Deep Generative Models

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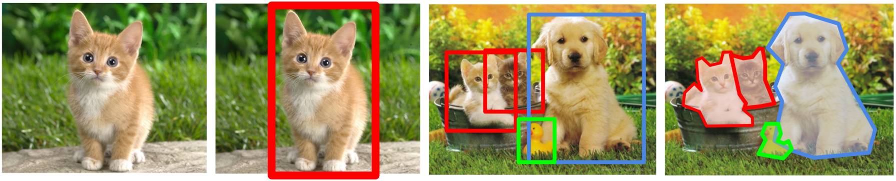
Supervised vs. Unsupervised Learning[1]

Supervised Learning

- **Data** $(\mathbf{x}, y)$: $\mathbf{x}$ is data, y is label/output.
- **Goal**: Learn a function to map $\mathbf{x} \rightarrow y$.

Classification | **Classification + Localization** | **Object Detection** | **Instance Segmentation**



CAT | CAT | CAT, DOG, DUCK | CAT, DOG, DUCK

Single object | Multiple objects

[1] Partially adapted from http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture13.pdf

Supervised vs. Unsupervised Learning[1]

Supervised Learning

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1. A park with a clock tower in the background
2. A place with a tall building in the background
3. A park with a tall tree in the middle

[1] Partially adapted from http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture13.pdf

Unsupervised Learning

- **Data x**: no labels.
- **Goal**: Learn some underlying hidden structure of the data:
  - Define different objective functions for different models.

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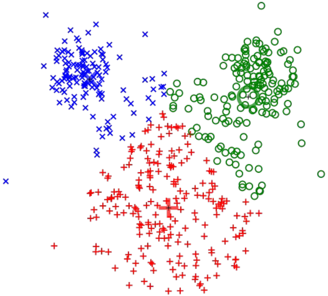

Figure: Kmeans

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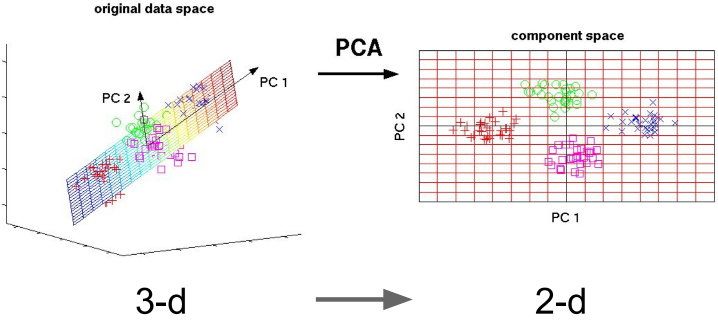

Figure: Principal component analysis (dimension reduction)

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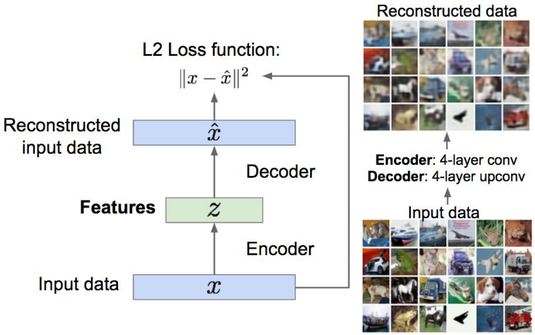

Figure: Autoencoders (feature learning)

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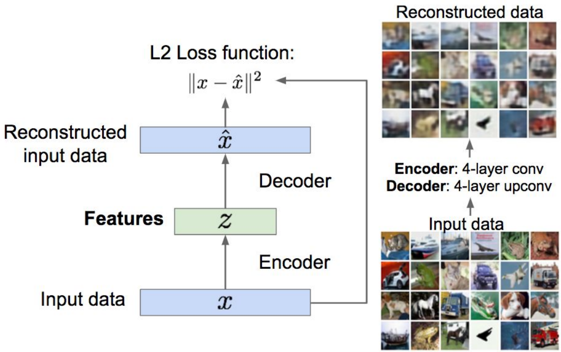

Figure: Autoencoders (feature learning)

$\Rightarrow$ Variational autoencoder (VAE)

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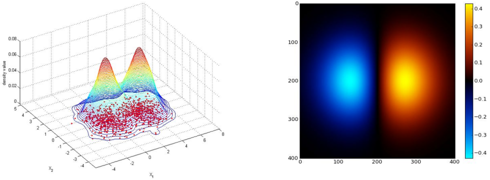
1-d density estimation



2-d density estimation

Unsupervised Learning

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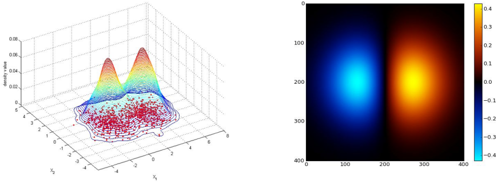
1-d density estimation



2-d density estimation

$\Rightarrow$ Generative adversarial networks (GAN)

Generative Models

Generate new samples from the same data distribution.

training data $\sim p_{\text{data}}(\mathbf{x})$

generated samples $\sim p_{\text{model}}(\mathbf{x})$

- Goal is to learn $p_{\text{model}}(\mathbf{x})$ such that it is close to $p_{\text{data}}(\mathbf{x})$.

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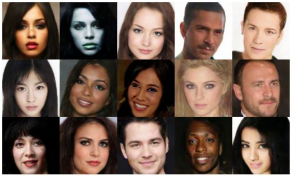
Several flavors

- Explicit density estimation: explicitly define and solve for $p_{\text{model}}(\mathbf{x})$:
  - *e.g.*, variational autoencoder (VAE) (in this case, $\mathbf{x}$ refers to the latent representation of the data)
- Implicit density estimation: learn a model that can sample from $p_{\text{model}}(\mathbf{x})$ w/o explicitly defining it:
  - *e.g.*, generative adversarial nets (GAN)

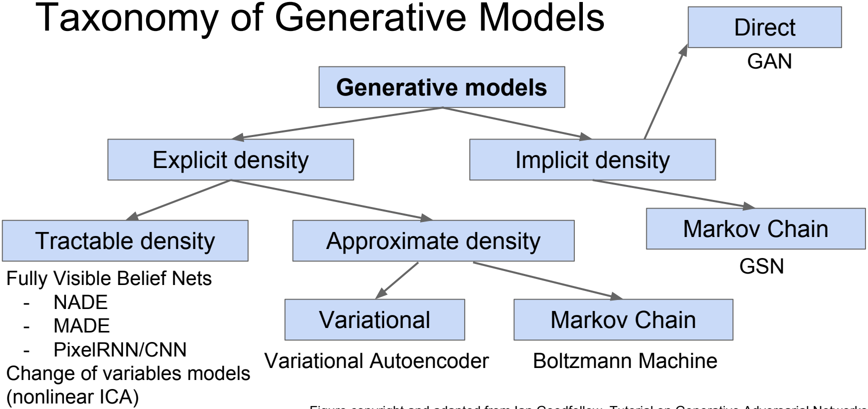
Why Generative Models?

1. Realistic samples for artwork, super-resolution, colorization *etc*.


2. Generative models of time-series data can be used for simulation and planning $\Rightarrow$ reinforcement learning applications.
3. Training generative models can also enable inference of latent representations that can be useful as general features.
4. Effective use of unlabeled data.

Taxonomy of Generative Models



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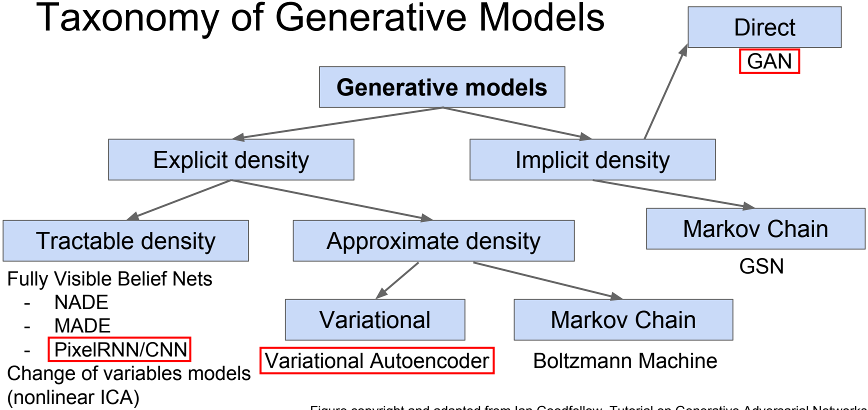
Taxonomy of Generative Models



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