Autoencoders and Representation Learning

Deep Learning Decal

Hosted by Machine Learning at Berkeley

Agenda

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Autoencoders

Regularized Autoencoders

Representation Learning

Representation Learning Techniques

Questions

Background

Review: Typical Neural Net Characteristics

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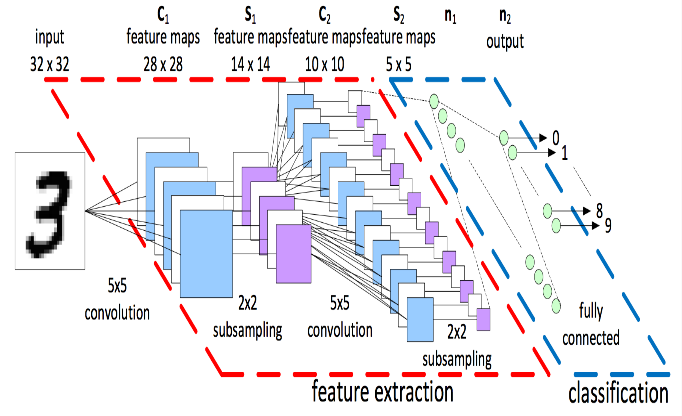
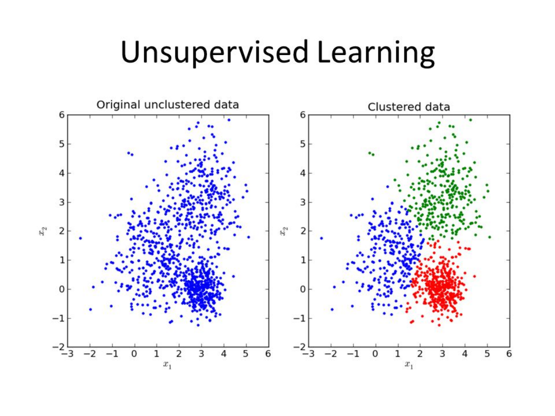
- Hidden Layer(s): Apply transformations with nonlinearity
- Output Layer: Result for *classification*, *regression*, *translation*, *segmentation*, *etc.*
- Models used for **supervised learning**

Example Through Diagram



Today's lecture: **unsupervised learning** with neural networks.



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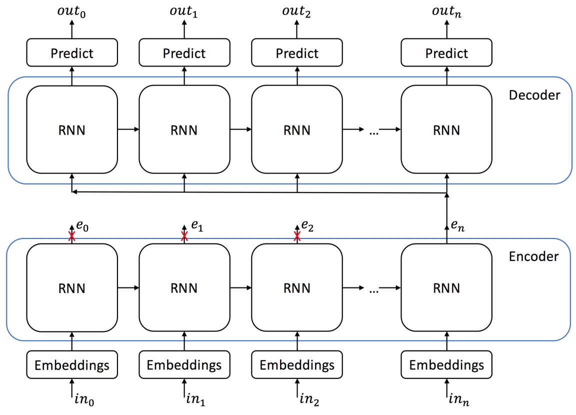
- Structure is almost always organized into **encoder** network, $\mathbf{f}$, and **decoder** network, $\mathbf{g}$: *model* $= \mathbf{g}(\mathbf{f}(\mathbf{x}))$
- Trained by gradient descent with **reconstruction loss:** measures differences between input and output e.g. MSE : $J(\theta) = |\mathbf{g}(\mathbf{f}(\mathbf{x})) - \mathbf{x}|^2$

Not an Entirely New Idea



Undercomplete Autoencoders

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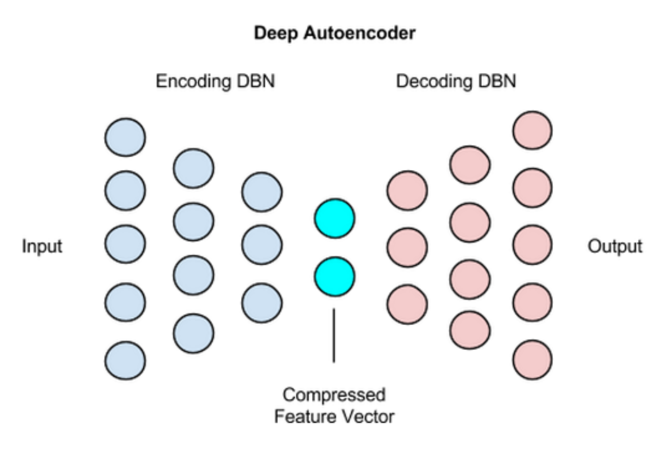
- If network has only linear transformations, encoder learns PCA. With typical nonlinearities, network learns generalized, more powerful version of PCA.

Visualizing Undercomplete Autoencoders



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- Pathological case: hidden layer is only one dimension, learns index mappings: $x^{(i)} \rightarrow i \rightarrow x^{(i)}$
    - Not very realistic, but completely plausible.

How Constraints Correspond to Effective Manifold Learning

ML@B

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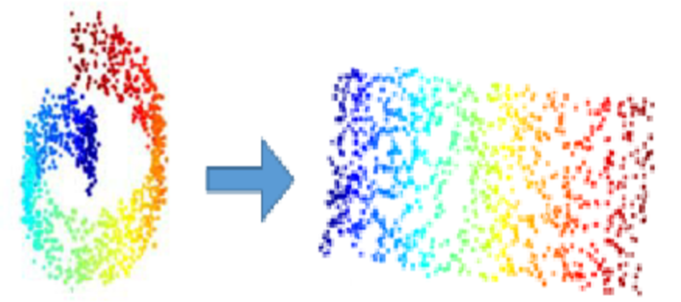
- → Autoencoders should only learn necessary variations to reconstruct training examples.

Visualizing Manifolds

Extract 2D manifold of data which exists in 3D:



Regularized Autoencoders

Stochastic Autoencoders

Rethink the underlying idea of autoencoders. Instead of encoding/decoding **functions**, we can see them as describing encoding/decoding **probability distributions** like so:

$$p_{encoder}(\mathbf{h}|\mathbf{x}) = p_{model}(\mathbf{h}|\mathbf{x})$$

$$p_{decoder}(\mathbf{x}|\mathbf{h}) = p_{model}(\mathbf{x}|\mathbf{h})$$

These distributions are called **stochastic** encoders and decoders respectively.

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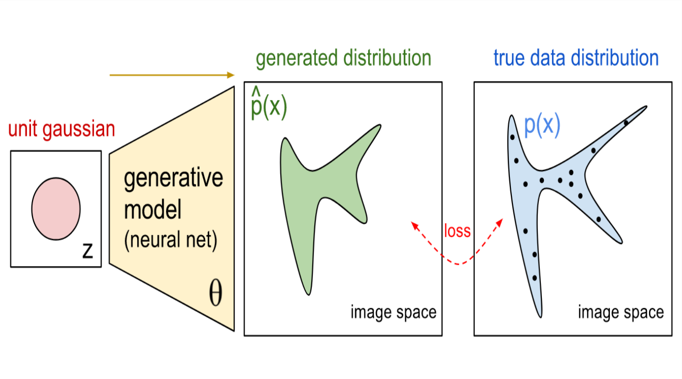
- Finding MLE of $\mathbf{x}, \mathbf{h} \approx$ maximizing $p_{model}(\mathbf{x}, \mathbf{h})$
- $p_{model}(\mathbf{h})$ is prior across latent space values. **This term can be regularizing.**

By assuming a prior over latent space, can pick values from underlying probability distribution!



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The log likelihood becomes:

$$-\ln p_{model}(\mathbf{h}) = \lambda \sum_i |h_i| + const. = \Omega(\mathbf{h})$$

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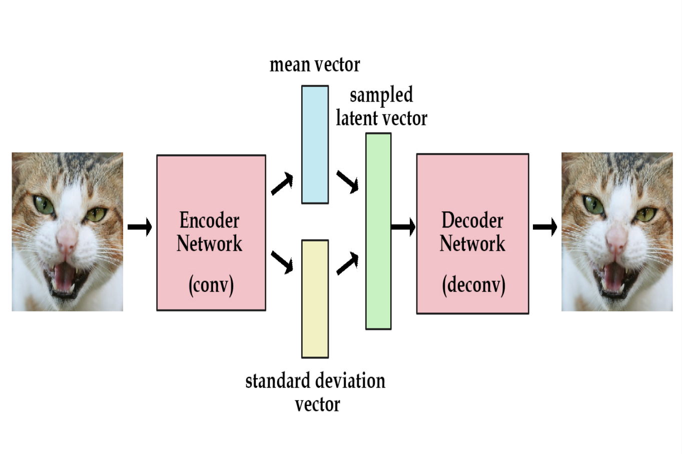
- Loss: Reconstruction + K-L Divergence

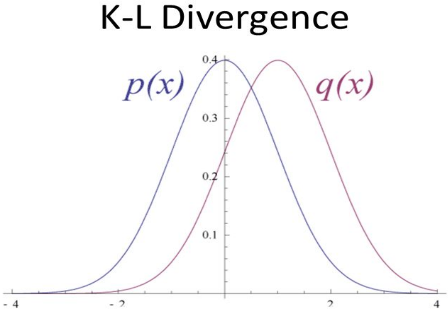
Visualizing Variational Autoencoders

Latent space explicitly encodes distribution statistics! Typically made to encode unit gaussian.



K-L Divergence

Variational Autoencoder Loss also needs K-L divergence. Measures difference between distributions



$$D_{\mathrm{KL}}(P\|Q) = \int_{-\infty}^{\infty} p(x) \log \frac{p(x)}{q(x)} \, \mathrm{d}x$$

Taken from Wikipedia page 'Kullback-Liebler Divergence

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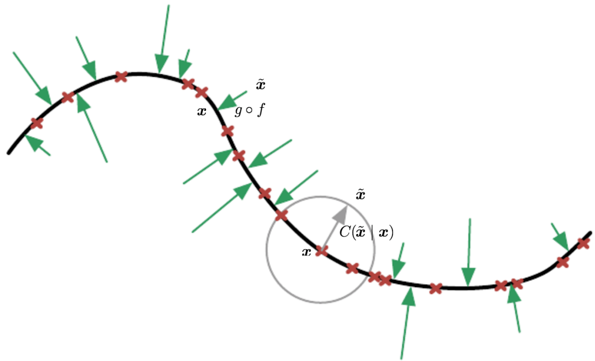
- $\mathbf{f}, \mathbf{g}$ will necessarily learn $p_{data}(\mathbf{x})$ because learning identity function will not give good loss.

Visualizing Denoising Autoencoders

By having to remove noise, model must know difference between noise and actual image.

Visualizing Denoising Autoencoders

The corrupting function $C(\cdot)$ can corrupt in any direction $\rightarrow$ autoencoder must learn "location" of data manifold and its distribution $p_{data}(\mathbf{x})$.



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$$\Omega(\mathbf{f}, \mathbf{x}) = \lambda \left| \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}} \right|_F^2$$

Jacobian and Frobenius Norm

The Jacobian Matrix for vector-valued function $f(x)$:

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The Frobenius Norm for a matrix M:

$$||M||_F = \sqrt{\sum_{i,j} M_{ij}^2}$$

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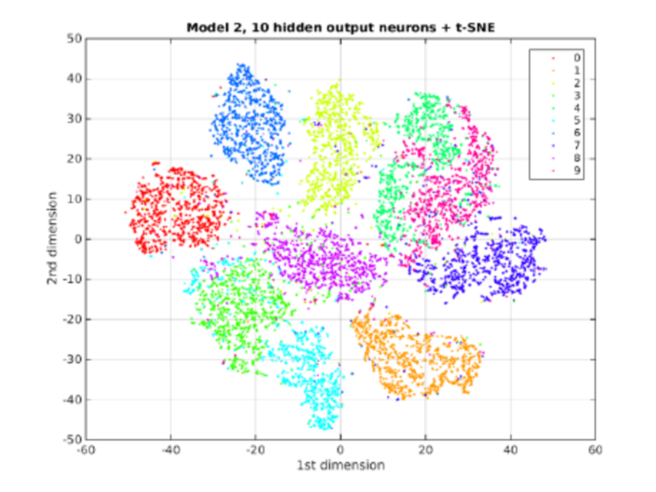
- This contractive effect is designed to only occur locally.
- The Jacobian Matrix will see most of its eigenvalues drop below 1 $\rightarrow$ contracted directions
- But some directions will have eigenvalues (significantly) above 1 $\rightarrow$ directions that explain most of the variance in data

Example: MNIST in 2D manifold



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- Be **insensitive** to inputs (regularization penalty) → learn actual data distribution

Connecting Denoising and Contractive Autoencoders

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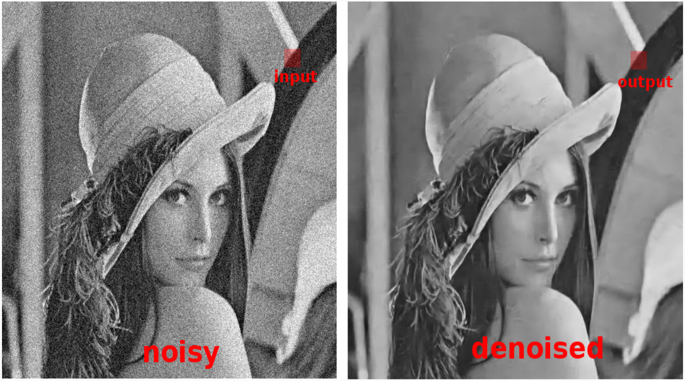
- Denoising Autoencoders make **reconstruction function** resist small, finite-sized perturbations in input.
- Contractive Autoencoders make **feature encoding function** resist infinitesimal perturbations in input.

Handling noise $\sim$ Contractive property



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- Common strategy: greedily pre-train layers and stack them
- For contractive autoencoders, calculating Jacobian for deep networks is expensive. Good idea to do layer-by-layer.

Applications of Autoencoders

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- **Information Retrieval:** Locate value in database which is just autoencoded key.
    - If you need binary for hash table, use sigmoid in final layer.

Representation Learning

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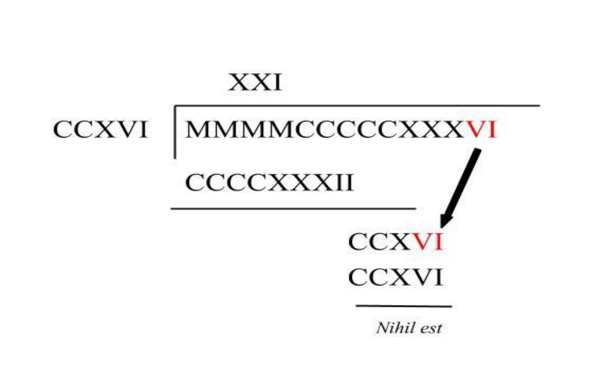

Other examples: **Variables** in algebra, **cartesian grid** for analytic geometry, **binary encodings** for information theory, electronics

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- Autoencoders: The entire mission of the architecture

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Fundamentally limited: $\sim \mathcal{O}(n)$ possible representations.

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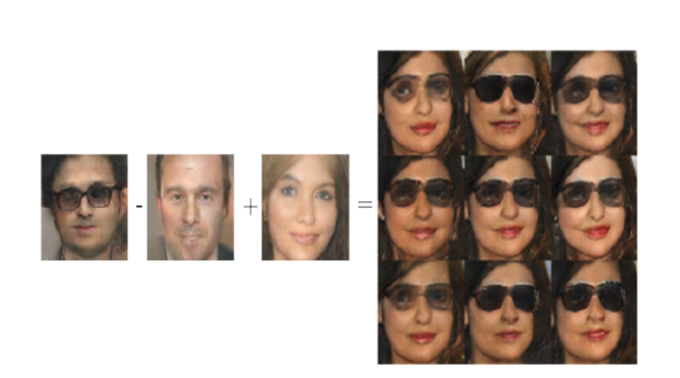
Pretty much always preferred: $\sim \mathcal{O}(k^n)$ possible representations, where k is number of values a feature can take on.

Benefits of Distributed Representations

Distributed representation → Data Manifold



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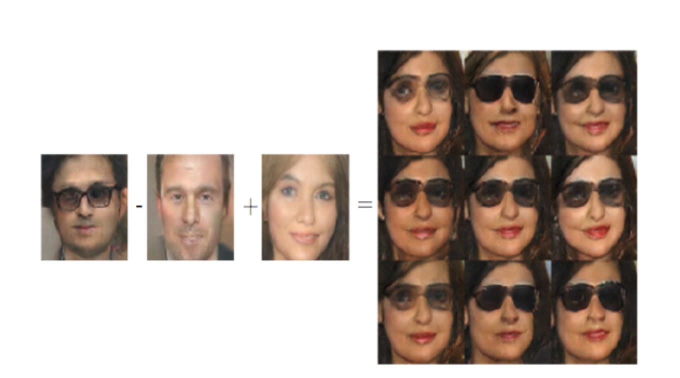

Also: less dimensionality, faster training

Representation Learning Techniques

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- Key Idea: **Leverage representations** learned for one task to solve another.
- Train **each layer** of feedforward net **greedily** as a representation learning alg. e.g. autoencoder.

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- **Fine tune**, i.e. jointly train, all layers once each has learned representations.

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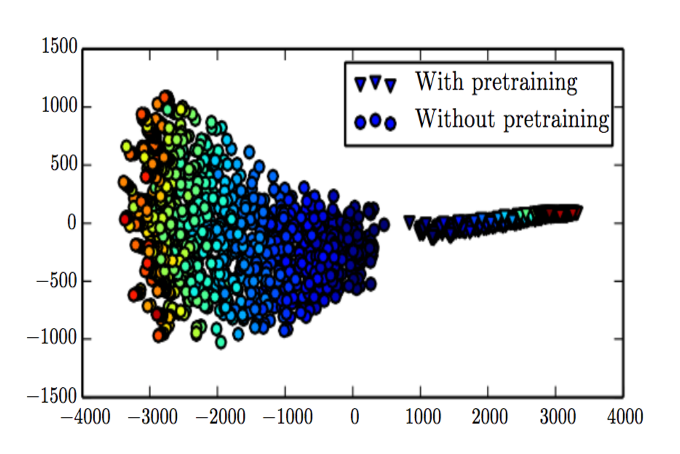
- Less effective for images - topology is already present.


With pretraining
Without pretraining
1500
1000
500
0
−500
−1000
−1500
−4000
−3000
−2000
−1000
0
1000
2000
3000
4000

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- Hopefully, **low-level** features from D_1 are useful for D_2, and fine-tuning is enough for D_2.

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- Learning of D_1 will establish latent space where dists. are separated. Then adjust to assign D_2 labels to transformed D_2 by pre-trained network.

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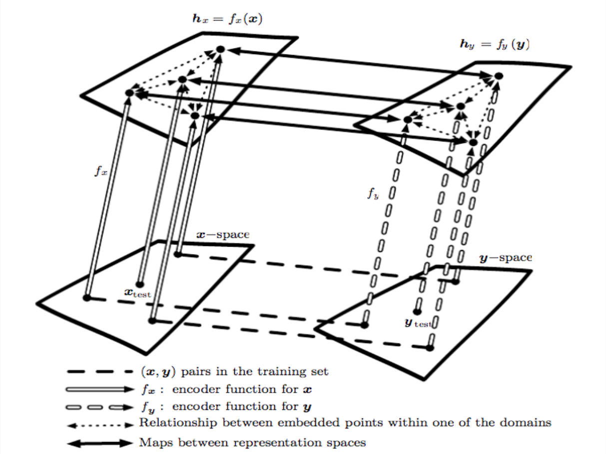
- Speakers may have diff. pitch depth, accents, etc $\rightarrow$different inputs.
- Training on D_1 gives model power to map noise to English in general. Just adjust to assign D_2 input to D_2 labels.



$h_x = f_x(x)$
$h_y = f_y(y)$
f_x
f_y
x—space
y—space
x_{test}
y_{test}
(x, y) pairs in the training set
f_x : encoder function for x
f_y : encoder function for y
Relationship between embedded points within one of the domains
Maps between representation spaces

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  - For example: T is sentences: cats have four legs, pointy ears, fur, etc. x is images, with y being label of cat or not.

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- **Easy Modeling:** representations that have sparse feature vectors which imply independent features

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- $p(y|x)$ depends on $p(x)$, hence h being causal is valuable.

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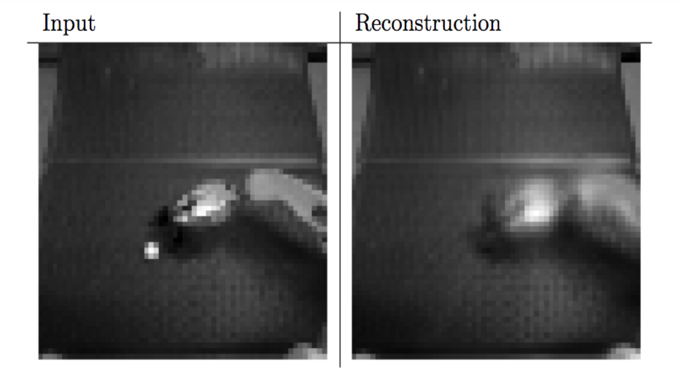
- Example: Autoencoders trained on images often fail to register important small objects like ping pong balls.

Failure of Traditional Loss Functions



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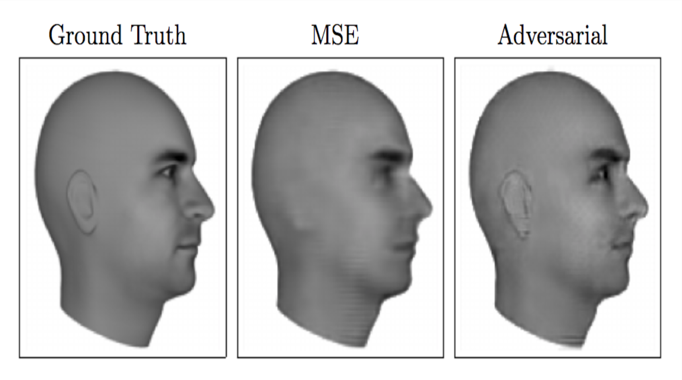
- Framework of **Generative Adversarial Networks** (more later in course).

Comparing Traditional to Adversarial



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- The crux of deep learning is representation learning.
- The crux of intelligence is probably representation learning.

Questions

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