EV Consumption

-Yash Nema

Business Objective:

To predict based on past charging behavior for a car when and how much energy would a car consume at a Household.

Goal is to equip their customers with insights on the energy consumption by their EVs and recommend how the customer could save money or make better choices with their EV charging behavior.

So, the goal of the project is to understand charging patterns and recommend when the customer should charge their EV.

Problem Challenges:

Hourly EV consumption is impacted by

- Car Model: Each Car model can have a different battery capacity and time to charge.
- Car Utility: A customer maybe driving every day to work or another customer might be taking out the car only once a week to do nearby shopping, so utilization of the battery life and charging needs may vary. Also it maybe possible that some customers charge their cars everyday even from 80% to 100% and another customer may be charging their car only when battery level reaches 10%.
- Geo location: Customer's location may impact car utility. Staying in remote areas or having limited charging stations in the vicinity might lead the customer to drive longer distances everyday and may end up needing to charge the car more often.
- Weather: Conditions may impact the Charging pattern like the extreme environments may impact the battery capacity or battery usage
- Charging pattern: Some cars may take charge 50% in 30 minutes and may take another hour for the remaining 50% charge. On the other hand, another car might need 1 hour to charge 50% of the batter and another 1 hour for the remaining 50%.
- Battery degradation: As in any electronic device over time the charging pattern may change, and capacity might degrade leading to longer charging times and higher energy consumption.

Solution:

Due to the above challenges, the following steps were taken to create the model:

1) Individual Household data files like "house_num634.csv" were combined to get the below dataset.

House.Number	EV_data	State	Zip3	EV	Time
1340	EV0	CA	910	1556.0405	3/10/2020 0:00
1340	EV0	CA	910	389.01013	3/10/2020 1:00
1340	EV0	CA	910	4668.1216	3/10/2020 2:00
1340	EV0	CA	910	2374.572	3/10/2020 3:00
1340	EV0	CA	910	88.10896	10/22/2020 19:00
957	EV0	KS	661	4500.633	3/7/2020 22:00
957	EV0	KS	661	5090.87	3/12/2020 21:00
957	EV0	KS	661	7040.153	3/12/2020 22:00
1164	EV2	SC	296	2387.291	10/22/2020 17:00
1164	EV2	SC	296	609.69	10/22/2020 18:00
1164	EV2	SC	296	179.435	10/22/2020 19:00
1164	EV2	SC	296	459.13	10/31/2020 17:00
117	EV3	TX	787	2158	11/4/2019 2:00
117	EV3	TX	787	7158.404	11/4/2019 3:00
117	EV3	TX	787	534.908	11/4/2019 4:00
117	EV3	TX	787	5521.345	11/5/2019 1:00

Fig (1)

2) Data transformation was applied to get energy consumption and trend for each car. Example household 764 has EV0 and EV1, so energy consumption will be obtained for each hour for EV0 and EV1 respectively and a car id is created as "764_EV0" and "764_EV1" respectively. As in below dataset.

EV_House_id	House_id	EV_id	State	Zip3	Time	EV
1340_EV0	1340	EV0	CA	910	3/10/2020 0:00	1556.04
1340_EV0	1340	EV0	CA	910	3/10/2020 1:00	389.01
1340_EV0	1340	EV0	CA	910	3/10/2020 2:00	4668.12
1340_EV0	1340	EV0	CA	910	3/10/2020 3:00	2374.57
1340_EV0	1340	EV0	CA	910	10/22/2020 19:00	88.11
957_EV0	957	EV0	KS	661	3/7/2020 22:00	4500.63
957_EV0	957	EV0	KS	661	3/12/2020 21:00	5090.87
957_EV0	957	EV0	KS	661	3/12/2020 22:00	7040.15
957_EV0	957	EV0	KS	661	3/12/2020 23:00	1437.39
957_EV0	957	EV0	KS	661	3/13/2020 0:00	94.31
957_EV0	957	EV0	KS	661	3/19/2020 18:00	5349.17
957_EV0	957	EV0	KS	661	3/19/2020 19:00	7622.90
957_EV0	957	EV0	KS	661	3/21/2020 19:00	3945.62
957_EV0	957	EV0	KS	661	3/21/2020 20:00	7684.80
957_EV0	957	EV0	KS	661	3/21/2020 21:00	7443.02

Fig (2)

3) Now, that we have car level data, we need to predict future car energy consumption looking at:

- Recent data needs to have more weight than past data (accounting for battery degradation and life).
- Identify Car model or the specific charging behavior.
- Cars say in California are likely to show similar behavior as they will be impacted by similar Weather conditions, electricity prices or battery degradation.

4) Will be implementing LSTM Model with 325_EV0 Car id. Picking single car as we don't have to worry about different charging patterns or car model or various utility patterns.

5) Here the data is resampled at 4 hour level and total energy consumption is calculated. Then the shifted hour lags by 4 hours each are modeled as inputs.
6) EV_Final is the 0-4 hour total EV consumption of the day, and EV_lag_6 is the next days 0-4 hour which will be the target variable.
7) Standard Scaling is applied to input and output variables before inputting to the LSTM model

	EV_Final	EV_lag_1	EV_lag_2	EV_lag_3	EV_lag_4	EV_lag_5	EV_lag_6
0	467.300	926.915	934.598	1474.866	945.358	4659.243	1165.945
1	926.915	934.598	1474.866	945.358	4659.243	1165.945	911.545
2	934.598	1474.866	945.358	4659.243	1165.945	911.545	1170.556
3	1474.866	945.358	4659.243	1165.945	911.545	1170.556	1150.575
4	945.358	4659.243	1165.945	911.545	1170.556	1150.575	911.547
...	...	...	...	...	...	...	...
2005	1129.705	1104.993	0.000	1129.706	113.408	NaN	NaN
2006	1104.993	0.000	1129.706	113.408	NaN	NaN	NaN
2007	0.000	1129.706	113.408	NaN	NaN	NaN	NaN
2008	1129.706	113.408	NaN	NaN	NaN	NaN	NaN
2009	113.408	NaN	NaN	NaN	NaN	NaN	NaN

Model Input

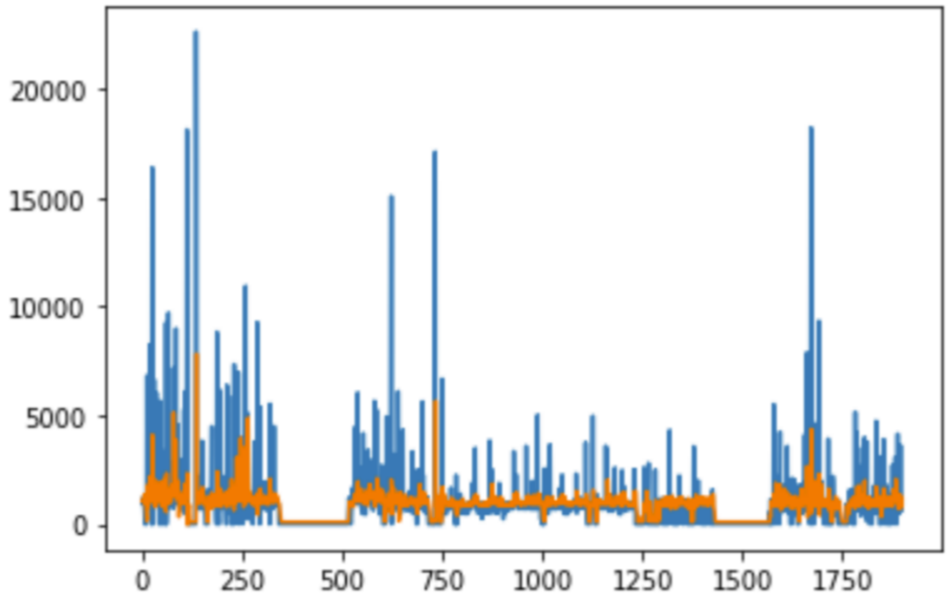
Results:

Model	Features	Nodes	Layers	Batch Normalization	Optimizer	Loss	Epochs	Batch Size
1	Input total EV econsumption for every 4 hours and Ouput is same 4 hours after 1 day	6	1	No	Adam	MSE	100	1
2		100	1	Yes	Adam(clipvalue=1.0)			1
3		6	2					6
4		6	2					100
5		12	2					50
6		12	2					25
7		12	3					24
8		24,48,24	3					24
9		6,12,6	3					24
10		6	2					24

Model Inputs

Model	Features	train test split	MAPE	MSE	Accuracy
1	X: total EV consumption for every 4 hours till EOD and y is same 4 hours after 1 day	0.9	MAPE of training set: 1039242.75 MAPE of testing set: 2449441.43	Train Score: 1414.49 RMSE Test Score: 5404.03 RMSE	0.15
2			MAPE of training set: 66547321.69 MAPE of testing set: 273570434.34	Train Score: 28161.12 RMSE Test Score: 102391.56 RMSE	-335.62
3			MAPE of training set: 1705275.62 MAPE of testing set: 3095482.84	Train Score: 1467.35 RMSE Test Score: 5334.06 RMSE	0.08
4			MAPE of training set: 981785.12 MAPE of testing set: 2599886.58	Train Score: 1465.26 RMSE Test Score: 5404.21 RMSE	0.08
5			MAPE of training set: 981785.12 MAPE of testing set: 2599886.58	Train Score: 1460.21 RMSE Test Score: 5416.54 RMSE	0.09
6			MAPE of training set: 869438.47 MAPE of testing set: 2058465.51	Train Score: 1451.73 RMSE Test Score: 5365.22 RMSE	0.1
7			MAPE of training set: 797347.75 MAPE of testing set: 2148156.29	Train Score: 1476.54 RMSE Test Score: 5378.59 RMSE	0.07
8			MAPE of training set: 2983116.96 MAPE of testing set: 5904270.79	Train Score: 1519.12 RMSE Test Score: 5372.82 RMSE	0.02

Model Results



Expected vs Predicted Energy Consumption

Conclusion:

In the above LSTM architecture, we were able to predict future 4 hours of the EV consumption with 15% accuracy.

In future would try to test for more cars and see the minimum datapoints needed for recommendation. Then would like to build a distribution function based on each car house id behaviors or try to predict the car house id combination behavior using clustering and then building LSTM model over the dataset to predict future energy consumption trend.