Smart Learning Pilot for Electric Vehicles Charging Stations

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Abstract

As we are replacing internal combustion vehicles with electric vehicles (EVs) for preventing emissions, the demand of EVSE (Electric Vehicles Service Equipment), also known as charging stations, is also growing. The problem with just installing large quantities of electric vehicle charging stations is that they are likely to become regular parking spaces for EVs, this costs money, and it prevents other users to use the service. To optimize EVSE usage, one approach is to understand people's behavior every time they use the service. In this simulation, we will be using two different datasets from Caltech [1] and Cal Poly (California Polytechnic State University, San Luis Obispo) [2] to understand the user behavior. These datasets will be compared to a virtual (synthetic) dataset that was created. The gradient descent algorithm will be use to predict energy consumption and overstaying (when a car stays at a charging station after it is done charging). Each time a user connects his/her car, certain information (e.g. vehicle model) will be collected, and the data will be used to make a more accurate estimate of energy consumption and possible overstay, independent from what the user inputs. As a study done by Caltech on EV users, "predicting session duration and energy based on learned distribution from actual behavior in the past is more reliable than asking users to predict these parameters directly" [1]. The flexibility of being able to change the synthetic model's parameters makes it convenient to test in a new site where we don't have a lot of information. By learning the behavior of EV users, we will be able to make better decisions on optimizing the usage for future EV charging stations.

Background

Figure 1: Boxplots showing Caltech dataset from 2018, overstay has some correlation with the arrival time for an electric vehicle user.

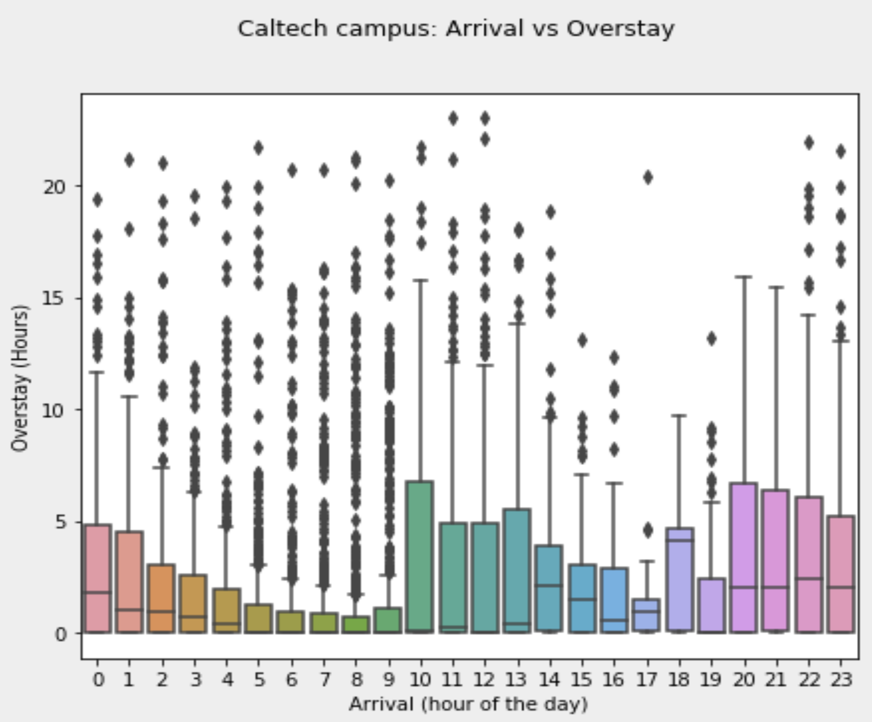
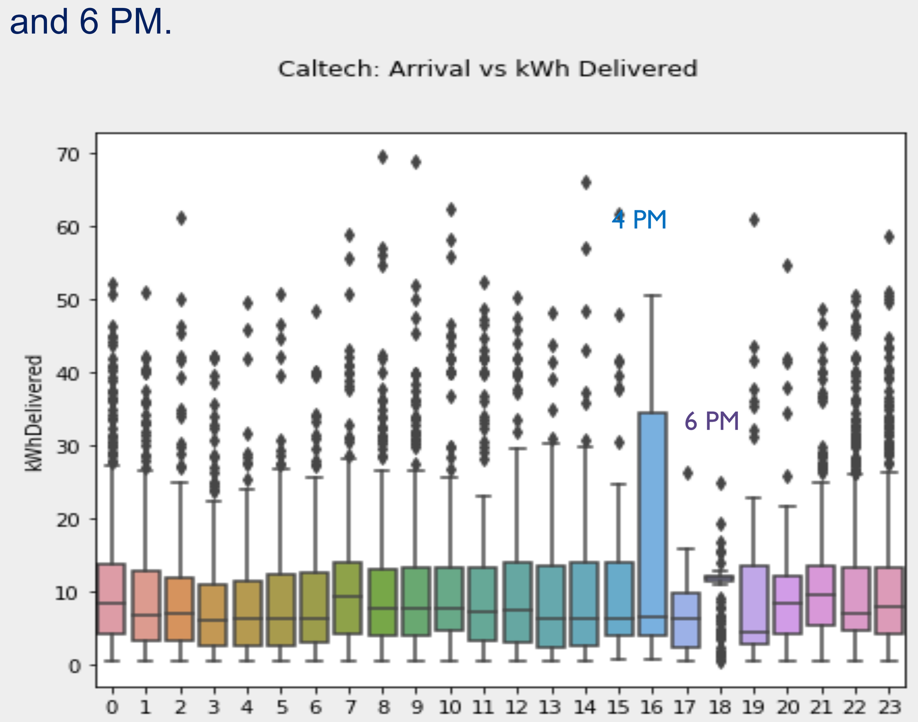


Figure 2: Boxplots showing energy consumed according to time - by looking at the actual energy being consumed according to arrival time. The energy consumed are almost the same for the different times, except 4 PM and 6 PM.



Simulation

Generating arrival and departure times

As we can see from Figures 1 and 2, there are some variables that have some correlation with one another.
To better understand overstay hours or amount of energy consumed by an EV, knowing some attributes is fundamental. For synthetic data, Poisson Process was used to generated arrival rate for each hour of the day. Departure times were uniformly generated using arrival times as conditional. Comparing synthetic values with a randomly selected sample from Cal Poly dataset, we get Figures 3 and 4, respectively. In Figure 5, the two results are compared.

Figure 3: Arrival times only include from 5am - 10pm.

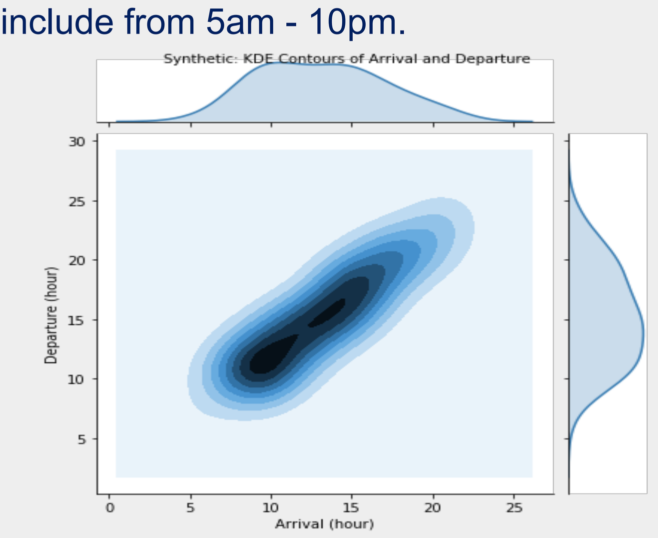


Figure 4: A sample from 2018 Cal Poly data, outliers are included.

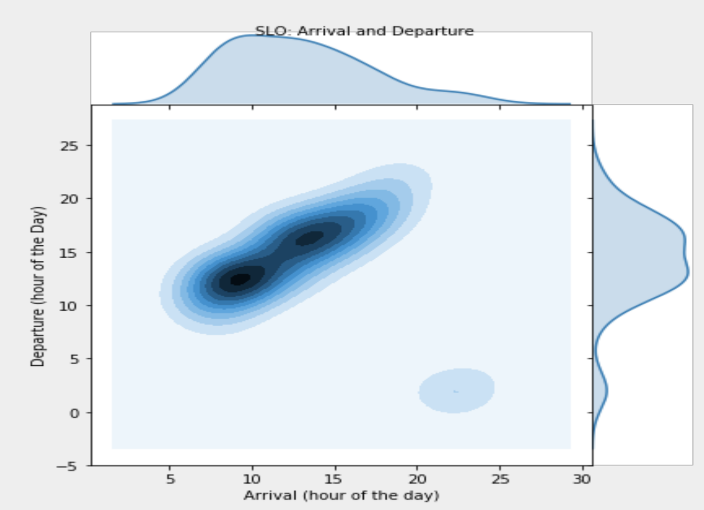
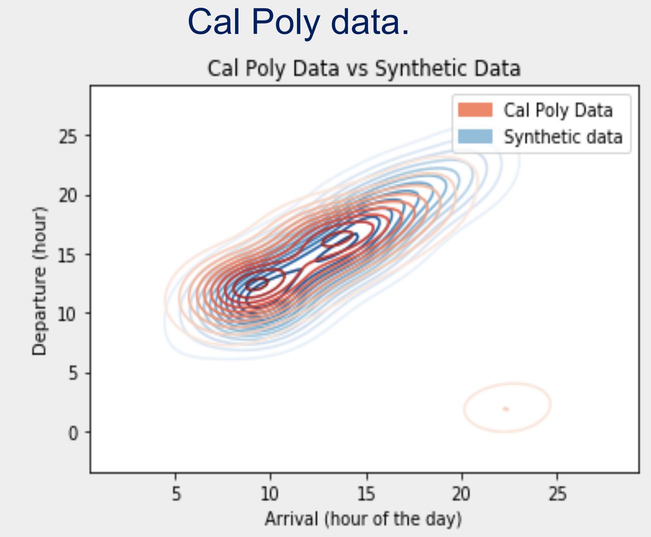


Figure 5: Synthetic data and a sample from Cal Poly data.



Generating energy consumed

To predict the energy consumed by EVs in the synthetic data, each total time was multiplied by a uniformly random value from [a, b] (used: a = 0.3, b = 0.999) and then multiply it by 7.2 kW. Even though maximum power level provided by a charging station is known, each EV has its own power level. This makes it hard to estimate the energy consumed given the hours in charging mode. As seen in Figure 6, the energy randomly generated is more linear compared to Cal Poly data. This might be because when a battery reaches a total charge percentage, the charging rate slows down [3]. In addition, Cal Poly stations have a charging maximum power level of 6.6 kW (J1772) in contrast to our power level of 7.2 kW.

1)
Linear Model:
$f_\theta(x) = \theta_0 + \theta_1 x_1 + \ldots + \theta_p x_p = \boldsymbol{\theta} * \mathbf{x}$
x = vector representing p attributes of a user
$\boldsymbol{\theta}$ = weights

2)
MSE Loss:
$L(\boldsymbol{\theta}, \mathbf{X}, \mathbf{y}) = \frac{1}{n}\sum_{i=1}^{n}(yi - f_\theta(\mathbf{X}_i))^2$
X = matrix
$\mathbf{X}_i$ = vector

3)
Gradient for MSE Loss:
$\nabla L(\boldsymbol{\theta}, \mathbf{X}, \mathbf{y}) = -\frac{2}{n}\sum_{i=1}(yi - \boldsymbol{\theta} * \mathbf{X}_i)(\mathbf{X}_i)$

Figure 6: Energy consumed given the time connected as charging mode.

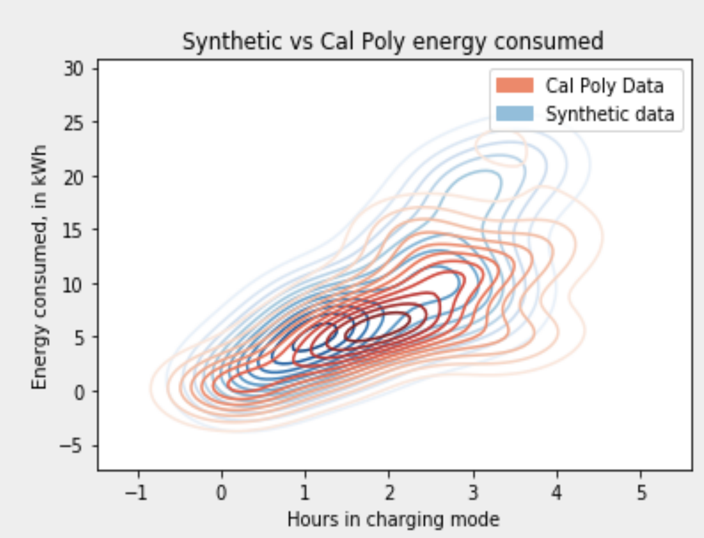


Figure 7: Electric vehicles charging.[4]

Applying the gradient descent algorithm on a sample of Caltech's dataset using arrival time and hours in charging mode as attributes, Figures 8 and 9 were generated. By using the energy consumed and the total time (departure - arrival), we are able to predict overstay, this is shown in Figure 10. The plots look slightly different, this is because we are only using two attributes. The model is expected to improve once more information from EV users are collected.
(Note on Figure 8: optimal values (MSE Loss: 38.27) found on a sample size of 82 from Caltech was use to predict the energy on an entire new sample size of 82. Caltech dataset set is 15289)

Figure 8: Caltech: Estimated vs real energy.

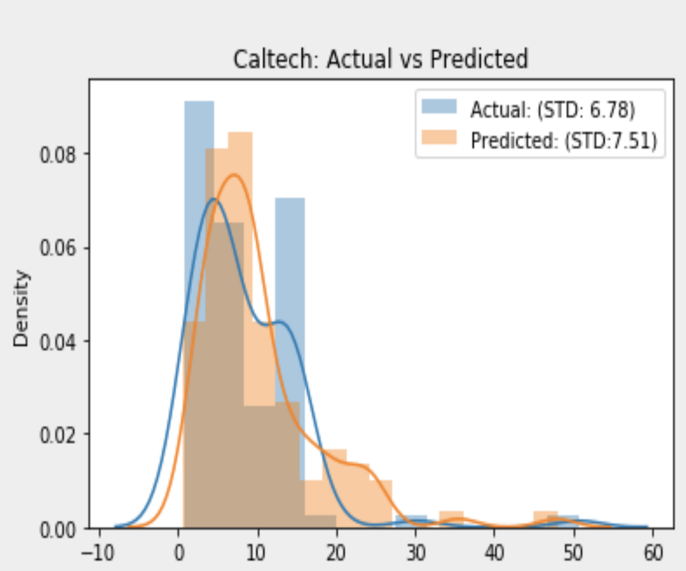


Figure 9: Residual for predicted energy.

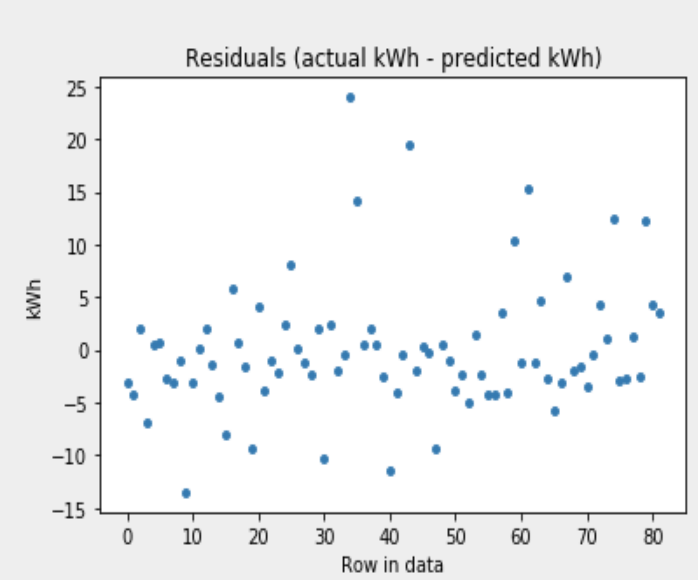
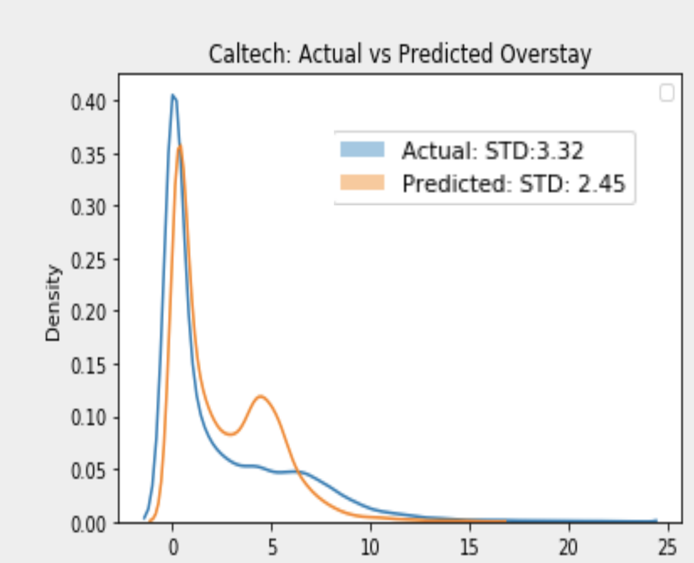


Figure 10: Estimating overstay.



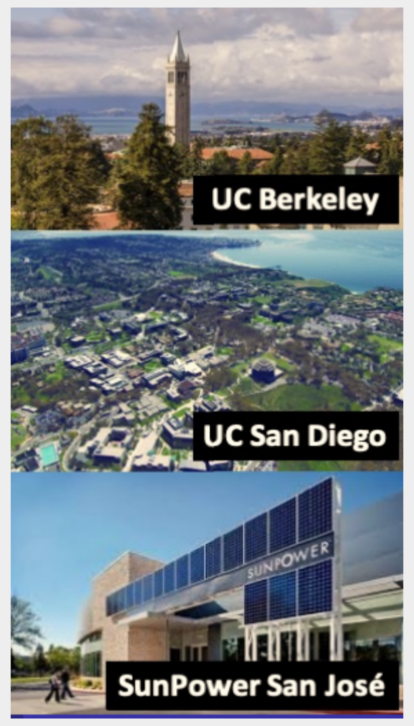
Results and Future Work

By using gradient descent algorithm, we were able to predict energy consumed and overstay time from Caltech (similar graphs were found for Cal Poly and synthetic data). This helps us understand users' behavior and therefore determine when to apply different charging conditions. The next step for this simulation is to test it for different sites.

UC Berkeley: 8 ports, Level 2 (~7.5 kW): Coming early 2020

UC San Diego: 10 ports, Level 2 (~7.5 kW): Coming Fall 2019

SunPower San José: 10 ports, Level 2 (~7.5 kW): Coming late Summer 2019



Figures 11-13

Conclusion

This research is an effort to better understand on how to make better decisions for future installations of EV charging stations. California is a leader in using renewable energy solutions, and the growth of EV users is expected to grow very fast [5]. Therefore, optimizing the usage of charging stations is fundamental on making them more flexible for users.

Contacts

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References

[1] Lee, Zachary J, Tongxin Li, and Steven H., Low "ACN- Data: Analysis and Applications of an Open EV Charging Dataset". *Proceedings of the Tenth International Conference on Future Energy Systems. June 2019.* Accessed: August 03, 2019 at 5:00 PM.

[2] Special thanks to ChargePoint, Inc. for providing us with Cal Poly charging stations data.

[3] Westbrook, Justin " Here is Why Automakers Don't Advertise How Long It Takes to Charge an EV". *Jalopnik* .Web. Accessed: August 03, 2019 at 3:00 PM.

[4] "PLUGGING IN: INSTALLING AN EV CHARGING STATION" *Touchstone Energy Cooperatives, Web* Accessed: August 05, 2019 at 3:00 PM

[5] Peter Slowik, Nic Lutsey, "Expanding the electric vehicle market in U.S. cities (ICCT, 2017)". Accessed: August 07, 2019 at 4:00 PM.