AI for Everyone

Presidential Initiative for Artificial Intelligence and Computing

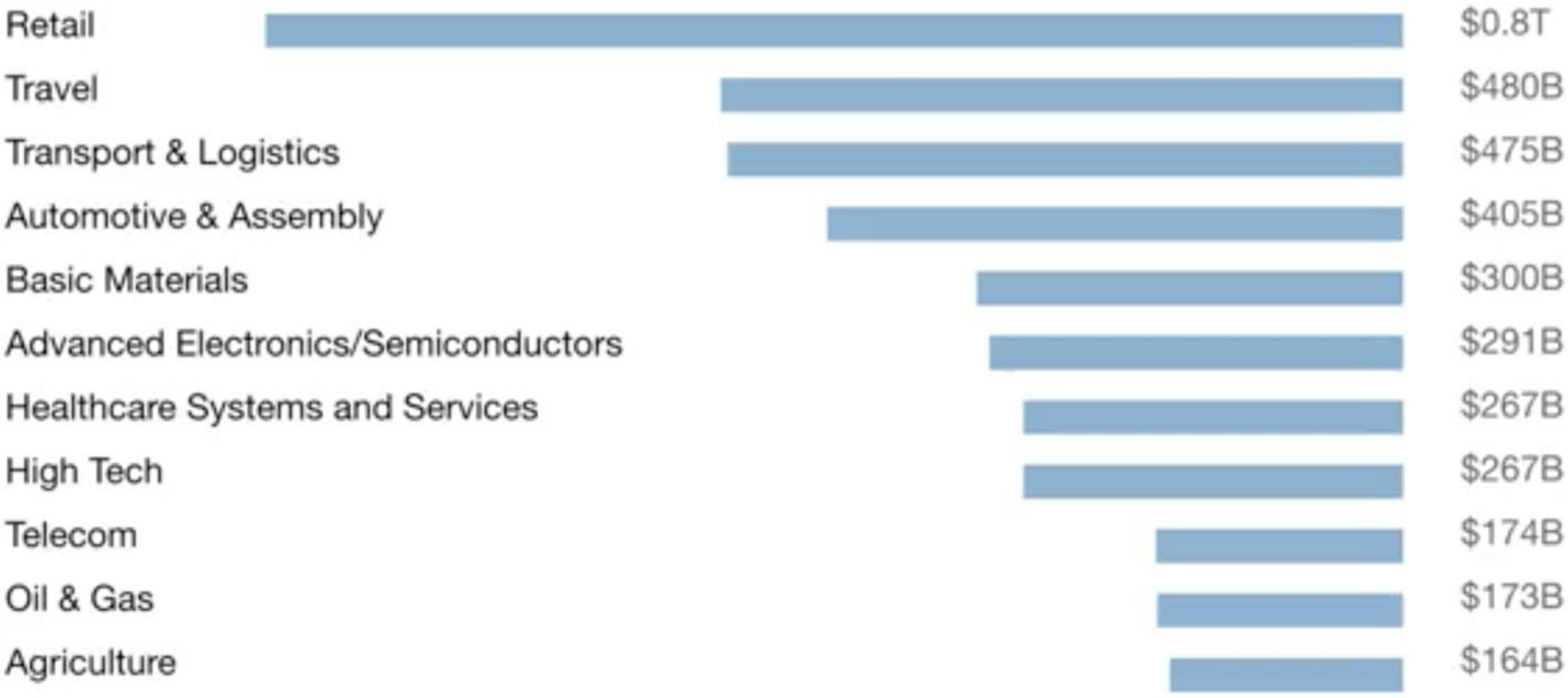
Objectives of this Course

1. The meaning behind common AI terminology, including neural networks, machine learning, deep learning, and data science
2. What AI realistically can--and cannot--do
3. How to spot opportunities to apply AI to problems in your own organization
4. What it feels like to build machine learning and data science projects
5. How to work with an AI team and build an AI strategy in your company
6. How to navigate ethical and societal discussions surrounding AI

$13 Trillion

AI value creation by 2030

[Source: McKinsey Global Institute]



A lot of the value created by AI will be outside the software industry. AI will have a huge impact on all the major industries.

There are 2 types of AI

ANI

Artificial Narrow Intelligence

LOTS OF PROGRESS

ALMOST NO PROGRESS

AGI

Artificial General Intelligence

Artificial Narrow Intelligence (ANI)

These are AIs that do one thing such as:

- smart speaker
- self-driving car
- AI to do web search
- AI applications in farming or in a factory.

These types of AI are one trick ponies but when you find the appropriate trick, this can be incredibly valuable.

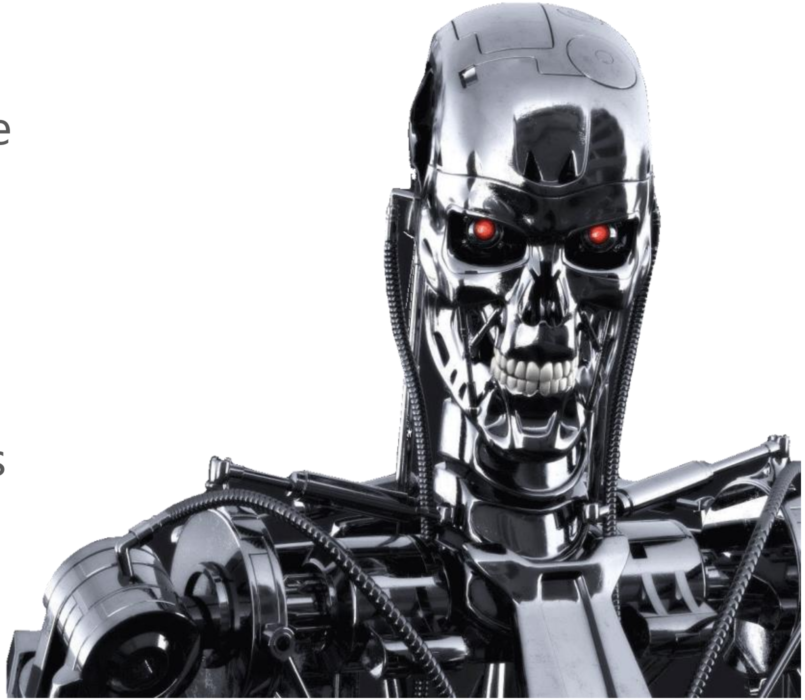
Artificial General Intelligence (AGI)

That is the goal to build AI.

They can do anything a human can do or maybe even be superintelligent and do even more things than any human can.

Progress in ANI vs AGI

The rapid progress in ANI has caused people to conclude that there's a lot of progress in AI, which is true. But that has caused people to falsely think that there might be a lot of progress in AGI as well which is leading to some irrational fears about evil clever robots coming over to take over humanity anytime now.



Achieving AGI Will Take Time

AGI is an exciting goal for researchers to work on, but it requires many technological breakthroughs before we get there and it may be decades or hundreds of years or even thousands of years away.

Machine Learning

Supervised Learning

If the input is an audio clip, and the AI's job is to output the text transcript, then this is speech recognition.

Input (A)
Audio

Output (B)
Text (0/1)

Application
Speech Recognition

Supervised Learning

If you want to input English and have it output a different language, Chinese, Spanish, something else, then this is machine translation.

Input (A)
English

Output (B)
Chinese

Application
Machine Translation

Supervised Learning

All the large online ad platforms have a piece of AI that inputs some information about an ad, and some information about you, and tries to predict, will you click on this ad or not?

Input (A)
Ad + User Info

Output (B)
Click? (0/1)

Application
Machine Translation

Supervised Learning

If you want to build a self-driving car, one of the key pieces of AI is the AI that takes as input an image, and some information from radar, or from other sensors, and outputs the position of other cars, so your self-driving car can avoid the other cars.

Input(A)
Image, radar
info

Position of other
cars

Self-Driving Car

Supervised Learning

In Manufacturing, we take as input a picture of something you've just manufactured, such as a picture of a cell phone coming off the assembly line., and you want to output, is there a scratch, or is there a dent, or some other defects on this thing you've just manufactured? This is **visual inspection** which is helping manufacturers to reduce or prevent defects in the things that they're making.

Input (A)
Image of a phone

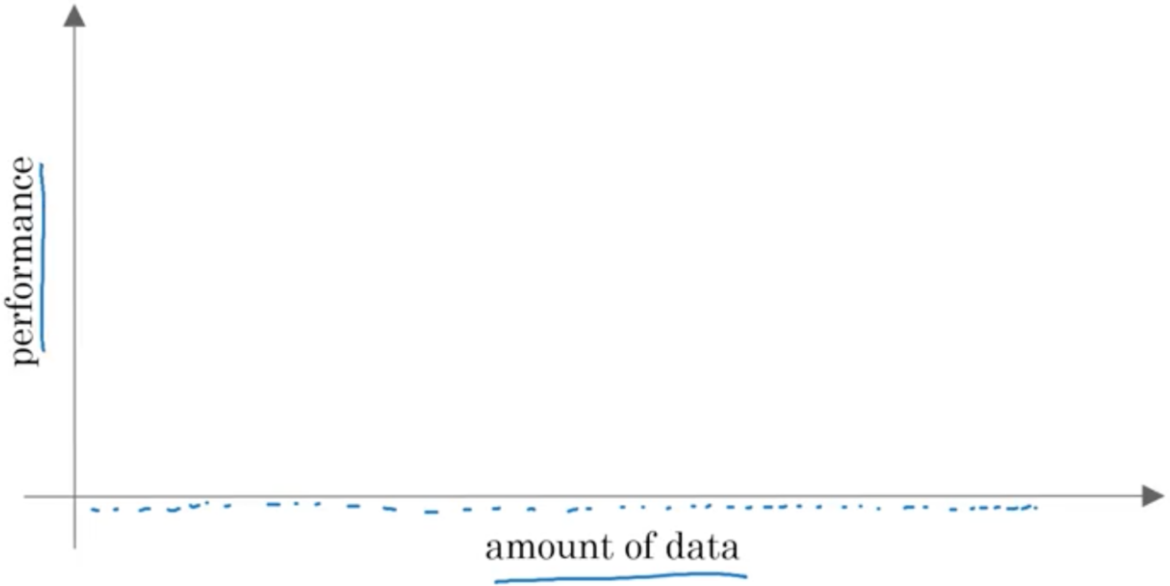
Output (B)
Defects (0/1)

Visual Inspection

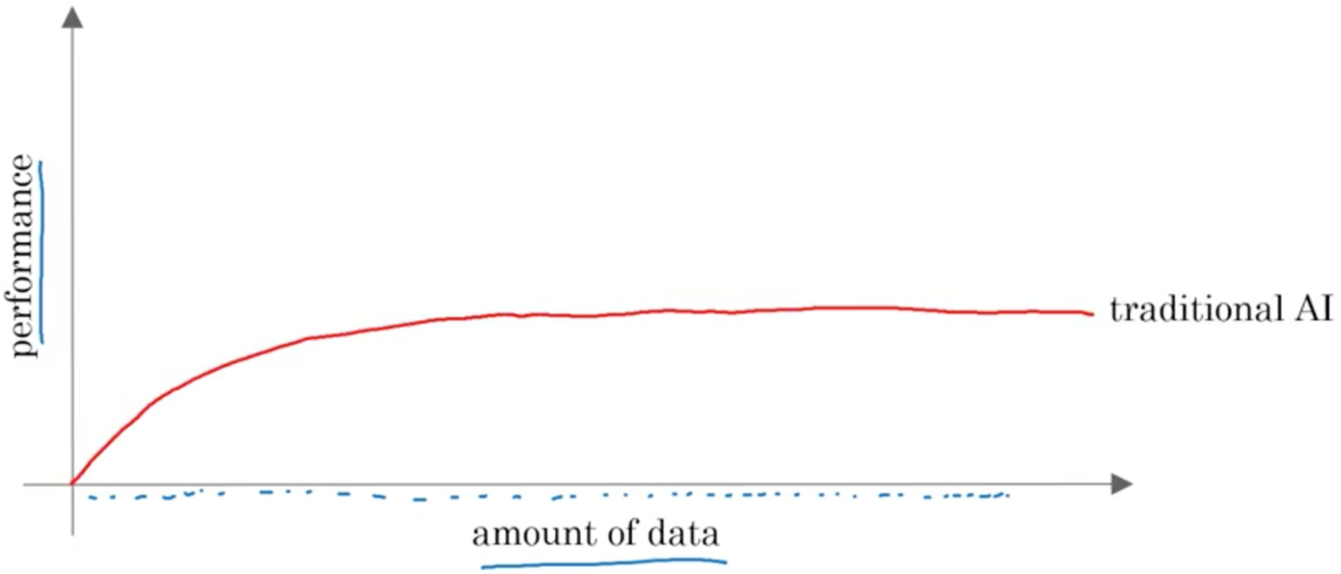
Supervised Learning

This set of AI called supervised learning, just learns input to output, or A to B mappings. On one hand, input to output, A to B it seems quite limiting. But when you find a right application scenario, this can be incredibly valuable.

Why Now?



Why Now?



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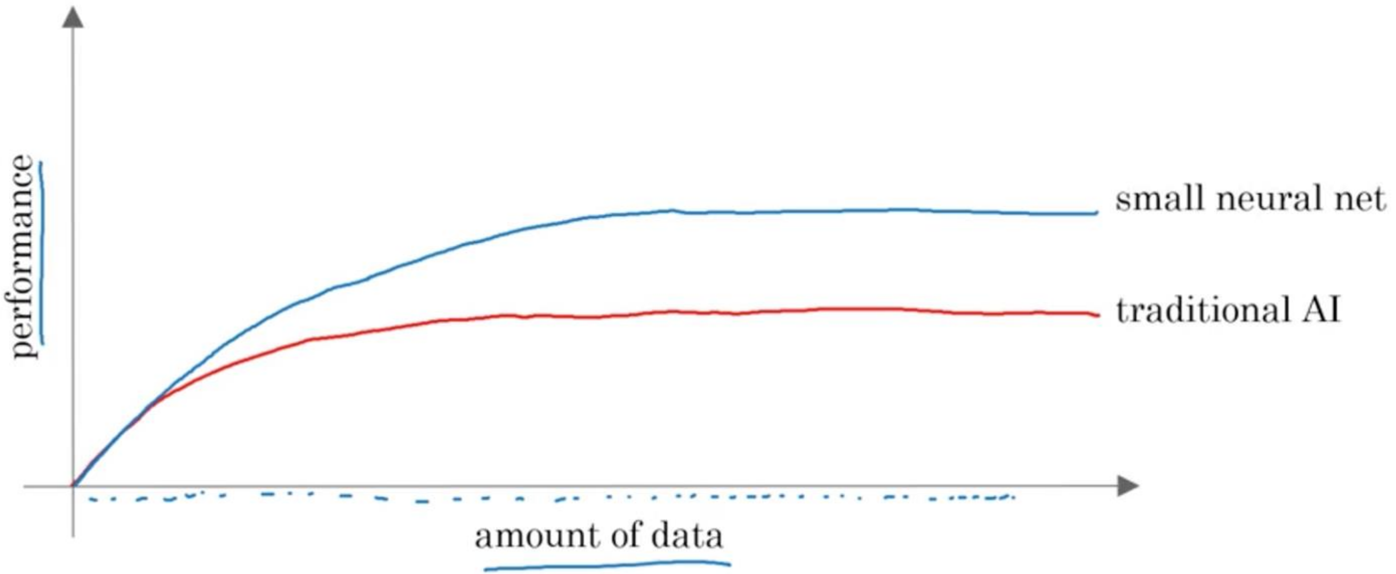
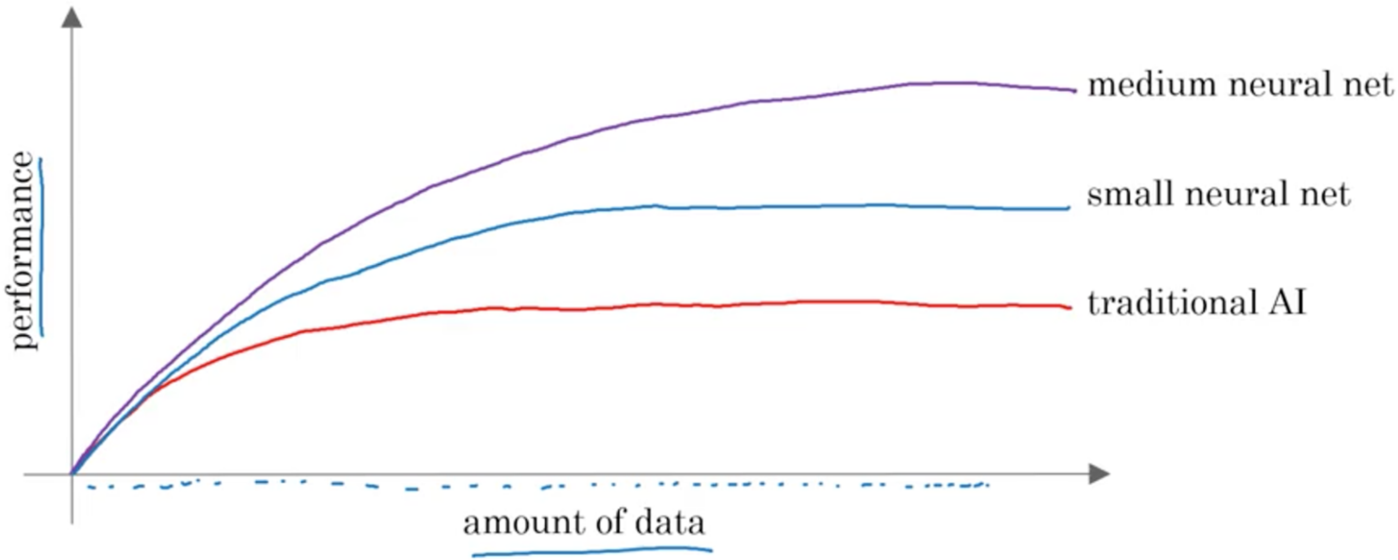
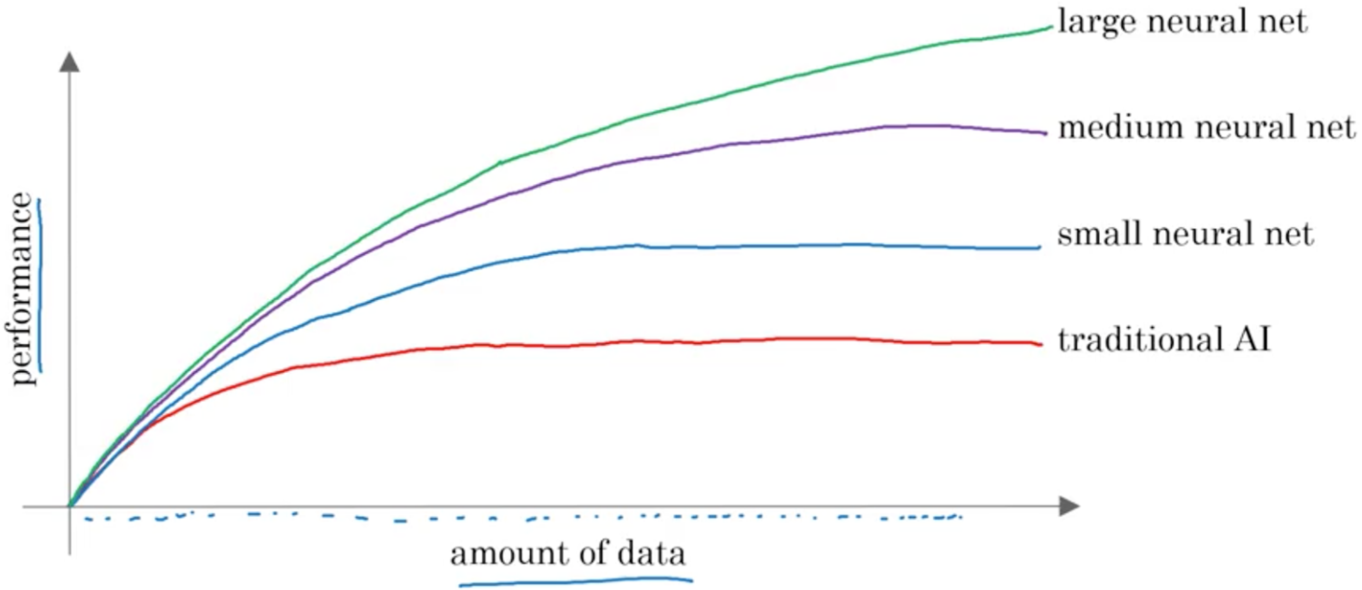

small neural net
traditional AI
performance
amount of data

Why Now?



medium neural net
small neural net
traditional AI
performance
amount of data

Why Now?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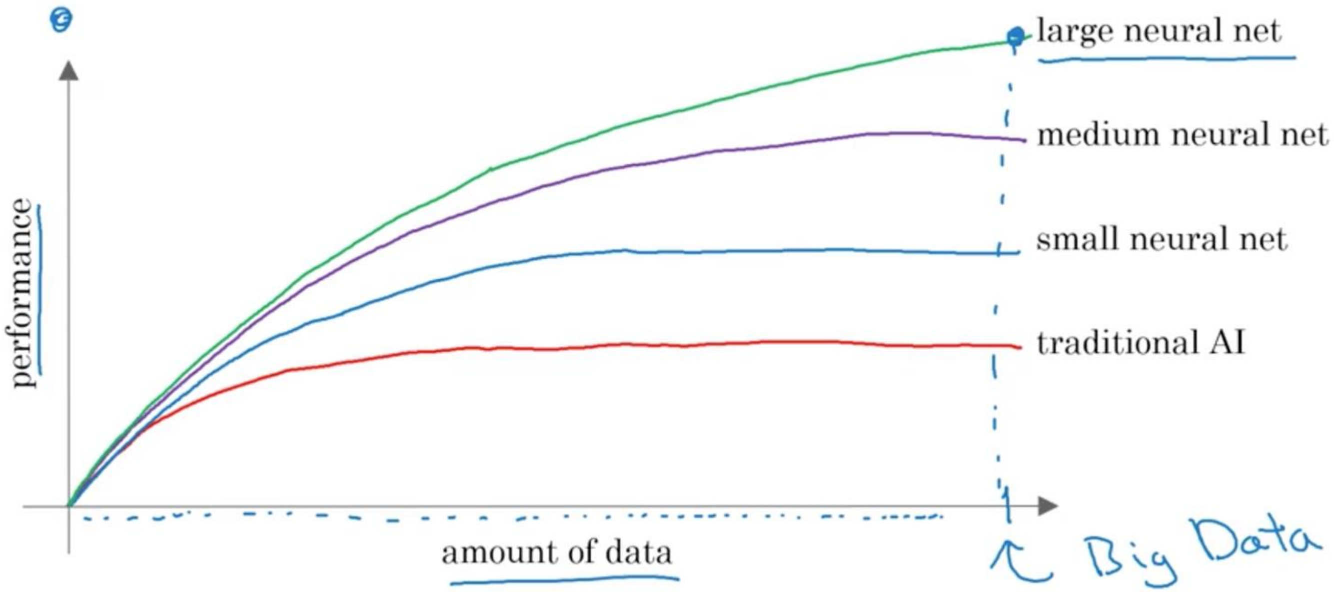

large neural net
medium neural net
small neural net
traditional AI
performance
amount of data
Big Data

The Rise of Fast Computers

So, the rise of fast computers with specialized processors such as graphics processing units or GPUs has enabled many companies, not just giant tech companies, but many many other companies to be able to train large neural nets on a large enough amount of data in order to get very good performance and drive business value.

What is the most important idea in AI?

Machine Learning

What is Supervised Learning?

A to B mappings

Input to Output mappings

What enables machine learning to work so well?

What is Data

A Table of Data (Dataset)

Size of House (Square Feet)	Price ($1000)
523	115
645	150
708	210
1034	280
2290	355
2545	440
A	**B**

A Table of Data (Dataset)

Size of House (Square Feet)	# of Bedrooms	Price ($1000)
523	1	115
645	1	150
708	2	210
1034	3	280
2290	4	355
2545	4	440
A		**B**

Data is often unique to your business

Data is often unique to your business, and this is an example of a dataset that a real estate agency might have that they tried to help price houses.

It's up to you to decide what is A and what is B, and how to choose these definitions of A and B to make it valuable for your business.

Another example

If you have a certain budget and you want to decide what is the size of house you can afford, then you might decide that the input A is how much does someone spend and B is just the size of the house in square feet, and that would be a totally different choice of A and B that tells you, given a certain budget, what's the size of the house you should be maybe looking at.

A Table of Data (Dataset)

Size of House (Square Feet)	# of Bedrooms	Price ($1000)
523	1	115
645	1	150
708	2	210
1034	3	280
2290	4	355
2545	4	440
B		**A**

Acquiring data

- Manual labeling

Acquiring data

- From observing behaviors of humans

User ID	Time	Price ($)	Purchased
4783	Jan 21 08:15.20	7.95	yes
3893	Mar 3 11:30.15	10.00	yes
8384	Jun 11 14:15.05	9.50	no
0931	Aug 2 20:30.55	12.90	yes

Acquiring data

- From observing behaviors of machines

Machine	Temperature	Pressure (psi)	Machine Fault
17987	60	7.65	N
34672	100	25.50	N
08542	140	75.50	Y
98536	165	125	Y
Input A			**Input B**

Acquiring data

- Download from websites / partnerships
  - Thanks to the open internet you can find so many datasets available for free online
    - Computer vision or image datasets
    - Self driving car datasets
    - Speech recognition datasets
    - Medical imaging datasets
  - Keep in mind licensing and copyright

Use and misuse of data

Give me three years to build up my IT team, we're collecting so much data.

Then after three years, I'll have this perfect dataset.

We'll do AI then.

What's wrong with this approach?

Use and misuse of data

It turns out that's a really bad strategy.

Once you've started collecting some data, go ahead and start showing it or feeding it to an AI team.

Then the AI team can give feedback to your IT team on what types of data to collect and what types of IT infrastructure to keep on building.

Example

Maybe an AI team can look at your factory data and say, "Hey. You know what? If you can collect data from this big manufacturing machine, not just once every ten minutes, but instead once every one minute, then we could do a much better job building a preventative maintenance systems for you."

Machine	Temperatur e	Pressure (psi)	Machine Fault
17987	60	7.65	N
34672	100	25.50	N
08542	140	75.50	Y
98536	165	125	Y
Input A			**Input B**

Use and misuse of data

"Hey, I have so much data. Surely, an AI team can make it valuable."

What's wrong with this statement?

Use and misuse of data

Unfortunately, this doesn't always work out.

More data is usually better than less data, but I wouldn't take it for granted that just because you have many terabytes or gigabytes of data, that an AI team can actually make that valuable.

Don't throw data at an AI team and assume it will be valuable.

Data is Messy

Not a
cat

Not a
cat

Cat

Cat

Data is Messy

If you have bad data, then the AI will learn inaccurate things.

Data problems:

- Incorrect labels
- Missing values

Multiple types of data

- Unstructured Data: Images, audio, text

Example

You can have incorrect labels or just incorrect data. For example, this house is probably not going to sell for $0.1 just for one dollar.

Or, data can also have missing values such as we have here a whole bunch of unknown values.

This is structured data.

Size of House (Square Feet)	# of Bedrooms	Price ($1000)
523	1	115
645	1	0.001
708	unknown	210
1034	3	unknown
unknown	4	355
2545	unknown	440

Machine Learning vs Data Science

Size of House (Square Feet)	# of Bedrooms	# of Bathrooms	Newly Renovated	Price ($1000)
523	1	2	N	115
645	1	3	N	150
708	2	1	N	210
1034	3	3	Y	280
2290	4	4	N	355
2545	4	5	Y	440
A				**B**

Running AI System

A software that which automatically returns output B for input A.

If you have an AI system running, serving dozens or hundreds of thousands or millions of users, that's usually a machine-learning system.

Data Science

If you want to have a team analyze your dataset in order to gain insights. **The output of a data science project is a set of insights that can help you make business decisions**

So, a team might come up with conclusions like:

- "Hey, did you know if you have two houses of a similar size, they've a similar square footage, if the house has three bedrooms, then they cost a lot more than the house of two bedrooms, even if the square for this is the same."

Data Science

- "Did you know that newly renovated homes have a 15% premium, and this can help you make decisions such as, given a similar square footage, do you want to build a two bedroom or three bedroom size in order to maximize value? "
- "Is it worth an investment to renovate a home in the hope that the renovation increases the price you can sell a house for?"

The output of a data science project is a set of insights that can help you make business decisions, such as what type of house to build or whether to invest in renovation.

Machine Learning vs Data Science

Machine Learning

"Field of study that gives computers the ability to learn without being explicitly programmed."

- Arthur Samuel (1959)

A machine learning project will often result in a piece of software that runs, that outputs B given A.

Formal Definition of Data Science

Data science is the science of extracting knowledge and insights from data.

So, the output of a data science project is often a slide deck, the presentation summarizes conclusions for executives to take business actions or summarizes conclusions for a product team to decide how to improve a website.

Example of ML vs DS in the online ad industry

Large platforms have AI that quickly tells them what's the ad you're most likely to click on. This is a machine learning system. It inputs information about the user and about the ad and outputs whether the user will click on the ad or not.

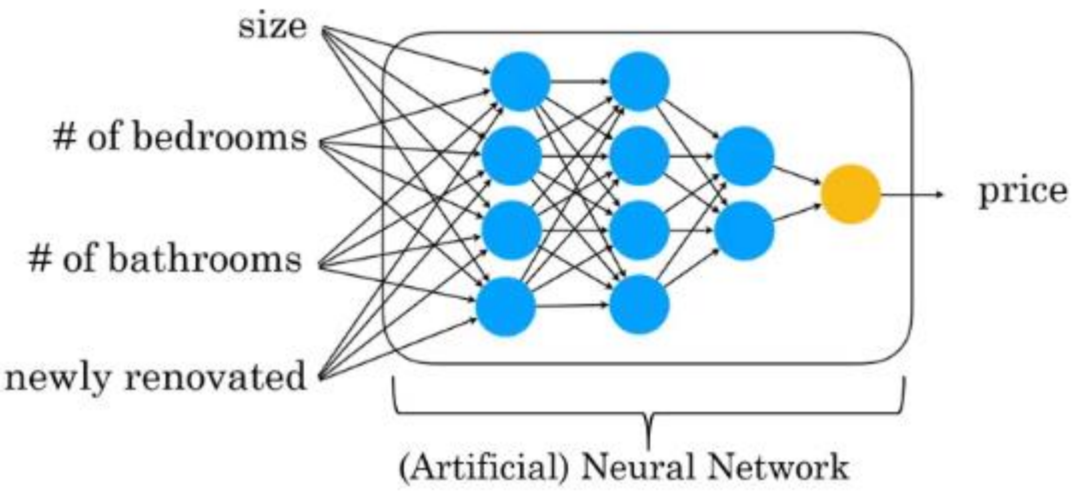
These systems run 24/7 and drive ad revenue for these platforms.

Example of ML vs DS in the online ad industry

If analyzing data tells you, for example, that the travel industry is not buying a lot of ads, but if you send more salespeople to sell ads to travel companies, you could convince them to use more advertising, then that would be an example of a data science project.

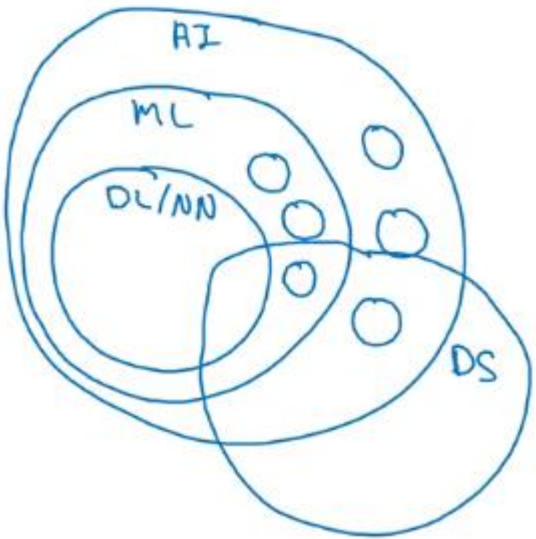
The data science conclusion results in the executives deciding to ask a sales team to spend more time reaching out to the travel industry.

Deep Learning



AI and related disciplines

- Machine Learning
- Data Science
- Deep Learning / Neural Network
- Supervised Learning
- Un supervised learning
- Reinforcement Learning



What makes a company AI company?

- Strategic data acquisition
- Unified datawarehouse
- Pervasive automation
- New roles such as MLE

AI Transformation

1. Execute pilot projects to gain momentum
2. Build an in-house AI team
3. Provide broad AI training
4. Develop an AI strategy
5. Develop internal and external communications

Deciding about a new project

- Technical diligence
  - Is it feasible project?
  - Can AI do that?
- Pretty much any thing you can do with a second of thought can be automated using supervised learning

Supervised learning tasks

Input (A)	Output (B)	Application
email	spam? (0/1)	spam filtering
audio	text transcripts	speech recognition
English	Chinese	machine translation
ad, user info	click? (0/1)	online advertising
image, radar info	position of other cars	Self-driving car
image of phone	defect? (0/1)	visual inspection

What machine learning today can and cannot do

The toy arrived two days late, so I wasn't able to give it to my niece for her birthday.
Can I return it?

"Refund request"

Input text $\longrightarrow$ Refund/Shipping/Other

$A \longrightarrow B$

Oh, sorry to hear that.
I hope your niece had a good birthday.
Yes, we can help with….

Examples of what ML can and can’t do?

- Identifying the intent of the customer - Possible
- Writing an emphatic response to customer’s email – Not possible or difficult

Technical diligence rules

- You are learning a simple concept
- Do you have large training data

More examples

- Self driving car
  - Input is from sensors, camera
  - Output where are the other cars
- Recognizing gesture of traffic police, construction work, people– not possible
  - Critical application requires good accuracy

X-ray diagnosis

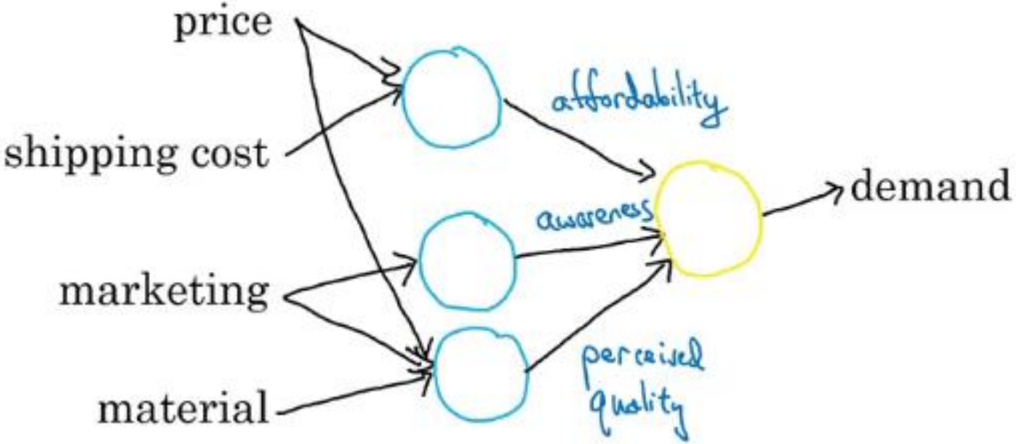
- Diagnosing a disease from X-ray images– possible
- Diagnosing a disease after reading a book

Strengths and weakness of ML

- Works when,
  - Learning a simple concept
  - Lots of data available
- Doesn’t work when,
  - Learning a complex concept
  - Asked to work on new type of data such as X-ray images in different conditions and angles

Demand prediction based on price

- Price -> Demand can be modeled using a neural network using a neuron
  - (Perceptron model)
- Network of neurons (ANN)
  - Price
  - Shipping Cost
  - Marketing
  - Meterial

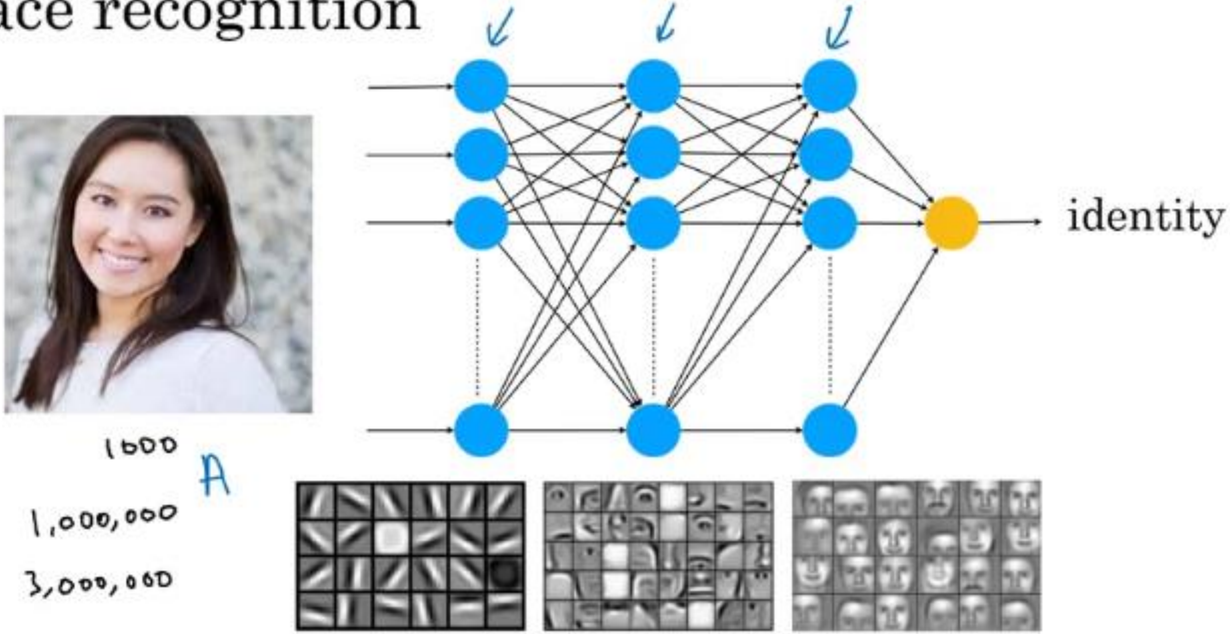


price
shipping cost
marketing
material
affordability
awareness
perceived quality
demand

Face recognition

- Pictures comprise pixels
    - Color images and channels
- A neural network corresponds to pixels
- Earlier layers will detect edges, then lobes and then objects

Face recognition



1000

1000

A

1,000,000

3,000,000

Speech Recognition

Amazon
Echo / Alexa

Google
Home

Apple
Siri

Baidu
DuerOS

Key steps of Echo / Alexa

- Collect data
    - Labelled voice
- Train model
    - Iterate many times
- Deploy the model
    - Get more data and update model

Key steps of a machine learning project

Self-driving car

1. Collect data

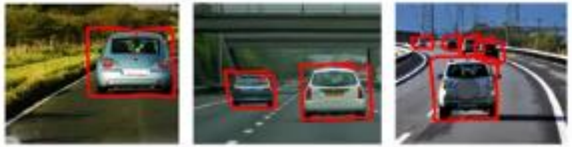


image ⟶ position of other cars

2. Train model

   Iterate many times until good enough

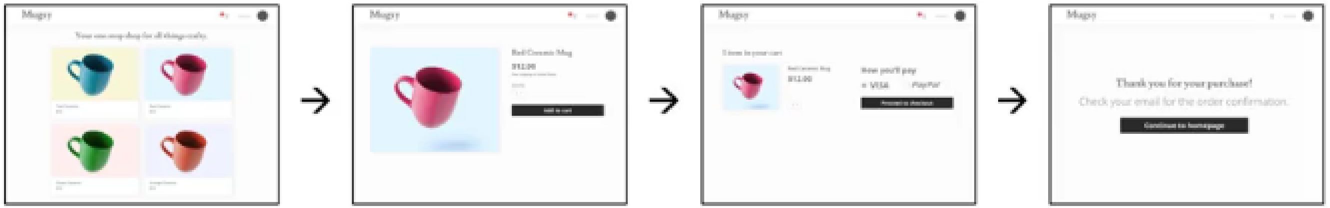
3. Deploy model

   Get data back

   Maintain / update model

Example: Optimizing a sales funnel

Visit website → Product page → Shopping cart → Checkout



Key steps of a data science project

Optimizing a sales funnel

User ID	Country	Time	Webpage
2009	Spain	08:34:30 Jan 5	home.html
2897	USA	13:20:22 May 18	redmug.html
4893	Philippines	22:45:16 Jun 11	mug.html

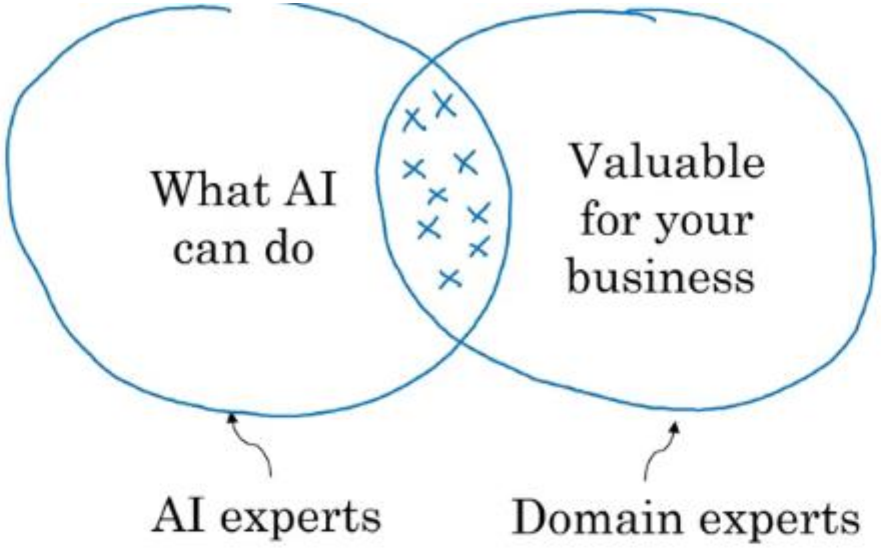
1. Collect data
2. Analyze data
   Iterate many times to get good insights
3. Suggest hypotheses/actions
   Deploy changes
   Re-analyze new data periodically

Machine Learning changing job functions

- Sales
  - Identifying sales opportunities
  - Prioritizing
- Manufacturing line manager
  - Optimize manufacturing
  - Machine learning can spot defects
- Recruiting
  - Identify how people prefer recruitment
  - Spot good candidates

- Marketing
  - Optimize website
  - A/B testing
  - Recommendation system
- Agriculture
  - What to plant?
  - Precision agriculture

How to chose an AI project?



Brainstorming framework

- Automate task rather than job
  - Automating call center: picking phone, emails, issue refund, call routing
  - Automating radiologist: X-ray, mentoring other doctors, consulting,
- Main drivers of business value
- What are the main pain points in your business?

Is it always necessary to have big data?

- Having more data is good
- With small datasets you can make progress
- 10, 100 or 1000 data points can be a good start

Technical diligence

- Can AI system meet desired performance
- How much data is needed
- Engineering timeline

Business diligence

- Lower costs
- Increase revenue
- Launch new product or business

Ethical diligence

- Is this going to make society better?

Build Vs Buy

- ML projects can be inhoused or outsourced
- DS projects are generally inhoused
- Buy industry standard, only build specialized products

How to work with AI team

- Specify your acceptance criteria
    - 95% accuracy
    - Training, validation and Test dataset
- Don't expect 100% accuracy
    - Limitations of ML
    - Insufficient data
    - Mislabeled data
    - Ambiguous labels (human perception)

Machine Learning frameworks

Machine learning frameworks:

- TensorFlow
- PyTorch
- Keras
- MXNet
- CNTK
- Caffe
- PaddlePaddle
- Scikit-learn
- R
- Weka

Research publications:

- Arxiv

Open source repositories

- GitHub

CPU Vs GPU

CPU: Computer processor (Central Processing Unit)

GPU: Graphics Processing Unit

Cloud vs. On-premises

Edge Deployment

Case Studies

Smart speaker

Amazon
Echo / Alexa

Google
Home

Apple
Siri

Baidu
DuerOS

Steps or AI pipeline

- Trigger word: Hey Device
- Speech Recognition: Tell me a joke
- Intent Recognition: joke, time, music, weather
    - Log of training instances, variation in text
- Execute joke

Activity

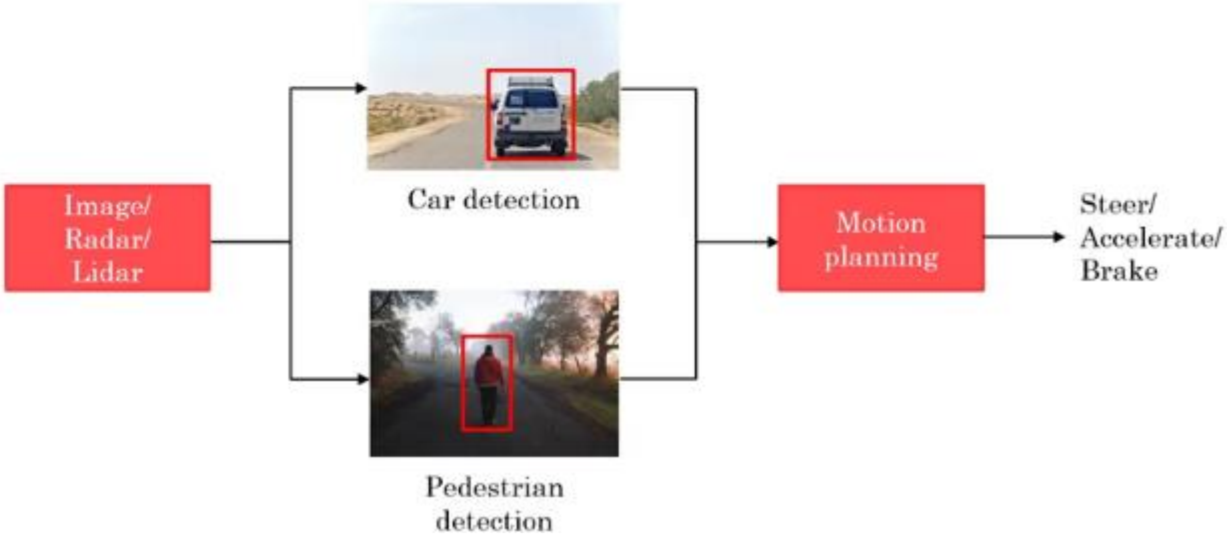
- Hey device, set timer for 10 minutes
  - What is the intent?
  - Extract duration
  - What command is to execute

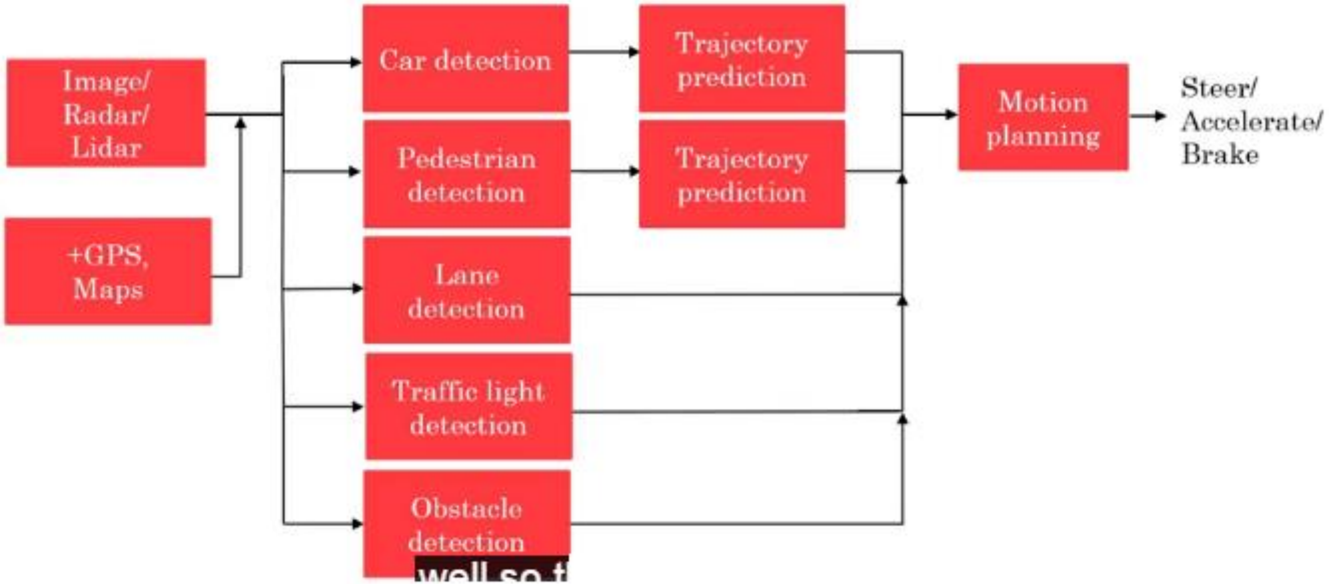
Smart speaker functions

- Play music
- Volume up/ down
- Make call
- Current time
- Units conversion
- Simple question

- These specialized execution routines are written by software engineer

Self driving car




Image/
Radar/
Lidar
+GPS,
Maps
Car detection
Pedestrian detection
Lane detection
Traffic light detection
Obstacle detection
Trajectory prediction
Trajectory prediction
Motion planning
Steer/
Accelerate/
Brake

AI teams

- AI team may have 100s of engineers
- A small team can have four or five members
- Example roles
  - Software Engineers
    - Execute joke, Set timer
  - Machine Learning Engineer
  - Machine Learning Researcher
    - Extend state-of-the-art
    - Applied ML scientist in between ML researcher and ML Engineer
  - Data Scientist
    - Provide insights

- Data Engineer
    - Organize data
    - Data is saved in cost effective way
    - We have lot of data, scalability is important
- AI Product Manager
    - What to build and feasible

Get started with a small team

- 1 Software engineer
- 1 ML engineer / Data scientist
- No body but your self

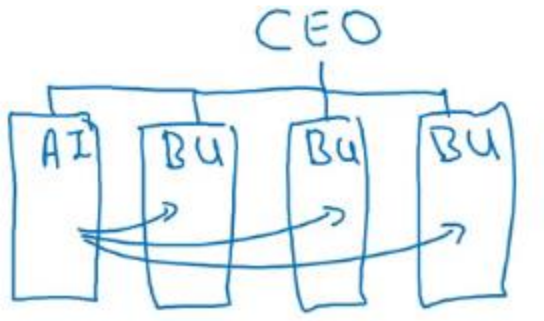
AI Transformation playbook

- Execute a pilot project to gain momentum
- Build an in-house AI team
- Provide broad AI training
- Develop an AI strategy
- Develop internal and external communication

Execute pilot project

- Start the fly wheel
- Show traction with in 6-12 months
- Can be in-house or out-sourced

Build an in-house AI team



- Develop tools that could be useful company wide
- Under CIO, CTO,CDO, CAIO

Provide broad AI training

Role	What they should learn
Executives and senior business leaders	• What AI can do for your enterprise • AI strategy • Resource allocation
Leaders of divisions working on AI projects	• Set project direction (technical and business diligence) • Resource allocation • Monitor progress
AI engineer trainees	• Build and ship AI software • Gather data • Execute on specific AI projects

Resources

- Online courses
- Books
- Curate rather than create content

Develop an AI strategy

- Leverage AI to create an advantage specific to your company
- Design strategy that align with virtuous cycle of AI
- Blue River – precision agriculture

- AI needs to be specialized or verticalized to your industry sectory
- Don’t compete with giants
- Creating a strategy
  - Strategic data acquisition
  - Unified data warehouse – Pull data into single repository, software can connect the dots
- Create network effect and platform advantages
  - Uber, Careem, Facebook

- Low cost strategy
- High value strategy

Develop internal and external communications

- Investor relations
- Government relations
- Consumer / user education
- Talent / recruitment
- Internal communication

Common pitfalls

Don't:

- Expect AI to solve everything
- Hire 2-3 ML engineers and count solely on them to come up with use cases

Do:

- Be realistic about what AI can and cannot do given limitations of technology, data, and engineering resources
- Pair engineering talent with business talent and work cross-functionally to find feasible and valuable projects

Don't:

- Expect the AI project to work the first time
- Expect traditional planning processes to apply without changes
- Think you need superstar AI engineers before you can do anything

Do:

- Plan for AI development to be an iterative process, with multiple attempts needed to succeed
- Work with AI team to establish timeline estimates, milestones, KPIs, etc.

Take your first step

- Get friends to learn about AI
- Start brainstorming projects
- Hire a few ML / DS to help
- Hire or appoint an AI leader (VP AI, CAIO)
- Discuss with CEO about possibilities of AI transformation

AI Application areas

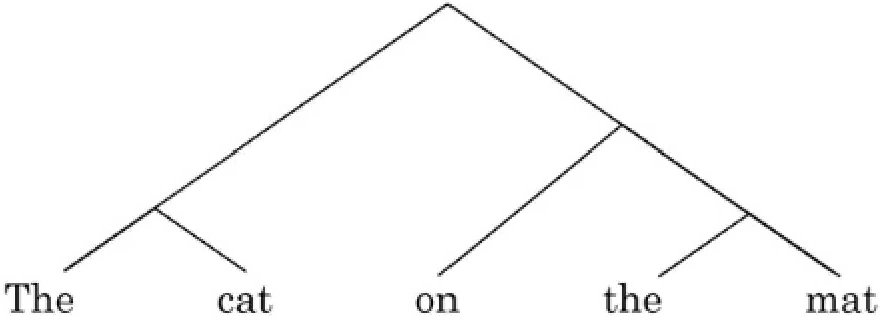
- Computer Vision
  - Image Classification / Object recognition
    - Face recognition
  - Object detection
  - Image segmentation
  - Tracking

Natural language processing

- Text classification (Spam / Non spam)
    - Sentiment recognition
- Information retrieval
    - Web search
- Named entity recognition
- Machine translation
- Part of speech tagging

The	cat	on	the	mat
Determiner	Noun	Preposition	Determiner	Noun

- Parsing

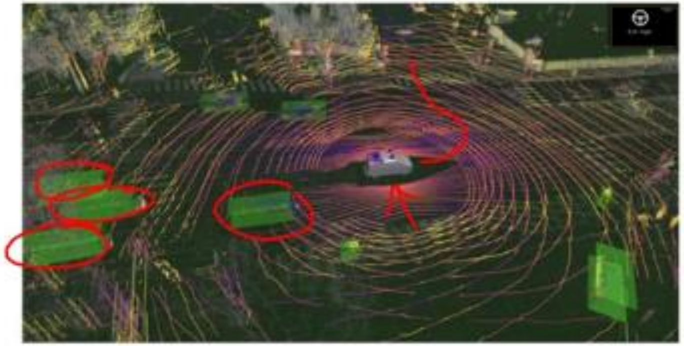


Speech

- Speech to text
- Trigger / wake word detection
- Speaker ID
- Speech synthesis (text-to-speech / TTS)

Robotics

- Perception: figuring out what's in the world around you
- Motion planning: finding a path for the robot to follow
- Control: sending commands to the motors to follow a path



General machine learning

- Unstructured data (images, audio, text)

image

audio

AIは、新たな電気だ

AI is the new electricity

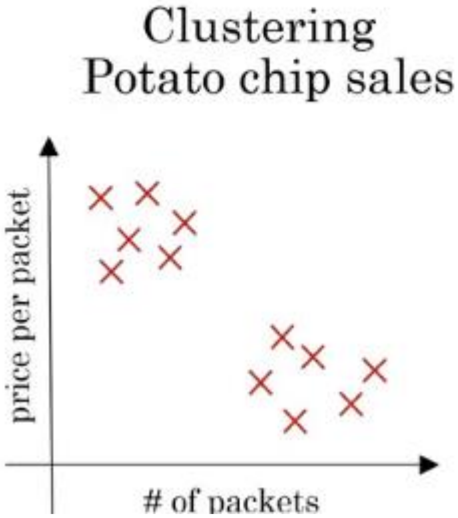
text

- Structured data

House size (square feet)	# of bedrooms	Price (1000$)
523	1	100
645	1	150
708	2	200

Clay batch #	Supplier	Mixing time (minutes)
001	ClayCo	35
034	GooClay	22
109	BrownStuff	28

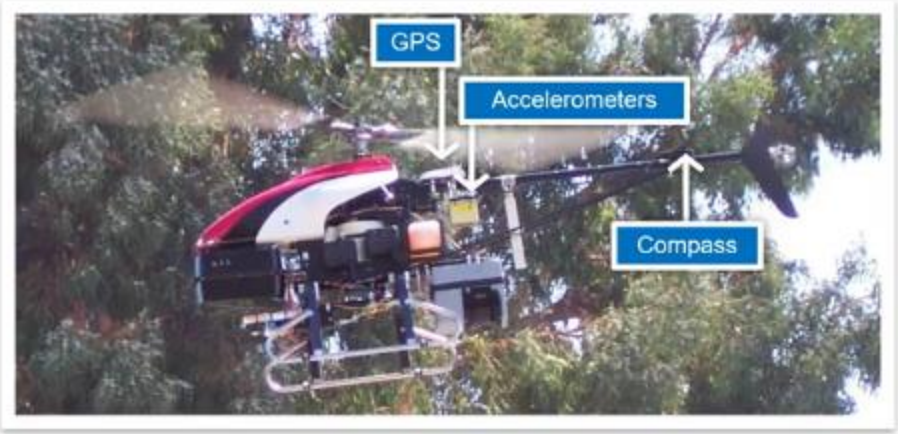
Unsupervised learning



- Supervised learning needs lot of data
- 10,000 defected coffee mug, human can easily do that with few examples

Transfer learning

Reinforcement learning



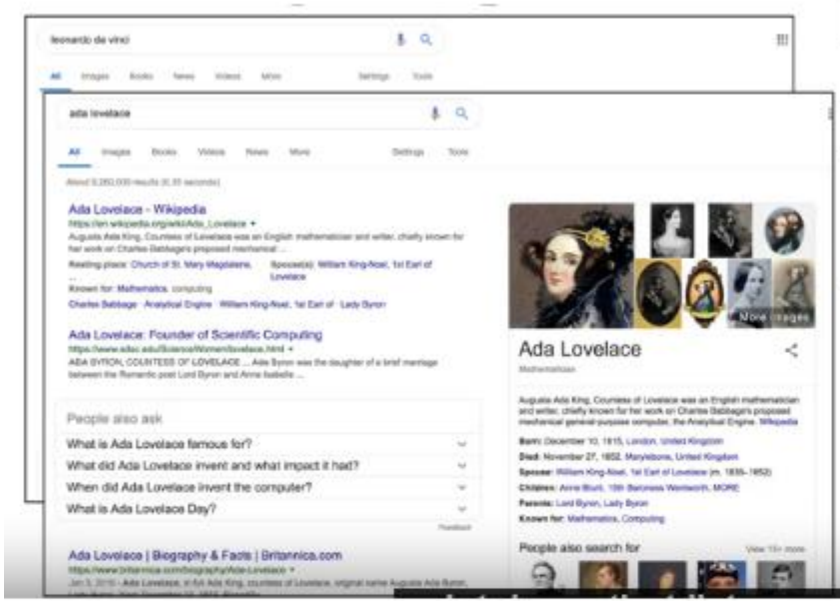
Use a "reward signal" to tell the AI when it is doing well or poorly. It automatically learns to maximize its rewards.

- Also useful in Games
- Not as much as economic value as supervised learning

Generative Adversarial Network (GAN)

- Synthesize new images from scratch
- Entertainment industry, film, animation

Knowledge graph



Ada Lovelace	
Born	Dec 10, 1815
Died	Nov 27, 1852
Bio	English mathematician and writer...

AI & Society

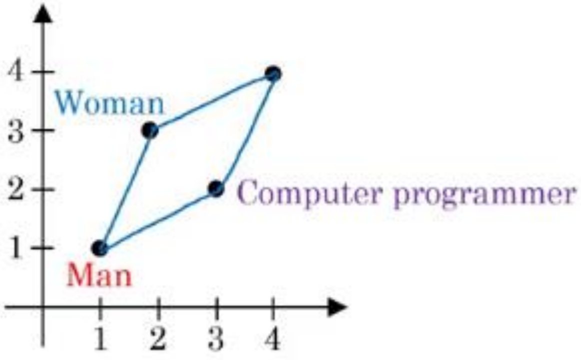
- AI is super power
- Goldilock rule
  - Neither too optimistic nor pessimistic
- Don’t over spend on unnecessary danger
- AI winter
- AI can’t do every thing, but will transform industries

Limitations of AI

- Performance limitations
  - With small amount of data
- Explainability is hard (sometimes doable): How should we trust
  - Humans are also not good at explaining
  - Barrier to acceptance
- Biased through biased data
- Adversarial attacks

AI can learn unhealthy stereotype

- Learn from internet
    - Man: Woman as Father: **Mother**
    - Man: Woman as King: **Queen**
    - Man : Computer programmer as women: **Home maker**
    - Man and woman can equally become programmer



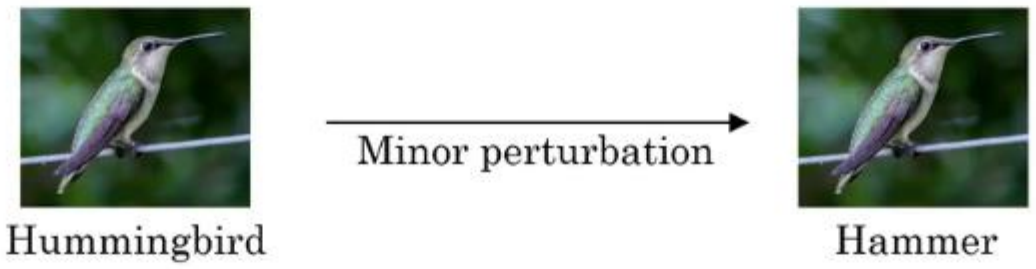
Why bias matters

- Hiring tool that discriminates against woman
- Facial recognition working better for specific ehtnicity
- Bank loan approavals
- Toxic effect of reinforcing unhealthy stereotypes

Combating bias

- Technical solution
  - Zero out bias
  - Use less biased or more inclusive data
- Transparency or auditing process
- Diverse workforce
  - Creates less biased applications

Adversarial attacks



- Spam Filters
- Hate speech filter

Physical attacks

“Milla Jovovich”

Fails to see stop sign

Adversarial defenses

- Cost to defend
- Slow speed
- May not be any incentive to attack, so should we invest in defense?
- Zero-sum against adversaries

Adverse uses of AI

- Deep Fakes
    - Synthesizing videos
    - Video of Obama
- Undermining of democracy and privacy
    - Oppressive surveillance
- Generating fake comments
- Spam Vs anti-spam, Fraud Vs anti-fraud

AI & Developing economy

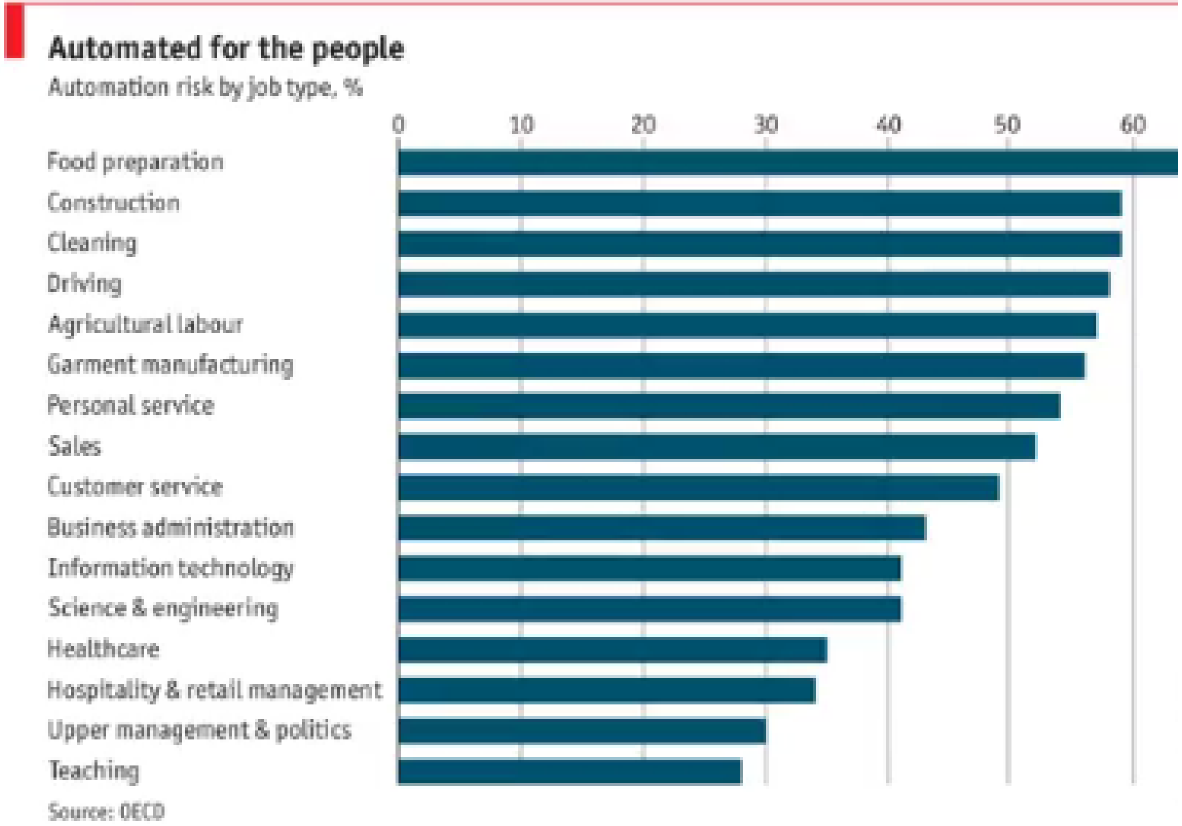
- Developing economies gradually moved up the ladder
- Lower end ladder are susceptible to automation such as agriculture
- Trampoline to move higher rungs
    - Leapfrog
    - Example of mobile phone
    - Mobile payments
- Online education

How developing economies can build AI?

- US and China leading
- But AI communities are still immature
- Focus on AI to strengthen country’s vertical industries
- Instead of focusing on AI in general, use AI where you are already good at
- Public private partnership
- Invest in education

AI and impact on jobs

- AI is automation on steroids
- Jobs displaced by 2030
    - 400-800 mn
- Jobs created by 2030
    - 555- 890 mn
- Is your job amenable to automation?



Automated for the people
Automation risk by job type, %
0
10
20
30
40
50
60
Food preparation
Construction
Cleaning
Driving
Agricultural labour
Garment manufacturing
Personal service
Sales
Customer service
Business administration
Information technology
Science & engineering
Healthcare
Hospitality & retail management
Upper management & politics
Teaching
Source: OECD

Some solutions to counter AI impact on jobs

- Conditional basic income: provide a safety net
- Life long learning society
- Political solutions
    - Legalization
- Work at intersection of your current joband AI

Summary

- What is AI?
- Building AI projects
- Building AI in your company
- AI & society