EVGen: Adversarial Networks for Learning Electric Vehicle Charging Loads and Hidden Representations

July 23, 2021

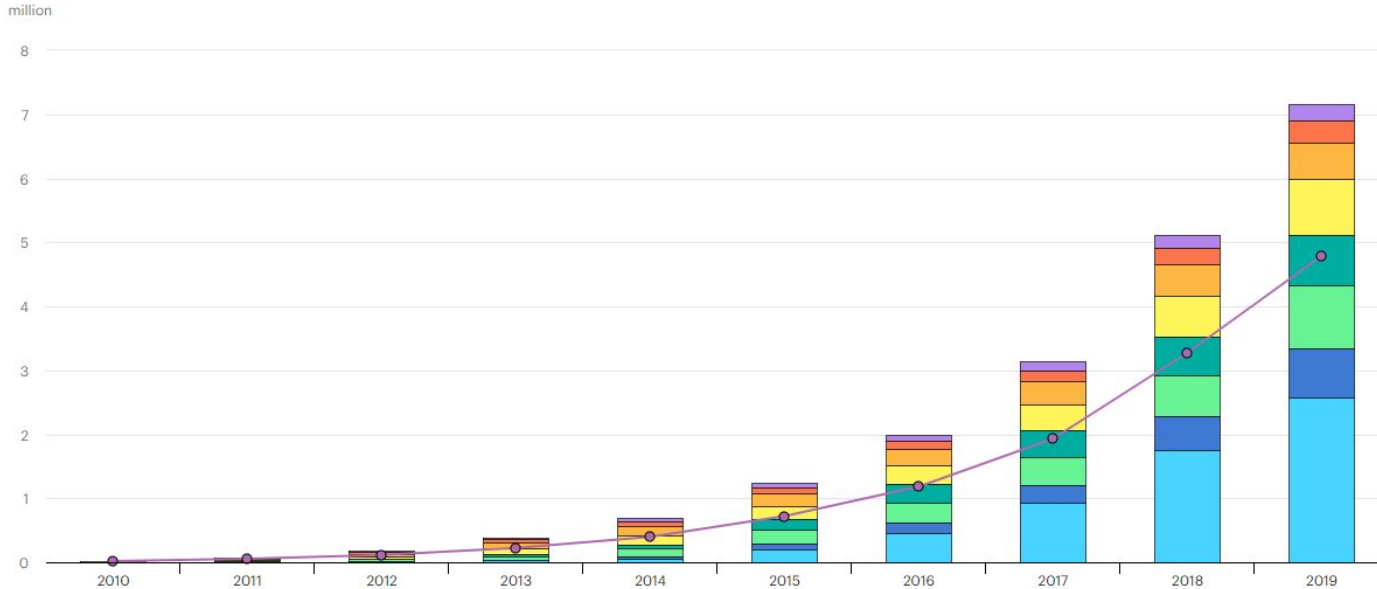Robert Buechler[1], Emmanuel Oreoluwa Balogun[1], Arun Majumdar[1], Ram Rajagopal[2]

[1] Mechanical Engineering Department, Stanford University
[2] Civil and Environmental Engineering Department, Stanford University

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Why is EV modeling important?

Global electric car stock, 2010-2019

Legend: China BEV · China PHEV · Europe BEV · Europe PHEV · United States BEV · United States PHEV · Other BEV · Other PHEV · World BEV

[1] IEA, "Global EV Outlook 2020," IEA, Paris, 2020. [Online]. Available: https://www.iea.org/reports/global-ev-outlook-2020.

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Why is EV modeling important?
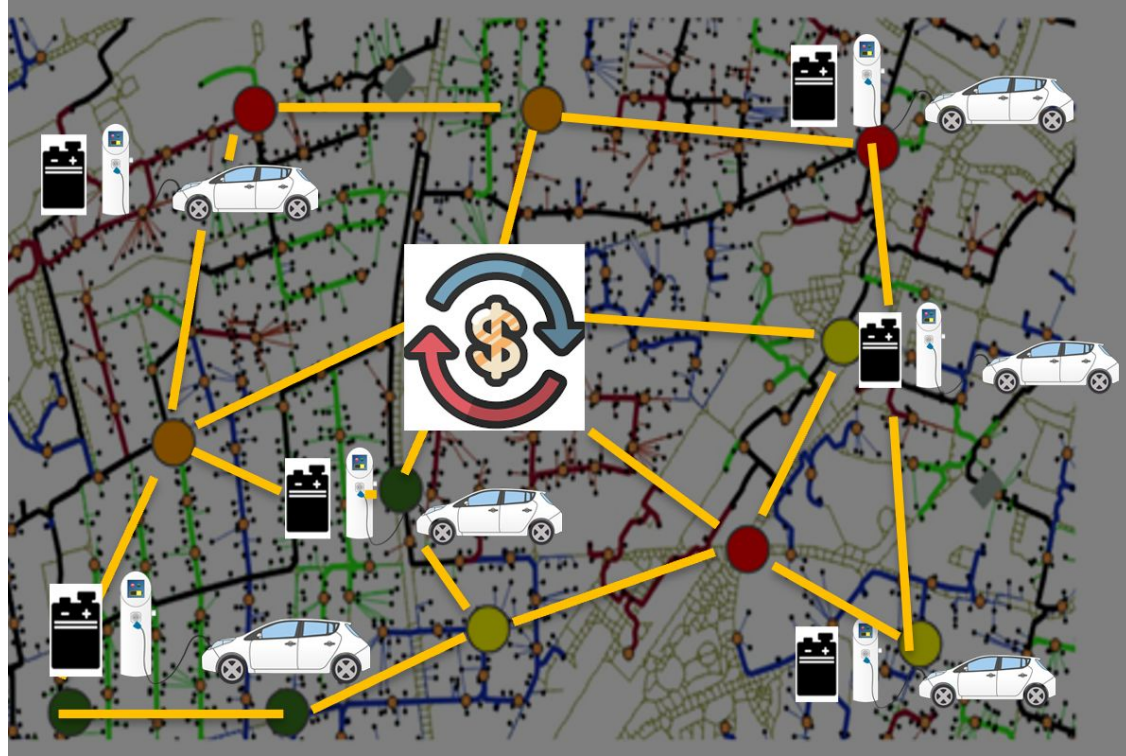
Representation Learning example

Controlling digit rotation

Controlling digit width

(c) Varying c_2 from -2 to 2 on InfoGAN (Rotation)

(d) Varying c_3 from -2 to 2 on InfoGAN (Width)

[2] X. Chen, Y. Duan, R. Houthooft, J. Schulman, I. Sutskever, and P. Abbeel, "InfoGAN: Interpretable Representation Learning by Information Maximizing Generative Adversarial Nets," *arXiv:1606.03657 [cs, stat]*, Jun. 2016, Accessed: Dec. 10, 2020. [Online]. Available: http://arxiv.org/abs/1606.03657.
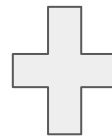
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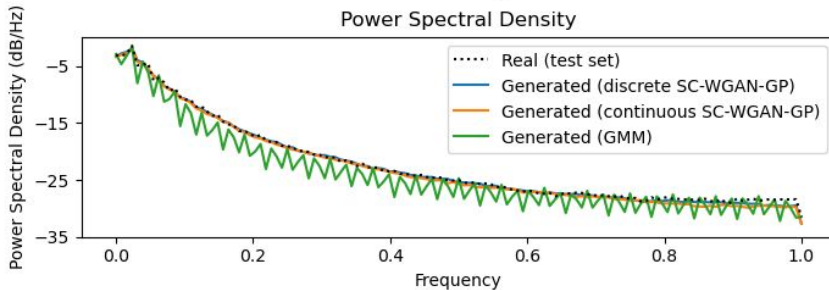# Baseline - Gaussian Mixture Model (GMM)
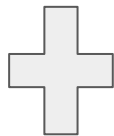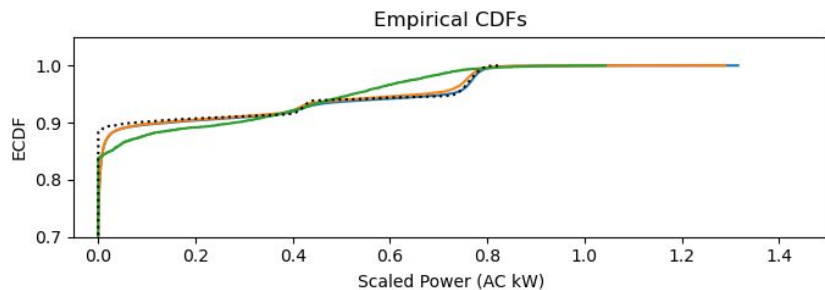
Charge Start Time + **Charge Duration** + **Average Power**
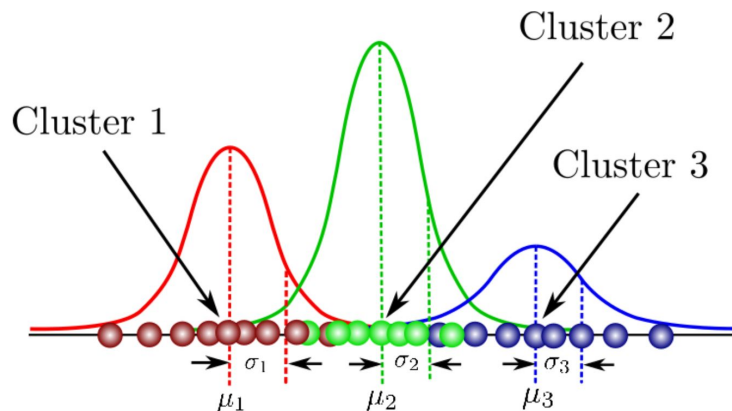
Adversarial Training with SC-WGAN-GP

Wasserstein Loss

$$L = \mathop{\mathbb{E}}_{\tilde{\mathbf{x}} \sim \mathbb{P}_g} [D(\tilde{\mathbf{x}})] - \mathop{\mathbb{E}}_{\mathbf{x} \sim \mathbb{P}_r} [D(\mathbf{x})] + \lambda_{GP} \mathop{\mathbb{E}}_{\hat{\mathbf{x}} \sim \mathbb{P}_{\hat{\mathbf{x}}}} [(||\nabla_{\hat{\mathbf{x}}} D(\hat{\mathbf{x}})||_2 - 1)^2]$$

Similarity Constraint [3]

$$SC(\mathbf{x}, c) = \frac{1}{N(N-1)} \sum_i \sum_{j \neq i} \left((1 - |c_i - c_j|) sim(\mathbf{x}_i, \mathbf{x}_j) + \frac{|c_i - c_j|}{sim(\mathbf{x}_i, \mathbf{x}_j)} \right)$$

X → **Critic** → Score

z , **c** → **Generator**

[3] X. Li, L. Chen, L. Wang, P. Wu, and W. Tong, "SCGAN: Disentangled Representation Learning by Adding Similarity Constraint on Generative Adversarial Nets," IEEE Access, vol. 7, pp. 147928–147938, 2019, doi: 10.1109/ACCESS.2018.2872695.
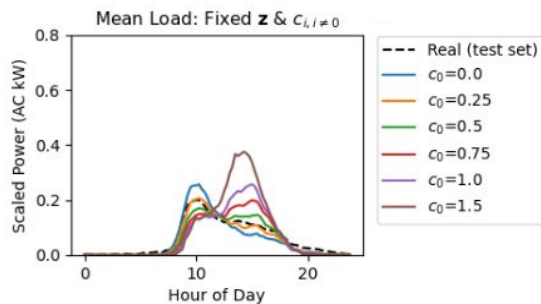
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Results
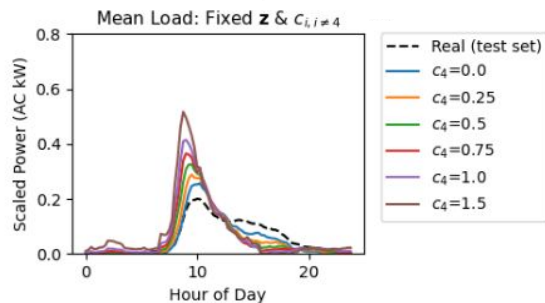
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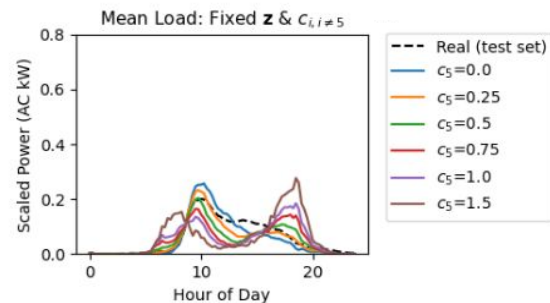# Results: Continuous Encoding

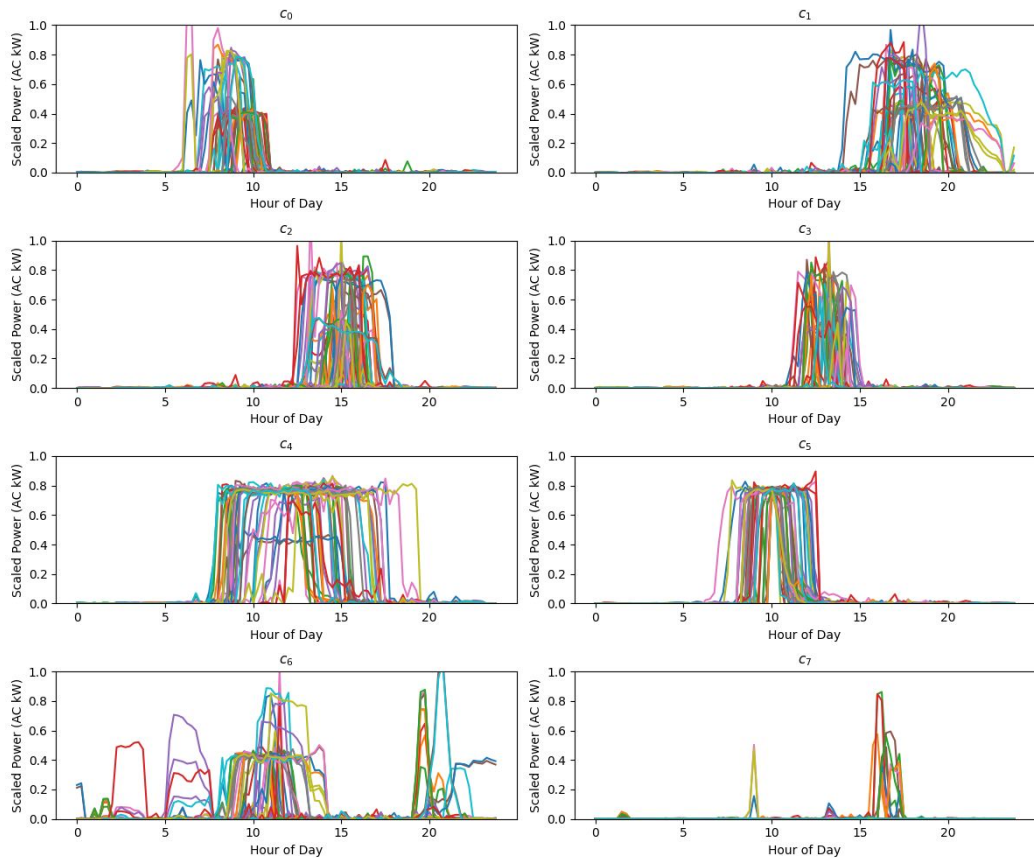Continuous variable #1

Continuous variable #4

Continuous variable #5

Results: Discrete Encoding

- Each cell is a different discrete variable.

- Model is clearly able to disentangle different types of EV charging

Limitations & Possible Improvements

- The model is able to extrapolate beyond the dataset, but the extrapolation is not very interpretable.

- Statistical redundancy in charging types learned.

- Dataset is limited in spatial scope; a much larger dataset that covers major US cities could further augment this work.

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Thank you

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