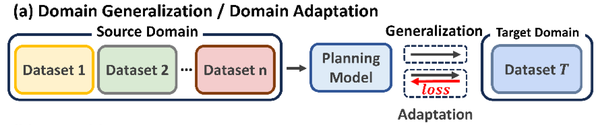
Interaction-Merged Motion Planning: Effectively Leveraging Diverse Motion Datasets for Robust Planning

Giwon Lee[1*], Wooseong Jeong[1*], Daehee Park[2], Jaewoo Jeong[1], and Kuk-Jin Yoon[1]
[1]Visual Intelligence Lab., KAIST, Korea , [2]Intelligent Systems and Learning Lab., DGIST, Korea

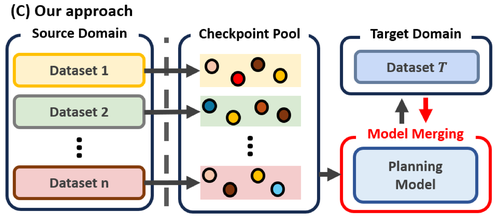
ICCV OCT 19-23, 2025 HONOLULU HAWAII

Task & Motivation

- **Motion planning** focus on generating a plan that can perform various downstream tasks, such as ensuring safety, efficiency, and successful arrival at the destination
- With the emergence of diverse trajectory datasets, data-driven approaches have gained significant traction in motion planning for their adaptability to various driving scenarios.
- However, integrating diverse motion datasets is challenging due to domain differences in agent behaviors and interactions.
- Previous methods (e.g., Domain Adaptation, Ensemble Learning) causes domain imbalance and knowledge interference.



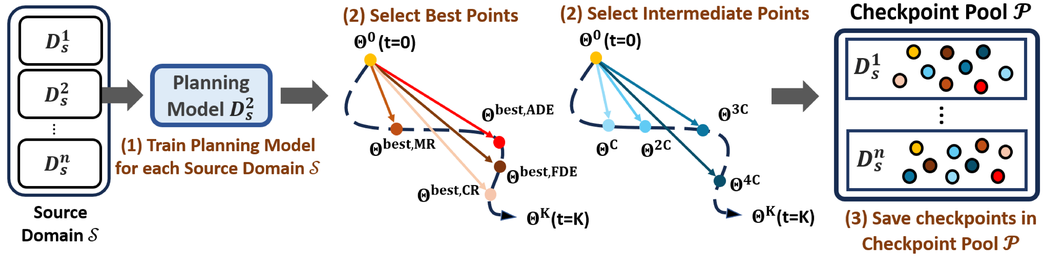
- Therefore, an efficient method is needed to transfer cross-domain knowledge while preserving interactions between agents.
- Motivated by this, we adopt **model merging** to retain source knowledge and combine weights for the target domain, enabling effective plan generation.



Main Method

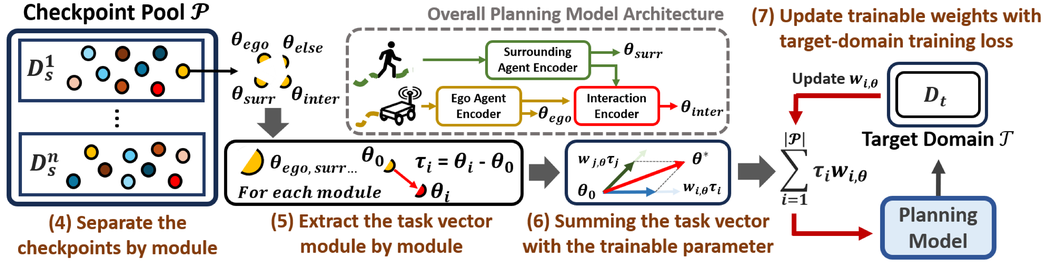
- **IMMP** follows a two-step process:
- Step 1: **Interaction Conserving Pre-Merging**, sufficiently extracting diverse information from the source domain.
- Step 2: **Interaction Transfer with Merging**, merging module-level task vectors to adaptively transfer diverse interactions to the target domain.

Step1: Interaction Conserving Pre-Merging



- We train the planning model on each source dataset and save checkpoints at the best metrics for each downstream task in motion planning as well as at intermediate epochs.

Step2: Interaction Conserving Pre-Merging



- From the collected checkpoint pool, we decompose checkpoints into common modules of the planning architecture and extract task vectors along with the initial point.
- These task vectors are combined as learnable parameters and optimized with the training loss on the target domain, effectively transferring source-domain knowledge to the target domain.

Experimental Results

- Our method achieves state-of-the-art performance across three planning models and two target domain settings, demonstrating its parallel applicability to diverse planning frameworks.

Table 1. Qualitative comparison of the proposed IMMP with baseline methods. Each baseline is implemented across various planning models.

Model	Method	SIT [4] Effectiveness ADE ↓	SIT [4] Safety Col. Rate ↓	SIT [4] Goal Success FDE ↓	SIT [4] Goal Success Miss Rate ↓	THOR [52] Effectiveness ADE ↓	THOR [52] Safety Col. Rate ↓	THOR [52] Goal Success FDE ↓	THOR [52] Goal Success Miss Rate ↓	Cost
GameTheoretic [32]	Domain Generalization [17]	0.8338	9.87E-04	1.8594	0.9355	0.3804	1.21E-03	0.8705	0.6957	×1
	Domain Adaptation [16]	0.4388	1.26E-03	1.0611	0.7201	0.1133	2.90E-04	0.2516	0.1268	×1
	Target Only	0.4343	3.41E-04	0.9014	0.6272	0.1003	2.64E-04	0.2153	0.0929	×1
	Ensemble-WTA [2]	0.3695	5.75E-05	0.8283	0.6185	0.2112	4.03E-04	0.4082	0.2996	×7
	Ensemble-AVG [2]	0.5415	1.89E-04	1.1617	0.8159	0.3142	4.86E-04	0.6181	0.6027	×7
	Averaging [10, 68]	0.6726	2.34E-04	1.4340	0.9611	0.2742	5.17E-04	0.5624	0.5711	×1
	Task Arithmetic [22]	0.4132	1.37E-04	0.8936	0.7364	0.2679	3.87E-04	0.5651	0.4812	×1
	Ties Merging [72]	1.1876	5.53E-04	2.2440	0.9872	0.5253	2.49E-03	0.8212	0.6201	×1
	IMMP	0.3380	5.12E-05	0.7626	0.6446	0.1165	3.48E-04	0.2562	0.1330	×1
	IMMP + Finetune	**0.3157**	**4.28E-05**	**0.7300**	**0.5934**	**0.0975**	**2.56E-04**	**0.2108**	**0.0912**	×1
DTPP [21]	Domain Generalization [17]	1.0116	1.18E-03	2.1255	0.9350	0.3446	1.42E-03	0.6873	0.5948	×1
	Domain Adaptation [16]	0.4640	2.45E-04	1.0116	0.7573	**0.1460**	2.50E-04	**0.2291**	**0.0772**	×1
	Target Only	0.4832	5.73E-04	0.9839	0.6852	0.1528	2.57E-04	0.2394	0.0910	×1
	Ensemble-WTA [2]	0.6125	**2.01E-04**	1.2067	0.8217	0.2241	5.15E-04	0.4591	0.4127	×7
	Ensemble-AVG [2]	0.7460	3.36E-04	1.5439	0.9175	0.2145	3.41E-04	0.4095	0.3302	×7
	Averaging [10, 68]	0.6303	2.79E-04	1.2699	0.8641	0.3075	6.75E-04	0.5807	0.4901	×1
	Task Arithmetic [22]	0.6062	3.73E-04	1.2138	0.8542	0.2885	4.18E-04	0.5057	0.4693	×1
	Ties Merging [72]	1.0741	2.25E-03	2.0873	0.9384	0.5141	2.15E-03	0.6764	0.5514	×1
	IMMP	0.4388	2.58E-04	0.9067	**0.6220**	0.1958	2.46E-04	0.3210	0.1558	×1
	IMMP + Finetune	**0.3793**	4.22E-04	**0.8336**	0.6336	0.1470	**2.17E-04**	0.2421	0.0905	×1
DIPP [20]	Domain Generalization [17]	1.3268	1.09E-03	2.7111	0.9756	0.3398	1.27E-03	0.6983	0.6163	×1
	Domain Adaptation [16]	0.4697	3.93E-04	1.0331	0.7886	0.2660	9.68E-04	0.5272	0.4773	×1
	Target Only	0.5671	6.68E-04	0.9801	0.7253	0.1771	2.17E-04	0.2713	0.1156	×1
	Ensemble-WTA [2]	0.7784	4.36E-04	1.5916	0.8275	0.2604	7.00E-04	0.4874	0.4435	×7
	Ensemble-AVG [2]	0.9737	5.79E-04	1.9442	0.9750	0.2562	5.46E-04	0.5134	0.4754	×7
	Averaging [10, 68]	1.4383	1.74E-03	2.7763	0.9820	0.4329	1.47E-03	0.7534	0.6710	×1
	Task Arithmetic [22]	1.2614	1.66E-03	2.4944	0.9564	0.4196	1.39E-03	0.7120	0.6915	×1
	Ties Merging [72]	1.6028	1.85E-03	3.0906	1.0000	0.5141	2.15E-03	0.6764	0.5515	×1
	IMMP	0.5112	**1.60E-04**	0.9358	0.7944	0.2335	5.87E-04	0.3219	0.1842	×1
	IMMP + Finetune	**0.4096**	5.27E-04	**0.8915**	**0.6789**	**0.1204**	**1.94E-04**	**0.2236**	**0.0769**	×1

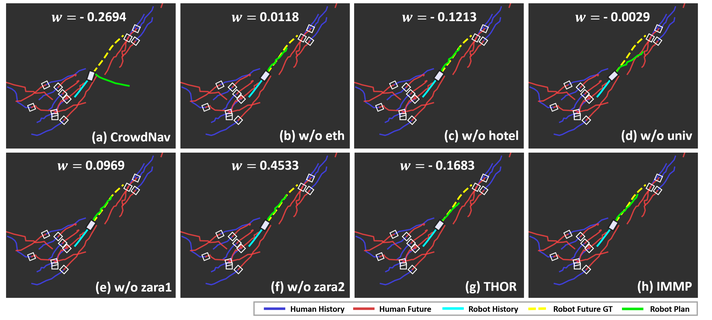


Figure 1. Qualitative results on the SIT dataset with the GameTheoretic planner. (a)–(g) show SIT inferences from models trained on individual source domains. The values w indicate the average task-vector contributions in the IMMP planner.