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

Michael Wilbur, Ayan Mukhopadhyay, Sayyed Mohsen Vazirizade, Philip Pugliese, Aron Laszka, Abhishek Dubey

ECML PKDD 2021
VIRTUAL
13-17 September

UNDERSTANDING THE PROBLEM

- In U.S., transportation accounts for 35% of CO_2 emissions and 28% of energy consumption. Public transportation is responsible for 21.1 million metric tons of CO_2 each year.
- For fixed line bus systems, adopting electric vehicles (EVs) and hybrid vehicles (HVs) reduces greenhouse gas emissions and long-term operational costs.
- However, EVs and HVs have high upfront costs and must be integrated into existing diesel (ICEV) fleets.
- **Therefore, most agencies are tasked with managing a mixed-fleet of ICEVs, HVs and EVs.**

ICEV HV EV

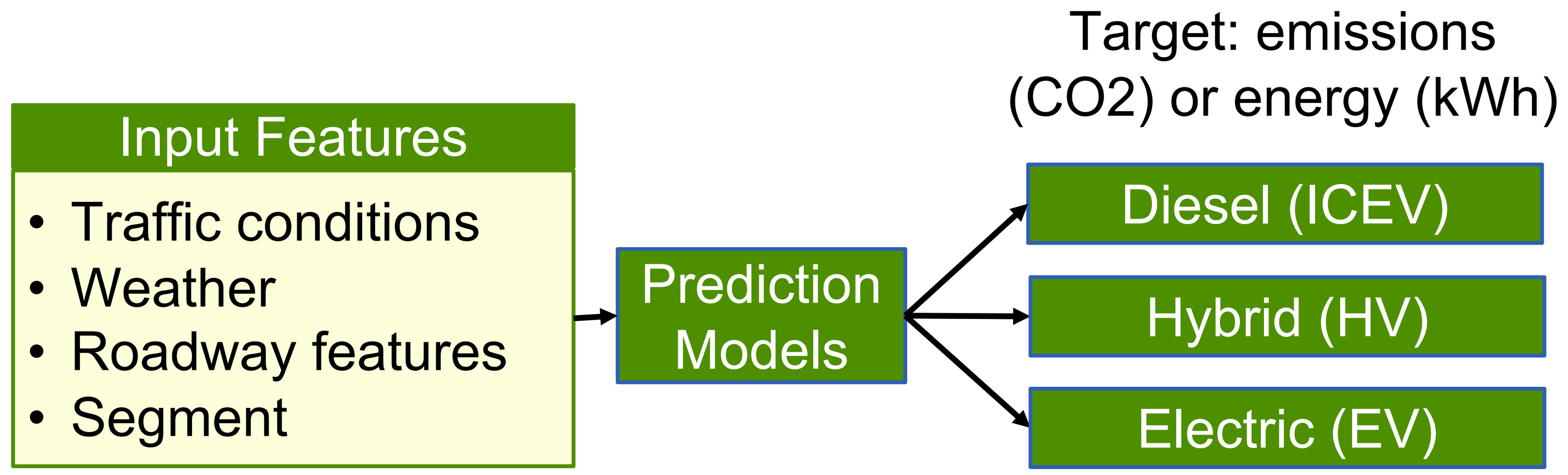

Fig. 1 – The energy prediction problem. The goal is to predict emissions (CO2) or energy (kWh) for each vehicle class along a stretch of roadway.

- **State-of-the-art:** train separate neural network models for each vehicle class.
- **Insight:** training separate models for each type of vehicle ignores generalizable information that is not explicitly modeled in the feature space.

APPROACH

- We are focused on two specific scenarios faced by transit agencies managing mixed-fleets.

Scenario 1

- Transit agency operates many ICEVs, HVs and EVs.
- **Goal:** improve accuracy of forecasting energy (emissions) prediction for all tasks.
- **Approach:** MTL

Scenario 2

- 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
- **Approach:** ITL

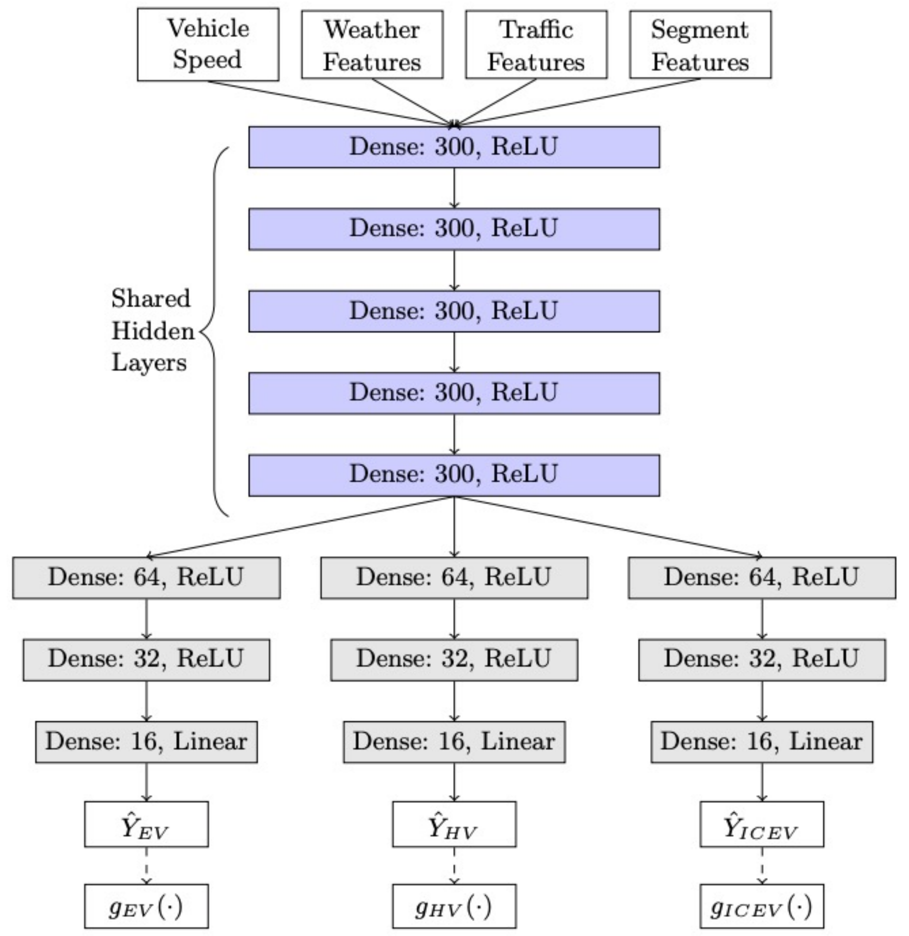

Fig. 2a – MTL Model

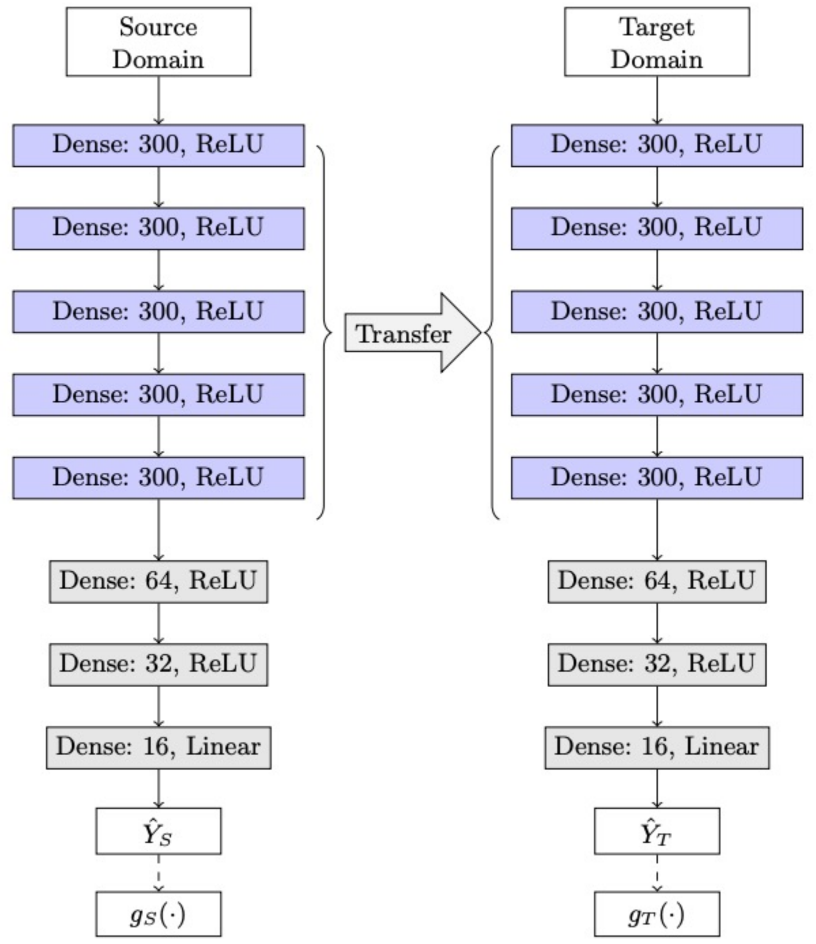

Fig. 2b – ITL Model

DATA AND MODEL BASELINES

- Data collected over a 6 months with our partner agency the Chattanooga Area Regional Transportation Agency (CARTA).
- Vehicle telemetry data from ViriCiti and CleverDevices.
- Weather from DarkSky, traffic from HERE.
- Baseline models: vehicle-specific neural network models.

MTL - EVALUATION

- **Experiment 1:** 80% train and 20% test, train 10 models and compare average improvement in MSE and MAE (Table 1).
- **Experiment 2:** 30 datasets generated through bootstrapping, get average bias per sample.

Table 1 - % improvement MTL vs baselines

Vehicle Type	MSE	MAE	Bias
ICEV	8.6%	6.4%	5.1%
HV	17.0%	9.0%	10.8%
EV	7.0%	4.0%	1.0%

ITL - EVALUATION

Table 2 - % improvement (MSE) when 2% of data available in target class

Source	Target	Improvement
ICEV	HV	31%
ICEV	EV	13%
HV	ICEV	19%
HV	EV	22%

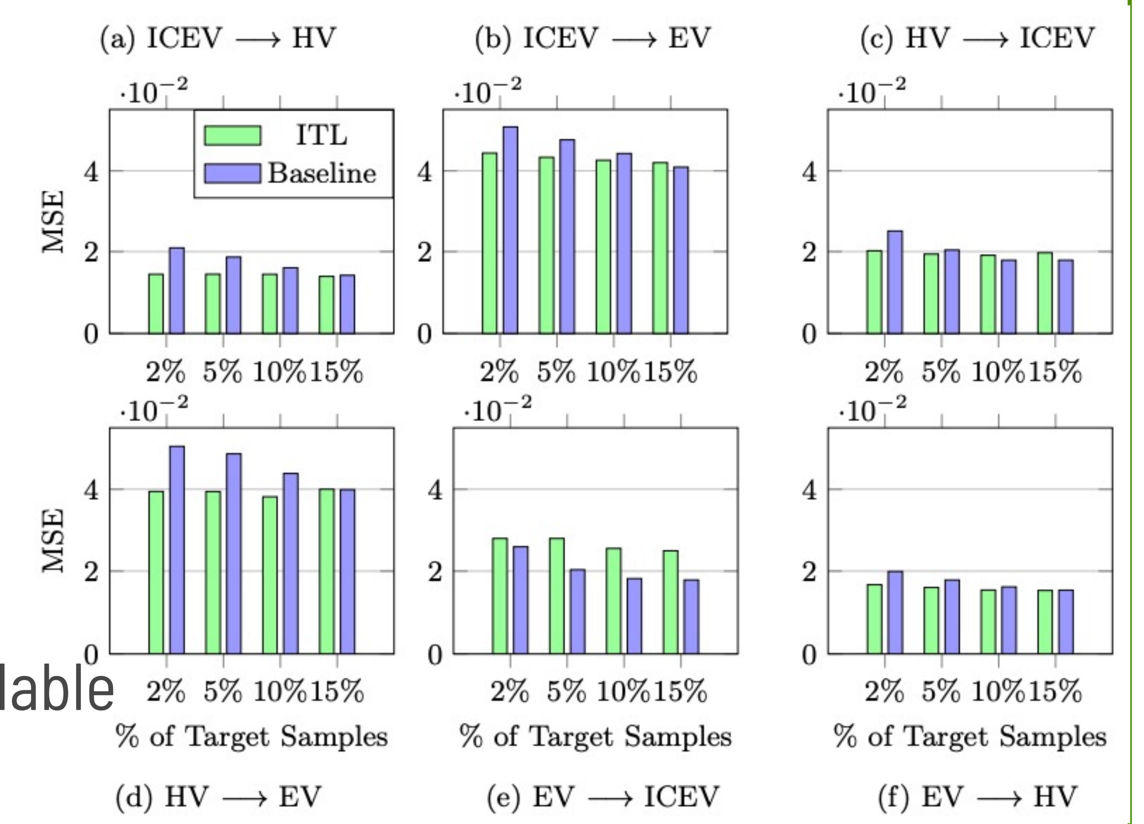

Fig. 3 - Average MSE compared to fract of data samples used for training in the target vehicle class (source -> target).

- Train model on full data available in source domain.
- Vary data available in target domain from 2% - 15%.
- Improved forecasting accuracy for all target classes when ICEV and HV used as source.
- Negative transfer EV -> ICEV.

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.

Corresponding author email: michael.p.wilbur@vanderbilt.edu

This material is based upon work supported by the National Science Foundation under grant 1952011 and Department of Energy, Office of Energy Efficiency and Renewable Energy (EERE), under Award Number DE-EE0008467.