Neural Networks and Deep Learning

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This Lecture:
Introduction — Part 2

Course: Neural Networks and Deep Learning
IE 7615

This Lecture

- **Deep learning — successes and potential**
- **Limitations ?**
- **Types of learning**

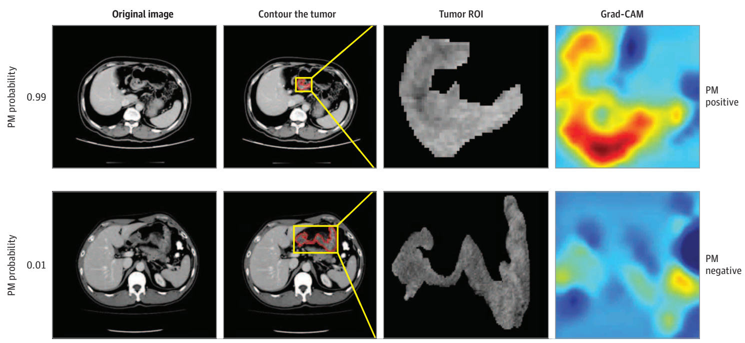
Application Areas (Recap)

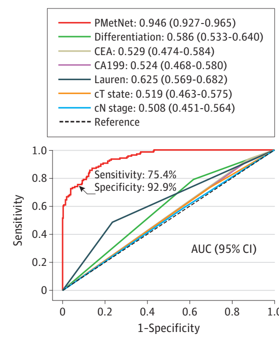
A few examples (out of many)	
Machine Vision	Speech & Language Processing (NLP)
Face Recognition, Object Recognition	Autonomous Vehicles
Self-driving cars	Robotics
Forecasting	Assistive Robotics
Wheather, climate, etc.	Bioinformatics
Computational biology, neuroscience	"X-"informatics
Analytics (text, video, etc.)	Economics, Financial forecasting
Medical diagnostics	Insurance
Biomed data analysis; healthcare	Fraud detection
Drug development	Image/photo tagging
Personalized medicine	
… many others…	

- **Span of potential applications enormous**
- **But beware of misapplication and overkills!**

Deep Neural Networks for Noninvasive Prediction of Occult Peritoneal Metastasis in Gastric Cancer (Recap)

- **Jiang *et al.*, JAMA Network Open, January 5, 2021**
- **Noninvasive preoperative (pre-surgery) assessment of occult peritoneal metastasis of gastric cancer**
- **Potentially useful to aoid unnecessary surgery and risk of associated complications**
- **CT imagery**
- **1978 patients**
- **Densely connected convolutional neural network (CNN)**
- **Discrimination performance of network substantially higher than conventional clinicopathological factors**

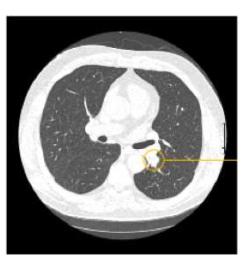


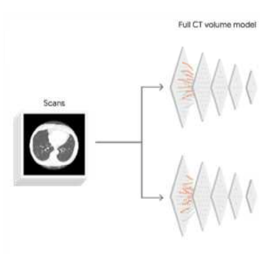


[Jiang, 2021]

Deep Neural Networks for Lung Cancer Screening (Recap)

- **Ardila *et al.*, Nature Medicine, May 2019**
- **Predict lung cancer risk by comparing patient's current and prior CT imaging**
- **Deep convolutional neural networks (CNN)**
- **6,716 National Lung Cancer Screening Trial (NLST) cases**
- **94.4% AUC performance**
- **Performance better or comparable with human readers (radiologists)**

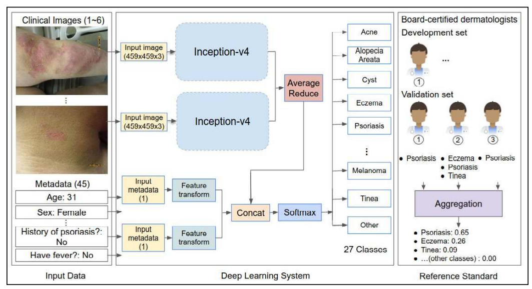




[Ardila, 2019]

Deep Neural Networks for Skin Lesion Classification (Recap)

- **Liu *et al.*, 2019**
- **Differential diagnosis of 26 skin conditions from photographs and medical histories**
- **14,021 development cases, 3,756 evaluation cases**
- **Variable number of deep convolutional neural network modules to process images**
  - **Inception-v4**
- **Shallow module for patient demographic information and medical history (metadata)**



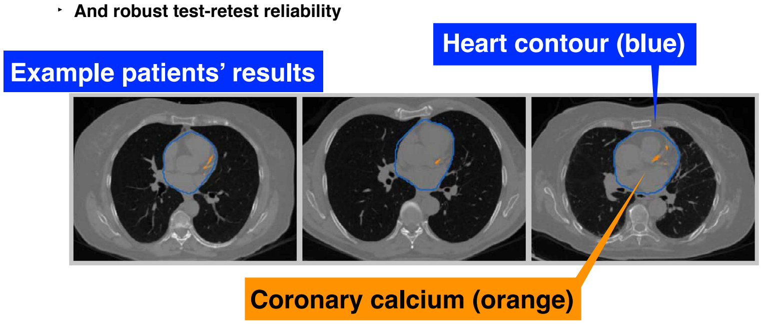
[Liu, 2019]

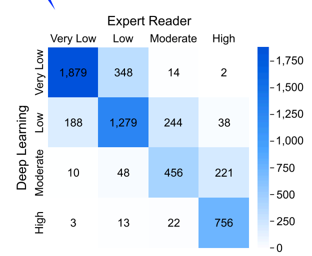
Deep Neural Networks for Breast Cancer Screening (Recap)

- **McKinney *et al.*, Nature, January 1, 2020**
- **Breast cancer prediction from mammograms**
- **Ensemble of three deep-learning models**
- **Exploit ImageNet, RetinaNet, ResNet**
- **All models implemented in TensorFlow**
- **Platform includes Google TPU hardware**
- **System performance — potential to perform better than trained radiologists**
  - **False positives reduction: 5.7% and 1.2% (US and UK)**
  - **False negative reduction: 9.4% and 2.7%**
  - **Able to generalize from UK data to US data**
  - **Able to outperform human experts**
    - **Six readers (radiologists)**
    - **AUC-ROC performance higher than that of human readers by 11.5% margin**

Deep Neural Networks for Cardiovascular Risk Prediction (Recap)

- Zeleznik *et al.*, Nature Communications, Jan. 2021
- Coronary artery calcium — predictor of cardiovascular events
- Visible on all CT chest scans computed tomography (CT) scans
  - But quantification requires expertise, time, and specialized equipment
- Robust automatic quantification by deep-learning system
  - Convolutional neural networks
- 20,084 individuals from asymptomatic, and stable and acute chest pain cohorts
- High correlation of deep-learning system with quantification by expert readers
  - And robust test-retest reliability

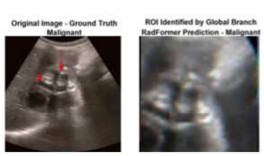


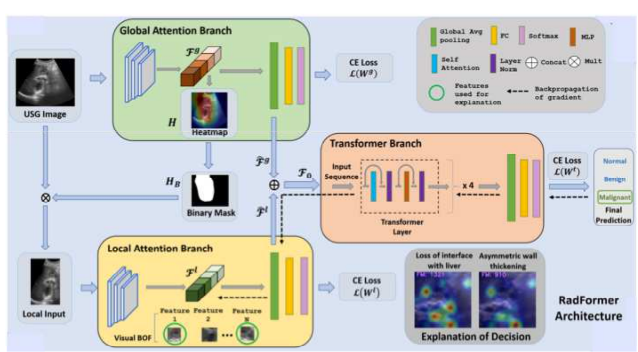


[Zeleznik, 2021]

Deep Neural Networks for Gallbladder Cancer Diagnostics (Recap)

- Basu *et al.*, 2022
- Diagnostics of gallbladder malignancies
- Input: ultrasound sonography images
- Transformer network architecture
- Basu *et al.* compared system results with conclusions of two expert radiologists
  - Found system performance was better



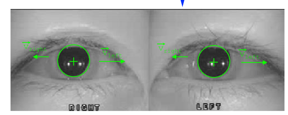


[Basu, 2022]

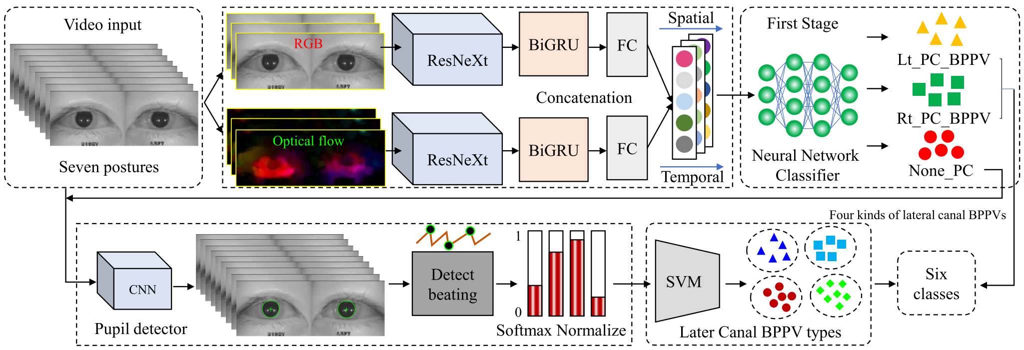
Deep Neural Networks for BPPV Diagnosis (Recap)

- **Pham *et al.*, Oct. 2022**
- **Diagnostics of benign paroxysmal positional vertigo (BPPV) types**
  - **Posterior canal types (Left, righT), Lateral canal types: geotropic BPPV (left, right), apogeotropic (left, right)**
- **Input: video stream of patient eye-motion during diagnostic medical exam (Dix-Hallpike test)**
- **Hybrid deep artificial neural network architecture**
  - **Exploit deep convolutional networks and recurrent networks**

Nystagmus

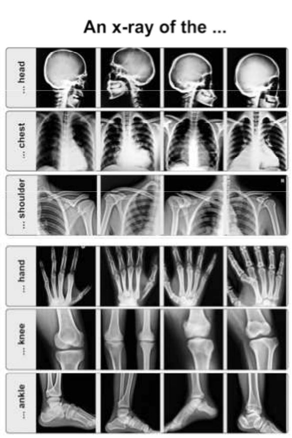


[Pham, 2022]



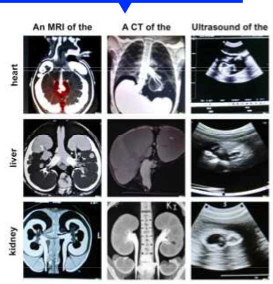
Deep Generative Models for Medical Imagery (Recap)

- **Adams *et al.*, 2022**
- **AI in radiology**
  - **Using DALL-E 2 generative model for text-to-image generation, image augmentation, and manipulation**
  - **DALL-E 2 learns relevant representations of X-ray images**
    - **Zero-shot text-to-image generation of new images, continuation of image beyond original boundaries**

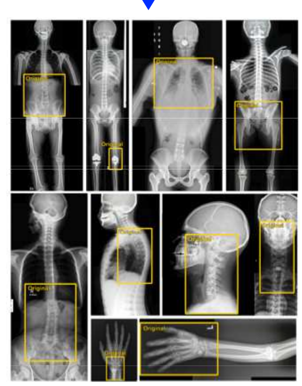


X-ray images from short texts

MRI, CT, and ultrasound images from short texts



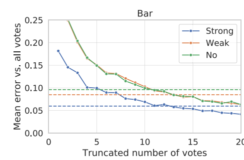
Extending images (input areas marked in yellow)



[Adams, 2022]

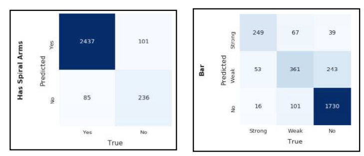
Deep Neural Networks for Understanding Universe (Recap)

- **Walmsley *et al.*, MNRAS 509, 2022**
  - **Deep neural networks for astronomy and astrophysics research**
  - **Visual morphological classification of galaxies from images**
    - **Morphology of galaxies— key to understanding galactic evolution**
- **Data — *Dark Energy Camera Legacy Survey* images of galaxies**
- **Ensemble of convolutional neural networks**
  - **Exploit EfficientNet-B0 architecture with modifications**
- **Predict morphology features of galaxies**
  - **E.g., spiral arms, bars, etc.**
  - **Measured against confident volunteer classifications**
    - **Galaxy Zoo volunteers**
  - **Trained networks reach up to 99% accuracy**
    - **Measured against ~10 volunteers, could be viewed as achieving superhuman performance**

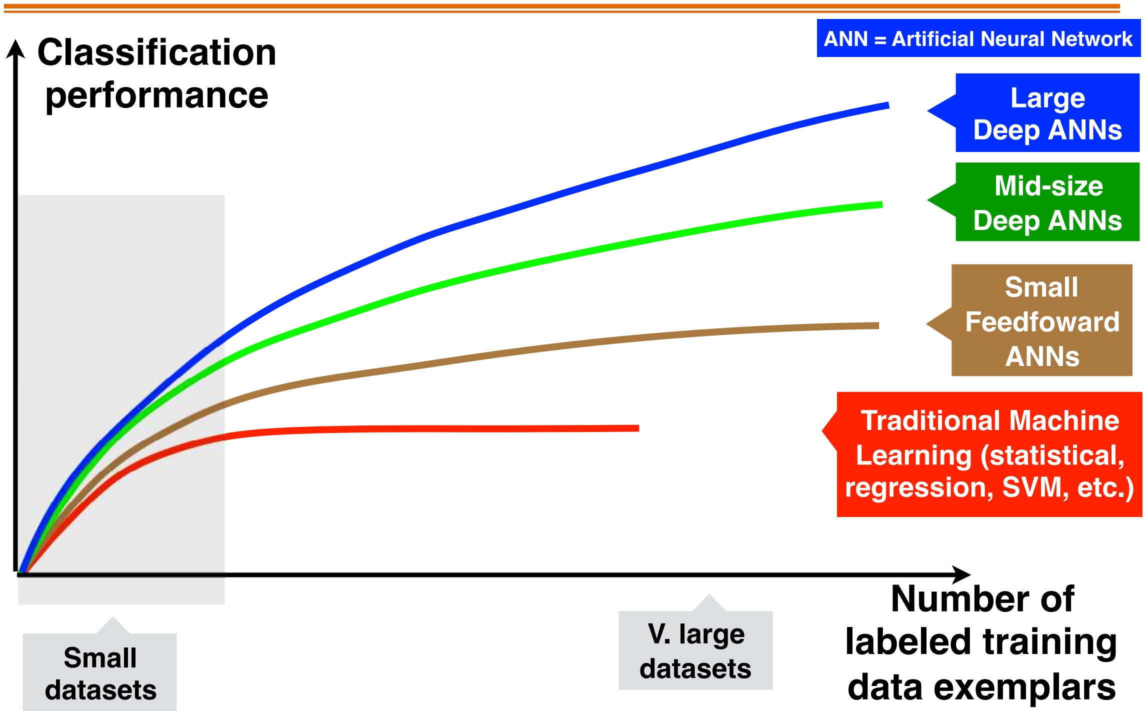


[Walmsley, 2022]

Network (dashed)



Deep Learning vs. Other Machine Learning Paradigms



Deep Learning / Artificial Intelligence
What might be ahead

- **Progressively more robust and versatile learning (reasoning)**
- **Ability to decide and act to accomplish goals**
  - **Leading to further questions and challenges, e.g., which goals, whose goals?**
- **Exhibit what we know as human emotions**
  - **At much higher level than today's *affective computing***
  - **Different in their essence from today's *affective computing***
    - **Although we do not yet know what this would entail since realm of emotions is not yet understood**
- **Ability to self-improve**
  - **Reorganize**
  - **Self-redesign**

This Lecture

- **Deep learning — successes and potential**
- **Limitations ?**
- **Types of learning**

Deficiencies or Limitations?
Watson's Error

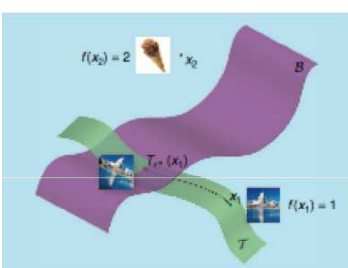
**In 2011,
IBM Watson system
won "Jeopardy!" TV game
against human champions**

… but …

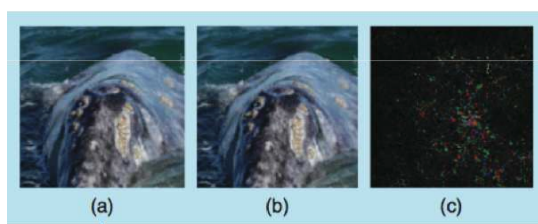
- **Category: "U.S. Cities"**
- **Answer: "*Its largest airport was named for a World War II hero; its second largest, for a World War II battle*"**
- **Rutter and Jennings: "What is Chicago?"**
- **Watson: "What is Toronto?"**

Deficiencies or Limitations?
Deep-Learning Robustness Issues

- **Non-robustness of deep networks [Fawzi et al. 2017]**
- **Adversarial perturbations**



[Fawzi, 2017]

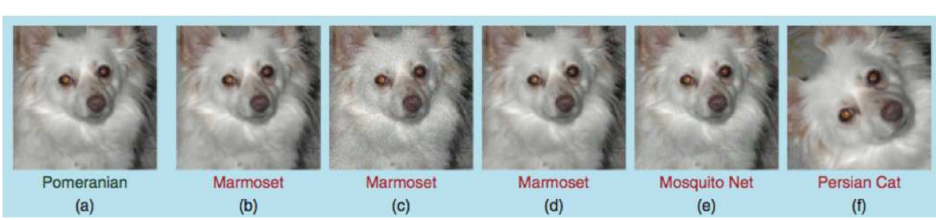


[Fawzi, 2017]

Original WHALE

Perturbed TURTLE

Adversarial Perturbation



[Fawzi, 2017]

This Lecture

- Deep learning — successes and potential
- Limitations ?
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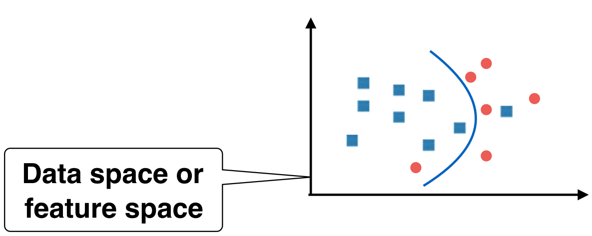
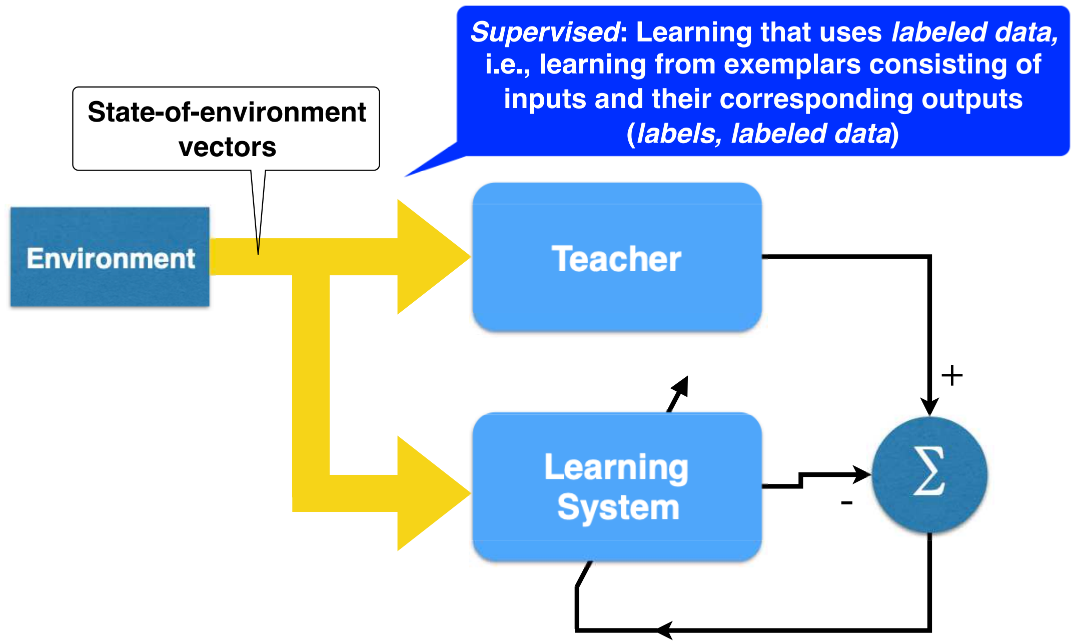
Machine Learning in a Nutshell

- “Typical” interpretation
  - Derive decision boundary that “best” separates regions of different data-categories (classes of data)
- Statistical Learning Theory (Vapnik)
  - Derive “recipe” for categorizing given data
- Features
  - Functions of data
  - Meant to represent data — salient aspects of data



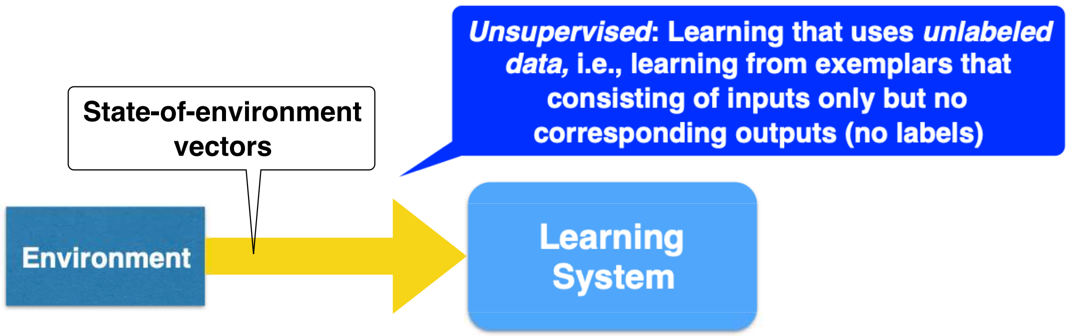
Supervised Learning



Supervised Learning

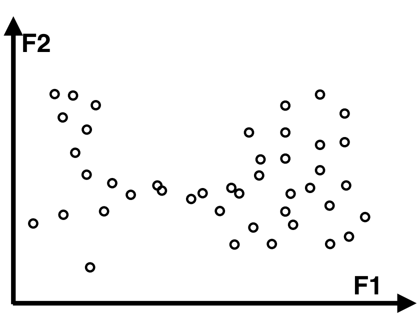
- Training data consist of inputs and outputs
  - Training set
- Previously unseen (novel) input to be categorized
  - Test set
  - Categorize/classify = determine output given input
- Output types
  - Discrete (categorical) — classification task
  - Continuous — regression task

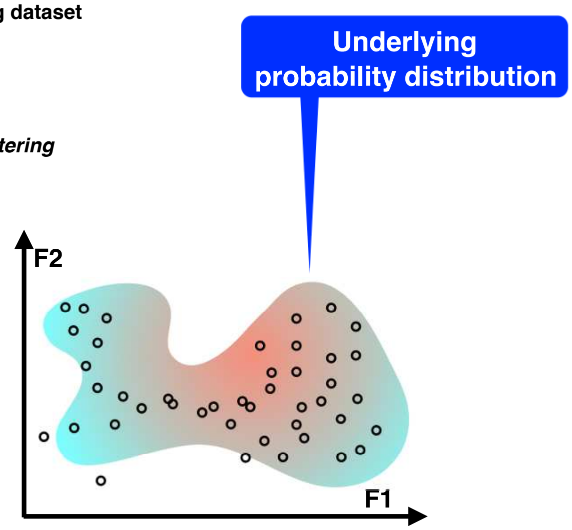
Unsupervised Learning



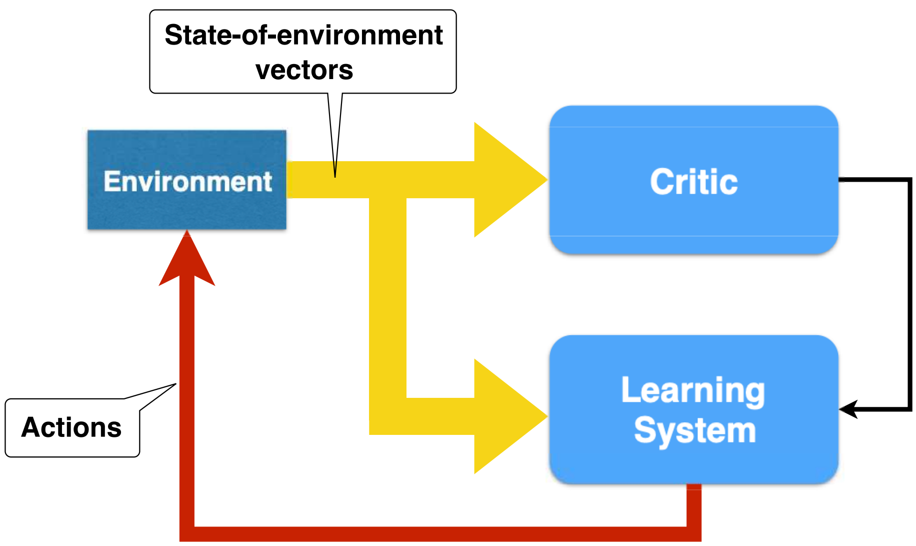
Unsupervised Learning Tasks

- Training set contains data without labels
- Learning — from unlabeled data, learn some useful characteristics of data or process that underlies unlabeled data
  - Learn explicitly probability-distribution underlying dataset
  - Learn to generate new data (synthesis)
  - Learn to remove noise from data — *denoising*
  - Determine clusters ("sub-groups") in data — *clustering*
  - etc.



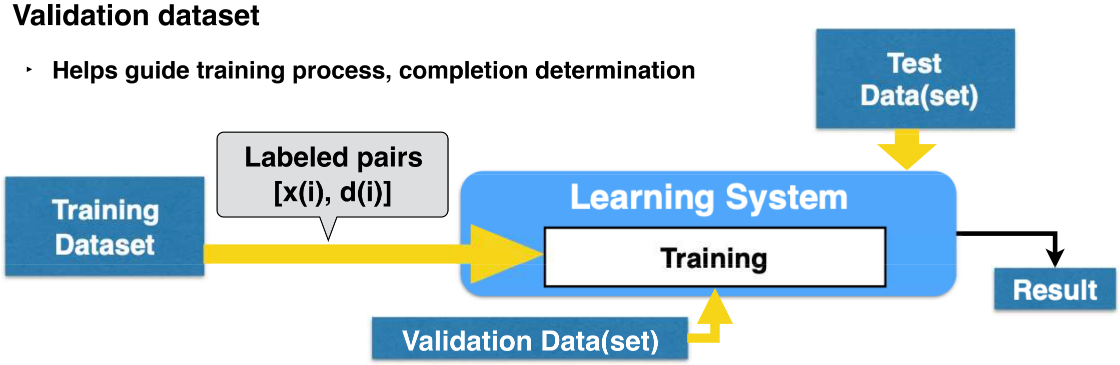


Reinforcement Learning



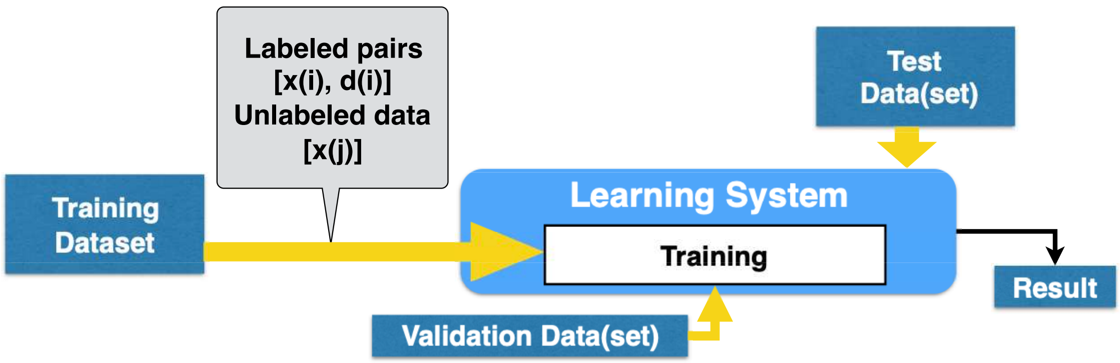
Supervised Learning

- Training — learning phase
  - Training dataset — collection of labeled (annotated) exemplars
- Testing — operation of trained system
  - Test dataset — data to classify (categorize, recognize)
    - Labels used ONLY for performance assessment (not for classification)
- Validation dataset
  - Helps guide training process, completion determination

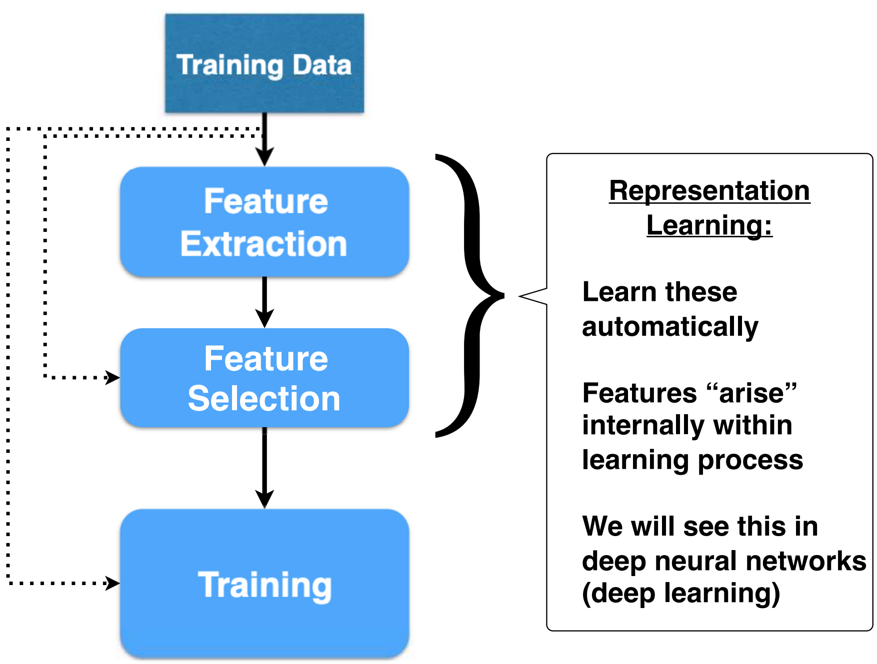


Semisupervised Learning

- Some training data annotated
  - Have category labels
- More training data available — but no labels
  - E.g., large collection of images, only some annotated



Features



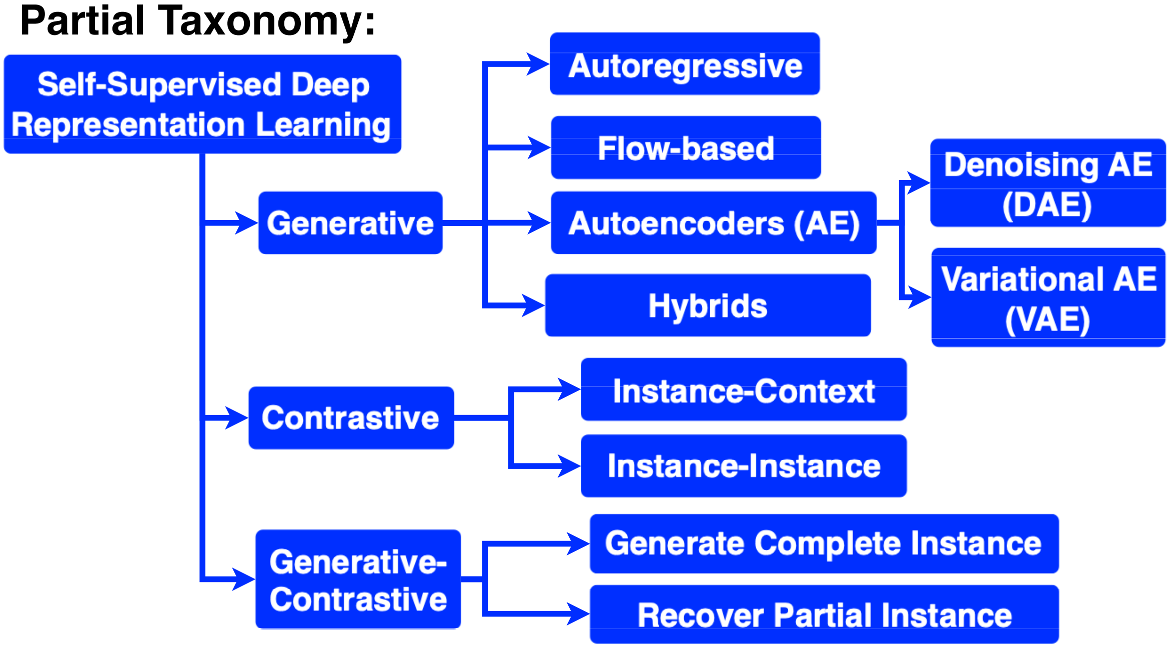
Current Advanced Trends in Deep Learning

- **Representation learning**
- **Learning from unlabeled data**
  - **Semi-supervised learning**
  - **Self-supervised learning — learning to classify from unlabeled data**
- **Transfer learning**
  - **Train on "pretext" ("proxy") task**
  - **Transfer (apply) trained deep network to different tasks**
    - **Pre-train on one task**
    - **Fine-tune for another task**
- **Few-shot learning**
  - **Learn from few training instances**
    - **Two-shot learning, one-shot learning**
  - **Zero-shot learning**

We will return to these later in this course

Deep Self-Supervised Representation Learning

Partial Taxonomy:



More about this later in the course

Questions?