Application of Generative Adversarial Networks (GANs) in Smart Buildings

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Acknowledgement

- This lecture is developed from my previous work with LBNL. I would like to thank Tianzhen Hong, and other team members in Tianzhen's group
- I was inspired a lot from the following resources
  - *Ian Goodfellow, Generative Adversarial Networks (NIPS 2016 tutorial)*
  - *UC Berkeley, 2017, Deep Learning Decall, Autoencoders and Representation Learning*
  - *Stanford University, 2020, Convolutional Neural Networks for Visual Recognition, lecture 13*
  - *University of Washington, 2017, A Compressed Overview of Sparsity*

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Generative AI

- AI generated faces
  - https://generated.photos/faces/

- AI generated music
  - https://www.musi-co.com/listen/streams

Agenda

- Generative models
- Generative Adversarial Network (GAN)
- Application of GAN in smart building
- Discussion

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- Application of GAN in smart building
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Generative models

- Definition
  - Given training data, generate new samples from the same distribution
- Motivation
  - Generate data
    - For fun: artwork, music
    - For simulation/planning
  - Learn the hidden pattern of data in the latent space

Generative models

- A major task of unsupervised learning
  - Supervised learning
  - Unsupervised learning
  - Reinforcement learning

- Evaluation
  - Fidelity: generated samples should be indistinguishable from the real data
  - Diversity: generated samples should be distributed to cover the real data
  - Usefulness: generated samples should be just as useful as the real data

Generative models

Two model types

- Explicit density: the model explicitly define and solve the representation in the latent space
- Implicit density: the model can sample from representation in the latent space w/o explicitly defining it

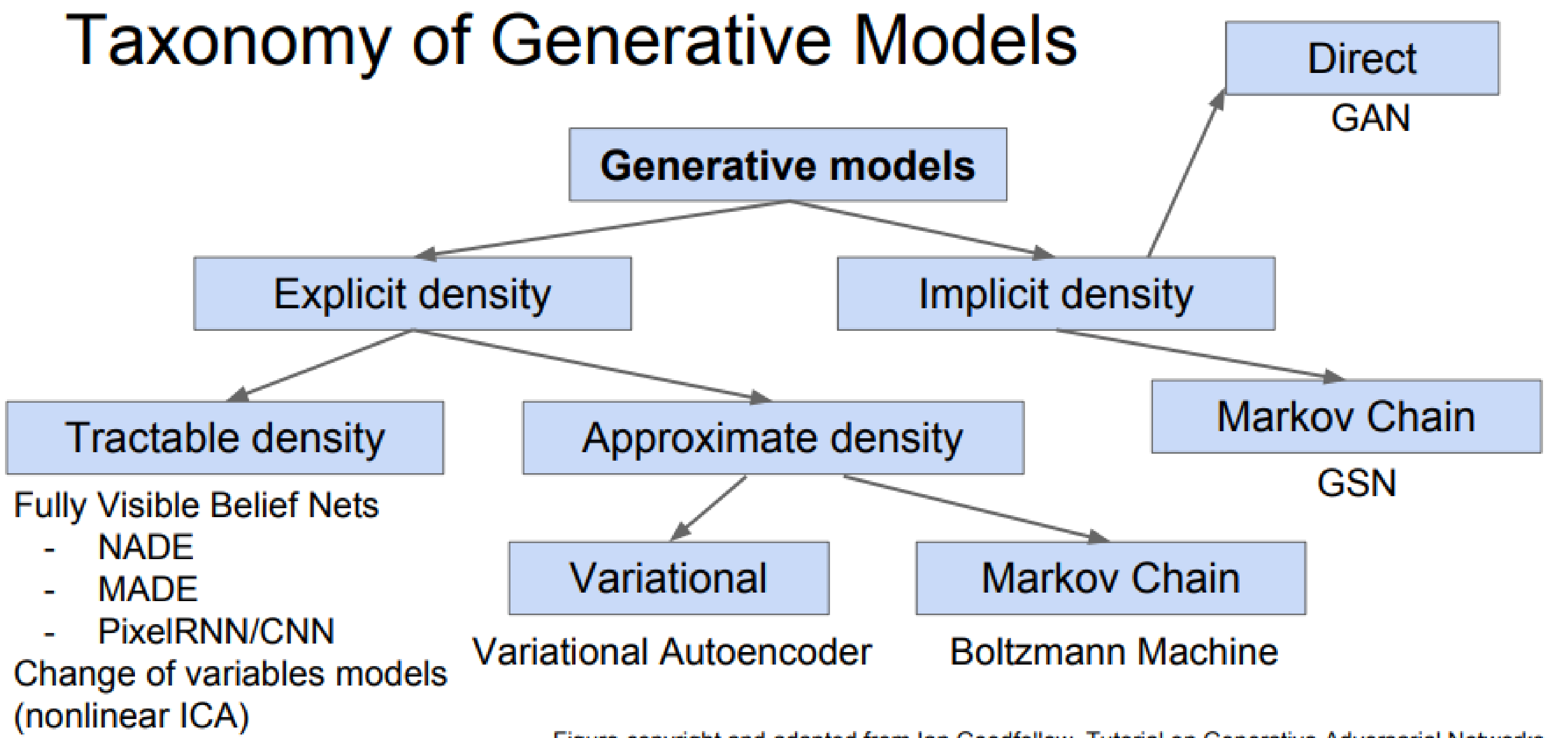


Figure copyright and adapted from Ian Goodfellow, Tutorial on Generative Adversarial Networks, 2017.

Source: Ian Goodfellow, Generative Adversarial Networks (NIPS 2016 tutorial)

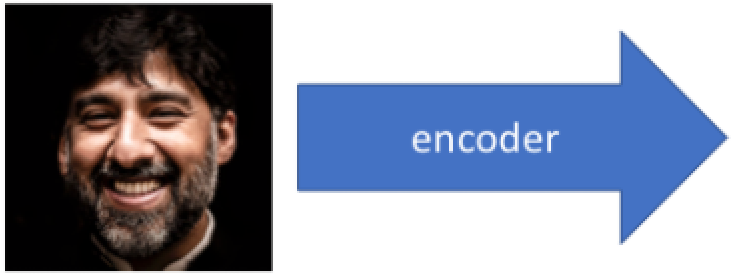
Representation in the latent space

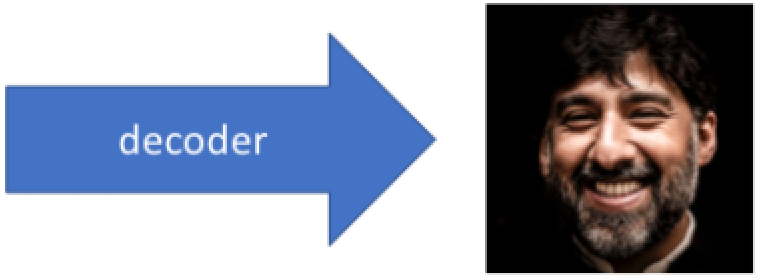
- The goal of data mining and machine learning is to construct and exploit the intrinsic low-rank feature space of a given data set

Data
Dimension: ~ millions

Information/knowledge
Dimension: 6

All ML tasks contain the encoding step
Generative models has the decoding step





Source: JEREMY JORDAN, Variational autoencoders, https://www.jeremyjordan.me/variational-autoencoders/

Encoding: develop a compressed representation (*latent space*) of the input data

Decoding: generate new data from the sampled vectors in the latent space

Agenda

- Generative models
- Generative Adversarial Network (GAN)
  - Idea
  - Math: objective function
  - Training
- Application of GAN in smart building
- Discussion

Explicit Generative Models

- Conventionally, generative models learn the latent representation explicitly
  - PixelRNN, PixelCNN

$$\underset{\substack{\uparrow\\ \text{Likelihood of}\\ \text{image x}}}{p(x)} = \prod_{i=1}^{n} \underset{\substack{\uparrow\\ \text{Probability of i'th pixel value}\\ \text{given all previous pixels}}}{p(x_i|x_1,...,x_{i-1})}$$

  - Variational AutoEncoder (VAE)

Source: Stanford University, 2020, Convolutional Neural Networks for Visual Recognition, lecture 13

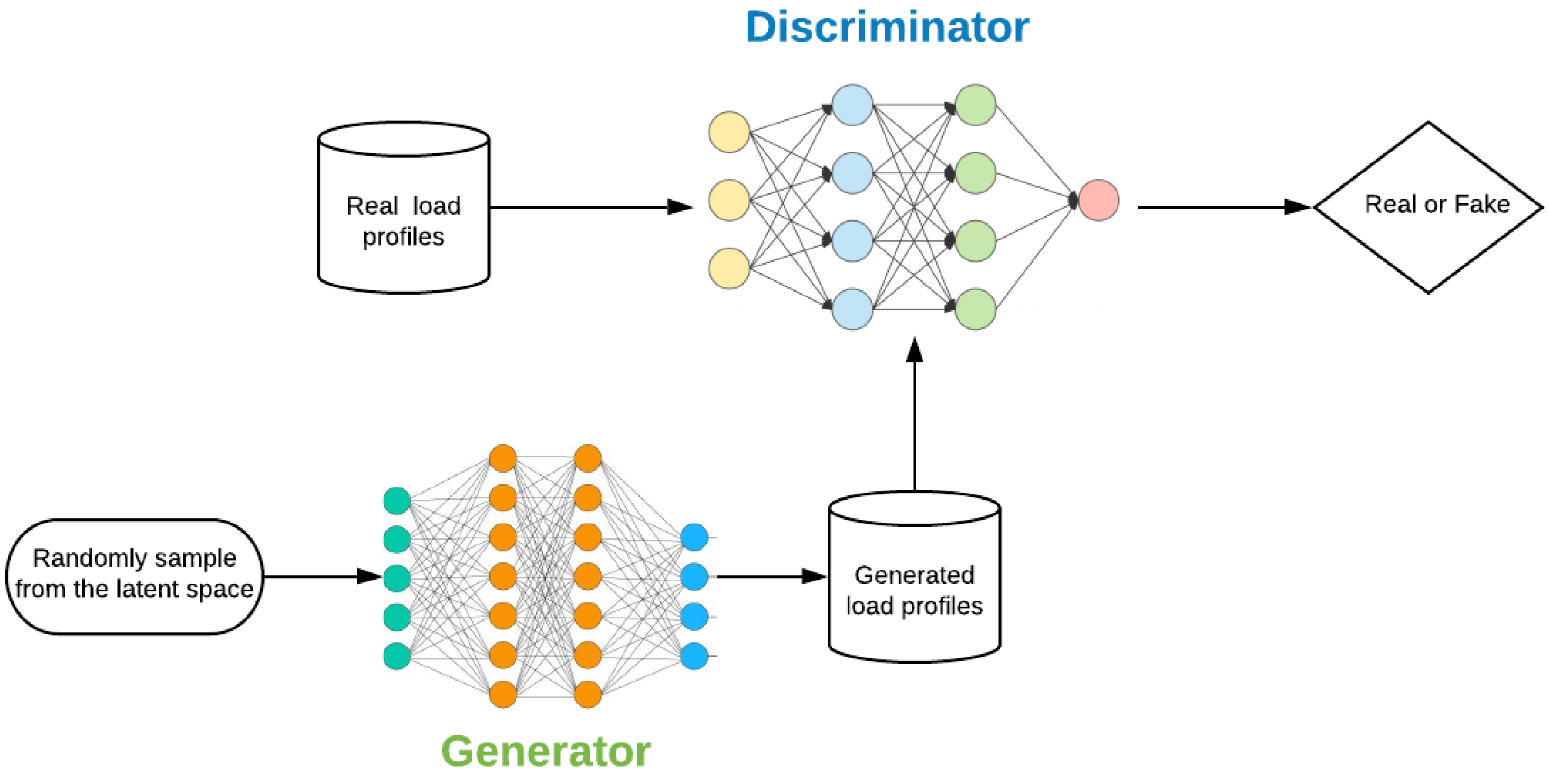
$$\begin{aligned}
\log p_\theta(x^{(i)}) &= \mathbf{E}_{z\sim q_\phi(z|x^{(i)})}\left[\log p_\theta(x^{(i)})\right] \quad &&(p_\theta(x^{(i)}) \text{ Does not depend on } z)\\
&= \mathbf{E}_z\left[\log \frac{p_\theta(x^{(i)} \mid z)p_\theta(z)}{p_\theta(z \mid x^{(i)})}\right] &&(\text{Bayes' Rule})\\
&= \mathbf{E}_z\left[\log \frac{p_\theta(x^{(i)} \mid z)p_\theta(z)}{p_\theta(z \mid x^{(i)})}\frac{q_\phi(z \mid x^{(i)})}{q_\phi(z \mid x^{(i)})}\right] &&(\text{Multiply by constant})\\
&= \mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - \mathbf{E}_z\left[\log \frac{q_\phi(z \mid x^{(i)})}{p_\theta(z)}\right] + \mathbf{E}_z\left[\log \frac{q_\phi(z \mid x^{(i)})}{p_\theta(z \mid x^{(i)})}\right] &&(\text{Logarithms})\\
&= \mathbf{E}_z\left[\log p_\theta(x^{(i)} \mid z)\right] - D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z)) + D_{KL}(q_\phi(z \mid x^{(i)}) \,||\, p_\theta(z \mid x^{(i)}))
\end{aligned}$$

Generative Adversarial Network

- *Do not learn the explicit representation*
- GAN
  - Inspired from the Game-theory
  - Learn to generate from training data through 2-player game
    - Generator
    - Discriminator
- History
  - First proposed by Ian Goodfellow in 2014
  - Quickly becomes a hot topic
  - 2017: the Year of GAN

Generative Adversarial Network

- The game between two agents
  - Generator
  - Discriminator



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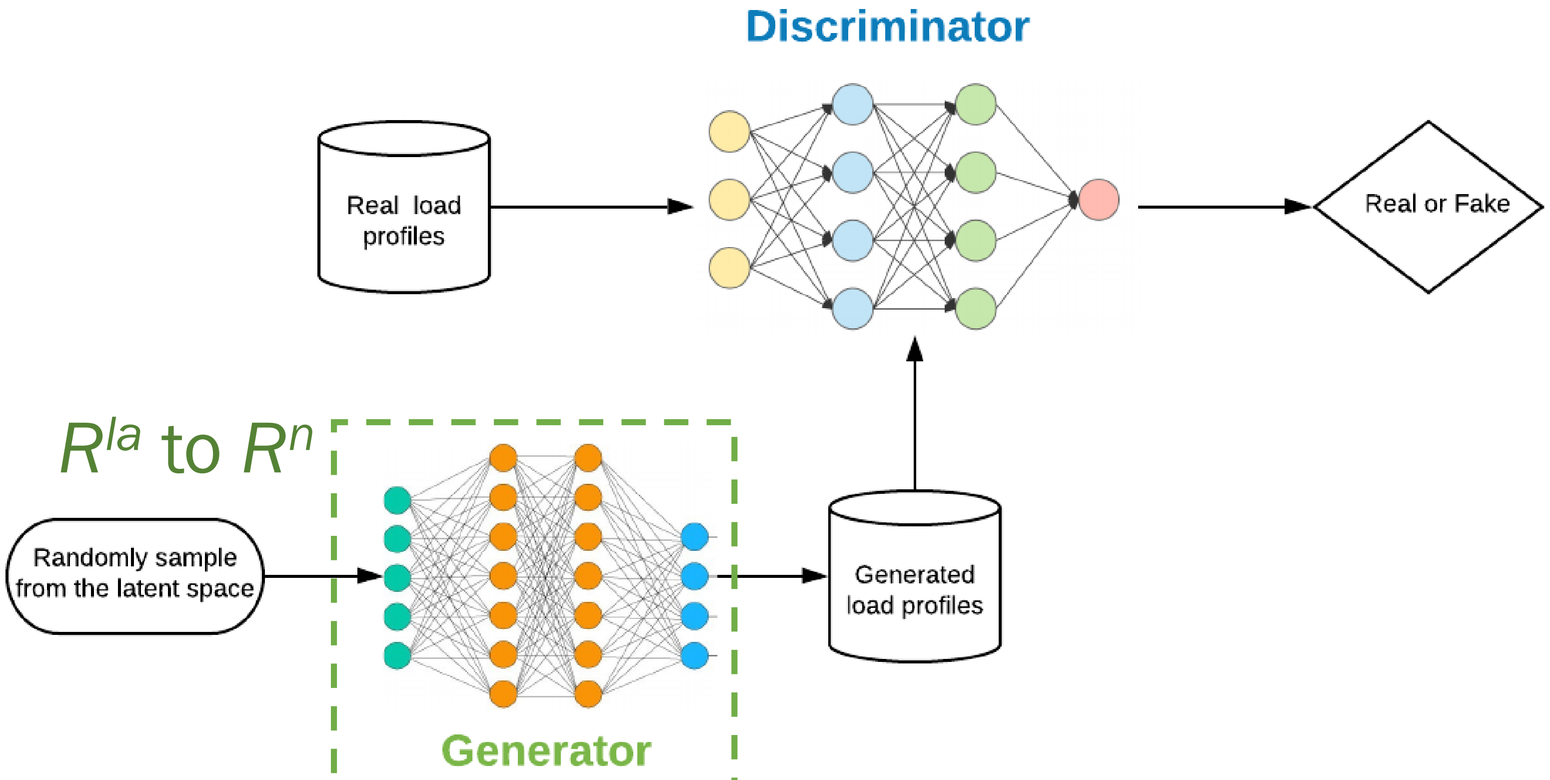
Generative Adversarial Network

- Generator: generator data from latent space (decoder)



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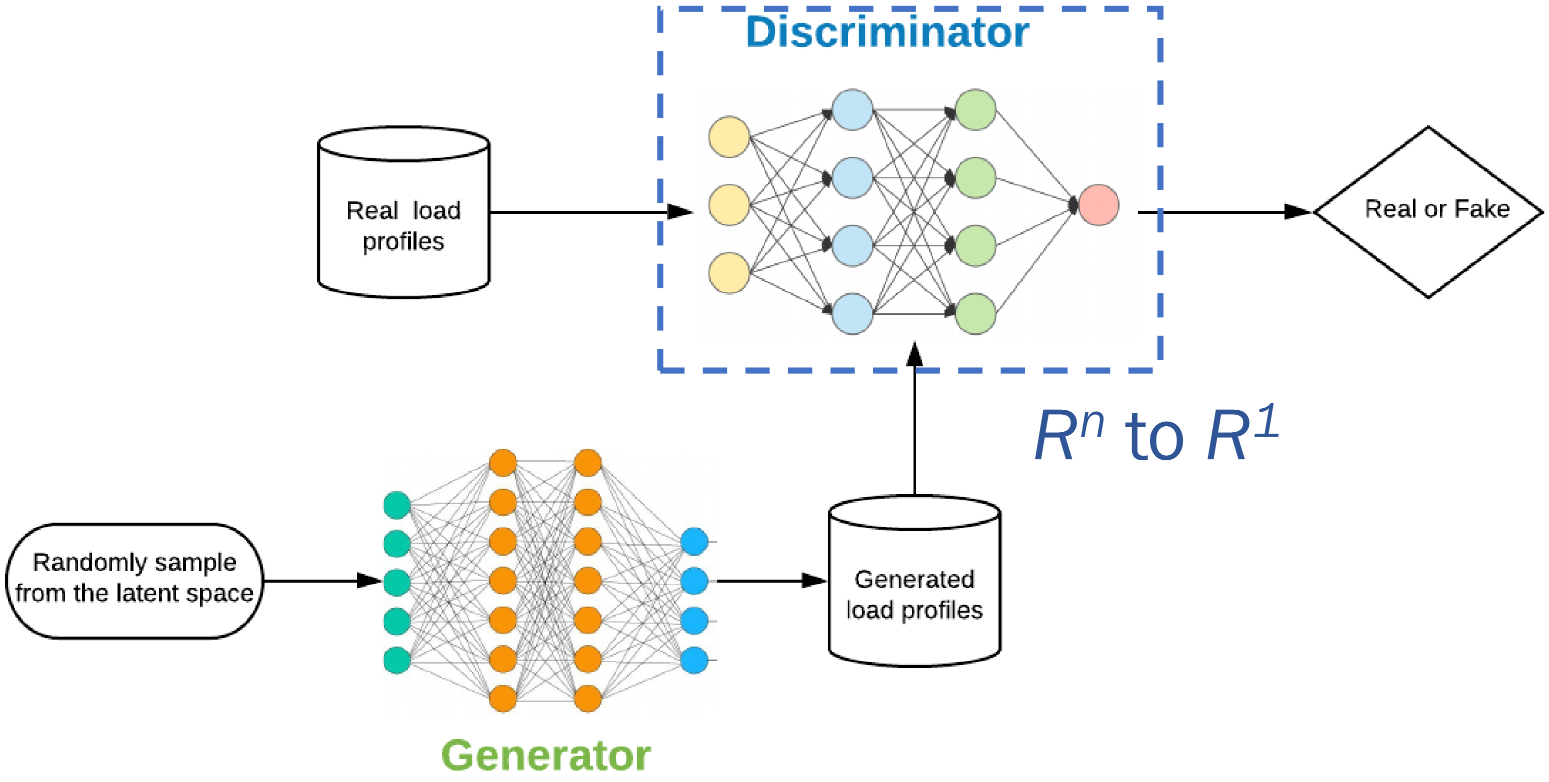
Generative Adversarial Network

- **Generator:** generator data from latent space (decoder)
- **Discriminator:** discriminate whether it is real or fake (generated)

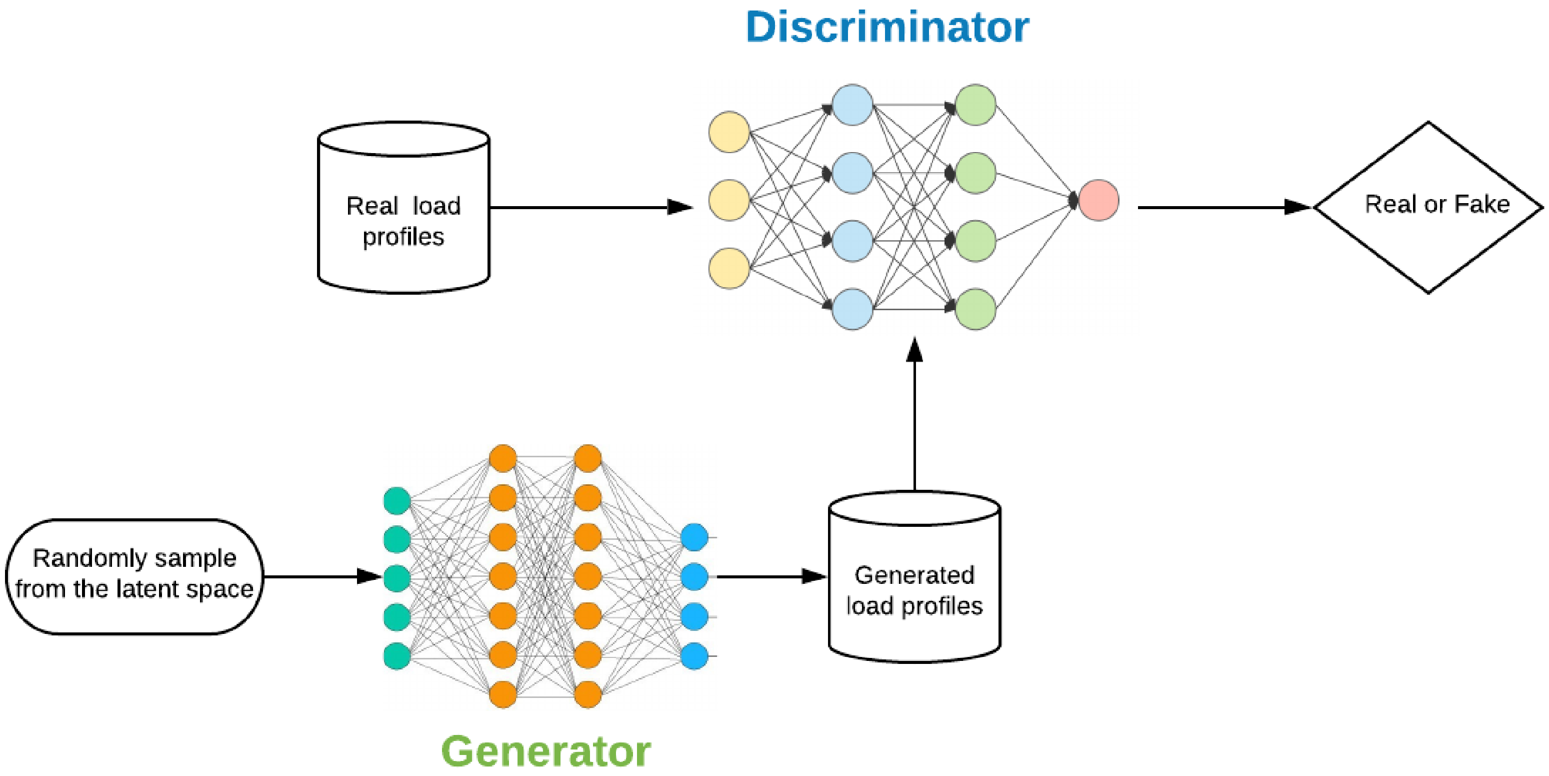


R^n to R^1

Generative Adversarial Network

- **Generator**: try to fool the discriminator by generating real-looking data
- **Discriminator**: distinguish between real and fake (generated) data

- The latent space has a lower dimension than the original space
- Any point in this latent space could be mapped to a valid data point
- Randomly sampling adds stochasticity



Generative Adversarial Network

- Generator: try to fool the discriminator by generating real-looking data
- Discriminator: distinguish between real and fake (generated) data
- Objective function
  - Discriminator

$$\max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log \underbrace{D_{\theta_d}(x)}_{\text{Discriminator output for real data x}} + \mathbb{E}_{z \sim p(z)} \log(1 - \underbrace{D_{\theta_d}(G_{\theta_g}(z))}_{\text{Discriminator output for generated fake data G(z)}}) \right]$$

  - Generator

$$\min_{\theta_g} \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))$$

Source: Stanford University, 2020, Convolutional Neural Networks for Visual Recognition, lecture 13

Training GANs

- 2-player game

Alternate between:

1. **Gradient ascent** on discriminator

$$\max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

2. **Gradient descent** on generator

$$\min_{\theta_g} \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))$$

- Using Back-Propagation
  - Fix the discriminator when training generator
  - Fix the generator when training discriminator

Training GANs

- Putting it all together

for number of training iterations **do**

for k steps **do**

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
- Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D_{\theta_d}(x^{(i)}) + \log(1 - D_{\theta_d}(G_{\theta_g}(z^{(i)}))) \right]$$

end for

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Update the generator by ascending its stochastic gradient (improved objective):

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log(D_{\theta_d}(G_{\theta_g}(z^{(i)})))$$

end for

Train discriminator *k* times

Train generator *1* time

Source: Stanford University, 2020, Convolutional Neural Networks for Visual Recognition, lecture 13

Training GANs is a challenge

- Tips and tricks for training GANs
  - https://github.com/soumith/ganhacks

1. Normalize the inputs

- normalize the images between -1 and 1
- Tanh as the last layer of the generator output

2: A modified loss function

In GAN papers, the loss function to optimize G is `min (log 1-D)`, but in practice folks practically use `max log D`

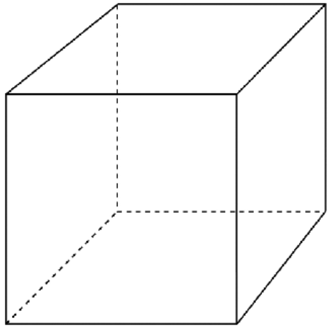
- because the first formulation has vanishing gradients early on
- Goodfellow et. al (2014)

In practice, works well:

- Flip labels when training generator: real = fake, fake = real

3: Use a spherical Z

- Dont sample from a Uniform distribution



- Sample from a gaussian distribution

5: Avoid Sparse Gradients: ReLU, MaxPool

- the stability of the GAN game suffers if you have sparse gradients
- LeakyReLU = good (in both G and D)
- For Downsampling, use: Average Pooling, Conv2d + stride
- For Upsampling, use: PixelShuffle, ConvTranspose2d + stride
  - PixelShuffle: https://arxiv.org/abs/1609.05158

6: Use Soft and Noisy Labels

- Label Smoothing, i.e. if you have two target labels: Real=1 and Fake=0, then for each incoming sample, if it is real, then replace the label with a random number between 0.7 and 1.2, and if it is a fake sample, replace it with 0.0 and 0.3 (for example).
  - Salimans et. al. 2016
- make the labels the noisy for the discriminator: occasionally flip the labels when training the discriminator

7: DCGAN / Hybrid Models

- Use DCGAN when you can. It works!
- if you cant use DCGANs and no model is stable, use a hybrid model : KL + GAN or VAE + GAN

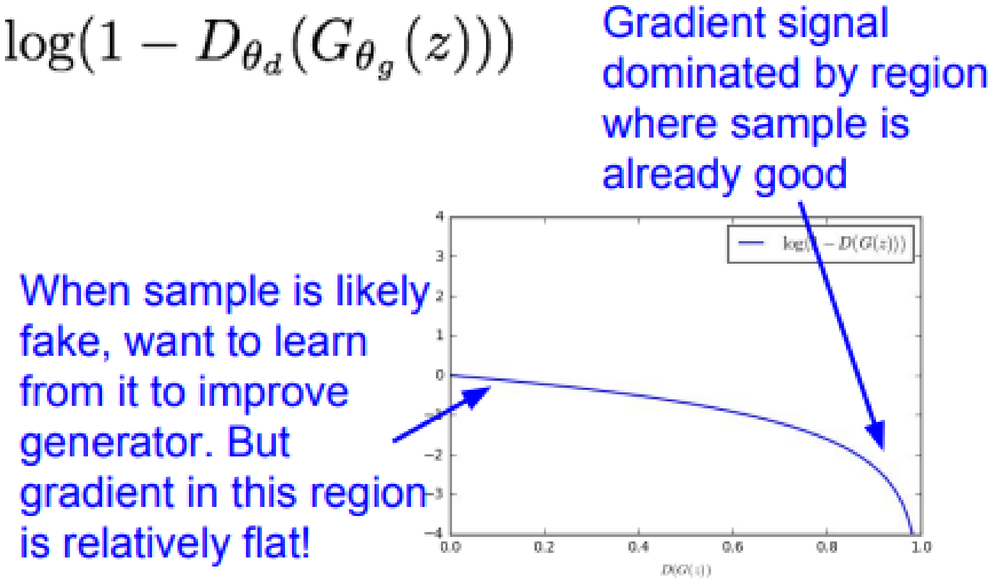
8: Use stability tricks from RL

- Experience Replay
  - Keep a replay buffer of past generations and occassionally show them
  - Keep checkpoints from the past of G and D and occassionaly swap them out for a few iterations
- All stability tricks that work for deep deterministic policy gradients
- See Pfau & Vinyals (2016)

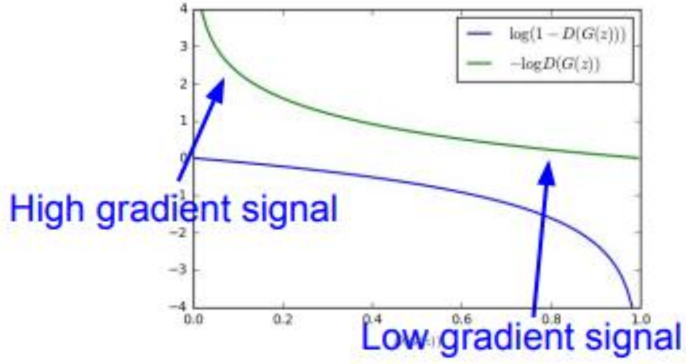
A modified loss function

- Loss function of generator

$$\min_{\theta_g} \mathbb{E}_{z\sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))$$



$$\max_{\theta_g} \mathbb{E}_{z\sim p(z)} \log(D_{\theta_d}(G_{\theta_g}(z)))$$



Source: Stanford University, 2020, Convolutional Neural Networks for Visual Recognition, lecture 13

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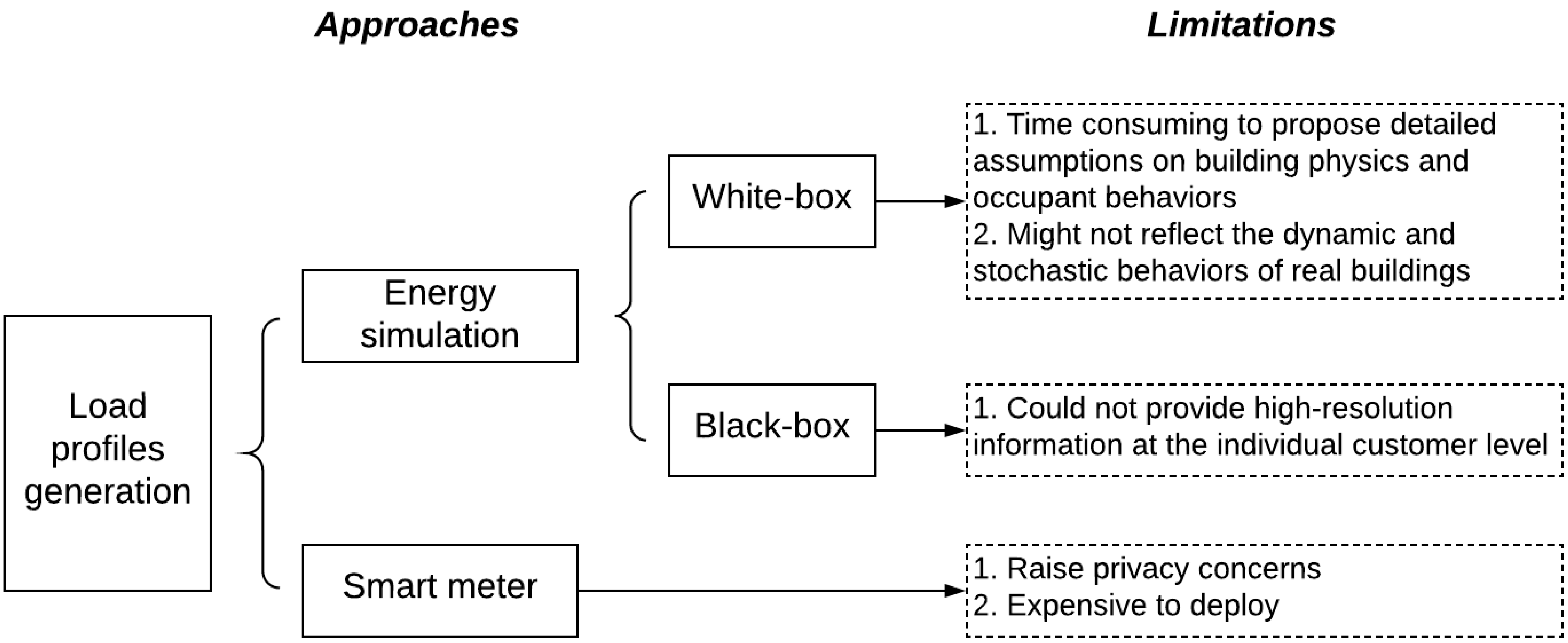
Application of GAN in smart building

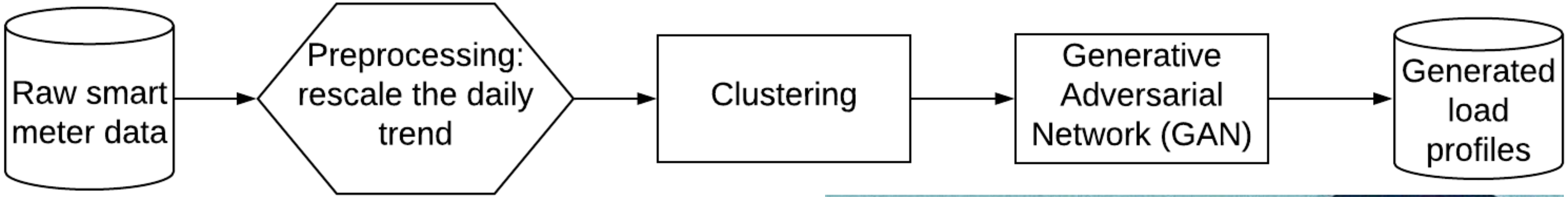
- Using GAN to generated building load profiles
  - Published as: Wang, Z. and Hong, T., 2020. Generating realistic building electrical load profiles through the Generative Adversarial Network (GAN). Energy and Buildings, 224, p.110299.
- Why we need to generate building load profiles
  - Wide application in the grid operation
    - Identification of unnecessary waste
    - Load forecasting for generation planning
    - …

Building load generation



Research question

- Can we generate building load directly from smart meter data?



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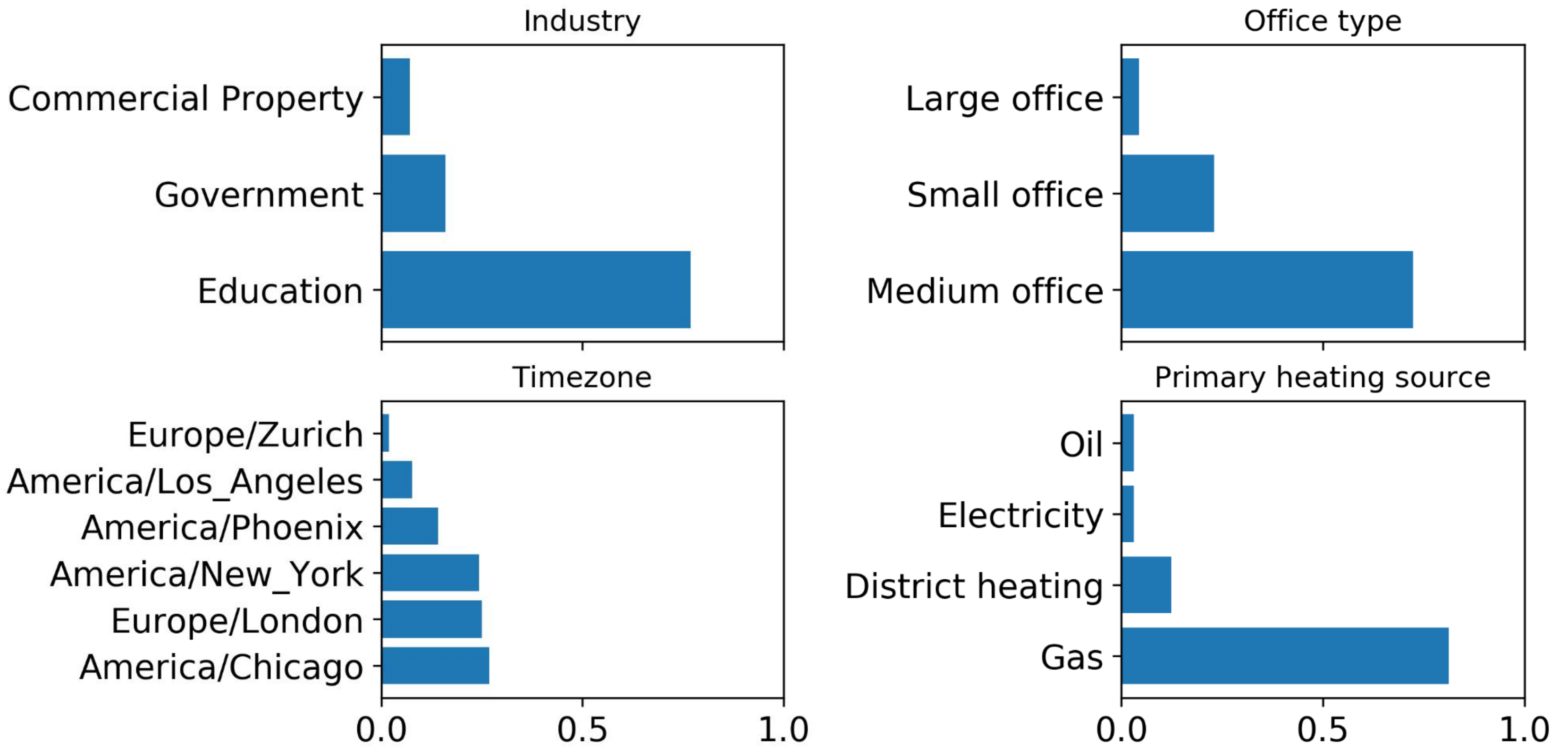
Data

- Building Data Genome Project database
  - 156 office buildings
  - 56,957 daily loads
  - Electrical
  - Hourly



Clustering

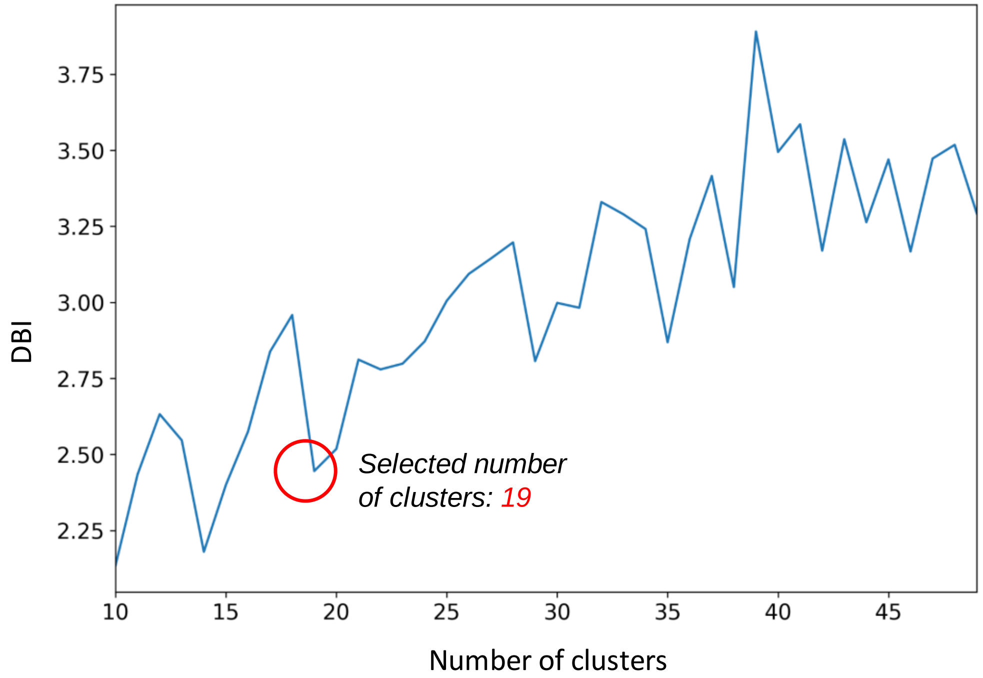
- Why we need clustering
  - Same cluster of load share similar patterns
  - GAN is learning these patters
  - If you combine different clusters together, the pattern is blurry and hard to learn
- Metrics to evaluate clustering
  - Davies-Bouldin Index (DBI)

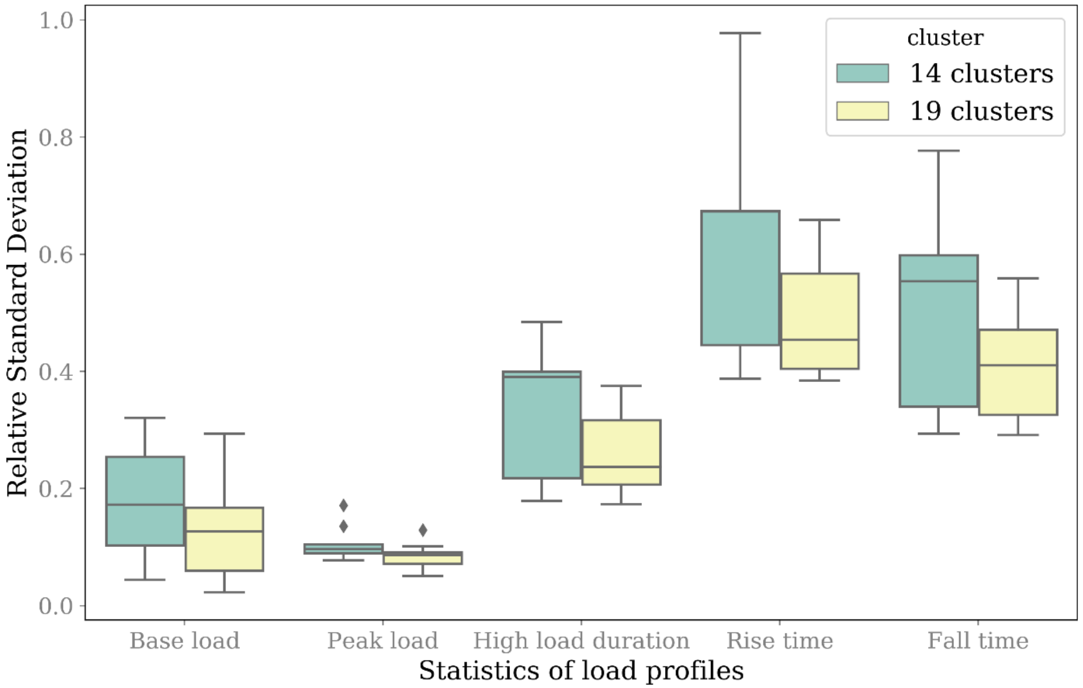
$$R_{ij} = \frac{s_i + s_j}{d_{ij}}$$

$$DBI = \frac{1}{k} \sum_{i=1}^{k} max_{i \neq j}(R_{ij})$$

Clustering: method

- K-means
- Select the number of clusters





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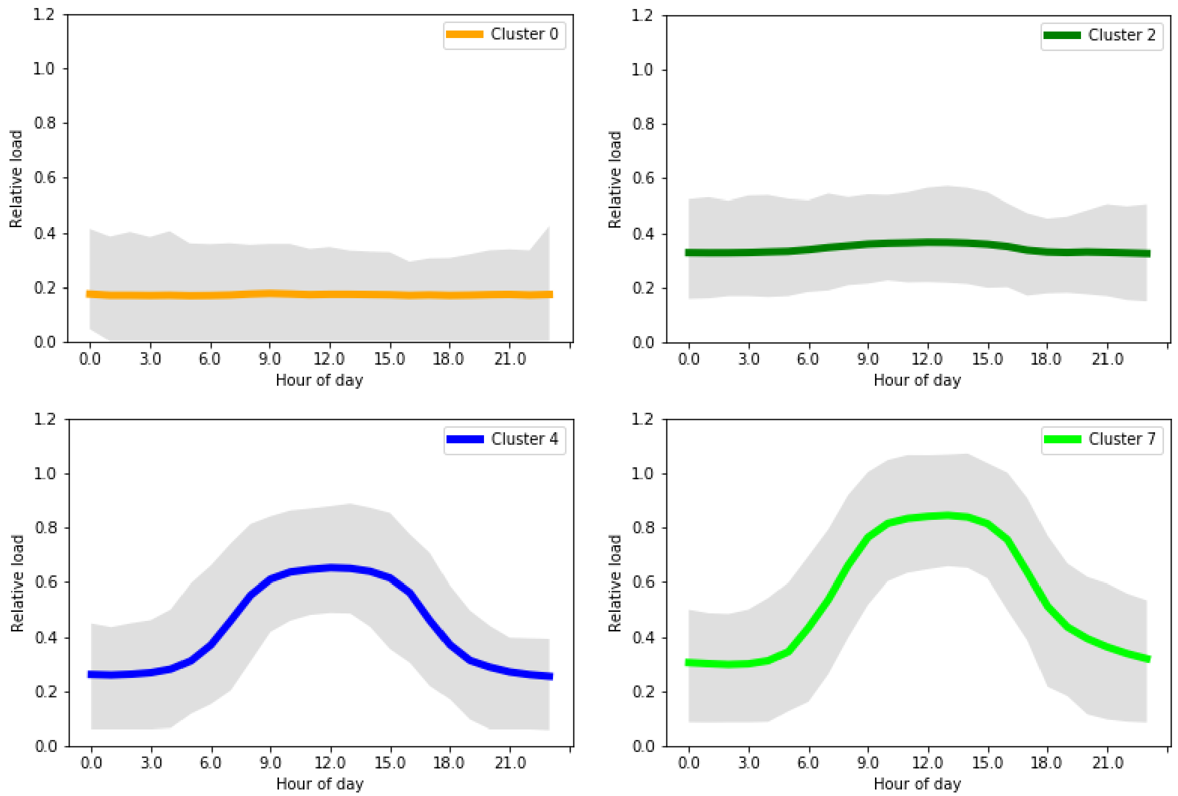
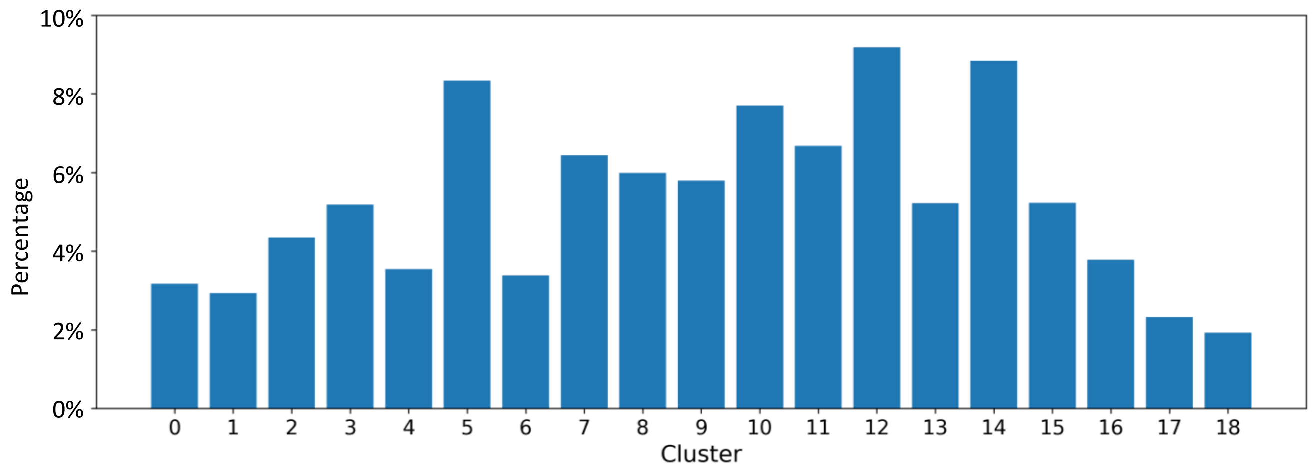
Clustering: result

- We identified 19 clusters
  - Working and non-working day patterns
  - High and low base-load





GAN: method

- We implemented GAN with Keras

Pseudocode

---

define the *discriminator neural network* and compile the *discriminator model*

define the *generator neural network*

define and compile *GAN model* by integrating the *generator* and *discriminator neural network*, and setting the parameter of *discriminator neural network* untrainable

for *epoch* in range(*epochs*):

 # train the discriminator

sample points randomly from the real load profile dataset

generate fake load profiles from randomly sample seeds with the *generator neural network*

combine and shuffle the real and fake load profiles together

train the *discriminator model* with the combined data points to minimize d_loss defined in *Equation 3* (training the parameters in the *discriminator neural network*)

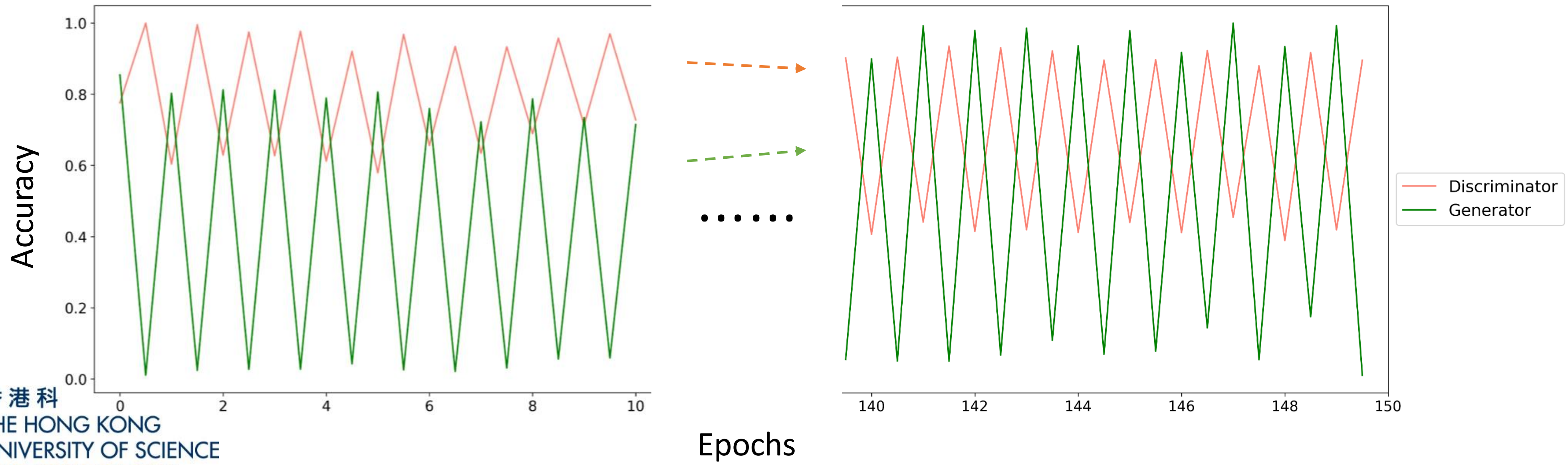
 # train the generator

sample seeds randomly from pre-defined normal distribution

train the *GAN model* with the sampled seeds to minimize g_loss defined in *Equation 4* (as the parameter of *discriminator* was set untrainable in the *GAN model*, we are essentially training the parameters in *generator neural network* only in this phase)

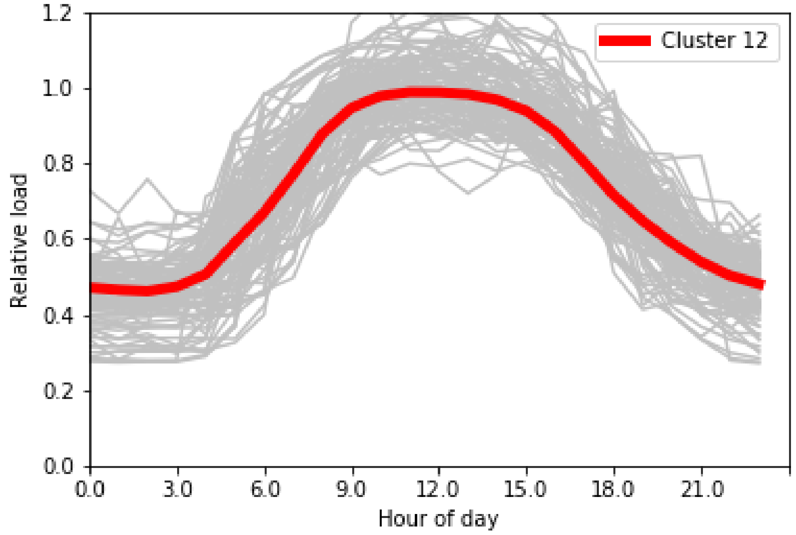
GAN: training

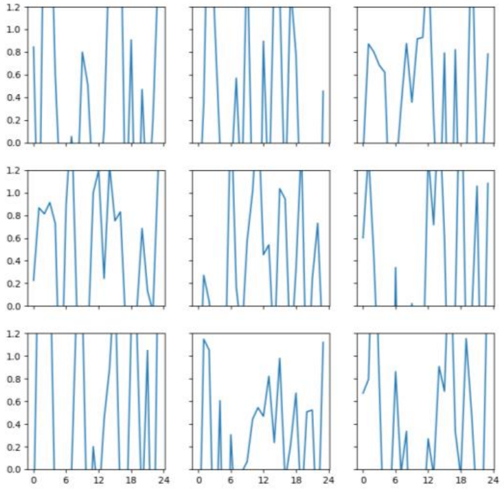
- Discriminator
  - the percentage of load profiles that can be detected correctly.
- Generator
  - the percentage of generated load profiles that are detected as “real” by the discriminator

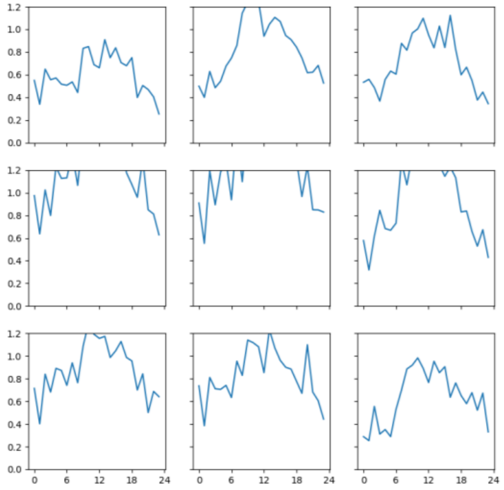


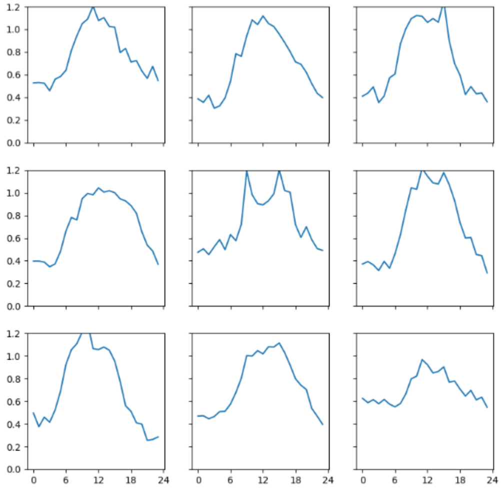
GAN: result

- Learn to capture the load dynamics
  - General trend
  - Random events



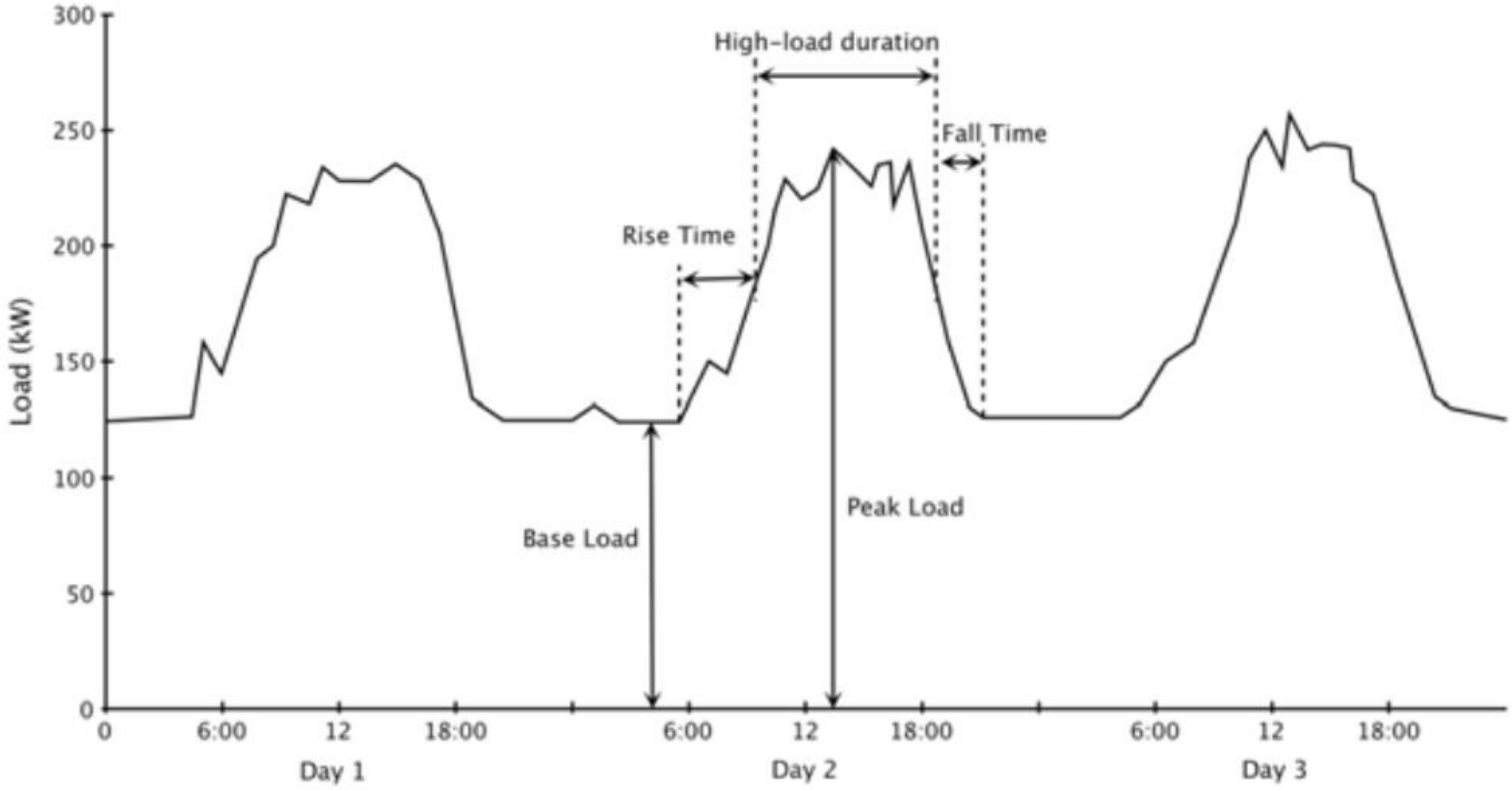




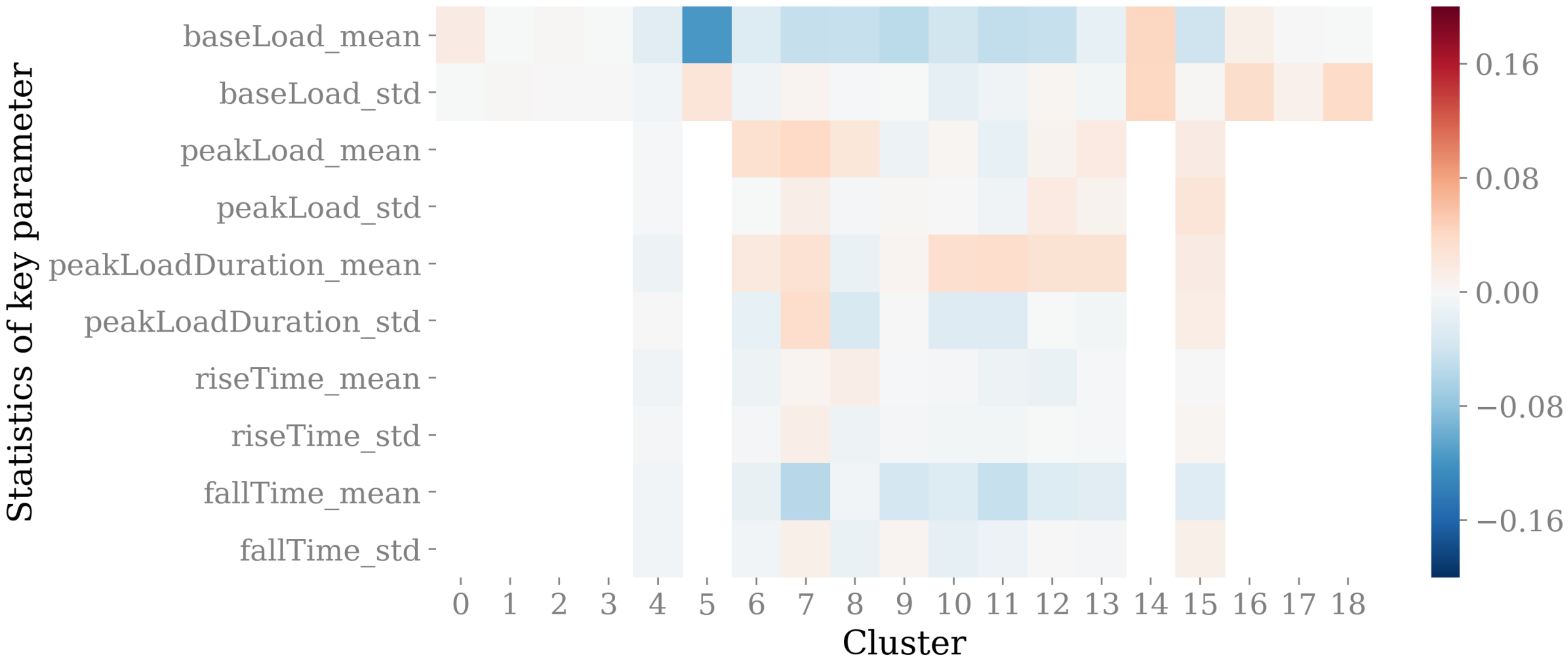


GAN: validation

- Diversity
- Fidelity
- Usefulness



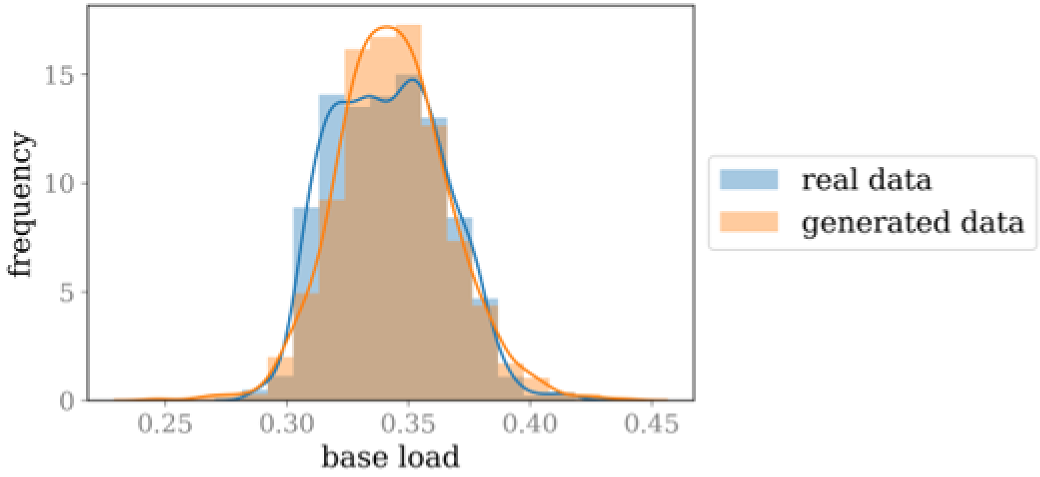
GAN: validation



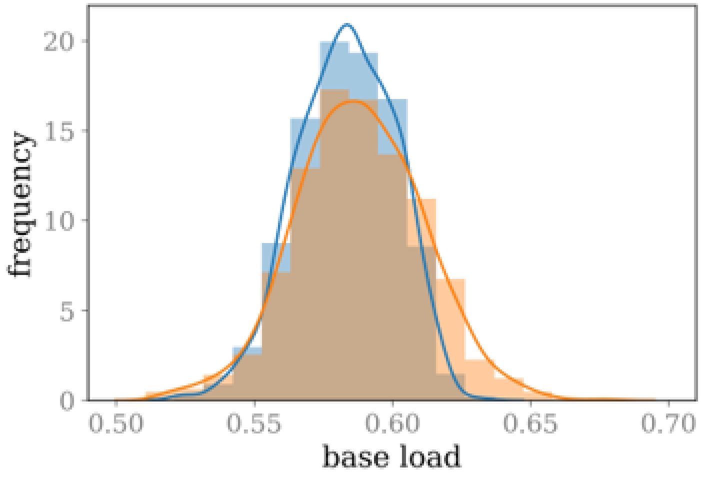
GAN: validation

- Distance between distributions
- Kullback–Leibler Divergence

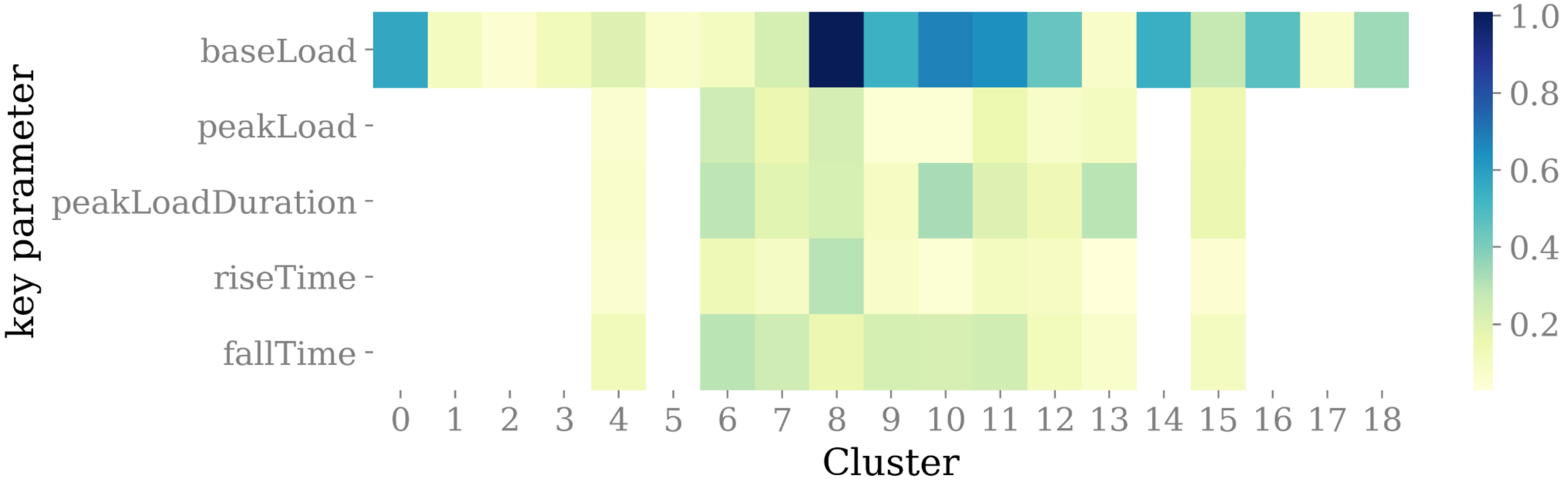
$$D_{\mathrm{KL}}(P \parallel Q) = -\sum_{x \in \mathcal{X}} P(x) \log\left(\frac{Q(x)}{P(x)}\right)$$



(c) cluster 2 (low KL divergence)

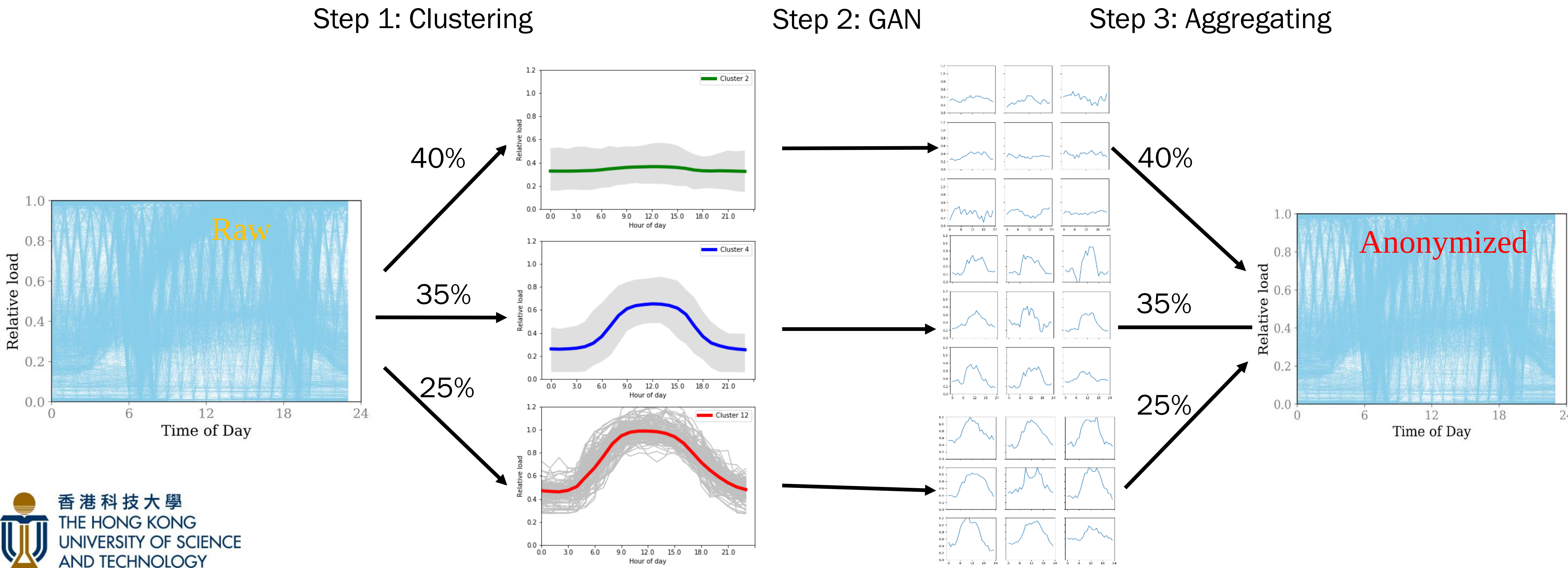


(d) cluster 8 (high KL divergence)



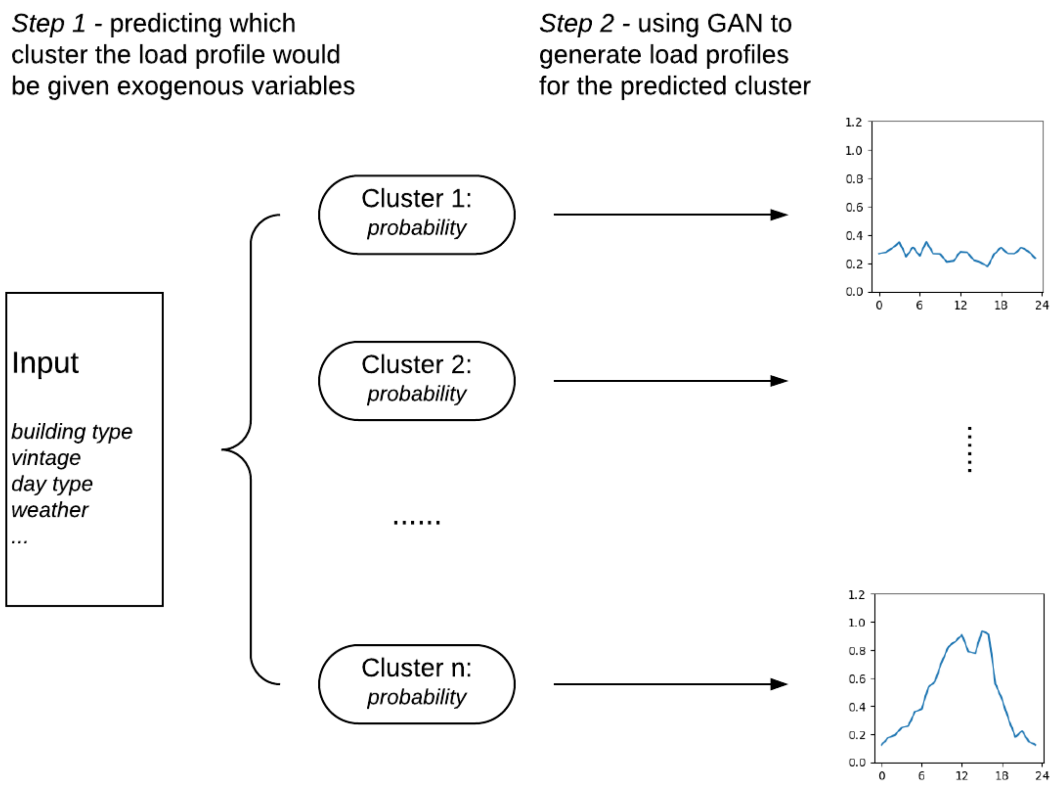
GAN: Applications

- Anonymize real building electrical load profiles



GAN: Applications

- Load prediction



- Validate load models or detect outliers

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Enhancement to GANs

- Wasserstein GAN
- Convolutional GAN
- LSGAN
- Time series GAN

Some enhancement for time-series data

- Need to capture
  - the distribution of features within each time point

$$\mathbb{E}_{\mathbf{s},\mathbf{x}_{1:T}\sim p}\big[\log y_{\mathcal{S}} + \textstyle\sum_t \log y_t\big] + \mathbb{E}_{\mathbf{s},\mathbf{x}_{1:T}\sim \hat{p}}\big[\log(1-\hat{y}_{\mathcal{S}}) + \textstyle\sum_t \log(1-\hat{y}_t)\big]$$

  - the dynamics of those variables across time

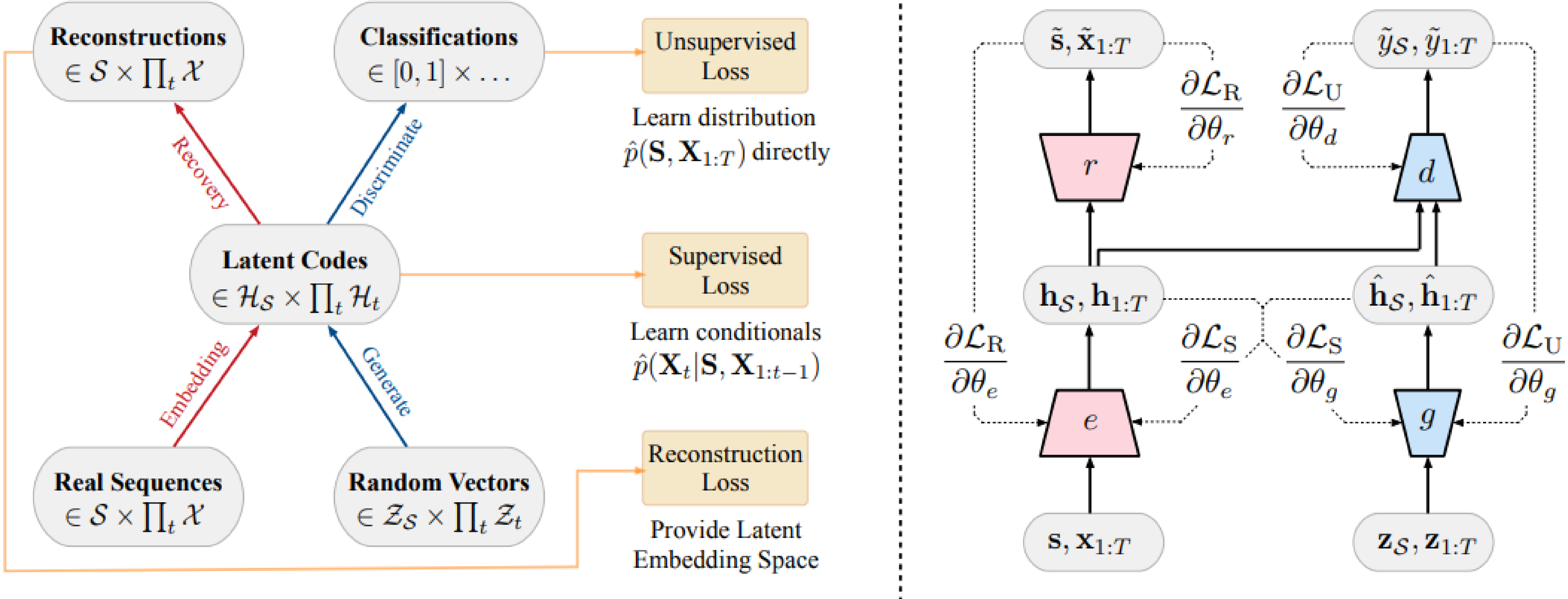
$$\textstyle\prod_t p(\mathbf{x}_t|\mathbf{x}_{1:t-1})$$

Solution 1

- Use recurrent neural network to capture the temporal dynamics
  - Long Short Term Memory
    - Mogren, O., 2016. C-RNN-GAN: Continuous recurrent neural networks with adversarial training. *arXiv preprint arXiv:1611.09904*.
  - Recurrent Neural Network
    - Esteban, C., Hyland, S.L. and Rätsch, G., 2017. Real-valued (medical) time series generation with recurrent conditional gans. arXiv preprint arXiv:1706.02633.

Solution 2

- TimeGAN
  - Yoon, J., Jarrett, D. and van der Schaar, M., 2019. Time-series generative adversarial networks. In Advances in Neural Information Processing Systems (pp. 5508-5518)
- Key idea: Incorporate the temporal dynamics into the objective functions



(a) Block Diagram

(b) Training Scheme

$$\mathcal{L}_\text{U} = \mathbb{E}_{\mathbf{s},\mathbf{x}_{1:T}\sim p}\big[\log y_\mathcal{S} + \textstyle\sum_t \log y_t\big] + \mathbb{E}_{\mathbf{s},\mathbf{x}_{1:T}\sim \hat{p}}\big[\log(1-\hat{y}_\mathcal{S}) + \textstyle\sum_t \log(1-\hat{y}_t)\big]$$

$$\mathcal{L}_\text{S} = \mathbb{E}_{\mathbf{s},\mathbf{x}_{1:T}\sim p}\big[\textstyle\sum_t \|\mathbf{h}_t - g_\mathcal{X}(\mathbf{h}_\mathcal{S}, \mathbf{h}_{t-1}, \mathbf{z}_t)\|_2\big]$$

$$\mathcal{L}_\text{R} = \mathbb{E}_{\mathbf{s},\mathbf{x}_{1:T}\sim p}\big[\|\mathbf{s} - \tilde{\mathbf{s}}\|_2 + \textstyle\sum_t \|\mathbf{x}_t - \tilde{\mathbf{x}}_t\|_2\big]$$

TimeGAN: contribution/novelty

- Use a supervised loss to better capture temporal dynamics
- Use an embedding network that provides a lower-dimensional adversarial learning space

- https://github.com/jsyoon0823/TimeGAN

Conclusion

- We introduced generative models and latent space
- We learned Generative Adversarial Networks (GAN): math and psudo-code
- We applied GAN to generate building load profiles
- We discussed future work and enhancements to GAN

Thanks and Questions

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