

# Intro to Modern Computer Vision

(with an emphasis on self-driving cars)

By Julianne LaChance and Jonathan Lu

Note: We stole a bunch of slides from Drs. Andras Ferencz, Olga Russakovsky, Joshua Hug and Artur Filipowicz

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The New York Times Magazine Share

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# The Great A.I. Awakening

How Google used artificial intelligence to transform Google Translate, one of its more popular services — and how machine learning is poised to reinvent computing itself.

BY GIDEON LEWIS-KRAUS DEC. 14, 2016



# Motivation

Full-Resolution Residual Networks (FRRNs) for Semantic Image Segmentation in Street Scenes



<https://www.youtube.com/watch?v=PNzQ4PNZSzc>

# Overview

- Motivation
- Applications
- A very brief history of neural nets
- Computer vision for social good
- Autonomous Vehicles
- Ethics and Policy of Self-Driving Cars
- Summary

# Applications

# Image Classification and Retrieval

## Classification



**mite      container ship      motor scooter      leopard**

|             |                   |               |              |
|-------------|-------------------|---------------|--------------|
| mite        | container ship    | motor scooter | leopard      |
| black widow | lifeboat          | go-kart       | jaguar       |
| cockroach   | amphibian         | moped         | cheetah      |
| tick        | fireboat          | bumper car    | snow leopard |
| starfish    | drilling platform | golfcart      | Egyptian cat |

A horizontal collage of four photographs. From left to right: a bright red, classic sedan from the front; several small, orange mushrooms with white spots growing on a log; a close-up of a dalmatian dog's face; and a lemur sitting on a branch.

| grille      | mushroom           | cherry                | Madagascar cat  |
|-------------|--------------------|-----------------------|-----------------|
| convertible | agaric             | dalmatian             | squirrel monkey |
| grille      | mushroom           | grape                 | spider monkey   |
| pickup      | jelly fungus       | elderberry            | titi            |
| beach wagon | gill fungus        | fordshire bullterrier | indri           |
| fire engine | dead-man's-fingers | currant               | howler monkey   |

## Retrieval



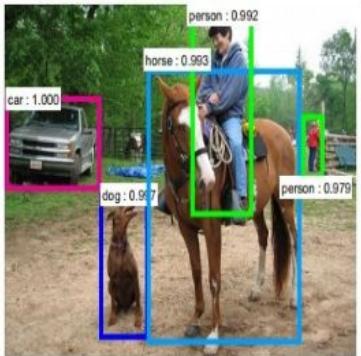
A horizontal row of seven carved pumpkins. From left to right: 1. A bat with a crescent moon and stars. 2. A bat with a crescent moon and stars. 3. A stylized flame or fire design. 4. A simple jack-o'-lantern face with a wide grin. 5. A skull with sharp teeth. 6. A ghost with a long, thin body and arms. 7. A jack-o'-lantern face with a wide grin.

A horizontal collage of six photographs showing different dogs. From left to right: 1. A small dog with white and brown spots standing outdoors. 2. A large Saint Bernard dog standing on a paved surface. 3. A large Saint Bernard dog lying down on a paved surface. 4. Two dogs, one black and white and one dark-colored, standing together. 5. A small white dog sitting next to a person's legs. 6. A brown and white dog looking up at another dog.

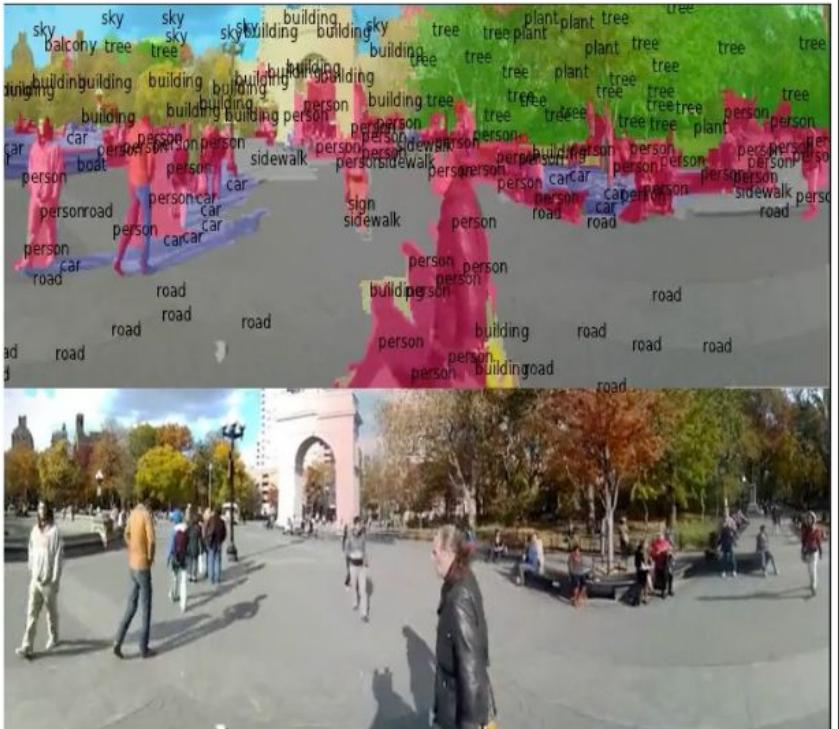
[Krizhevsky 2012]

# Object Detection and Segmentation

Detection



Segmentation



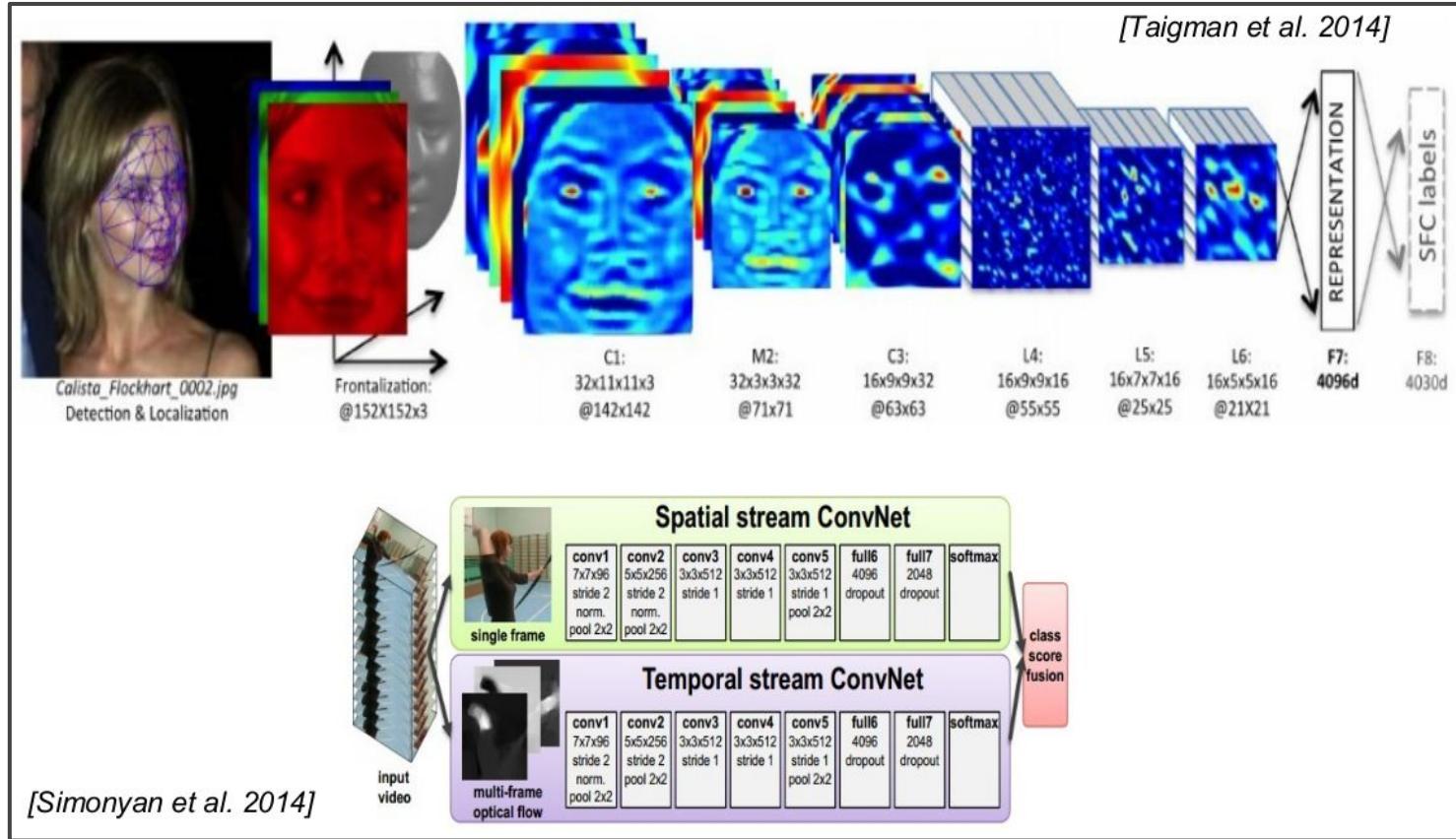
[Faster R-CNN: Ren, He, Girshick, Sun 2015]

[Farabet et al., 2012]

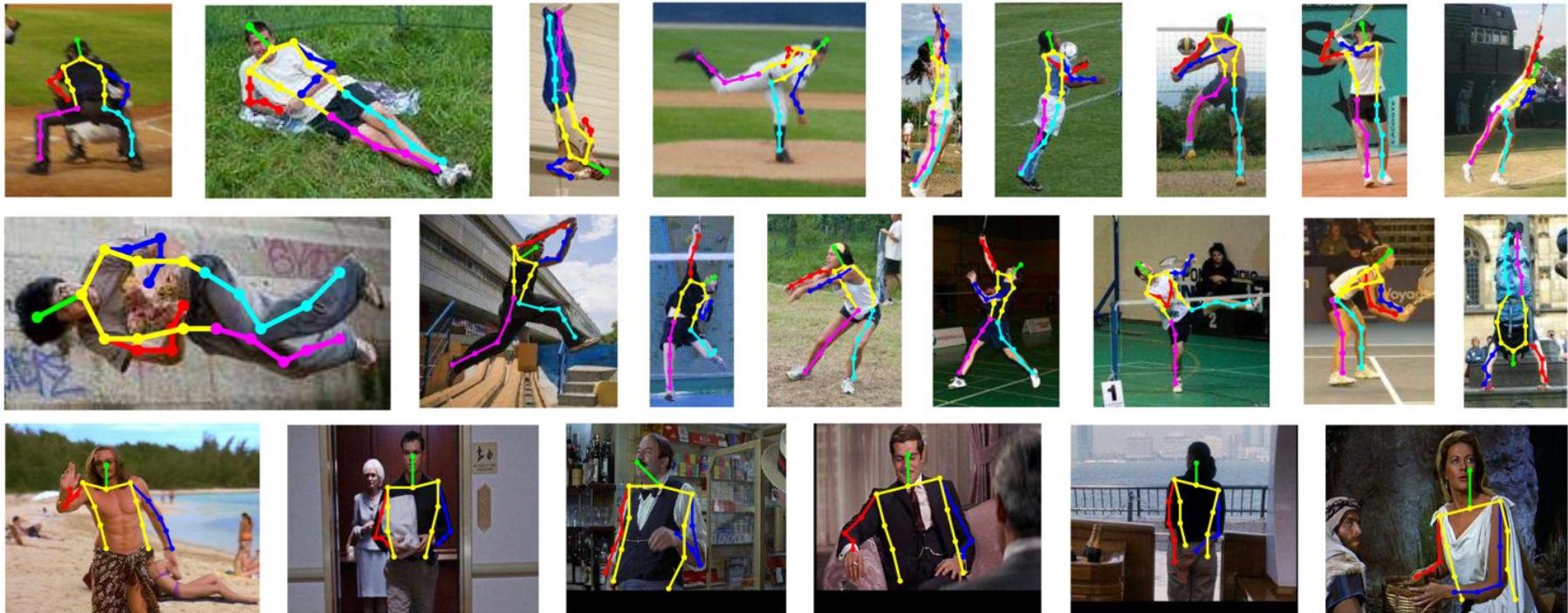
# Semantic Image Segmentation



# Face and Activity Recognition



# Human Pose Estimation



# Image Captioning

| Describes without errors  | Describes with minor errors   | Somewhat related to the image   | Unrelated to the image  |
|---|---|---|---|
|  |  |  |  |
| <p>A person riding a motorcycle on a dirt road.</p>                               | <p>Two dogs play in the grass.</p>  | <p>A skateboarder does a trick on a ramp.</p>                                     | <p>A dog is jumping to catch a frisbee.</p>   |
|  |  |  |  |
| <p>A group of young people playing a game of frisbee.</p>                         | <p>Two hockey players are fighting over the puck.</p>                             | <p>A little girl in a pink hat is blowing bubbles.</p>                            | <p>A refrigerator filled with lots of food and drinks.</p>                          |
|  |  |  |  |
| <p>A herd of elephants walking across a dry grass field.</p>                      | <p>A close up of a cat laying on a couch.</p>                                     | <p>A red motorcycle parked on the side of the road.</p>                           | <p>A yellow school bus parked in a parking lot.</p>                                 |

[Vinyals et al., 2015]

# “Deep Art”



# Medical Applications

APRIL 3, 2017

## Stanford researchers create deep learning algorithm that could boost drug development

*Combining computer science and chemistry, researchers show how an advanced form of machine learning that works off small amounts of data can be used to solve problems in drug discovery.*



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amazingly subtle information, enabling them medical images as well as a doctor. But in training that involves thousands to trillions it work all that well in situations where there

### Computers trounce pathologists in predicting lung cancer type, severity

Automating the analysis of slides of lung cancer tissue samples increases the accuracy of tumor classification and patient prognoses, according to a new study.

AUG 16  
2016

Computers can be trained to be more accurate than pathologists in assessing slides of lung cancer tissues, according to a new study by researchers at the [Stanford University School of Medicine](#).



# Beating humans at their own games

Google's DeepMind AI has been secretly schooling online Go players

AlphaGo spent the past few days playing anonymous matches on public servers.



Andrew Dalton, @dolftown  
01.04.17 in Robots

3

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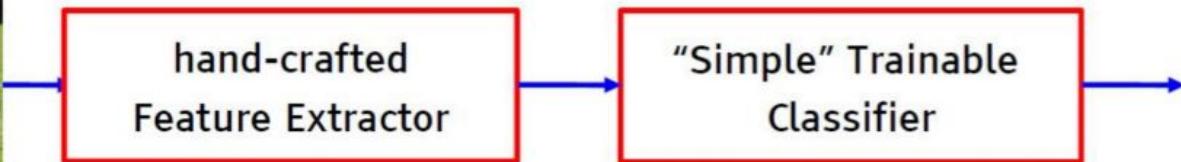
## Historic Achievement: Microsoft researchers reach human parity in conversational speech recognition



# A very brief history of neural nets

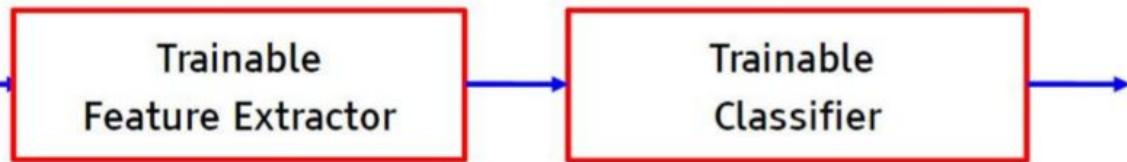
# Old school machine learning versus today:

- Fixed engineered features (or kernels) + trainable classifier

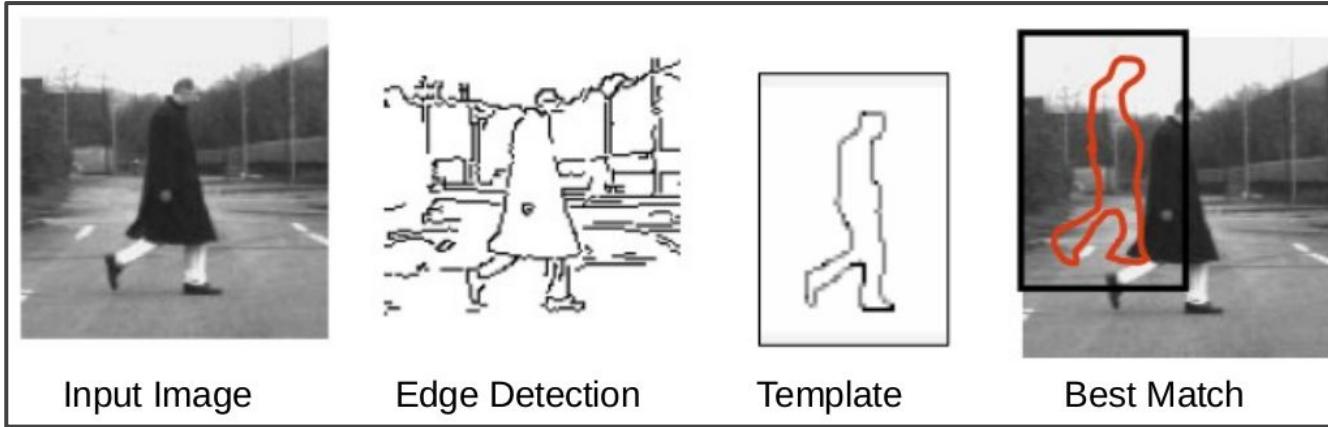


VS.

- End-to-end learning / feature learning / deep learning



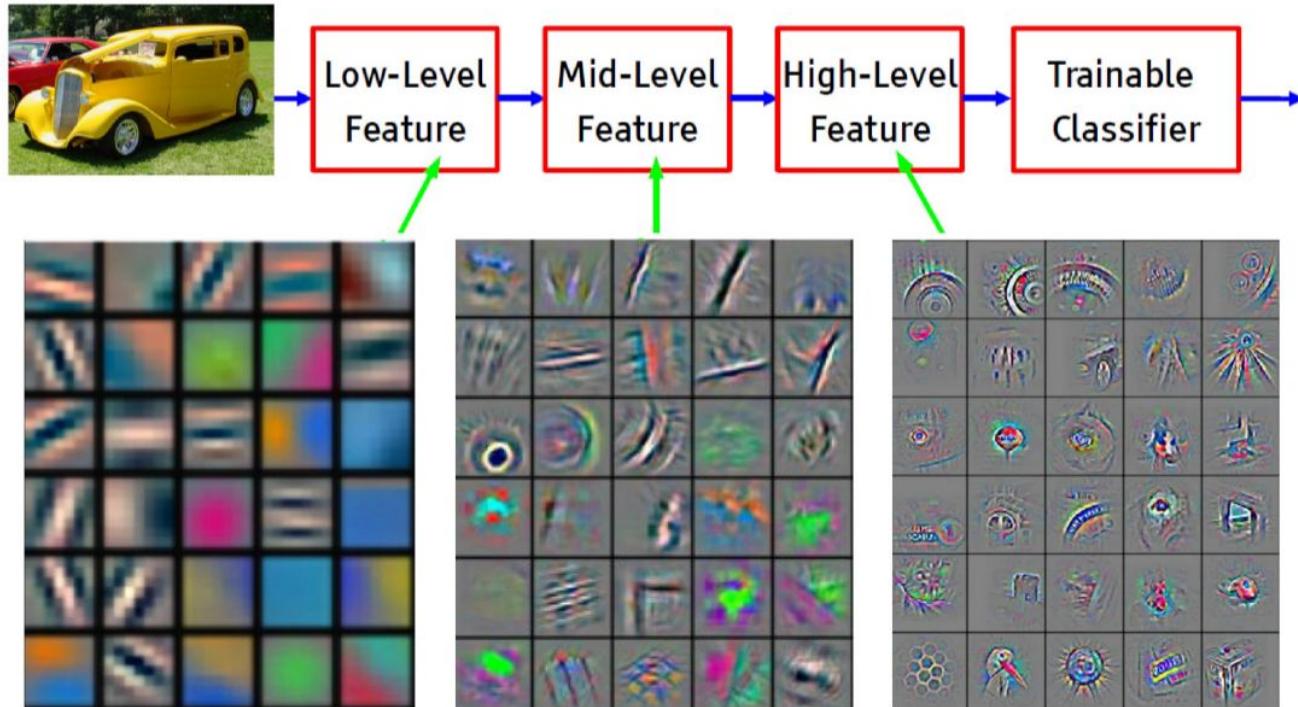
# Old school machine learning versus today:



1999: Chamfer matching to do pedestrian detection

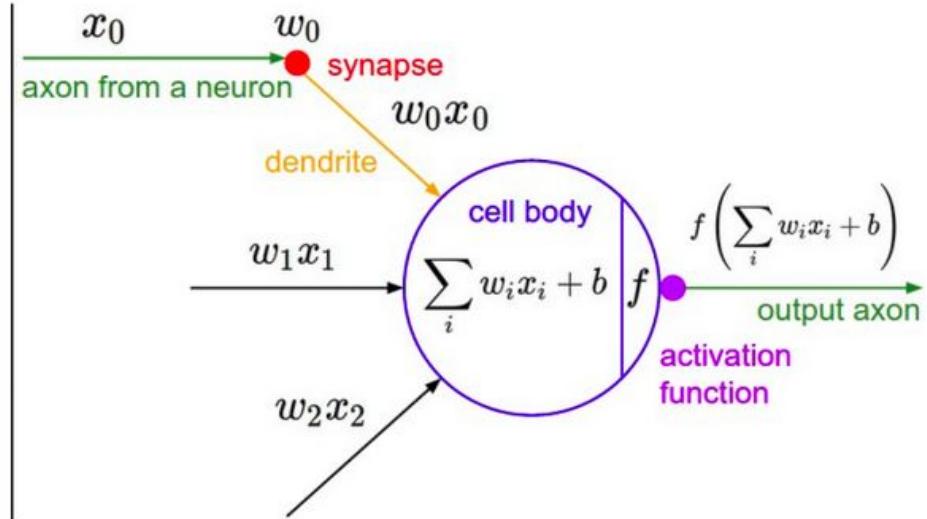
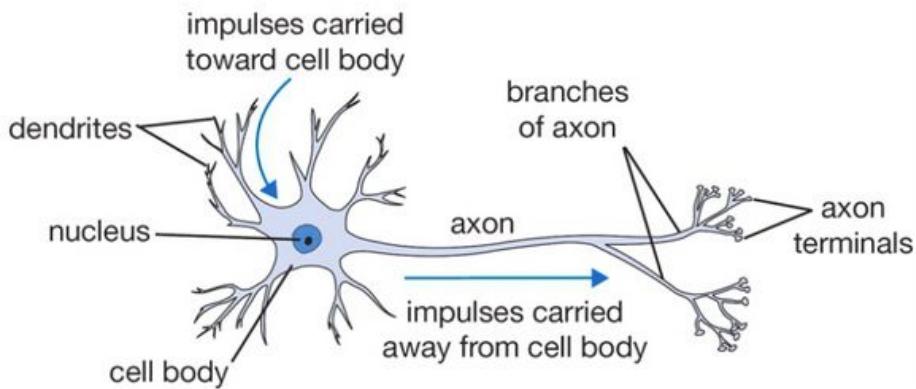
# Low level → high level features

In deep learning we have multiple stages of non linear feature transformation

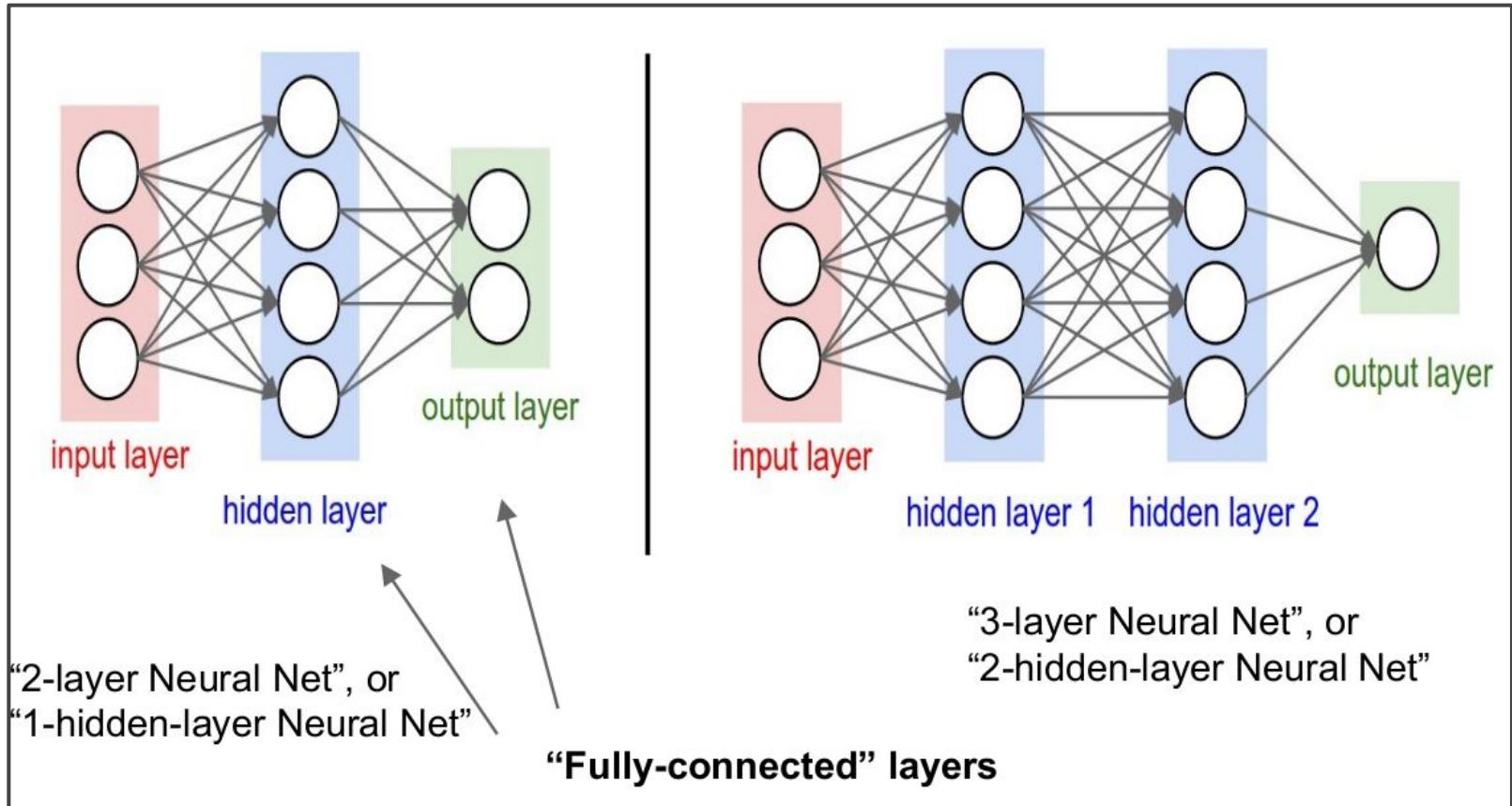


Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

# Why “neural” networks?



# Neural networks



# Example: MNIST dataset

label = 5



label = 0



label = 4



label = 1



label = 9



label = 2



label = 1



label = 3



label = 1



label = 4



label = 3



label = 5



label = 3



label = 6



label = 1



label = 7



label = 2



label = 8



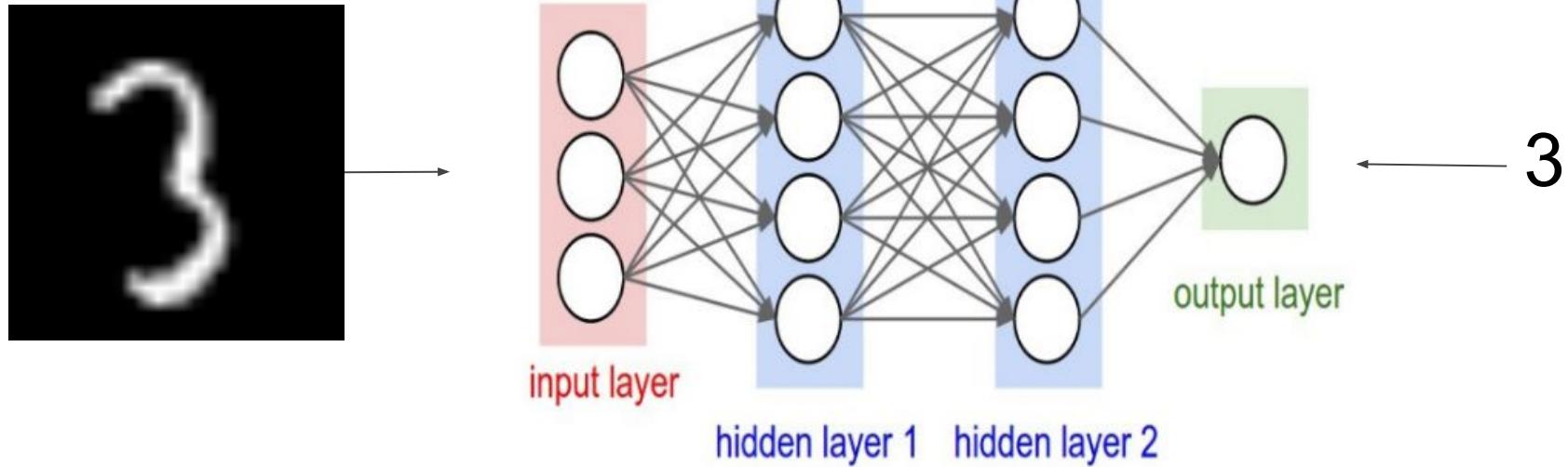
label = 6



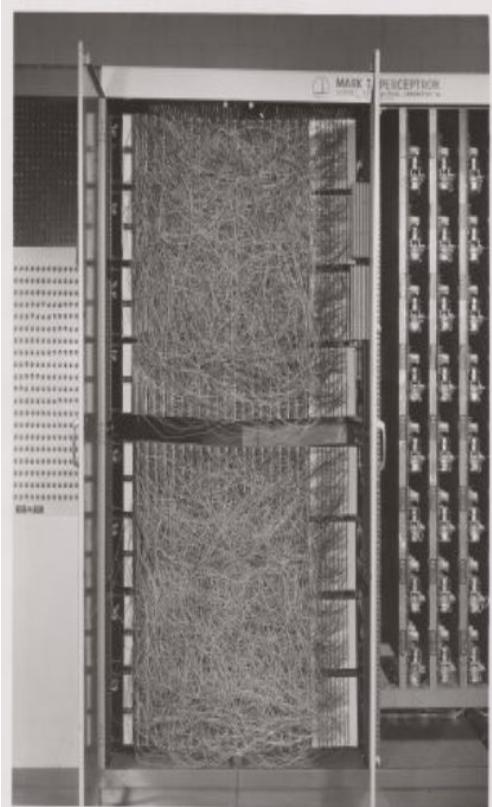
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# Example: MNIST dataset



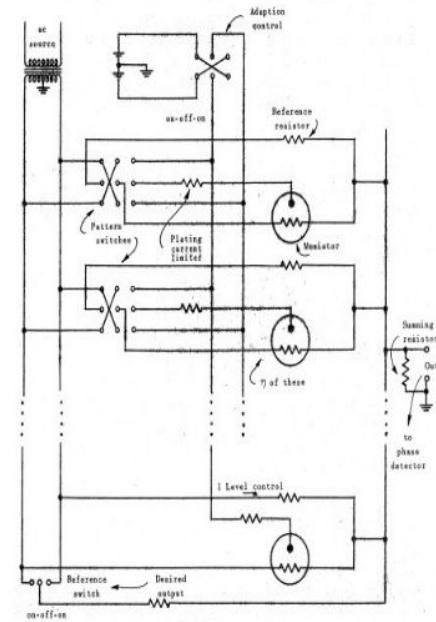
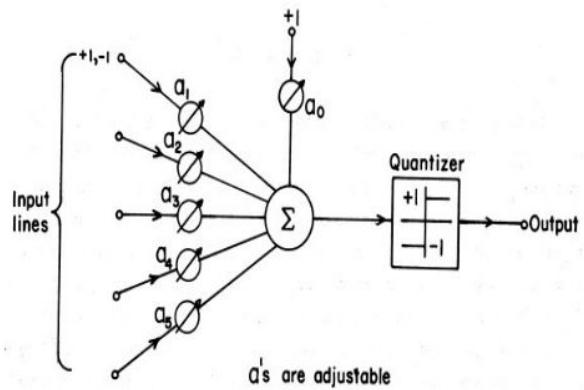
# The first artificial neural networks



- 1957: The Mark I Perceptron machine was the first implementation of the perceptron algorithm.
- The machine was connected to a camera that used  $20 \times 20$  cadmium sulfide photocells to produce a 400-pixel image.
- Recognized letters of the alphabet.
- Update rule:

$$w_i(t+1) = w_i(t) + \alpha(d_j - y_j(t))x_{j,i}$$

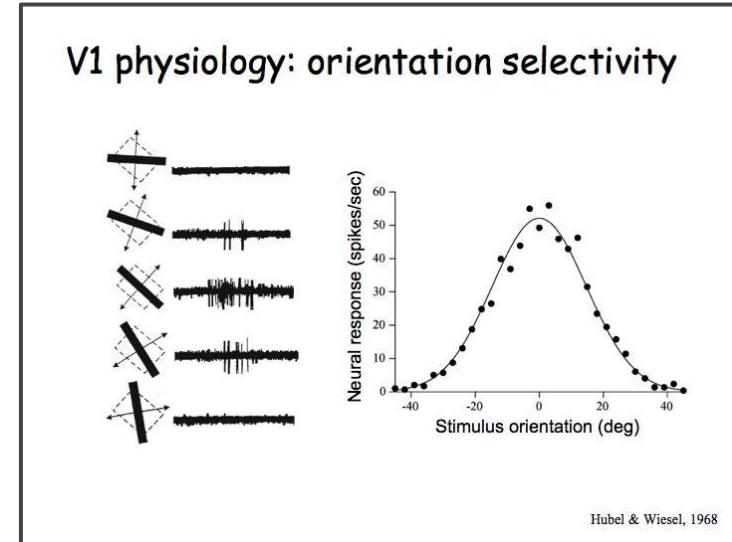
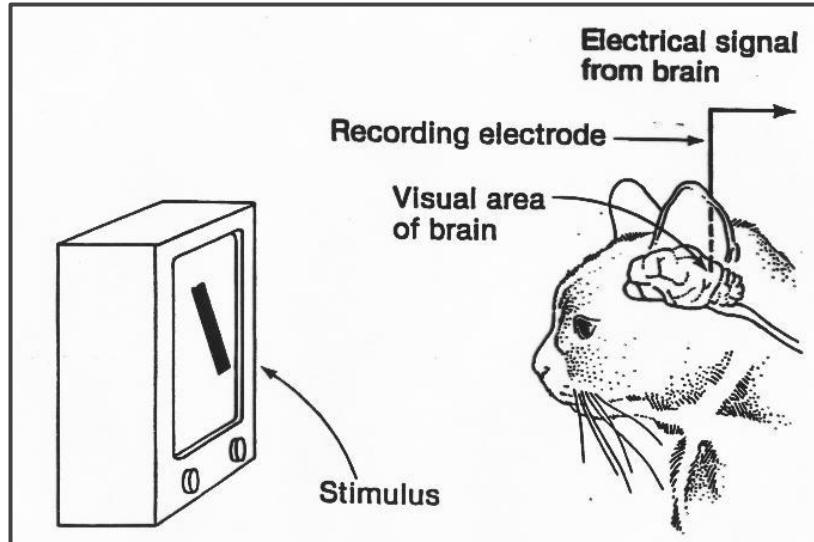
# The first artificial neural networks



- 1960 Adaline/Madaline: (Many Adaptive Linear Neuron)

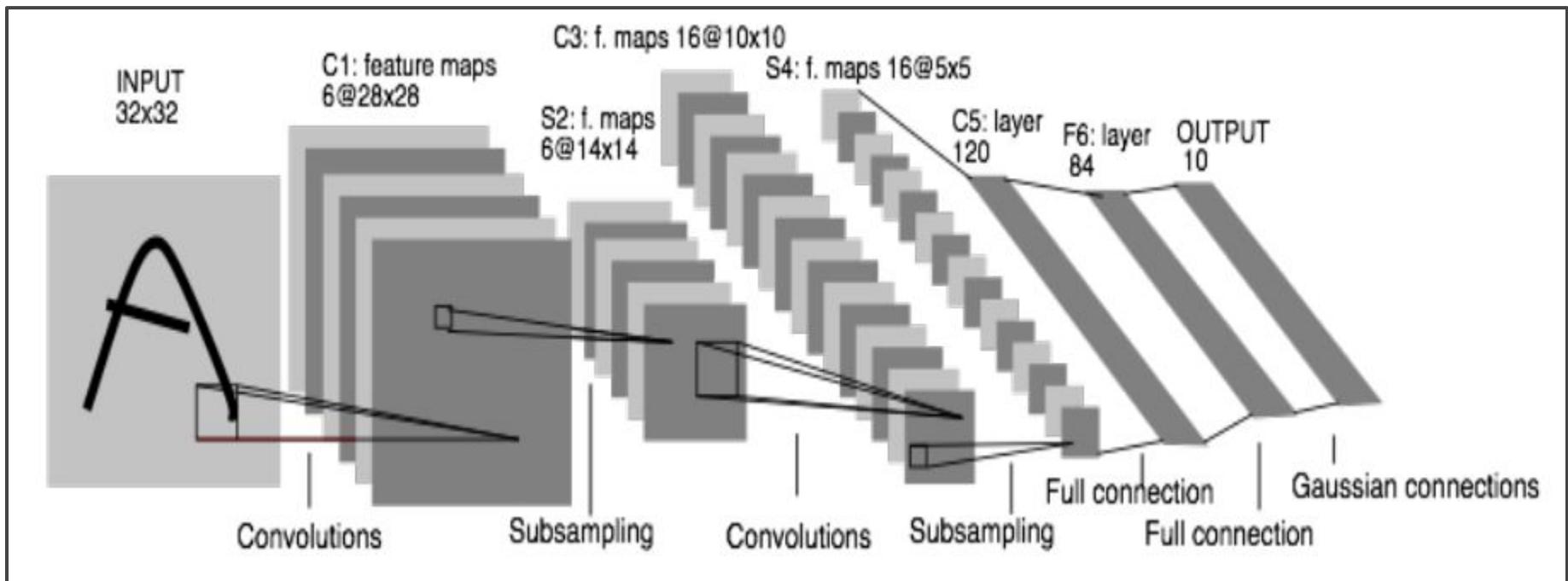
# Processing in the visual system

- 1959: first Hubel and Wiesel experiments
  - The team inserted a microelectrode into the primary visual cortex of an anesthetized cat, then projected patterns of light and dark on a screen in front of the cat. Neuronal responses to the patterns were recorded.
  - Visual parcels in the neo-cortex found to generate edge detectors, motion detectors, stereoscopic depth detectors and color detector.

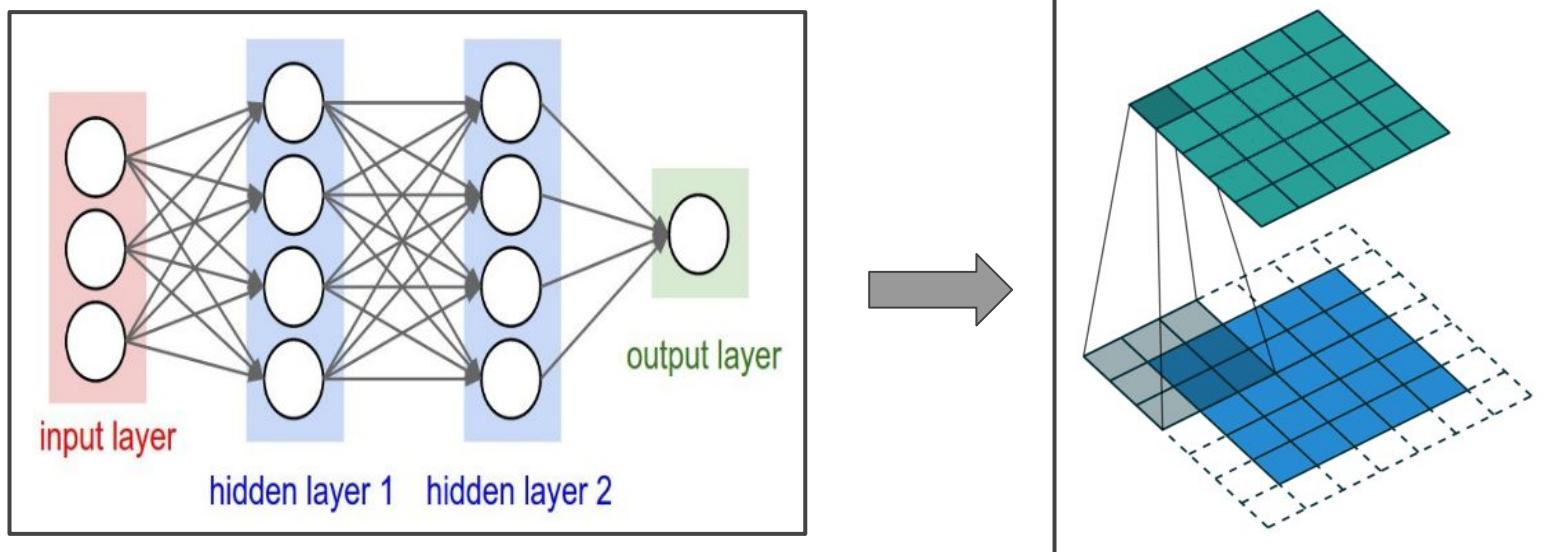


# The first artificial neural networks

- 1986: First time back-propagation becomes popular (for training neural networks efficiently)
- 1998: LeCun develops convolutional neural networks for handwritten digit classification



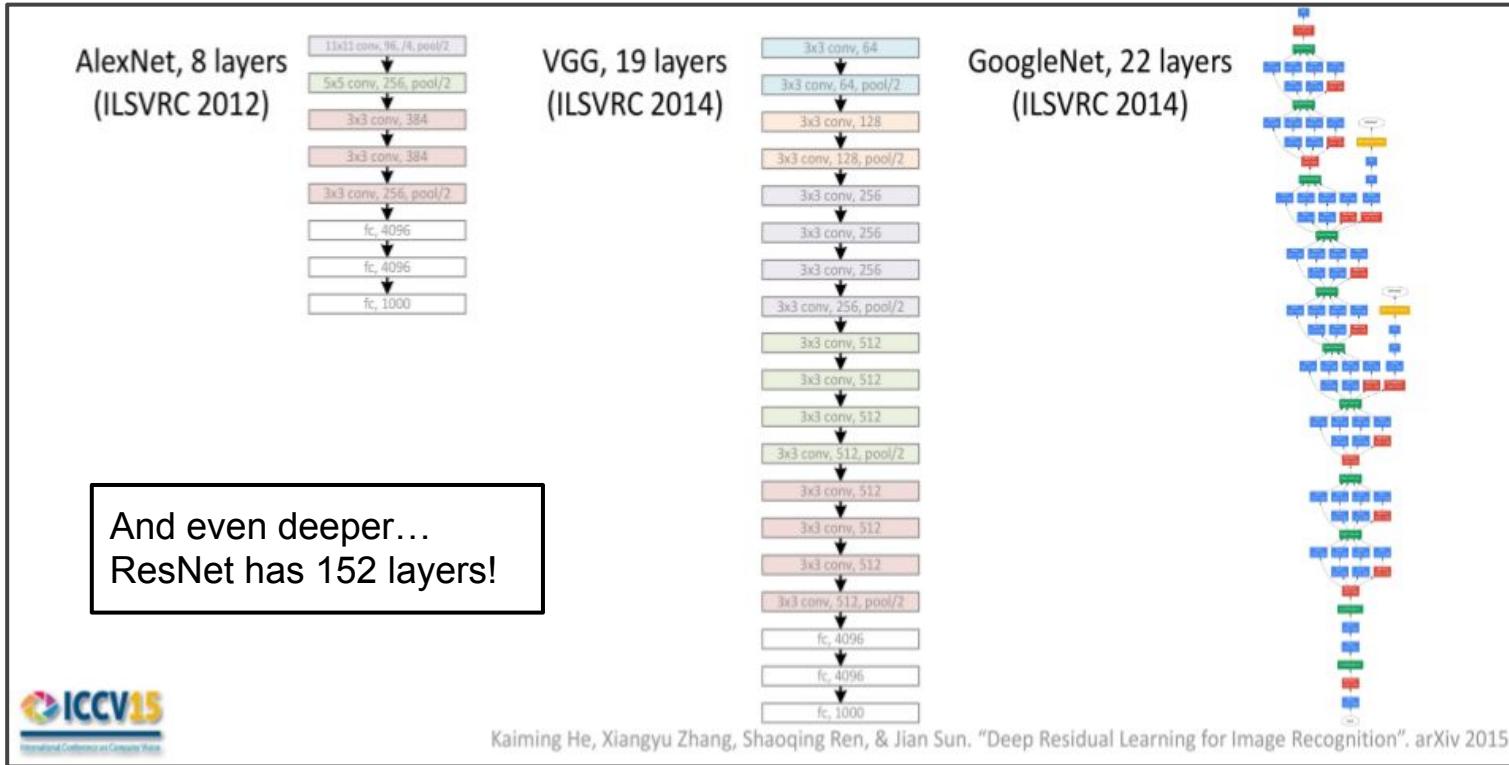
# Convolutional neural networks



- Traditional neural networks are composed of ***fully-connected layers***, in which neurons are connected to every neuron in the previous layer. But this is impractical for use in images.
- Instead, we utilize a ***convolution*** operation, tiling regions with the same set of shared weights. The features learned are effectively filters on the input regions.

# Modern artificial neural networks

- 2012: First strong modern results for image classification, followed by a “revolution of depth”.



# What really prompted the modern age of AI?

1. The prevalence of household GPUs  
(thanks, gamers)
2. The development of massive, high-quality data sets

# Computer Vision for Social Good

# Discussion Question:

What are some ways computer vision  
algorithms can be used for social good?

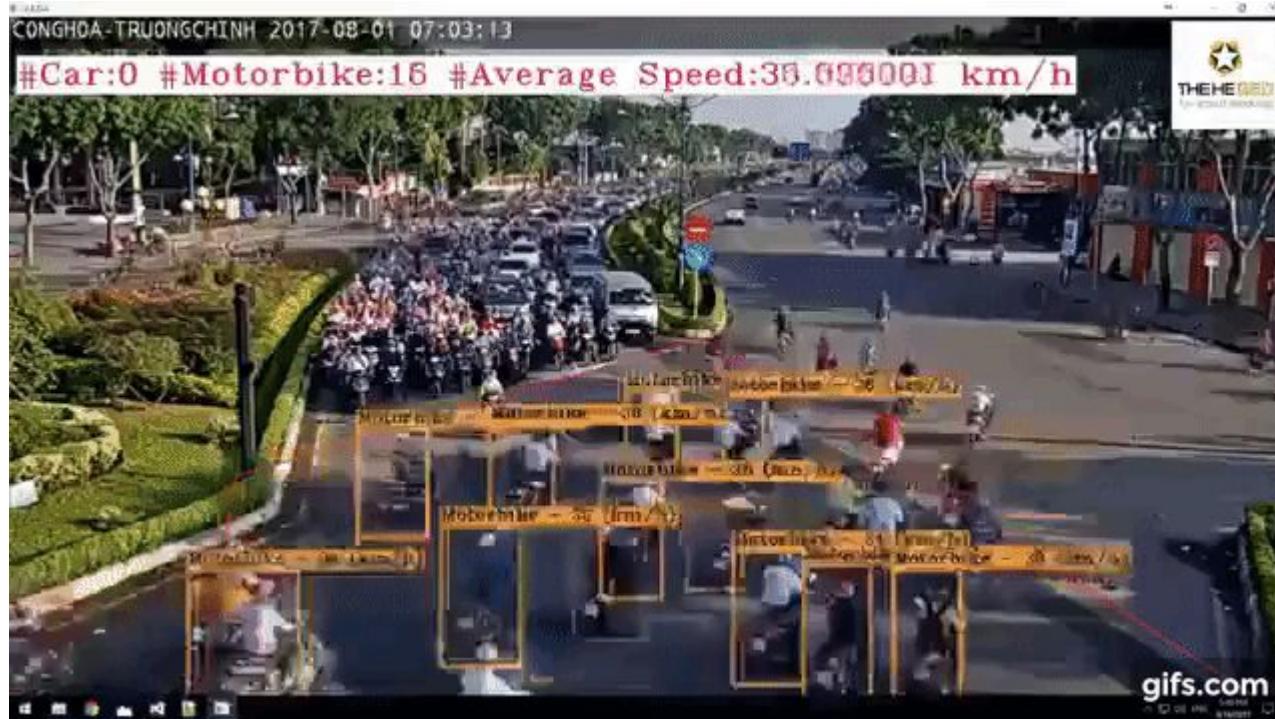
# Applications of Computer Vision

- Classification/Retrieval
- Object Detection/Segmentation
- Semantic Image Segmentation
- Face and Activity Recognition, Pose Estimation
- Image/Video Captioning

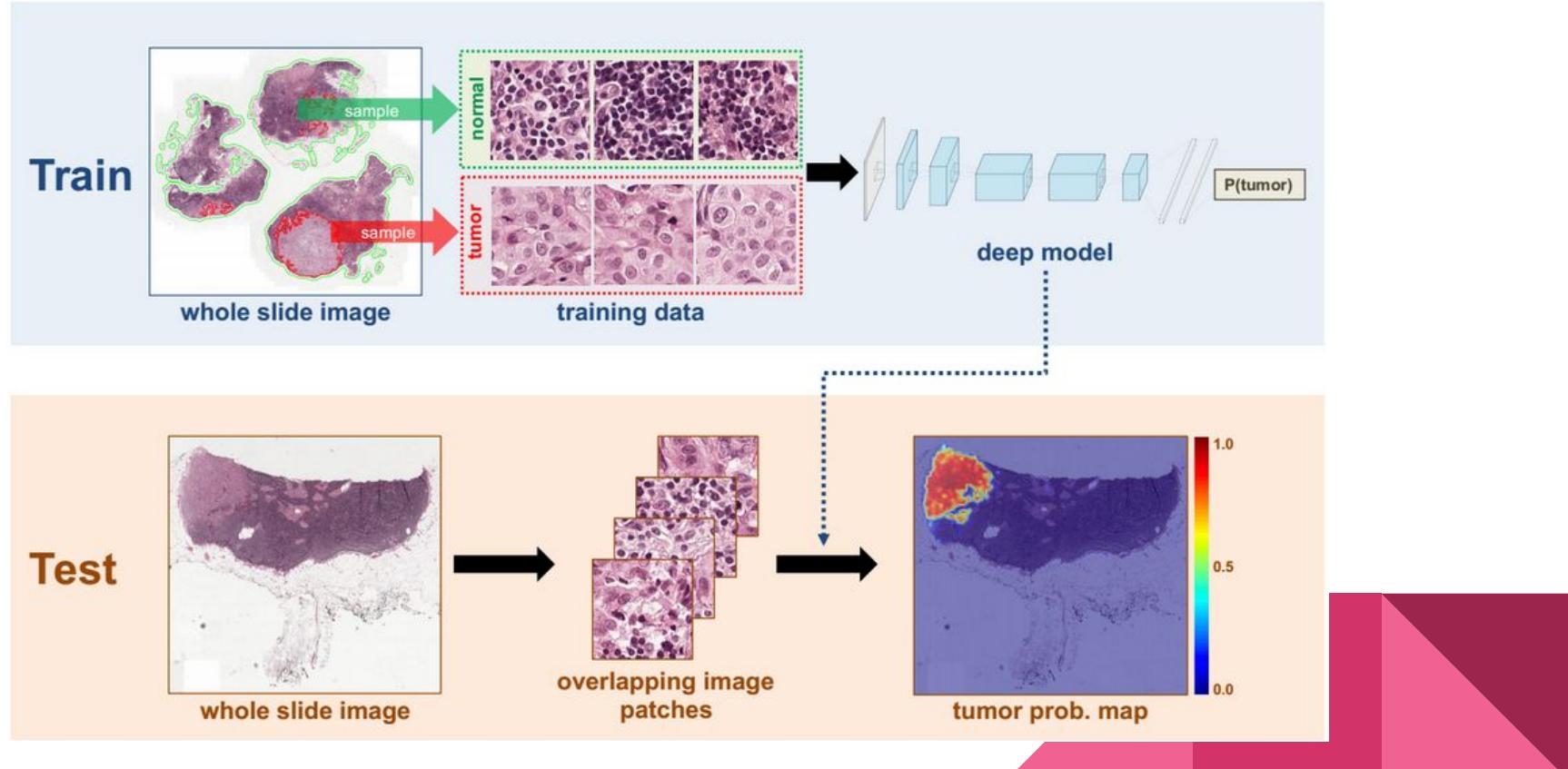
# Object Detection + Classification: Traffic Video Analysis for Assessing Safety Risks

- Nearly 2,000 people die annually as a result of being involved in traffic-related accidents in Jakarta, Indonesia.
- The city government has invested resources in thousands of traffic cameras to help identify potential short-term (e.g. vendor carts in a hazardous location) and long-term (e.g. poorly engineered intersections) safety risks.

# Traffic Counting and Classification

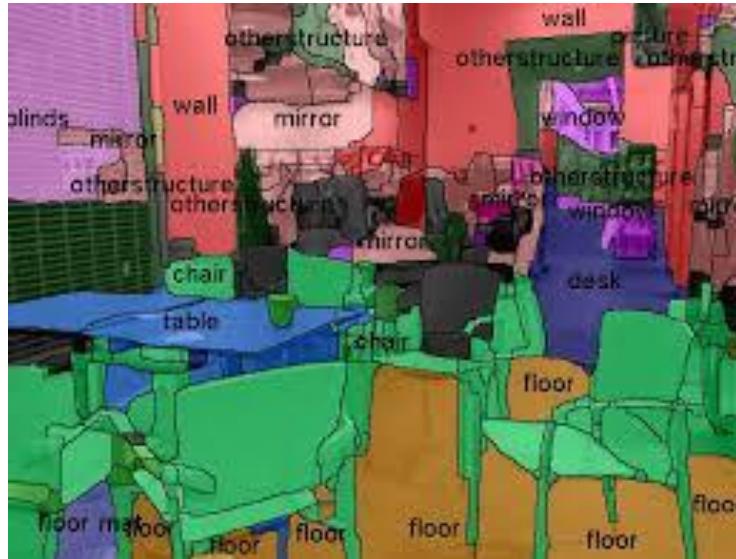


# Object Detection/Segmentation: Breast Cancer Diagnoses

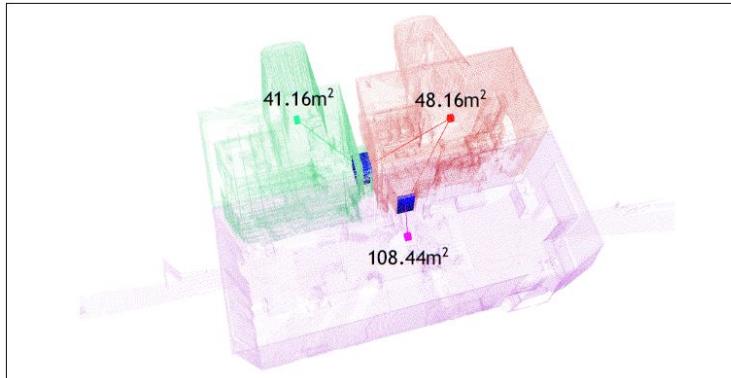
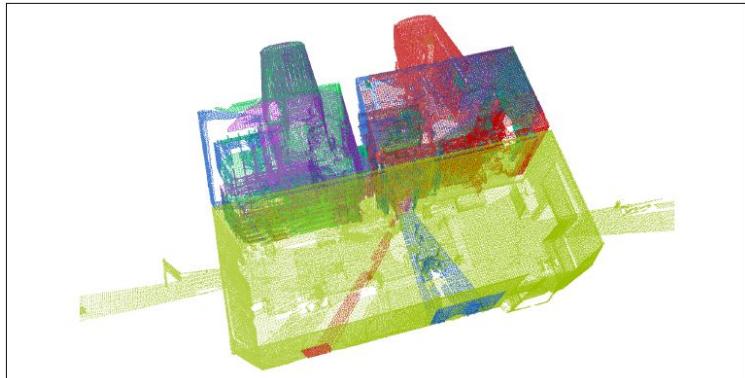
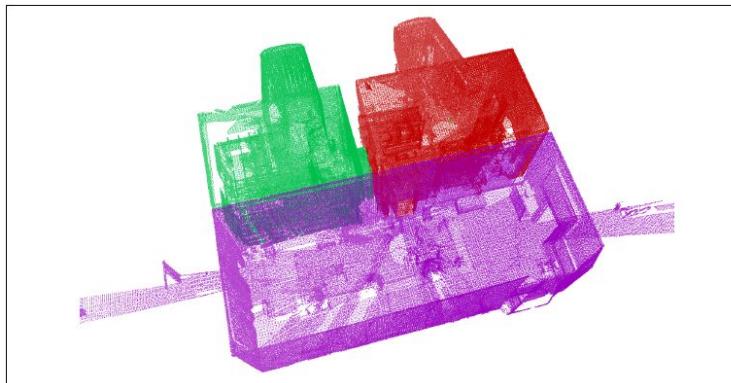
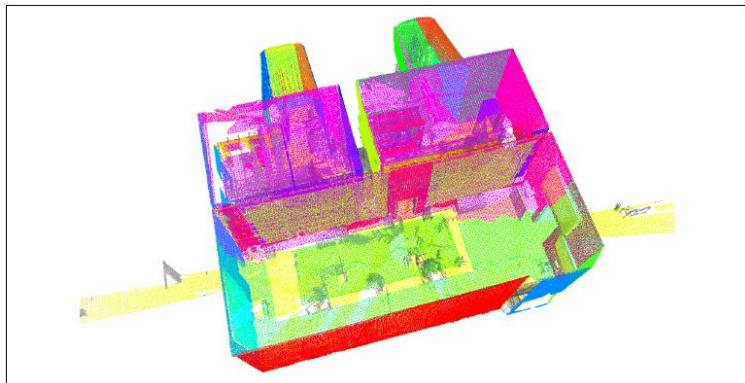


# Semantic Segmentation: Indoor Scene Understanding

- If we wish to design better indoor spaces for handicap accessibility, first we need to understand what stuff is present in our current living and working spaces.



# Semantic Segmentation: Accessibility Design



# Identifying Individuals / Motion Tracking

- The IBEIS Project: how to use safari pictures (taken by tourists!) to help ecologists study large herds of animals.
- Deep learning is used to:
  - Find animals in each photo, and
  - Identify individual animals based on their markings.
- Helps develop new methods to combat extinction.



**HOW MANY  
ZEBRAS &  
GIRAFFES  
ARE THERE AT THE NAIROBI  
NATIONAL PARK?**

Join in the 'Great Zebra and Giraffe Count' & help  
Scientists find out!

All you have to do is grab a camera (not a cellphone), drive around Nairobi Park for an hour or so on the 1st or 2nd of March and take as many pictures of zebras and giraffes as you can.

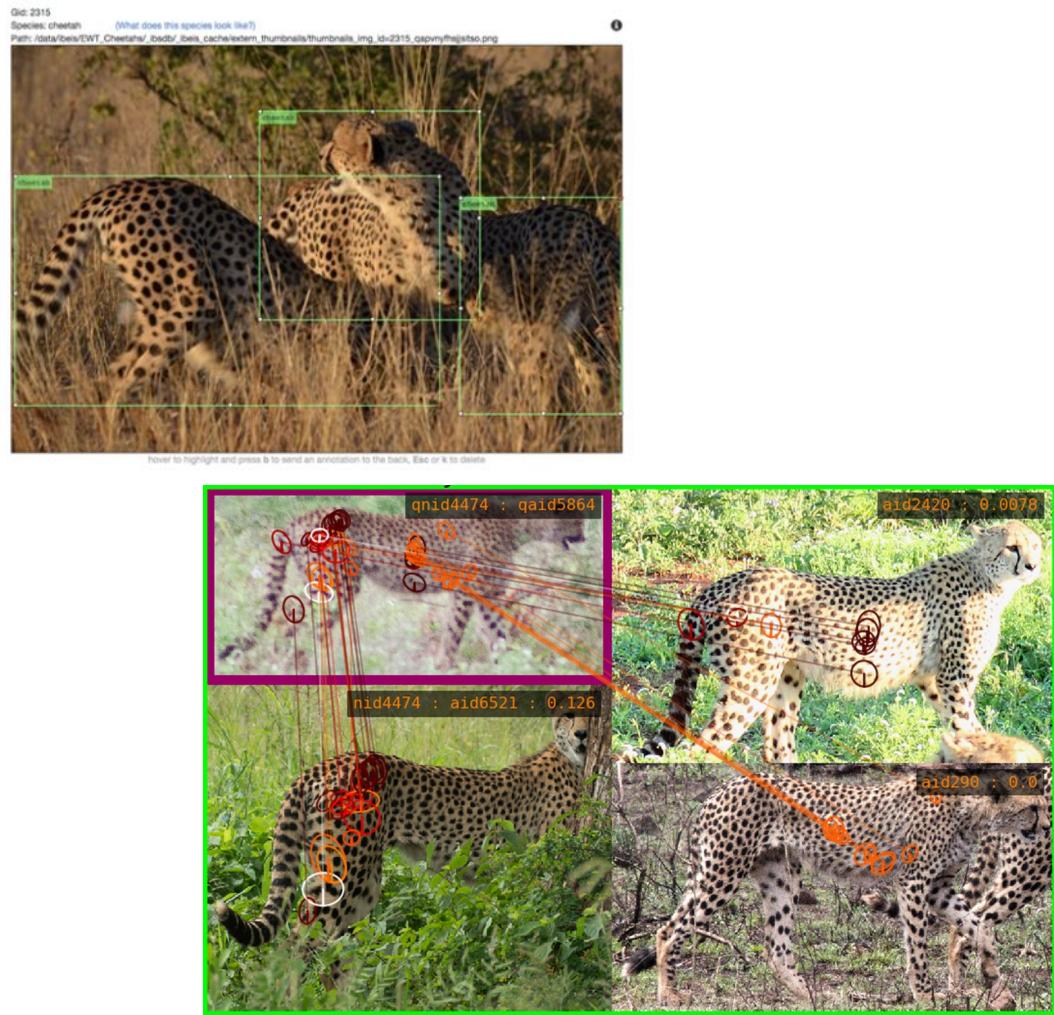
Scientists working with the Kenya Wildlife Service will do the rest! They will use IBEIS (Image-Based Ecological Information System) software to find all the zebras and giraffes in the photos and to recognize individual animals. IBEIS will help carry out a 'sight-resight' analysis that will estimate the overall numbers of the animals in the park.

**SO:**

- Form a team
- Pre-Register
- Show up, get briefed, get set up
- Be assigned a route and drive it
- Stop and take the pictures
- Share your card
- Receive a thank you gift
- And stay tuned for the analysis results will be emailed to you.

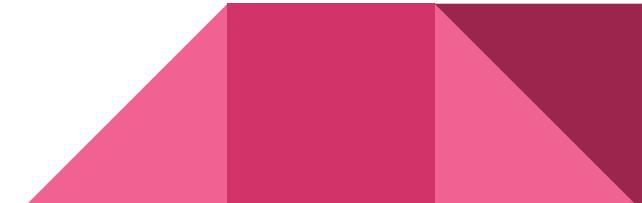
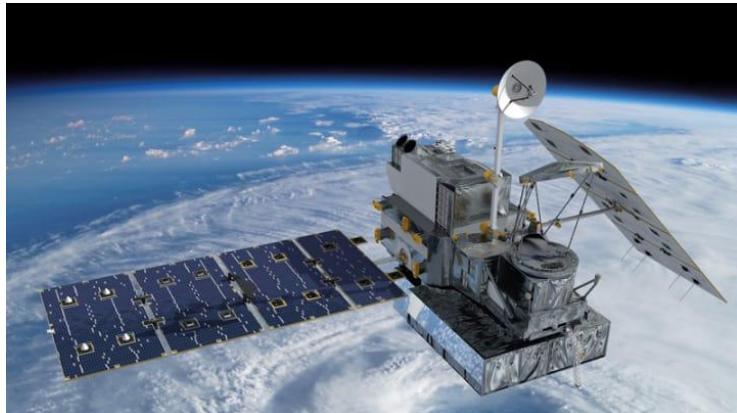
And best of all, have fun and help scientists learn about the zebras and giraffes of Nairobi National Park

Image Based Ecological Information System  
**IBEIS**

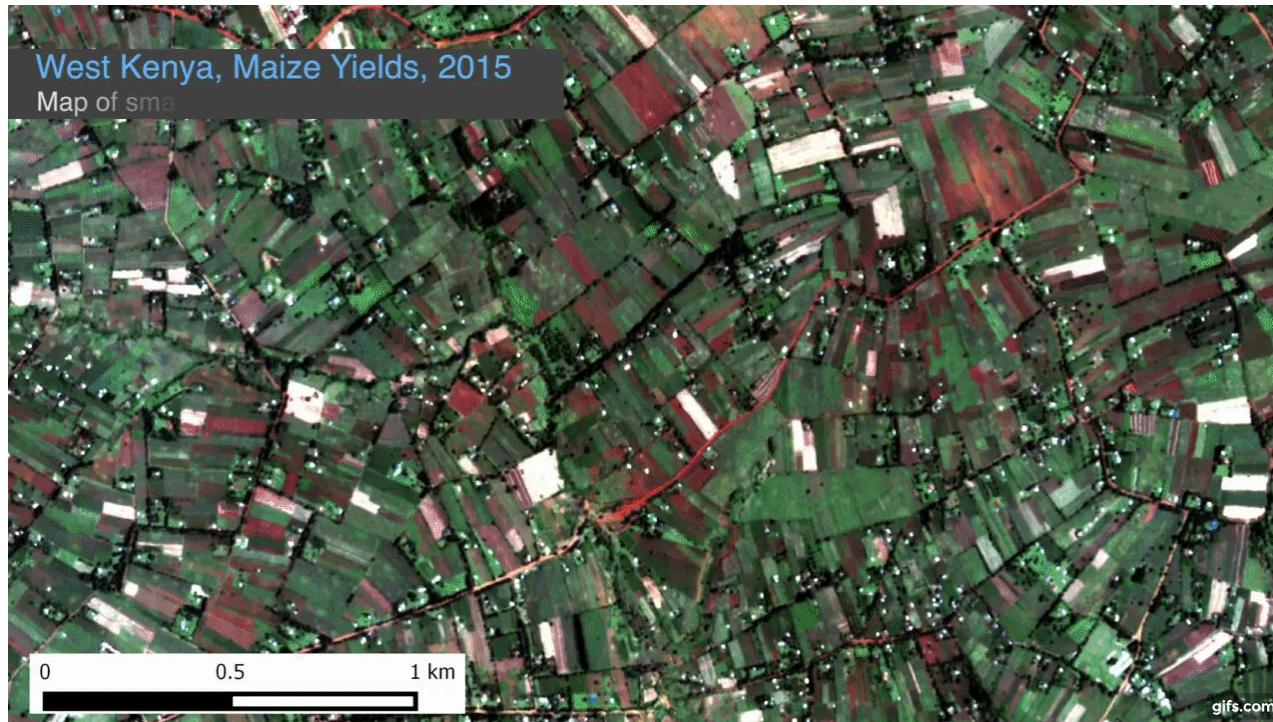


# Computer Vision for Policy Design + Planning

- How can we use existing data to improve civil planning?
- One idea: using satellite images to measure farm yields, and learn strategies to support small-scale farmers.



# Policy Design + Planning



# Computer Vision for Social Good

Takeaway:

Extremely powerful tools can be built by cleverly applying modern techniques for tasks like object detection, classification, and so on.

It's up to you to find creative new ways to solve old problems.

# Autonomous Vehicles

# LIDAR: How autonomous vehicles “see”



- LIDAR works sort of like radar: a device on top of the vehicle emits pulses of infrared light (invisible to the human eye) and measures how long they take to come back after hitting nearby objects .

# So you might look something like this...



# Some systems are augmented with cameras



- Visual input is more intuitive to human developers.  
So it makes it easier to do things like lane detection.



# Why have self-driving cars?

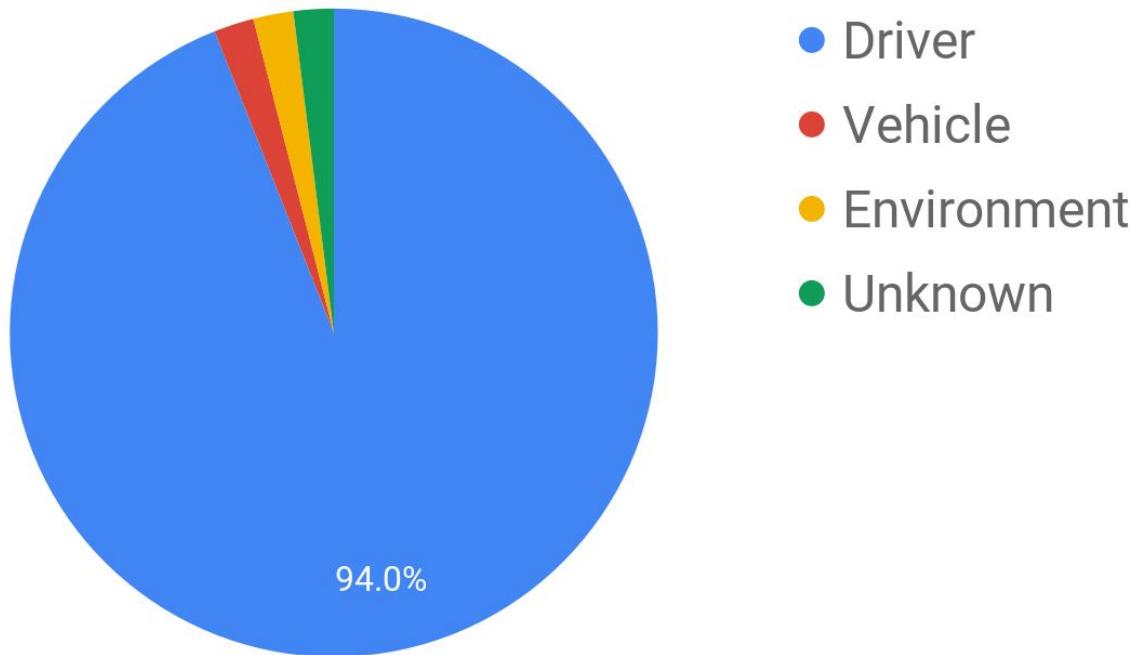
# Why have them? Safety.

- 35,092/yr die in car crashes
- Leading Cause of death for Teens
  - 16,375/year! (of ~40 mill)
- 90% of Crashes could be prevented!



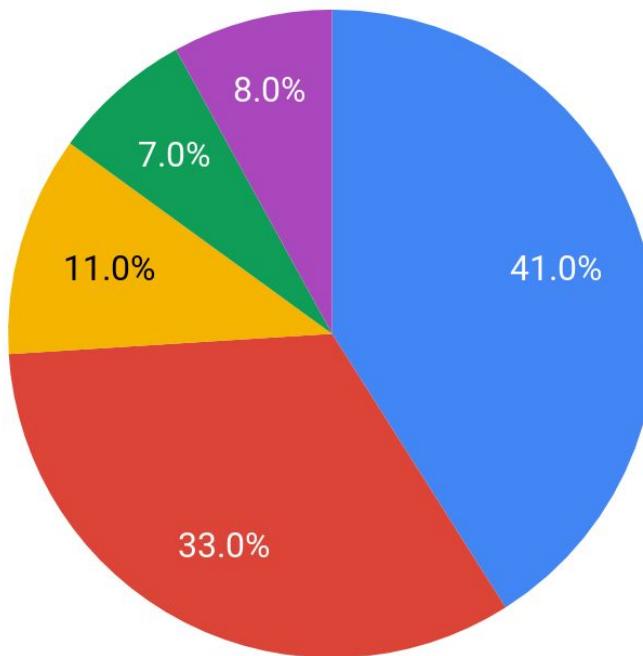
# Why have them? Safety.

Causes of Vehicle Crashes



# Why have them? Safety.

Driver-Related Causes of Crashes



- Recognition Error
- Decision Error
- Performance Error
- Non-performance Error
- Other

# Why have them? Quality of Life.

- Commute, Traffic
- Mobility, if you can't drive!
  - Elderly, Disabled, Young
  - But must be accessible!
- Savings!
  - \$1.3 Trillion for U.S. Economy  
(8% GDP)



# Where are we now?

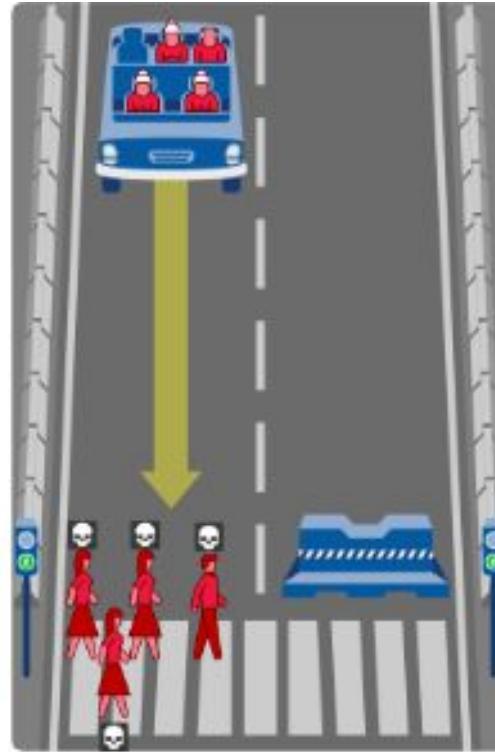
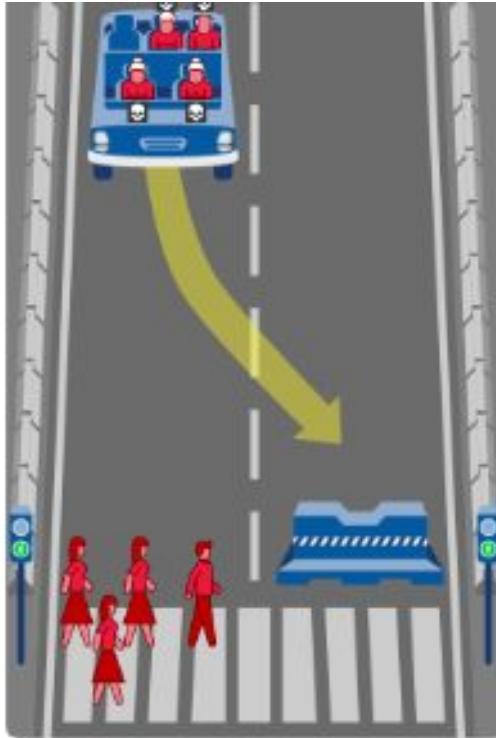
- Small Steps
  - Automatic Parking
  - Autopilot
  - Lane-keep assist
- 2018 Uber Crash
- Projections: 2018-2030



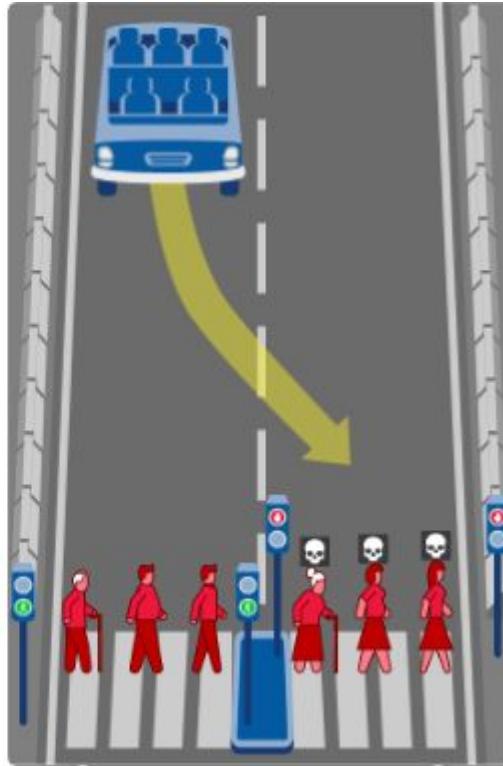
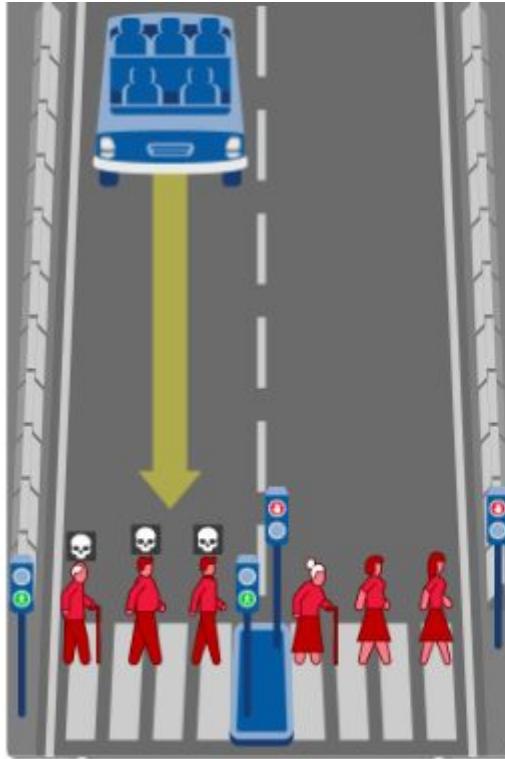


# How will these impact society?

# What should the car do?



# What should the car do?



# Technology Replaces Jobs

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Which of these can be automated? What else?



## US Labor Pool

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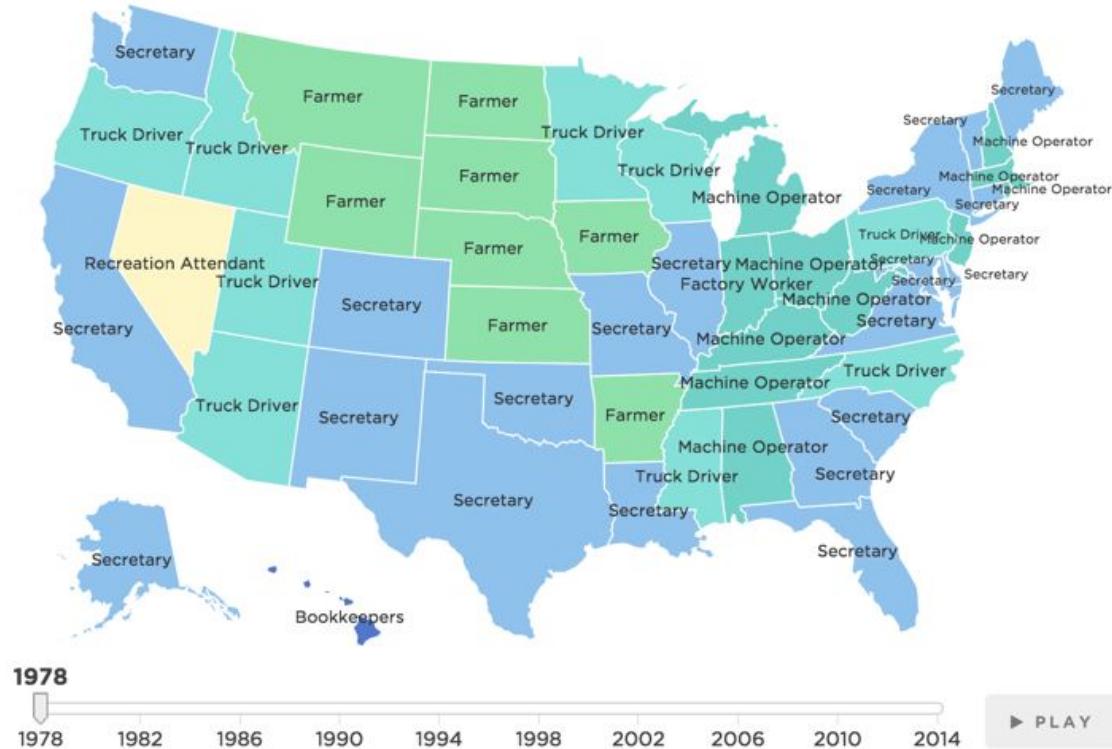
Of the following, what was the most common job in 2014?

1. Machine Operator
2. Farmer
3. Nurse
4. Truck Driver
5. Secretary
6. Teacher

FOLLOWUP

In how many states is this the most common job?

# What are the most common jobs?



<http://www.npr.org/sections/money/2015/02/05/382664837/map-the-most-common-job-in-every-state>

## US Labor Pool

---

Of the following, what was the most common job in 2014?

1. Machine Operator
2. Farmer
3. Nurse
4. **Truck Driver**
5. Secretary
6. Teacher

FOLLOWUP

In how many states is this the most common job? **29**



3.5 million truck drivers (~3% of workforce)  
unemployed.  
How do you handle this?

# Possibilities

- Tax AI
- Job Training Programs
- Universal Basic Income
- Auction Permits for Self-driving Vehicles



# Summary

- Motivation
- Applications
- A very brief history of neural nets
- Self-Driving Cars
- Ethics and Policy Questions



# Questions?

# References

- Slides 2; 6-14; 16-24: Olga Russakovsky and Andras Ferencz. “Introduction to Computer Vision” lecture slides:  
<http://www.cs.princeton.edu/courses/archive/fall17/cos429/outline.html>
- Slides 27-29: Olga Russakovsky. “Advanced Topics in Computer Science- Visual Recognition” lecture slides:  
[https://registrar.princeton.edu/course-offerings/course\\_details.xml?courseid=002129&term=1184](https://registrar.princeton.edu/course-offerings/course_details.xml?courseid=002129&term=1184)
- Slides 30-36: Antonio Torralba and Alyosha Efros. “Unbiased Look at Dataset Bias”:  
<http://people.csail.mit.edu/torralba/research/bias/>
- Slide 37: Moritz Hardt. “Fairness in Machine Learning” lecture slides:  
<https://fairmlclass.github.io/>
- Slides 41-58: Riley Simmons-Edler and Berthy Feng. Visual Recognition seminar slides:  
<https://docs.google.com/presentation/d/1Nw7f63wNaoRWTa6j77rGwQjSULTAicnKqQQ7fveVbAk/edit#slide=id.p>

# Backup Slides

# Datasets and Bias

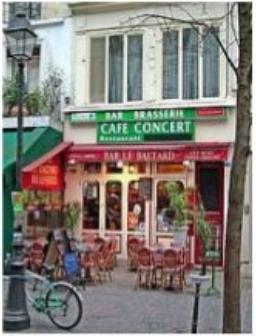
# But we must be careful!



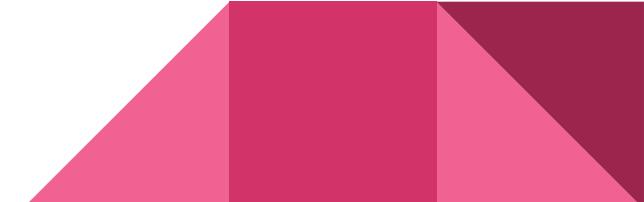
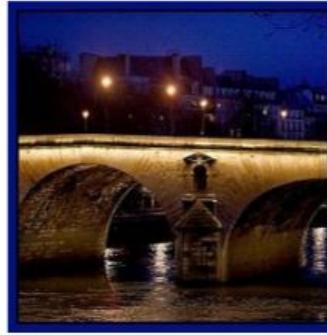
Do datasets provide a  
*good* representation of the  
world?

# Visual Data is Inherently Biased

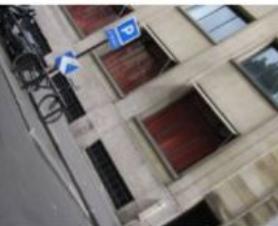
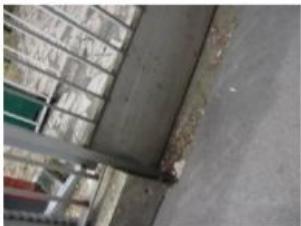
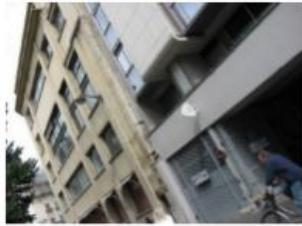
- Internet is a tremendous repository of visual data (Flickr, YouTube, Picassa, etc)
- But it's not random samples of visual world



# Flickr Paris



# Sampled Alyosha Efros's Paris



# Sampling Bias

- People like to take pictures on vacation



# Photographer Bias

- People want their pictures to be recognizable and/or interesting



vs.



# Social Bias



Little Leaguer



Kids with Santa



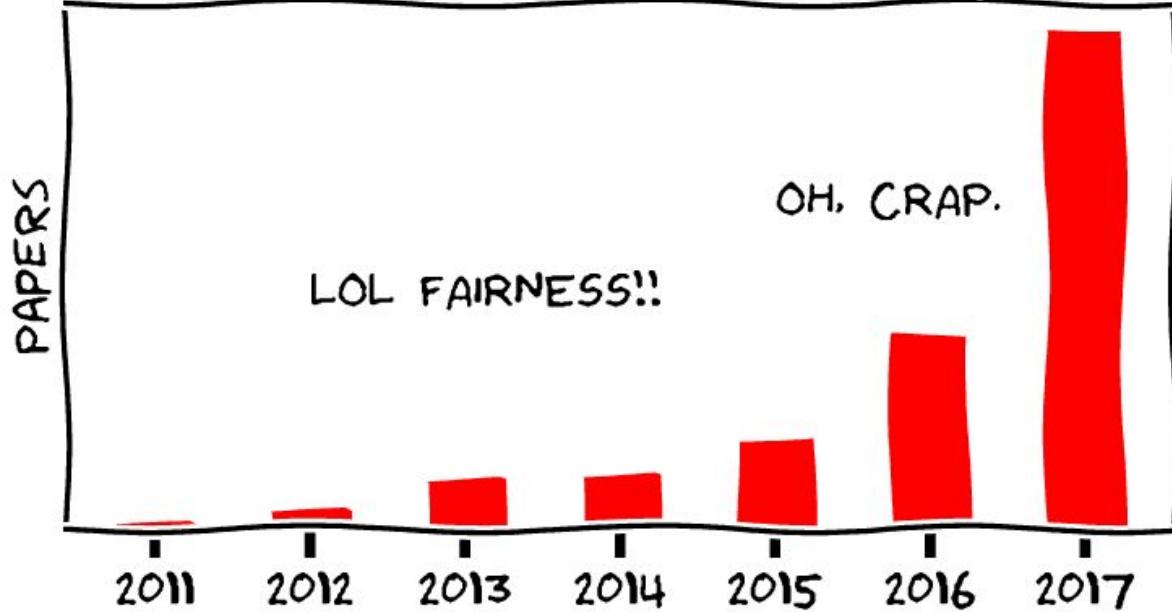
The Graduate



Newlyweds

**“100 Special Moments” by Jason Salavon**

## BRIEF HISTORY OF FAIRNESS IN ML



# Where does bias come from?

Collection:

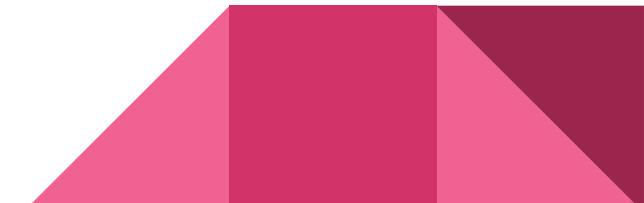
- Demographic, geographic, behavioral, temporal biases,

Measurement:

- What do we choose to measure? How do we measure (e.g., *grit*)?

Pre-existing biases

- gender roles in text and images, racial stereotypes in language



# To learn more about bias in AI:

- ?

## **LEVEL 0**



There are no autonomous features.

## LEVEL 0



There are no autonomous features.

## LEVEL 1



These cars can handle one task at a time, like automatic braking.

## LEVEL 0



There are no autonomous features.

## LEVEL 1



These cars can handle one task at a time, like automatic braking.

## LEVEL 2



These cars would have at least two automated functions.

## LEVEL 0



There are no autonomous features.

## LEVEL 1



These cars can handle one task at a time, like automatic braking.

## LEVEL 2



These cars would have at least two automated functions.

## LEVEL 3



These cars handle "dynamic driving tasks" but might still need intervention.

## LEVEL 0



There are no autonomous features.

## LEVEL 1



These cars can handle one task at a time, like automatic braking.

## LEVEL 2



These cars would have at least two automated functions.

## LEVEL 3



These cars handle "dynamic driving tasks" but might still need intervention.

## LEVEL 4



These cars are officially driverless in certain environments.

## LEVEL 0



There are no autonomous features.

## LEVEL 1



These cars can handle one task at a time, like automatic braking.

## LEVEL 2



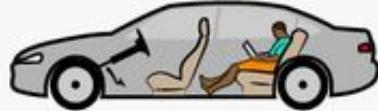
These cars would have at least two automated functions.

## LEVEL 3



These cars handle "dynamic driving tasks" but might still need intervention.

## LEVEL 4



These cars are officially driverless in certain environments.

## LEVEL 5



These cars can operate entirely on their own without any driver presence.

# Technology: More Wealth-- but More Inequality

