Motion Style Transfer: Modular Low-Rank Style Transfer for Deep Trajectory Forecasting

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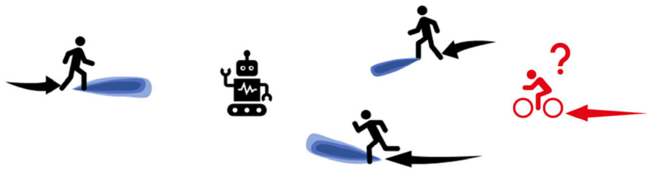
I. OVERVIEW

Challenge

Despite great success on large-scale datasets, deep forecasting models suffer from inferior performance when they encounter unseen novel scenarios.



Research Problem

Efficiently adapt a forecasting model pretrained on source domain with sufficient data to a target domain.

Contributions

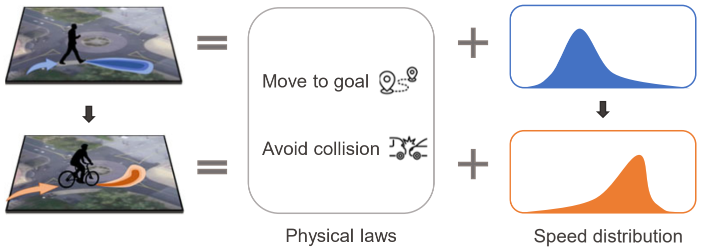
1. Formulate motion adaptation as style transfer.
2. Motion style adapters to model the style shifts.
3. Modularized strategy to improve sample efficiency.

II. MOTION STYLE TRANSFER

Motion style: The way an agent interacts with its surroundings, e.g., preferred speed, social distance.

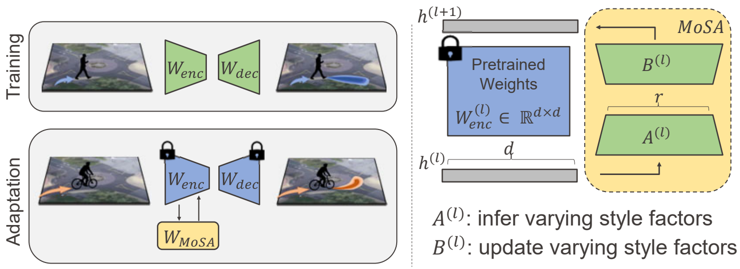
Decoupling motion dynamics

- Physical laws behind motion dynamics are invariant.
- Only need to account for the changes in motion style.



We view adaptation as learning style shifts ($S \rightarrow S'$).

III. MOTION STYLE ADAPTERS



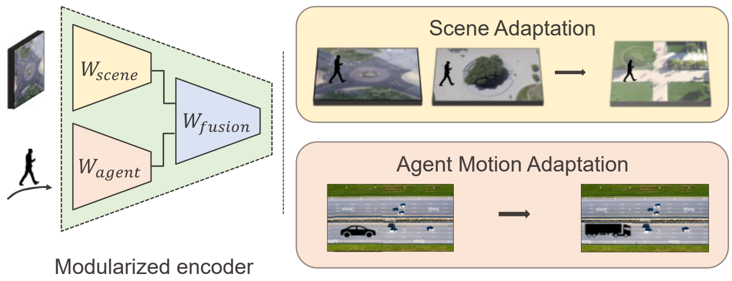
$A^{(l)}$: infer varying style factors
$B^{(l)}$: update varying style factors

- Freeze pre-trained model → Invariant physical laws.
- Motion style adapters → Model underlying style shifts.

Hypothesis: Style shifts reside in a low-dimensional space resulting in our bottleneck design ($r \ll d$).

IV. MODULARIZED ADAPTATION

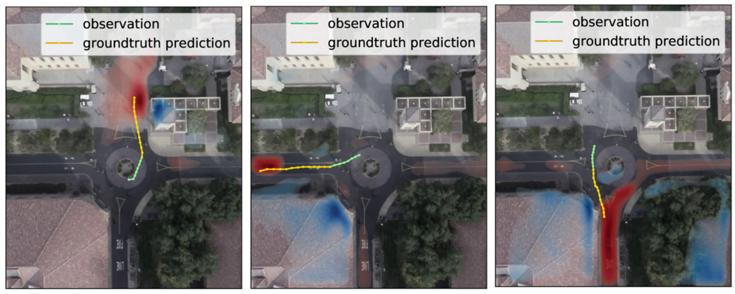
We factorize physical context from past agent motion.



MoSA can be flexibly injected to different encoders.

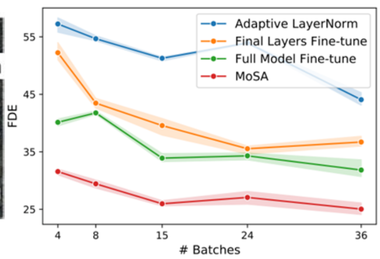
V. EXPERIMENTS

Agent Style Transfer on SDD (🚶 → 🚴)



- For cyclists, the red region has increased focus in prediction after adaptation, while blue region has decreased probability of moving there.
- MoSA reduces generalization error by 30% using 30 samples while updating 0.5% additional parameters.

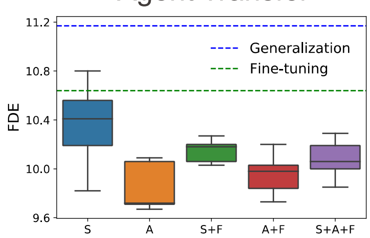
Scene Style Transfer on Level 5



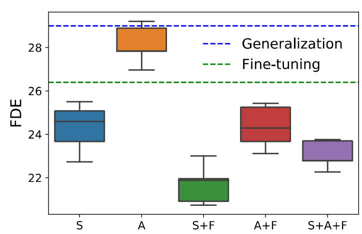
- Trained on the green route, adapted to blue route.
- MoSA outperforms competitive baselines by > 20%.

Modularized Adaptation on inD

Agent Transfer



Scene Transfer



- Module updates: S → scene, A → agent, F → fusion.
- Modularization strategy leads to performance gains.

References: From Goals, Waypoints & Paths To Long Term Human Trajectory Forecasting ICCV'21 | Learning Social Etiquette, CVPR'16 | The inD Dataset, IEEE Intelligent Vehicles 2020 | One Thousand and one hours, CoRL'20.