Energy and Emission Prediction for Mixed-Vehicle Transit Fleets Using Multi-Task and Inductive Transfer Learning

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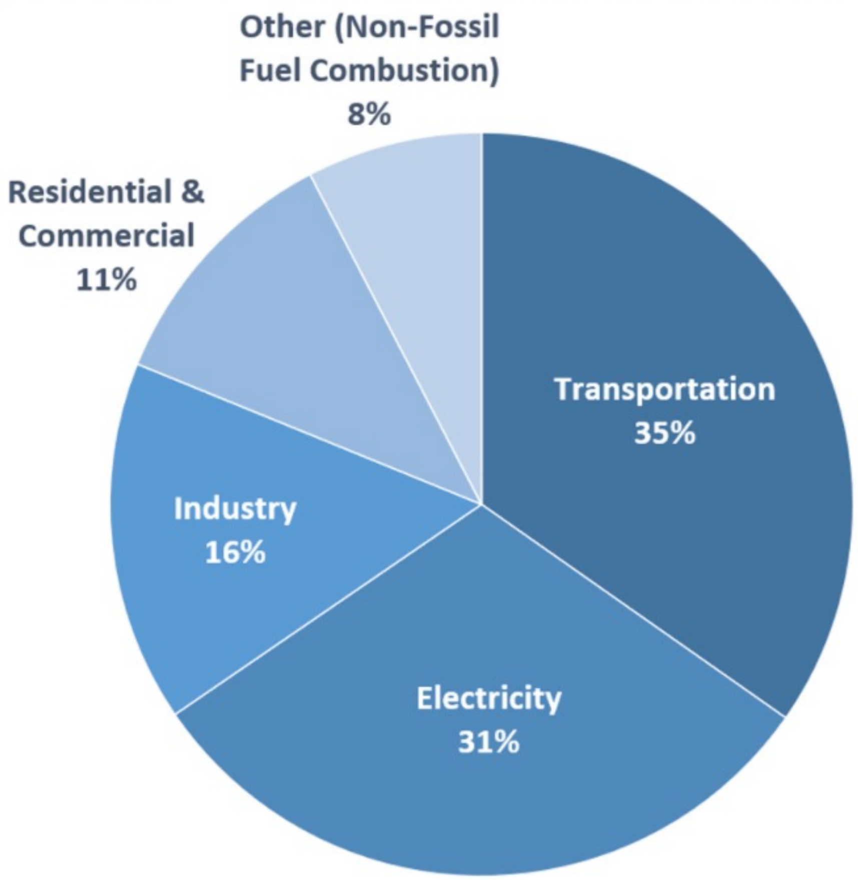
Introduction

- In U.S., transportation accounts for 35% of CO_2 emissions [1] and 28% of energy consumption [2]
- Public transportation is responsible for 21.1 million metric tons of CO_2 emissions [3]

2019 U.S. Carbon Dioxide Emissions by Source [2]



[1] EIA. 2019. U.S. Energy Information Administration: Use of energy explained – Energy use for transportation (2019). https://www.eia.gov/ energyexplained/use-of-energy/transportation.php

[2] U.S. Environmental Protection Agency (2021). Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2019 (https://www.epa.gov/ghgemissions/overview-greenhouse-gases#carbon-dioxide)

[3] EPA. 2020b. U.S. Transportation Sector Greenhouse Gas Emissions. https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey= P100ZK4P.pdf

Introduction

Adopting EVs and HVs reduces greenhouse gas emissions and operational costs

Challenges

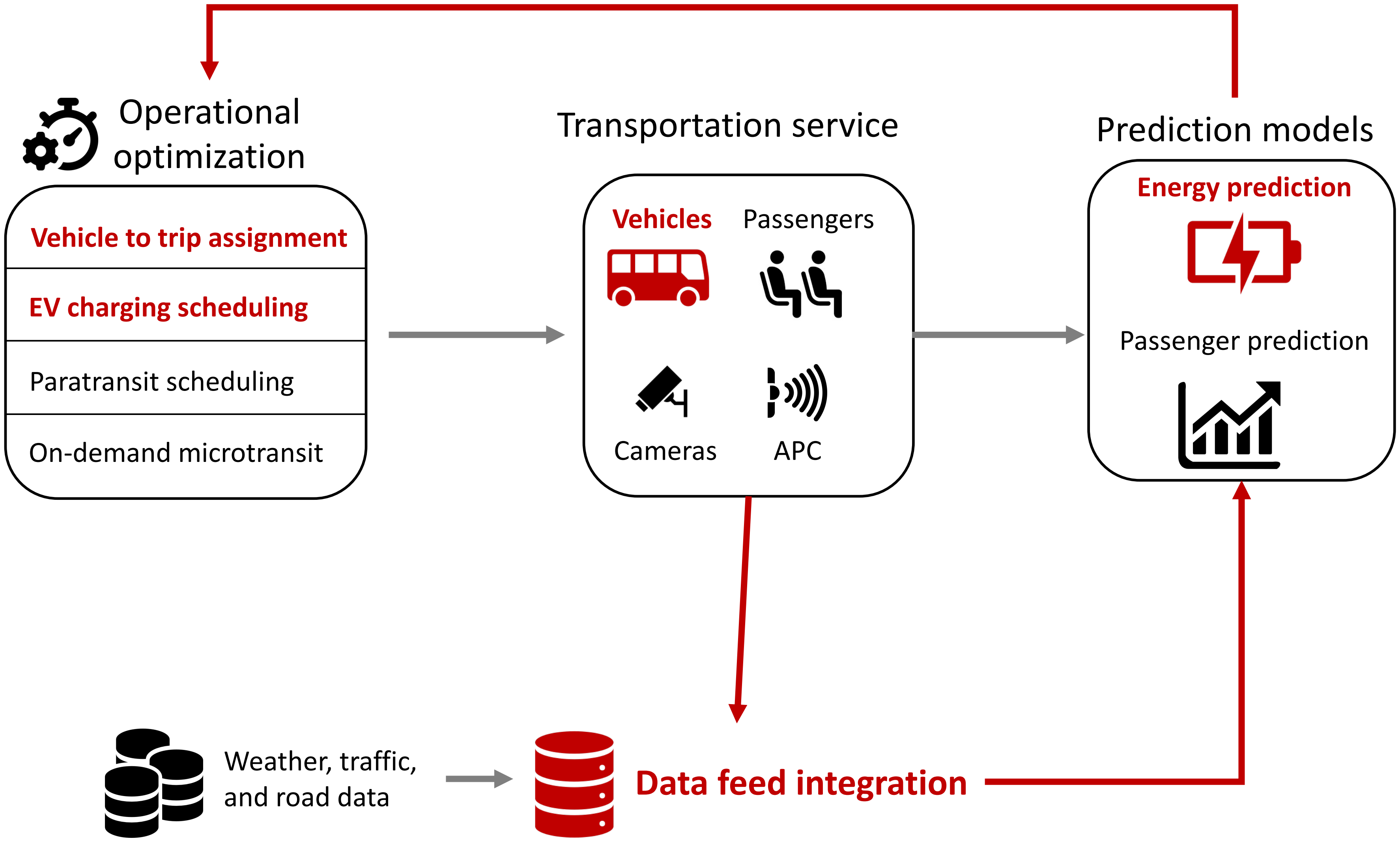
- A new EV costs approximately twice as much as a new ICEV vehicle ($1M, including charging infrastructure)
- Limited battery capacity and driving range
- **Most agencies can only afford a mixed-fleet of vehicles**

ICEV

HV

EV

Optimizing Transit Operations



Our focus is on energy prediction models for ICEVs, HVs and EVs

The Energy Prediction Problem

Prediction Pipeline

Input Features

- Traffic conditions
- Weather
- Roadway features
- Segment

→ **Prediction Models** →

Target: emissions (CO2) or energy (kWh)

- Diesel (ICEV)
- Hybrid (HV)
- Electric (EV)

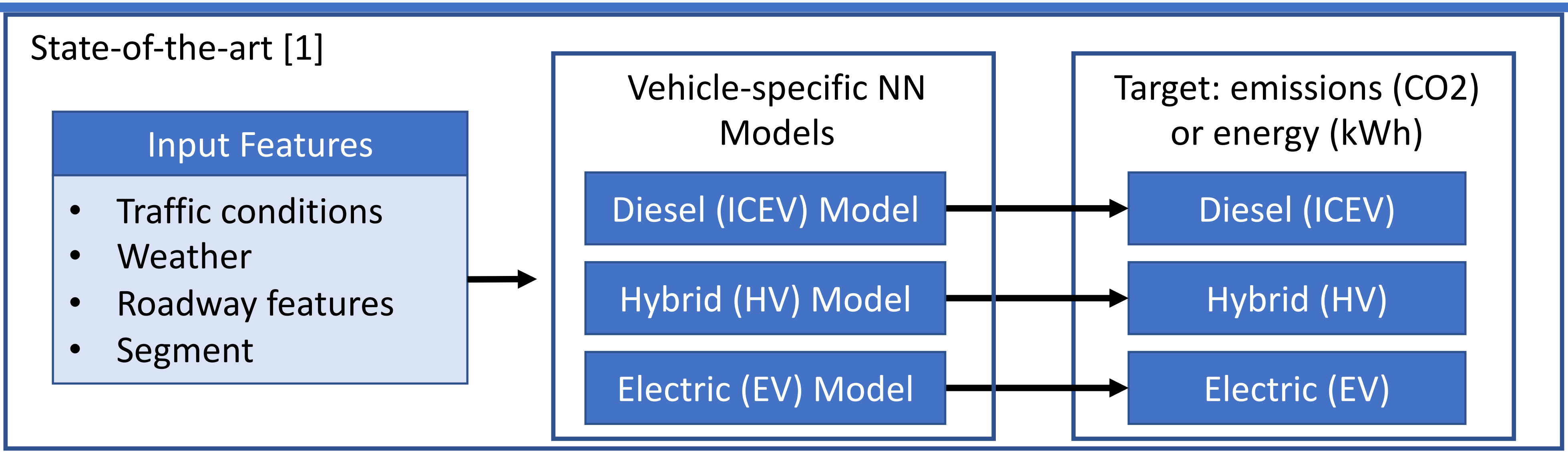
Note: Linear conversion between emissions (CO2) and energy (kWh) [1,2]

Bus Stop

Goal: predict energy along route segments (stretches of roadway between stops)

[1] EIA energy conversion calculator. https://www.eia.gov/energyexplained/units-andcalculators/energy-conversion-calculators.php (2021)
[2] EPA greenhouse gases calculator. https://www.epa.gov/energy/greenhouse-gasesequivalencies-calculator-calculations-and-references (2021)

Real-world Operational Challenges



Insight: Training separate models for each type of vehicle ignores generalizable information that is not explicitly modeled in the feature space.

1. Ayman, Afiya, et al. "Data-Driven Prediction and Optimization of Energy Use for Transit Fleets of Electric and ICE Vehicles", ACM Transactions of Internet Technology, 2020.

Contributions

Scenario

- Transit agency operates many ICEVs, HVs and EVs
- Transit agency has a significant variation in the number of vehicles from each class

Goal

- Improve accuracy of forecasting energy (emissions) prediction for all tasks
- Learn model from task with sufficient data and transfer the learned abstraction to improve accuracy for class with insufficient data

Approach

- Multi-task Learning (MTL)
- Inductive transfer learning (ITL)

Preliminaries and Model Formulation

Three Domains: $\mathcal{D}_{ICEV}, \mathcal{D}_{HV}, \mathcal{D}_{EV}$

- Domain $\mathcal{D}$
- Feature space $\mathcal{X}$ and input samples $\{x_1, x_2, \dots\} \in \mathcal{X}$
- Output space $\mathcal{Y}$ and output samples $\{y_1, y_2, \dots\} \in \mathcal{Y}$
- f is a predictive function over $y \in \mathcal{Y}$ conditional on $x \in \mathcal{X}$
- Task $\mathcal{T} = \{\mathcal{Y}, f(\cdot)\}$

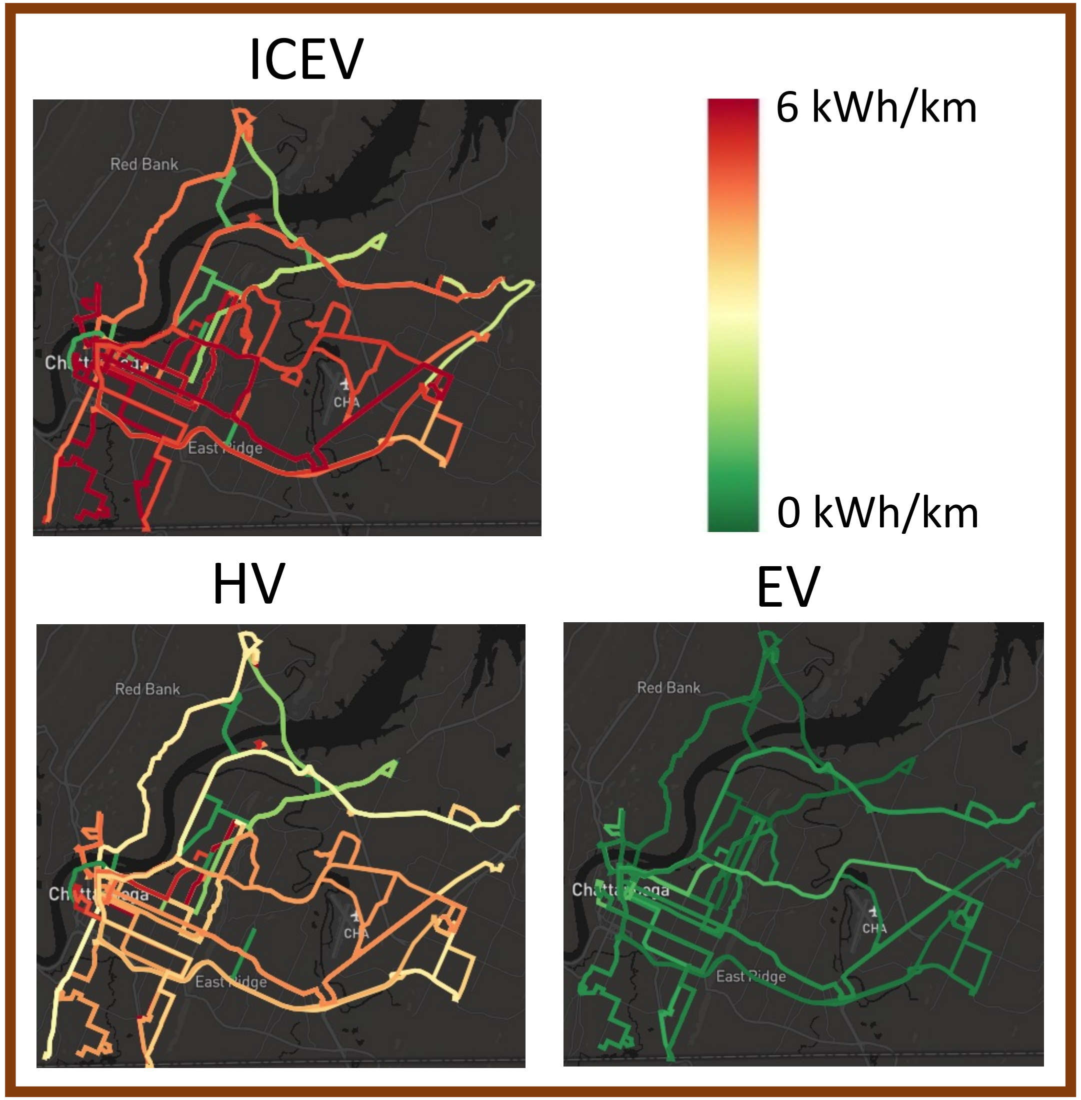
ICEV

HV

EV

Output Space

kWh/km Per Route

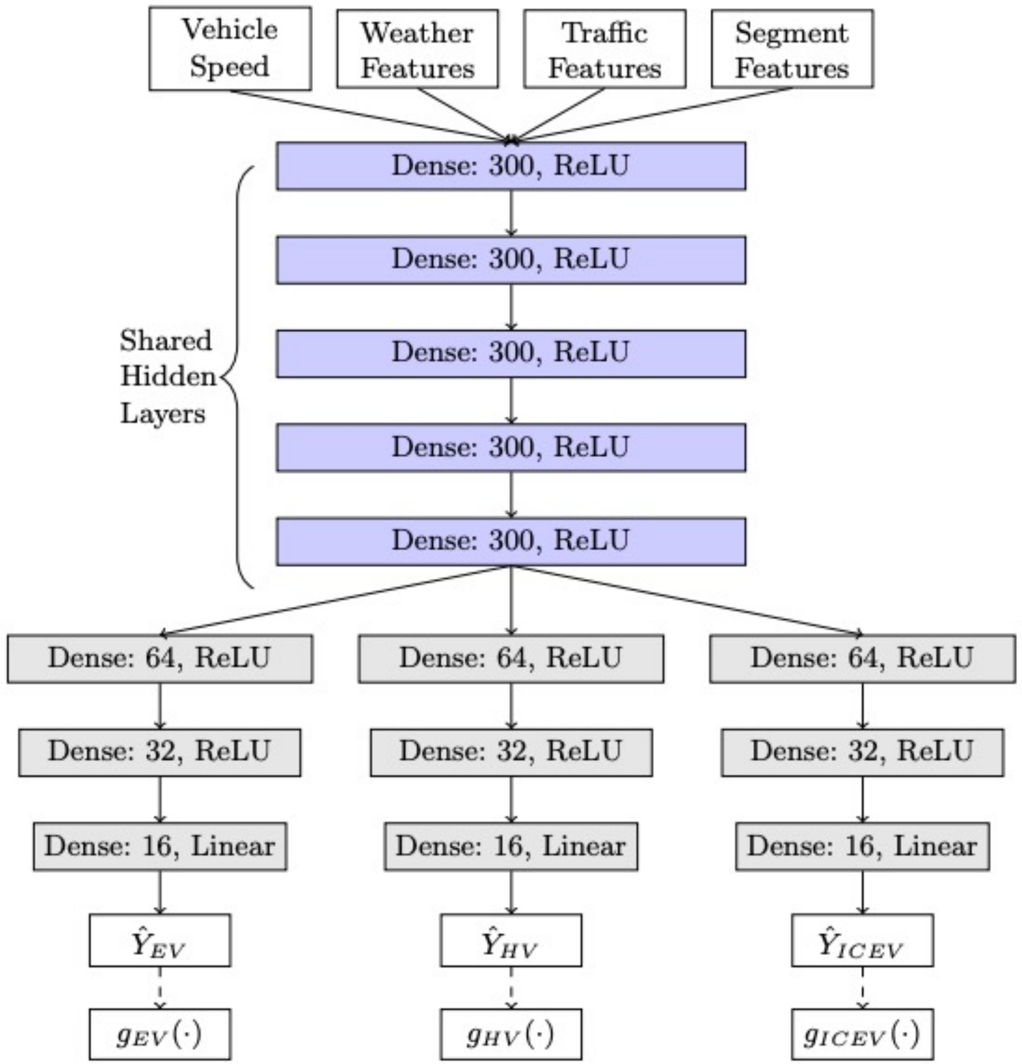


- EVs have regenerative breaking (energy consumed can be negative), while HVs and ICEVs do not
- Each vehicle class responds differently to network conditions
- Therefore, $P(Y_{EV}|X_{EV}) \neq P(Y_{HV}|X_{HV}) \neq P(Y_{ICEV}|X_{ICEV})$

Goal is to learn tasks $\mathcal{T}_{EV} \neq \mathcal{T}_{HV} \neq \mathcal{T}_{ICEV}$ given $\mathcal{D}_{EV} = \mathcal{D}_{HV} = \mathcal{D}_{ICEV}$

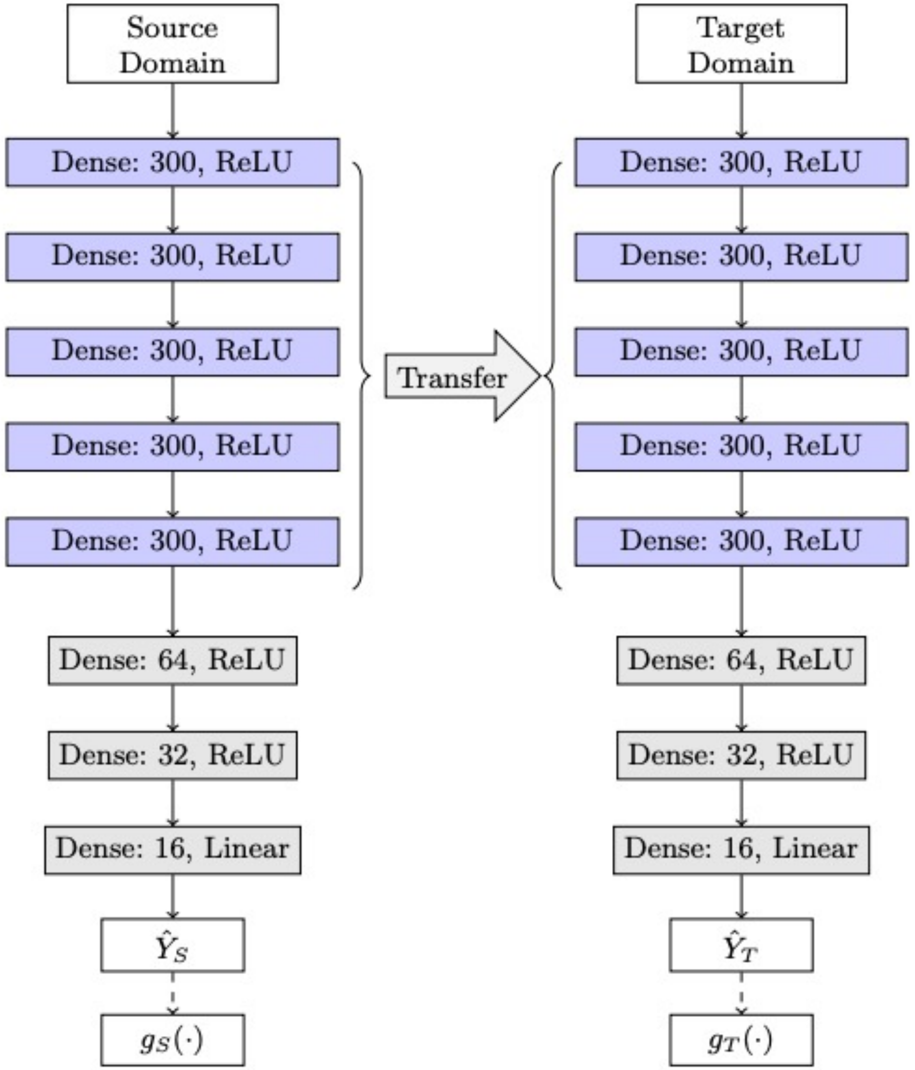
Approach - MTL Model

- Case: transit agency operates many ICEVs, HVs and EVs
- Goal: improve accuracy of forecasting energy (emissions) prediction for all tasks
- Method: hard parameter sharing (shared hidden layers) -> learn generalizable patterns between vehicle classes to improve learning
- Vehicle specific layers



Approach - ITL Model

- Case: transit agency has a significant variation in the number of vehicles from each class
- Goal: learn model from task with sufficient data and transfer the learned abstraction to improve accuracy for class with insufficient data
- Source domain: significant samples available for training
- Target domain: limited samples available for training



Data Collection

Data collected over a 6 months with our partner agency - Chattanooga Area Regional Transportation Agency (CARTA).

Data Sources

Data Source	Description	Features	Frequency	Scope
ViriCiti - ICEVs	vehicle telemetry	fuel, GPS	1 Hz	3 vehicles
ViriCiti - HVs	vehicle telemetry	fuel, GPS	1 Hz	4 vehicles
ViriCiti - EVs	vehicle telemetry	current, voltage, GPS	1 Hz	3 vehicles
Clever Devices	automated vehicle location	trip ID, vehicle ID	0.1 Hz	all vehicles
HERE	traffic (per TMC)	jam factor, current speed, free flow speed	0.016 Hz	major roads, highways
DarkSky	weather	visibility, wind speed, precipitation intensity, humidity, temperature	0.003 Hz	whole city
Static GTFS	transit schedule	routes, trip ID, stop sequences, stop locations, schedule times	static	whole city
GIC - Elevation	LiDAR elevation	location, elevation	static	whole city
Trip Segments	multiple sources	length, time to travel, average speed, roadway type	static	whole city

Challenges in Mapping Trajectories to Segments

Mapping of trajectory data to segments is noisy and computationally challenging

GPS readings are noisy

Spatial Challenges

Overlapping segments: Segments 1 and 5 traverse the same section in opposite directions.

Intersecting segments: Vehicle locations near the intersection of segments 1 and 4 can lead to incorrect mapping. Stops not shown.

Mapping Vehicle Trajectories to Routes

- Trajectory (T): set of GPS coordinates from vehicle
- Route (R): ordered set of route segments
- Route segment (SEG): road segment between two stops
- W : # of lookahead segments
- B: Max distance between segment and vehicle GPS

Goal: map each location $l_i \in T$ to a segment $SEG \in R$

Bus Stop

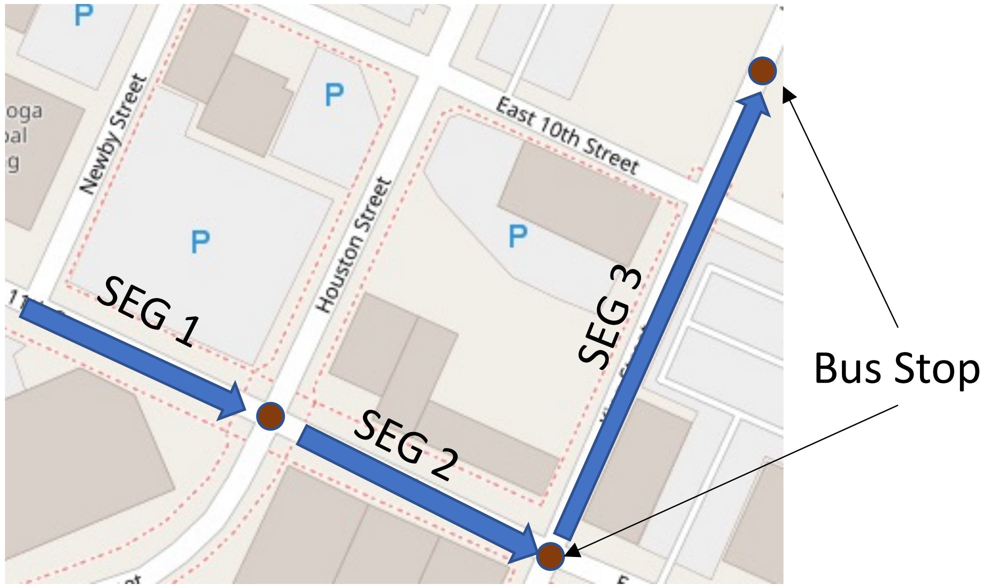
Segments determined from static GTFS routes

Mapping Vehicle Trajectories to Routes

Intuition

- Initalize T, R, W, B
- Set index of current segment ($c = 1$)
- For each GPS point $l_i \in T$ we consider the set $\{SEG_c, \dots, SEG_{c+W}\}$.
- Map l_i to nearest SEG in $\{SEG_c, \dots, SEG_{c+W}\}$.
- Update index of current segment

Short lookahead - alleviates duplicate matches from segments further away in the route and minimizes computational requirements



Data Cleaning and Join

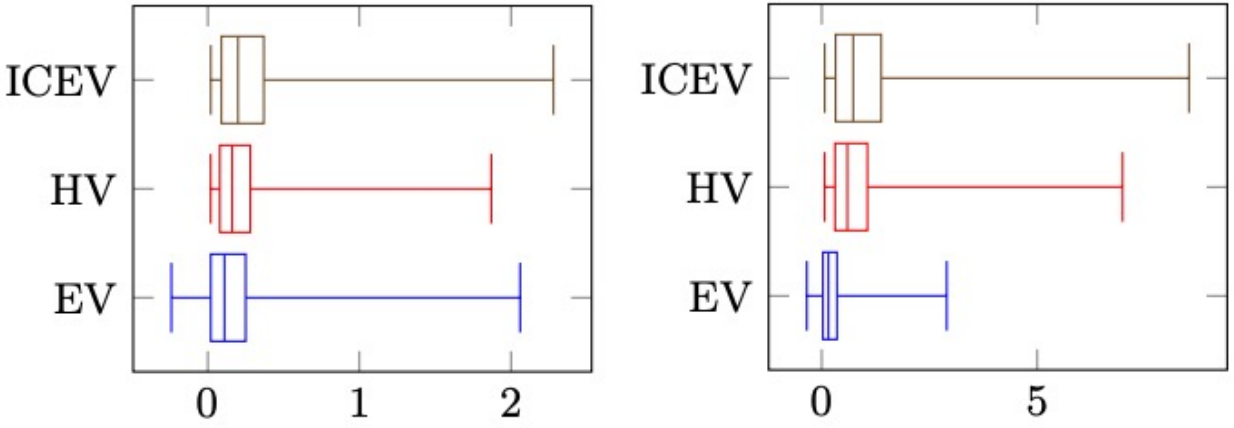
1. Each trip is a trajectory. Trajectories are split between stops using the mapping procedure. Each sample is a portion of a trajectory between two stops.
2. ICEVs and HVs fuel consumed is in liters.
3. EVs provide SOC readings but the precision so too low. Therefore energy consumed is given by: $E_i = A_i * V_i(TS_i - TS_{i-1})$
   1. E_i, A_i, V_i are energy consumed (Joule), current (Ampere) and voltage (Volt) respectively.
   2. TS_i is time (seconds) at timestep i.
   3. To get energy on a segment the energy consumed is accumulated for all locations on that segment.
4. Weather features are taken from the closest weather station at the time in which the vehicle started traversing the segment. Traffic (jam factor, speed ratio) taken when vehicle starts traversing segment.
5. List of input features are provided on slide 19.

Evaluation

- Investigation of covariates for energy (emission) prediction
- Hyperparameter tuning and baseline models
- MTL model evaluation
- ITL model evaluation

Covariates for Energy (emission) Prediction

- ICEVs, HVs and EVs respond differently to some covariates
  - Average speed
  - Change in elevation
  - Temperature



(a) Emissions (kg CO2) (b) Energy consumption (kWh)

Pearson Correlation of input features with emissions

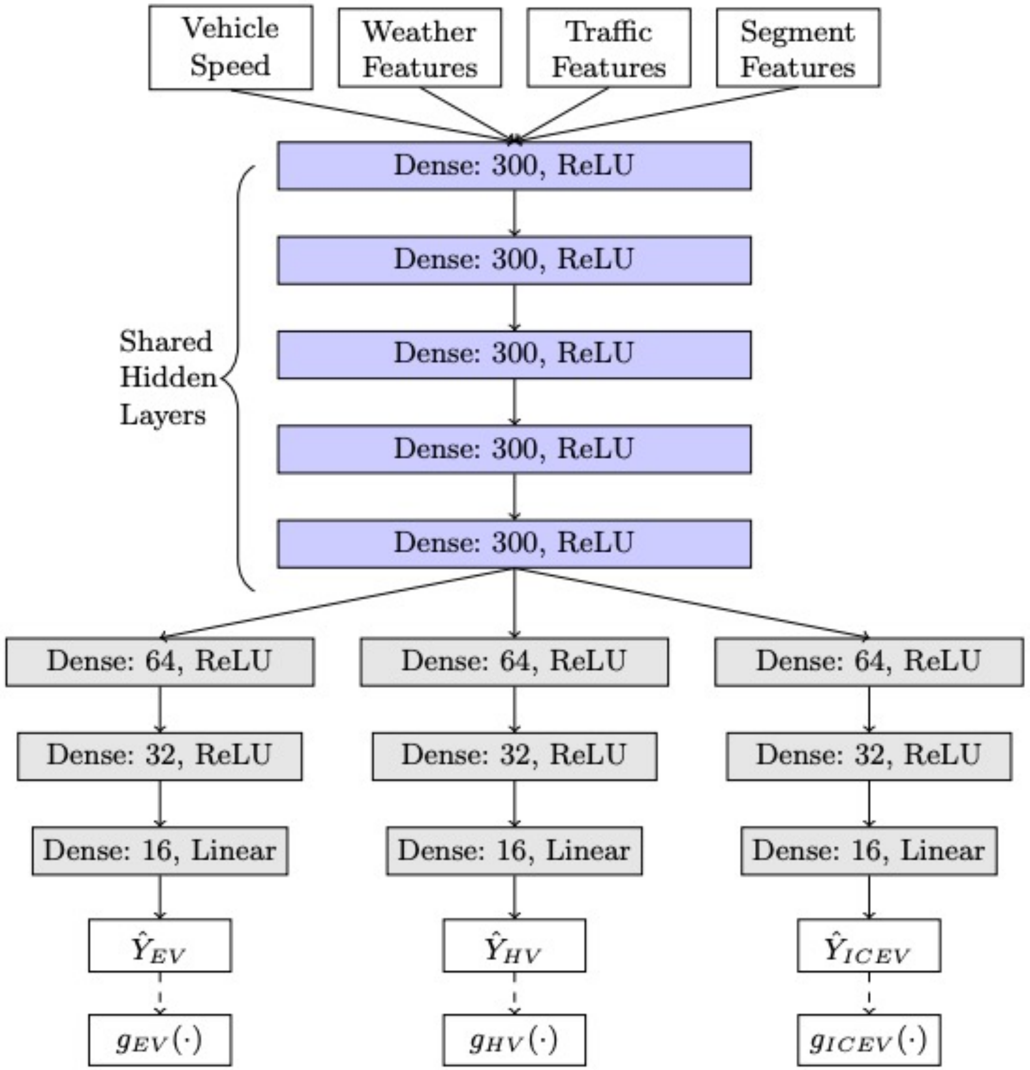
	ICEV	HV	EV
Average Speed	-0.262	-0.134	-0.093
Segment Length	0.886	0.916	0.860
Time to Travel	0.865	0.838	0.752
Change in Elevation	0.539	0.505	0.523
Max Elevation Change	0.103	0.135	0.222
Speed Ratio	0.028	0.038	0.038
Jam Factor	-0.016	-0.026	-0.015
Temperature	-0.005	0.013	-0.037
Precipitation	-0.005	-0.008	-0.003
Visibility	0.004	0.006	0.008
Wind Speed	0.011	0.004	-0.002
Humidity	0.001	-0.008	-0.009
Wind Gust	0.000	-0.002	-0.012

Evaluation - Hyperparameter Tuning and Baseline Models

Hyperparameter Tuning

- Randomly select 43,022 samples from each vehicle class
- 80% of the samples for training and 20% for testing
- 10% of training samples used for evaluation
- Tested shared hidden layer widths of {200, 300, 400} and shared hidden layer depths of {3, 4, 5}
- Tested learning rates of {0.01, 0.005, 0.001, 0.0005, 0.0001}
- Tested batch sizes of {64, 128, 256, 512}
- MSE loss function, ReLU activation, linear output
- Adam optimizer

Baseline models: vehicle-specific neural networks



MTL Evaluation

Experiment Setup

- Baselines: vehicle-specific neural networks
- 80% train (10% used for evaluation) and 20% test
- 10 MTL models trained (30 total baseline, 10 in each class)

Percent Improvement Over Baselines

- ICEVs: 8.6% (MSE) 6.4% (MAE)
- HVs: 17.0% (MSE) 9.0% (MAE)
- EVs: 7.0% (MSE) 4.0% (MAE)

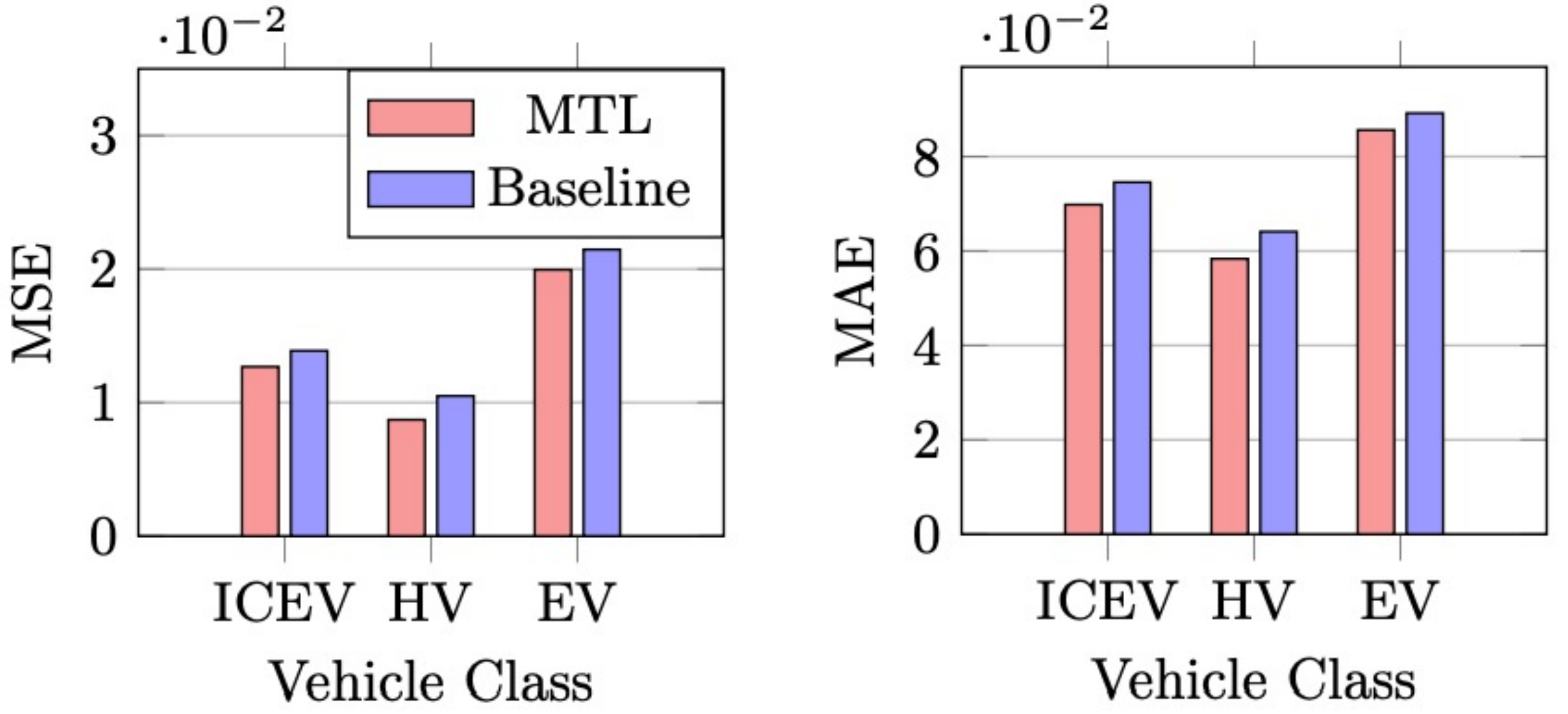


Fig. Average MSE and MAE of MTL model compared to baseline on testing set. Prediction target: emissions (kg CO2)

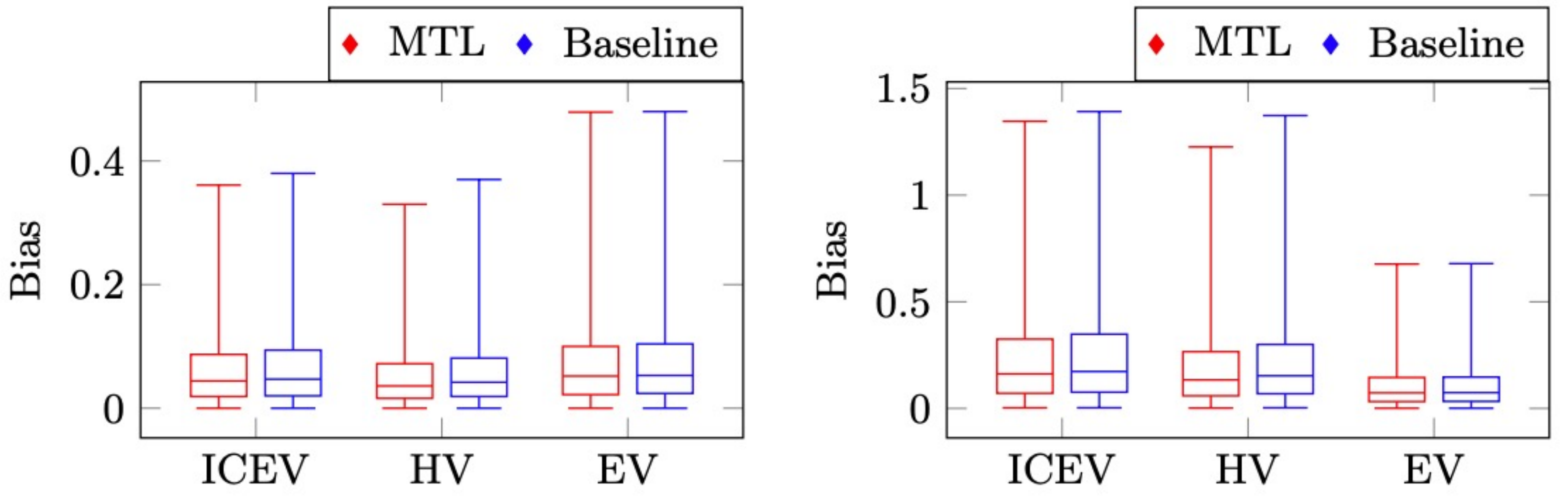
MTL Evaluation

Experiment Setup

- Baselines: vehicle-specific neural networks
- 30 datasets generated through bootstrapping

Mean Percent Improvement Over Baselines

- ICEVs: 5.1% (Bias)
- HVs: 10.8% (Bias)
- EVs: 1.0% (Bias)



(a) Emissions (kg CO_2) (b) Energy (kWh)

Fig. Distribution of MTL and baseline model bias per sample for each vehicle class from bootstrap evaluation, 30 bootstrap iterations. Prediction target: (a) emissions and (b) energy.

ITL Evaluation

- ITL model is trained on full dataset in the source vehicle class and is evaluated on the target vehicle class (source -> target)
- Improved forecasting accuracy for all target classes when ICEV and HV used as source
- Negative transfer EV -> ICEV

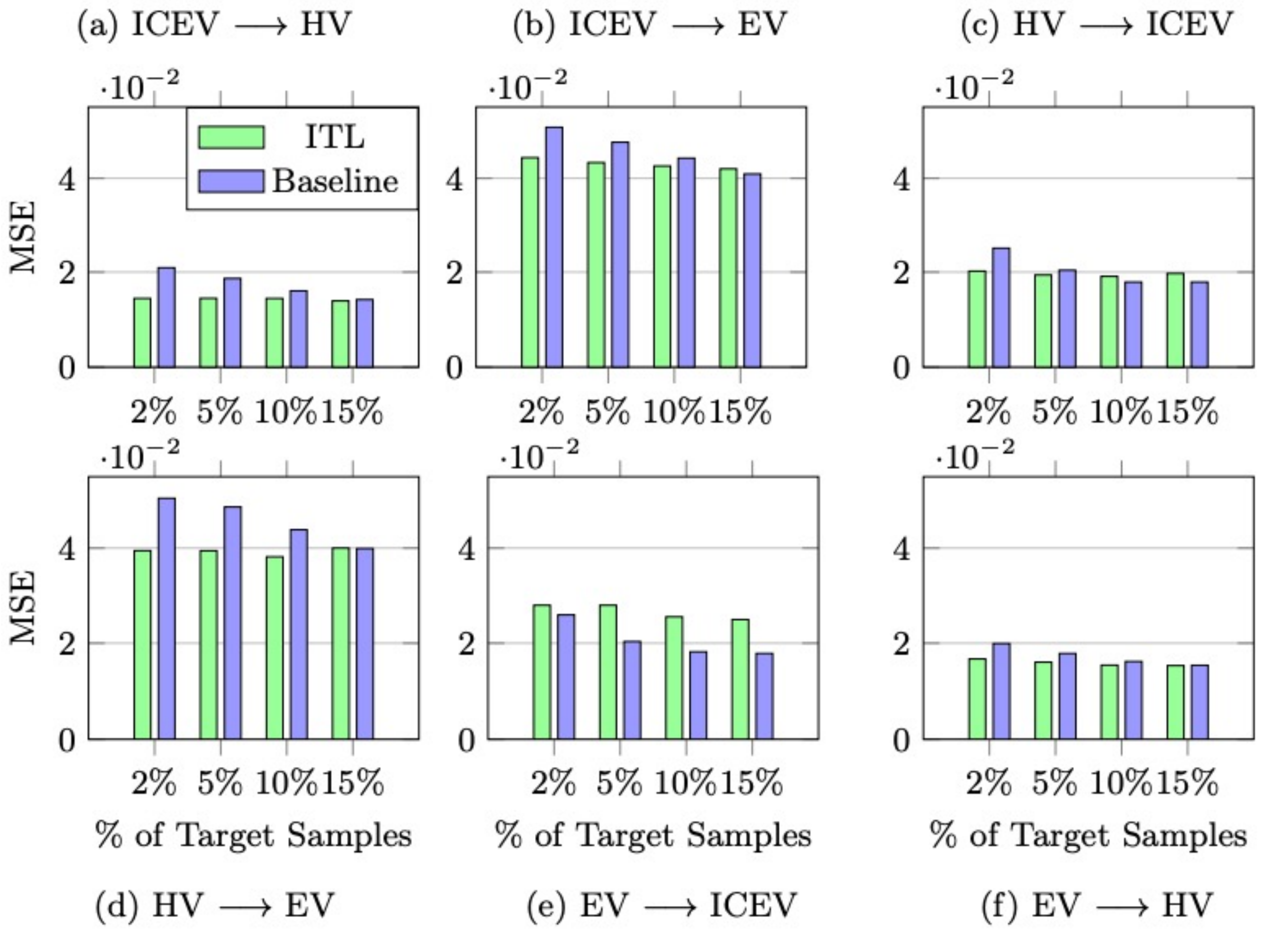


Fig. : ITL models compared to corresponding baselines. Average MSE compared to fraction of data samples used for training in the target vehicle class. Prediction target: emissions (kg CO2)

t-SNE Investigation of ITL Model

- t-SNE parameters: number of components=2, perplexity=10, initialization=PCA, number of samples=860 (2% of dataset)
- Fig 1: t-SNE on raw input features for each data sample from the source domain.
- Fig 2: t-SNE on the output of shared-hidden layers for each data sample from the target domain.

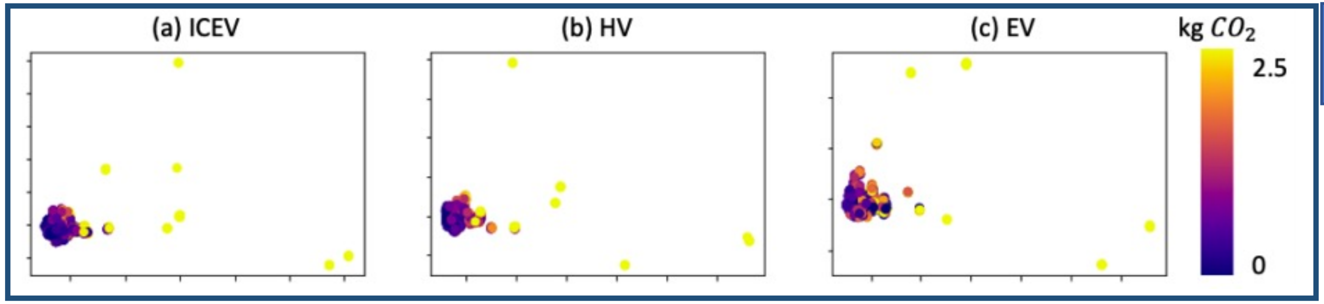


Fig. 1

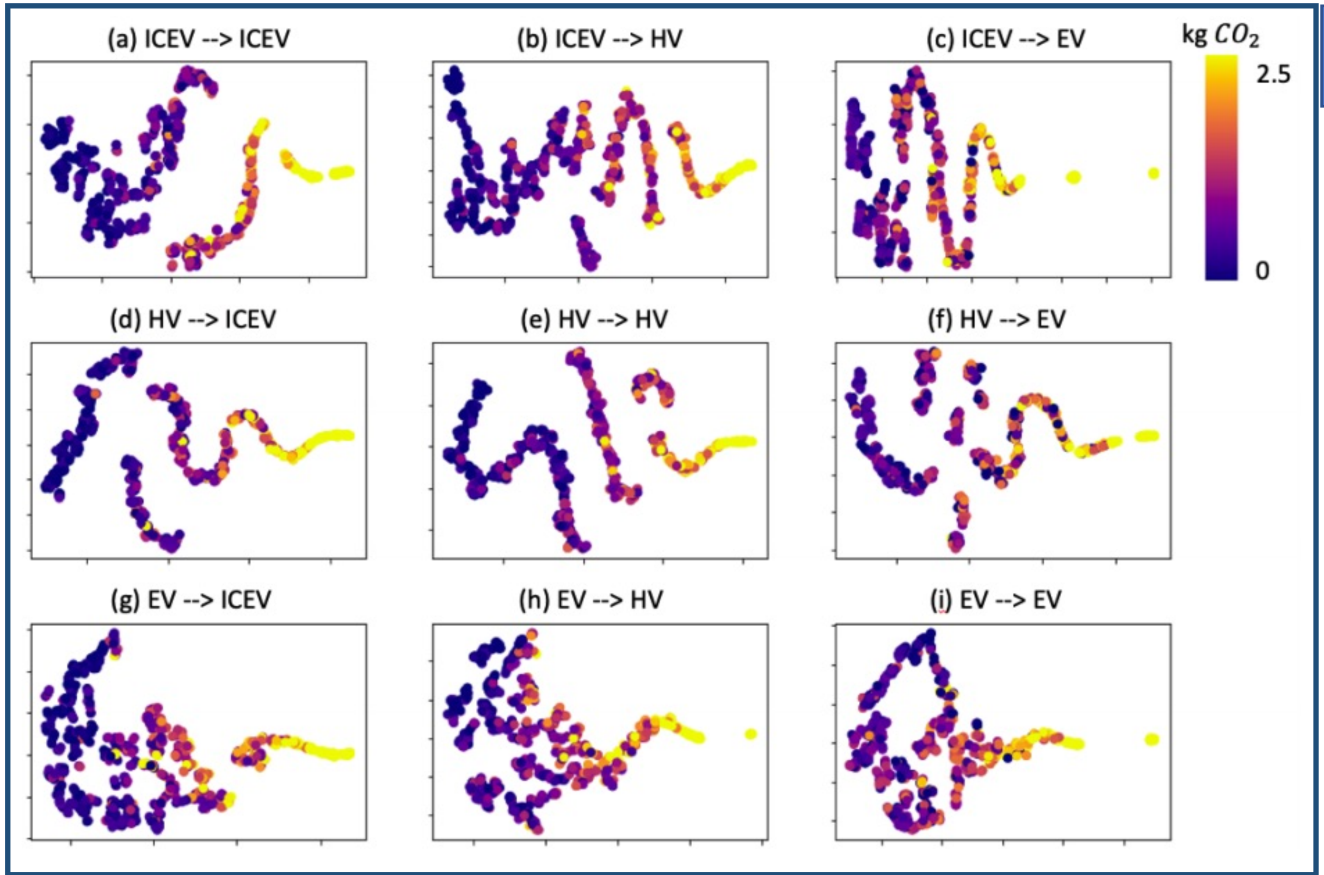
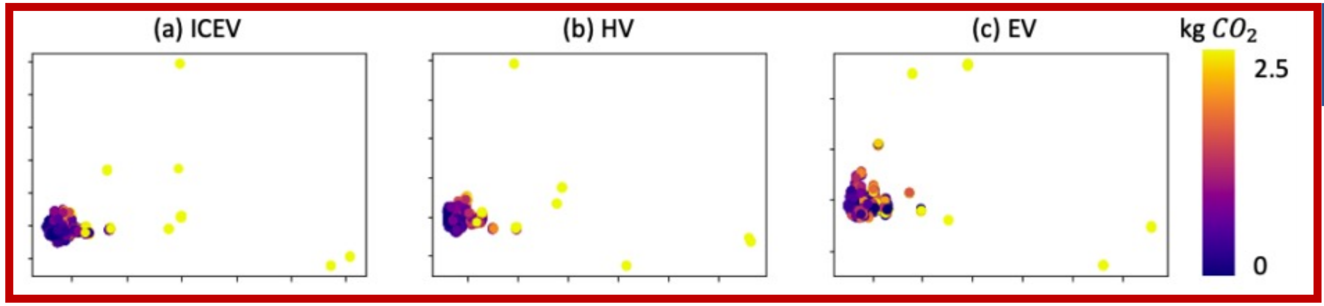


Fig. 2

t-SNE Investigation of ITL Model

- **Fig 1 (a-c) all three plots on the raw input features are similar, collaborating that input features are similar across tasks**
- Fig 2 (a-f) effectively discriminate the samples with high emissions and low emissions
- Fig 2 (g-i) EV source model shows poor discrimination, reflecting the negative transfer



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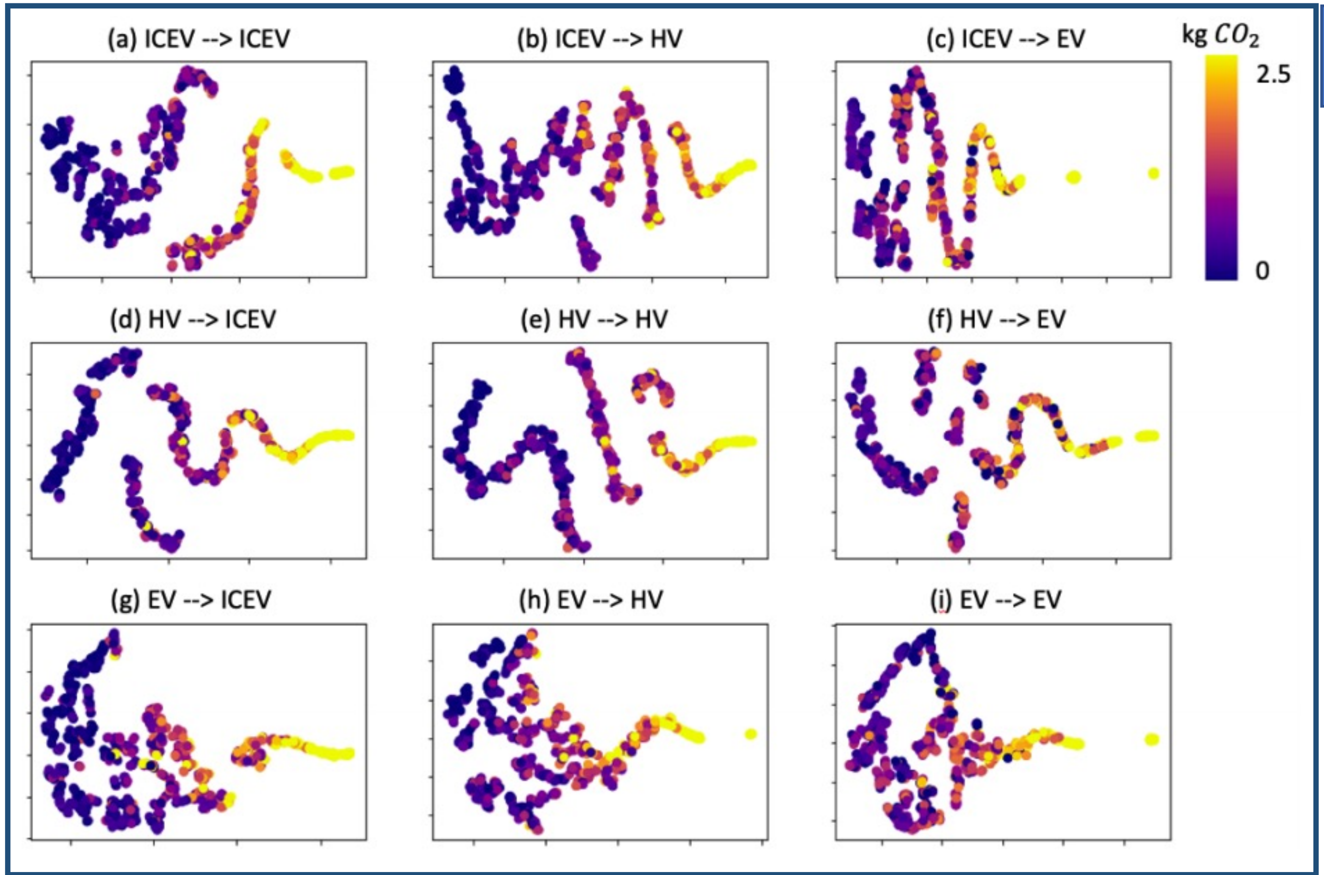

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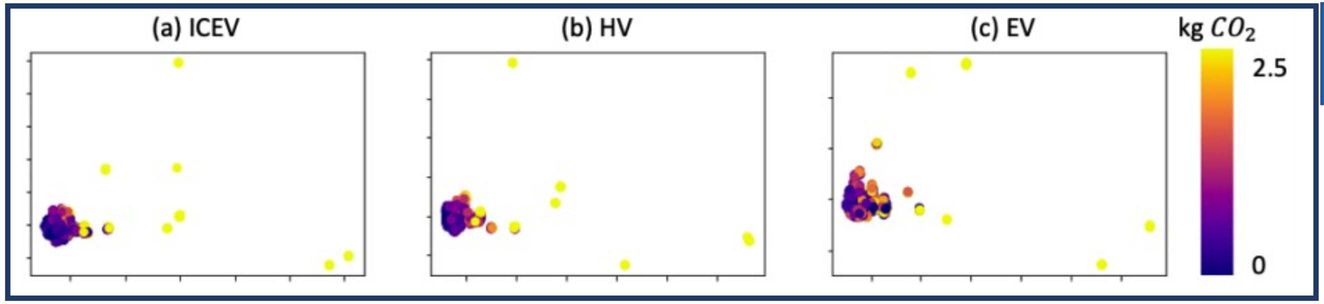

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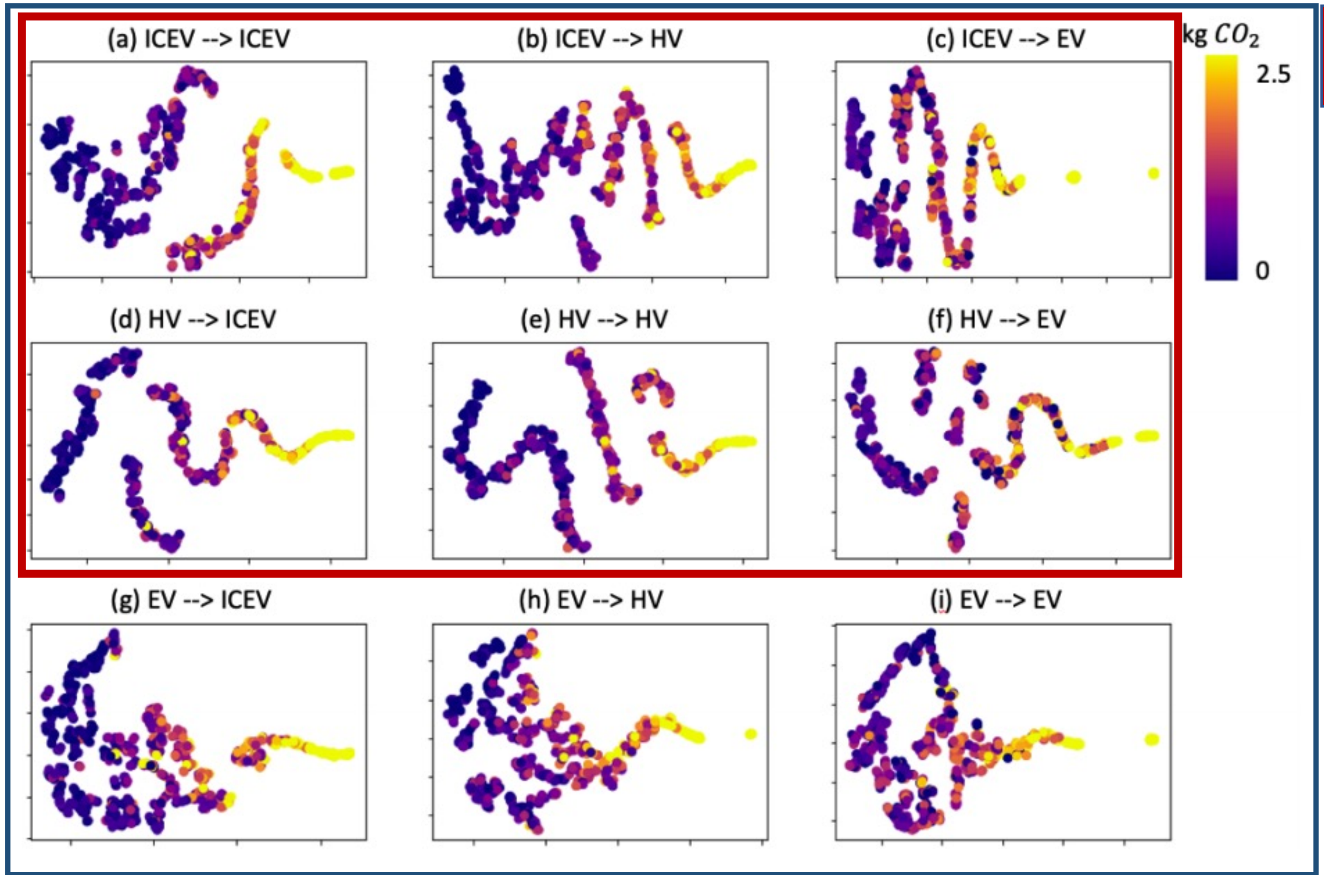

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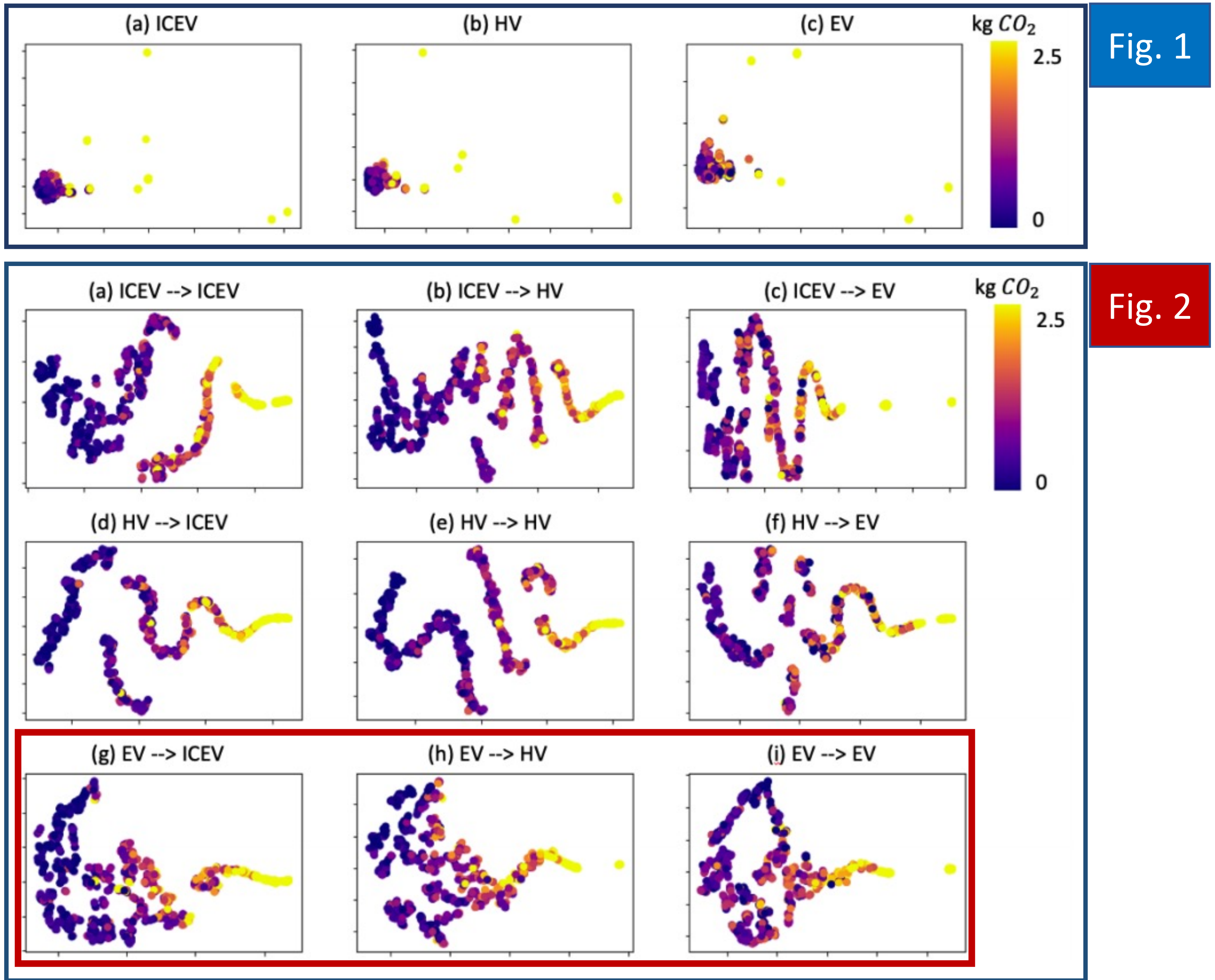

Discussion and Conclusion

Scenarios Addressed

- We presented an MTL solution for the case when transit agency operates many ICEVs, HVs and EVs
- We presented an ITL solution for the case when transit agency has a significant variation in the number of vehicles from each class

Key Findings

- MTL improves prediction accuracy and reduces bias
- ITL is most effective when data is limited in target class
- EV energy (emissions) is harder to predict than HV and ICEV
- Negative transfer when EV is source and ICEV is target, though this situation rarely arises in practice