Summary: Learning and Future of AI

Artificial Intelligence @ Allegheny College

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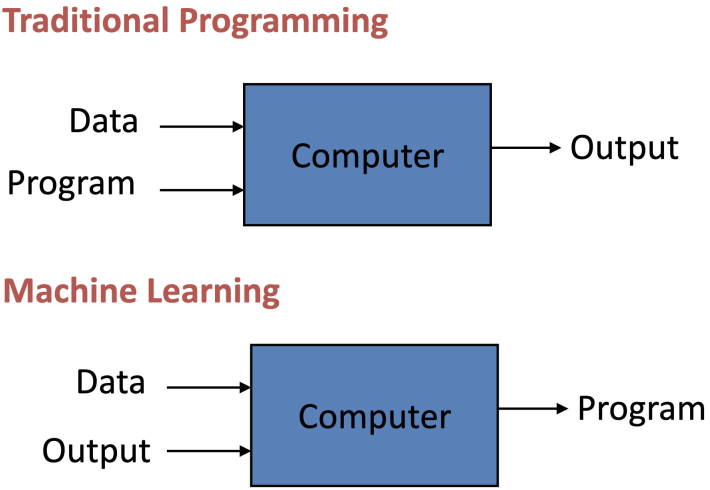
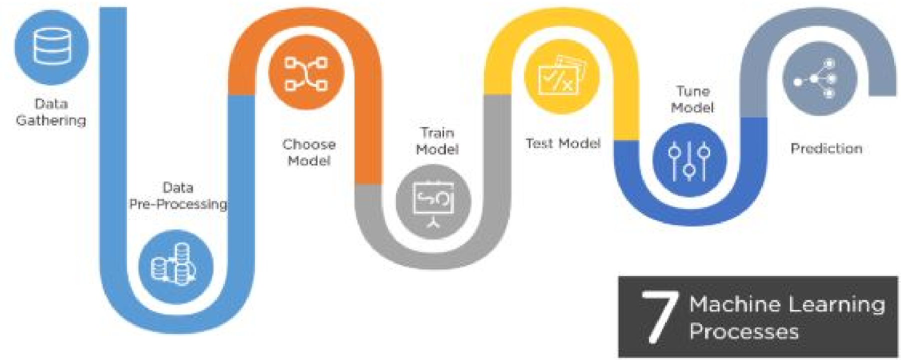
Ref: OpenAI NeurIPS 2021 Tutorial

Learning


Traditional Programming
Data
Program
Computer
Output
Machine Learning
Data
Output
Computer
Program

Learning


Data
Gathering
Data
Pre-Processing
Choose
Model
Train
Model
Test Model
Tune
Model
Prediction
7 Machine Learning
Processes

Traditional Types of Learning

- **Supervised** learning
  - Training data + desired outputs (labels)

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- **Reinforcement** learning
  - Rewards from sequence of actions

Unsupervised Learning

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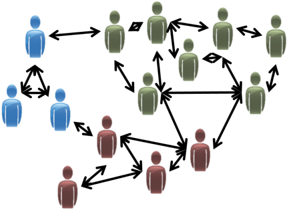
Tasks:

- Clustering (to group similar data into a finite number of clusters / groups)
- Vector Quantization (compress / decode dataset into a new representation but maintaining internal information)
- Outlier Detection (select highly unusual cases/sequences)

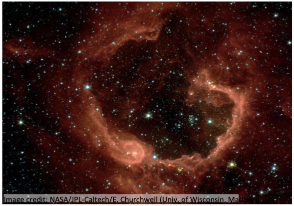
Unsupervised Learning

Organize computing clusters



Social network analysis

Market segmentation



Astronomical data analysis

Reinforcement Learning

- Given a sequence of states and actions with (delayed) rewards, output a policy
  – Policy is a mapping from states to actions that tells you what to do in a given state.

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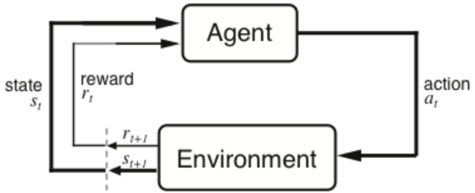
  – Policy is a mapping from states to actions that tells you what to do in a given state.
- **Examples**:
  - credit assignment problem,
  - game playing,
  - robot in a maze

Reinforcement Learning



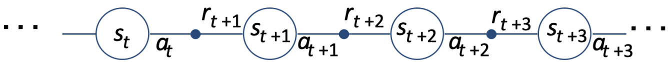
Agent and environment interact at discrete time steps : $t = 0, 1, 2, K$

Agent observes state at step t: $s_t \in S$

produces action at step t: $a_t \in A(s_t)$

gets resulting reward : $r_{t+1} \in \Re$

and resulting next state : s_{t+1}



Self-Supervised Learning

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- Construct supervised learning tasks out of unsupervised datasets.
- Self-supervised learning tasks are also known as pretext tasks.
- In general, withhold some part of the data and the task a neural network to predict it from the remaining parts.
- Can train a self-supervised model to learn data representations by contrasting multiple augmented views of the same example.

Why Self-Supervised Learning?

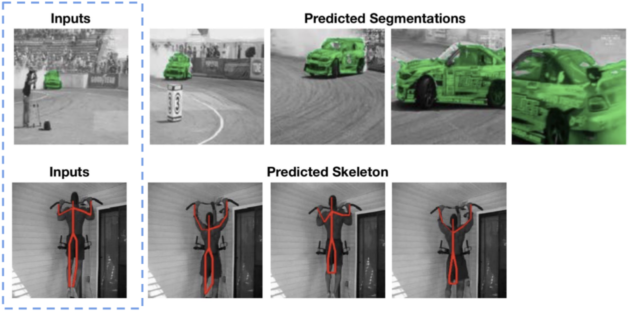
- Expense of producing a new dataset for each task storage pipelines, etc.
- Take advantage of vast amount of unlabeled data on the internet (images, videos, language).
- Cognitive motivation: How animals / babies learn.

Goal of Self-Learning

- Learn equally good (if not better) features without supervision.
- Be able to deploy similar quality systems without relying on too many labels.
- Generalize better potentially because you learn more about the world.

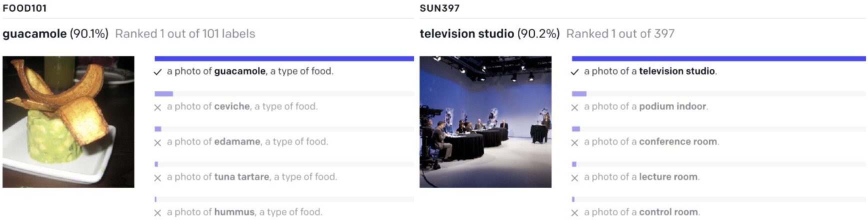
Examples

Video colorization (Vondrick et al 2018), as a self-supervised learning method, resulting in a rich representation that can be used for video segmentation and unlabelled visual region tracking, without extra fine-tuning.



Examples

Despite of not training on supervised labels, the zero-shot CLIP (Radford et al. 2021) classifier achieve great performance on challenging image-to-text classification tasks.



Methods for Framing Self-Supervised Learning Tasks

Self-prediction:

Given an individual data sample, the task is to predict one part of the sample given the other part.

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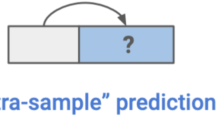
The part to be predicted pretends to be missing.



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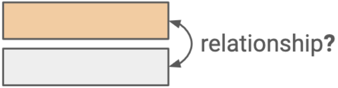
The multiple samples can be selected from the dataset based on some known logics (e.g. the order of words / sentences), or fabricated by altering the original version.



"Inter-sample" prediction

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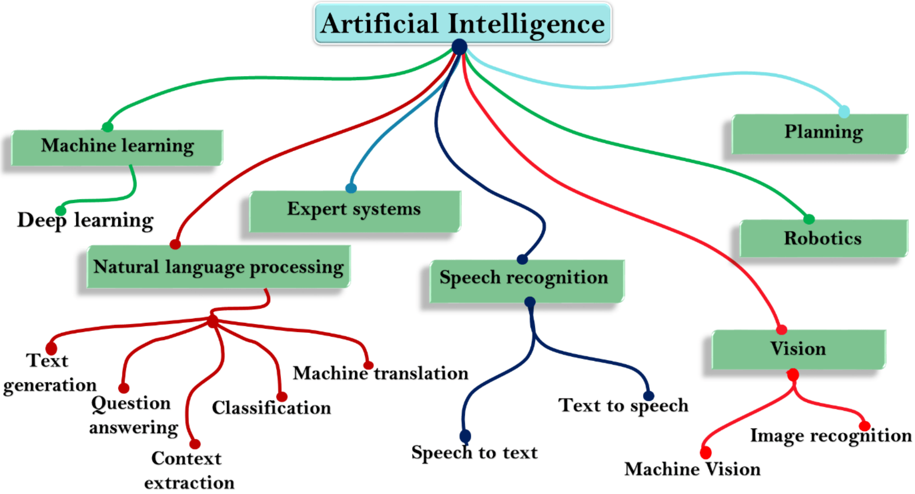
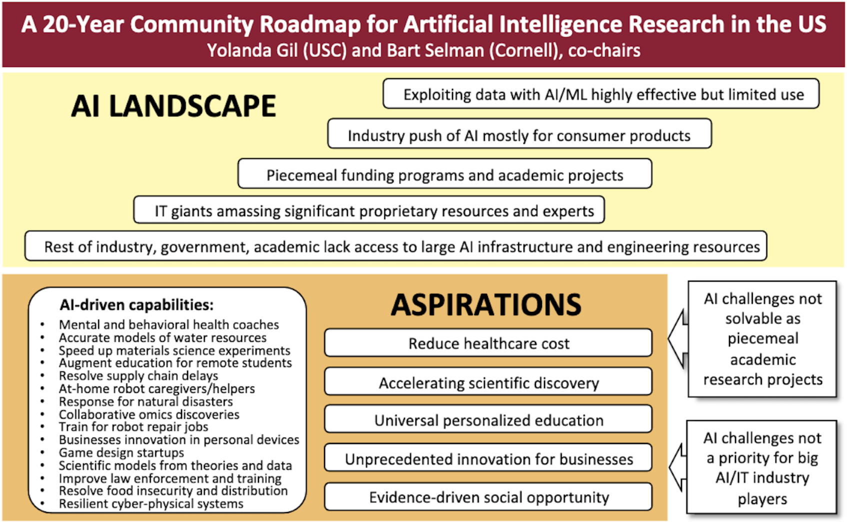
- **Semi-supervised learning**
  - small number of input-output relationships
- **Self-supervised learning**
  - the underlying structure of data, no labeled data inputs


Artificial Intelligence
Machine learning
Deep learning
Expert systems
Planning
Robotics
Natural language processing
Speech recognition
Vision
Text generation
Question answering
Context extraction
Classification
Machine translation
Speech to text
Text to speech
Image recognition
Machine Vision

Future of AI: AAAI 2019 Report



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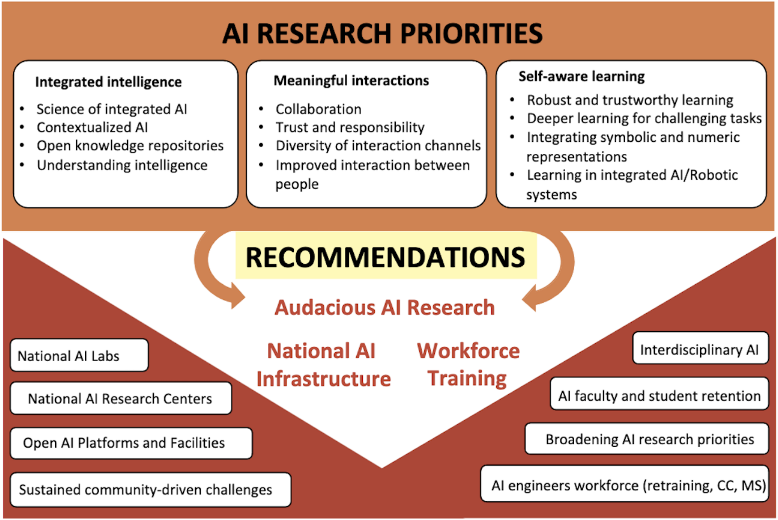


Future of AI

- AutoML
- Machine learning + Quantum computing
- Continued growth of generative AI
- AI ethics + compliance
- Wider application of AI (healthcare, making things - beer/perfumes)

Future of AI

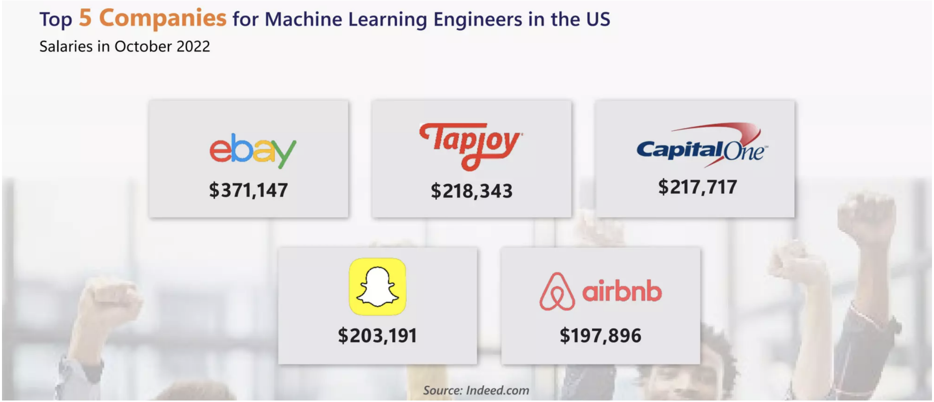
"In about 60% of the occupations, only 1/3rd of tasks could be automated. AI will replace up to 40% of jobs by 2030."

– Excerpts from PwC Research

Opportunities

Source: Payscale, Talent.com

Opportunities



Source: Indeed.com

Opportunities