

# Artificial Intelligence

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***Presidential Initiative for Artificial Intelligence and Computing***

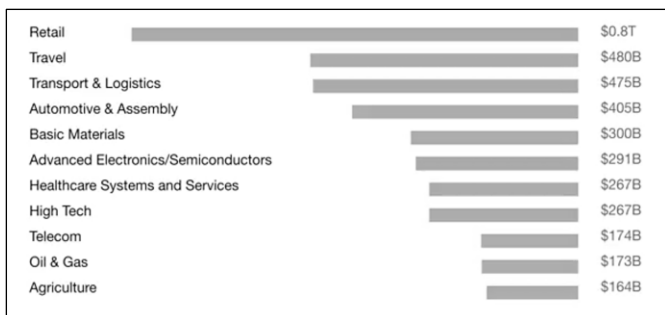
# AI For Everyone

## 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

AI value creation by 2030 is **\$13 Trillion** by

**Source: McKinsey Global Institute**



## Artificial Intelligence

“A branch of computer science dealing with the simulation of intelligent behavior in computers.”

“The capability of a machine to imitate intelligent human behavior.”

### There are 2 types of AI

#### ANI (Artificial Narrow Intelligence)

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.

#### AGI (Artificial General Intelligence)

That is the goal to build AI.

They can do anything a human can do or maybe even be super intelligent 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

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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

**Machine learning** focuses on the development of computer programs that can access data and use it learn for themselves.

## Supervised Learning

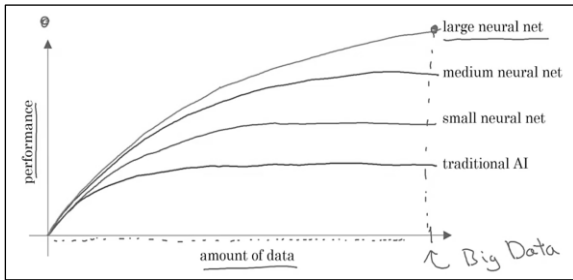
“This set of AI called supervised learning, just learns input to output, or A to B mappings. On one hand, input to output, A to B it seems quite limiting. But when you find a right application scenario, this can be incredibly valuable.” E.g.,

1. If the input is an audio clip, and the AI's job is to output the text transcript, then this is speech recognition.
2. If you want to input English and have it output a different language, Chinese, Spanish, something else, then this is machine translation.
3. 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?
4. 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.
5. 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)	Output (B)	Application
email	→ spam? (0/1)	spam filtering
audio	→ text transcript	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

# AI For Everyone

## Why Now?



## 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 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 Data

Raw facts and figure are called Data.

## A Table of Data (Dataset)

### Example of a table of data (dataset)

size of house (square feet)	# of bedrooms	price (1000\$)	image	label	
523	1	115		cat	✓ "Google cat"
645	1	150		not cat	✗
708	2	210		cat	✓
1034	3	280		cat	✓
2290	4	355		not cat	✗
2545	4	440		cat	✓

Handwritten notes: A → B (under size of house), B (under # of bedrooms), A (under price), A → B (under image), B (under label), A → B (under image), B (under label), A → B (under image).

## 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

- Download from websites / partnerships

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- 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

## Acquiring data

### - Manual labeling



### - From observing behaviors

user ID	time	price (\$)	purchased	machine	temperature (°C)	pressure (psi)	machine fault
4783	Jan 21 08:15:20	7.95	yes	17987	60	7.65	N
3893	March 3 11:30:15	10.00	yes	34672	100	25.50	N
8384	June 11 14:15:05	9.50	no	08542	140	75.50	Y
0931	Aug 2 20:30:55	12.90	yes	98536	165	125.00	Y

### - Download from websites / partnerships

## 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?

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

### What's wrong with this statement?

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.**

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## 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

Data is messy			
- Garbage in, garbage out			
- Data problems			
- Incorrect labels			
- Missing values			
- Multiple types of data			
images, audio, text			
unstructured unstructured data structured			

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

## 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.

## Machine Learning vs Data Science

# Machine learning vs. data science

Home prices

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

ML.  $A \rightarrow B$

Running AI system  
(e.g., websites / mobile app)

DS

Homes with 3 bedrooms are more expensive than homes with 2 bedrooms of a similar size.

Newly renovated homes have a 15% premium.

## Machine learning vs. data science

Machine learning	Data science
"Field of study that gives computers the ability to learn without being explicitly programmed."	Science of extracting knowledge and insights from data.
software	slide deck
-Arthur Samuel (1959)	

## 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**

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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."
- "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
- "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

"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

1. 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.

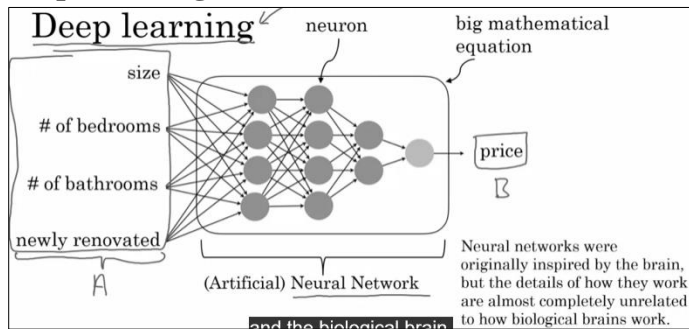
These systems run 24/7 and drive ad revenue for these platforms.

2. 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.

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## Deep Learning

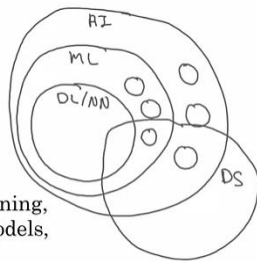


## AI and related disciplines

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

## AI has many tools

- Machine learning and data science
- Deep learning / neural network
- Other buzzwords: Unsupervised learning, reinforcement learning, graphical models, planning, knowledge graph, ...



## What makes a company AI company?

- Strategic data acquisition
- Unified data warehouse
- 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 anything you can do with a second of thought can be automated using supervised learning

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## A lesson from the rise of the Internet

### Internet Era

Shopping mall + website  
≠ Internet company

- A/B testing
- Short iteration time
- Decision making pushed down to engineers and other specialized roles

### AI era

Any company + deep learning  
≠ AI company

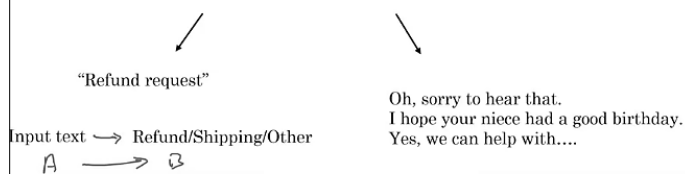
- Strategic data acquisition
- Unified data warehouse
- Pervasive automation
- New roles (e.g., MLE) and division of labor

## 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?



## 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

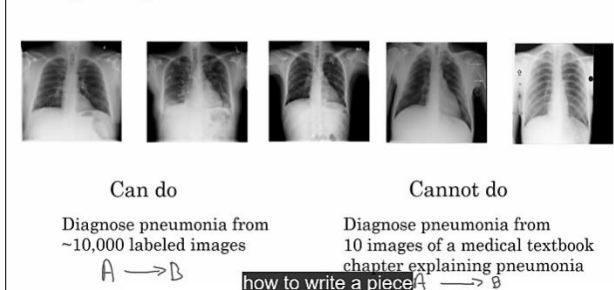
## X-ray diagnosis

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

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## X-ray diagnosis



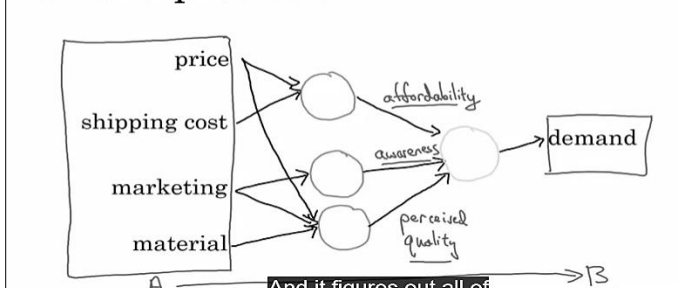
## Strengths and weakness of ML

- 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
  - Material

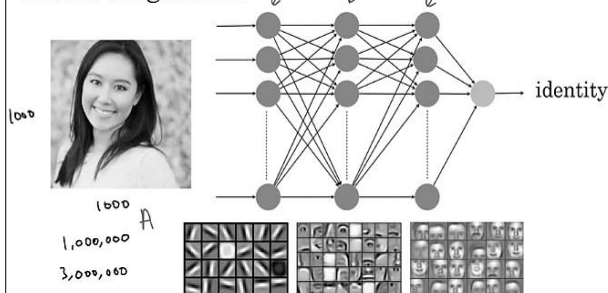
## Demand prediction



## 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



## Speech Recognition



## Key steps of Echo / Alexa

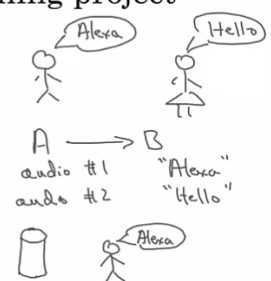
## Starting an AI project

- Workflow of projects
- Selecting AI projects
- Organizing data and team for the projects

## Key steps of a machine learning project

### Echo / Alexa

1. Collect data
2. Train model
  - Iterate many times until good enough
3. Deploy model
  - Get data back
  - Maintain / 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

## Data Science Project Workflow

### Example: Optimizing a sales funnel



## Key steps of a data science project

### Optimizing a sales funnel

1. Collect data

2. Analyze data

Iterate many times to get good insights

3. Suggest hypotheses/actions

Deploy changes

Re-analyze new data periodically

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



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## Key steps of a data science project

### Manufacturing line



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

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

Mug Batch #	Humidity	Temperature in kiln (F)	Duration in kiln (hours)
301	0.002%	1410°	22
302	0.003%	1520°	24
303	0.002%	1420°	22

## Sales

### Data science



### Machine learning

Name	Title	Company size	Email	Priority
Taylor	CEO	3050	tay@a..	high
Janet	Manager	230	jan@b..	medium
David	Intern	30	dave@c..	low

Optimize sales fun Let's look at more examples. Automated lead sorting

## Manufacturing line manager

### Data science



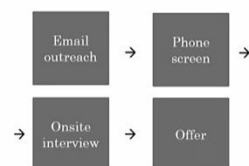
### Machine learning



Optimize manufact a big impact on manufacturing d visual inspection

## Recruiting

### Data science



### Machine learning

Jane Doe	Personal Info	Education	Professional	Employment	→ Yes
Tiffany Doe	Personal Info	Education	Professional	Employment	→ No

Optimize recruit into automated resume screening resume screening

## Marketing

### Data science



### Machine learning



A/B testing many large online personalized product recommendation

## Agriculture

### Data science



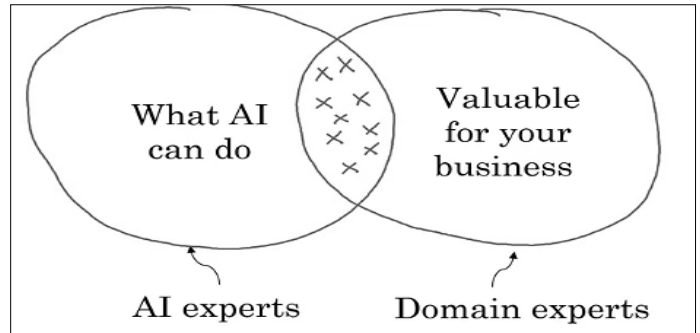
Crop analytics

### Machine learning



Precision weed killing

## How to choose 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?

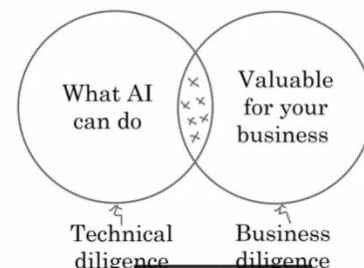
- Having more data is good
- With small datasets you can make progress
- 10, 100 or 1000 data points can be a good start

## You can make progress even without big data

- Having more data almost never hurts.
- Data makes some businesses (like web search) defensible.
- But with small datasets, you can still make progress.



## Due diligence on project



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## Due diligence on project

Technical diligence	Business diligence
<ul style="list-style-type: none"> <li>Can AI system meet desired performance</li> <li>How much data is needed</li> <li>Engineering timeline</li> </ul>	<ul style="list-style-type: none"> <li>Lower costs</li> <li>Increase revenue</li> <li>Launch new product or business</li> </ul> <div>             } current business              } new business           </div>

## Ethical diligence

- Is this going to make society better?

## Build Vs Buy

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

## Build vs. buy

- ML projects can be in-house or outsourced
- DS projects are more commonly in-house
- Some things will be industry standard – avoid building those.



## Specify your acceptance criteria

ok  
 ok  
 defect

Goal: detect defects with 95% accuracy

test set  
~1000

Provide AI team a dataset on which to measure their performance

## How AI teams think about data

Training set

 ok  
 defect  
 ok

Test set

 ok  
 ok  
 defect

66.7%

Learn A → B

## Pitfall: Expecting 100% accuracy

Test set

 ok  
 ok  
 defect

defect ok  
 ok defect?  
 ok

- Limitations of ML
- Insufficient data ←
- Mislabeled data ←
- Ambiguous labels ←

## AI technical tools

Machine learning frameworks:	Research publications:
<ul style="list-style-type: none"> <li>TensorFlow</li> <li>PyTorch</li> <li>Keras</li> <li>MXNet</li> <li>CNTK</li> <li>Caffe</li> <li>PaddlePaddle</li> <li>Scikit-learn</li> <li>R</li> <li>Weka</li> </ul>	<ul style="list-style-type: none"> <li>Arxiv</li> </ul>
	Open source repositories:
	<ul style="list-style-type: none"> <li>GitHub</li> </ul>

## CPU vs. GPU

CPU: Computer processor (Central Processing Unit)



GPU: Graphics Processing Unit



Cloud vs. On-premises

Edge

## 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

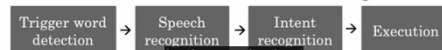
Hey device, set timer for 10 minutes

- What is the intent?
- Extract duration
- What command is to execute

## “Hey device, tell me a joke”

Steps to process the command:

- Trigger word/wakeword detection Audio → “Hey device”? (0/1)
- Speech recognition Audio → “tell me a joke” A → B
- Intent recognition “tell me a joke” A { joke? time? music? call? weather? } B
- Execute joke



AI pipeline

## “Hey device, set timer for 10 minutes”

Steps to process the command:

- Trigger word/wakeword detection Audio → “Hey device”? (0/1)
- Speech recognition Audio → “set timer for 10 minutes”
- Intent recognition “set timer for 10 minutes” → timer
- Extract duration “Set timer for 10 minutes” “Let me know when 10 minutes is up”
  - Start timer with set duration



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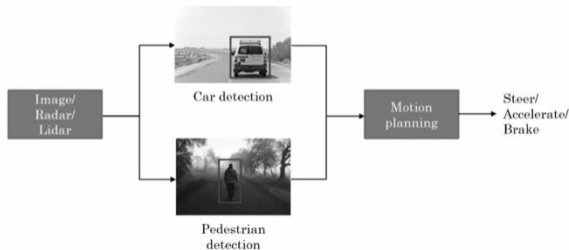
## Other functions

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

## Key steps:

1. Trigger/wakeword detection
2. Speech recognition
3. Intent recognition
4. Specialized program to execute command

## Steps for deciding how to drive



## Key steps:

1. Car detection



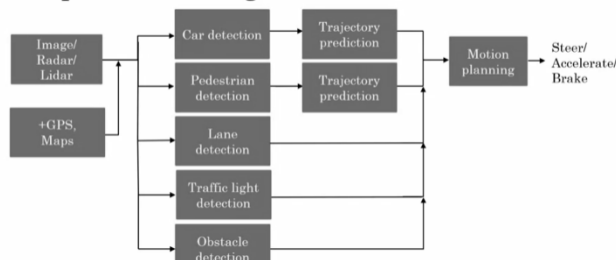
2. Pedestrian detection



3. Motion planning



## Steps for deciding how to drive



## Example roles

- Software Engineer
    - E.g., joke execution, ensure self-driving reliability, ...
  - Machine Learning Engineer
    - $A \rightarrow B$
  - Machine Learning Researcher
    - Extend state-of-the-art in ML
- Applied ML Scientist

## 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

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- 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

## Getting started with a small team

- 1 Software Engineer, or
- 1 Machine Learning Engineer/Data Scientist, or
- Nobody but yourself

## 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

## 1. Execute pilot projects to gain momentum

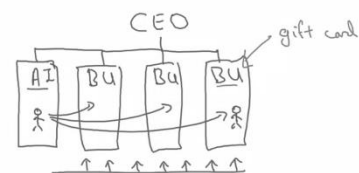
- More important for the initial project to succeed rather than be the most valuable
- Show traction within 6-12 months
- Can be in-house or outsourced

## 3. Provide broad AI training

Role	What they should learn
Executives and senior business leaders	<ul style="list-style-type: none"> <li>• What AI can do for your enterprise</li> <li>• AI strategy</li> <li>• Resource allocation</li> </ul>
Leaders of divisions working on AI projects	<ul style="list-style-type: none"> <li>• Set project direction (technical and business diligence)</li> <li>• Resource allocation</li> <li>• Monitor progress</li> </ul>
AI engineer trainees	<ul style="list-style-type: none"> <li>• Build and ship AI software</li> <li>• Gather data</li> <li>• Execute on specific AI projects</li> </ul>

The smart CLO knows they should *curate* rather than *create* content

## 2. Build an in-house AI team



BU= Business Unit

AI function can be under CTO, CIO, CDO, etc. or a new CAIO

the chief data officer  
or the Chief Digital

deeplearning.ai

Andrew Ng

# AI For Everyone

# PIAIC+ Coursera

## 3. Provide broad AI training

Role	What they should learn
Executives and senior business leaders	<ul style="list-style-type: none"> <li>What AI can do for your enterprise</li> <li>AI strategy</li> <li>Resource allocation</li> </ul>
Leaders of divisions working on AI projects	<ul style="list-style-type: none"> <li>Set project direction (technical and business diligence)</li> <li>Resource allocation</li> <li>Monitor progress</li> </ul>
AI engineer trainees	<ul style="list-style-type: none"> <li>Build and ship AI software</li> <li>Gather data</li> <li>Execute on specific AI projects</li> </ul>

The smart CLO knows they should *curate* rather than *create* content.

## 4. Develop an AI strategy

- Leverage AI to create an advantage specific to your industry sector
- Design strategy aligned with the “Virtuous Cycle of AI”



## AI pitfalls to avoid

### 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

## AI pitfalls to avoid

### 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.

## Some initial steps you can take

- Get friends to learn about AI
  - This course
  - Reading group
- Start brainstorming projects
  - No project is too small
- Hire a few ML/DS people to help
- Hire or appoint an AI leader (VP AI, CAIO, etc.)
- Discuss with CEO/Board possibilities of AI Transformation
  - Will your company be much more valuable and/or more effective if it were good? you would also consider trying

## Computer Vision

- Image classification/Object recognition
  - Face recognition
- Object detection
- Image segmentation
- Tracking



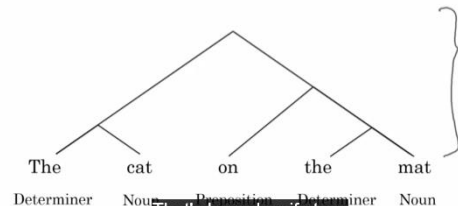
## Natural Language Processing

- Text classification
  - Sentiment recognition
- Information retrieval
  - E.g., web search
- Name entity recognition
- Machine translation

Email → Spam/Non-Spam  
 Product description → Product category  
 “The food was good” → ★★★★★  
 “Service was horrible” → ★  
 Queen Elizabeth II knighted Sir Paul McCartney for his services to music at the Buckingham Palace  
 AIは、新たな電気だ  
 AI is the new electricity

## Natural Language Processing

- Others: parsing, part-of-speech tagging



## Speech

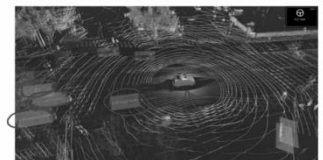


- Speech recognition (speech-to-text)
- Trigger word/wakeword detection
- Speaker ID
- Speech synthesis (text-to-speech, TTS)

The quick brown fox jumps over the lazy dog.

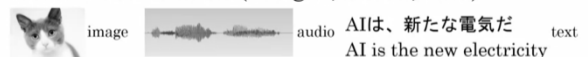
## Robotics

- 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)

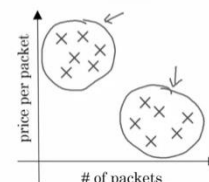


- Structured data

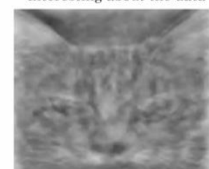
House size (square feet)	# of bedrooms	Price (1000\$)	Clay batch #	Supplier	Mixing time (minutes)
523	1	100	001	ClayCo	35
645	1	150	034	GooClay	22
708	2	200	109	BrownStuff	28

## Unsupervised learning

### Clustering Potato chip sales




Given data (without any specific desired output labels), find something interesting about the data



Finding cats from YouTube videos


# Transfer learning

## Car detection



100,000 images

## Golf cart detection



100 images

Learn from task A, and use knowledge to help on task B

A black and white aerial photograph of a quadcopter drone flying over a dense forest. Three white rectangular boxes with black text are overlaid on the image, connected by lines to specific components on the drone. The first box, labeled 'GPS', points to a small antenna on the top of the drone's frame. The second box, labeled 'Accelerometers', points to a sensor module located near the center of the drone. The third box, labeled 'Compass', points to a module on the underside of the drone, near the rear propellers.

## Synthesize new images from scratch



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

<b>Northern Rooster Hotel</b>	Address	45 Rooster St, LA
Phone	(650) 555-3992	
Wifi	yes	
Pool	no	

# AI and society

- AI and hype
- Limitations of AI
  - Bias
  - Adversarial attacks
- AI, developing economies, and jobs

} AI and Ethics

- AI and hype
- Limitations of AI
  - Bias
  - Adversarial attacks
- AI, developing economies, and jobs
- Conclusion

} AI and Ethics

- Too optimistic: Sentient / super-intelligent AI killer robots coming soon
- Too pessimistic: AI cannot do everything, so an AI winter is coming
- Just right: AI can't do everything, but will transform industries

- Performance limitations
- Explainability is hard (but sometimes doable)



Right-sided  
Pneumothorax  
(collapsed lung)



- Man : Woman as Father : Mother
- Man : Woman as King : Queen
- Man : Computer programmer as Woman : ~~Homemaker~~  
Computer programmer

Man: (1,1)  
 Computer programmer: (3,2)  
 Woman: (2,3)  
 Homemaker: (4,4)

[Bolukbasi et al. (2016). Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings.]

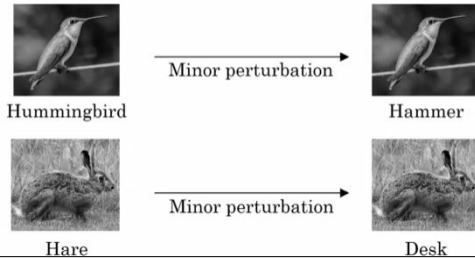
- Hiring tool that discriminated against women
- Facial recognition working better for light-skinned than dark-skinned individuals
- Bank loan approvals
- Toxic effect of reinforcing unhealthy stereotypes

# AI For Everyone

## Combating bias

- Technical solutions:
  - E.g., “zero out” the bias in words
  - Use less biased and/or more inclusive data
- Transparency and/or auditing processes
- Diverse workforce
  - Creates less biased applications

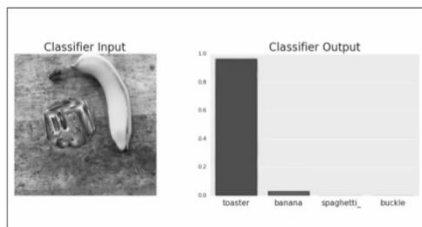
## Adversarial attacks on AI



## Physical attacks



## Physical attacks



[Sharif et al. (2016). Accessorize to a Crime: Real and Stealthy Attacks on State-of-the-Art Face Recognition.]  
[Evkholt et al. (2018). Physical Adversarial Examples for Object Detectors.]

## Adversarial defenses

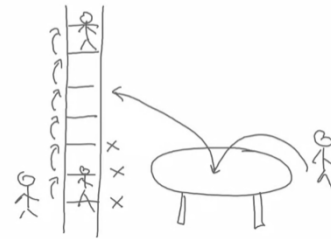
- Defenses do exist, but incur some cost
- Similar to spam vs. anti-spam, we may be in an arms race for some applications

## Adverse uses of AI

- DeepFakes
  - Synthesize video of people doing things they never did
- Undermining of democracy and privacy
  - Oppressive surveillance
- Generating fake comments
- Spam vs. anti-spam and fraud vs. anti-fraud

# PIAIC+ Coursera

## Developing economies



“Leapfrog”

- Mobile phones
- Mobile payments
- Online education

## How developing economies can build AI

- US and China are leading, but all AI communities are still immature
- Focus on AI to strengthen a country’s vertical industries
- Public-private partnerships to accelerate development
- Invest in education

## AI’s impact on jobs worldwide

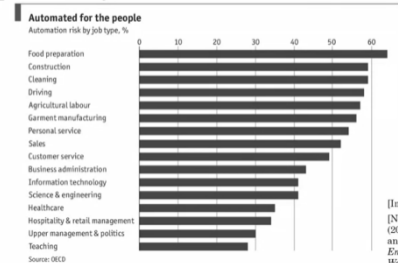
Jobs displaced  
by 2030

400-800 mil

Jobs created  
by 2030

555-890 mil

## AI’s impact on jobs worldwide



[Image credit: Economist.com]  
[Nedelkoska, L. and G. Quintini. (2018). Automation, skills use and training. *OECD Social, Employment and Migration Working Papers*, No. 202.1  
Source: OECD]

## Some solutions

- Conditional basic income: provide a safety net but incentivize learning
- Lifelong learning
- Political solutions

## What you’ve learned

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

Keep learning!

- Online courses, books, blogs, ...
- [deeplearning.ai](https://deeplearning.ai) mailing list

Thank you!

John Ng

*Best of Luck*