Welcome to

Machine Learning: Deep Learning

Check out our homepage: deep.cs.jhu.edu

How AI is Revolutionizing the Field You Are In

Mathias Unberath, PhD
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Computing Dot Products and Max() a Lot

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EN.601.482/682 Deep Learning

Overview

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Welcome to EN.601.482/682 Deep Learning

A Bit About Me

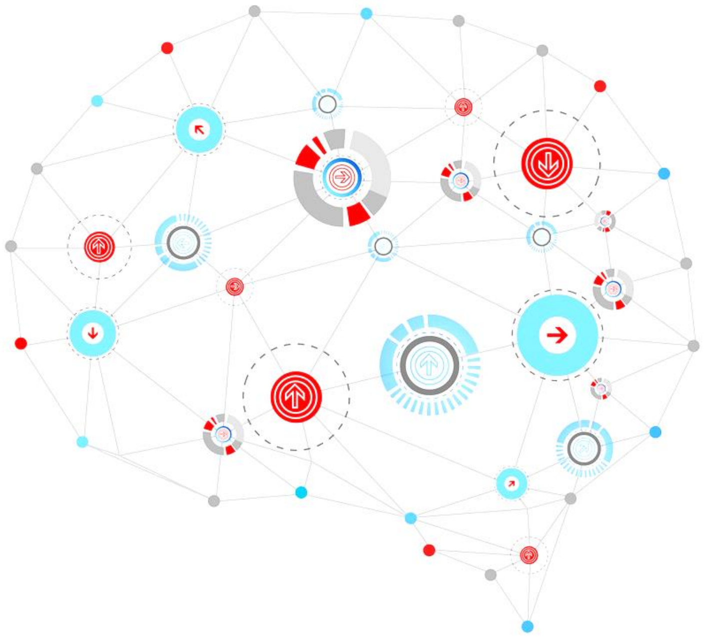
- Background
- Research

A Little More About the Course

- Learning Objectives
- Assignments

Introduction

- Brain Stuff
- Why the hype?



A Bit About Me

- **How do I pronounce your name?**
  Ma-tee-us Oon-bear-uht

- **I go by Mathias**, as long as we…
  – … act mutually respectfully
  – … do not assume other faculty do this, too

- **What do you do outside of work?**
  – Spend time with family
    I have a wife, two kids, and a cat
  – Run, hike, climb

A Bit About Me

Born in Romania

Raised in Nuremberg

Studied in Erlangen, Finland, and CA (USA)

A Bit About My Research

Advanced **R**obotics and **C**omputationally **A**ugmente**D** **E**nvironments (**ARCADE**)

We develop collaborative intelligent systems that support clinical workflows to increase access to – and expand the possibilities of highest-quality healthcare.

We synergistically advance

- **Computer Vision**,
- **Machine Learning**,
- **Imaging**, and
- **Interaction Design**

… to develop collaborative systems that are embodied in emerging technology.

Course Logistics

A Little More About the Course

Very Important

- **You are here, so you found the room!**
  Great!
- Now, make sure to join Piazza
  - Ask questions
  - Answer questions, raise interesting points

- **Consult the syllabus!**

A Typical Week Schedule

Monday and Wednesday

- Lectures
- Introduce new concepts

Friday

- Review of materials
- Sometimes, new perspective on material
- Homework “walk throughs”

Contribute to creating a pleasant learning environment

Course Logistics

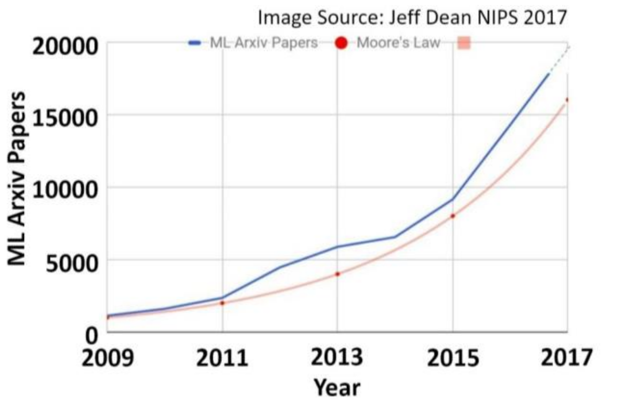
Learning Objectives

Learning Objectives

- Understand neural networks
- Know the terminology of machine and deep learning
- Comprehend the architectures mentioned in the next lecture…
… and maybe even build them
- Fearlessly design, build, train networks,…
… and reason about pitfalls and design choices
- Gain intuition,…
… but realize you will not become an expert in one course

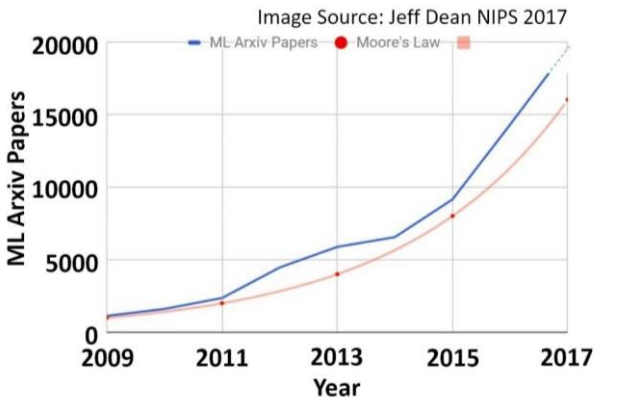
Learning Objectives

- This is an introductory course to deep learning
- While we will try to cover everything important…
  … it is impossible to cover everything!



→ **Set you up for further research/work in this area**

Learning Objectives



- This is an introductory course to deep learning

- While we will try to cover everything important…
  … it is impossible to cover everything!

→ **Set you up for further research/work in this area**

- If **you are already familiar** with most of the topics **deep learning**:
  This course is maybe not for you.

- If **you have never heard anything** about **machine learning** in general:
  We will introduce some concepts but be prepared to buckle up!

Topics

Basic formalism

- Multi-layer perceptrons
- Convolutional neural networks
- Sequence models (and a bit of natural language processing)

Advanced concepts

- Generative models
- Un-supervised and self-supervised learning
- Challenges (generalization, bias, ethics, …)
- Advanced concepts and applications

Material and Reading

- Several books, including the deep learning book

- Lots of online resources, including the
  - Stanford course on CNNs
  - CMU course on deep learning
  - …

- Many more resources **linked in slides** and on Piazza

- The above resources are also used to build slides

Grading

50% Homework Assignments

25% Midterm exam (Week of Nov 27^{th})

25% Final Project

Assignment 7 will be a bonus point mechanism – it will be sufficient to nudge you up a bit, but not the saving grace.

Course Logistics

Homework

Homework

Homework comes in two flavors

- 3 written assignments
- 3+1 programming assignments

Late assignment submissions:

- You have 5 late days (smallest quantity: “**1 day**”, largest quantity: “**5 days**”)
- You do not need to request late submission
- You will keep track of your late days
- Once you have no more and submit late → No credit on the assignment

There is no dedicated introduction to Python, PyTorch, CoLaboratory, or Cloud, but we will provide some resources and a pre-recorded recitation session.

Course Logistics

Final Project

Final Project

Topic choice will be (relatively) free

Deliverables

1. Attend at least one project office hour
2. Submit project proposal outline (for our formal review and suggestions)
3. Get excited, work on the project
4. Submit a structured (brief!) final report
5. Final session: Pitch presentation and in-depth breakouts

6. ?
7. Profit

A Note on Academic Integrity

You are here because you want to learn about Deep Learning!

Understand the material, and grades will follow!

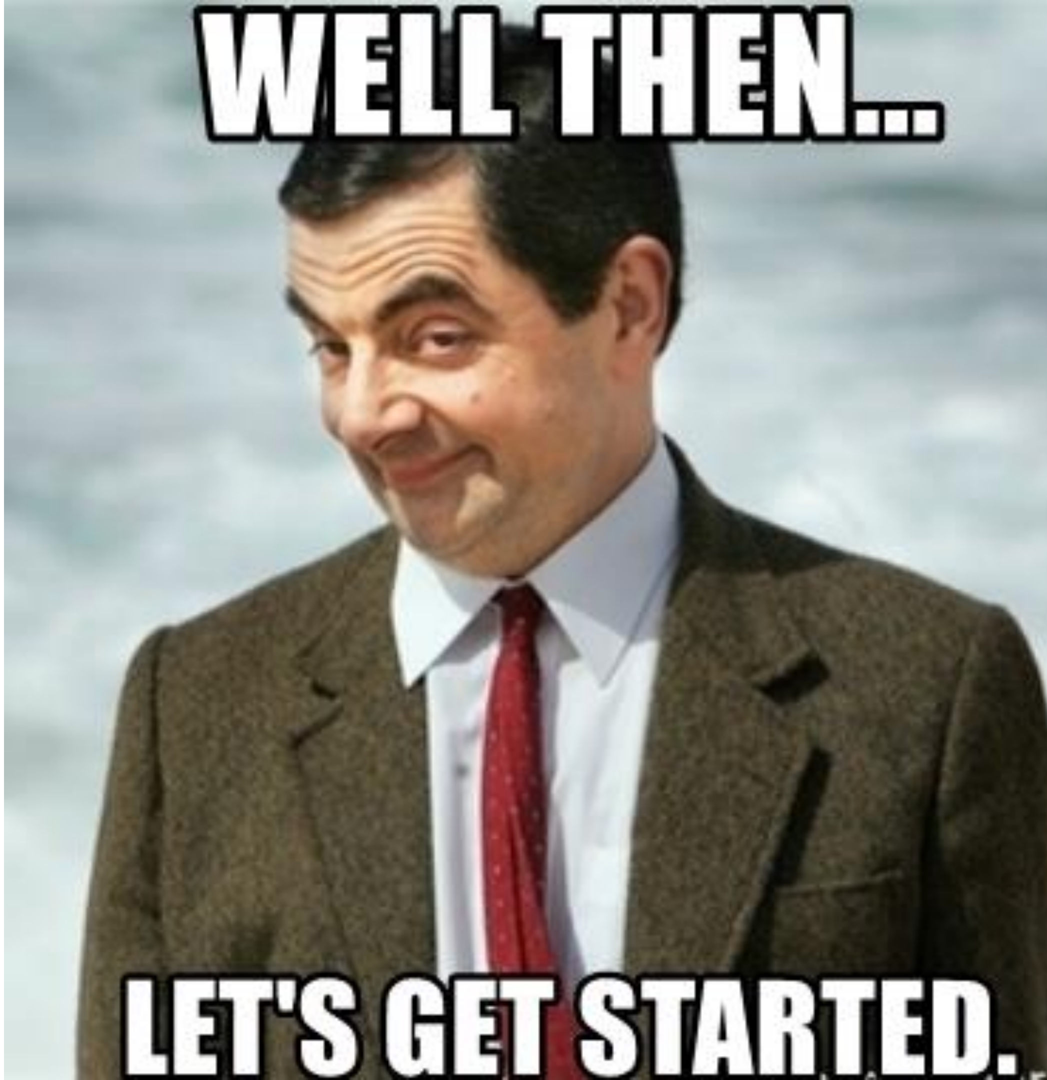
Lots of resources to help you succeed!

- In person classes with the opportunity to ask questions
- Lecture recordings of our classes to improve recollection and study
- Recitations
- Homework orientation sessions
- Office hours, and more

Make use of these resources so that you don't feel the need to cheat!

Course Logistics

Let’s Get Started!

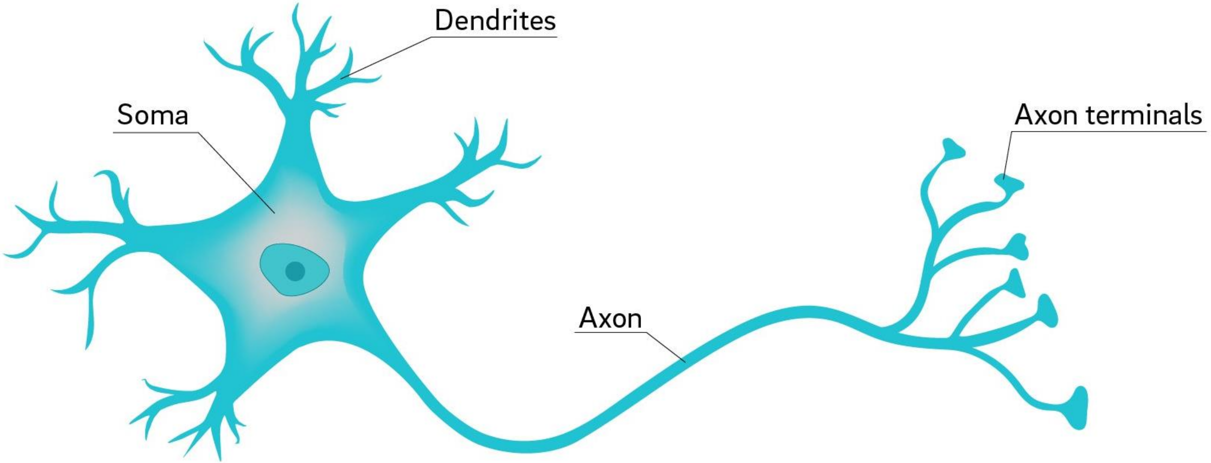


Overview

Brain Stuff

Why talk about the brain?

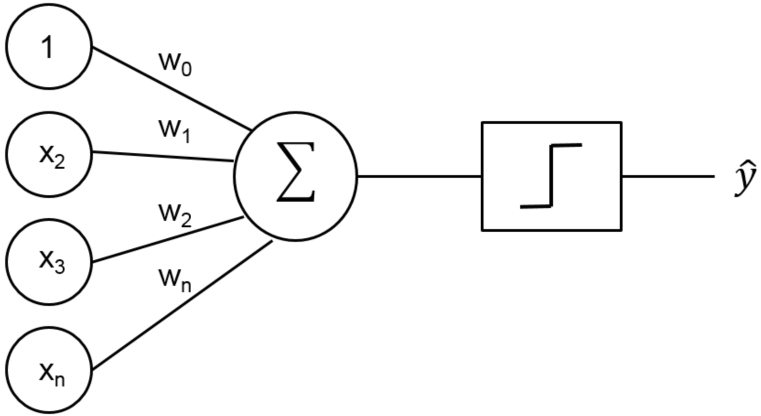
- Neural networks imply connections to neurons



- Signal comes in through dendrites into soma
- Then connects via the axon to other neurons
- Fires if input exceeds a certain threshold

Why talk about the brain?

- Neural networks imply connections to neurons



Look familiar?

- Signal comes in through dendrites into soma
- Then connects via the axon to other neurons
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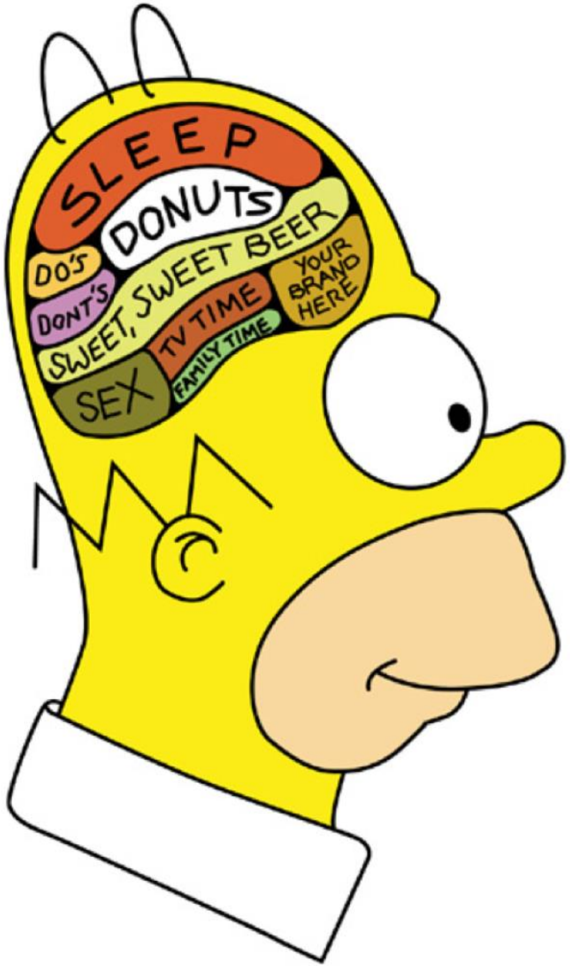
Human Brain

Our “computing wetware” in numbers

- Approx. 10^{11} neurons
- Approx. 10^{14} synapses
- Firing rates 100 – 1000 Hz

Modeling challenges

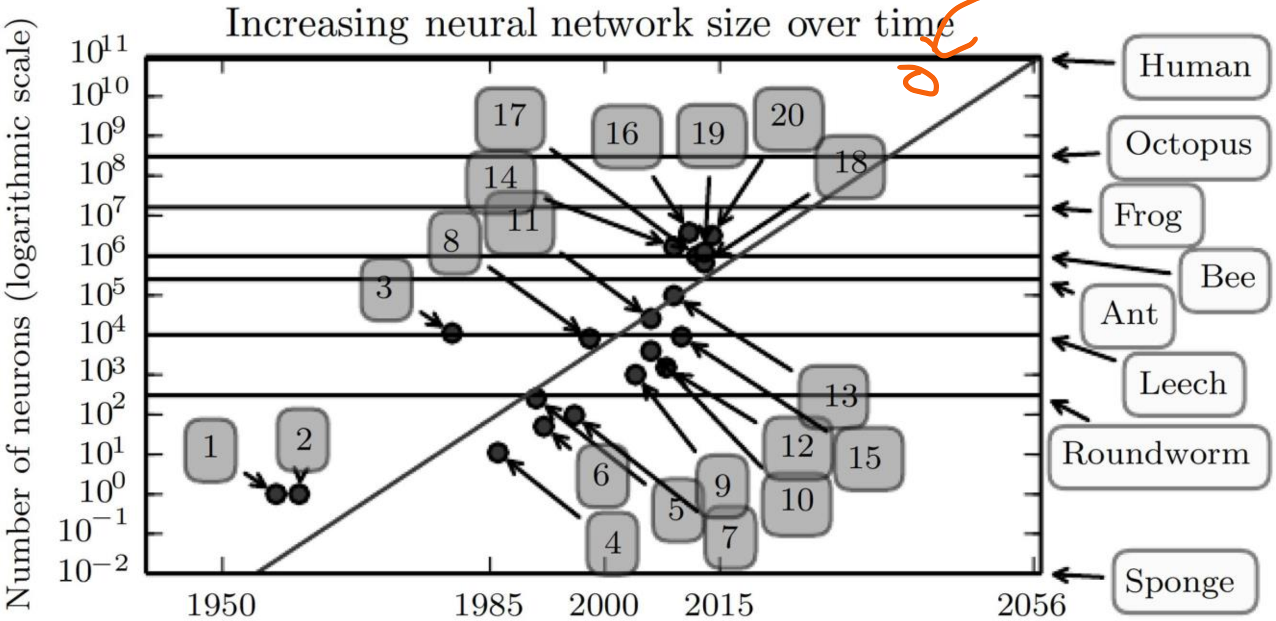
- Asynchronous, distributed*
- Scale and complexity
- Diversity
- Abstractions (equivalence, etc.)



* Zeki, S. (2015). A massively asynchronous, parallel brain. Phil Trans Royal Soc, 370(1668).

Biology vs. Computers: Number of Neurons

GPT-3

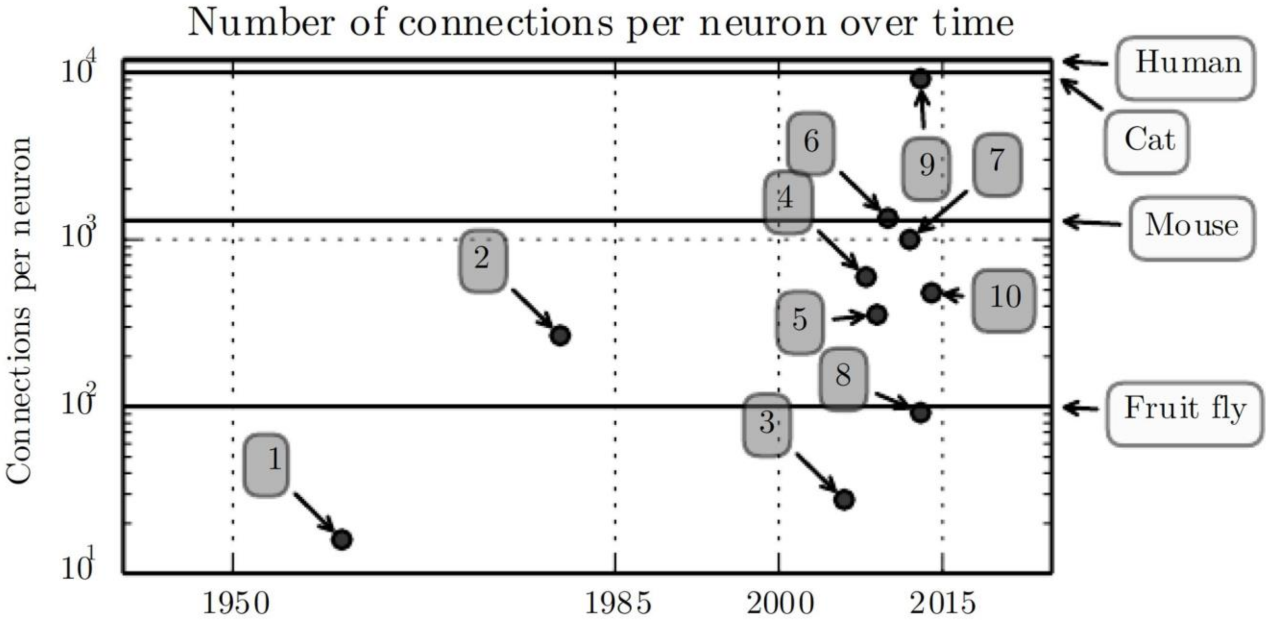


1. Perceptron (1958)

16. GPU-accelerated multilayer perceptron (2010)

20. GoogLeNet (2014)

Biology vs. Computers: Connections per Neuron



6. GPU-accelerated multilayer perceptron (2010)

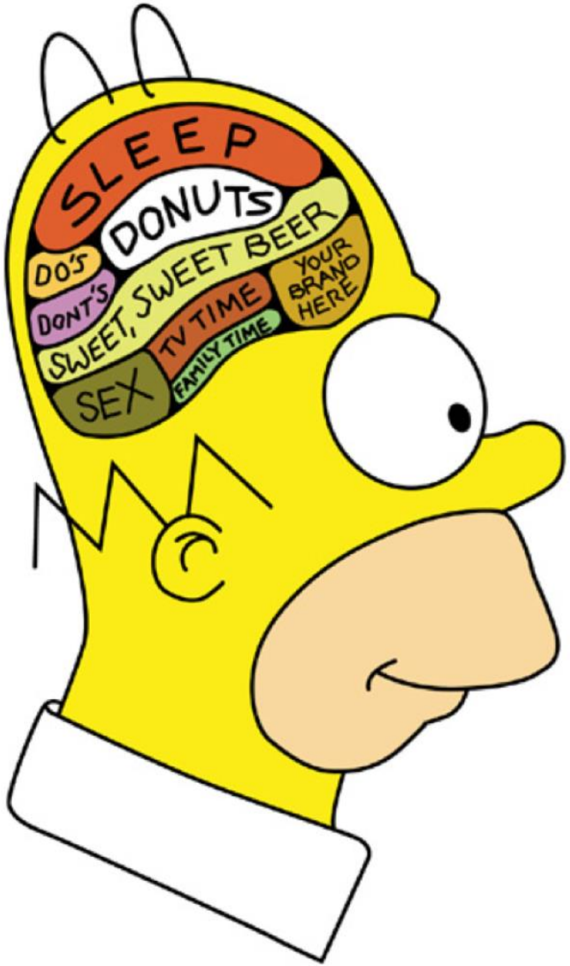
10. GoogLeNet (2014)

Take Away for Now

Connectionism (Alexander Bain, 1873)

“The information is in the **connections**.”

… we will get back to this later …

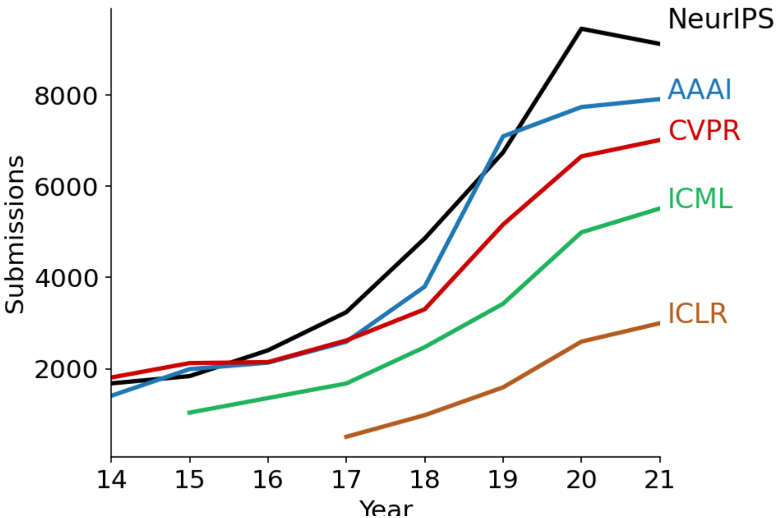


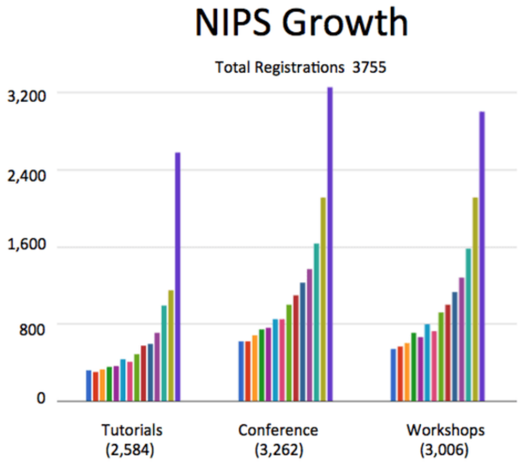
Bain, A. (1873). Mind and Body the Theories of Their Relation. Henry S. King & Company.

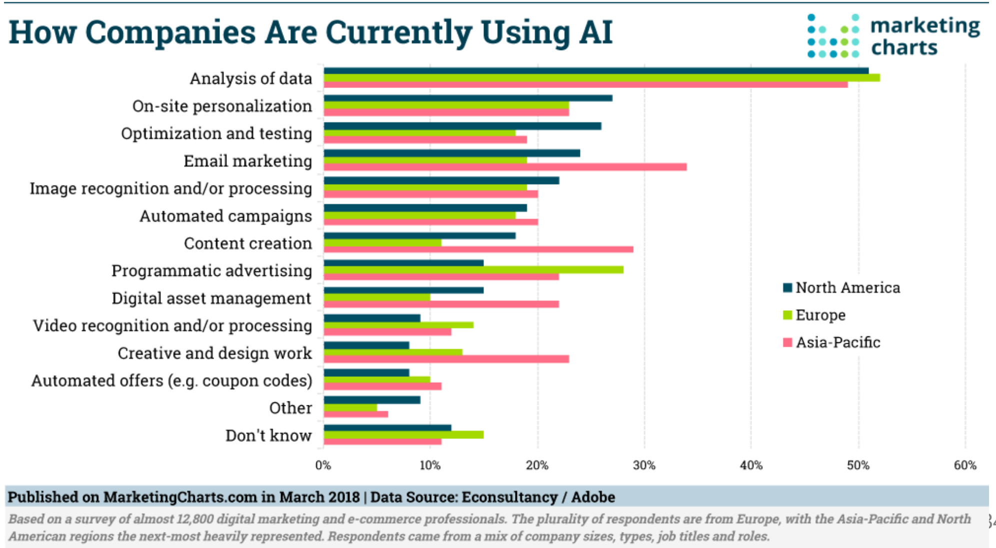
Overview

Why the hype?

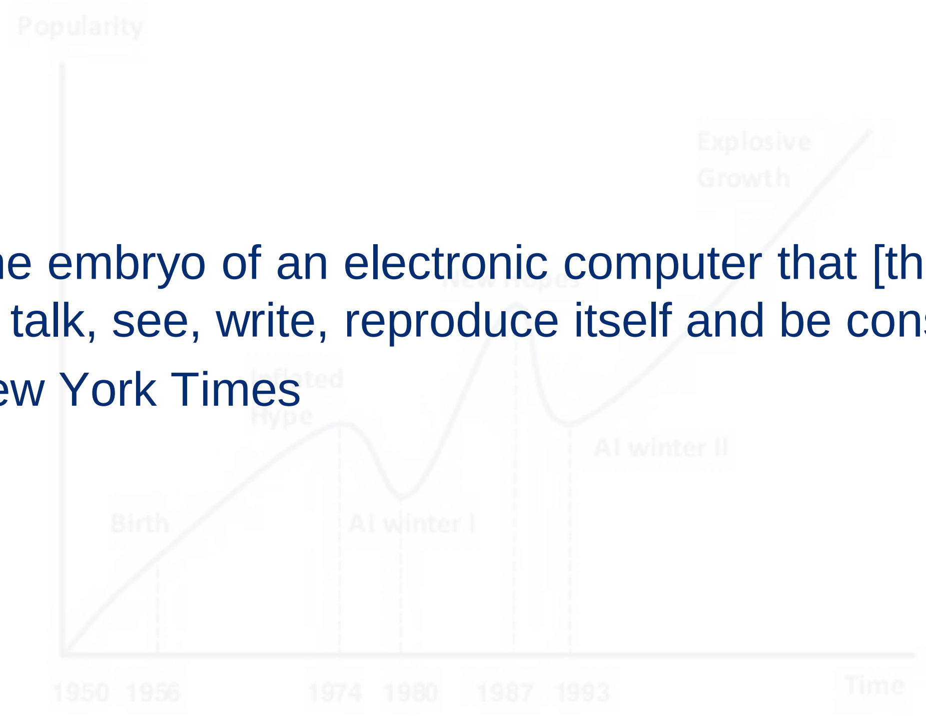
Neural Networks are Taking Over!







A History of Being "The Next Big Thing"



Timeline of AI Development

- **1950s-1960s**: First AI boom - the age of reasoning, prototype AI developed
- **1970s**: AI winter I
- **1980s-1990s**: Second AI boom: the age of Knowledge representation … capable of reproducing human …
- **1990s**: AI winter II
- **1997**: Deep Blue beats Gary Kasparov
- **2006**: University of Toronto develops Deep Learning
- **2011**: IBM's Watson won Jeopardy
- **2016**: Go software based on Deep Learning beats world's champions

Taken from Links International.

"… the embryo of an electronic computer that [the Navy] expects will be able to walk, talk, see, write, reproduce itself and be conscious of its existence"

— New York Times

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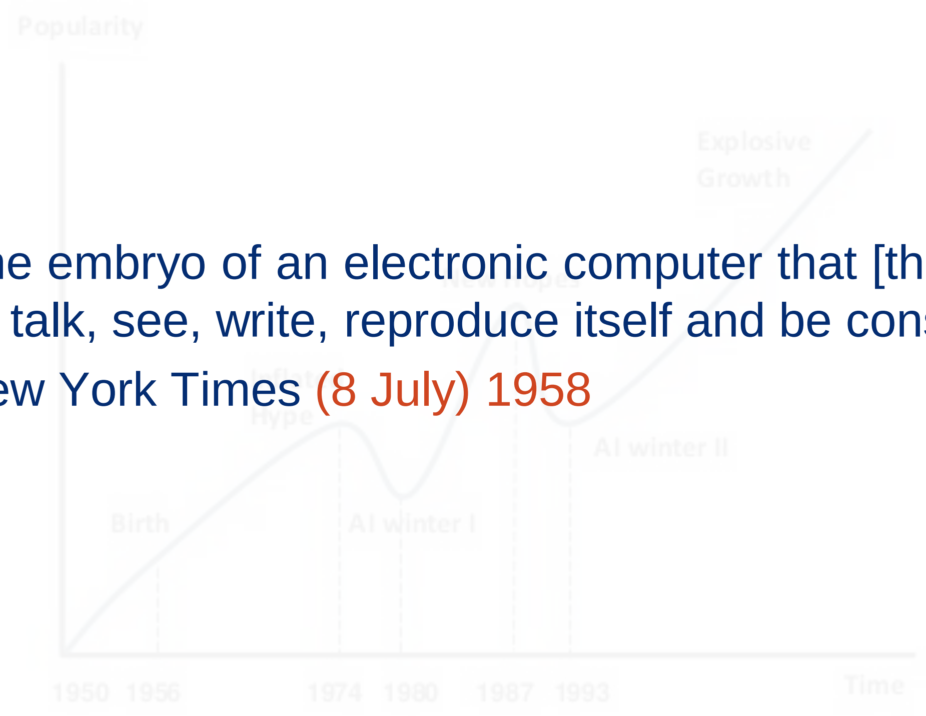

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— New York Times (8 July) 1958

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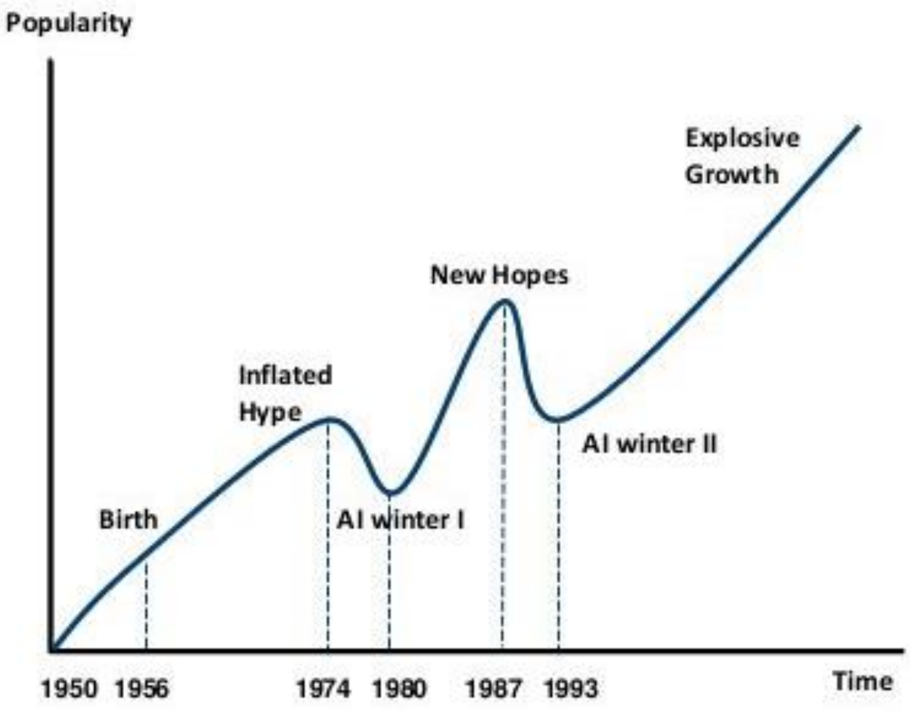

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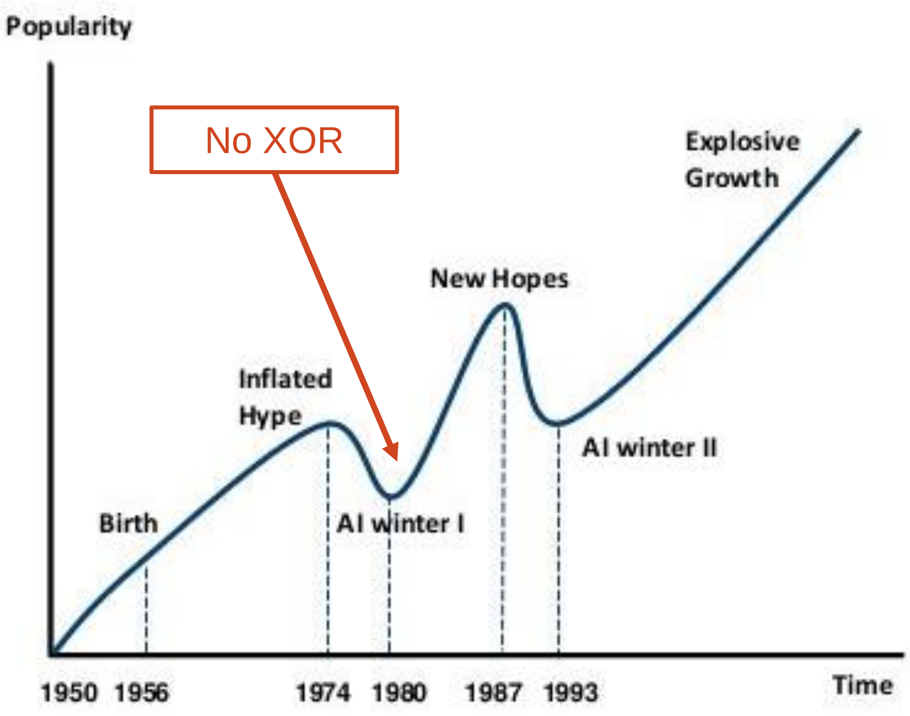

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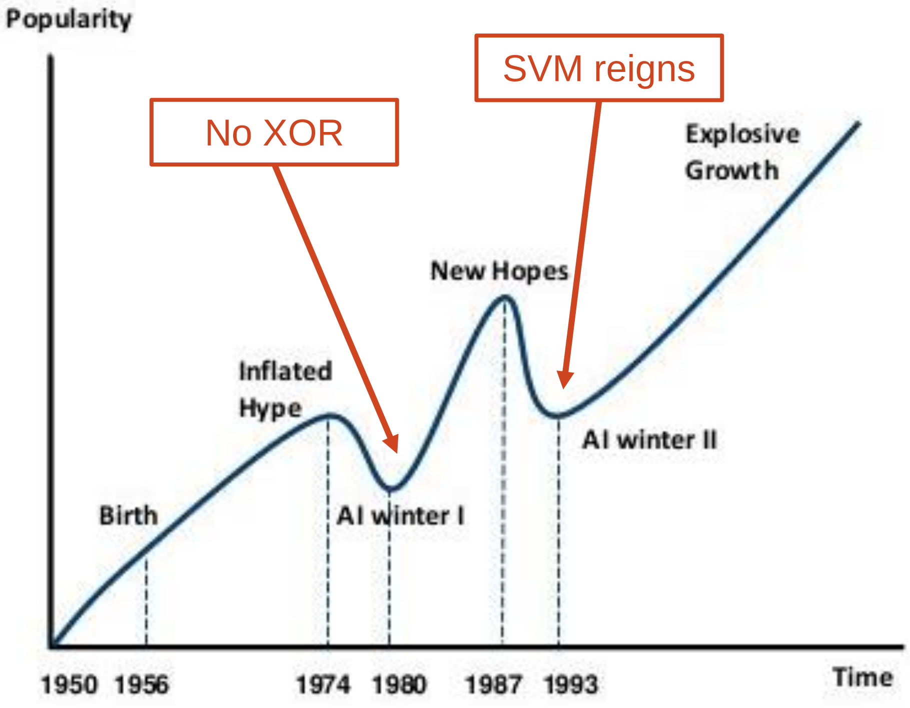

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Taken from Links International.

“If a typical person can do a mental task with less than one second of thought, we can probably automate it using AI either now or in the near future.”

— Ng, A. (2016). What Artificial Intelligence Can and Can’t Do Right Now. Harvard Business Review.

Neural Networks Have Been Taking Over!

- Neural networks have become one of the major thrust areas recently in various pattern recognition, prediction, and analysis problems

- Neural networks have re-defined the state-of-the-art in many problems
  Not seldomly, by a large margin!

- Let’s look at some examples!
  We will learn about several of them in greater detail during the course.

Machine learning problems and state-of-the-art results.

Natural Language Processing and Speech Recognition

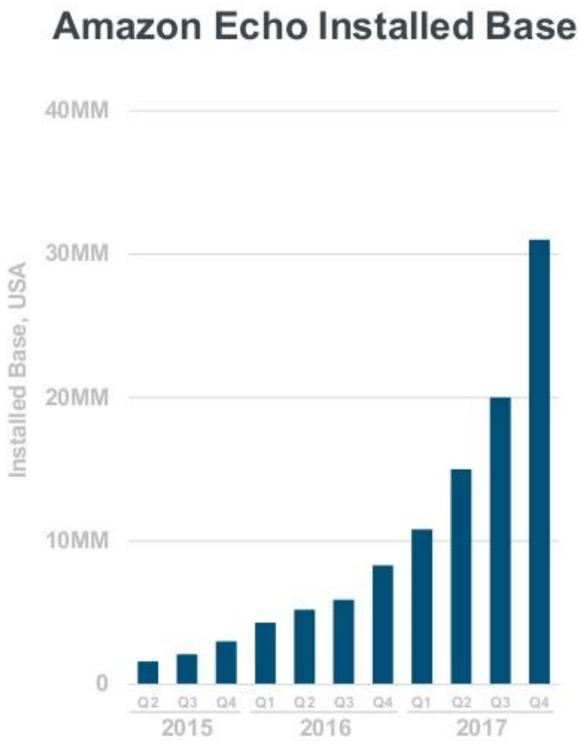
Google Assistant

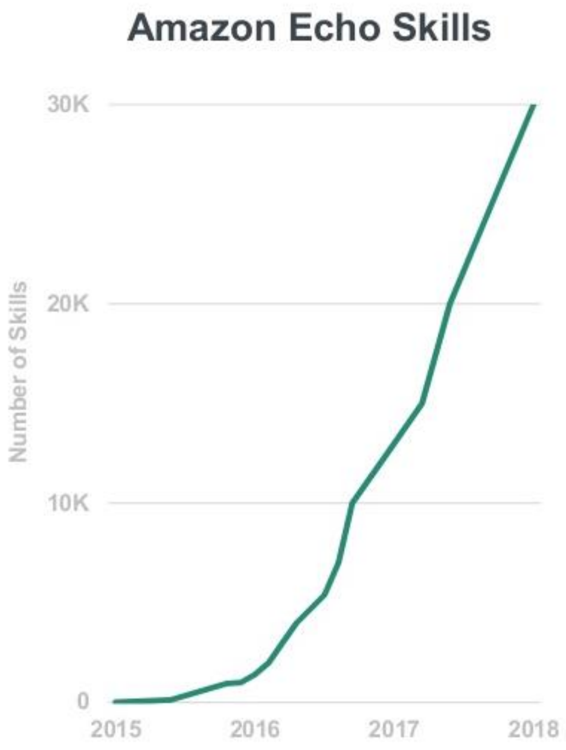
~ 20% of mobile queries are made via voice (May, 2016)

~ 70% of requests are Natural / Conversational Language (May, 2017)

Kleiner Perkins, Internet Trends 2017/18 report

Natural Language Processing and Speech Recognition

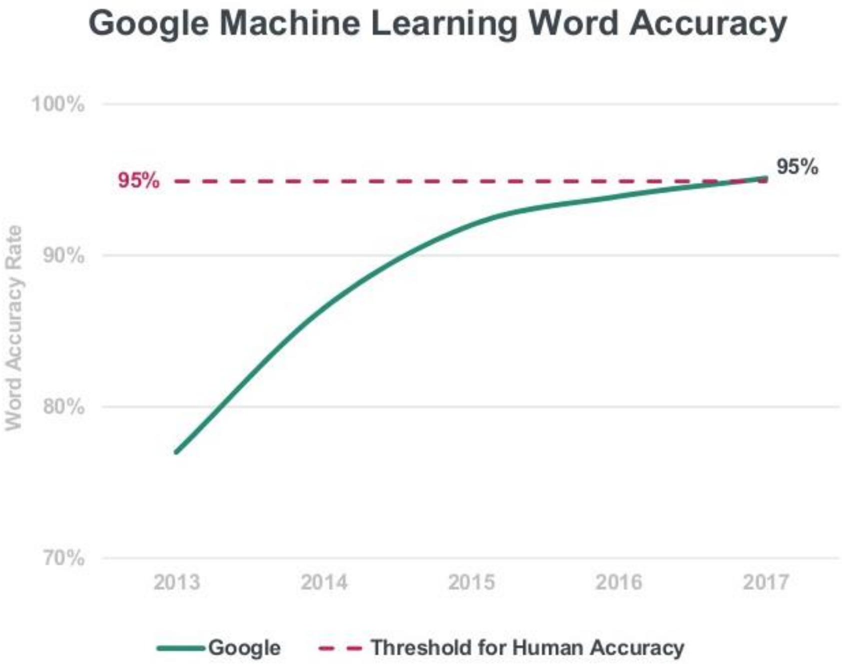




Kleiner Perkins, Internet Trends 2017/18 report

Natural Language Processing and Speech Recognition

For dictation it is generally agreed that accuracy rate < 95% is not acceptable.
Syntax and/or domain specific, e.g. time pressure, alternative methods, etc.



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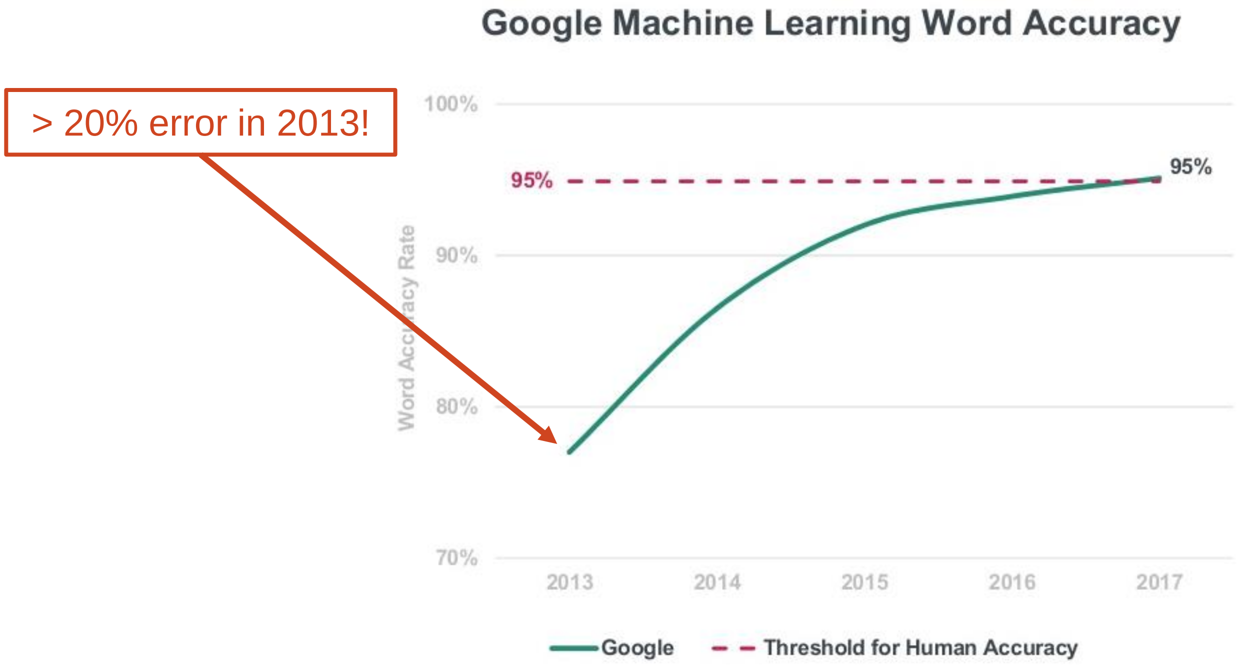

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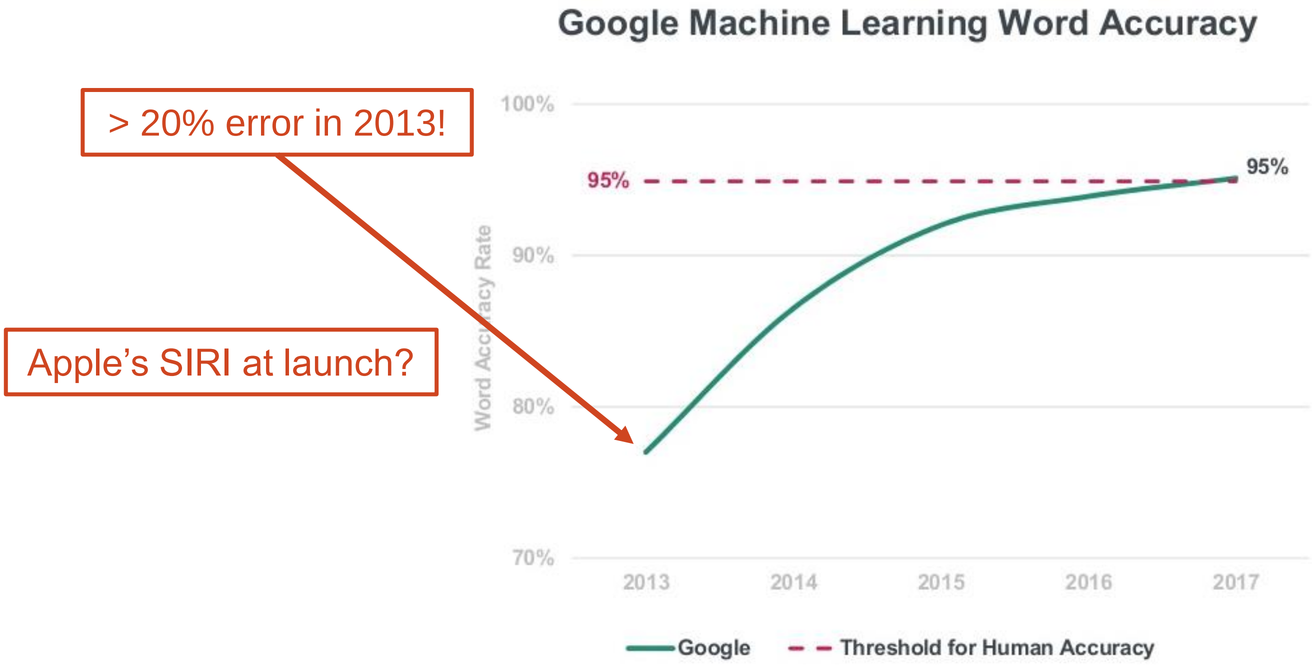

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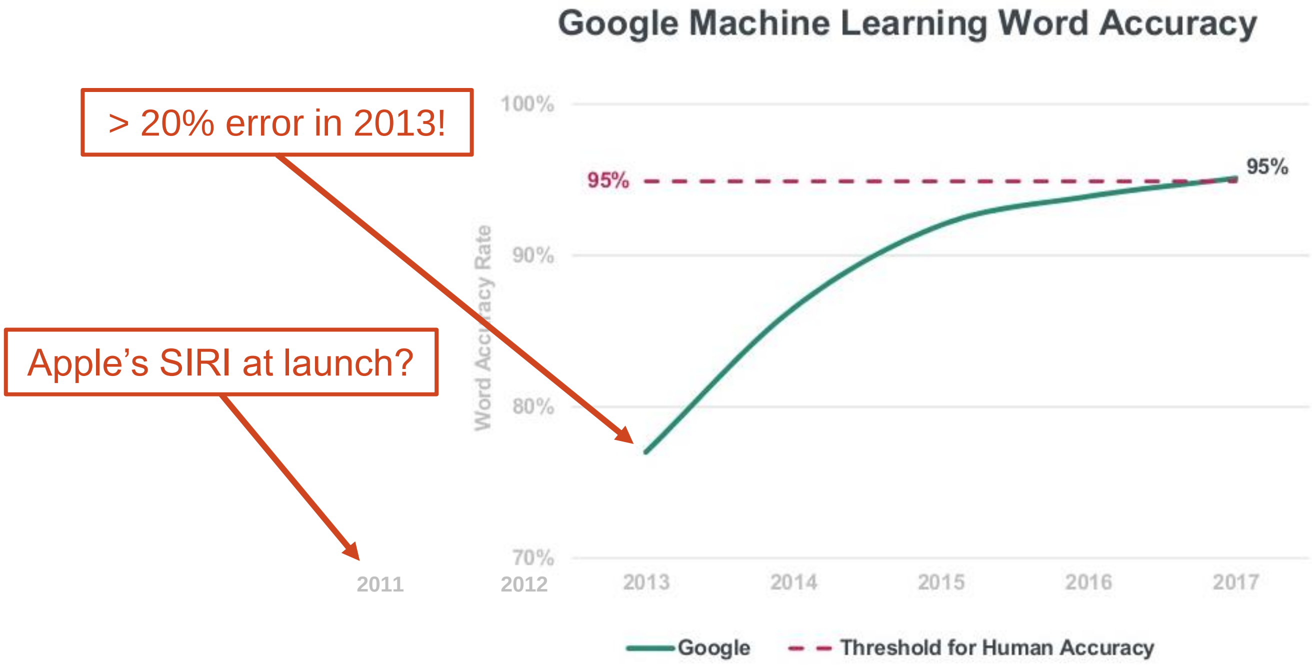

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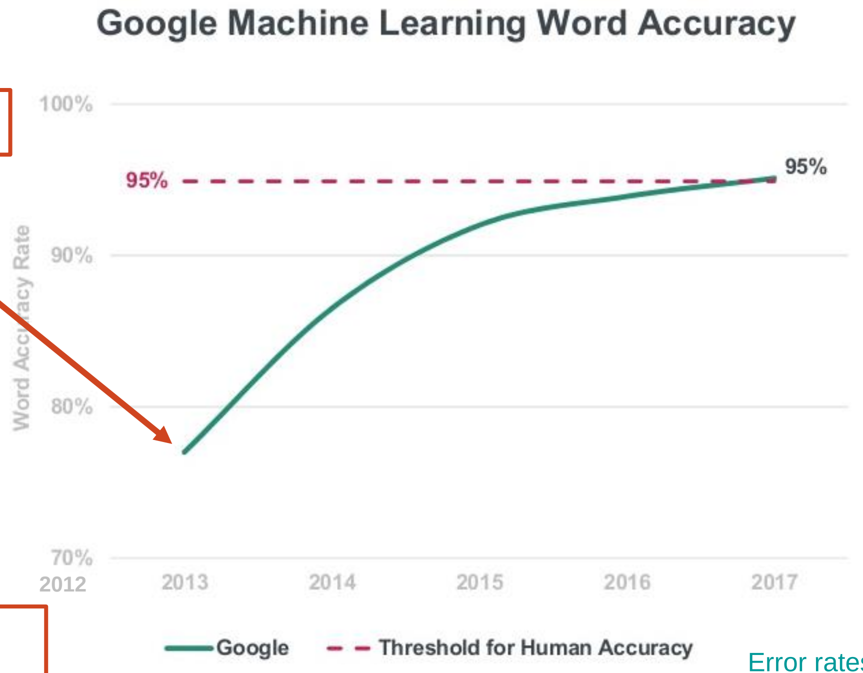


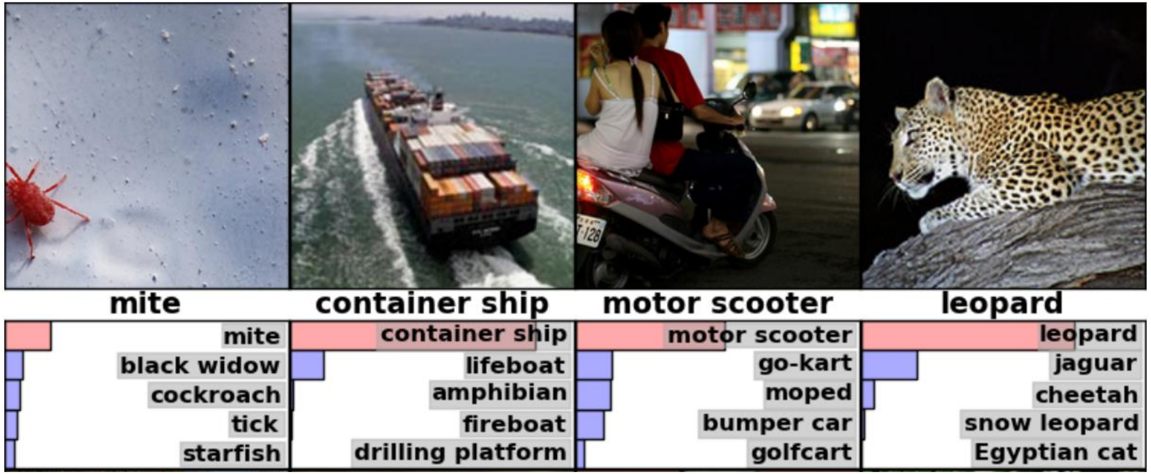
> 20% error in 2013!

Apple's SIRI at launch?

Word error rate: ~ 18%
Sentence error rate: ~ 85%

[Error rates Siri vs Microsoft]
[Kleiner Perkins, Internet Trends 2017/18 report]

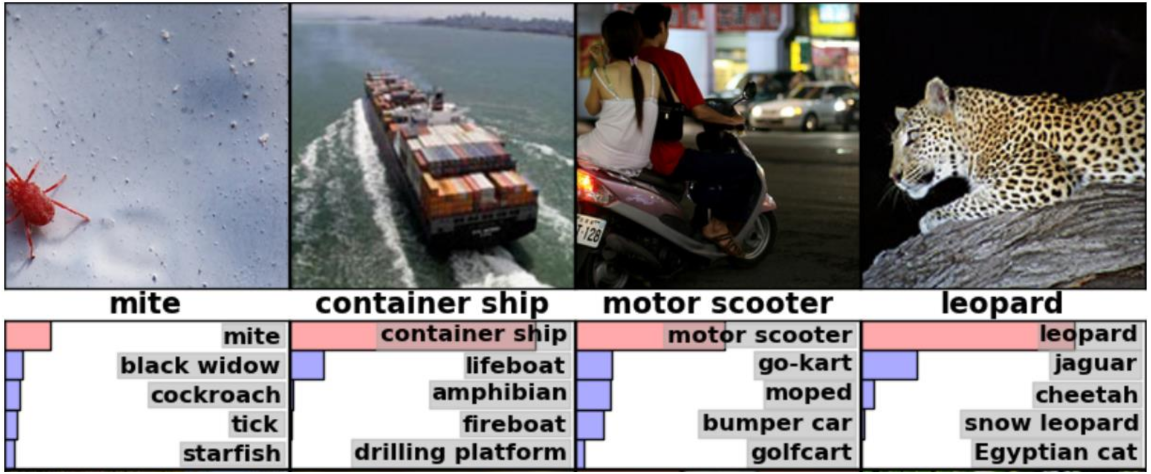
Image Classification



Andrej Karpathy blogpost.

- The ImageNet dataset by the numbers:
  1.2 Mio training images, 1000 classes, 100.000 testing images, Top-5 error
- Out of Fei-Fei Li's group at Stanford in 2009 **(Impact Award at CVPR 2019!)**
- A standard dataset for benchmarking vision algorithms (pre-training!)

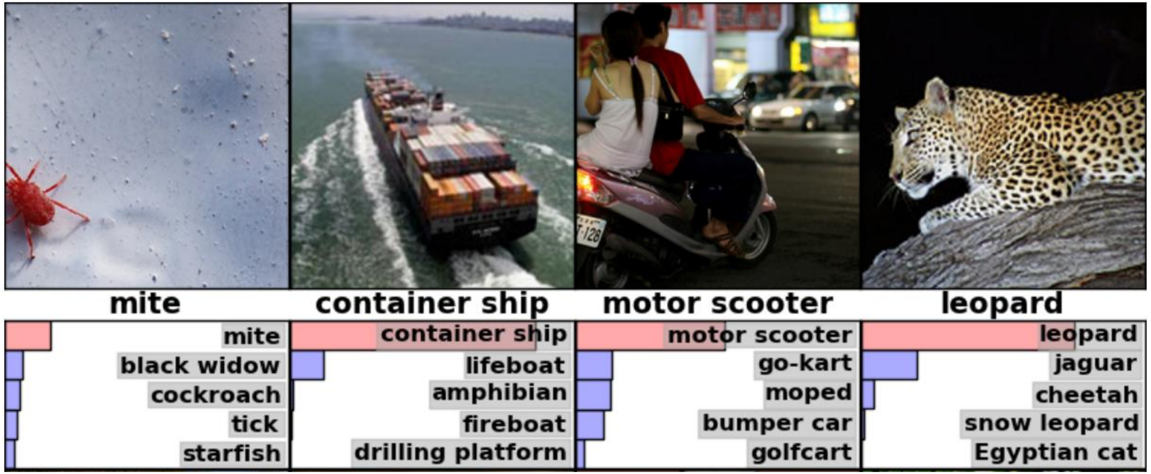
Image Classification



Andrej Karpathy blogpost.

- CNNs achieve super-human performance on ImageNet!

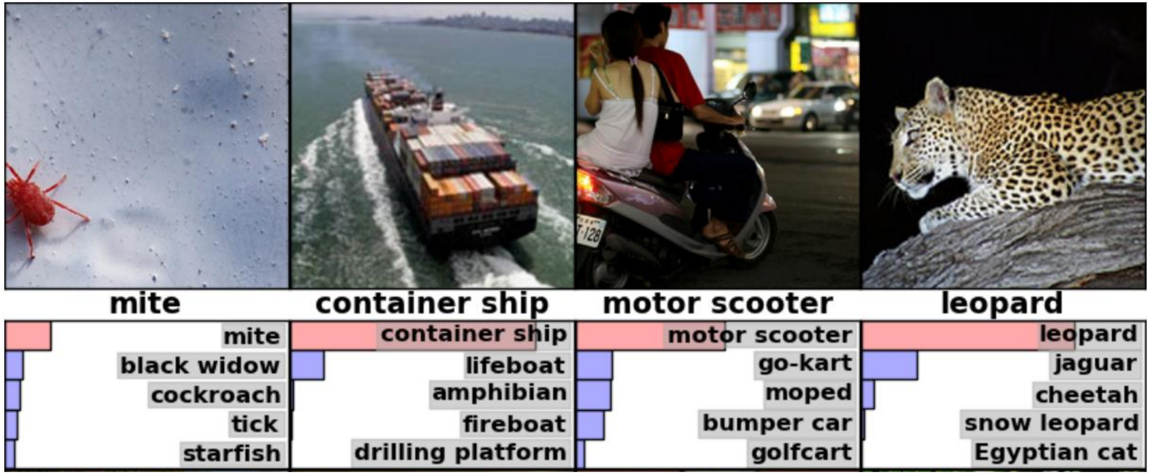
Image Classification



Andrej Karpathy blogpost.

- CNNs achieve ~~super-human~~ super-Karpathyan performance on ImageNet!
- Andrej Karpathy on 1500 ImageNet samples: 5.1% Top-5 error in Sep. 2014
- At that time: GoogLeNet leading with ~6.7%

Image Classification



Andrej Karpathy blogpost.

- Early 2015 already beaten!
- Now (2017): 3.8% Top-5, 17.3% Top-1 errors!

  Zoph, B. et al. (2017). Learning transferable architectures for scalable image recognition. arXiv:1707.07012.

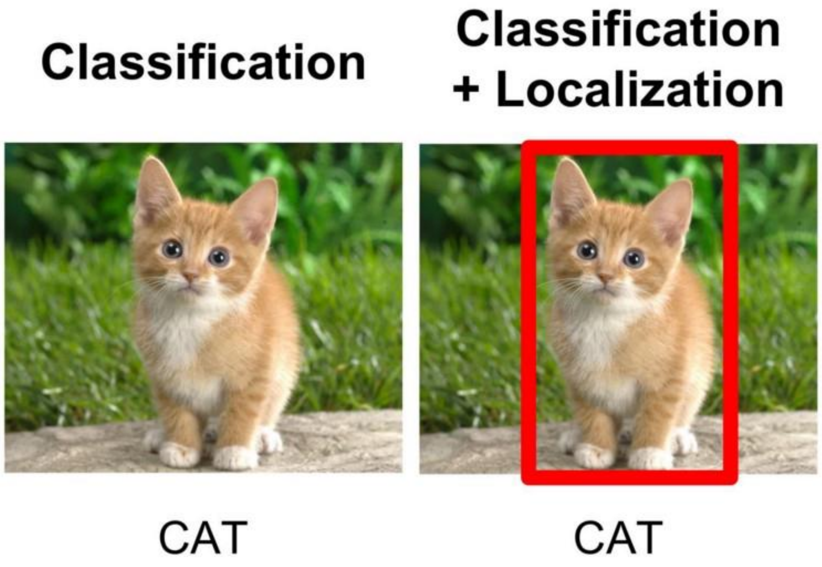
From Classification to Instance Segmentation

Single object

Multiple objects

[Ouaknine, A. (2018) Review of DL for Object Detection Blog Post]

From Classification to Instance Segmentation



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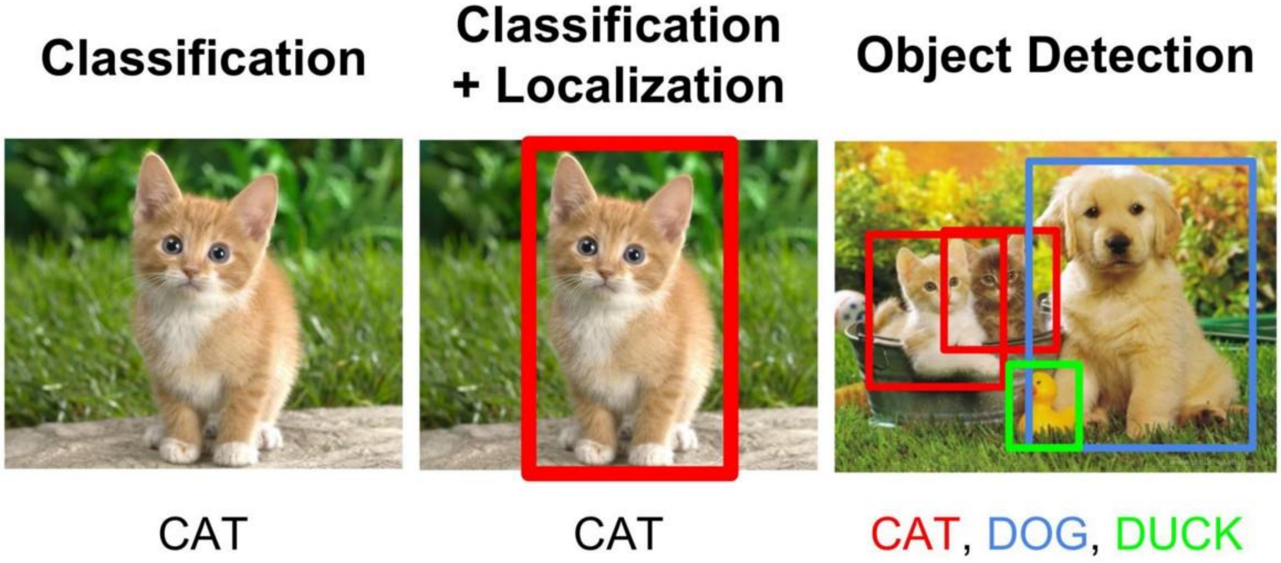

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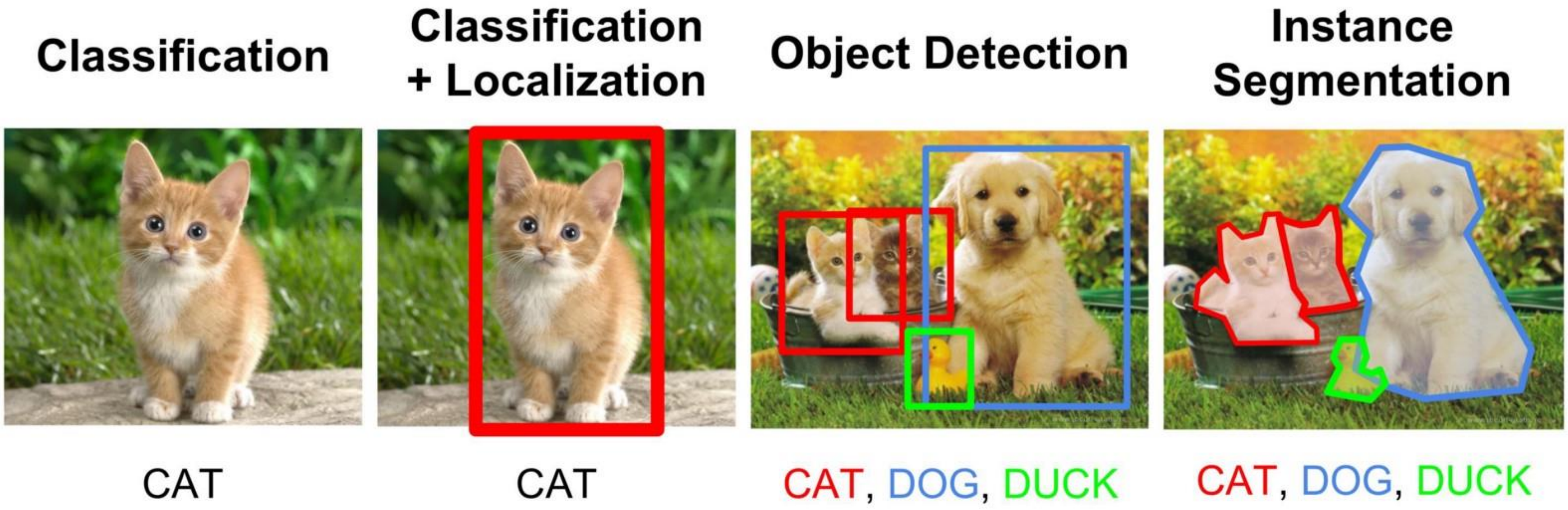

Single object

Multiple objects

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Single Instance Segmentation

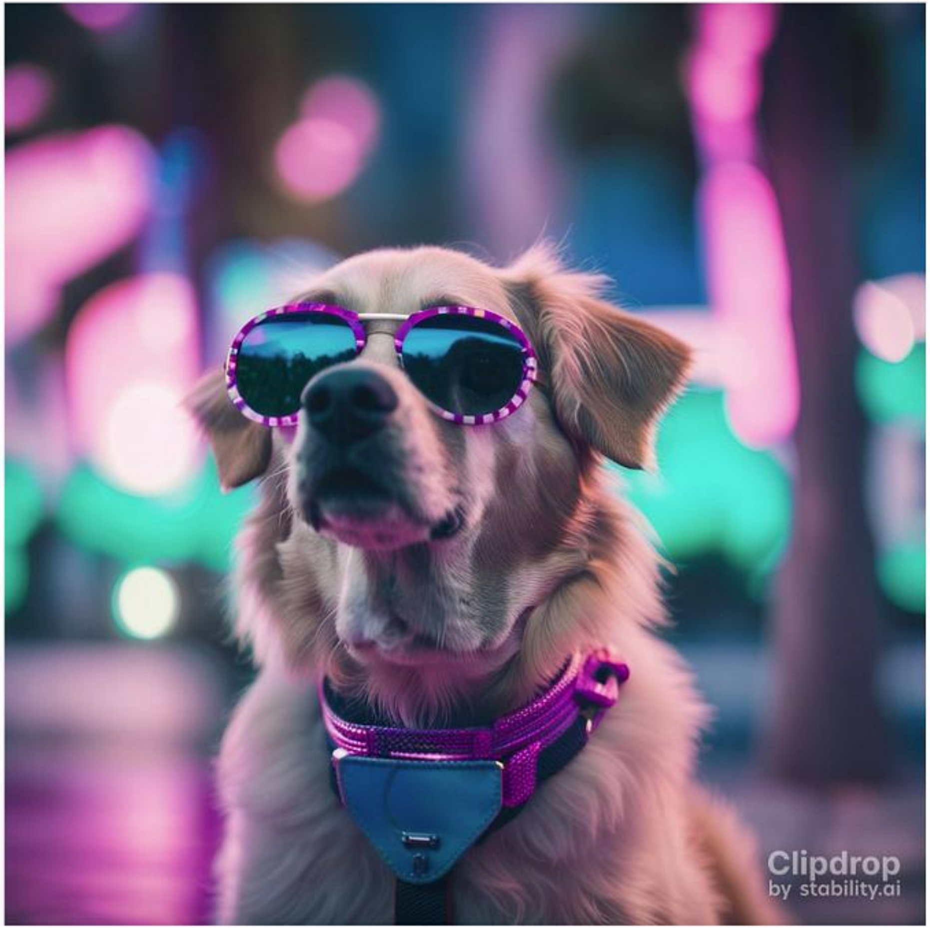
100+ FPS on iPhone 7 and 40+ FPS on Pixel 2

[Google AI Blog (March 2018) Mobile Real-time Video Segmentation]

The following results were generated in **Real-time**

Bolya, D., Zhou, C., Xiao, F., & Lee, Y. J. (2019). YOLACT++: Better Real-time Instance Segmentation. arXiv preprint arXiv:1912.06218.

SDXL 0.9



MidJourney v5.2

You are an expert in teaching at the higher ed level and expert in academic dishonesty. Please help me answer this question: What do you consider cheating using large language models for homework assignments?

Using large language models such as GPT-3 for homework assignments can be considered cheating because it undermines the learning goals of the assignment, and it can also be considered plagiarism.

One of the main goals of homework assignments is to help students practice and solidify their understanding of the material. When students use language models to complete their assignments, they are not engaging with the material in the same way and are not developing the same level of understanding and mastery as they would if they were to complete the assignment on their own.

Additionally, when students use language models to generate answers for their assignments, they are effectively presenting work that is not their own, which constitutes plagiarism. This not only undermines their own learning but also the integrity of the institution.

It's important to note that many institutions have strict policies in place when it comes to academic dishonesty, and students found to be cheating in this way may face serious consequences, including failing the assignment, the course, or even being expelled from the institution.

It's also important to note that using language models to assist with homework assignments can be beneficial if done in a controlled way under the guidance of an instructor. Some instructors may choose to allow the use of these tools as long as the students are transparent about their use and properly cite any information that is obtained from the model.

Deep Learning and the Employment Market

This guy didn't know about neural networks (a.k.a deep learning)

This guy learned about neural networks (a.k.a deep learning)

[CMU lecture on Deep Learning]

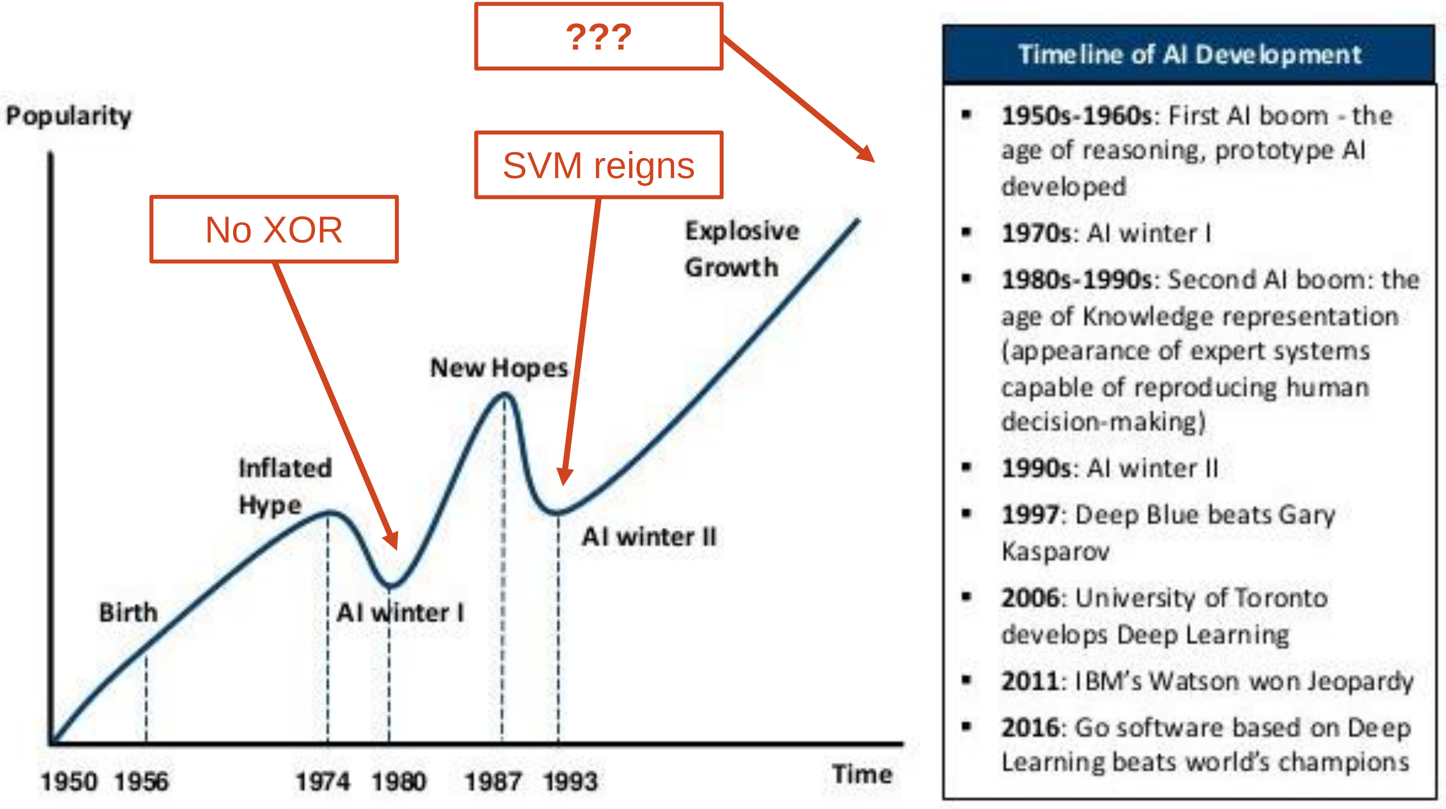
A History of Being “The Next Big Thing”

For most problems where DL has enabled transformationally better solutions (vision, speech), we have entered diminishing returns territory in 2016/17.

— François Chollet, Google, author of Keras, (18 December) 2017

Taken from Links International.

A History of Being “The Next Big Thing”



[Taken from Links International.](#)

A History of Being "The Next Big Thing"

"Deep learning is only part of the larger challenge of building intelligent machines because such techniques lack ways of representing causal relationships (such as between diseases and their symptoms), and are likely to face challenges in acquiring abstract ideas like "sibling" or "identical to." They have no obvious ways of performing logical inferences, and they are also still a long way from integrating abstract knowledge, such as information about what objects are, what they are for, and how they are typically used."

— Marcus, G. (2018). Deep learning: A critical appraisal. 1801.00631.

So, where does deep learning stand?

A History of Being "The Next Big Thing"

"Deep learning is only part of the larger challenge of building intelligent machines because such techniques lack ways of representing causal relationships (such as between diseases and their symptoms), and are likely to face challenges in acquiring abstract ideas like "sibling" or "identical to." They have no obvious ways of performing logical inferences, and they are also still a long way from integrating abstract knowledge, such as information about what objects are, what they are for, and how they are typically used."

— Marcus, G. (2018). Deep learning: A critical appraisal. 1801.00631.

So, where does deep learning stand?

After this course, you should have a solid understanding!

Overview

Questions?