Reliable Energy Consumption Modeling for an Electric Vehicle Fleet

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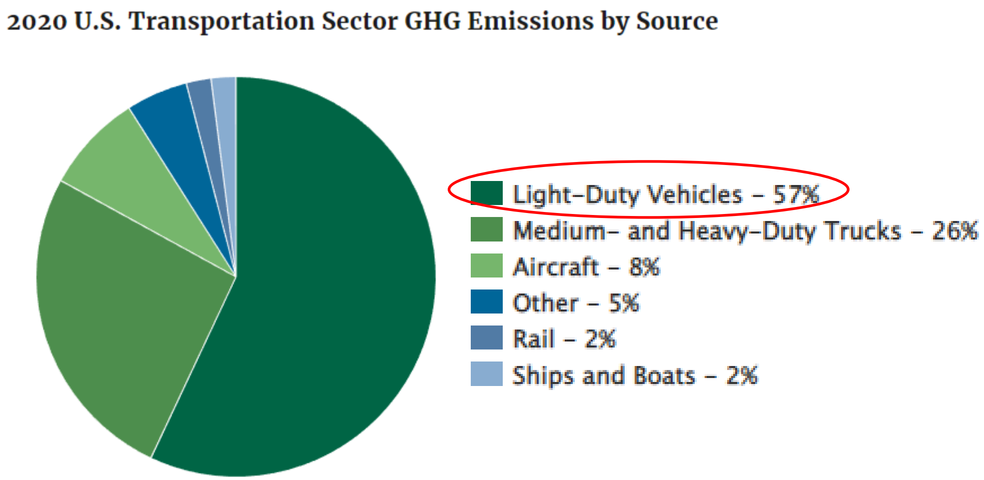
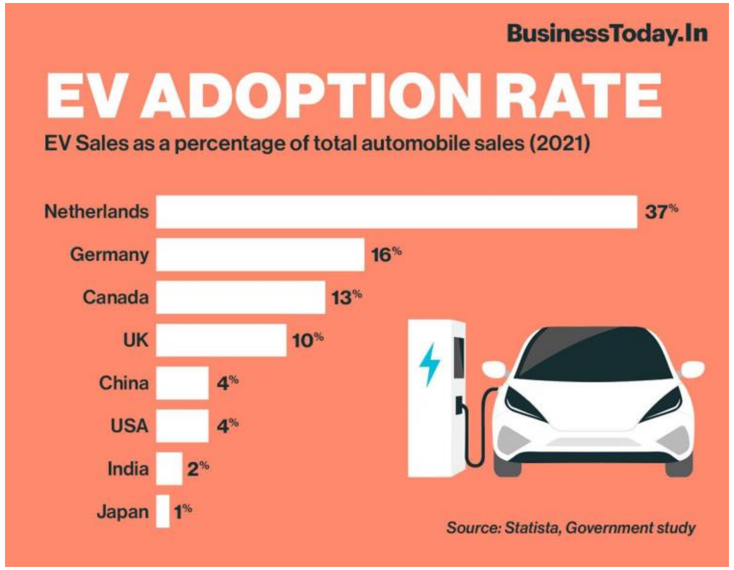
Electric Vehicles

- Transport has the highest reliance on fossil fuels of any sector and accounts for 27% of CO_2 emissions

- Numerous government incentives and support to accelerate adoption of Electric Vehicles

- But, still there are several concerns:
  - limited driving range per charge,
  - long charging time,
  - battery replacement cost,
  - battery technology,
  - limitations related to infrastructure.





Limited Driving Range

At the end-user Level:
(Range Anxiety)

Naïve Solution:

- Increase battery capacity
- Increase no. of charging stations

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At the organizational Level:
(Planning Dilemmas)

- Route Planning and logistics
- Driver Planning
- Battery Sizing
- Maintenance Planning
- Bidding Prognostics for a particular route segment

EV's Energy Consumption estimation and modeling is crucial

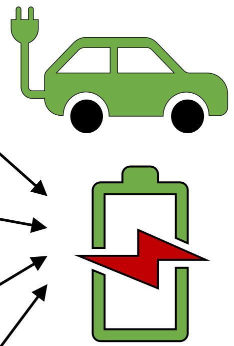
Energy Consumption Modelling is non-trivial

Driving Behaviour factors- harsh acceleration/ braking, KE Loss

External traffic factors - peak /off-peak, trip duration, stop duration, number of stops

Vehicle internal factors – motor efficiency, initial battery SoC

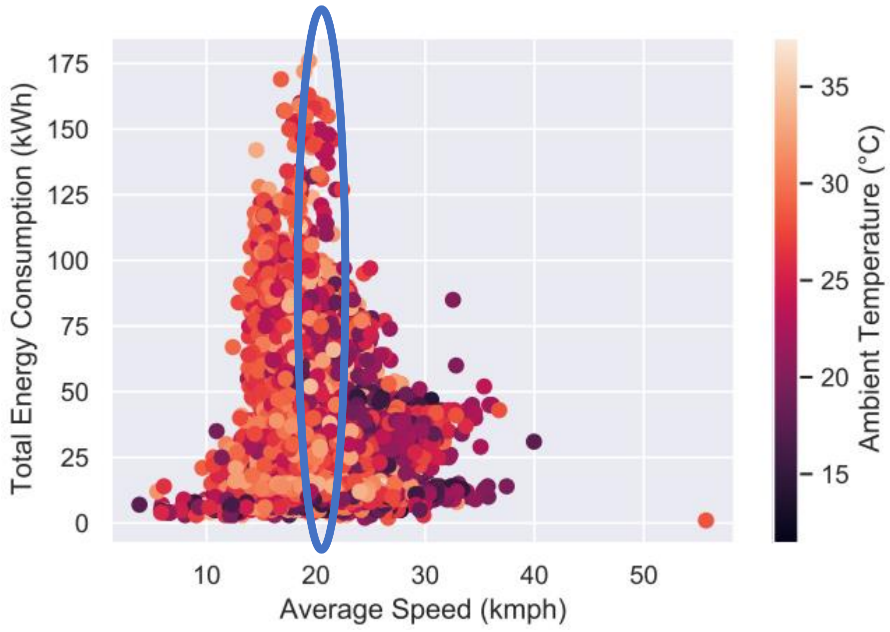
HVAC load - ambient temperature, diff of ambient and saloon



Battery Energy Consumption

Challenges:

1. Limited parameter observability
2. Modeling a subset of features by itself is not a good indicator of energy consumption levels.



Problem Statement

Accurately predict Total Energy Consumption by using information available only prior to the start of a trip

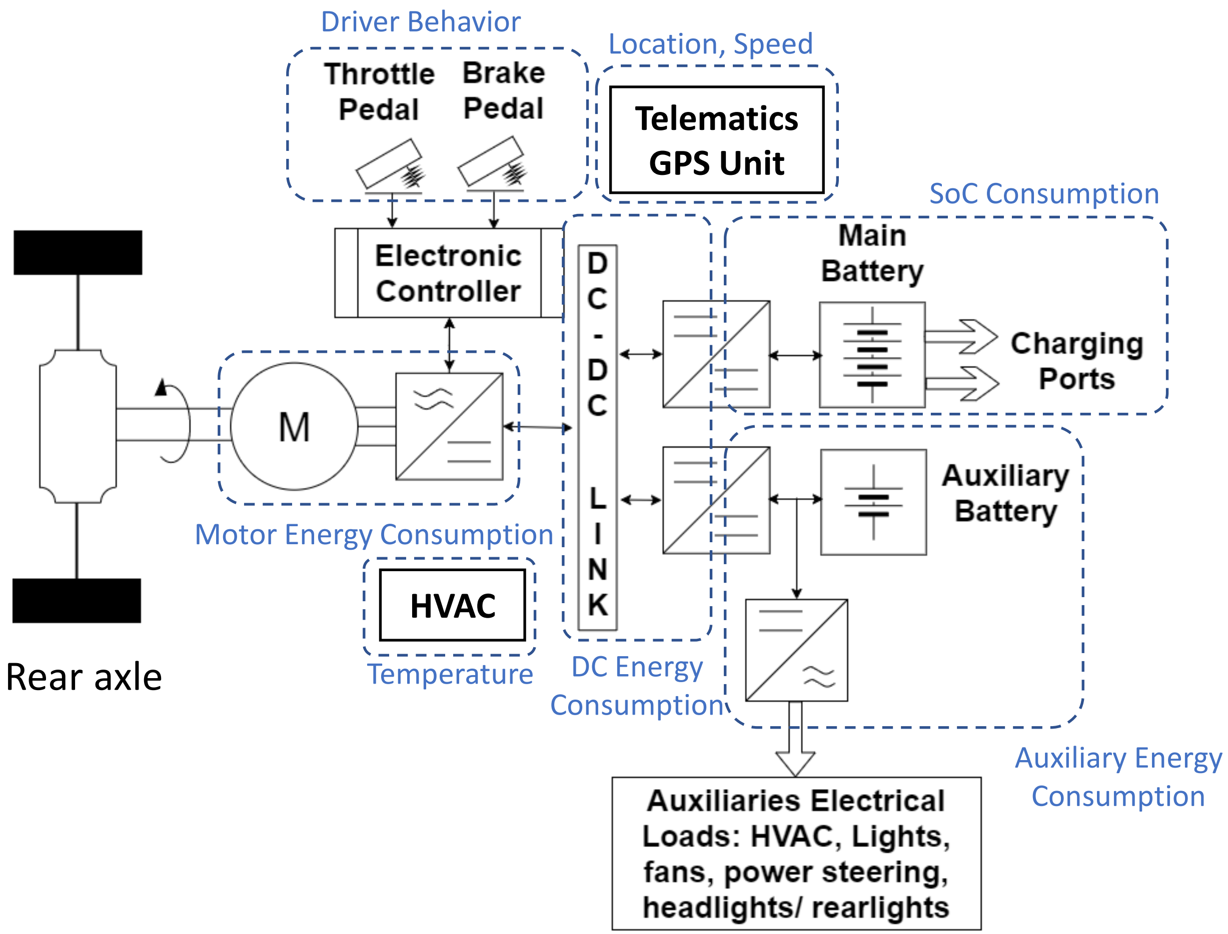
Our Solution:

- **Data-centric:** Derive all the features that directly or indirectly affects vehicle's energy consumption based on domain knowledge and vehicle telemetry.

- **Two-stage:**
  - **Stage- 1 (pre-trip):** Derive the features which are available prior to a trip. e.g., distance, time, etc.
  - **Stage -2 (on-trip):** Estimate the features for the trip using historical data**.** e.g., driving behavior- harsh braking

  We **combine both pre-trip and estimated on-trip features** to predict the "*Total Energy Consumption prior to the start of a trip*".

Electric Vehicle Schematic



Intuitive Features/Labels	Data Logged in Vehicle
Motor Energy Consumption	• Motor input voltage • Motor input current
DC Energy Consumption	• Energy consumed in DC-DC converter and links
Auxiliary Energy Consumption	• Aux. Batt. Pack Voltage • Total aux. input current
Driver Behavior	• Throttle & Brake pedal positions • Pedal Pressure values
Location/Distance	• Latitude • Longitude • Vehicle odometer • GPS odometer
Speed	• Tachometer based wheel speed • GPS speed
Temperature from Heating, Ventilation & Air Conditioning	• Ambient Temperature • Saloon Temperature
Battery Energy Consumption	• Battery State of Charge (SoC) • Battery Status • Battery Pack Voltage • Battery Pack Current

Feature Selection

Logged features: These available apriori and can be logged during a trip

- **Trip time:** Difference of timestamps at the beginning and end of the trip.
- **Trip distance**: Summation of the Haversine distances between 2 geospatial points of 6s apart recorded as GPS attributes (lat, long) over the whole trip.
- **Average speed**: Mean wheel-based speed (tachometer) for the vehicle.
- **Ambient temperature**: Mean ambient temperature for the trip
- **Saloon temperature**: Mean temperature inside the bus indicating the usage of HVAC system.
- **Consumed state of charge**: Records the charge depletion of the high voltage battery during the trip. Difference of states between starting and end of a trip
- **DC-DC energy consumption**: Total Energy lost in switching activity of the battery voltage to HVDC to run the motor drive.
- **Auxiliary energy consumption**: Total Energy consumed by the auxiliary devices in the vehicle.
- **Motor energy consumption**: Total Energy fed as input to the AC motor.

Engineered Features

- **Traffic conditions:**

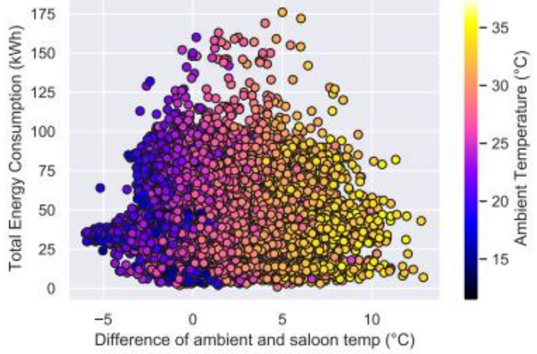
  Time of Day (TOD), Peak/off-peak Hours, Number of stops, Stop Duration.

- **Driver behavior:**

  Speed categories, regenerative braking energy, kinetic energy loss due to deceleration, kinetic energy gain due to acceleration, harsh acceleration counts, harsh braking counts, over speeding counts.

- **Geography :**

  Difference in altitude



- **Environmental conditions :**

  Difference between ambient and saloon temp.

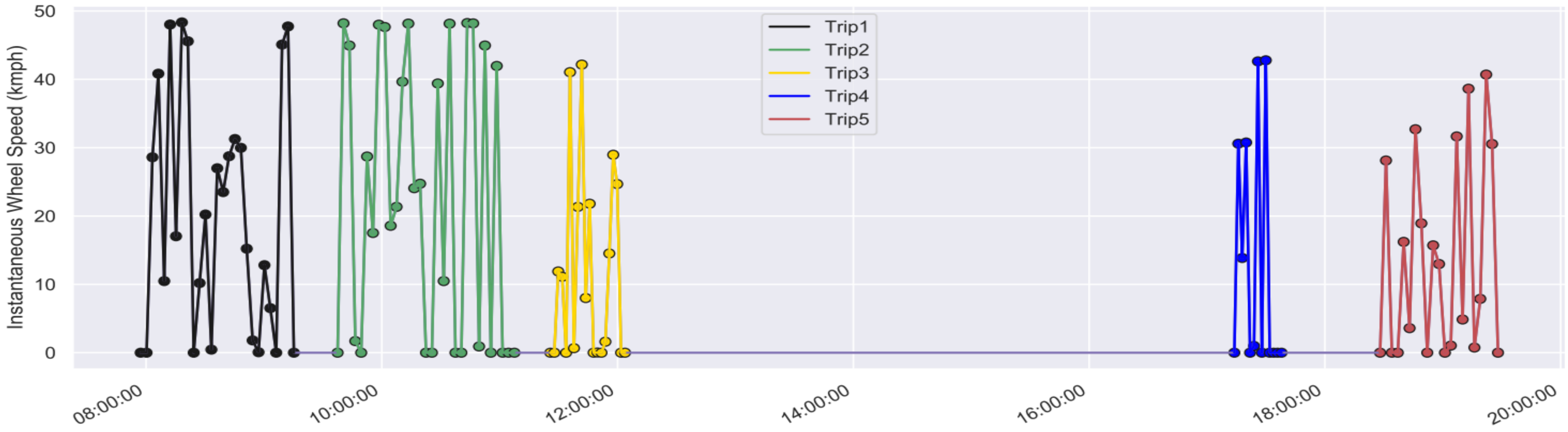
- **Travel specifications:**

  Trip length range, initial state of charge of battery before the start of the trip, efficiency of the motor.

Our Dataset Overview & Trip Definition

- Fleet of ***27 electric buses***
- Distance Coverage of ***460,000 km*** (having ***14413 trips***)
- Time series granularity of ***6 seconds***.

A "trip" is defined as a period of vehicle data where the ignition is on and it has less than 15 minutes of stops, i.e, we instantiate a new trip if the vehicle stops for more than 15 minutes (continuously) while travelling on a route.



Evaluation Metrics

We model energy consumption prediction as a regression problem

Metrics:

- **R2 score**: Coefficient of determination

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{m}(y_i - \bar{y})^2}$$

- **Mean Absolute Percentage Error (MAPE)**

$$MAPE = (\frac{1}{m}\sum_{i=1}^{m}\frac{|\ y_i - \hat{y}_i\ |}{y_i}) \times 100$$

- **Median Absolute Percentage Error (MedAPE)**

$$MedAPE = median(\frac{|\ y_i - \hat{y}_i\ |}{y_i}) \times 100$$

Training data and ML Models

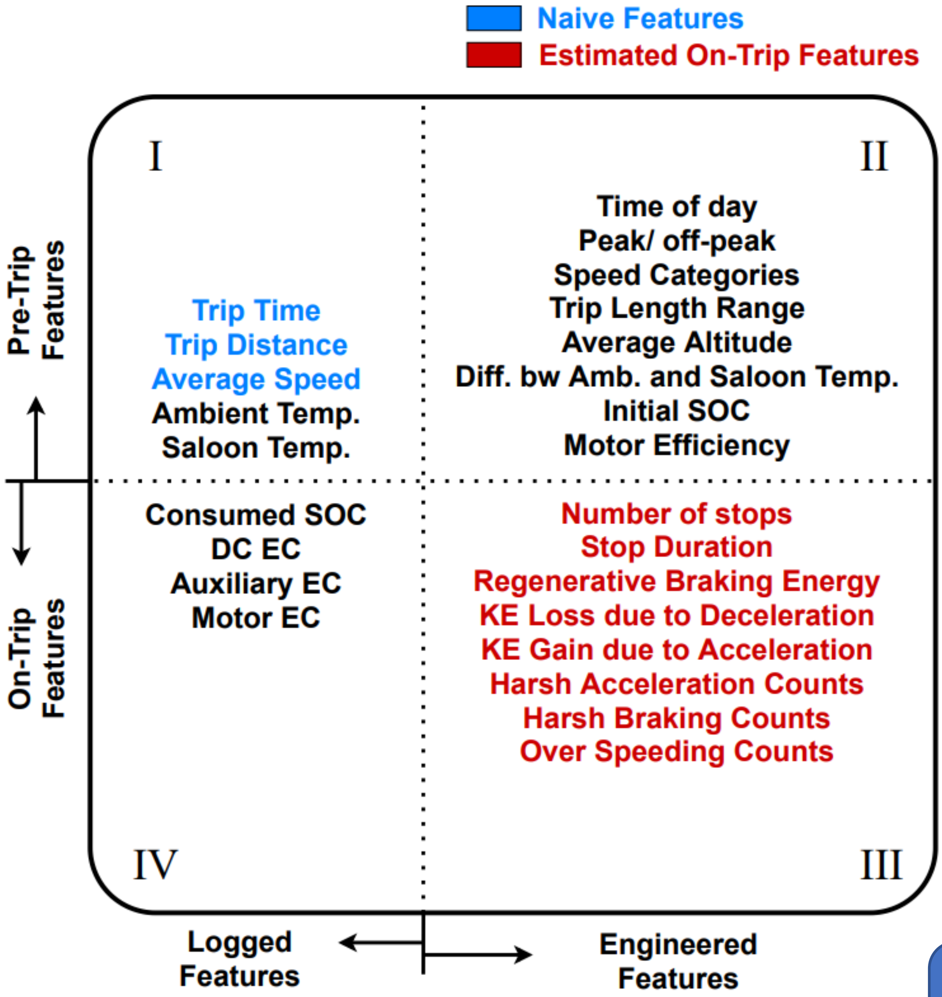
Dataset: A total of ***14413 trips*** from ***27 eBuses*** across a total of ***4 months*** period.

Random Data split of ***70/10/20****(%)* i.e., *10089, 1441, 2883 trips* for **training, validation and testing**.

Models focused on for the Results:

- **Light Gradient Boosting Machine (LightGBM):**
  - Fast training, buckets continuous features to discrete bins – Histogram based
- **Adaptive Boosting (AdaBoost) :**
  - Robust to overfitting since parameters not optimized jointly - depends on the choice of weak learners, noise in the dataset, dimensionality.

Ablation Study



#	Feature	Model	Evaluation Metric		
			R2 score	MAPE	MedAPE
1	ALL	LightGBM AdaBoost	0.994 0.998	3.745 1.516	2.867 1.118
2	NF	LightGBM AdaBoost	0.957 0.955	9.262 9.350	7.473 7.494
3	LF	LightGBM AdaBoost	0.989 0.988	4.369 4.572	3.396 3.584
4	PF(L)	LightGBM AdaBoost	0.965 0.963	8.072 8.154	6.485 6.769
5	PF(LEF)	LightGBM AdaBoost	0.968 0.967	7.623 7.768	6.112 6.227
6	PF(ON)	LightGBM AdaBoost	0.990 0.993	4.294 3.027	3.064 2.213

Results using proposed methodology

Our technique can predict energy consumption with 3-4% MAPE and 0.99 R2 score

Route Generalization

Evaluate the performance of the model trained on Route A and test on Route B

Length of the routes:

- Route A = 22.40km
- Route B = 20.96km

- Train on Route A and test on Route B:
  - Training set = 2047 trips
  - Test set = 595 trips
  - Results: MAPE = 7.3%

Our engineered features can capture diverse characteristics in the data and can be used to generalize across different routes

Applicability to other EV public dataset : Vehicle Energy Dataset

Features of Vehicle Energy Dataset:

- Covers only ***3 EVs*** (passenger car: 2013 Nissan Leaf)
- Battery Capacity of the car ***24kWh***
- Distance coverage: ~***7600 km***
- Logging Time granularity : ***1 seconds***
- Total Trips (294+202+11 = ***507 trips***)
- **Parameters logged**:

  Vehicle ID, GPS, Altitude, Vehicle Speed, Yes 600,000 Hybrid, Battery, Fuel Engine Signals, Ambient Temperature, Battery Usage, Auxiliary Power Signals, Battery V-I, Battery SOC

Engineer some of the described features

↓

Predict consumed state of charge per trip using our proposed 2-stage model

Models		Evaluation Metric	
		MAE	RMSE
Ours	**LightGBM**	**1.22**	**1.79**
	AdaBoost	1.382	1.99
SOTA	LSTM	1.47	7.78
	DNN	2.33	9.91

The proposed approach and feature engineering process can be easily applied to other EV datasets

Other Generalization Studies:

- Training with lesser data

  The performance of the 2-stage pipeline with PF(ON) features is tested by reducing the training data from 80% to 50% to 20% and results in similar estimation performance

- Longevity Study

  The proposed model when trained on trips from one time period (2 months) and tested on trips from another time period (2 months) results in a MAPE of 6.44% showing the generalization capability over other time periods.

- Vehicle Generalization

  We use data from a subset of the vehicles for training and test on the other subset of vehicles (non-overlapping vehicles) resulting in a MAPE of 6.16%.

Conclusion

- Modelling and estimating energy consumption of EVs in real-world is non-trivial
- We modeled the energy consumption for a fleet of buses using features which describe various aspects of a trip including **external factors** (like weather and traffic conditions), **vehicle internal factors**, **driver behaviour** etc.
- Our two-stage prediction approach with some intermediate features predicted using ML models along with directly observed features, can achieve an MAPE of $< 5\%$
- Our models generalize well for a new set of vehicles, routes and time periods
  - The proposed approach also generalizes well to other EV datasets
- With accurate estimation applications such as routing, fleet management, battery sizing, etc., would be able to benefit and make electric vehicle fleets an integral part

Thank You, and Questions?