Paper seminar #2

RILS LAB

Robot Intelligence Learning & System

원승우

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Paper List

1. Learning Representation for Multitask Learning through Self-Supervised Auxiliary Learning

2. 3D-Aware Multi-Task Learning with Cross-View Correlations for Dense Scene Understanding

3. NTKMTL: Mitigating Task Imbalance in Multi-Task Learning from Neural Tangent Kernel Perspective

4. LDC-MTL: Balancing Multi-Task Learning through Scalable Loss Discrepancy Control

5. TDSS: Task Dynamic-Synergistic Skill Adaptation for Boosting Efficient and Scalable Multi-Task Learning in Dense Visual Prediction

01

Learning Representation for Multitask Learning through Self-Supervised Auxiliary Learning

Seokwon Shin[1,2], Hyungrok Do[3], and Youngdoo Son[1,2,*]

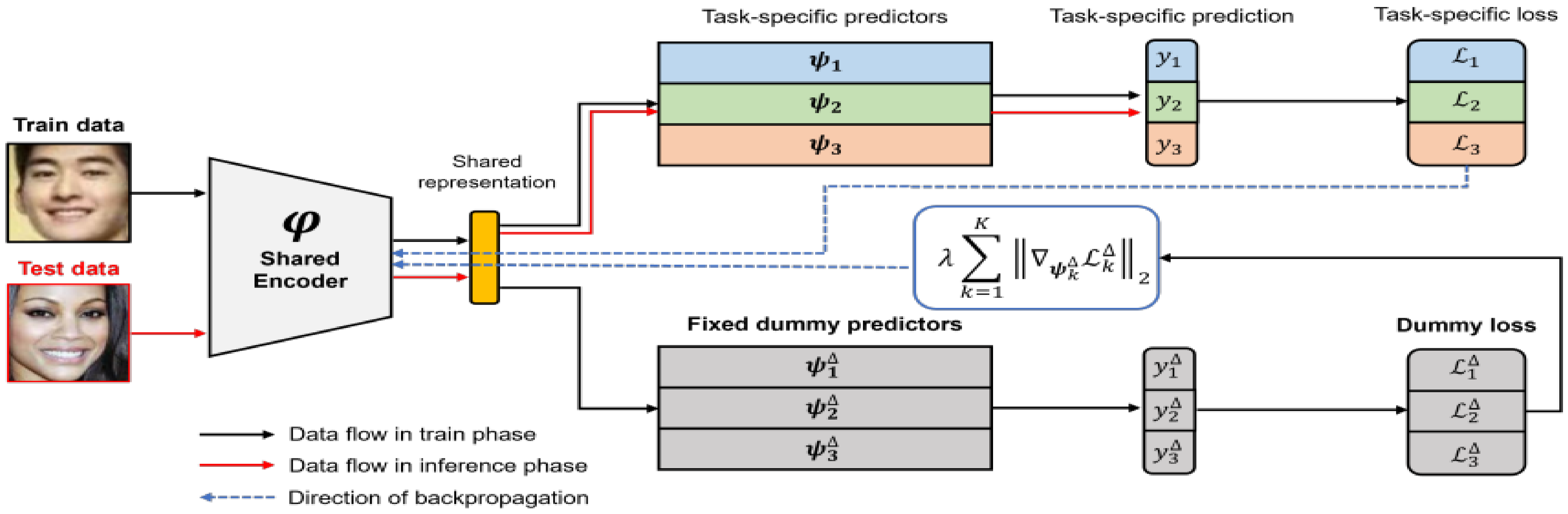
Publication	Citations
ECCV 2024	6

Learning Representation for Multitask Learning through Self-Supervised Auxiliary Learning

Seokwon Shin[1,2], Hyungrok Do[3], and Youngdoo Son[1,2,*]

- 문제 설정

: Shared Encoder에서 생성되는 Representation의 범용성을 증가시키기 위한 연구가 아직 부족함



Learning Representation for Multitask Learning through Self-Supervised Auxiliary Learning

Seokwon Shin[1,2], Hyungrok Do[3], and Youngdoo Son[1,2,*]

- 해결 방법

: 각 task에 실제 predictor와 별도로, random initialization 후 고정된 **dummy predictor**를 추가함.

→ Dummy predictor loss의 gradient norm을 regularization으로 최소화하는 방향으로 학습

$$L_{DRG} = \sum_{k=1}^{K} \left[L_k^{main} + \lambda \left\| \nabla_{\theta_{T_k}^{\Delta}} L_k^{dummy} \right\|_F \right]$$

Learning Representation for Multitask Learning through Self-Supervised Auxiliary Learning

Seokwon Shin[1,2], Hyungrok Do[3], and Youngdoo Son[1,2,*]

- 해결 이유

: 범용성을 optimal predictor와 arbitrary dummy predictor 사이의 loss 차이가 작을수록 높다고 정의

$$\mathcal{U} \propto \frac{1}{f(\theta^{\Delta}) - f(\theta^{*})}$$

Loss가 predictor parameter에 대해 convex하다는 가정 아래,

$$f\left(\theta^{\Delta}\right) - f(\theta^{*}) \leq \left\|\nabla f\left(\theta^{\Delta}\right)\right\|_F \left\|\theta^{\Delta} - \theta^{*}\right\|_F$$

→ Dummy predictor의 gradient norm을 줄이면 arbitrary predictor에서도 쉽게 사용할 수 있는 **universal shared representation**을 학습하도록 encoder를 유도됨

Learning Representation for Multitask Learning through Self-Supervised Auxiliary Learning

Seokwon Shin[1,2], Hyungrok Do[3], and Youngdoo Son[1,2,*]

- Contribution

1. 범용성을 optimal task specific-head의 Loss와 arbitrary head의 Loss 차이의 역수로 정의
2. 범용성이 arbitrary Head에 대한 손실 함수 gradient가 Fobenius 노름에 반비례함
3. 범용성을 증가시키기 위한 새로운 정규화 방법인 DGR 방법을 제안
4. 다양한 Benchmark Dataset에서 성능이 향상됨
5. DGR 방법이 Input data에 대해 적절한 품질의 Representation을 생성함

02

3D-Aware Multi-Task Learning with Cross-View Correlations for Dense Scene Understanding

Xiaoye Wang♣* Chen Tang◇ Xiangyu Yue◇ Wei-Hong Li♠†
♣University of Cambridge ◇The Chinese University of Hong Kong ♠University of Bristol

github.com/WeiHongLee/CrossView3DMTL

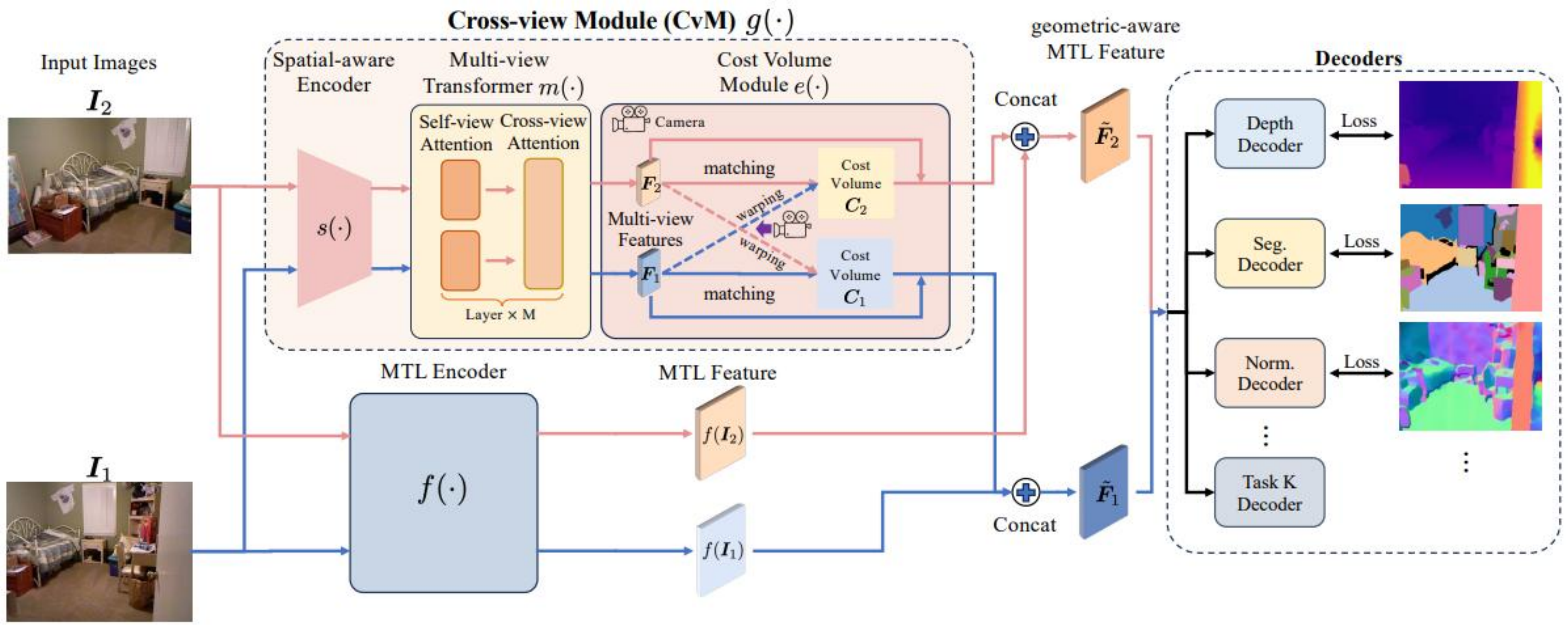
Publication	Citations
CVPR 2026	0

3D-Aware Multi-Task Learning with Cross-View Correlations for Dense Scene Understanding

Xiaoye Wang[♣*] Chen Tang[◇] Xiangyu Yue[◇] Wei-Hong Li[♠†]
[♣]University of Cambridge [◇]The Chinese University of Hong Kong [♠]University of Bristol
github.com/WeiHongLee/CrossView3DMTL

- 문제 설정

: 2D image와 pixel-level supervision만으로 task 관계를 학습해, 서로 다른 view 및 task 사이의 **geometric consistency가 부족함**



3D-Aware Multi-Task Learning with Cross-View Correlations for Dense Scene Understanding

Xiaoye Wang[♣*] Chen Tang[◇] Xiangyu Yue[◇] Wei-Hong Li[♠†]
[♣]University of Cambridge [◇]The Chinese University of Hong Kong [♠]University of Bristol
github.com/WeiHongLee/CrossView3DMTL

- Contribution

1. Cross-view correlation을 이용한 3D-aware MTL 제안
2. 기존 MTL 모델에 결합 가능한 architecture-agnostic CvM 설계
3. Single-view와 multi-view training 모두 지원
4. Inference에서는 single image만 사용하면서 기존 MTL 성능 향상

※ Eigen Value + NTK Matrix란?

① Eigen Value (고유값)

: 행렬이 어떤 방향의 벡터를 얼마나 크게 변화시키는지를 나타내는 값

$$K_{q_i} = \lambda_i q_i$$

※ λ_i ↑ → 해당 방향의 변화가 큼

① NTK Matrix

: 모델 parameter가 변할 때, 각 input의 output이 서로 얼마나 비슷하게 변하는지를 나타내는 행렬

$$K_{uv} = \left\langle \frac{\partial f(\theta, x_u)}{\partial \theta}, \frac{\partial f(\theta, x_v)}{\partial \theta} \right\rangle$$

03

NTKMTL: Mitigating Task Imbalance in Multi-Task Learning from Neural Tangent Kernel Perspective

Xiaohan Qin, Xiaoxing Wang, Ning Liao, Junchi Yan‡
School of CS & School of AI, Shanghai Jiao Tong University
Shanghai Innovation Institute

Publication	Citations
NIPS 2025	0

NTKMTL: Mitigating Task Imbalance in Multi-Task Learning from Neural Tangent Kernel Perspective

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School of CS & School of AI, Shanghai Jiao Tong University
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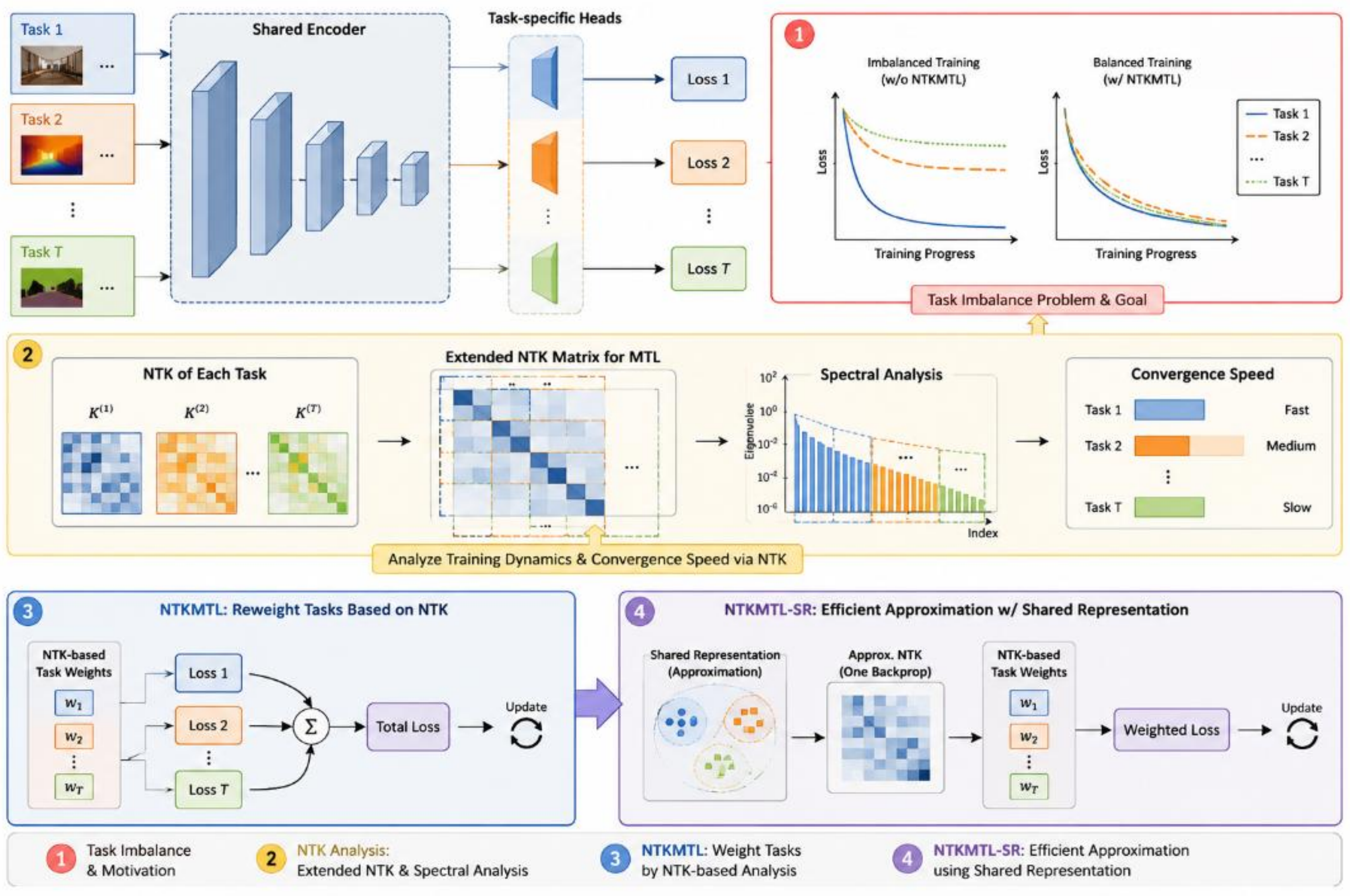
- 문제 설정

: Task별 convergence speed 차이로 일부 task가 학습을 지배하는 **task imbalance**가 발생하며, 기존 loss 변화량만으로는 이를 정확히 측정하기 어렵다.



NTKMTL: Mitigating Task Imbalance in Multi-Task Learning from Neural Tangent Kernel Perspective

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Shanghai Innovation Institute

- 해결 방법

: 각 task의 training dynamics를 **NTK eigenvalue**로 분석하고, task별 최대 eigenvalue λ_i에 따라 loss weight를 조정함.

$$\omega_i = \sqrt{\frac{\tilde{\lambda}}{\lambda_i}}, \qquad \tilde{\lambda} = \frac{1}{K}\sum_{i=1}^{K} \lambda_i$$

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- 해결 이유

$$E(t) = O(t) = y \qquad \rightarrow \qquad E(t) = e^{-\eta K t} E(0)$$

$$K = Q \Lambda Q^{\intercal} \qquad \rightarrow \qquad Q^{\intercal} E(t) = E(t) = e^{-\eta K t} Q^{\intercal} E(0)$$

NTK 기반 gradient flow에서 prediction error는 다음과 같이 감소함.

→ 큰 eigenvalue를 가진 task는 빠르게, 작은 eigenvalue를 가진 task는 느리게 수렴

NTKMTL: Mitigating Task Imbalance in Multi-Task Learning from Neural Tangent Kernel Perspective

Xiaohan Qin, Xiaoxing Wang, Ning Liao, Junchi Yan‡
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Shanghai Innovation Institute

- Contribution

1. NTK 관점에서 MTL의 task imbalance를 이론적으로 설명

2. NTK eigenvalue 기반 task weighting 방법 제안

3. Shared representation으로 NTK를 근사하는 효율적인 **NTKMTL-SR** 제안

4. Supervised MTL과 Multi-task RL에서 성능 검증

04

LDC-MTL: Balancing Multi-Task Learning through Scalable Loss Discrepancy Control

Peiyao Xiao* Chaosheng Dong† Shaofeng Zou‡ Kaiyi Ji*§

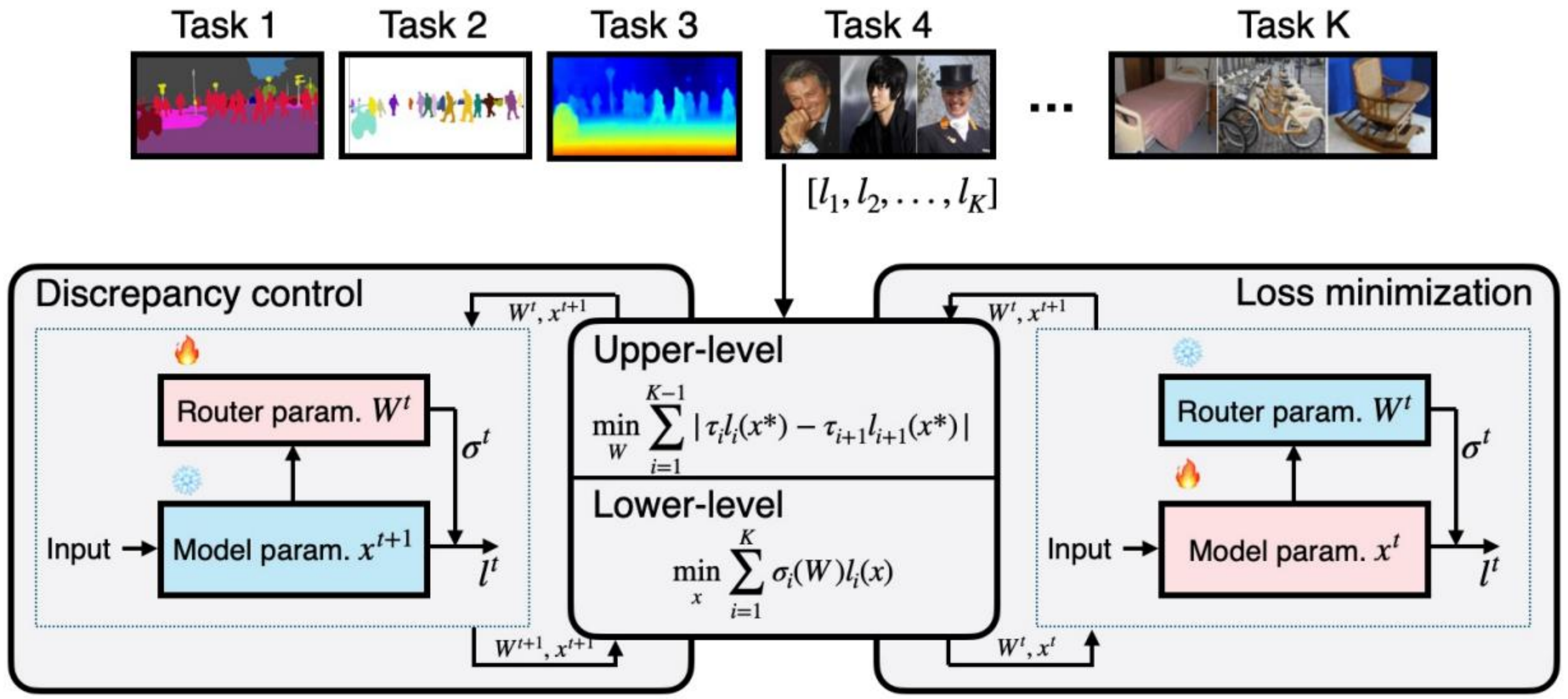
Publication	Citations
ECCV 2026	6

LDC-MTL: Balancing Multi-Task Learning through Scalable Loss Discrepancy Control

Peiyao Xiao* Chaosheng Dong† Shaofeng Zou‡ Kaiyi Ji*§

- 문제 설정

: Task별 loss scale과 convergence speed가 달라 일부 task가 학습을 지배함



LDC-MTL: Balancing Multi-Task Learning through Scalable Loss Discrepancy Control

Peiyao Xiao* Chaosheng Dong† Shaofeng Zou‡ Kaiyi Ji*§

- Contribution

1. Loss discrepancy를 직접 제어하는 bilevel MTL formulation 제안
2. Second-order gradient가 필요 없는 $O(1)$ time·memory algorithm 제안
3. Gradient conflict가 함께 감소함을 실험적으로 확인
4. Pareto stationary point에 대한 convergence guarantee 제시

05

TDSS: Task Dynamic-Synergistic Skill Adaptation for Boosting Efficient and Scalable Multi-Task Learning in Dense Visual Prediction

Haiming Yao [1,3], Qiyu Chen[2,3], Wei Luo[1,3], Zheng Zhang[3], Jianxing Liao[3], Wei You[3]*

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Publication	Citations
AAAI 2026	0

TDSS: Task Dynamic-Synergistic Skill Adaptation for Boosting Efficient and Scalable Multi-Task Learning in Dense Visual Prediction

Haiming Yao [1,3], Qiyu Chen[2,3], Wei Luo[1,3], Zheng Zhang[3], Jianxing Liao[3], Wei You[3]*
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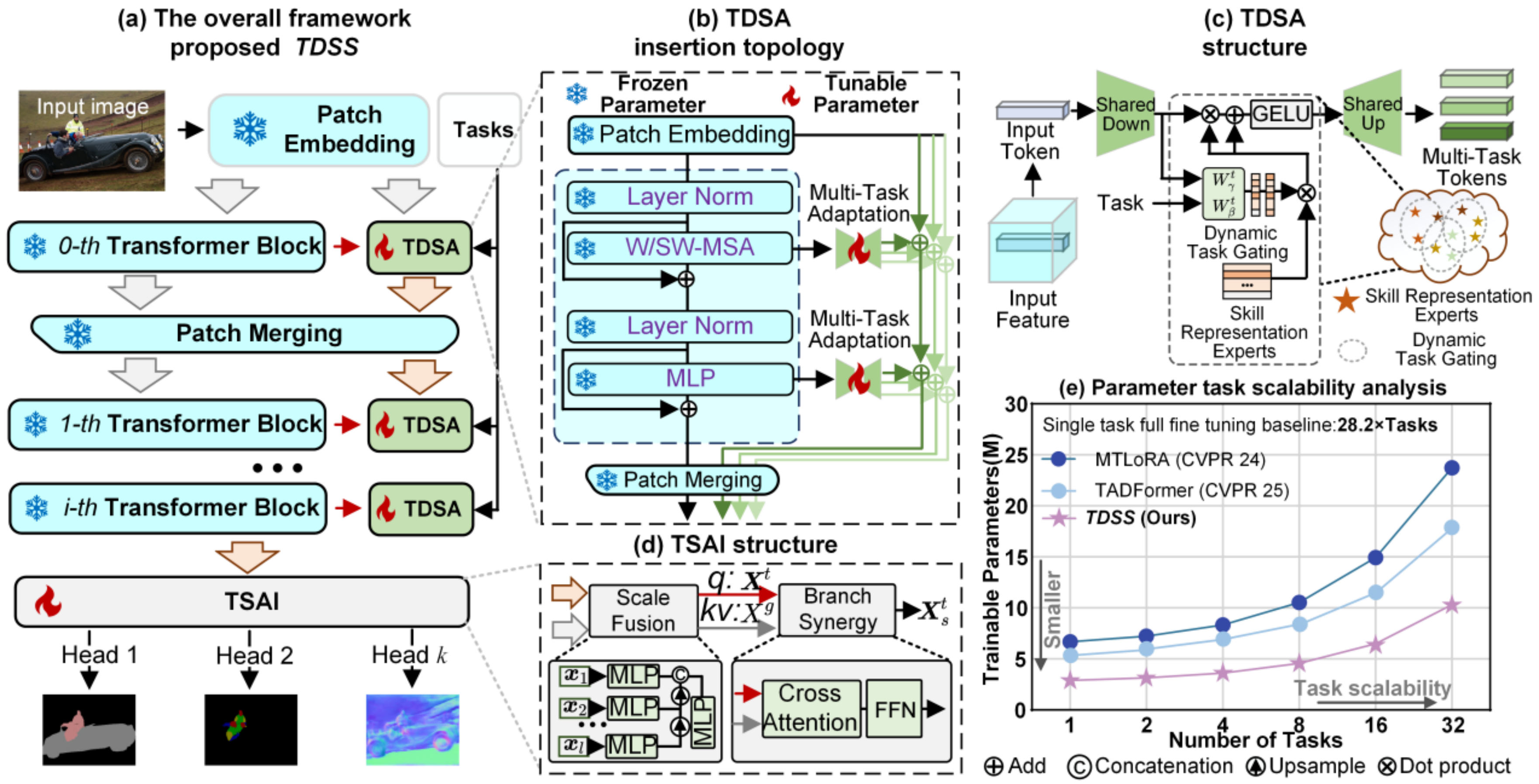
- 문제 설정

: 기존 multi-task PEFT는 task별 모듈과 반복적인 backbone 실행이 필요해 **확장성이 낮고**, cross-task interaction도 충분히 활용하지 못한다.



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- Contribution

1. Multi-task PEFT의 backbone execution, task scalability, cross-task interaction 문제를 정의
2. Shared skill 기반 TDSA와 cross-task interaction을 위한 TSAI 제안
3. Task 수와 관계없이 backbone을 한 번만 실행
4. 3.52M trainable parameters만으로 기존 PEFT 방법보다 높은 성능 달성

Thank you

Question & Disscusion

RILS LAB