### What We Did Not Cover

#### COMPSCI 371D — Machine Learning

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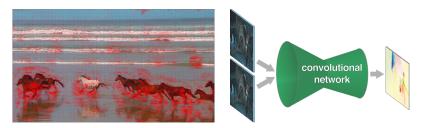
# What We Did Not Cover

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- 6 Addressing Multiple Learning Tasks Together
- Prediction over Time

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#### Much More Detail

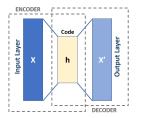
- Computationally efficient training algorithms: Optimization techniques
- Deep learning architectures for special problems: Image motion analysis, video analysis, ...



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#### **Beyond Discriminative Neural Networks**

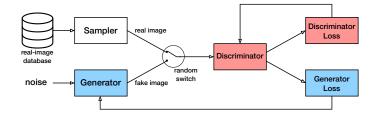
- Abstraction for its own sake: Auto-encoders
- A game-theoretical technique to draw from a distribution: Generative Adversarial Networks





Which image is fake?

#### **Generative Adversarial Networks**



- Discriminator guesses if input is real or fake
- Discriminator loss penalizes wrong predictions
- Generator loss penalizes correct predictions
- After training keep only the generator

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### Statistical Machine Learning

- How to measure the size of  $\mathcal{H}$ : Vapnik-Chervonenkis dimension, Rademacher complexity
- How large must *T* be to get an *h* that is within *ϵ* of a performance target with probability greater than 1 *δ*: Probably Approximately Correct (PAC) learning
- *H* is *learnable* if there exists a size of *T* that is large enough for this goal to be achieved
- Which  $\mathcal{H}s$  are learnable?
- How large must S be to get a performance measure accurate within ε: Concentration bounds, statistical estimation theory, PAC-like techniques

# **Other Supervised Techniques**

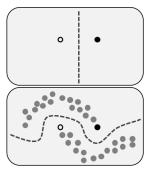
- Boosting: How to use many bad predictors to make one good one
  - Similar in principle to ensemble predictors, different assumptions and techniques
- Learning to rank

Example: Learning a better Google

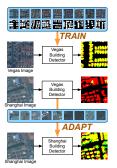
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# Reducing the Burden of Labeling

- Semi-supervised methods: Build models of the data x to leverage sparse labels y
- Domain adaptation: Train a classifier on source-domain labeled data (x, y) and target-domain unlableled data x so that is works well in the target domain

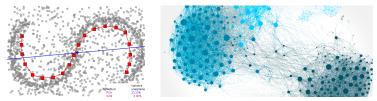


https://en.wikipedia.org



# **Unsupervised Methods**

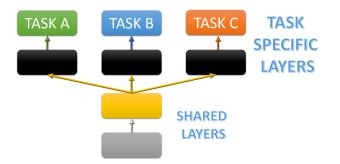
- Dimensionality reduction:
  - Compressing  $X \subseteq \mathbb{R}^d$  to  $X' \subseteq \mathbb{R}^{d'}$  with  $d' \ll d$ 
    - Principal or Independent Component Analysis (PCA, ICA)
    - Manifold learning, GANs
- Clustering:
  - K-means
  - Expectation-Maximization
  - Agglomerative methods
  - Splitting methods



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# Addressing Multiple Learning Tasks Together

 Multi-task learning: How to learn representations that are common to different but related prediction tasks



# Prediction over Time

- State-space methods
  - Time series analysis
  - Stochastic state estimation
  - System identification
- Recurrent neural networks
- Reinforcement learning: Actions over time Learning policies underlying observed sequences

