Deep Spatio-Temporal Forecasting of Electrical Vehicle Charging Demand

Tackling Climate Change with Machine Learning

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Introduction

- Electric Vehicles (EVs) offers low carbon emission solutions to reverse rising emission trends assuming the energy provided is green.
- Forecasting the Charging demand can help energy providers supplying green energy to meet the demand.
- One of the challenges in forecasting the EV charging demand is to model the complex spatial and temporal dependencies between Charging Stations.

Spatio-Temporal Forecasting

Consider a temporal signal $X = \{x_1, x_2, \cdots, x_t\}$ and a topology G over the spatial domain.

Spatio-temporal forecasting can be viewed as learning a function f on topology G with temporal signal X.

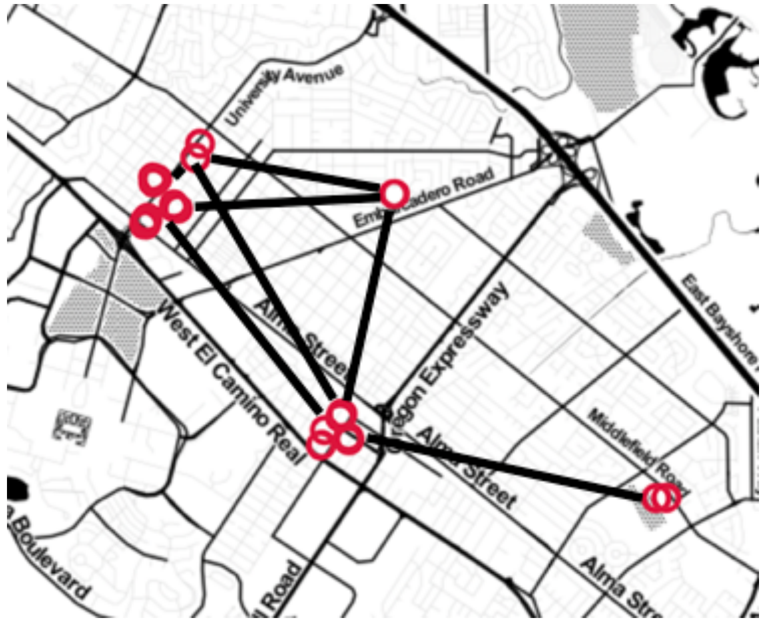
$$[X_{t+1}, \cdots, X_{t+T}] = f(G; (X_{t-n}, X_{t-1}, X_t)).$$

We parameterise the function f with *Deep Learning*

Topology

We consider multiple ways to model the topology:

1. A raster map over the spatial domain.
2. A Graph with EVCS as nodes and weighted edges with the distance between them



Modelling

To capture the spatial features, we apply:

1. Convolutional Neural Network
2. Graph Convolution Neural Network

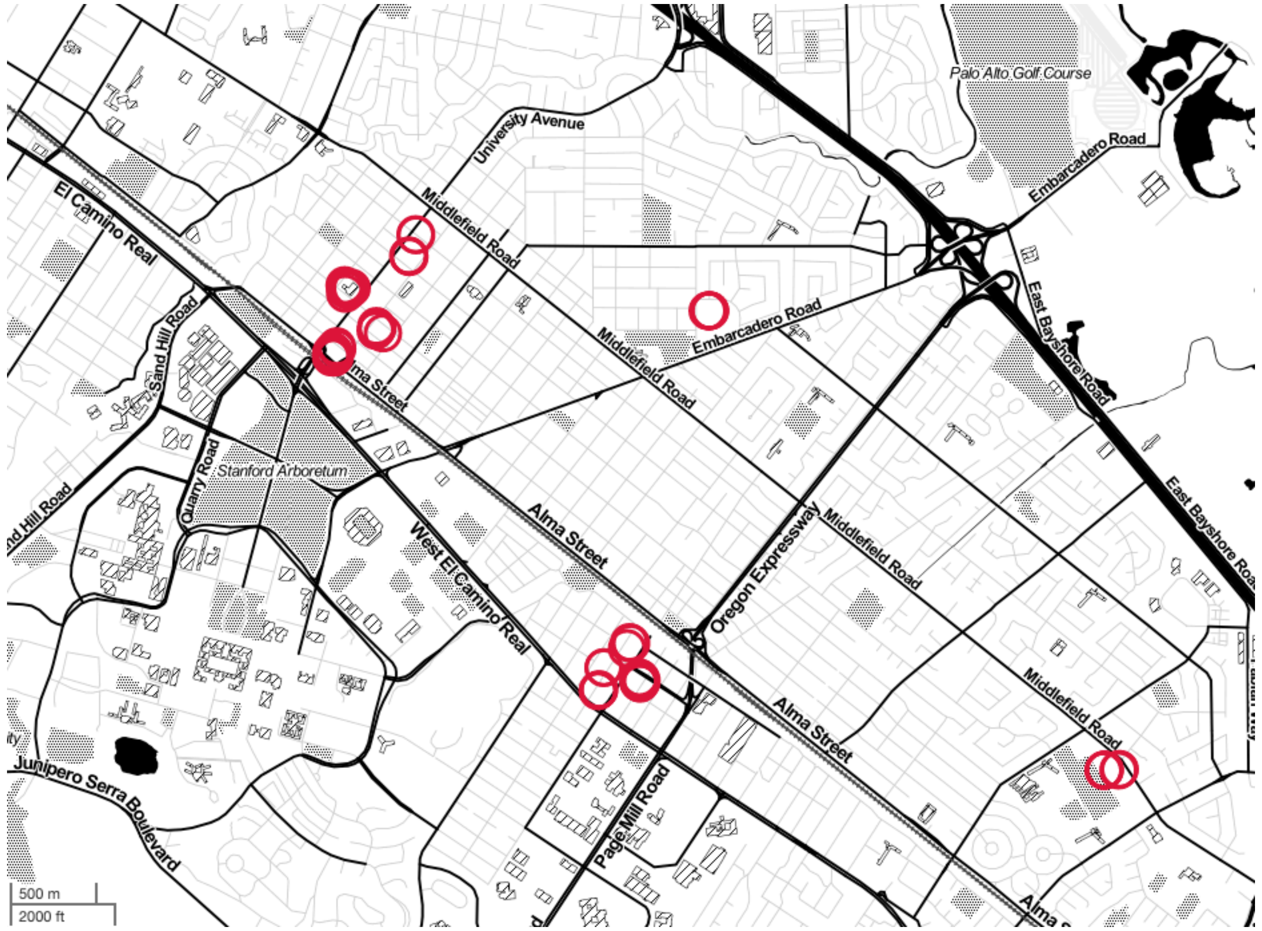
To capture temporal dynamics, we apply *Long Short-term memory* on the extracted spatial features.

We denote the forecasted value as $\widehat{X}_{t+1:t+T}$ and the realised value as $X_{t+1:t+T}$ and train the model under *mean absolute error*:

$$\mathcal{L} = |X_{t+1:t+T} - \widehat{X}_{t+1:t+T}| + \lambda\beta^2 .$$

Data

- The data consists of public EV charging transactional from Palo Alto[5].
  - Contains energy consumed for each charging session.
  - We focus on using energy consumption (kWh) for a transaction.
- The consumption is aggregated into a daily energy demand for each of the stations in Palo Alto.



[5] Data available at Link

Experimental results

We test the propose models for 3 different forecast horizons[6]:

Model	**1 Day**	**7 Days**	**30 Days**
AR(30)	178	251	252
VAR(30)	189	203	201
CNN	144	243	211
CNN + LSTM	95	192	187
T-GCN	**61**	**184**	**161**

[6] Code available at: Github.

Conclusion

- We have argued for the use of publicly available data for forecasting the electric vehicle charging demand.
- Based on the experimental results, Graph Convolutional Networks have superior forecasting performance compared to other methods.
- We hope that the results and arguments encourage researchers to use publicly available data for research into EV charging demand.