CS 4803 / 7643: Deep Learning

Topics:
- Unsupervised Learning
- Generative Models (PixelRNNs, VAEs)

Dhruv Batra
Georgia Tech

Administrativia

- HW1 and HW2 solutions released
  - https://gatech.instructure.com/courses/28059/files/
- HW3 out
  - Due: 11/06, 11:55pm

Overview

- Unsupervised Learning
- Generative Models
  - PixelRNN and PixelCNN
  - Variational Autoencoders (VAE)
  - Generative Adversarial Networks (GAN)

Supervised vs Unsupervised Learning

Supervised Learning

Data: (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.

Supervised vs Unsupervised Learning

$x \xrightarrow{CNN} y$

Supervised Learning

Data: (x, y)
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Goal: Learn a *function* to map x → y

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

→ Cat

Classification

Supervised vs Unsupervised Learning

Supervised Learning

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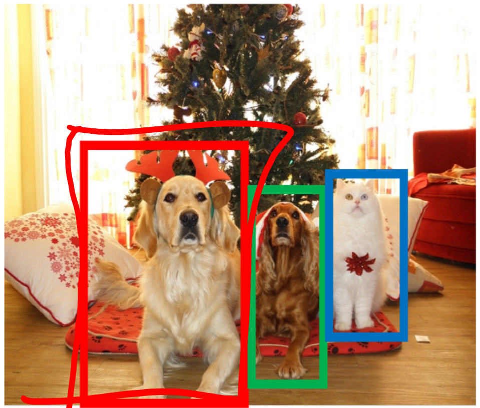
x



DOG, DOG, CAT

Object Detection

This image is CC0 public domain

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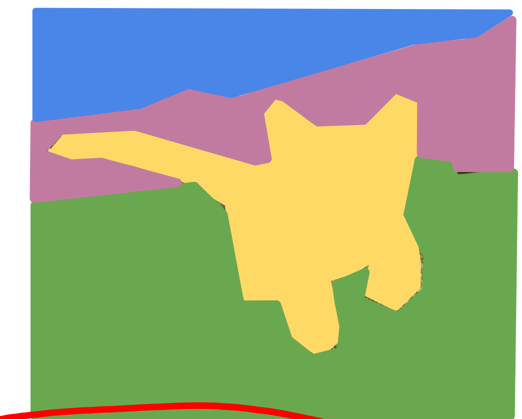

GRASS, CAT, TREE, SKY

Semantic Segmentation

Supervised vs Unsupervised Learning

Supervised Learning

Data: (x, y)
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Goal: Learn a *function* to map x → y

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

A cat sitting on a suitcase on the floor

x

y

Image captioning

Supervised vs Unsupervised Learning

Unsupervised Learning

Data: x
Just data, no labels!

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

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

Supervised vs Unsupervised Learning

Unsupervised Learning

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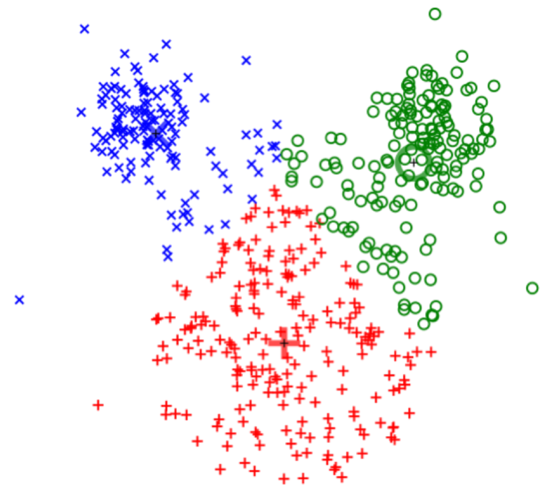

K-means clustering

Supervised vs Unsupervised Learning

Unsupervised Learning

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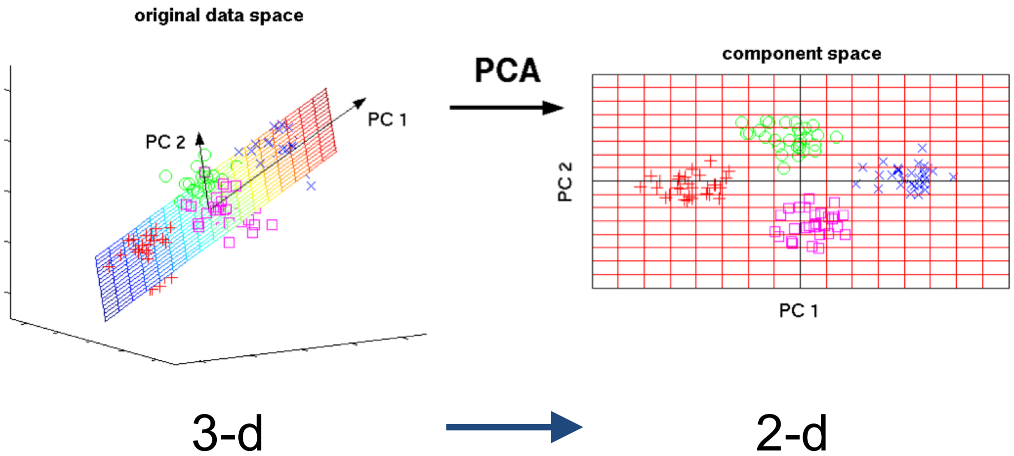
Goal: Learn some underlying hidden *structure* of the data

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



Principal Component Analysis
(Dimensionality reduction)

$\boxed{P(x)}$ $p(x, \ldots)$

Supervised vs Unsupervised Learning

Unsupervised Learning

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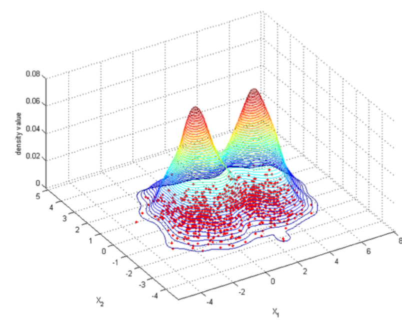
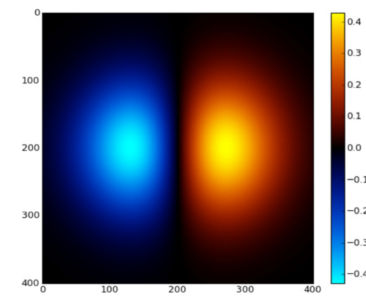
Examples: Clustering, dimensionality reduction, feature learning, density estimation, etc.

1-d density estimation





2-d density estimation

Tasks

Supervised Learning

x → Classification → y Discrete

x → Regression → y Continuous

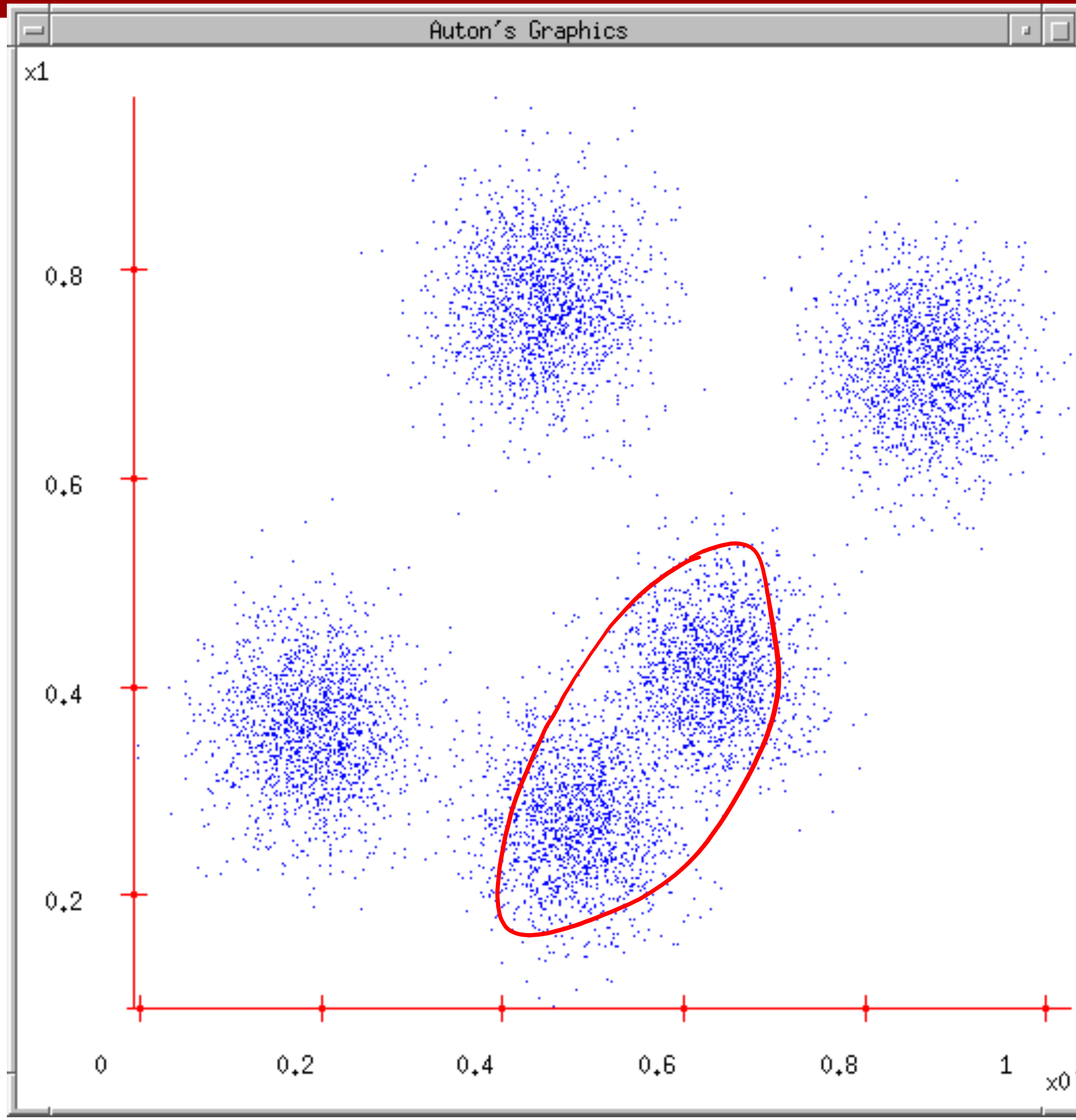
Unsupervised Learning

x → Clustering → c Discrete

x → Dimensionality Reduction → z Continuous

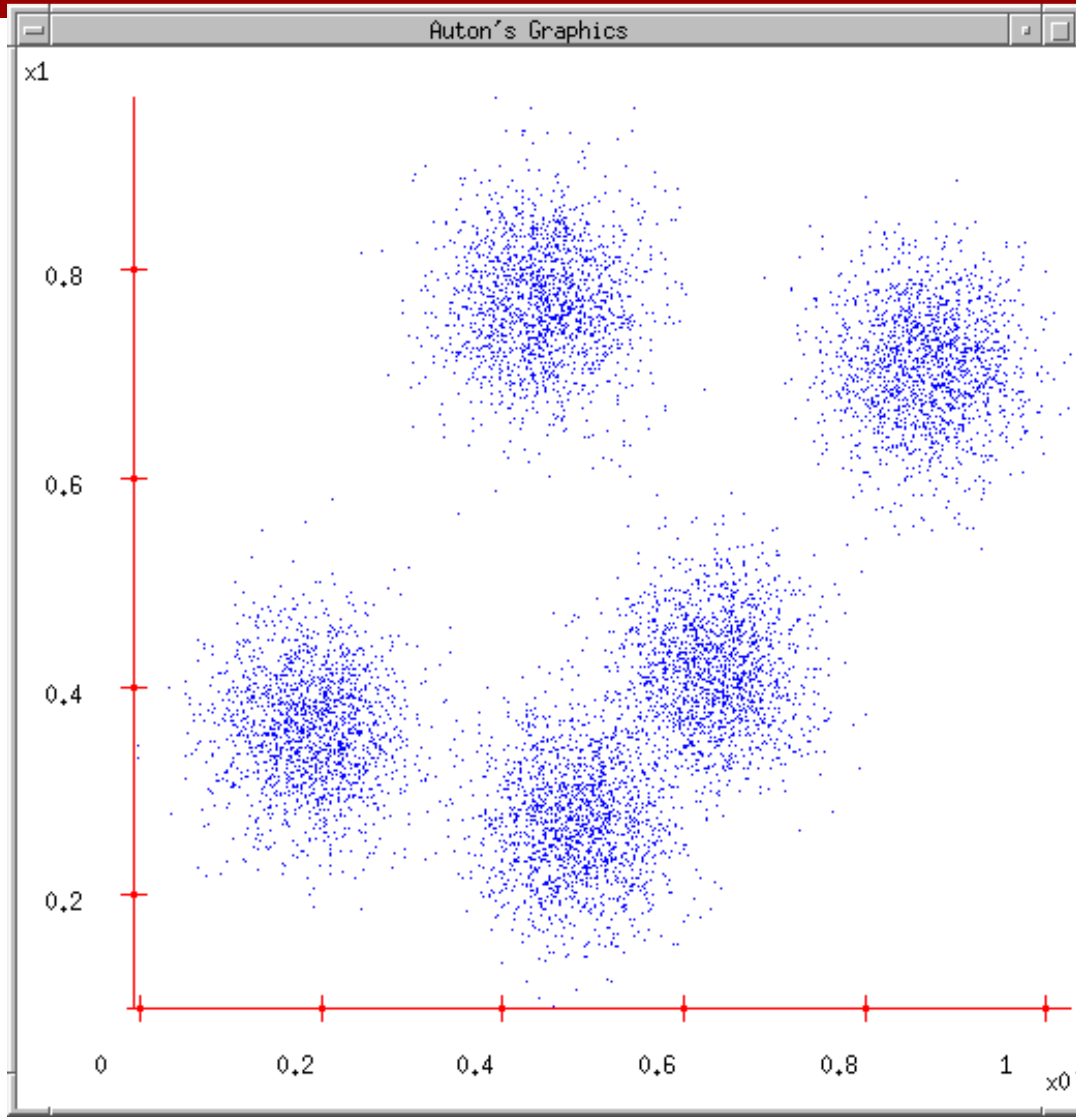
x → Density Estimation → p(x) On simplex

Some Data



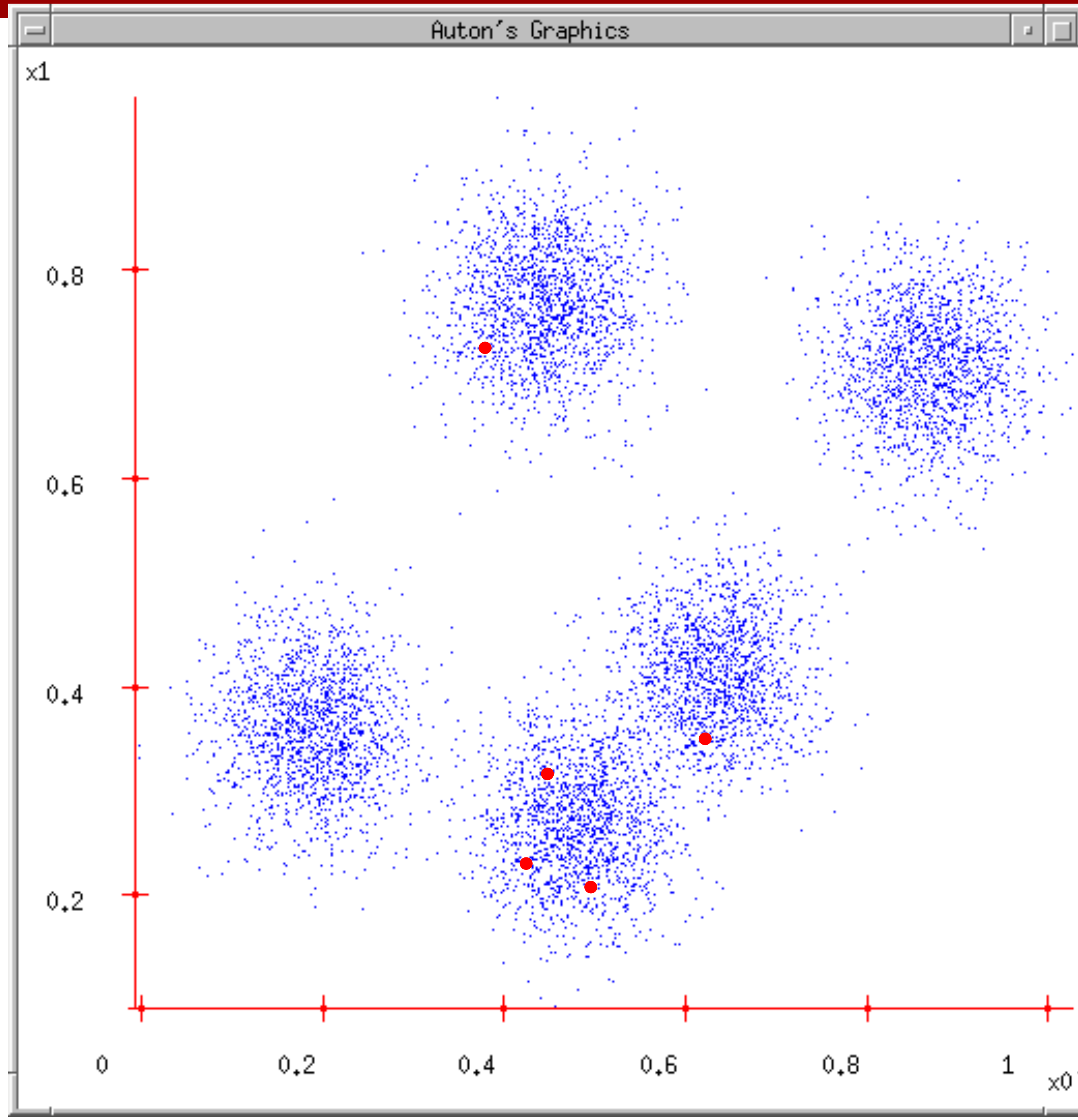
K-means

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



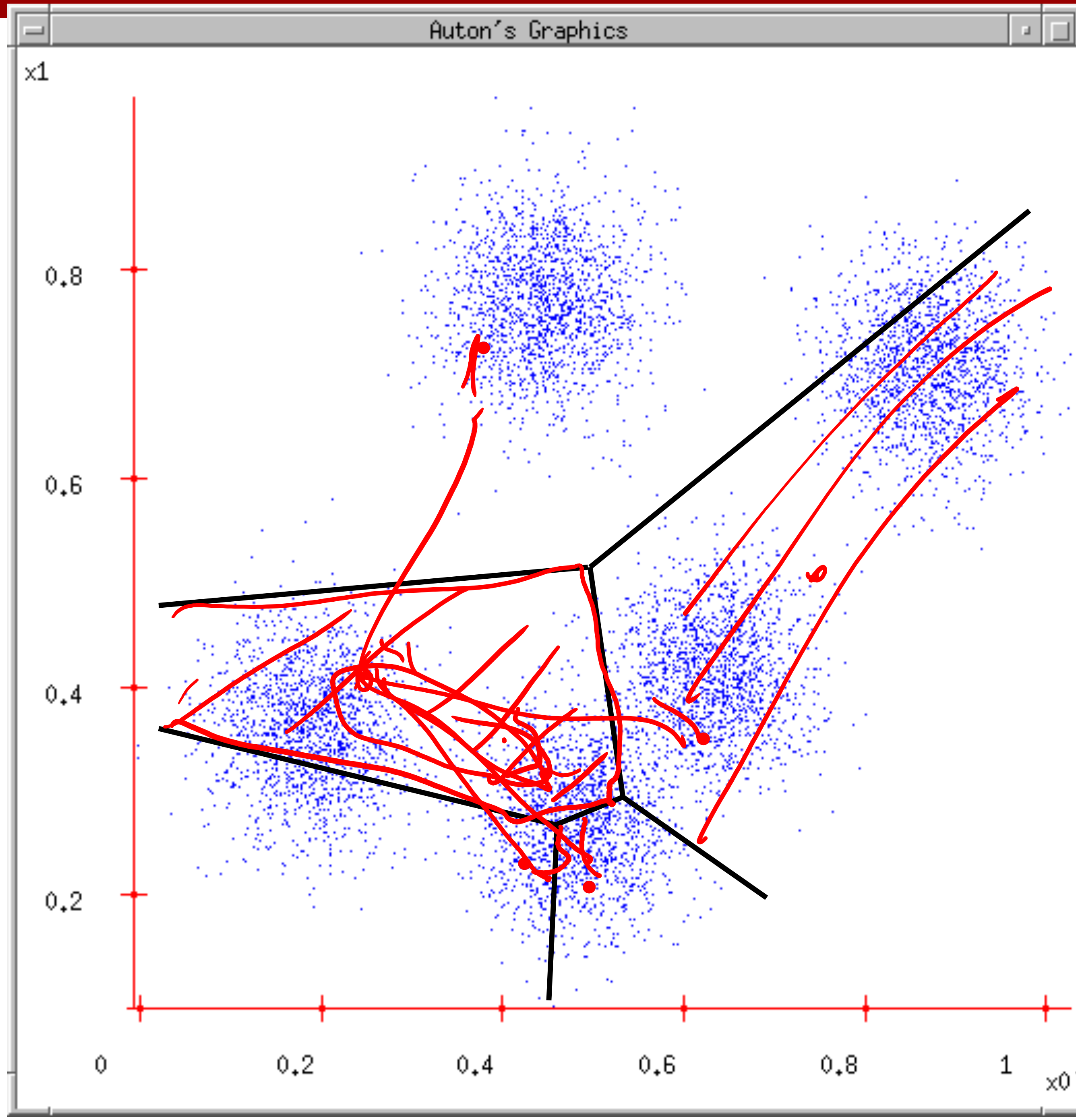
K-means

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



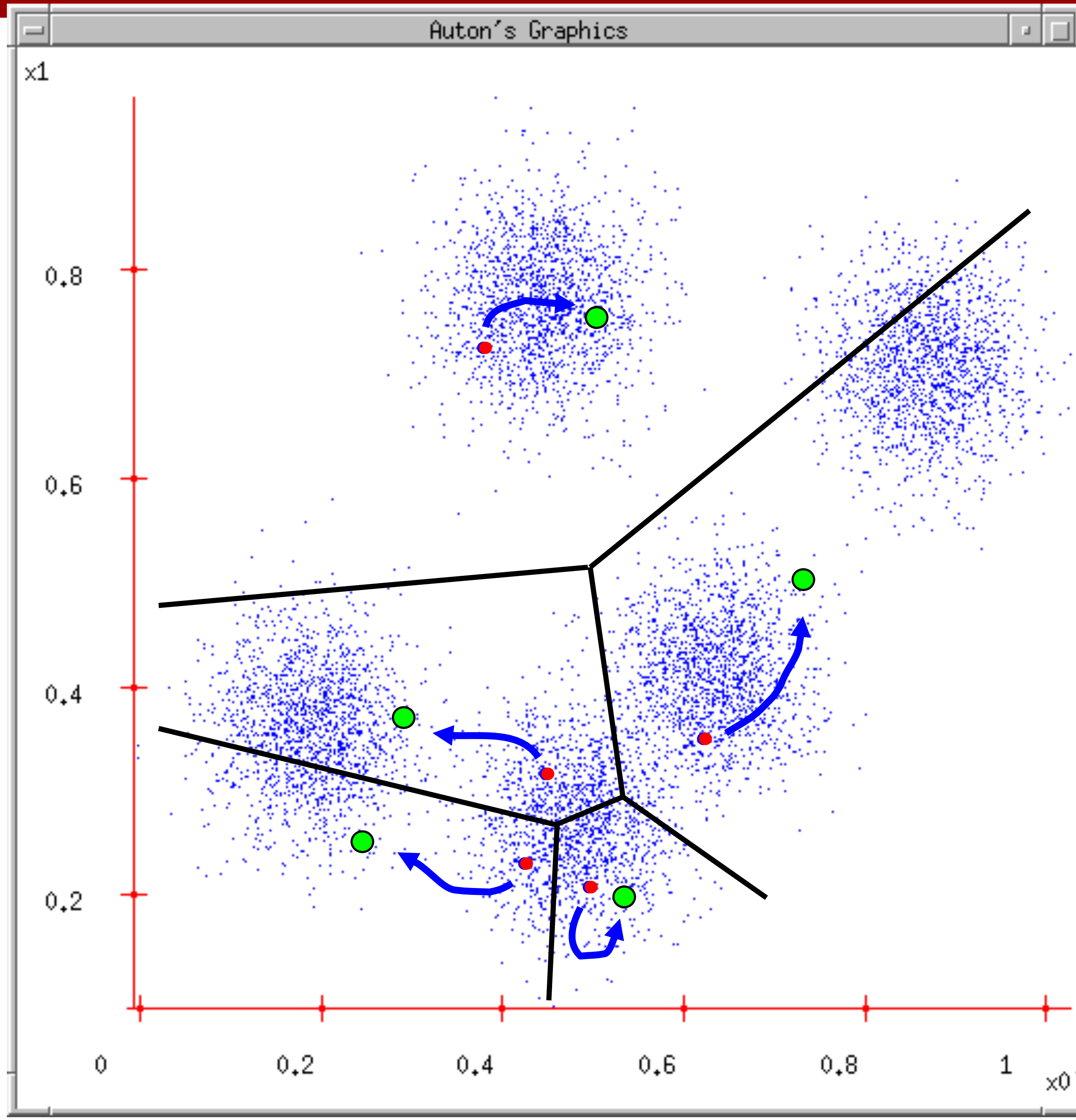
K-means

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. (Thus each Center "owns" a set of datapoints)



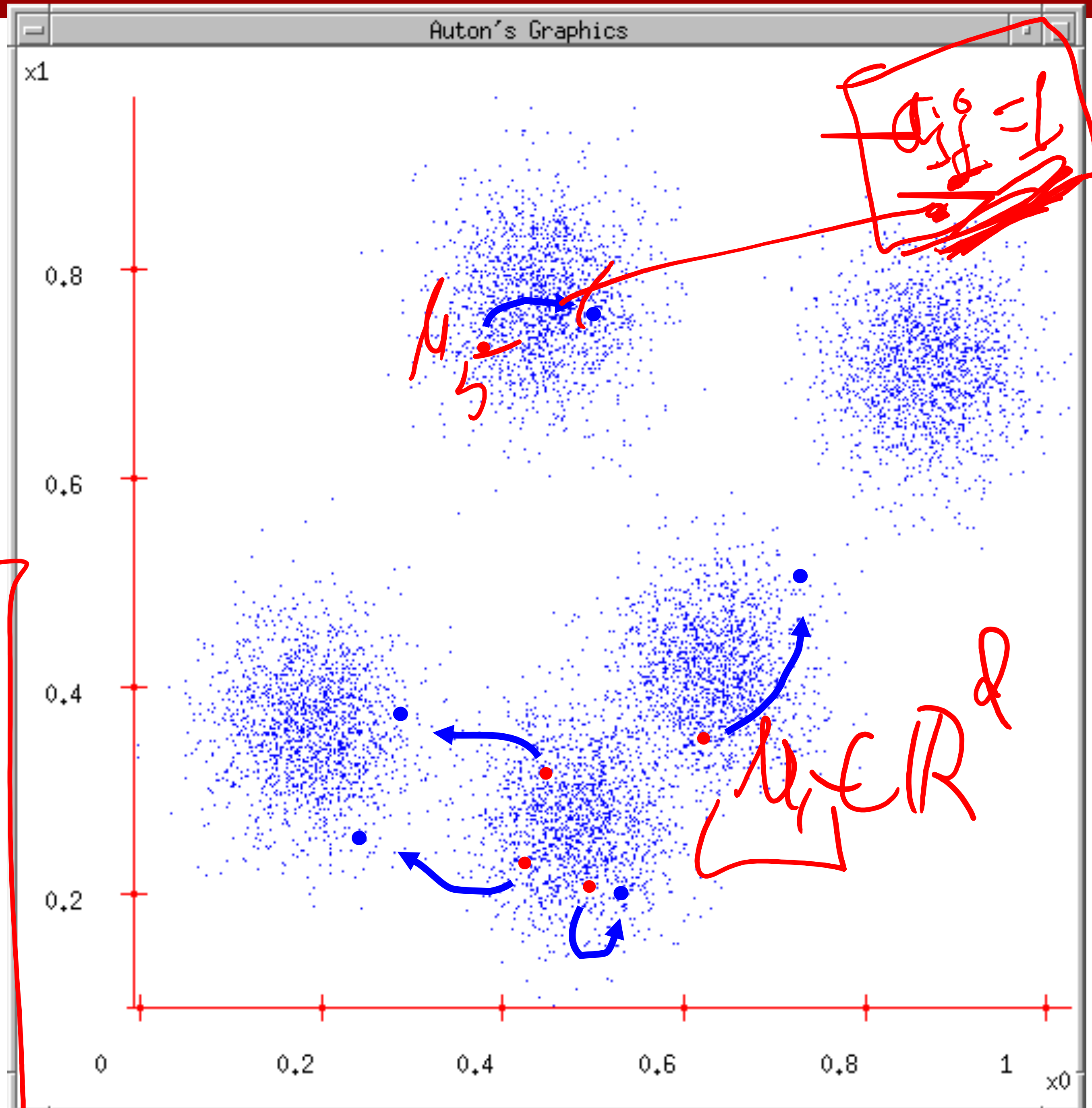
K-means

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



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



K-means

- Randomly initialize *k* centers
  - $\mu^{(0)} = \mu_1^{(0)},\ldots,\mu_k^{(0)}$
- **Assign**:
  - Assign each point i∈{1,…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

K-means

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

Supervised vs Unsupervised Learning

Supervised Learning

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Goal: Learn a *function* to map x -> y

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

Unsupervised Learning

Data: x
Just data, no labels!

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

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

Supervised vs Unsupervised Learning

Supervised Learning

Data: (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.

Unsupervised Learning

Training data is cheap

Data: x
Just data, no labels!

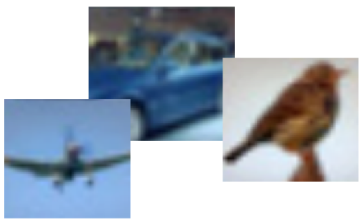
Holy grail: Solve unsupervised learning => understand structure of visual world

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

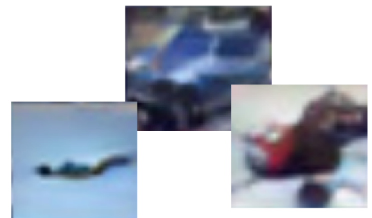
Examples: Clustering, dimensionality reduction, feature learning, density estimation, etc.

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 $p_{data}(x)$

$p_{model}(x)$

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

$\boxed{p(x,y)}$

$p(y|x)$ $p(x|y)$

- Discriminative Classification
  - Estimate p(y|x) directly
  - E.g. Logistic Regression

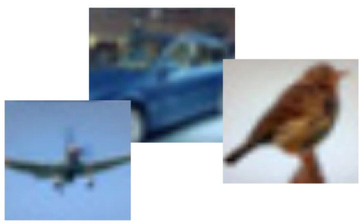
$p(x \mid y=car)$ $\boxed{P_\theta(y|x)}$ $p(x)$

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

$p(x)$

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 $p_{data}(x)$

Addresses density estimation, a core problem in unsupervised learning

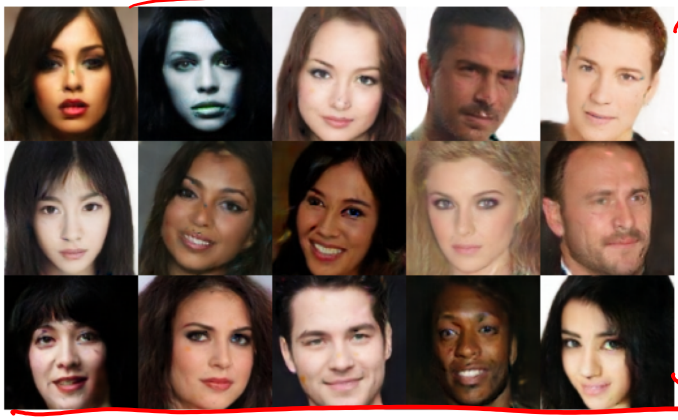
Several flavors:

- 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

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

Why Generative Models?

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


- Generative models of time-series data can be used for simulation and planning (reinforcement learning applications!)
- Training generative models can also enable inference of latent representations that can be useful as general features

Taxonomy of Generative Models

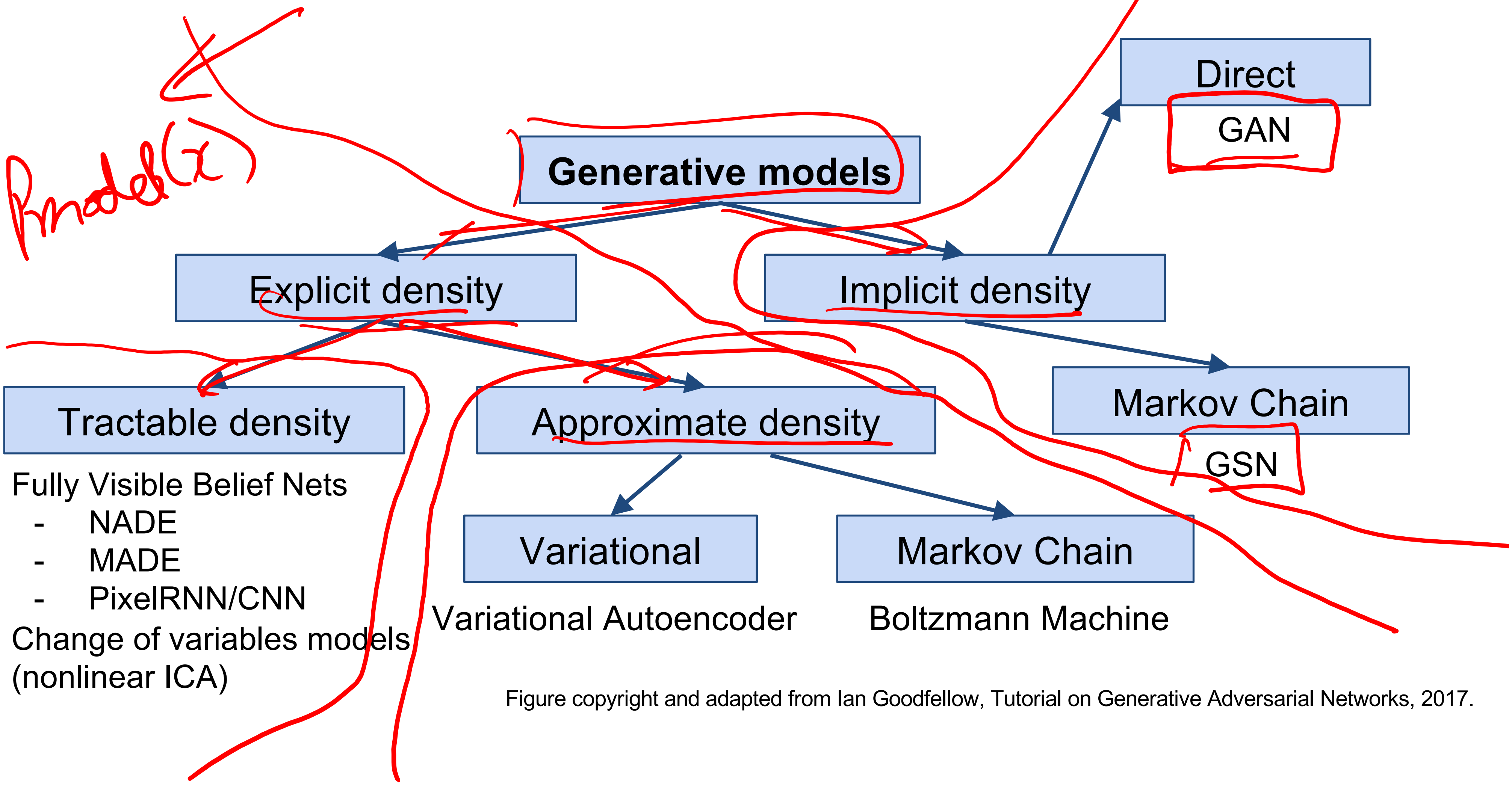
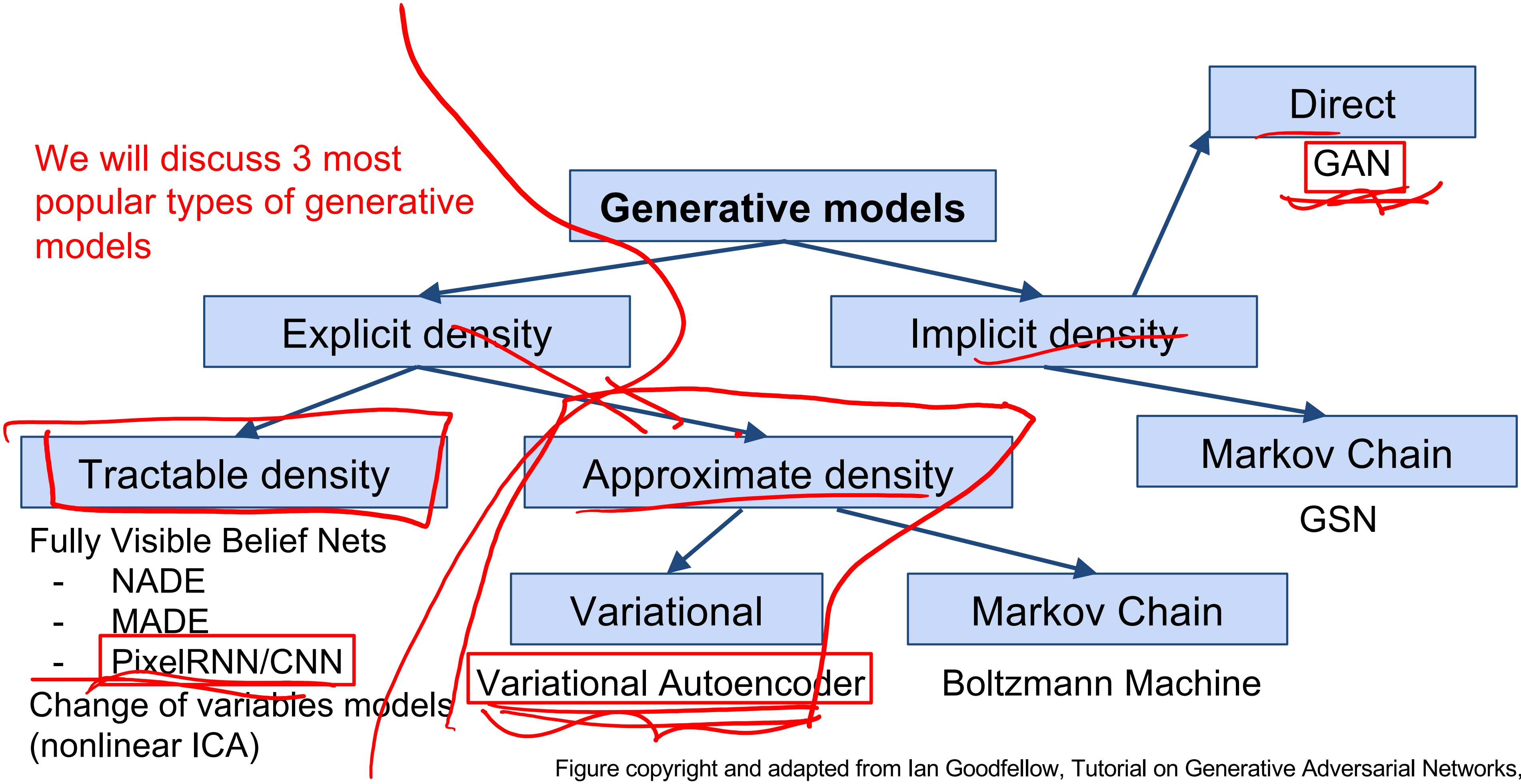


Figure copyright and adapted from Ian Goodfellow, Tutorial on Generative Adversarial Networks, 2017.

Taxonomy of Generative Models

We will discuss 3 most popular types of generative models



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PixelRNN and PixelCNN

Fully Observable Model

Explicit density model

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

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

Likelihood of image x

Probability of i'th pixel value given all previous pixels

Then maximize likelihood of training data $D = \{\vec{x}_1, \dots \vec{x}_n\}$

$x_1 \dots x_{i-1} \rightarrow \mathrm{NN}_\theta \rightarrow x_i$

$\max_\theta \log p_\theta(\vec{x})$

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Fully Observable Model

Explicit density model

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Likelihood of image x

Probability of i'th pixel value given all previous pixels

Then maximize likelihood of training data

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

Fully Observable Model

Explicit density model

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

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

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!

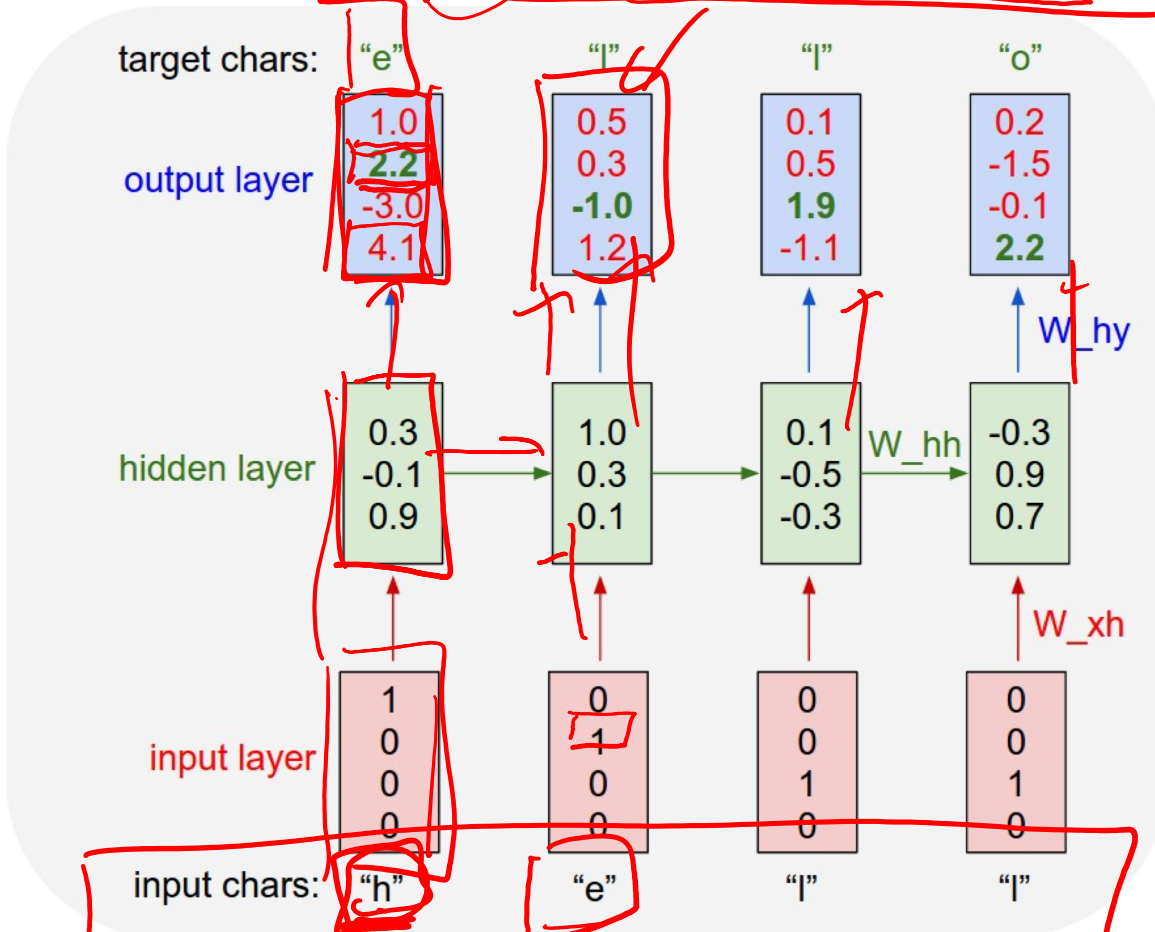
Then maximize likelihood of training data

$$\max_w \log P(x_1 \ldots x_5 \mid w) = \sum_t \log P(x_t \mid x_1 \ldots x_{t-1}, w)$$

Example: Character-level Language Model

Vocabulary: [h,e,l,o]

Example training sequence: **“hello”**



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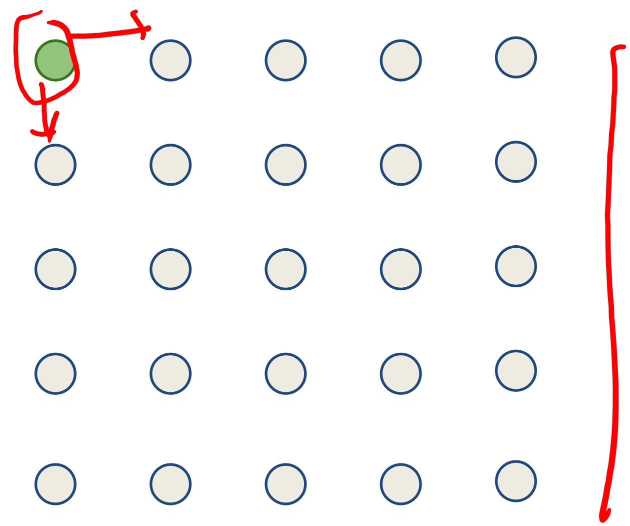
PixelRNN *[van der Oord et al. 2016]*

$p(x, \ldots x_{H \times W})$

Generate image pixels starting from corner

Dependency on previous pixels modeled using an RNN (LSTM)



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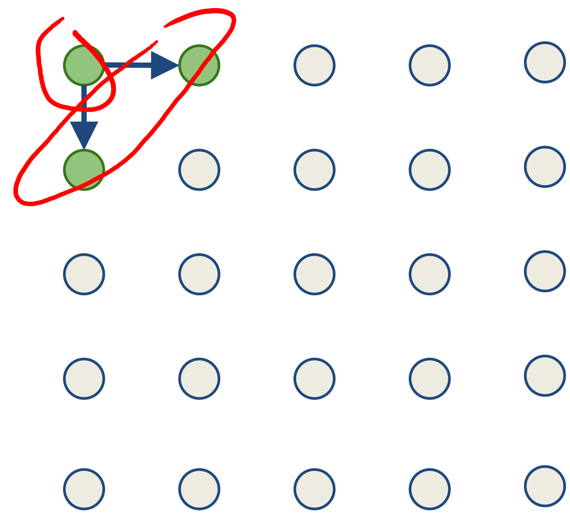

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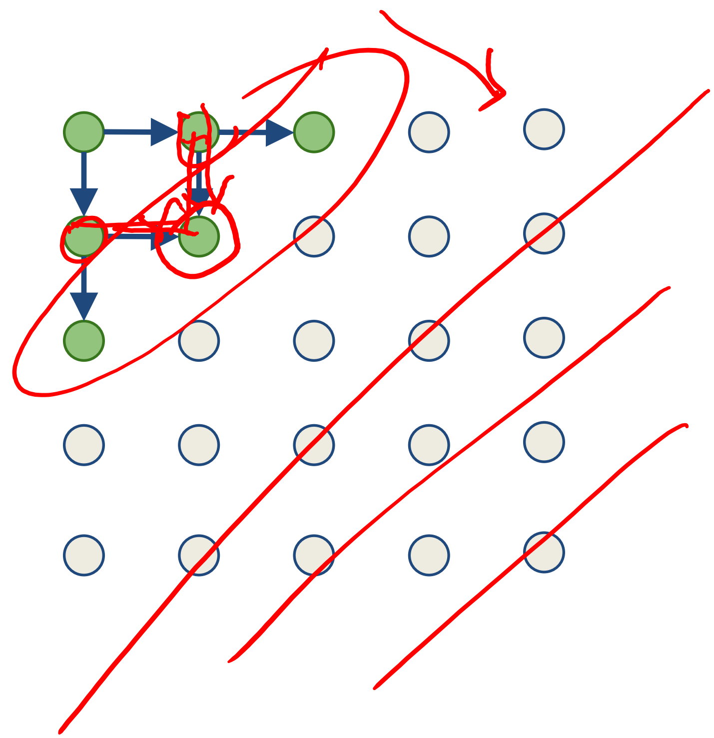
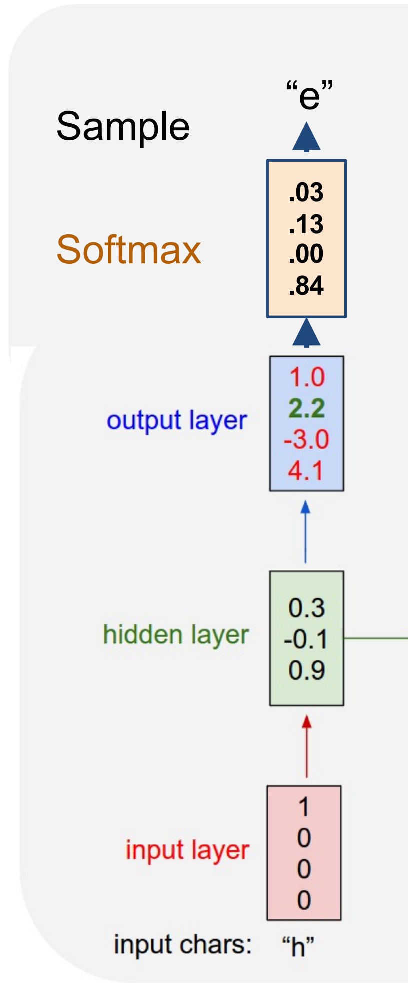


Test Time: Sample / Argmax / Beam Search

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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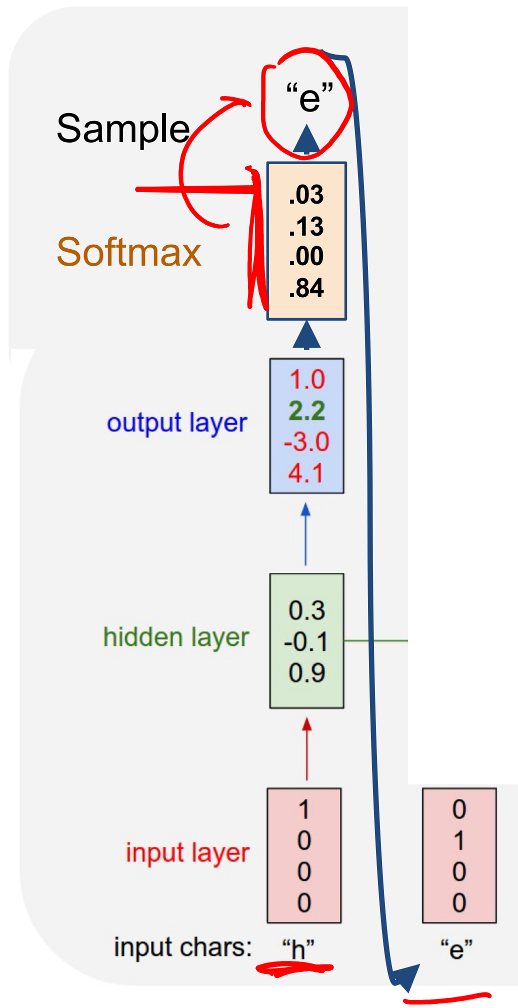

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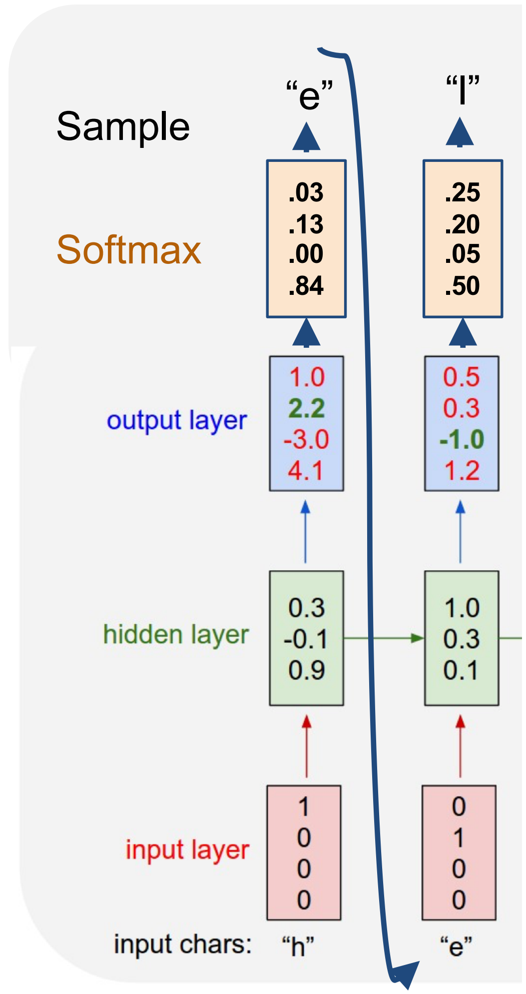

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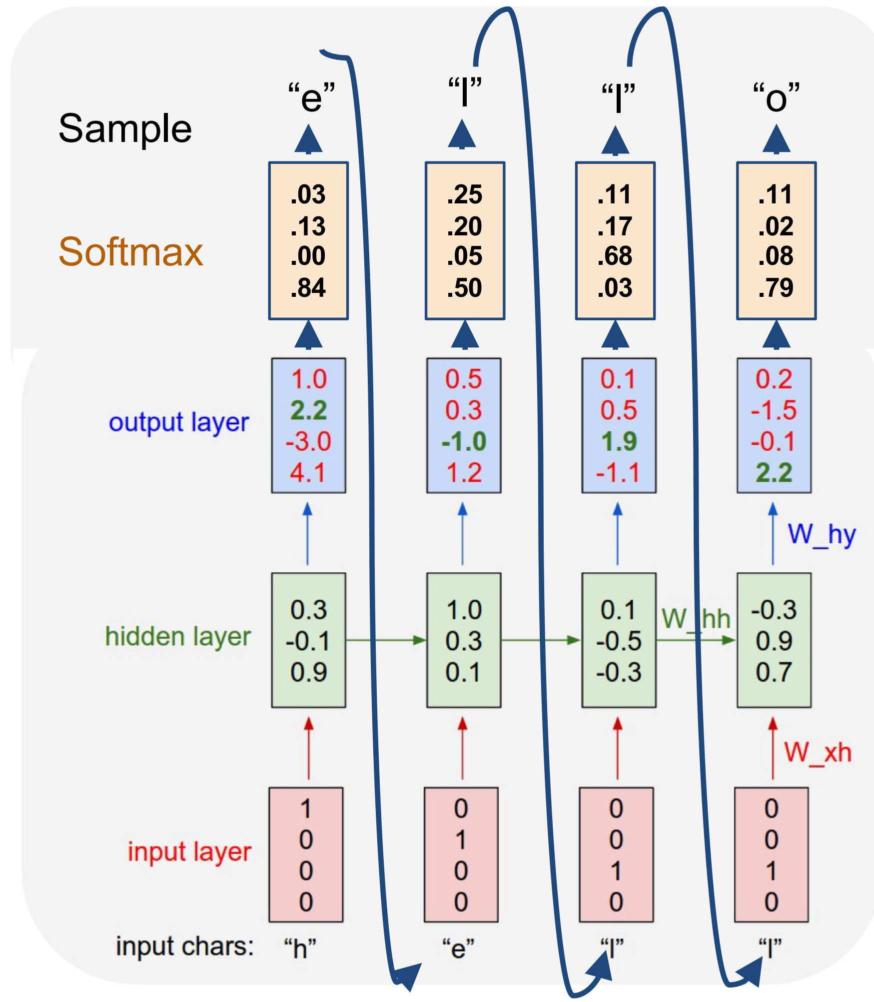

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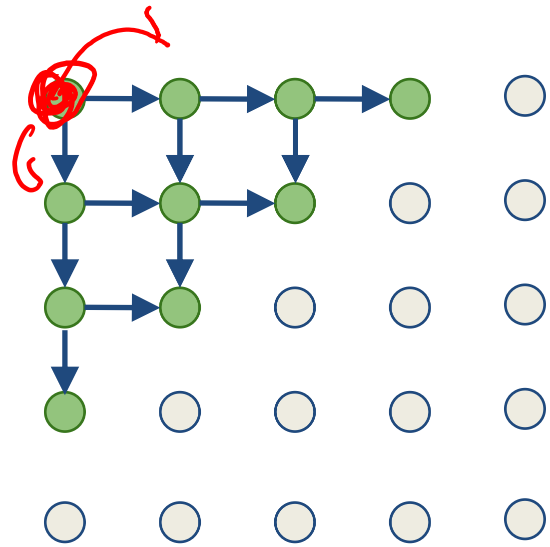
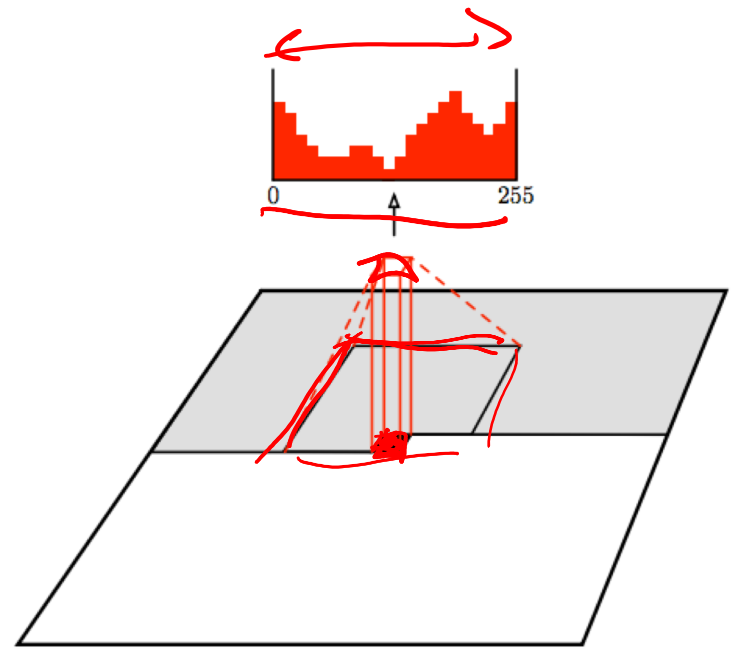


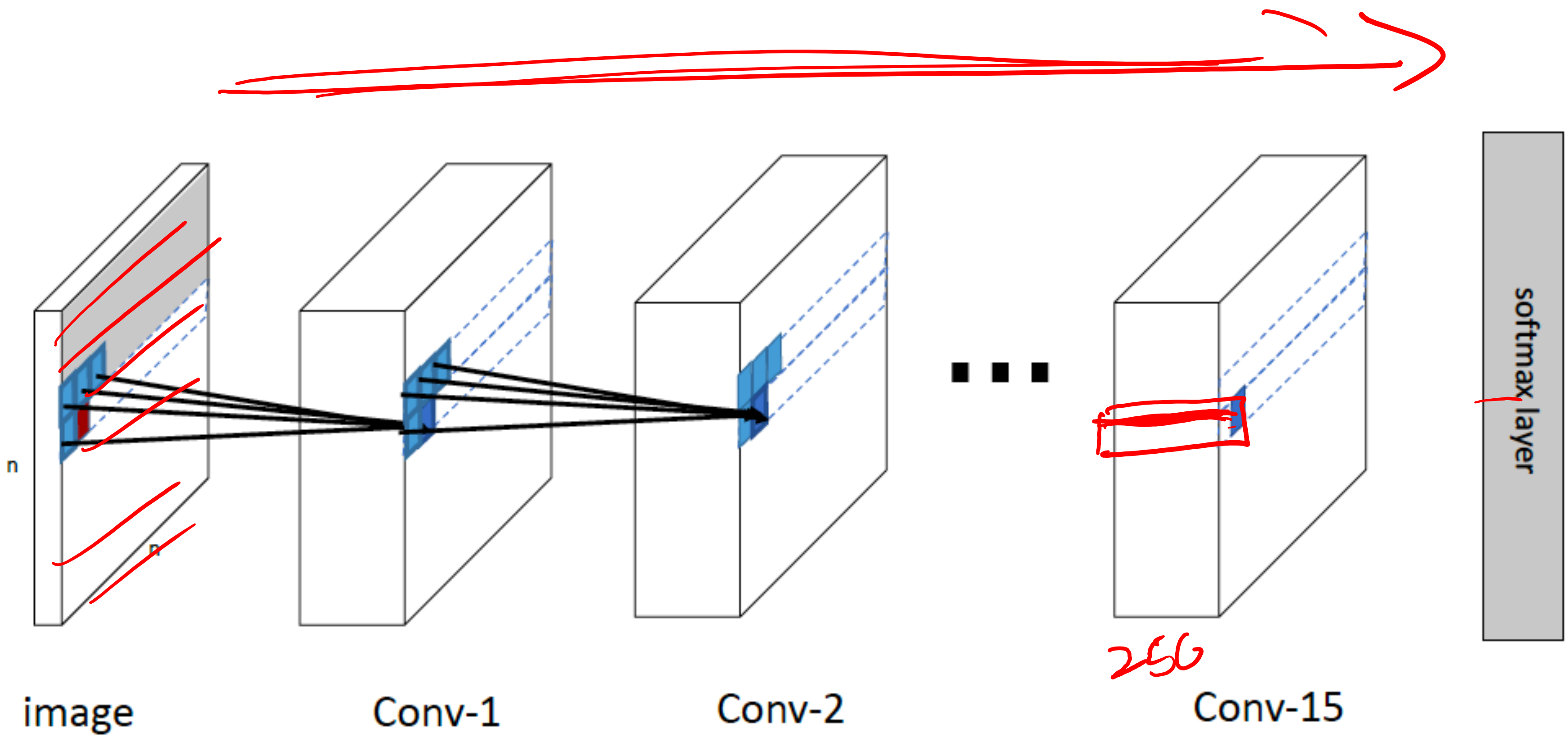
Drawback: sequential generation is slow!

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

Still generate image pixels starting from corner

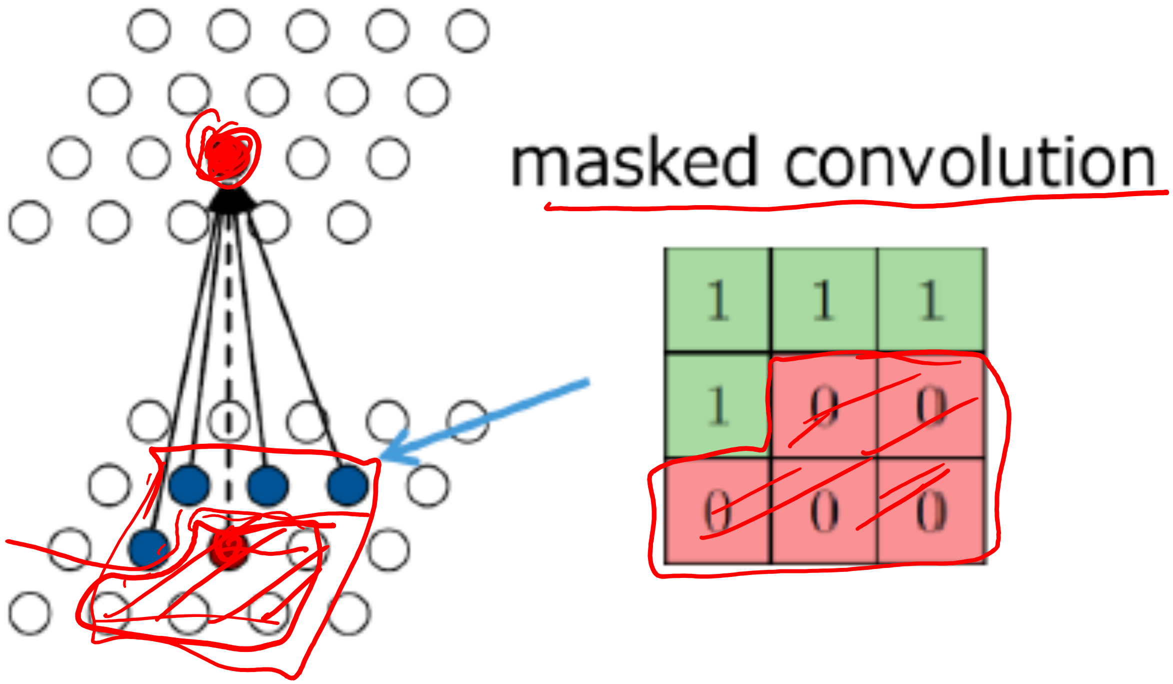
Dependency on previous pixels now modeled using a CNN over context region




n
n
softmax layer
256
image
Conv-1
Conv-2
Conv-15

Masked Convolutions

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



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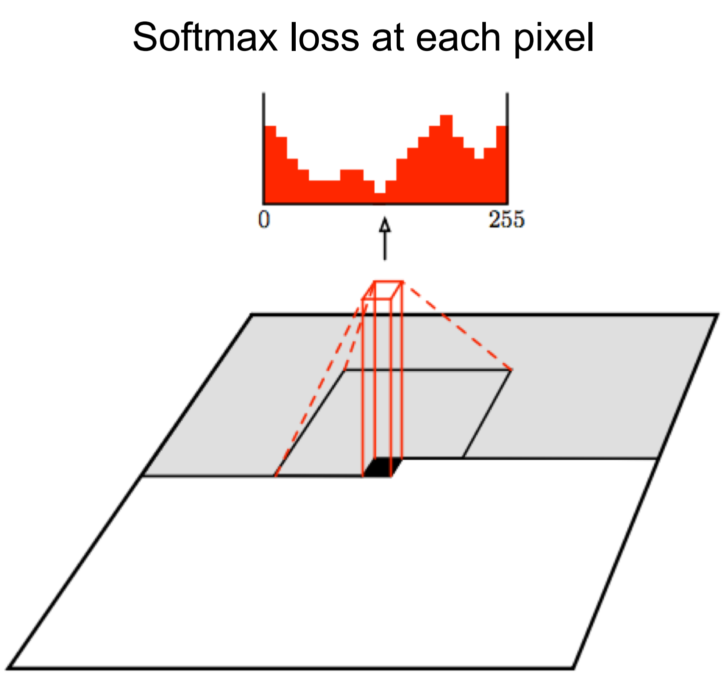


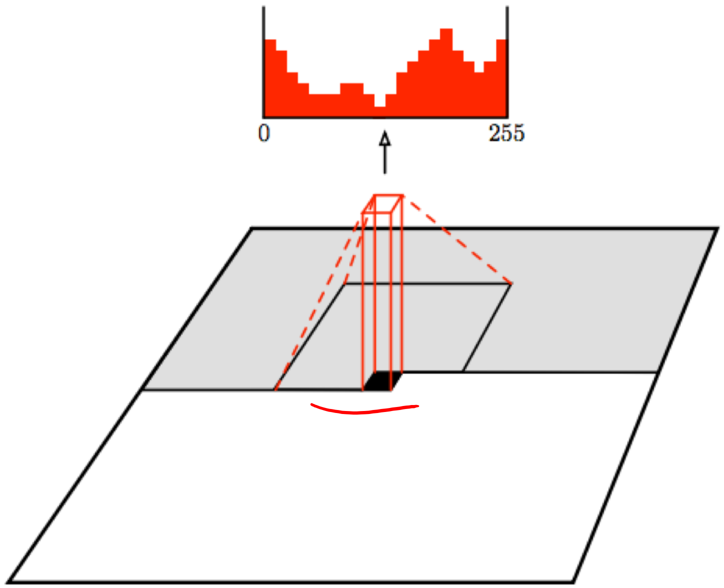
PixelCNN *[van der Oord et al. 2016]*

Still generate image pixels starting from corner

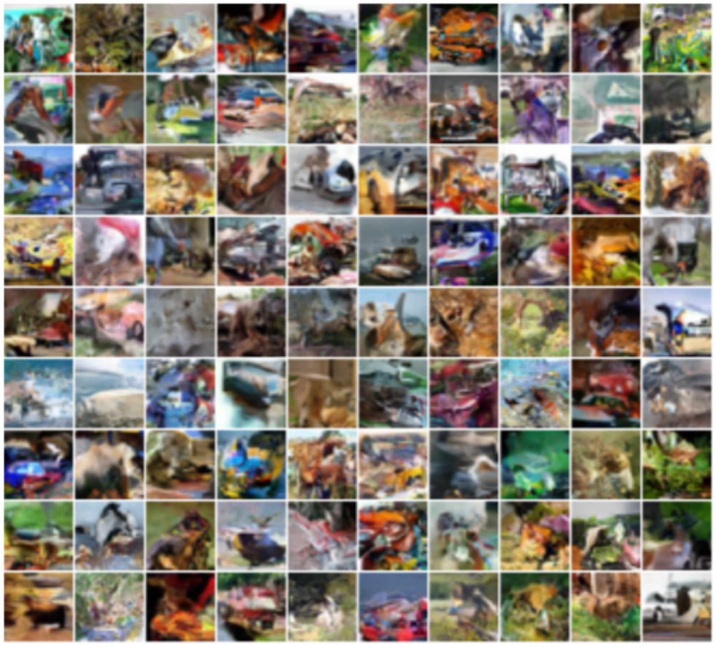
Dependency on previous pixels now modeled using a CNN over context region

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

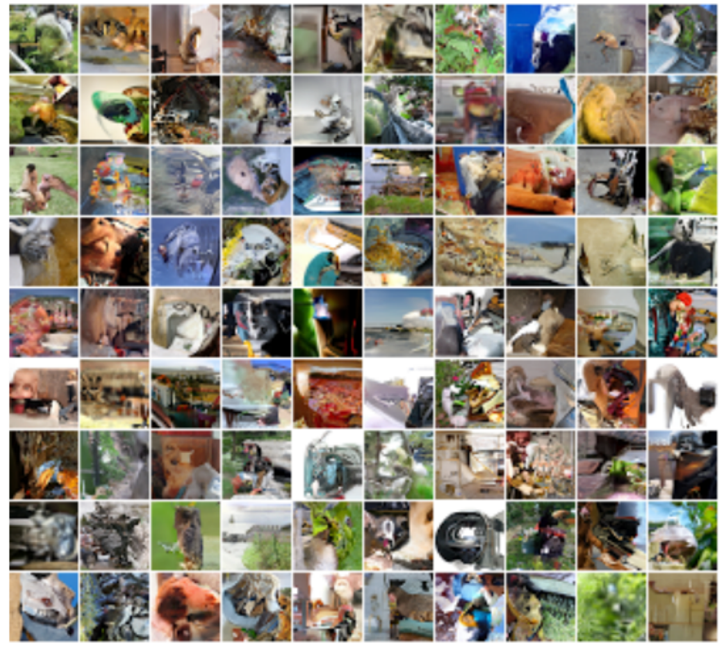
Generation must still proceed sequentially
=> still slow



Generation Samples



32x32 CIFAR-10



32x32 ImageNet

Image Completion

$p(\vec{x})$

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++)