1

$$-\log \frac{\boxed{e^{x_{y_1}}}}{e^{x_{y_1}} + \boxed{e^{x_{y_2}}} + \sum_{c \notin \{y_1, y_2\}} \boxed{e^{x_c}}}$$

positive for y_2

logits:



Multi-label Loss Function

- We derive a novel multi-label loss in a softmax formulation.

$$\ell = \mathsf{softplus}\left[T_{\mathcal{N}} \log \sum_{n\in\mathcal{N}} e^{\frac{x_n}{T_{\mathcal{N}}}} + T_{\mathcal{P}} \log \sum_{p\in\mathcal{P}} e^{-\frac{x_p}{T_{\mathcal{P}}}}\right]$$

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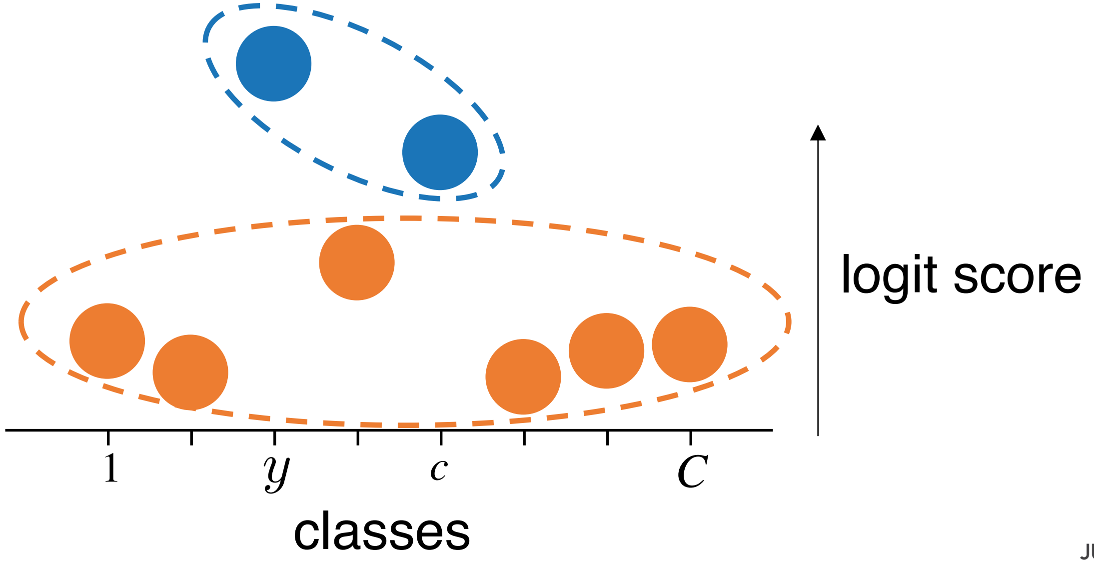
$$\ell = \text{softplus}\left[\underbrace{\boxed{T_{\mathcal{N}} \log \sum_{n \in \mathcal{N}} e^{\frac{x_n}{T_{\mathcal{N}}}}}}_{\text{Negative logits}} + \underbrace{\boxed{T_{\mathcal{P}} \log \sum_{p \in \mathcal{P}} e^{-\frac{x_p}{T_{\mathcal{P}}}}}}_{\text{Positive logits}}\right]$$



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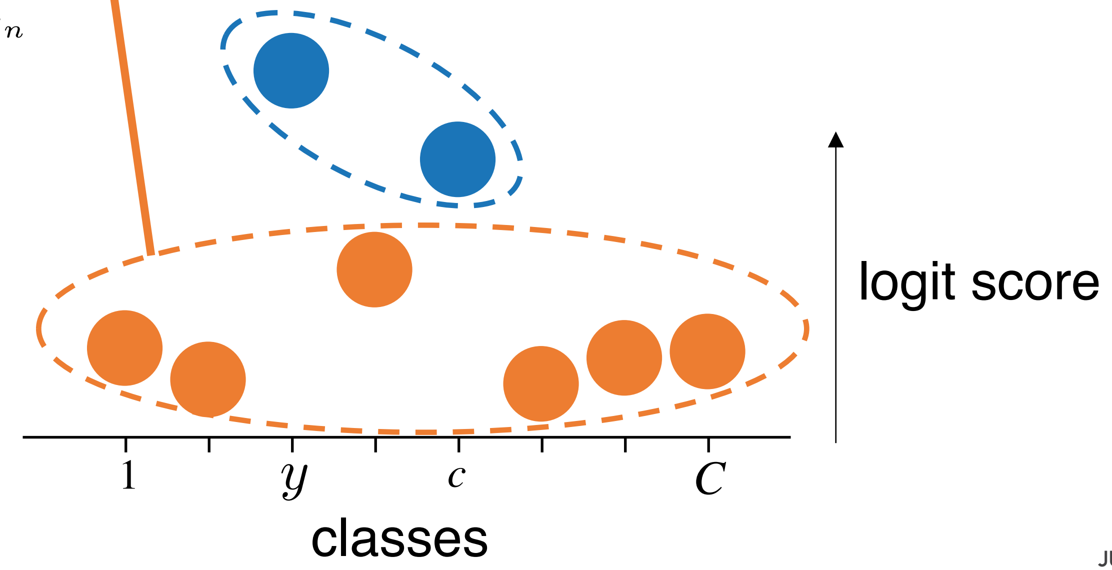
aggregation over
negative logits

$$\max_{n \in \mathcal{N}} x_n = \log \sum_{n \in \mathcal{N}} e^{x_n}$$



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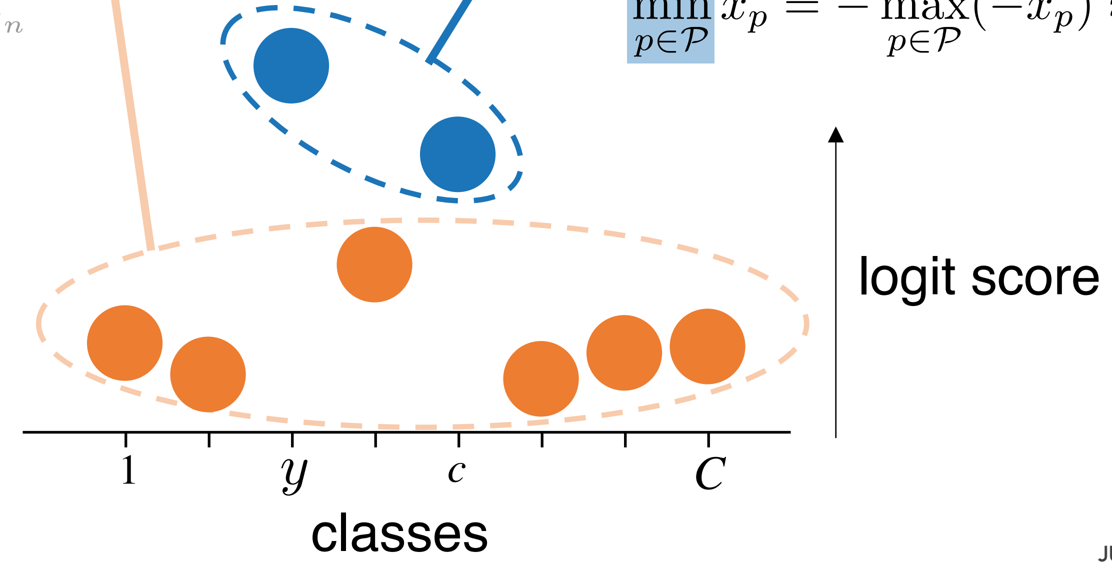
aggregation over negative logits

$$\max_{n\in\mathcal{N}} x_n = \log \sum_{n\in\mathcal{N}} e^{x_n}$$

aggregation over positive logits

$$\min_{p\in\mathcal{P}} x_p = -\max_{p\in\mathcal{P}}(-x_p) \approx -\log \sum_{p\in\mathcal{P}} e^{-x_p}$$



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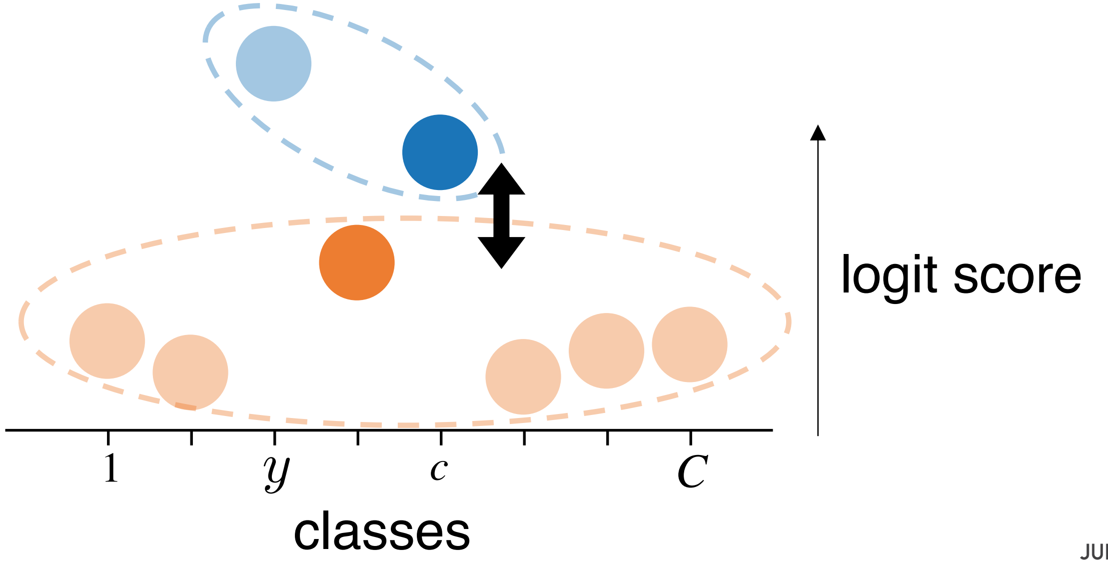
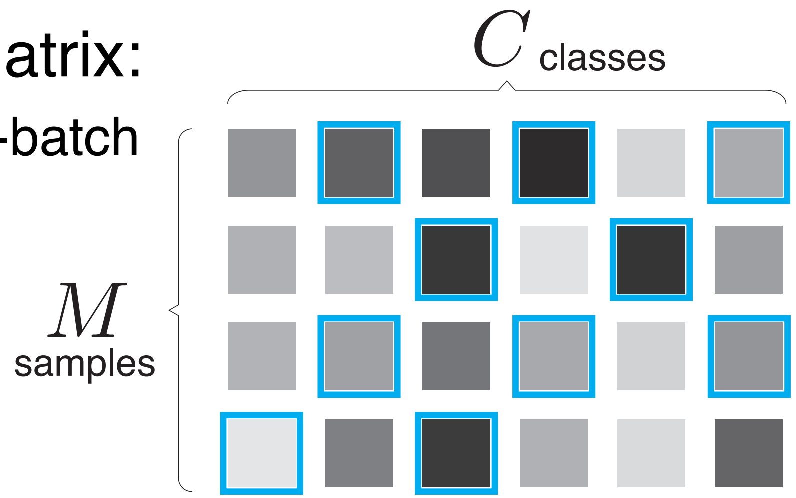


Two-way Formulation

- The multi-label loss function is applied in a **Two-Way** manner.

logit matrix:

sampled from mini-batch



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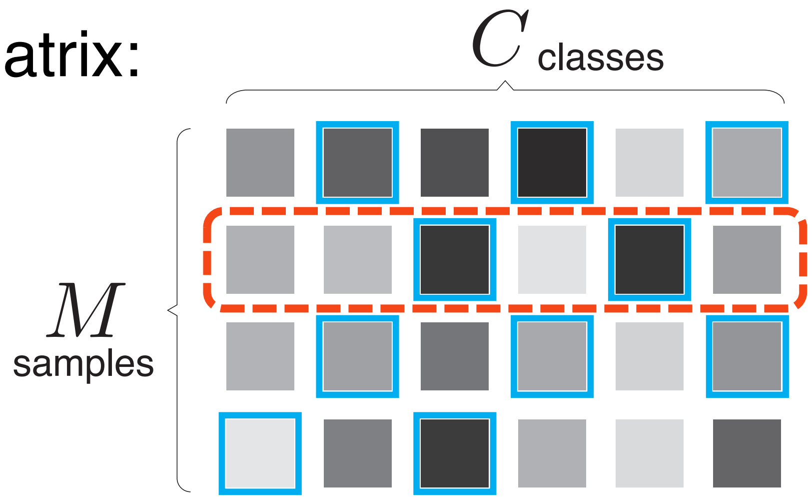
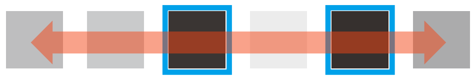


① **sample-wise** way

discriminates **classes**



at i-th sample

$$\ell_{i=2} = \texttt{softplus}\left[\log \sum_{n|y_{in}=0} e^{x_{in}} + T \log \sum_{p|y_{ip}=1} e^{-\frac{x_{ip}}{T}}\right]$$

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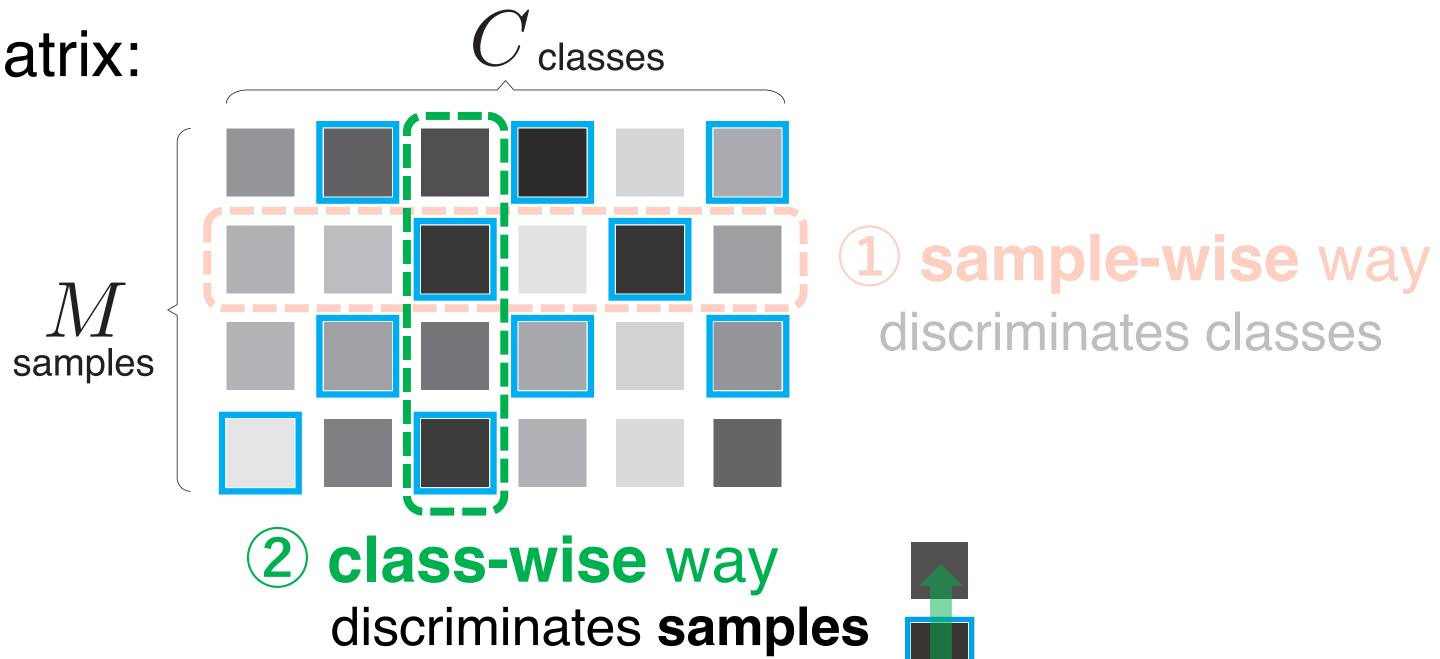
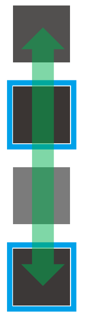


$$\ell^{c=3} = \texttt{softplus}\left[\log \sum_{i|y_{ic}=0} e^{x_{ic}} + T \log \sum_{j|y_{jc}=1} e^{-\frac{x_{jc}}{T}}\right]$$



at c-th class

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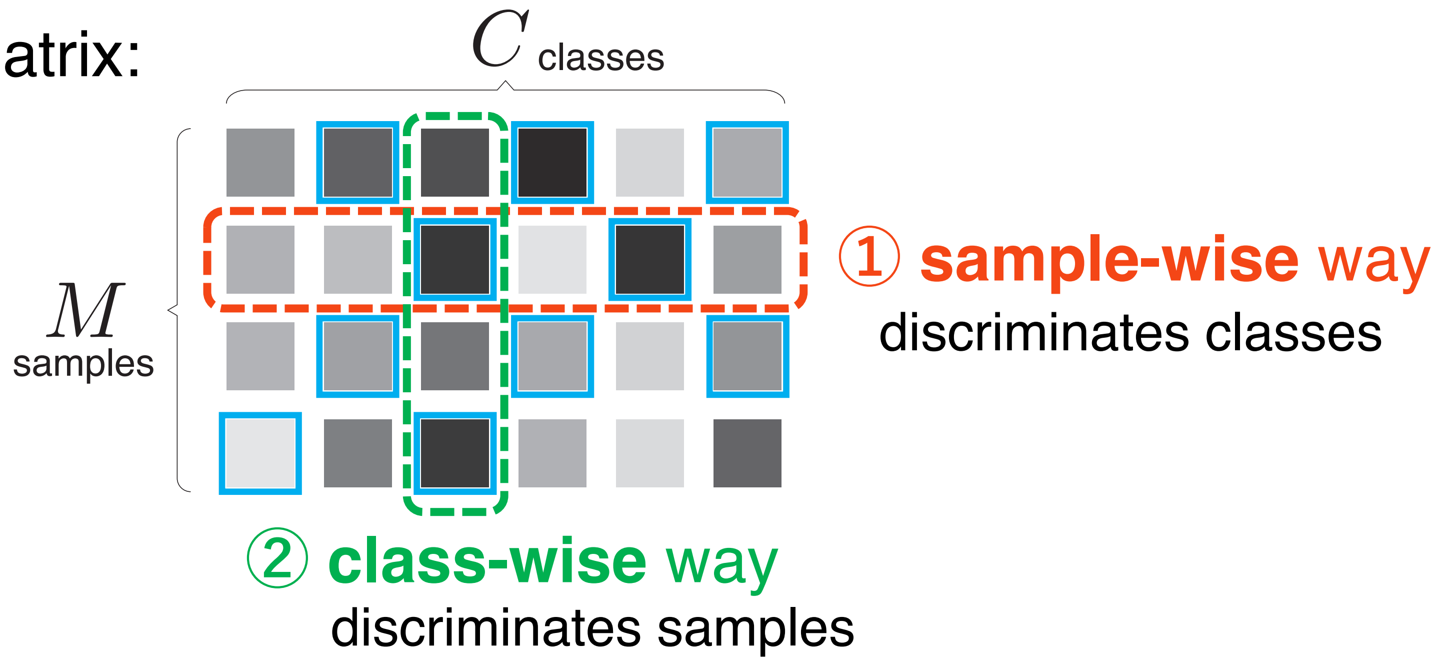


Two-way loss: $\bar{\ell} = \frac{1}{M}\sum_{i} \ell_i + \frac{1}{C}\sum_{c} \ell^c$

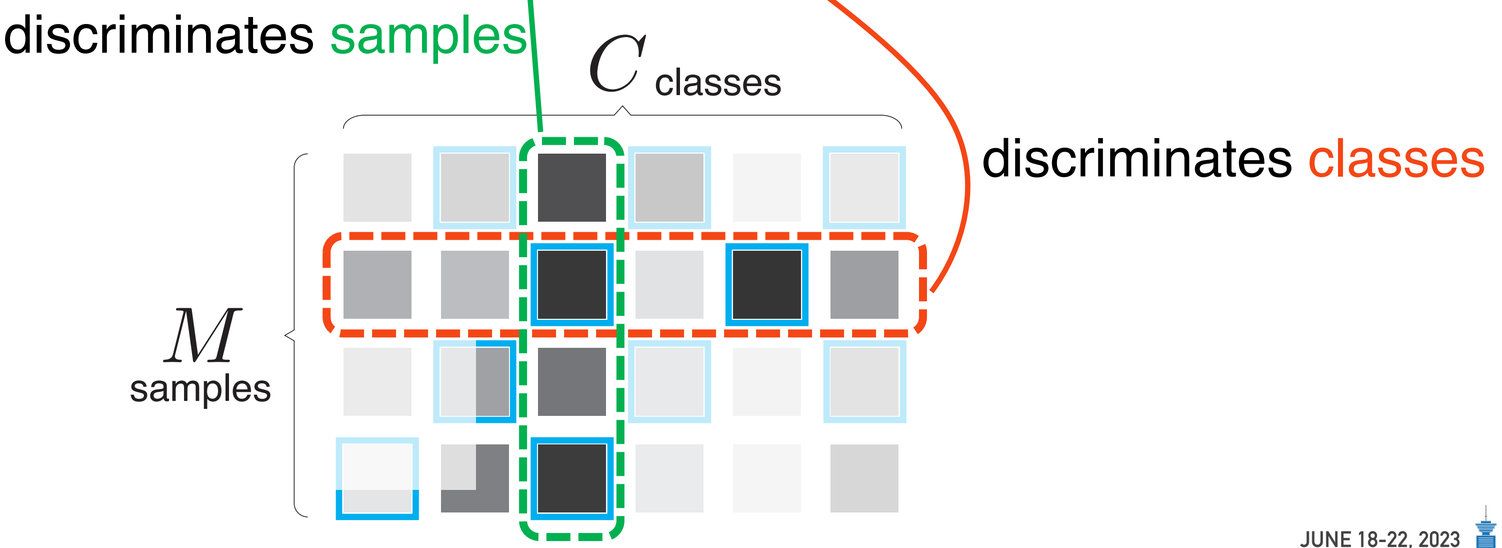
Experimental Results

- Ablation Study: **Ways**

	(a) Ours			(b) Softmax		
way	both	class	sample	both	class	sample
mAP@class	**74.11**	<u>73.06</u>	67.18	**69.19**	<u>68.13</u>	58.00
mAP@sample	**86.66**	82.75	<u>86.07</u>	**84.33**	69.15	<u>83.60</u>

MS-COCO dataset

- ☑ zebra
- ☑ giraffe
- ☑ car
- ☑ truck



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way	(a) Ours both	class	sample	(b) Softmax both	class	sample
mAP@class	**74.11**	73.06	67.18	**69.19**	68.13	58.00
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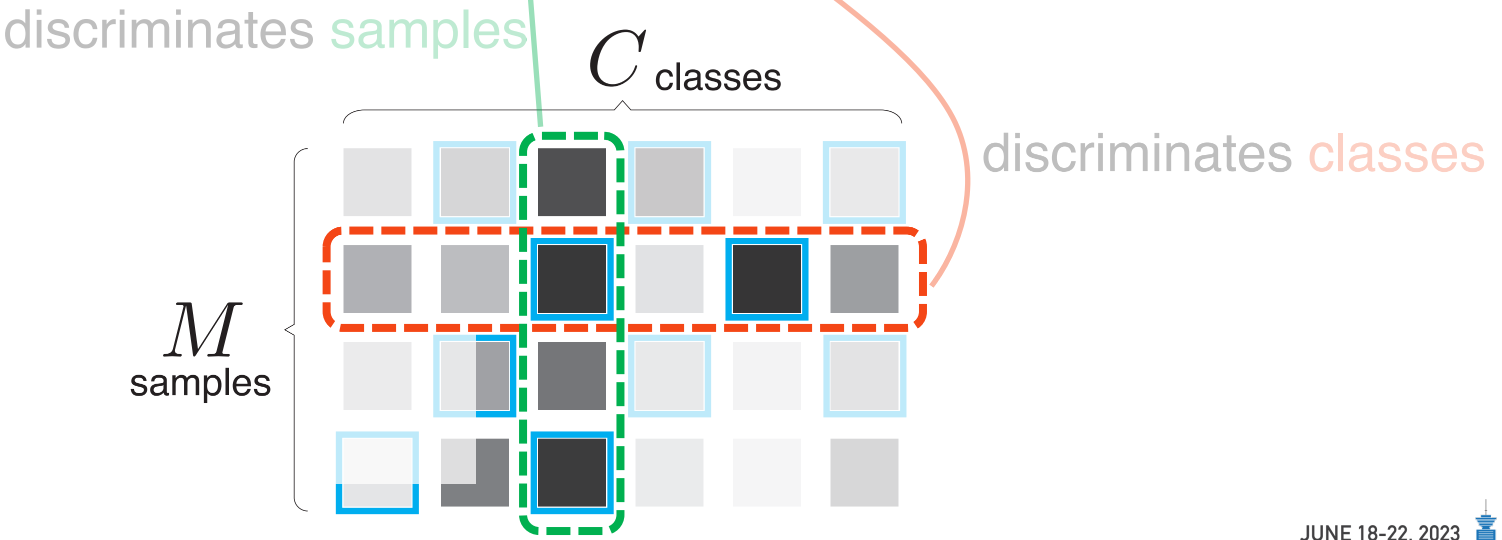

Experimental Results

- Performance comparison

various models

various datasets

	CNN	mAP@class ResNet50	mAP@class ResNeXt50	mAP@class DenseNet169	mAP@class RegNetY32gf	mAP@sample ResNet50	mAP@sample ResNeXt50	mAP@sample DenseNet169	mAP@sample RegNetY32gf
MSCOCO [19]	Softmax	58.00	59.53	58.21	64.14	83.60	84.46	83.13	86.92
	BCE	67.71	69.68	64.04	73.38	79.65	80.62	76.14	83.21
	Focal [18]	69.42	71.33	67.18	74.99	84.38	85.22	83.33	87.51
	ASL [2]	70.92	73.04	69.25	76.70	85.05	86.06	84.40	88.29
	Ours	**74.11**	**75.44**	**73.51**	**79.57**	**86.66**	**87.11**	**86.62**	**89.54**
VISPR [23]	Softmax	36.61	36.97	28.64	36.79	85.23	**85.43**	83.75	85.90
	BCE	44.22	45.34	39.73	46.11	72.39	73.14	69.31	73.75
	Focal [18]	46.89	47.76	40.78	48.75	84.35	84.26	82.91	85.29
	ASL [2]	48.53	49.53	42.61	51.03	84.81	84.99	83.99	86.15
	Ours	**51.89**	**52.79**	**48.57**	**53.75**	**85.64**	85.40	**85.88**	**86.67**
VAW [25]	Softmax	52.59	53.33	47.30	55.02	77.68	78.09	75.97	78.99
	BCE	51.21	51.31	44.53	52.25	72.43	72.29	66.50	72.43
	Focal [18]	54.38	54.50	48.94	56.77	77.66	77.70	75.81	78.71
	ASL [2]	55.39	55.72	48.17	57.88	78.05	78.32	75.91	79.03
	Ours	**56.42**	**57.00**	**54.28**	**59.33**	**78.81**	**78.95**	**78.36**	**80.07**
WIDER [17]	Softmax	63.91	65.14	63.61	66.47	83.09	83.74	83.02	84.65
	BCE	70.16	71.40	70.16	73.26	77.62	78.56	77.36	79.94
	Focal [18]	65.88	67.29	64.49	68.72	82.27	82.92	81.89	83.66
	ASL [2]	67.99	69.71	67.34	71.11	83.44	84.12	83.38	85.00
	Ours	**72.28**	**72.77**	**73.03**	**74.92**	**85.43**	**85.43**	**85.87**	**86.97**

Thank you !