CS 4803 / 7643: Deep Learning

Topics:

- Unsupervised Learning
- Generative Models

Michael Cogswell

(subbing for Dhruv Batra)

Georgia Tech

Overview

- Unsupervised Learning
  - Comparison to Supervised and Reinforcement Learning
  - Review of K-Means

- e.g., Generative Models
  - Varieties
  - PixelRNN and PixelCNN

Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

Supervised vs Reinforcement vs Unsupervised Learning

Supervised Learning

Given: (x, y)
x is data, y is label

Goal: Learn a *function* to map x → y

Examples: Classification, regression, object detection, semantic segmentation, image captioning, etc.

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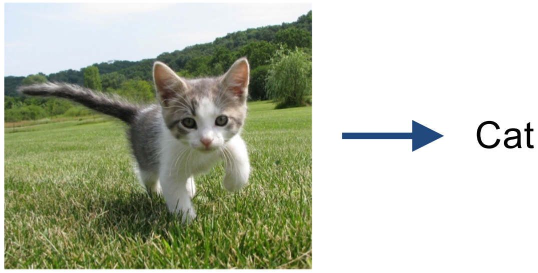

Classification

Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

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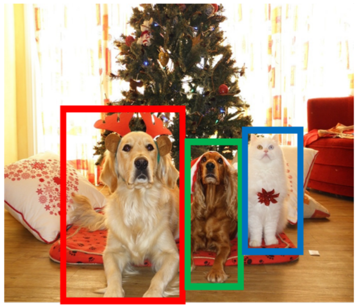

DOG, DOG, CAT

Object Detection

Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

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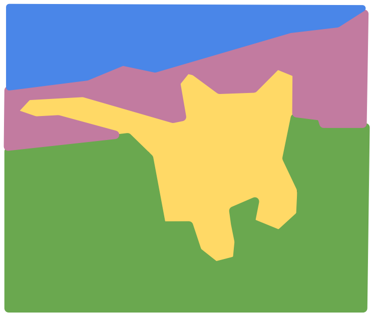

GRASS, CAT, TREE, SKY

Semantic Segmentation

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A cat sitting on a suitcase on the floor

Image captioning

Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

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Reinforcement Learning

Given: (e, r)

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Goal: Maximize expected reward

Examples: Robotic control, video games, board games, etc.

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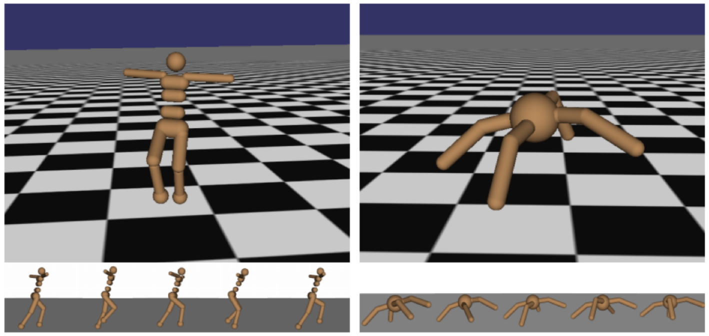

Robotic Locomotion

Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

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Atari Games

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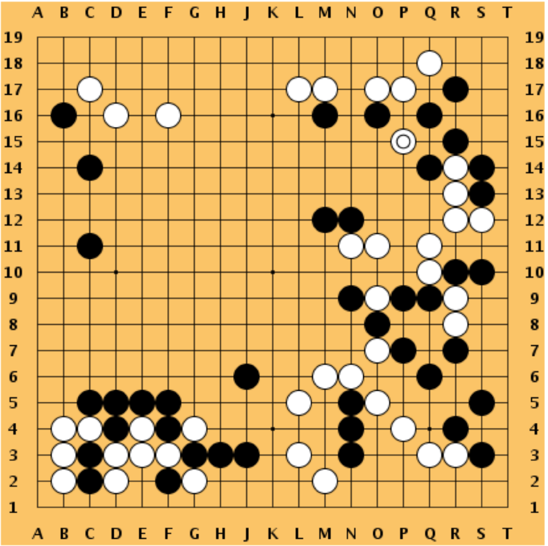

Go

Supervised vs Reinforcement vs Unsupervised Learning

Unsupervised Learning

Given: Data x

Just data, no labels!

Goal: Learn some underlying hidden *structure* of the data

Examples: Clustering, dimensionality reduction, feature learning, density estimation, etc.

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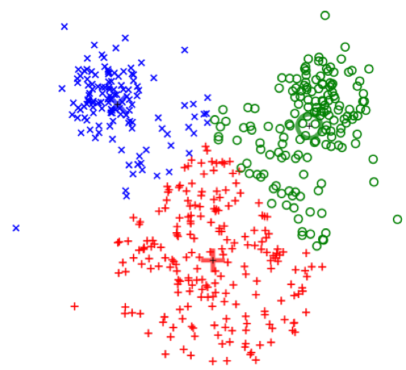

K-means clustering

Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

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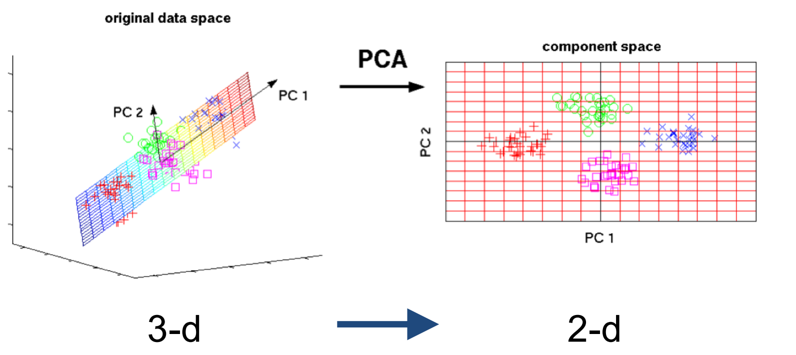

Principal Component Analysis
(Dimensionality reduction)

Supervised vs Reinforcement vs Unsupervised Learning

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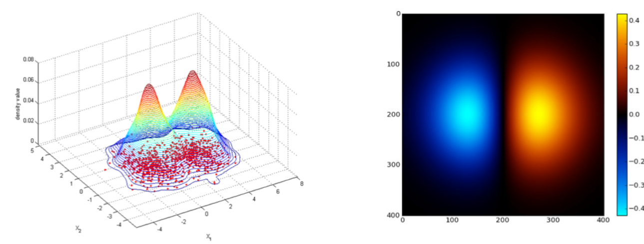
1-d density estimation



2-d density estimation

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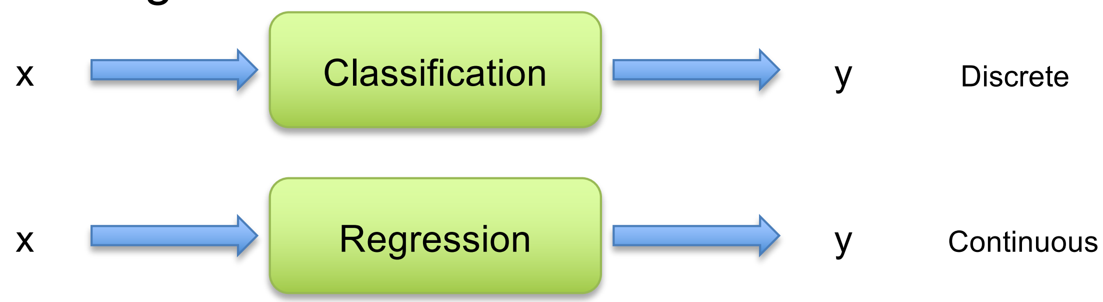
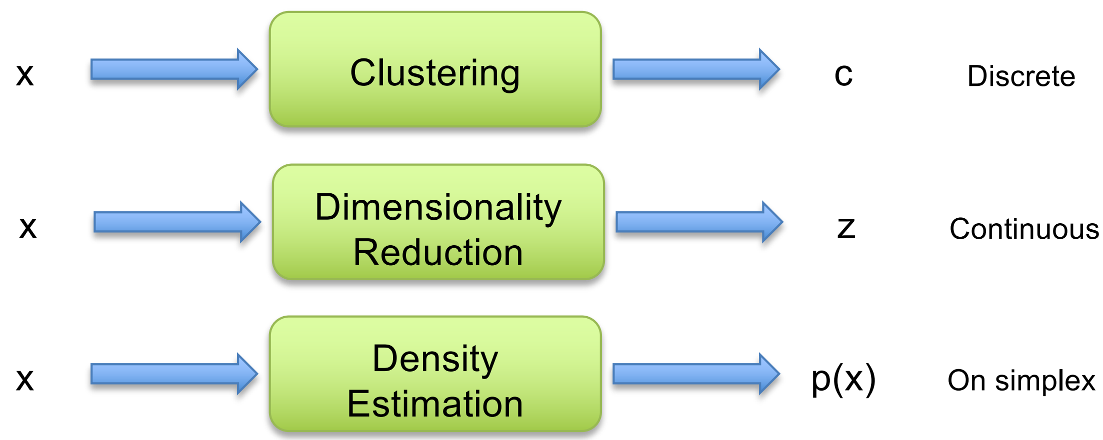
Tasks

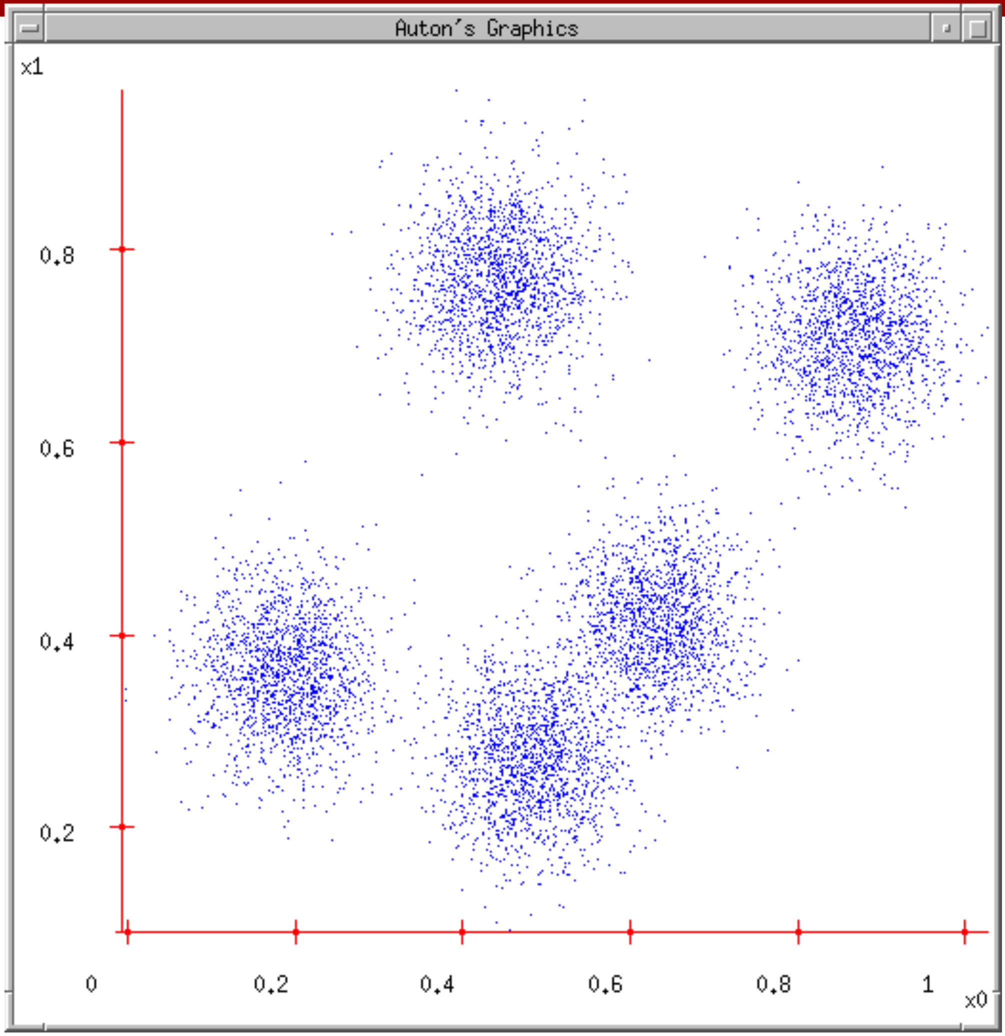
Supervised Learning



Unsupervised Learning

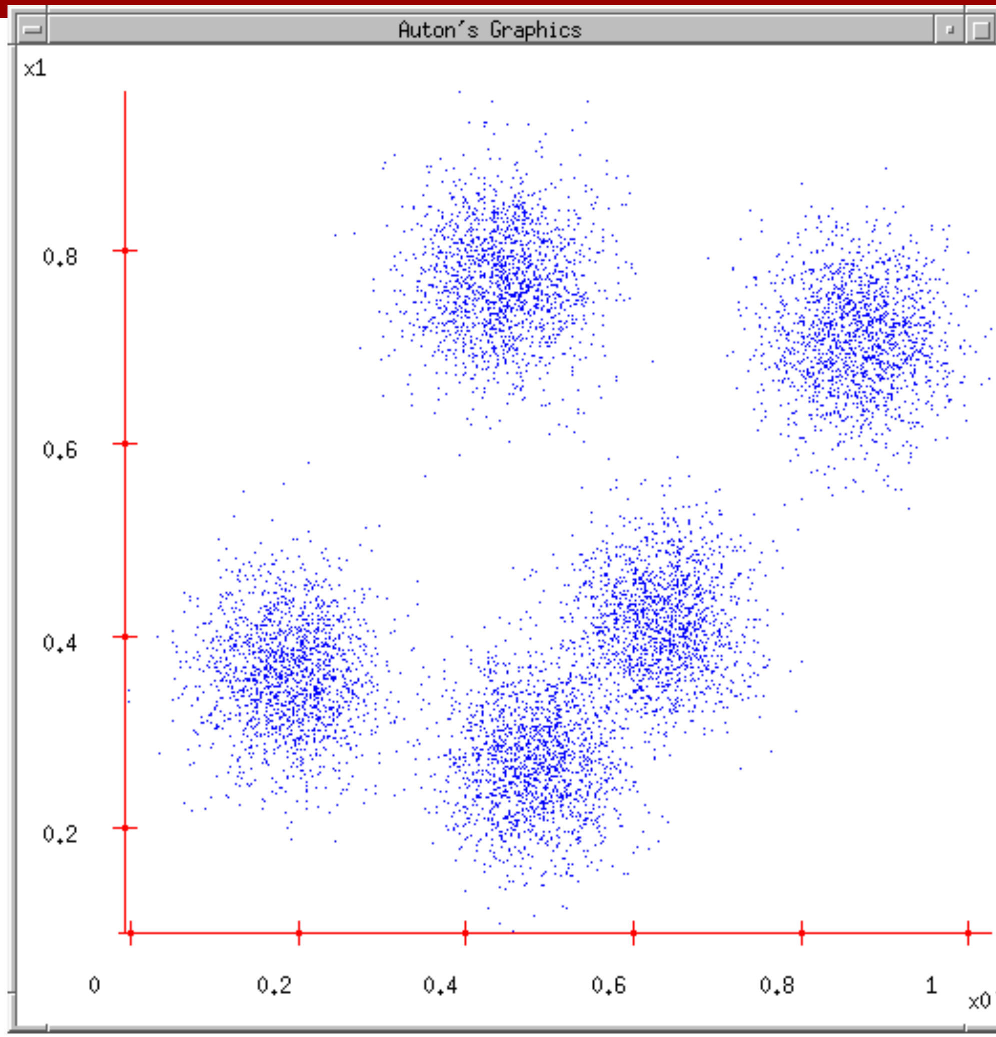


Some Data



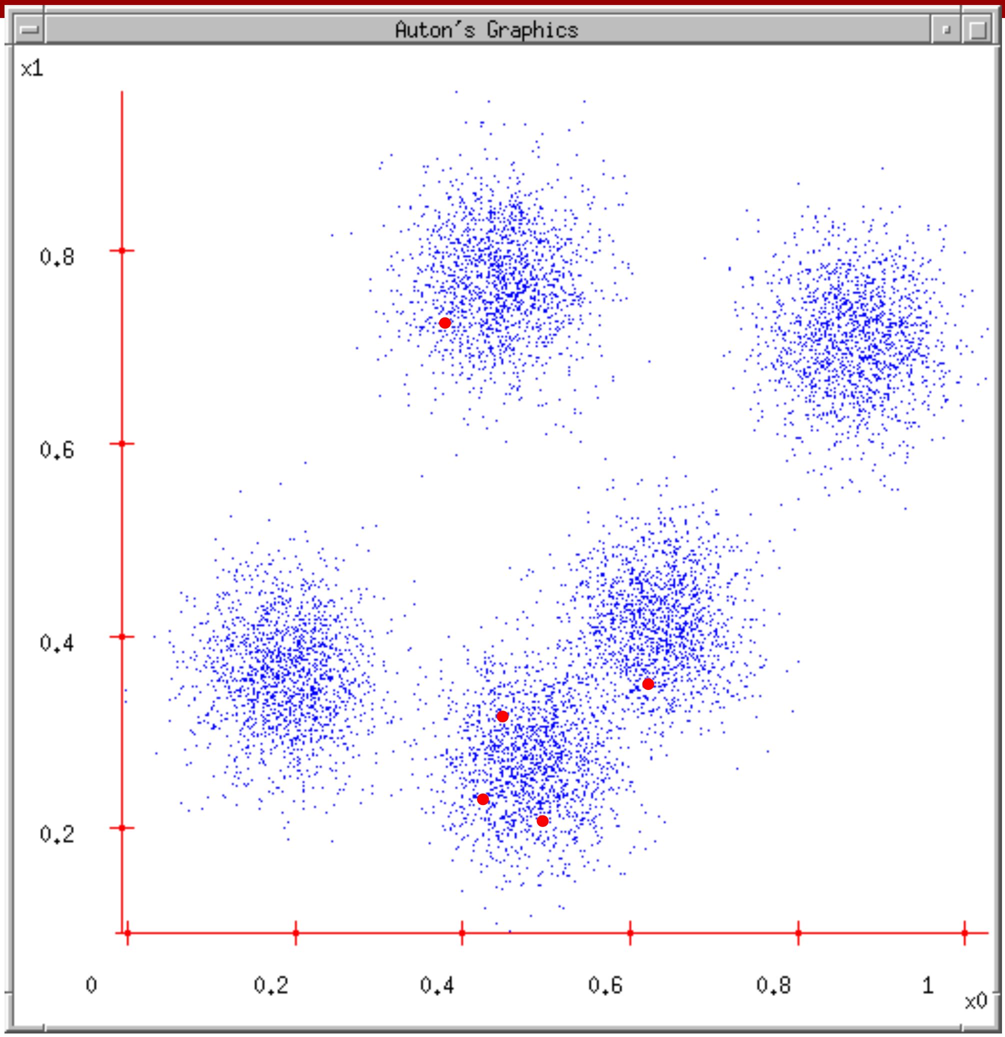
K-means

1. Ask user how many clusters they'd like. *(e.g. k=5)*



K-means

1. Ask user how many clusters they'd like. *(e.g. k=5)*
2. Randomly guess k cluster Center locations



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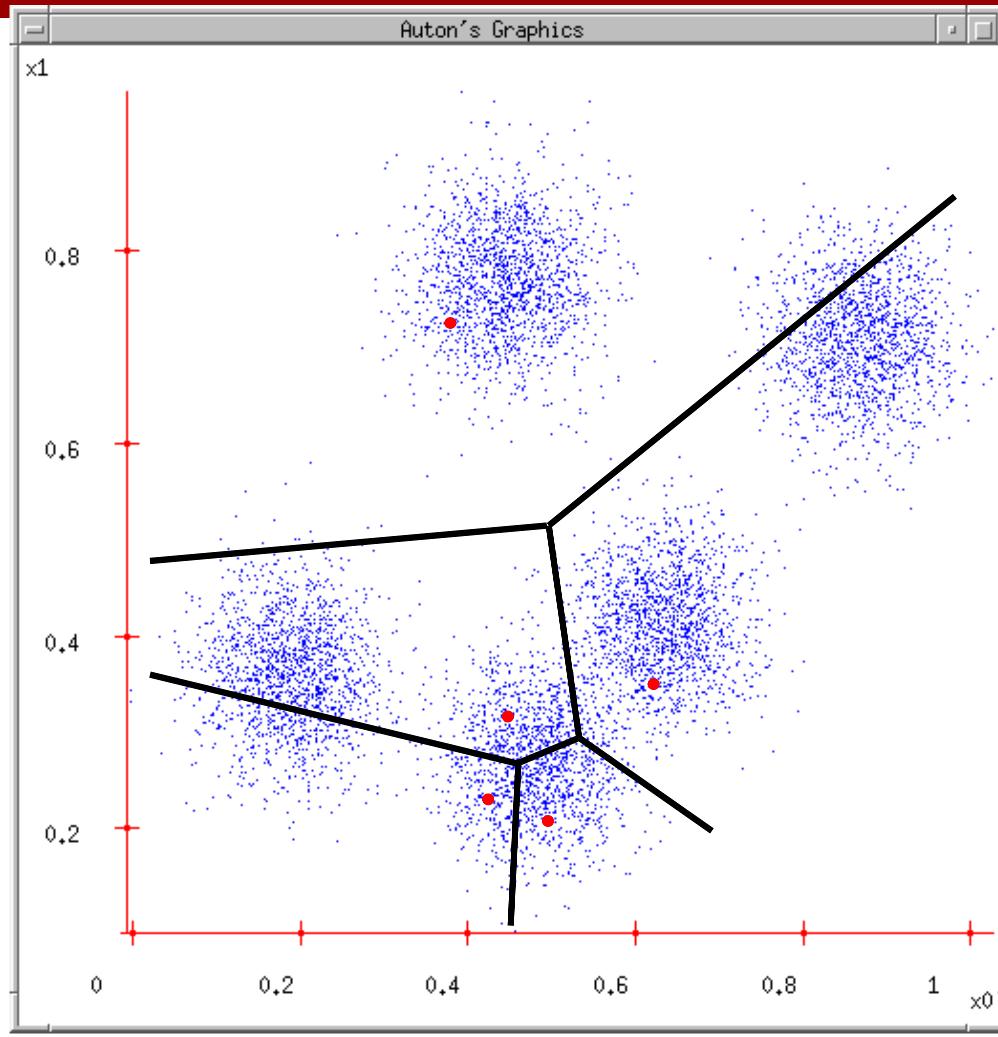
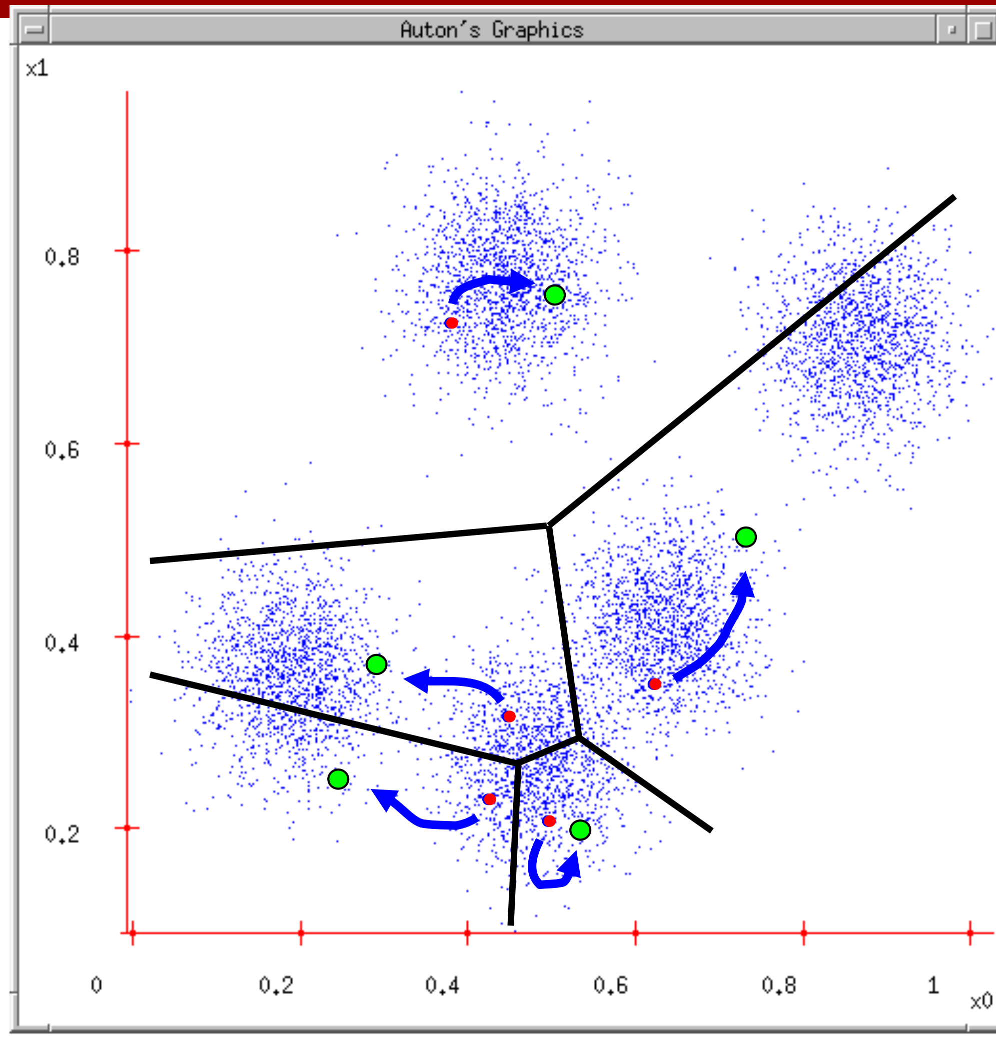
3. Each datapoint finds out which Center it's closest to.



K-means

1. Ask user how many clusters they'd like. *(e.g. k=5)*
2. Randomly guess k cluster Center locations
3. Each datapoint finds out which Center it's closest to.
4. Each Center finds the centroid of the points it owns…



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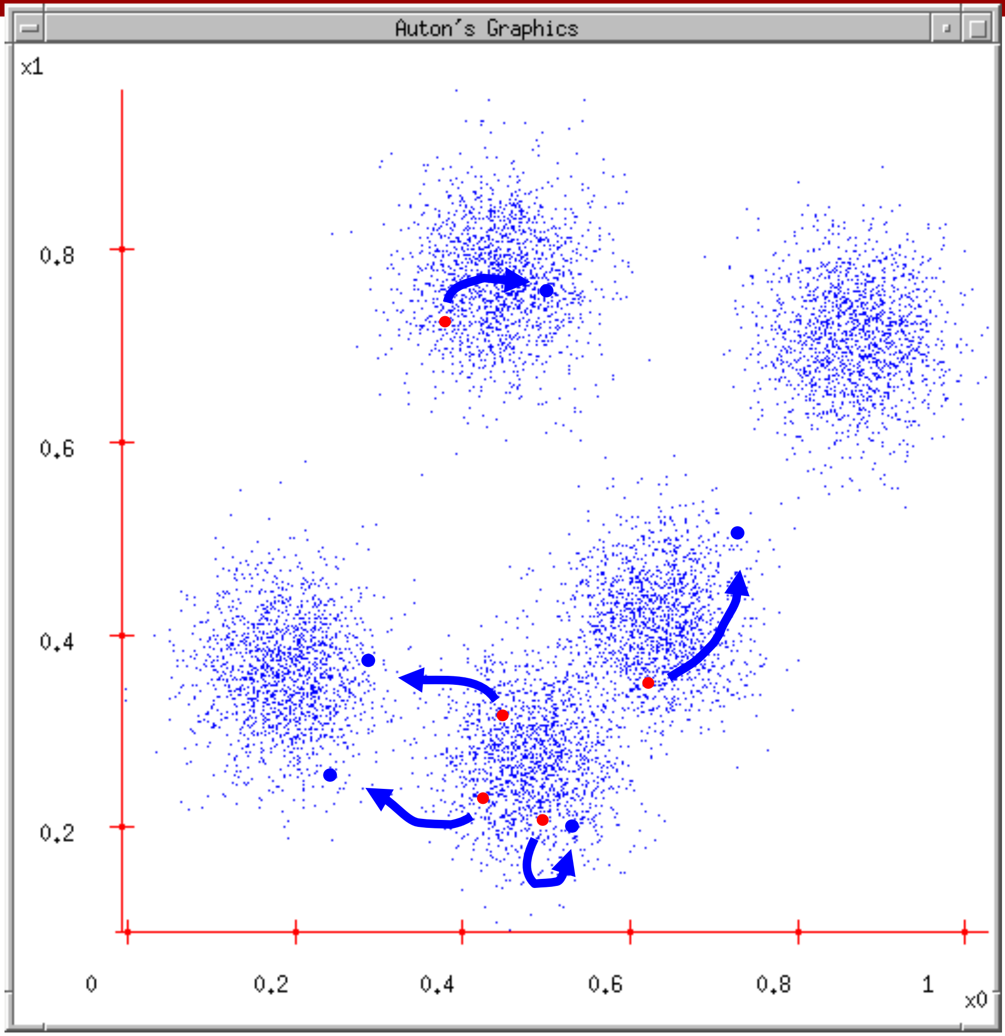
5. …and jumps there
6. …Repeat until terminated!



K-means

- Demo
  - http://stanford.edu/class/ee103/visualizations/kmeans/kmeans.html

K-means

- Randomly initialize *k* centers
  - $\mu^{(0)} = \mu_1^{(0)}, \ldots, \mu_k^{(0)}$

- **Assign**:
  - Assign each point $i \in \{1, \ldots n\}$ to nearest center:
  - $$C(i) \longleftarrow \underset{j}{\operatorname{argmin}} \, ||\mathbf{x}_i - \boldsymbol{\mu}_j||^2$$

- **Recenter**:
  - μ_j becomes centroid of its points

What is K-means optimizing?

- Objective F(μ,C): function of centers μ and point allocations C:
  –
  $$F(\boldsymbol{\mu}, C) = \sum_{i=1}^{N} ||\mathbf{x}_i - \boldsymbol{\mu}_{C(i)}||^2$$
  – 1-of-k encoding
  $$F(\boldsymbol{\mu}, \boldsymbol{a}) = \sum_{i=1}^{N} \sum_{j=1}^{k} a_{ij} ||\mathbf{x}_i - \boldsymbol{\mu}_j||^2$$

- Optimal K-means:
  – $\min_{\mu} \min_{a} F(\mu, a)$

Coordinate descent algorithms

- Want: $\min_a \min_b F(a,b)$
- Coordinate descent:
  - fix a, minimize b
  - fix b, minimize a
  - repeat
- Converges!!!
  - if F is bounded
  - to a (often good) local optimum
- K-means is a coordinate descent algorithm!

K-means as Co-ordinate Descent

- Optimize objective function:

$$\min_{\boldsymbol{\mu}_1,\ldots,\boldsymbol{\mu}_k} \min_{\boldsymbol{a}_1,\ldots,\boldsymbol{a}_N} F(\boldsymbol{\mu}, \boldsymbol{a}) = \min_{\boldsymbol{\mu}_1,\ldots,\boldsymbol{\mu}_k} \min_{\boldsymbol{a}_1,\ldots,\boldsymbol{a}_N} \sum_{i=1}^{N} \sum_{j=1}^{k} a_{ij} ||\mathbf{x}_i - \boldsymbol{\mu}_j||^2$$

- Alternate between
  - Fix μ, optimize a (i.e. C)
  - Fix a (i.e. C), optimize μ

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Unsupervised Learning

Training data is cheap

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Examples: Clustering, dimensionality reduction, feature learning, density estimation, etc.

Holy grail: Solve unsupervised learning => understand structure of visual world

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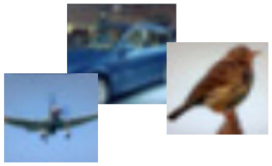
Generative Models

Given training data, generate new samples from same distribution



Training data ~ $p_{data}(x)$

Generated samples ~ $p_{model}(x)$

Want to learn $p_{model}(x)$ similar to $p_{data}(x)$

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Generative Classification vs Discriminative Classification vs Density Estimation

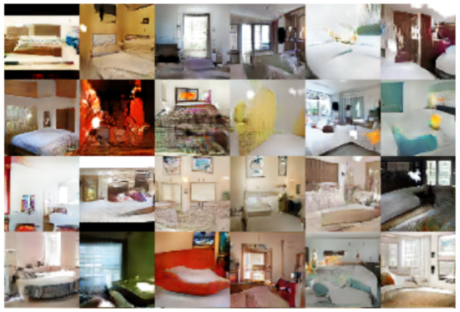
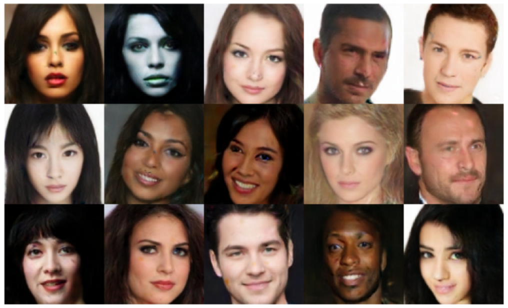
- Generative Classification
  - Model p(x, y); estimate p(x|y) and p(y)
  - Use Bayes Rule to predict y
  - E.g Naïve Bayes

- Discriminative Classification (not a Generative Model)
  - Estimate p(y|x) directly
  - E.g. Logistic Regression

- Density Estimation
  - Model p(x)
  - E.g. VAEs

Why Generative Models?

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


- Generative models of time-series data can be used for simulation and planning (model based reinforcement learning!)

- Training generative models can also enable inference of latent representations that can be useful as general features

Generative Models

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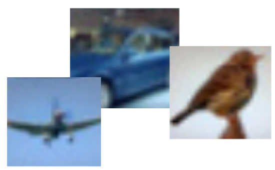
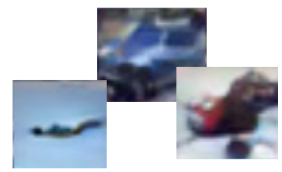


Training data ~ $p_{data}(x)$



Generated samples ~ $p_{model}(x)$

Want to learn $p_{model}(x)$ similar to $p_{data}(x)$

Addresses density estimation, a core problem in unsupervised learning

Several flavors:

- **Explicit** density estimation: explicitly define and solve for $p_{model}(x)$
- **Implicit** density estimation: learn model that can sample from $p_{model}(x)$ w/o explicitly defining it

Taxonomy of Generative Models

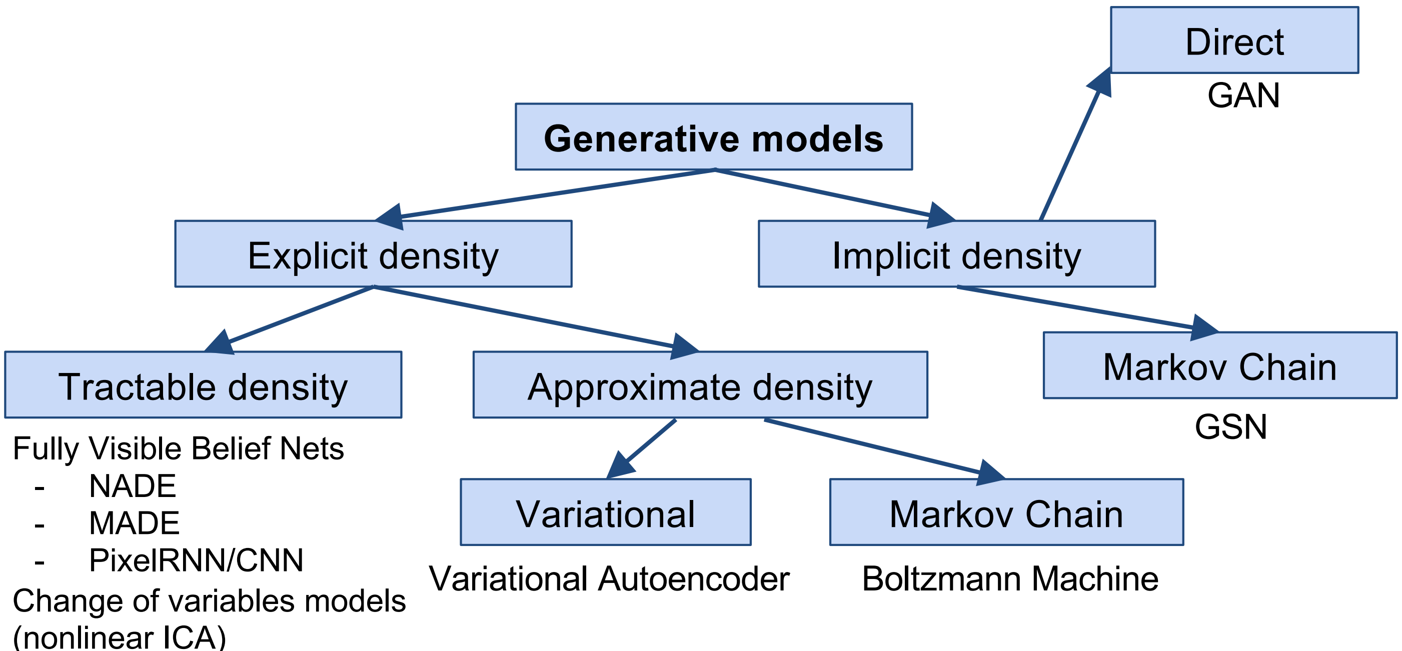
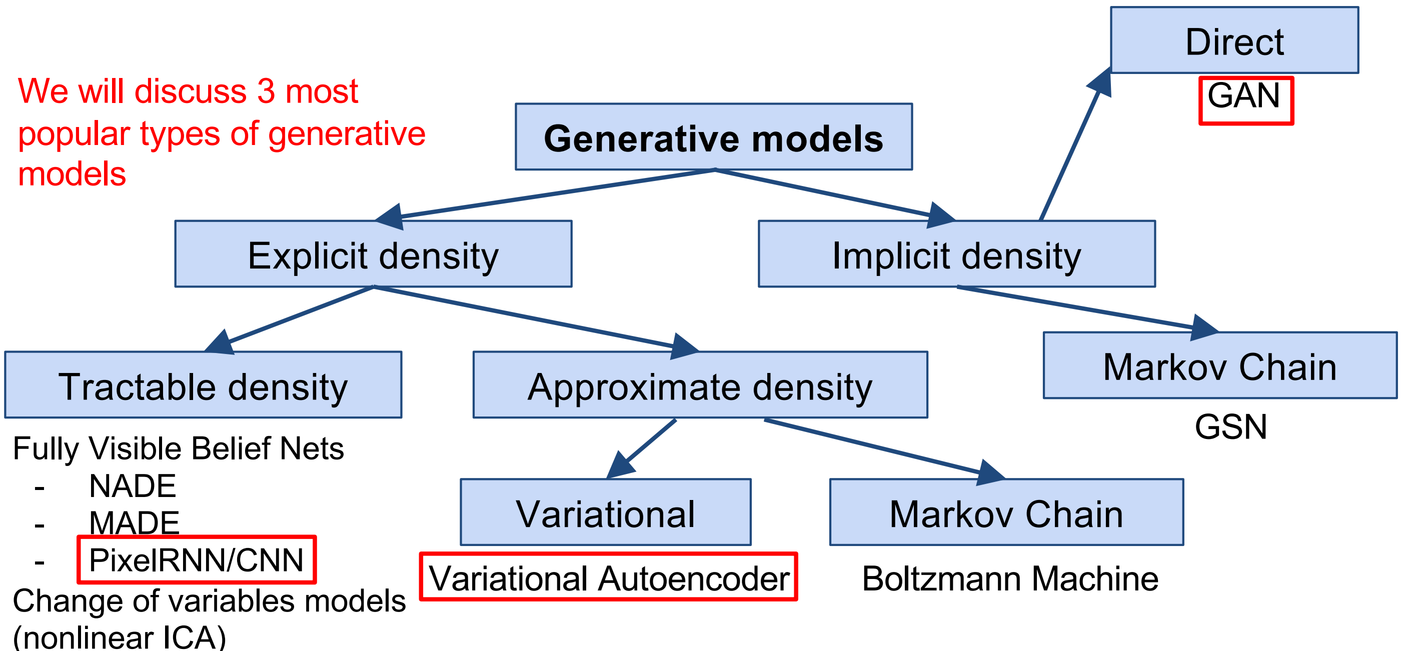


Figure copyright and adapted from Ian Goodfellow, Tutorial on Generative Adversarial Networks, 2017.

Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

Taxonomy of Generative Models

We will discuss 3 most popular types of generative models



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PixelRNN and PixelCNN

Fully Visible Belief Network

Explicit density model

Use chain rule to decompose likelihood of an image x into product of 1-d distributions:

$$p(x) = \prod_{i=1}^{n} p(x_i | x_1, ..., x_{i-1})$$

Likelihood of image x

Probability of i'th pixel value given all previous pixels

Then maximize likelihood of training data

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Complex distribution over pixel values => Express using a neural network!

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Likelihood of image x

Probability of i'th pixel value given all previous pixels

Will need to define ordering of "previous pixels"

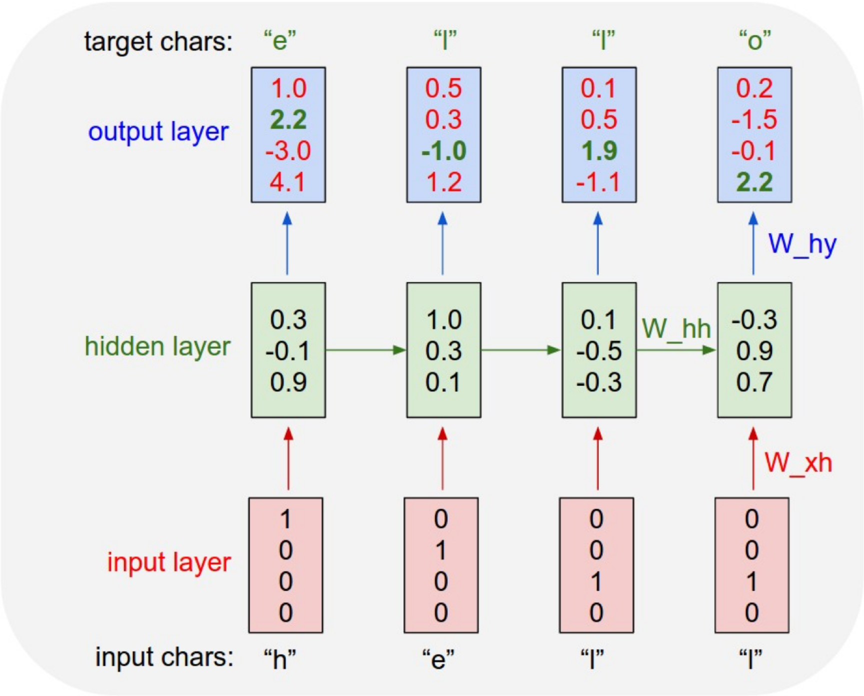
Complex distribution over pixel values
=> Express using a neural network!

Then maximize likelihood of training data

Example: Character-level Language Model

Vocabulary: [h,e,l,o]

Example training sequence: **“hello”**



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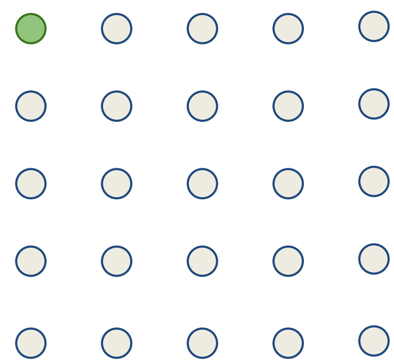
PixelRNN *[van der Oord et al. 2016]*

Generate image pixels starting from corner

Dependency on previous pixels modeled using an RNN (LSTM)



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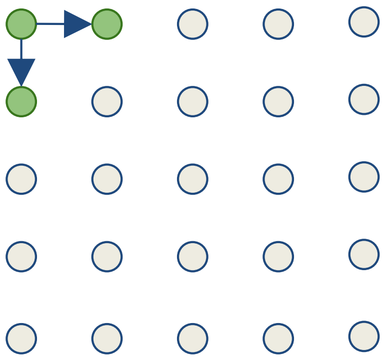

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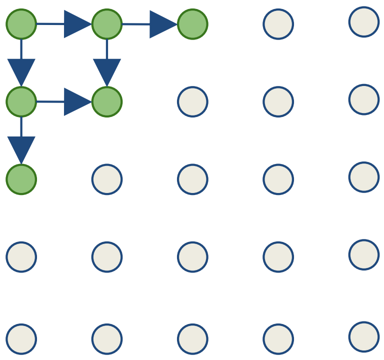

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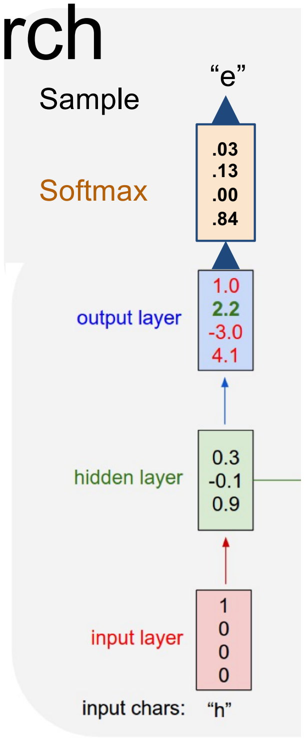
Test Time: Sample / Argmax / Beam Search

Example: Character-level Language Model Sampling

Vocabulary: [h,e,l,o]

At test-time sample characters one at a time, feed back to model



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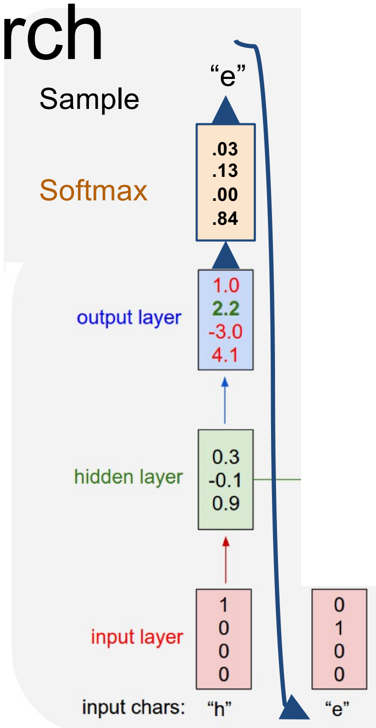

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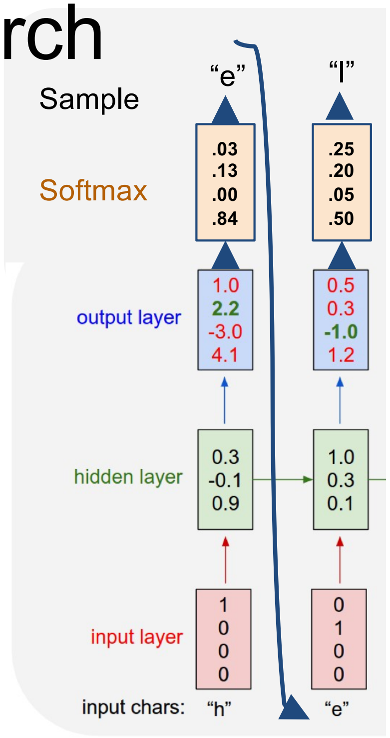

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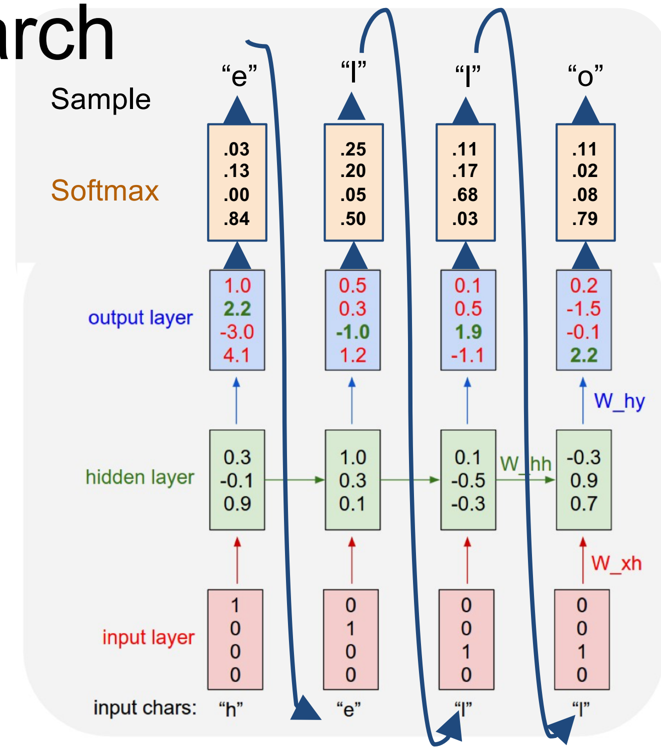

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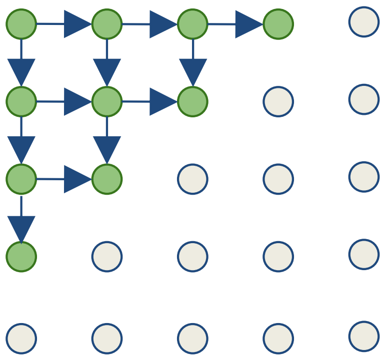
PixelRNN *[van der Oord et al. 2016]*

Generate image pixels starting from corner

Dependency on previous pixels modeled using an RNN (LSTM)

Drawback: sequential generation is slow!



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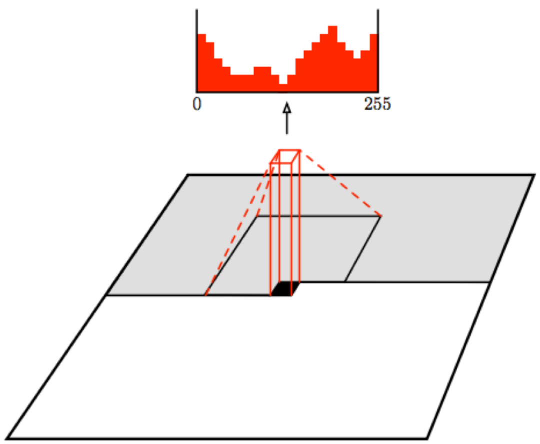
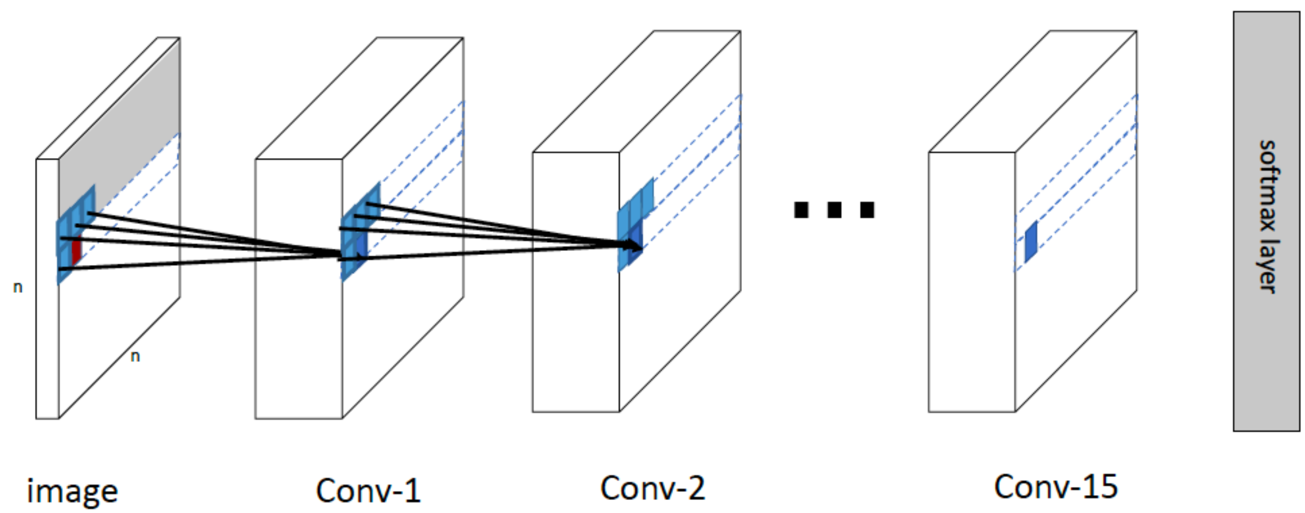
PixelCNN *[van der Oord et al. 2016]*

Still generate image pixels starting from corner

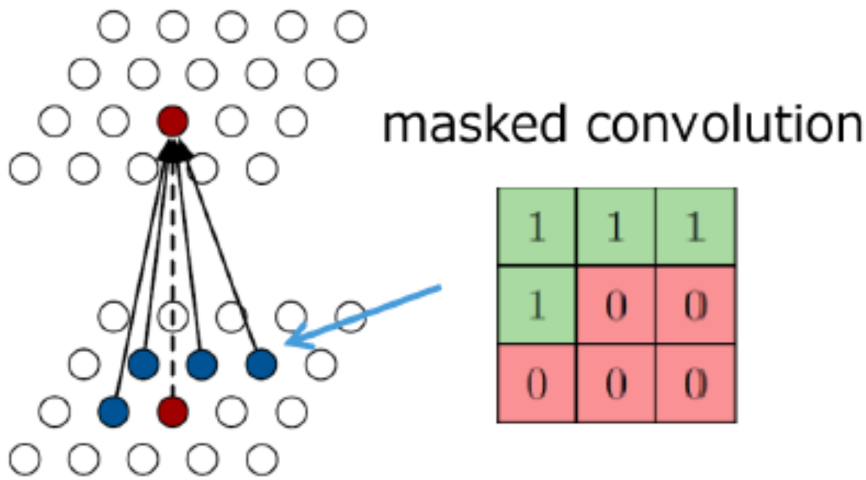
Dependency on previous pixels now modeled using a CNN over context region




n
n
softmax layer
image
Conv-1
Conv-2
Conv-15

Masked Convolutions

- Apply masks so that a pixel does not see "future" pixels



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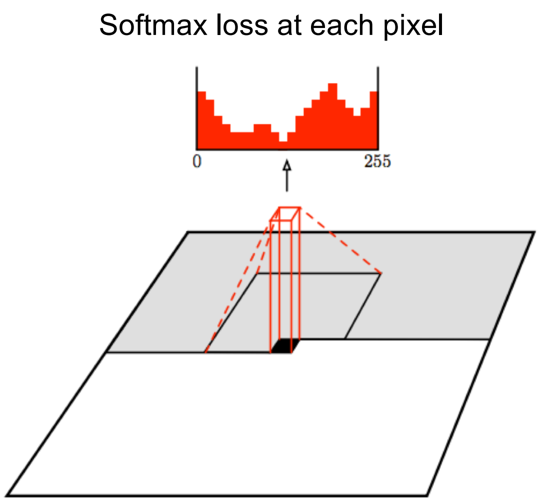


PixelCNN *[van der Oord et al. 2016]*

Still generate image pixels starting from corner

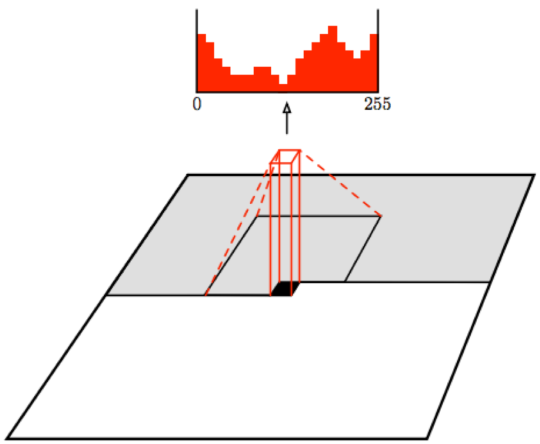
Dependency on previous pixels now modeled using a CNN over context region

Training: maximize likelihood of training images

Training is faster than PixelRNN
(can parallelize convolutions since context region values known from training images)

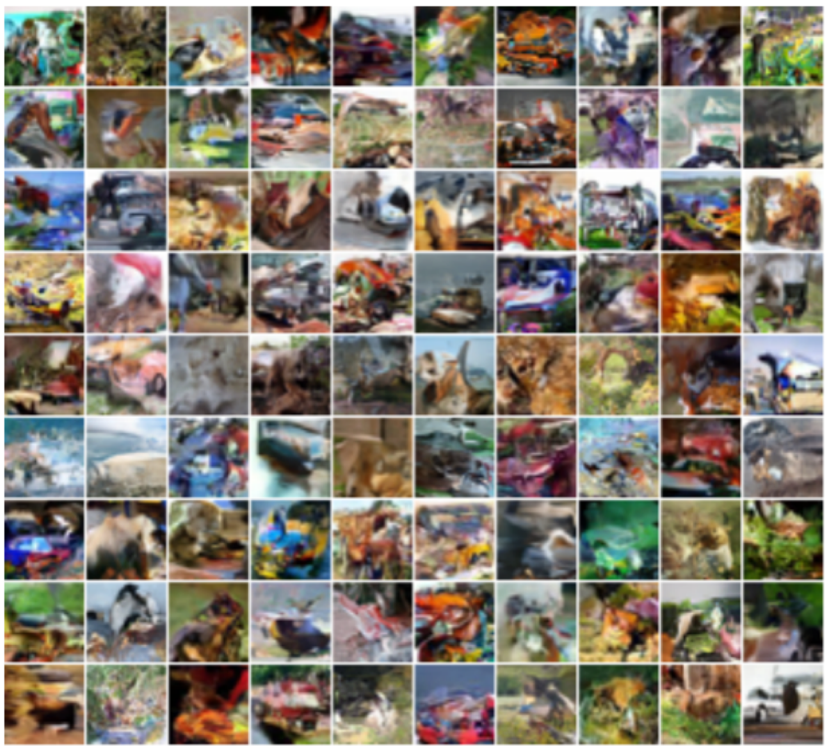
Generation must still proceed sequentially
=> still slow

Softmax loss at each pixel

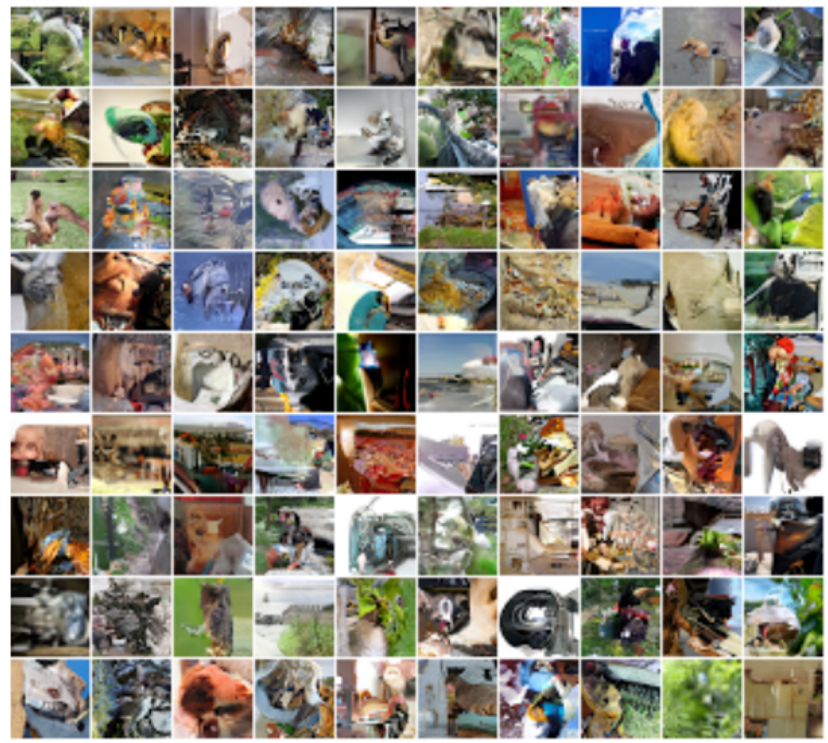


Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

Generation Samples (PixelRNN)



32x32 CIFAR-10



32x32 ImageNet

Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

Image Completion

Figure 1. Image completions sampled from a PixelRNN.

Results from generating sounds

- https://deepmind.com/blog/wavenet-generative-model-raw-audio/

PixelRNN and PixelCNN

Pros:

- Can explicitly compute likelihood p(x)
- Explicit likelihood of training data gives good evaluation metric
- Good samples

Con:

- Sequential generation => slow

Improving PixelCNN performance

- Gated convolutional layers
- Short-cut connections
- Discretized logistic loss
- Multi-scale
- Training tricks
- Etc…

See

- Van der Oord et al. NIPS 2016
- Salimans et al. 2017 (PixelCNN++)

Conclusion

- Unsupervised Learning
  - Comparison to Supervised and Reinforcement Learning
  - Review of K-Means

- e.g., Generative Models
  - Varieties
  - PixelRNN and PixelCNN

Slide Credit: Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

The End