Think Deep Learning: Overview

Ju Sun
Computer Science & Engineering
University of Minnesota, Twin Cities

January 21, 2020

Outline

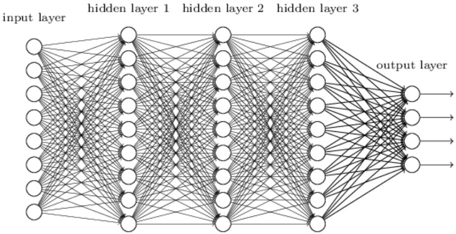
Why deep learning?

Why first principles?

Our topics

Course logistics

What is Deep Learning (DL)?



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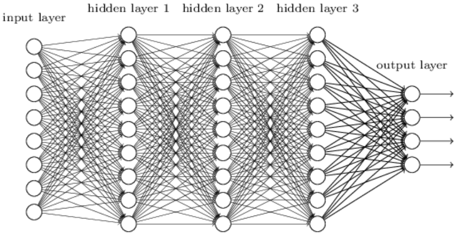

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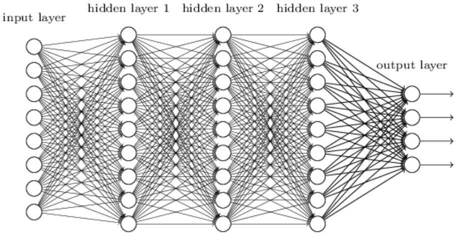

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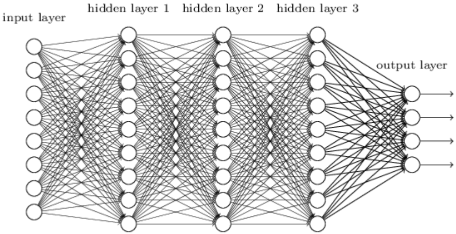

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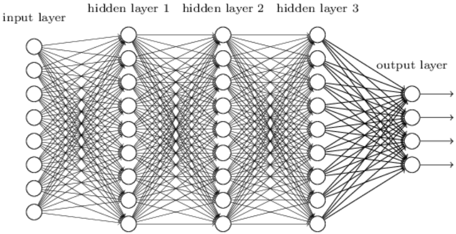

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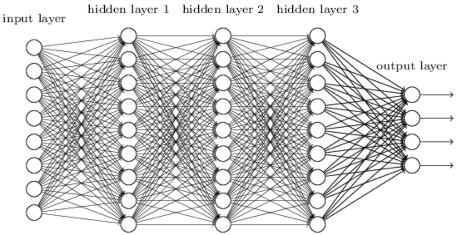

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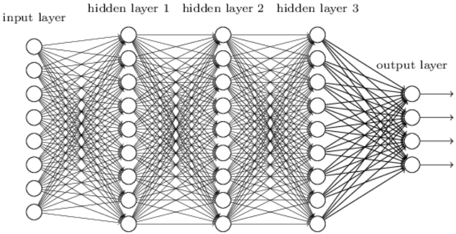

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- **Software** platforms for training DNNs (e.g., Tensorflow, PyTorch, MXNet)
- **Applications!** (e.g., vision, speech, NLP, imaging, physics, mathematics, finance)

Why DL?

DL leads to many things ...

Revolution: a great change in conditions, ways of working, beliefs, etc. that affects large numbers of people – *from the Oxford Dictionary*

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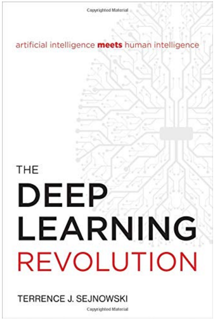
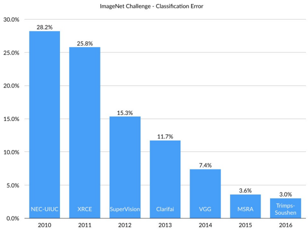


Terrence Sejnowski (Salk Institute)

DL leads to hope

Academic breakthroughs



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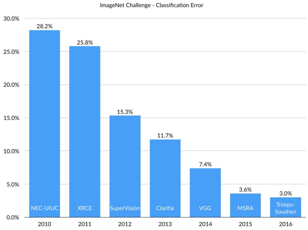

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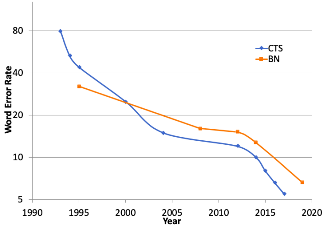

speech recognition credit: IBM

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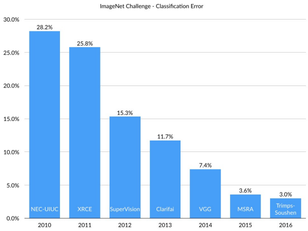

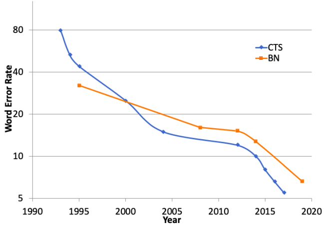

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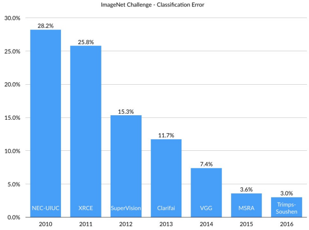

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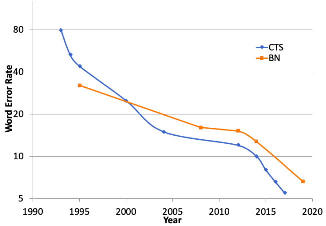

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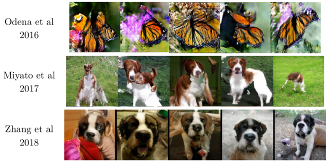

image generation credit: I. Goodfellow

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Commercial breakthroughs ...

self-driving vehicles credit: wired.com

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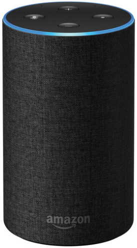

smart-home devices credit: Amazon

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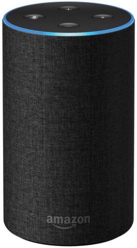

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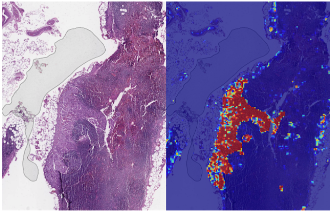

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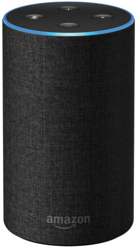

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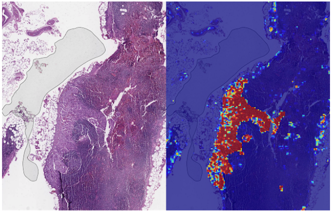

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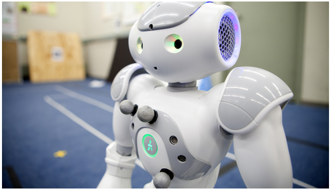

robotics credit: Cornell U.

DL leads to productivity

Papers are produced at an overwhelming rate

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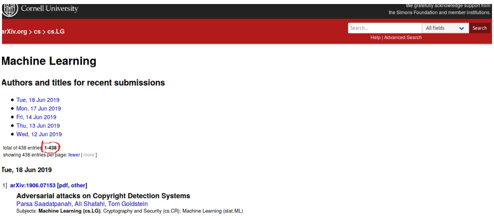

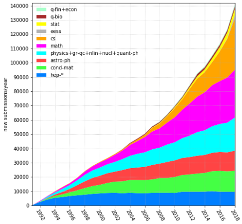

image credit: arxiv.org

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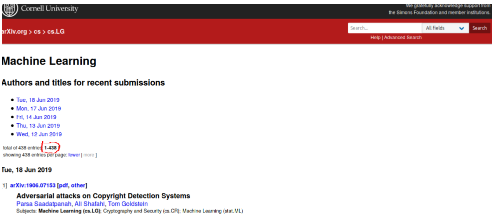

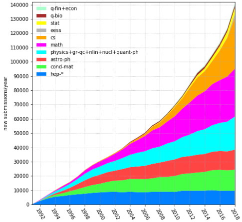

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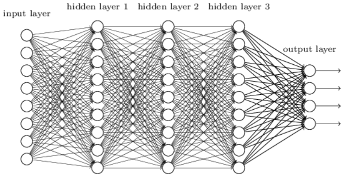
$$400 \times 0.8 \times 52 / 140000 \approx 11.9\%$$

DL Supremacy!?

DL leads to fame



Turing Award 2018 credit: ACM.org

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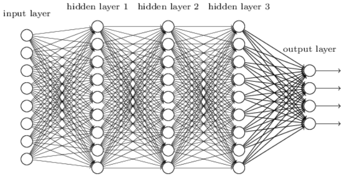

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Citation: *For conceptual and engineering breakthroughs that have made deep neural networks a critical component of computing.*

DL leads to frustration

esp. for academic researchers ...

It's working amazingly well, but we don't understand why

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Print

Deep, Deep Trouble

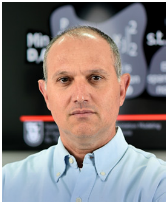
Deep Learning's Impact on Image Processing, Mathematics, and Humanity

By Michael Elad

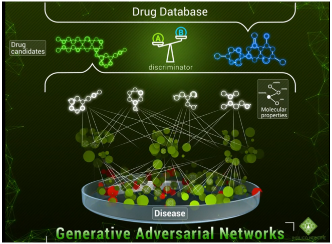
I am really confused. I keep changing my opinion on a daily basis, and I cannot seem to settle on one solid view of this puzzle. No, I am not talking about world politics or the current U.S. president, but rather something far more critical to humankind, and more specifically to our existence and work as engineers and researchers. I am talking about...**deep learning**.

While you might find the above statement rather bombastic and overstated, deep learning indeed raises several critical questions we must address. In the following paragraphs, I hope to expose one key conflict related to the emergence of this field, which is relevant to researchers in the image processing community.

First, a few words about deep learning to put our discussion into perspective. Neural networks have been around for decades, proposing a universal learning mechanism that could, in principle, fit to any learnable data source. In its feed-forward architecture, layers of perceptrons—also referred to as neurons—first perform weighted averaging



DL leads to new sciences



chemistry

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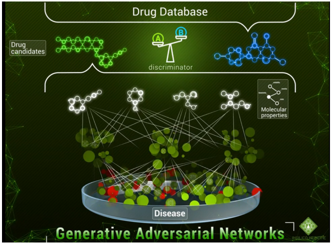

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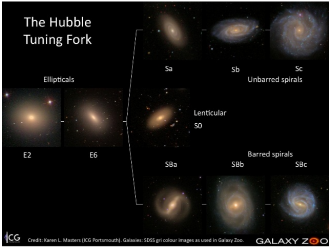

astronomy

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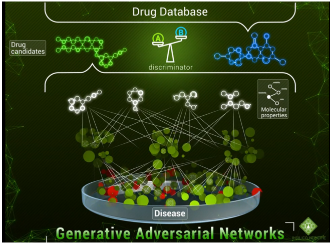

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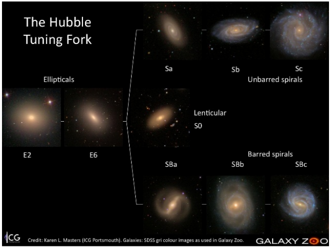

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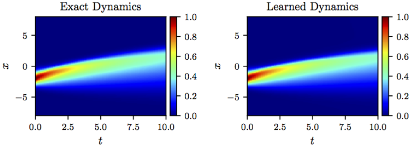

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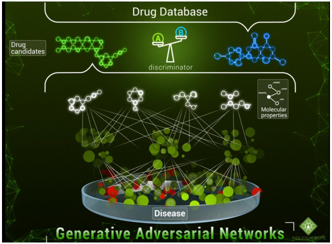

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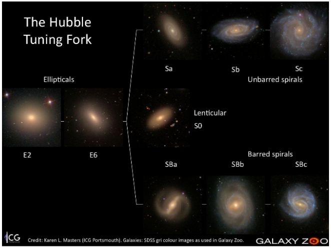

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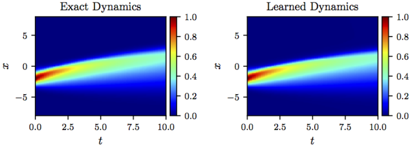

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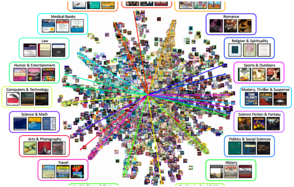

social science

DL leads to money

- Funding
- Investment
- Job opportunities

Outline

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Why first principles?

TensorFlow 2.0 PYTORCH

Why first principles?

TensorFlow 2.0 PYTORCH

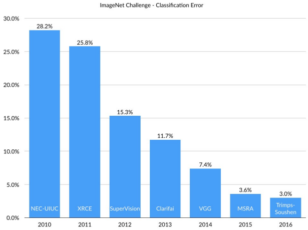
– Tuning and optimizing for a task require basic intuitions

Why first principles?

TensorFlow 2.0 PYTORCH

- Tuning and optimizing for a task require basic intuitions
- **Historical lesson**: model structures in data
- **Current challenge**: move toward trustworthiness
- **Future world**: navigate uncertainties

Structures are crucial



Cat

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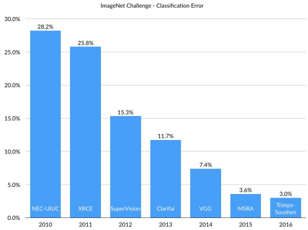
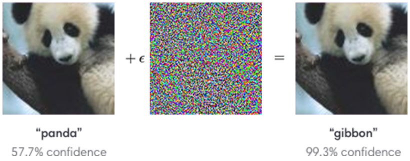


- Representation of images should ideally be translation-invariant.
- The 2012 breakthrough was based on modifying the classic DNNs setup to achieve translation-invariant.
- Similar success stories exist for sequences, graphs, 3D meshes.

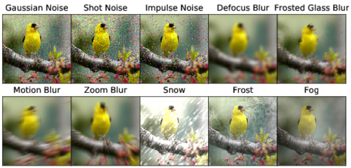
Toward trustworthy AI

Super human-level vision?



credit: openai.com

Adversarial examples



credit: ImageNet-C

Natural corruptions

- Trustworthiness: robustness, fairness, explainability, transparency
- We need to know first principles in order to improve and understand

Future uncertainties

- New types of data (e.g., 6-D tensors)
- New hardware (e.g., better GPU memory)
- New model pipelines (e.g., network of networks, differential programming)
- New applications
- New techniques replacing DL

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Outline of the course - I

Overview and history

Course overview (1)

Neural networks: old and new (1)

Outline of the course - I

Overview and history

- Course overview (1)
- Neural networks: old and new (1)

Fundamentals

- Fundamental belief: universal approximation theorem (2)
- Numerical optimization with math: optimization with gradient descent and beyond (2)
- Numerical optimization without math: auto-differentiation and differential programming (2)

Outline of the course - II

Structured data: images and sequences

- Work with images: convolutional neural networks (2)
- Work with images: recognition, detection, segmentation (2)
- Work with sequences: recurrent neural networks (2)

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Deterministic DNN

- To train or not? scattering transforms (2)

Outline of the course - II

Structured data: images and sequences

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Deterministic DNN

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Other settings: generative/unsupervised/reinforcement learning

- Learning probability distributions: generative adversarial networks (2)
- Learning representation without labels: dictionary learning and autoencoders (1)
- Gaming time: deep reinforcement learning (2)

Outline of tutorial/discussion sessions

Python, Numpy, and Google Cloud/Colab

Project ideas

Tensorflow 2.0 and Pytorch

Backpropagation and computational tricks

Research ideas

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Technology we use

- **Course Website:**

  `https://sunju.org/teach/DL-Spring-2020/`

  All course materials will be posted on the course website.

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- **Communication: Canvas** is the preferred and most efficient way of communication. All questions and discussions go to Canvas. Send emails in exceptional situations.

For bookworms...

- **Deep Learning** by Ian Goodfellow and Yoshua Bengio and Aaron Courville. MIT Press, 2016. Online URL: `https://www.deeplearningbook.org/` (comprehensive coverage of recent developments)
- **Neural Networks and Deep Learning** by Charu Aggarwal. Springer, 2018. UMN library online access (login required): Click here. (comprehensive coverage of recent developments)

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- **The Deep Learning Revolution** by Terrence J. Sejnowski. MIT Press, 2018. UMN library online access (login required): Click here. (account of historic developments and related fields)

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- **Deep Learning with Python** by François Chollet. Online URL: `https://livebook.manning.com/book/deep-learning-with-python` (hands-on deep learning using Keras with the Tensorflow backend)
- **Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems** by Aurélien Géron (2ed). O'Reilly Media, 2019. UMN library online access (available soon). (hands-on machine learning, including deep learning, using Scikit-Learn and Keras)

How to get A(+)?

- 60 % homework + 40 % course project

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Programming and Computing

python 3 — ≥ 3

TensorFlow 2.0 — ≥ 2.0

PYTORCH — ≥ 1.0

Programming and Computing

python 3 ≥ 3

TensorFlow 2.0 ≥ 2.0

PYTORCH ≥ 1.0

Computing

- Local installation
- Google Colab: `https://colab.research.google.com/` (Yes, it's free)
- Google Cloud ($50 credits per student) (similarly AWS and Azure)
- Minnesota Supercomputing Institute (MSI)

We're not alone

Related deep learning courses at UMN

- **Topics in Computational Vision: Deep networks** (Prof. Daniel Kersten, Department of Psychology. Focused on connection with computational neuroscience and vision)

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To learn more computational methods for large-scale optimization

- **IE5080: Optimization Models and Methods for Machine Learning** (Prof. Zhaosong Lu, Department of Industrial and Systems Engineering (ISyE))

Homework 0 today!

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If you struggle too much with it

- Find the right resources to pick up in the first week
- OR take the course in later iterations

Thank you!