

# Switchable Representation Learning Framework with Self-compatibility

Shengsen Wu, Yan Bai, Yihang Lou, Xiongkun Linghu, Jianzhong He,  
Ling-Yu Duan

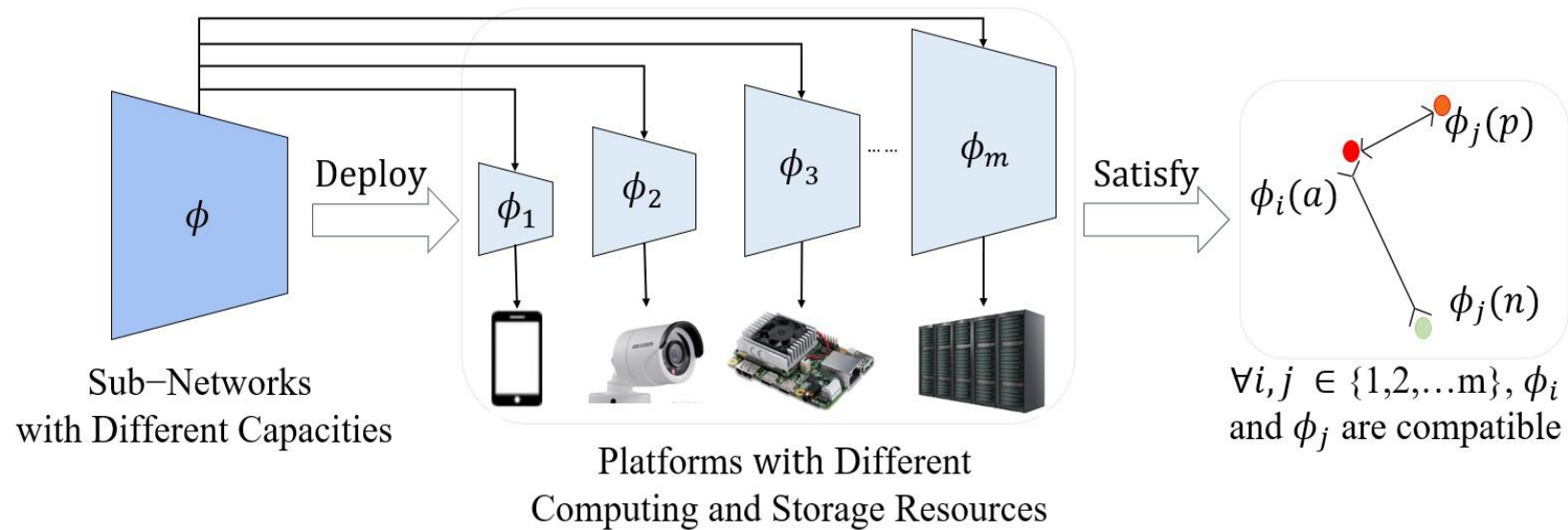
{sswu, yanbai, lingyu}@pku.edu.cn,

{louyihang1, jianzhong.he}@huawei.com, lhxk20@mails.tsinghua.edu.cn

WED-PM-342

# Abstract

- We generate a series of **compatible** sub-models with **different capacities** through one training process.
- We mitigate the gradient conflict when learning compatibilities from the perspective of the **magnitude** and **direction**.



# Current Work

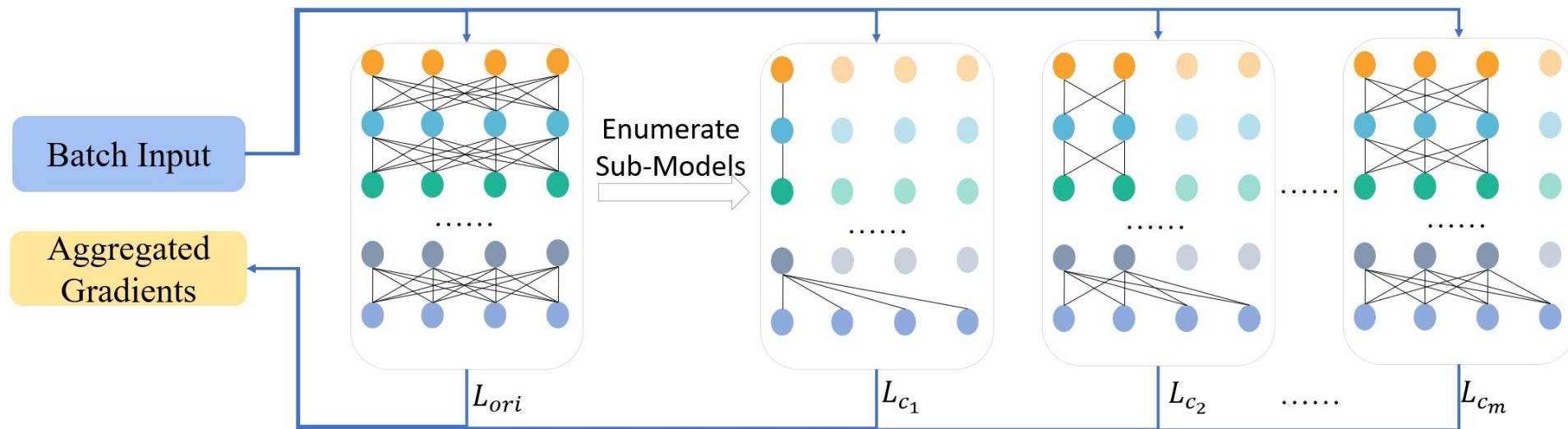
- **Dynamic Neural Networks**
  - Hand-crafted: dynamic depth, dynamic width, dynamic routing, dynamic parameters, etc.
  - Neural Architecture Search (NAS)
- **Difference between Current Work with Our Work**
  - Current works output with definite semantic information (e.g., class id, detection box) which are naturally interoperable.
  - Our works focuses on feature compatibility which is required by the Visual search system.

# Current Work

- Backward Compatible Learning
  - Given a fixed old model, align the learnable models with the fixed old one in metric space.
  - Focus on the optimization difficulties caused by the old model
- Difference between Current Work with Our Work
  - Current works focus on one-to-one compatible learning paradigms.
  - Our work studies a new compatible learning paradigm that aims to learn many-to-many compatibility among multiple learnable models.

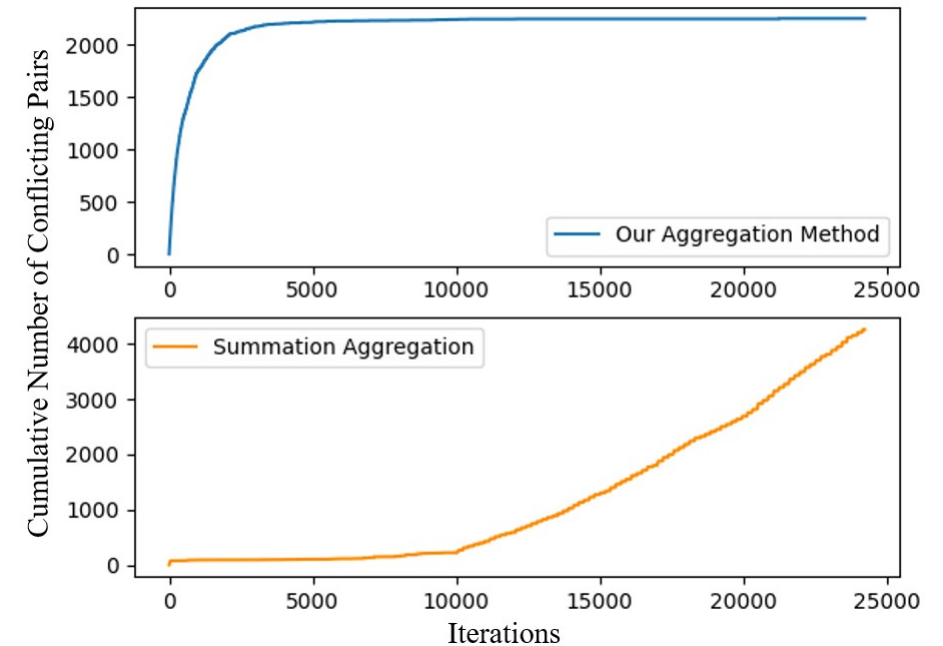
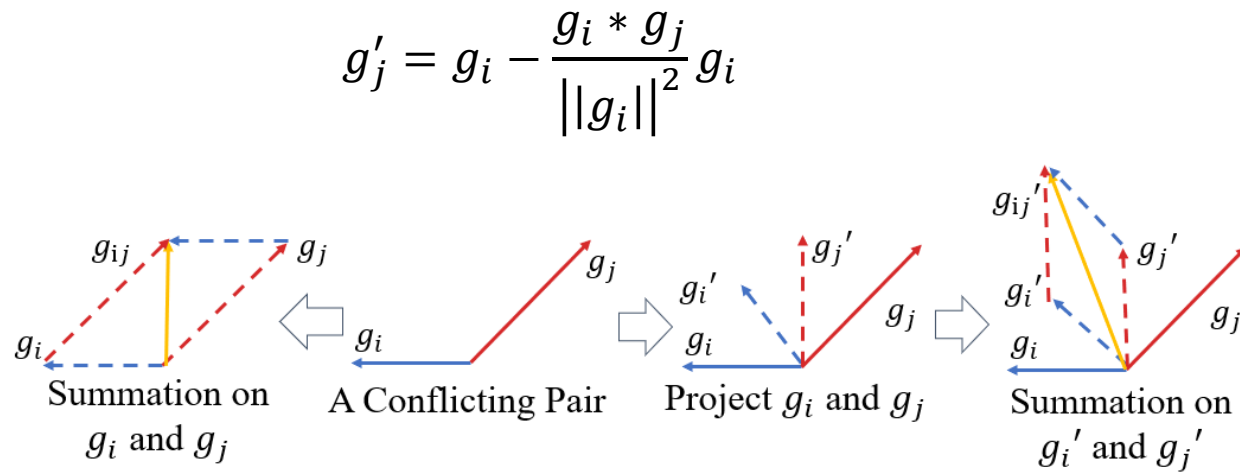
# Our Method

- Framework
  - Convert the traditional convolutional neural network into a switchable neural network.
  - Calculate compatible loss  $L_{c_1}, L_2, \dots, L_{c_m}$ , on different sub-models.
  - Optimize the sub-models by aggregating gradients.



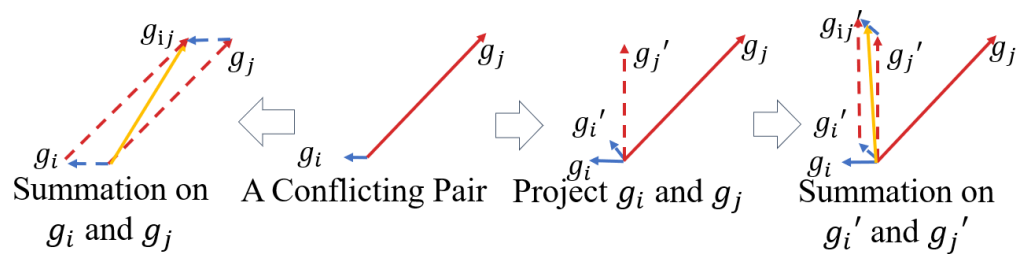
# Our Method

- Aggregation Method based on the Gradients Projection
  - Problem: Aggregating the gradients by summation may cause mutual interference, which means the improvements of sub-models are overestimated or underestimated.
  - Solution: Gradients with conflicting directions are projected to the orthogonal direction.

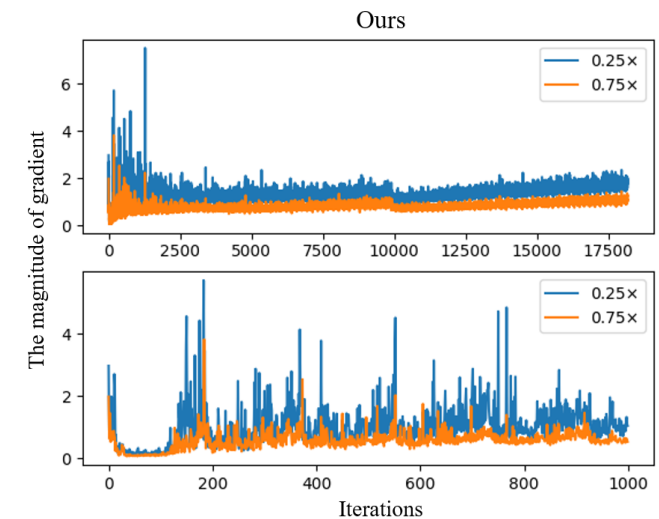
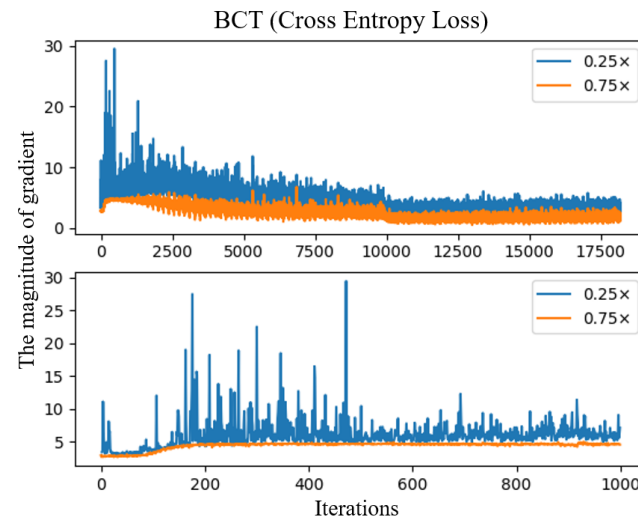


# Our Method

- Compatible Loss based on the Uncertainty Estimation
  - Problem: The imbalance of gradient magnitude between sub-models may also cause mutual interference.
  - Solution: Adjust the priorities of sub-models dynamically through uncertainty estimation.



$$L(\alpha_i^j) = \int \left[ \sum_{c=1}^C -y_{ic}^j \log(p_{ic}^j) \right] \frac{1}{\beta(\alpha_i^j)} \prod_{c=1}^C dp_i^j$$



# Performance

- Compatible Loss based on the Uncertainty Estimation

$M(\phi_q, \phi_g) \backslash \phi_g$	$\phi_{\frac{1}{16}}$	$\phi_{\frac{1}{4}}$	$\phi_{\frac{9}{16}}$	$\phi$	$\phi_{\frac{1}{16}}$	$\phi_{\frac{1}{4}}$	$\phi_{\frac{9}{16}}$	$\phi$
	Unified Model				Ours			
$\phi_{\frac{1}{16}}$	55.25	-	-	-	58.19	62.88	63.48	69.43
$\phi_{\frac{1}{4}}$	-	67.48	-	-	61.24	70.74	71.37	76.37
$\phi_{\frac{9}{16}}$	-	-	71.25	-	62.43	71.25	72.06	77.26
$\phi$	-	-	-	80.91	68.03	74.76	75.67	81.43
	BCT-S				Asymmetric-S			
$\phi_{\frac{1}{16}}$	54.40	58.10	60.22	61.29	48.79	51.96	54.09	56.31
$\phi_{\frac{1}{4}}$	55.71	66.38	68.29	69.71	52.24	62.45	64.98	67.23
$\phi_{\frac{9}{16}}$	56.50	68.30	68.42	71.99	54.44	64.74	67.97	71.28
$\phi$	61.79	69.73	71.93	73.61	56.54	67.30	71.91	78.38
	BCT				Asymmetric			
$\phi_{\frac{1}{16}}$	55.55	56.64	59.40	60.35	55.83	50.85	53.71	55.39
$\phi_{\frac{1}{4}}$	55.83	65.74	67.10	68.54	52.66	67.04	62.08	66.59
$\phi_{\frac{9}{16}}$	55.66	68.02	67.49	70.93	54.48	62.33	66.33	70.14
$\phi$	58.69	69.48	70.04	-	56.08	66.66	69.71	-

Baseline performance comparison on Market1501 (mAP). “Unified Model” are models without any compatible regularization



# Conclusion

- We propose a Switchable Representation Learning Framework with Self Compatibility for multi-platform model collaboration.
- The method enables us to obtain models with various capacities to fit different computing and storage resource constraints on diverse platforms.
- It learns many-to-many compatibility by uncertainty estimation and gradient projection.

# Conclusion

Thank you for listening!