

# Machine Learning: A Multidisciplinary View

SCIE1200 Guest Lecture  
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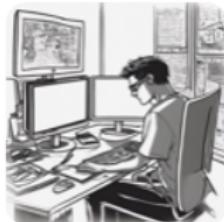
an academic...



teaching



proving



hacking



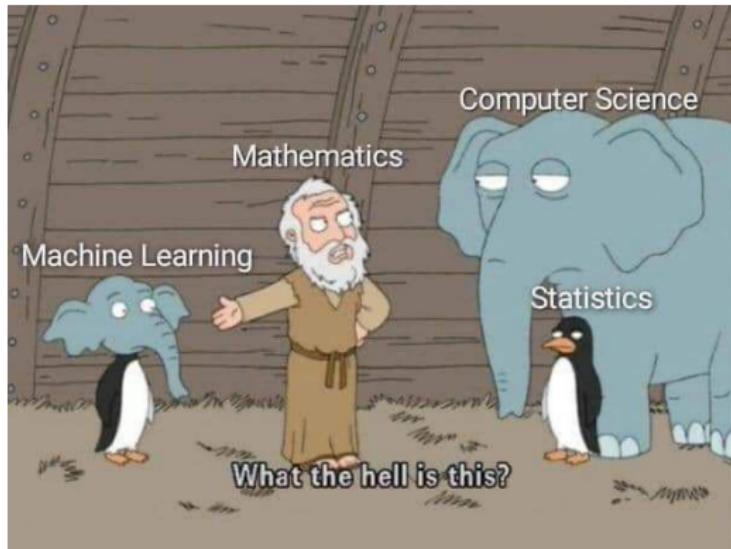
babysitting



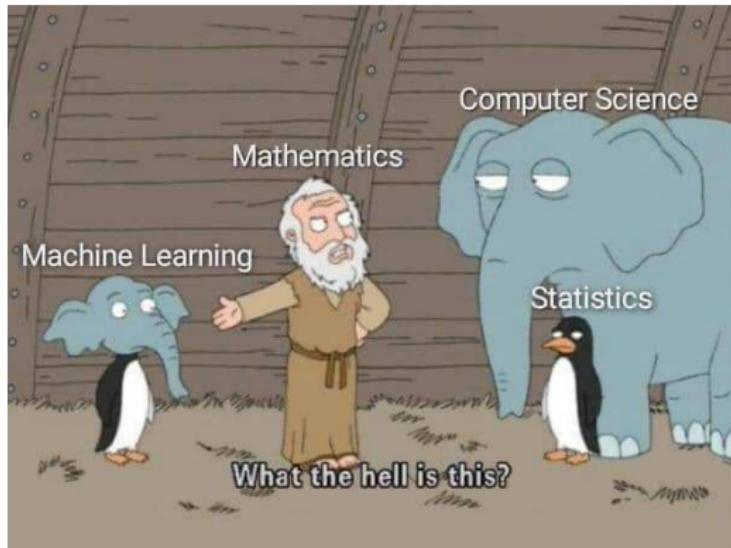
supervising some very intelligent people

*cartoons generated by AI*

## big picture #1



## big picture #1



*Looks like the person who made this wanted to say machine learning is just taking something from computer science and something from statistics, and ended up being not recognised by either community and scorned by mathematics...*

*This might be the view held by quite a few people in the past, but perhaps not any more - the picture would be something like machine learning is a rocket, pulling mathematics, computer science, statistics, biology, physics, ..., up to the sky :D*

*email to a colleague*

## big picture #2



an attempt by AI to draw my picture

## **big picture #3 (my work)**



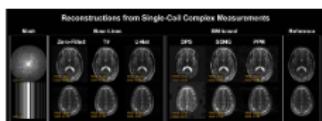
## autonomous driving



## routing behavior analysis

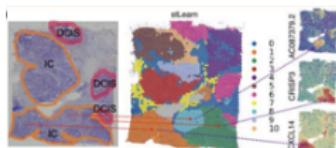


fishery stock assessment

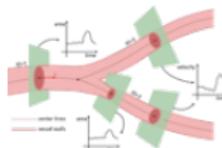


## MRI reconstruction

# theoretically grounded practical algorithms for learning & decision-making

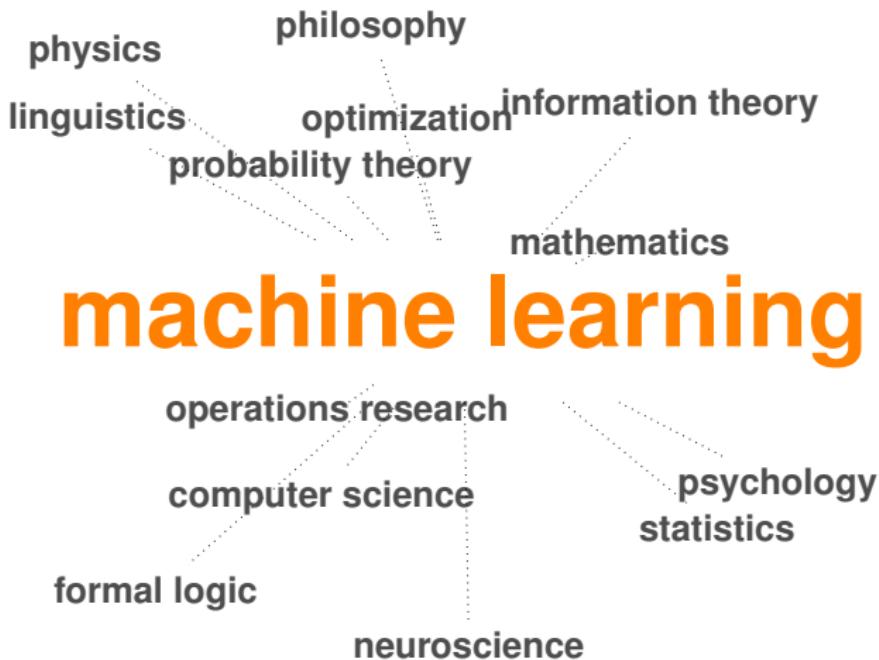


## spatial transcriptomics



haemodynamics modeling

## big picture #4 (synergy)



many ideas inspired by other fields & many applications in other fields

# Roadmap

a multidisciplinary big picture

machine learning as a transformer in many fields

a multidisciplinary view on machine learning research

ending remarks

# a transformer...



image generated by AI

# Imaginations...



Golem  
Judaism's Talmud (around 400)



Frankenstein  
Mary Shelley's 1818 novel



I, Robot  
Issac Asimov (1950)



The Iron Giant (1999)



Robots (2005)



WALL-E (2008)



Astro Boy (2009)



Big Hero 6 (2014)



Next Gen (2018)



A.I. Artificial Intelligence (2001)



Iron Man (2008)



X-Men



Ex Machina (2014)



Star Wars



Avengers



The Wandering Earth (2019)

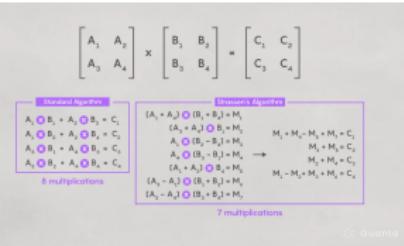
# and realities...



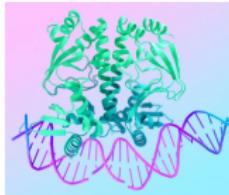
AlphaGo



self-driving car



AlphaTensor



AlphaFold



Siri



Cortana



Sora

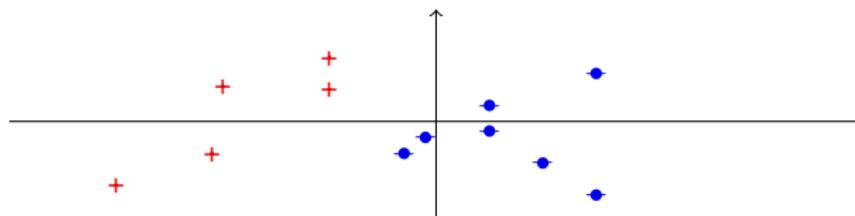


ChatGPT

and many others, powered by machine learning

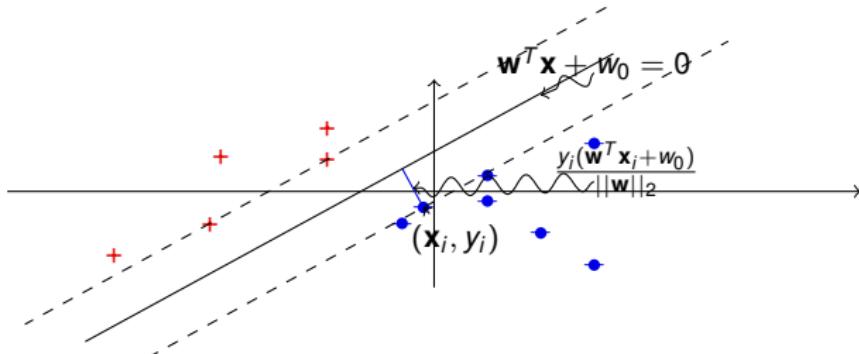
machine learning and ...

# ... and geometry!



**Q.** What's the best line to separate the red and blue points?

# ... and geometry!



Q. What's the best line to separate the red and blue points?

A. Support Vector Machines: the one farthest away from all points.

linearly separable data

$$\min_{\mathbf{w}, w_0} \frac{1}{2} \|\mathbf{w}\|_2^2$$

$$\text{s.t. } y_i(\mathbf{w}^\top \mathbf{x}_i + w_0) \geq 1, \quad i = 1, \dots, n.$$

nonlinearly separable data

$$\min_{\mathbf{w}, w_0, \xi_1, \dots, \xi_n} \frac{1}{2} \|\mathbf{w}\|_2^2 + C \sum_i \xi_i$$

$$\text{s.t. } y_i(\mathbf{w}^\top \mathbf{x}_i + w_0) \geq 1 - \xi_i, \quad i = 1, \dots, n,$$
$$\xi_i \geq 0, \quad i = 1, \dots, n.$$

## ... and physics!

**Maximum entropy principle** (Jaynes, 1957): the most noncommittal probabilistic models satisfying given constraints should be preferred.

## ... and physics!

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**Q.** A machine randomly outputs 1, 2, 3 with an observed mean of 2. what are the probabilities of these numbers?

# ... and physics!

**Maximum entropy principle** (Jaynes, 1957): the most noncommittal probabilistic models satisfying given constraints should be preferred.

**Q.** A machine randomly outputs 1, 2, 3 with an observed mean of 2. what are the probabilities of these numbers?

**A.**  $p_1 = p_2 = p_3 = 1/3$ , as it is the distribution that solves

$$\max - \sum_{i=1}^3 p_i \ln p_i$$

$$s.t. \quad p_1 + 2p_2 + 3p_3 = 2$$

Q. How to learn a model for labeling words with their parts-of-speech tags?

NNP VBZ PRP\$ JJ NN .  
SCIE1200 is my favourite course !

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A. Conditional Random Fields (Lafferty, McCallum, and Pereira, 2001): learn a distribution  $p(\mathbf{y} | \mathbf{x})$  of the label sequence given the input sequence, using the maximum entropy principle

$$\max H(p) = \sum_{\mathbf{x}} \pi(\mathbf{x}) \sum_{\mathbf{y}} -p(\mathbf{y} | \mathbf{x}) \ln p(\mathbf{y} | \mathbf{x})$$

s.t.  $\sum_{\mathbf{y}} p(\mathbf{y} | \mathbf{x}) = 1, \quad \forall \mathbf{x}$

$$p(\mathbf{y} | \mathbf{x}) \geq 0, \quad \forall \mathbf{x}, \mathbf{y}$$

$$\mathbb{E}(f_i) = \tilde{f}_i, \quad \forall i. \quad (\text{expected feature} = \text{empirical feature})$$

The solution has a form similar to a random field in physics (e.g., Ising model).

Ye et al. (2009) & Cuong et al. (2014): extend pairwise features to higher-order features.

Lafferty, McCallum, and Pereira. Conditional random fields: Probabilistic models for segmenting and labeling sequence data, 2001

Ye et al., Conditional random fields with high-order features for sequence labeling, 2009

Cuong et al., Conditional Random Field with High-order Dependencies for Sequence Labeling and Segmentation, 2014

**Q.** How to determine the reward being maximized by observed behaviors?



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**A.** Inverse reinforcement learning using maximum entropy principle (Ziebart et al., 2008)

$$\min_p D(p \parallel q) \quad \text{s.t.} \quad E_{\tau \sim p} \phi(\tau) = \tilde{\phi},$$

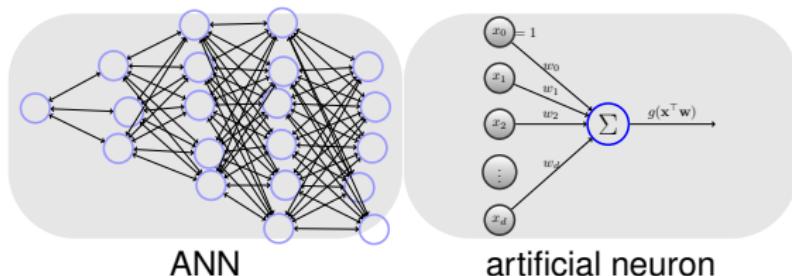
where  $D$  denotes the KL divergence,  $\tau = (s_1, a_1, \dots, s_T, a_T)$  a trajectory,  $\phi(\tau)$  the feature vector for  $\tau$ , and  $q(\tau)$  a given reference trajectory distribution.

⇒ a reward linear in the features.

Snowell, Singh, and Ye (2020): a generalized maximum entropy formulation and exact inference and learning algorithms.

# ... and biology/neuroscience

## artificial neural networks (ANNs)



- ANNs
  - interconnected simple computational units (neurons)
  - universal approximators
  - often trained to minimize loss
- Neurons
  - input from incoming edges, output along outgoing edges
  - computes nonlinearly transformed weighted input sum  $g(\mathbf{w}^\top \mathbf{x})$
  - nonlinearity  $g$  known as activation/transfer function

Q. How much fish is out there?



Q. How much fish is out there?



A. Lei, Zhou, and Ye (2024a,b): use structured neural networks to reliably “standardize” catch data to remove variations caused by factors other than abundance (e.g., fishing gear, skipper experience, weather).

# ending remarks



TensorFlow



Sonnet



Keras



many powerful libraries for you to use

theano

mxnet

Caffe2

The Caffe2 logo features a stylized coffee cup icon with two plus signs above it.

GLUON

The Gluon logo features a blue circular icon with a white 'G' shape inside.

PyTorch

The PyTorch logo features a red circle with a white plus sign inside.

DL4J

The DL4J logo features a black network graph icon with several nodes connected by lines.

ConvNetJS  
Deep Learning in your browser

The ConvNetJS logo features a small icon of a neural network layer above the text "ConvNetJS" and the tagline "Deep Learning in your browser".

scikit learn

The scikit-learn logo features a blue circle next to an orange circle, with the text "scikit" above "learn".

# AI achieves silver-medal standard solving International Mathematical Olympiad problems

25 JULY 2024

AlphaProof and AlphaGeometry teams

◀ Share



At present, these are great tools for mathematicians - they allow mathematicians to focus more on ideas and insights rather than the chores (not saying that an ingenious proof, such as one for an IMO question, is a chore), though the process of doing maths may be less fun without the strenuous effort to come up with ingenious solutions.

These tools don't ask good questions yet. They are still the mechanical proof assistant that exploits computers to efficiently search the proof space, except that they are now guided by AI to make more promising moves, so that the search completes in a reasonable amount of time.

One downside of these tools is that everything is done symbolically as in the traditional automatic theorem provers: the natural language theorem statements need to be converted to formal symbolic statements, and the proofs are written as formal symbolic statements, which are generally not fun to read. For example, AlphaProof uses the formal symbolic representation of Lean - see this [https://en.wikipedia.org/wiki/Lean\\_\(proof\\_assistant\)](https://en.wikipedia.org/wiki/Lean_(proof_assistant)) for some examples.

Perhaps someone will build an interface to support human-style mathematical writing in the near future. If that happens, I'll be curious how the new generation of maths students will do maths - will they lose the ability to come up with new ideas/insights because they don't do enough chores and thus never become mathematically mature?

email to a colleague

**use both artificial and human intelligence well :)**

Sources of knowledge, diverse and wide,  
Combining fields where insights reside,  
Ideas from math, stats, and code,  
Enhancing progress as data flows.

1 powerful tool that spans every domain,  
2gether with art, science, and human gain,  
Old theories renewed with modern might,  
Ongoing impact, reaching new heights.

*ChatGPT*

