

Summary: Learning and Future of AI

Artificial Intelligence @ Allegheny College

Janyl Jumadinova

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Ref: OpenAI NeurIPS 2021 Tutorial

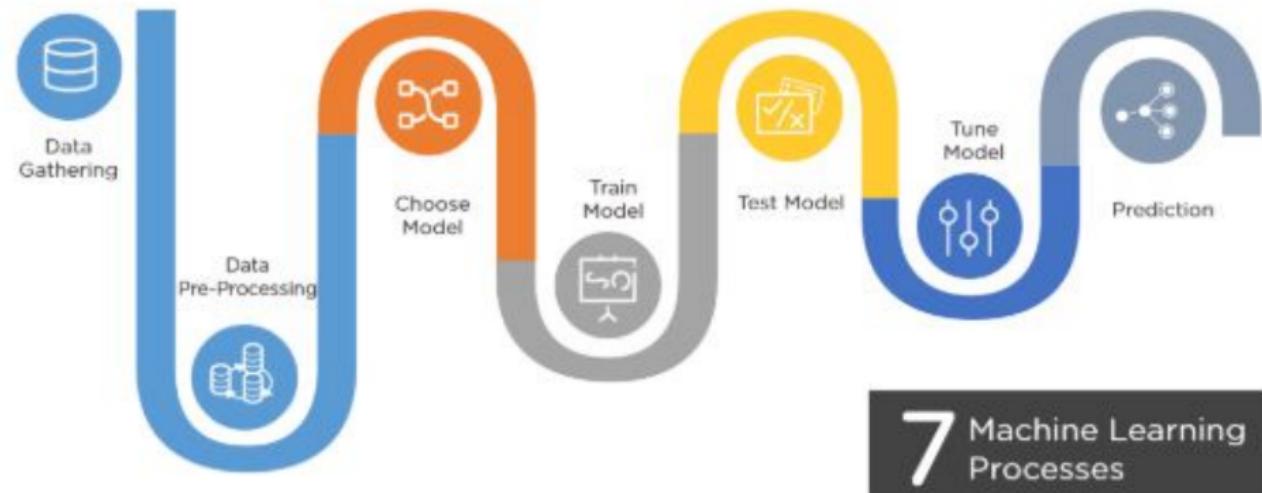
Traditional Programming



Machine Learning



Learning



Traditional Types of Learning

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

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

Unsupervised Learning

Given only inputs and automatically discover representations, features, structure etc.

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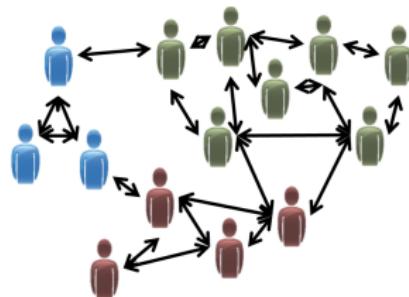
Tasks:

- **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



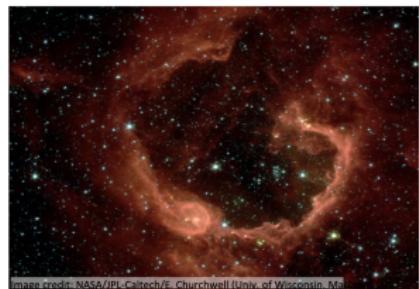
Organize computing clusters



Social network analysis



Market segmentation



Astronomical data analysis

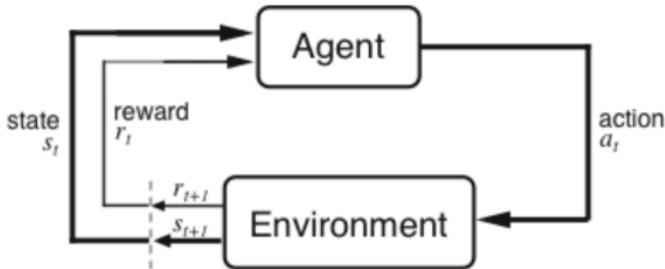
Reinforcement Learning

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- **Examples:**
 - credit assignment problem,
 - game playing,
 - robot in a maze

Reinforcement Learning



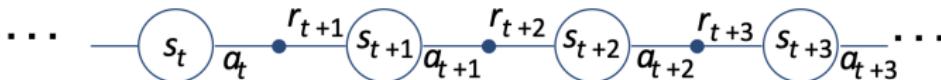
Agent and environment interact at discrete time steps : $t = 0, 1, 2, K$

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

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

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

and resulting next state : s_{t+1}



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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?

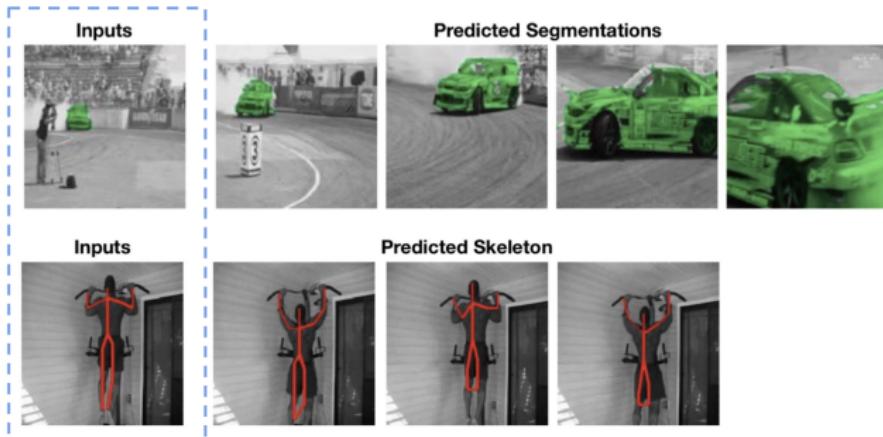
- Expense of producing a new dataset for each task storage pipelines, etc.
- Take advantage of vast amount of unlabeled data on the internet (images, videos, language).
- Cognitive motivation: How animals / babies learn.

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.

FOOD101

guacamole (90.1%) Ranked 1 out of 101 labels



✓ a photo of **guacamole**, a type of food.

✗ a photo of **ceviche**, a type of food.

✗ a photo of **edamame**, a type of food.

✗ a photo of **tuna tartare**, a type of food.

✗ a photo of **hummus**, a type of food.

SUN397

television studio (90.2%) Ranked 1 out of 397



✓ a photo of a **television studio**.

✗ a photo of a **podium indoor**.

✗ a photo of a **conference room**.

✗ a photo of a **lecture room**.

✗ a photo of a **control room**.

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.



“Intra-sample” prediction

Methods for Framing Self-Supervised Learning Tasks

Contrastive learning:

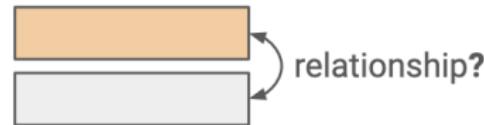
Given multiple data samples, the task is to predict the relationship among them.

Methods for Framing Self-Supervised Learning Tasks

Contrastive learning:

Given multiple data samples, the task is to predict the relationship among them.

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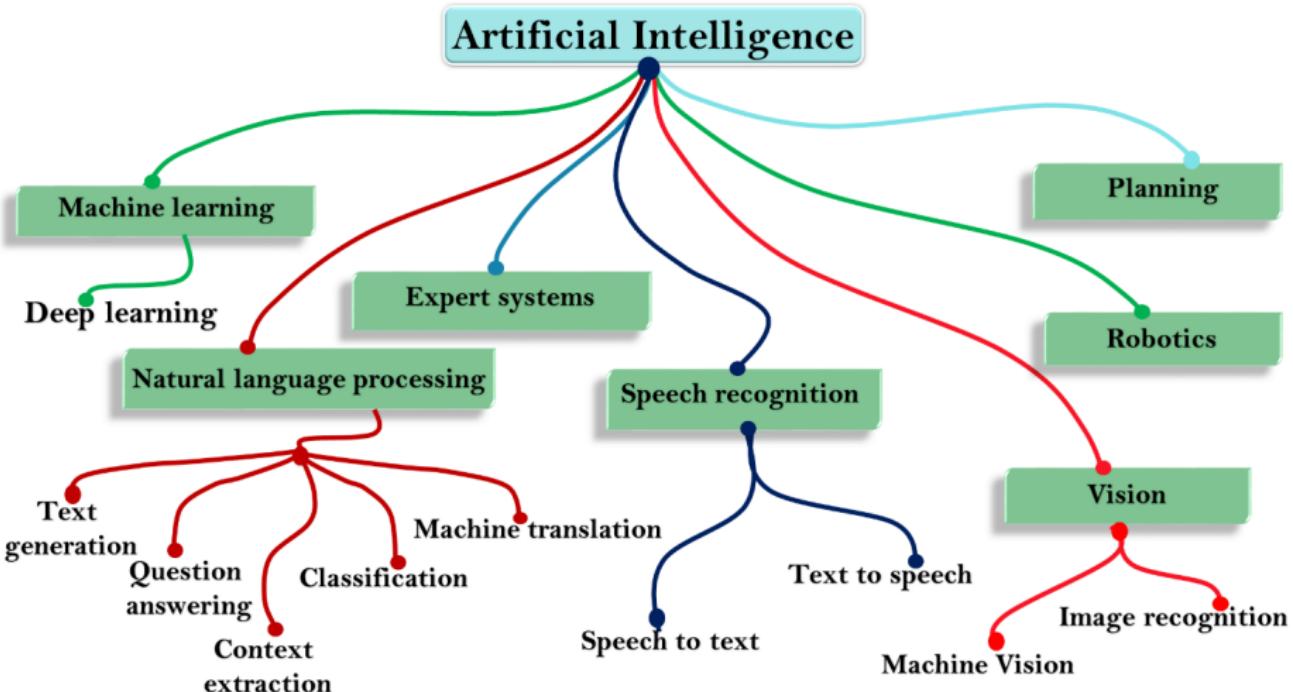
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- **Semi-supervised learning**
 - small number of input-output relationships
- **Self-supervised learning**
 - the underlying structure of data, no labeled data inputs



Future of AI: AAAI 2019 Report

A 20-Year Community Roadmap for Artificial Intelligence Research in the US

Yolanda Gil (USC) and Bart Selman (Cornell), co-chairs

AI LANDSCAPE

Exploiting data with AI/ML highly effective but limited use

Industry push of AI mostly for consumer products

Piecemeal funding programs and academic projects

IT giants amassing significant proprietary resources and experts

Rest of industry, government, academic lack access to large AI infrastructure and engineering resources

AI-driven capabilities:

- Mental and behavioral health coaches
- Accurate models of water resources
- Speed up materials science experiments
- Augment education for remote students
- Resolve supply chain delays
- At-home robot caregivers/helpers
- Response for natural disasters
- Collaborative omics discoveries
- Train for robot repair jobs
- Businesses innovation in personal devices
- Game design startups
- Scientific models from theories and data
- Improve law enforcement and training
- Resolve food insecurity and distribution
- Resilient cyber-physical systems

ASPIRATIONS

Reduce healthcare cost

Accelerating scientific discovery

Universal personalized education

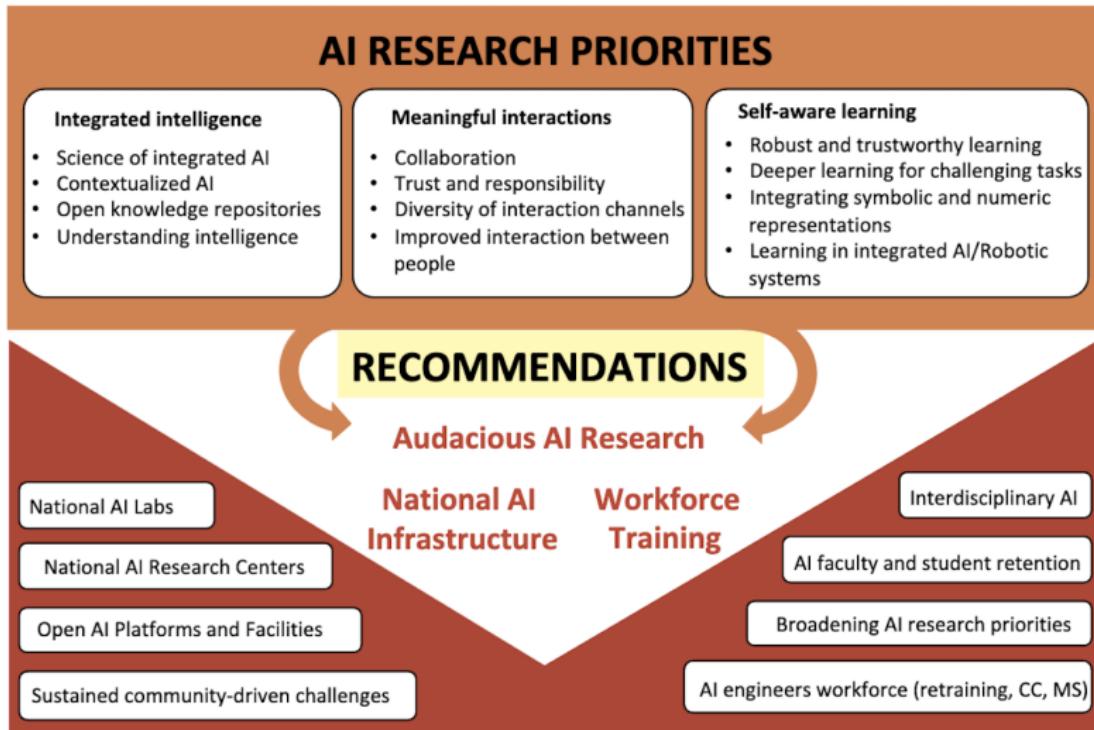
Unprecedented innovation for businesses

Evidence-driven social opportunity

AI challenges not solvable as piecemeal academic research projects

AI challenges not a priority for big AI/IT industry players

Future of AI: AAAI 2019 Report



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)

**"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

Top 6 Salaries of AI Positions in US



Top 6 AI Salaries as per Locations in US



Source: Payscale, Talent.com

Opportunities

Top 5 Companies for Machine Learning Engineers in the US

Salaries in October 2022

ebay

\$371,147

Tapjoy

\$218,343

CapitalOne

\$217,717



\$203,191



airbnb

\$197,896

Source: Indeed.com

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Opportunities

'OUT-ON-THE-HORIZON' AI ROLES

