

Introduction to Code-Free Machine Learning

Good Morning!

- 1) Download the presentation slides and activity worksheets at <http://bit.ly/3qk5pDC>
 - 2) If your nickname used in Teams is different from the registered name, please drop a message on the channel with the registered name for attendance tracking purpose.
 - 3) We will start at 9am sharp
- Sit back and relax for now 😊



Download from Github

zacktohsh / AICFML_DEC2020

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zacktohsh Main	4a32663	41 seconds ago	1 commits
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Automobile price data _Raw_.csv	Main		41 seconds ago
Car damage dataset.zip	Main		41 seconds ago
README.md	Main		41 seconds ago

README.md



An Introduction to Code-Free Machine Learning (December 2020)



Programme

Section 1:	What is Machine Learning Machine Learning Workflow
Section 2:	Activity 1 – First Machine Learning with Azure
Section 3:	Activity 2 - Deploying your experiment as a Web Service & Make Prediction using Excel
	Lunch Break
Section 4:	Transfer Learning Computer Vision: Activity 3 – Car Damage Assessment Classification
Section 5:	Natural Language Processing Activity 4 – Creating a Sentiment Analyser
Section 6:	Linking them together
Section 7:	Debrief



Introduction of trainer



Name
Zack Toh

Telegram
[@zacktohsh](https://t.me/zacktohsh)

Email
Zack_toh@rp.edu.sg



Past Projects (Crowd Detection) (18RIGO09)

SSDv1



SSDv2

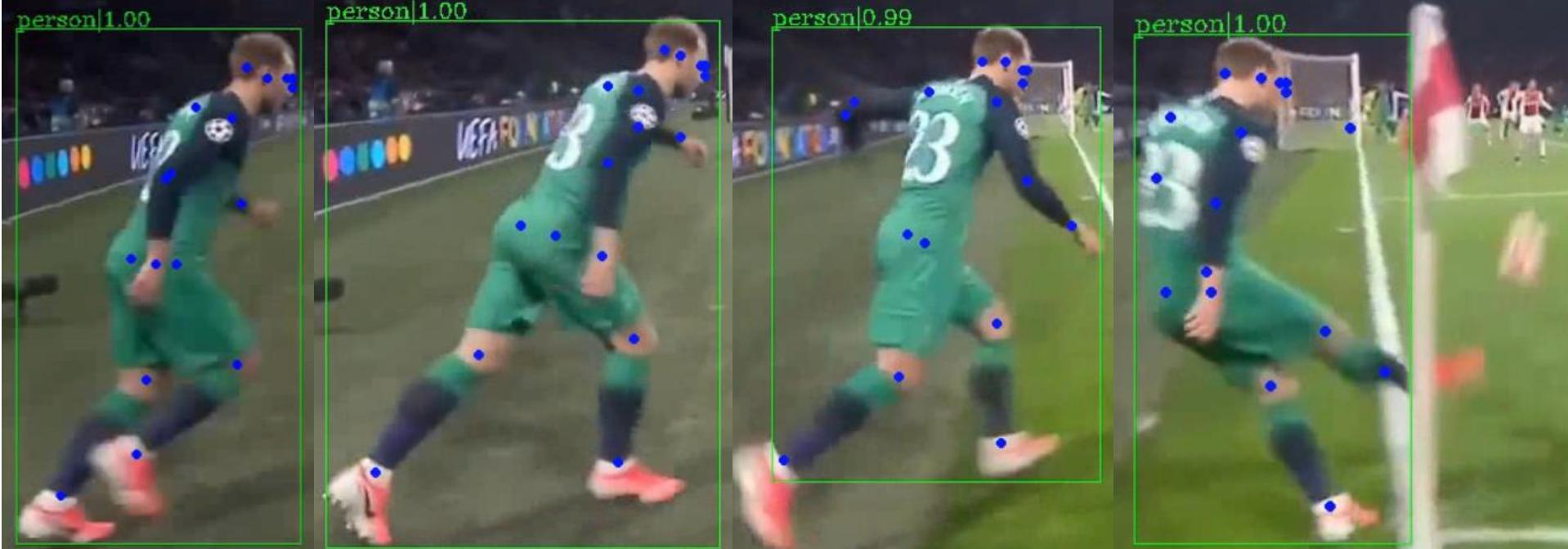


Yolo



Deep Learning for Sports Tagging (19RBF07)

Contextual awareness is the holy grail of computer vision. It aims at equipping a machine with the ability of deciphering what is happening in any given image. The automated tagging in sports is a new emerging area in sports industry. This project would contribute tremendously to the productivity and efficiency of sports tagging and dramatically reduce the labor needed in curating the sports statistic. The proposed prototype has high commercialization potential as shared by current sports tagging companies (e.g., Dartfish SA, Hudl and Prozone).



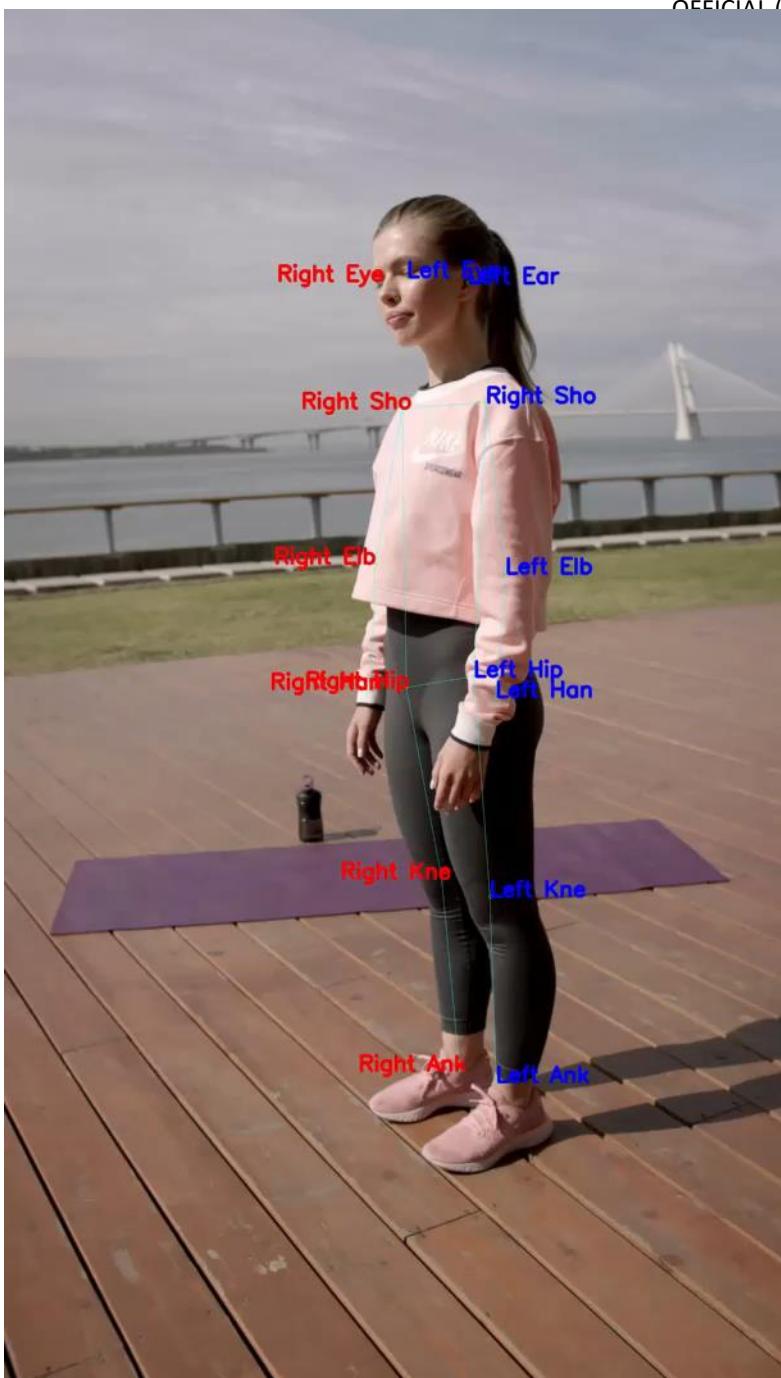
Processed Throw-in





Innovative Approach and Value (Current)





Pose Recognition

Video obtained from: <https://www.pexels.com/>

Pose generated with Posenet



Talk to flower

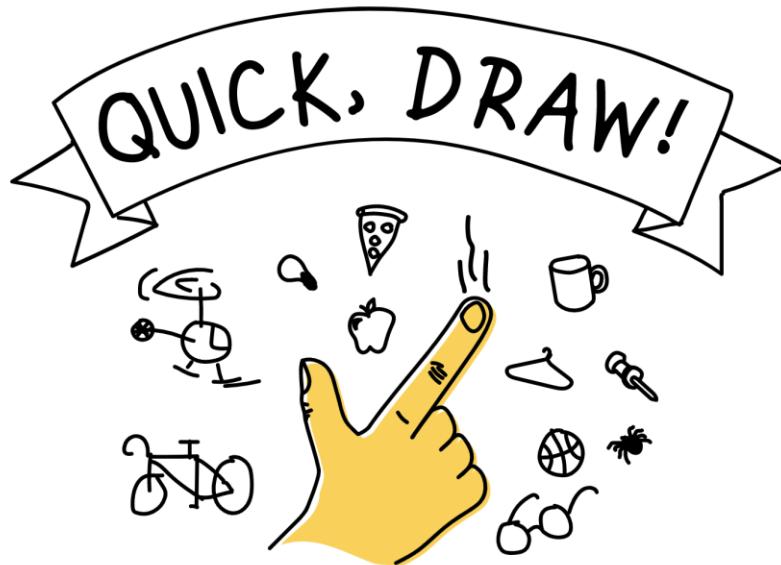


https://www.youtube.com/watch?v=nsPQvZm_rgM



Quickdraw Game

<https://quickdraw.withgoogle.com>



Can a neural network learn to recognize doodling?

Help teach it by adding your drawings to the [world's largest doodling data set](#), shared publicly to help with machine learning research.

Let's Draw!

Optional Activity

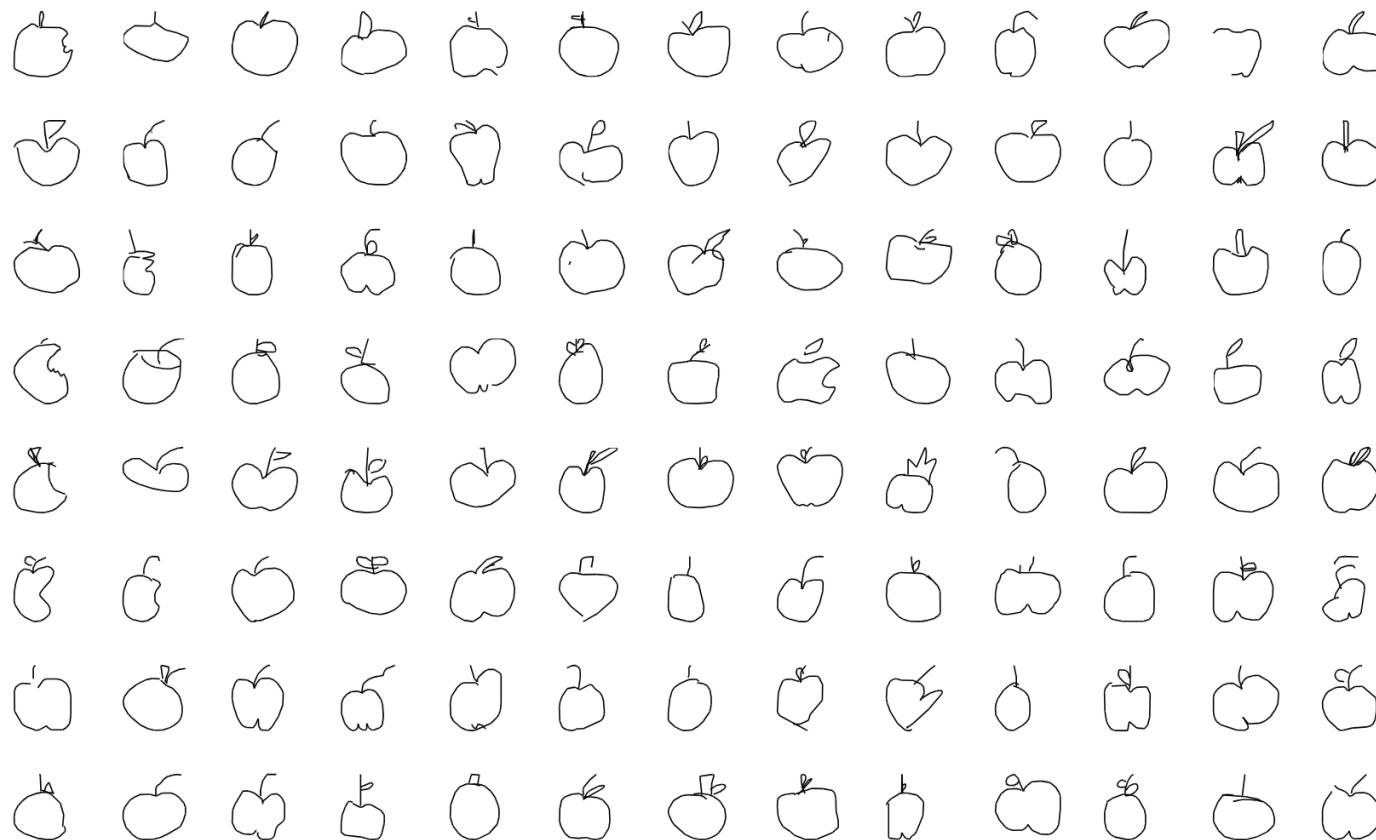


5 mins



How does ML work in QuickDraw?

- <https://quickdraw.withgoogle.com/data/apple>





Bias Bias Bias

When It Comes to Gorillas, Google Photos Remains Blind

Google promised a fix after its photo-categorization software labeled black people as gorillas in 2015. More than two years later, it hasn't found one.

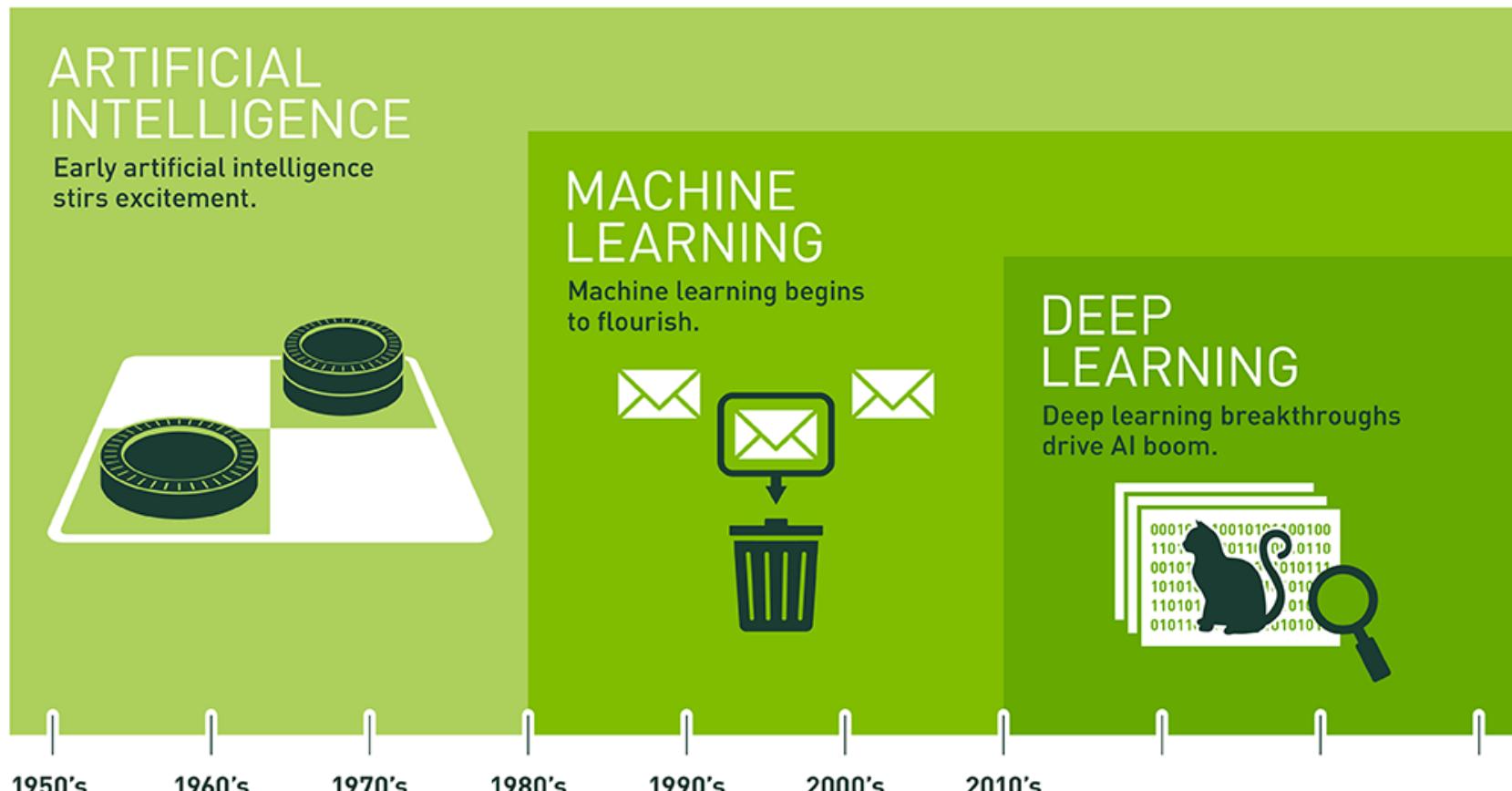


In WIRED's tests, Google Photos did identify some primates, but no gorillas like this one were to be found. RICK MADONIK/TORONTO STAR/GETTY IMAGES

<https://www.wired.com/story/when-it-comes-to-gorillas-google-photos-remains-blind/>



AI Time line



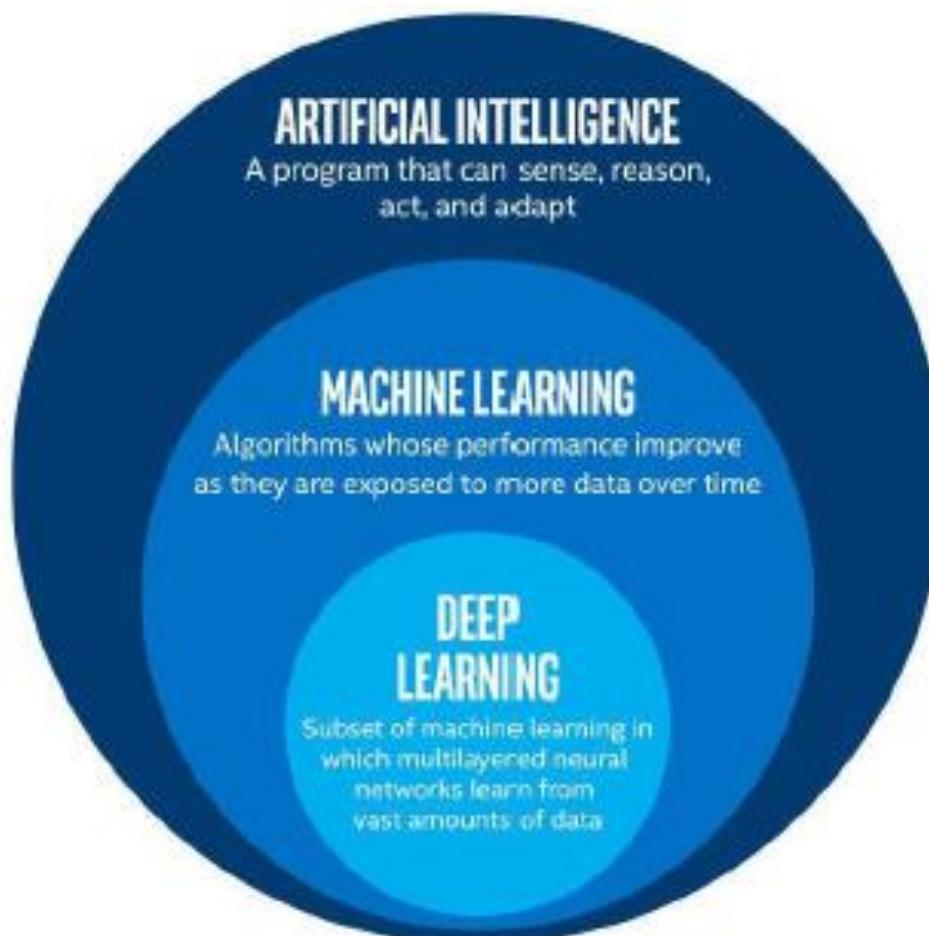
Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

Source: Nvidia



Machine Learning

- These programs learn from repeatedly seeing data, rather than being explicitly programmed by humans



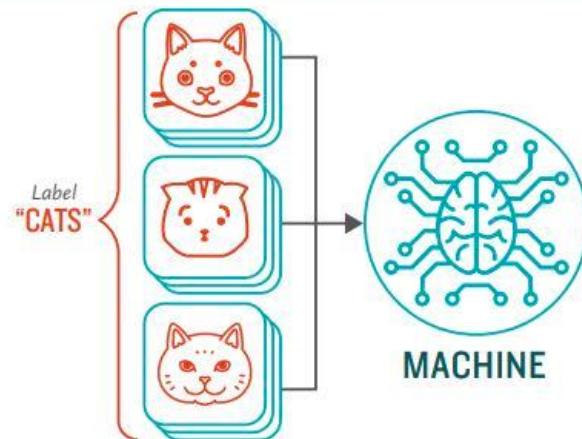


Supervised Learning

How **Supervised** Machine Learning Works

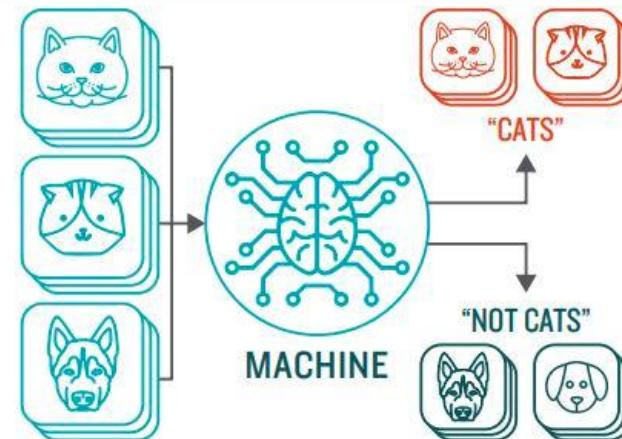
STEP 1

Provide the machine learning algorithm categorized or "labeled" input and output data from to learn

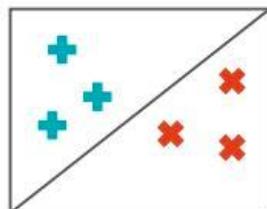


STEP 2

Feed the machine new, unlabeled information to see if it tags new data appropriately. If not, continue refining the algorithm

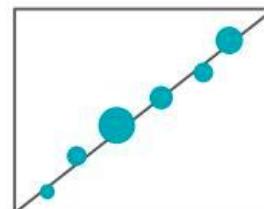


TYPES OF PROBLEMS TO WHICH IT'S SUITED



CLASSIFICATION

Sorting items into categories



REGRESSION

Identifying real values (dollars, weight, etc.)

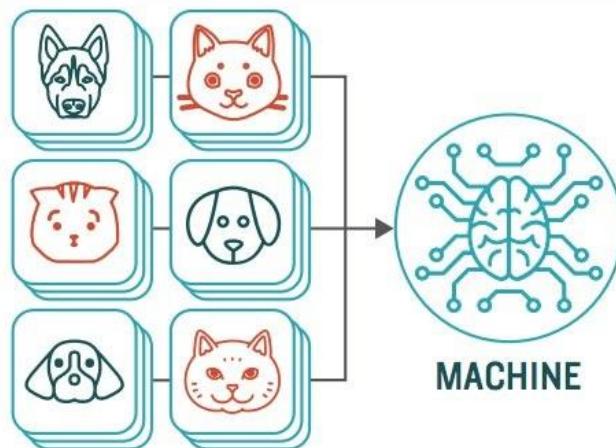


Unsupervised Learning

How **Unsupervised** Machine Learning Works

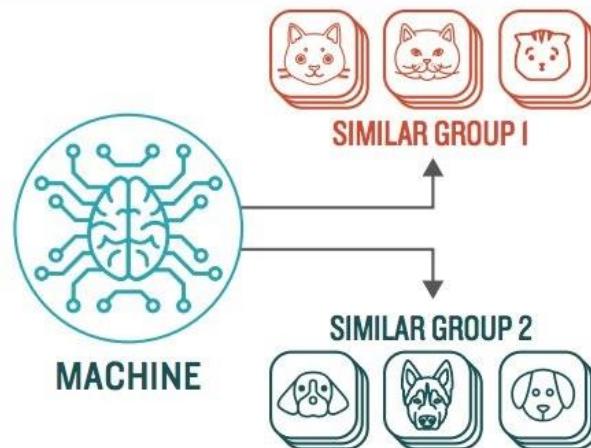
STEP 1

Provide the machine learning algorithm uncategorized, unlabeled input data to see what patterns it finds



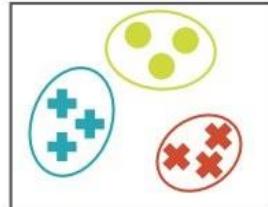
STEP 2

Observe and learn from the patterns the machine identifies



TYPES OF PROBLEMS TO WHICH IT'S SUITED

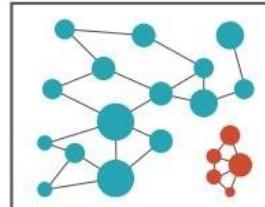
CLUSTERING



Identifying similarities in groups

For Example: Are there patterns in the data to indicate certain patients will respond better to this treatment than others?

ANOMALY DETECTION



Identifying abnormalities in data

For Example: Is a hacker intruding in our network?



Machine Learning

- **Two main types of learning**
 - Supervised Learning
 - Data points have known outcome
 - Goal is to make predictions - Classification and Regression
 - Unsupervised Learning
 - Data points have unknown outcome
 - Goal is to find structure within the data – Clustering
- **Other types of learning**
 - Reinforcement Learning
 - Genetic Algorithm



Machine Learning

- Applications in our daily lives

Spam Filtering

Web Search

Postal Mail Routing

Fraud Detection

Movie
Recommendations

Vehicle Driver
Assistance

Web Advertisements

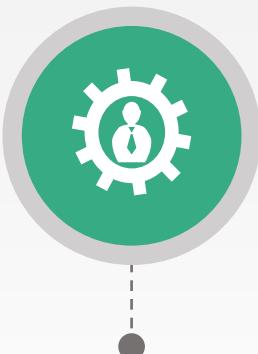
Social Networks

Speech Recognition



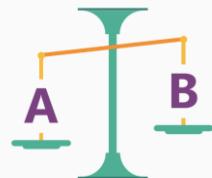
5 fundamental questions

**Is this weird?
(Anomaly detection)**



Is this pressure gauge reading normal?
Is this message from the internet typical?

**Is this A or B?
(Classification)
(discrete values)**



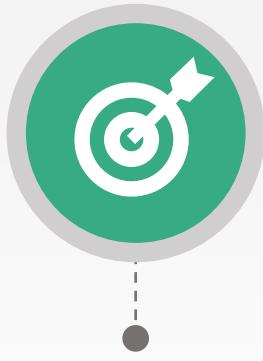
Will this tire fail in the next 1,000 miles: Yes or no?
Which brings in more customers: a \$5 coupon or a 25% discount?

**How many?
How Much?
(Regression)
(Continuous)**



What will the temperature be next Tuesday?
What will my fourth quarter sales be?

**How is this organized?
(Clustering)**



Which viewers like the same types of movies?
Which printer models fail the same way?

**What should I do?
(Reinforce Learning)**

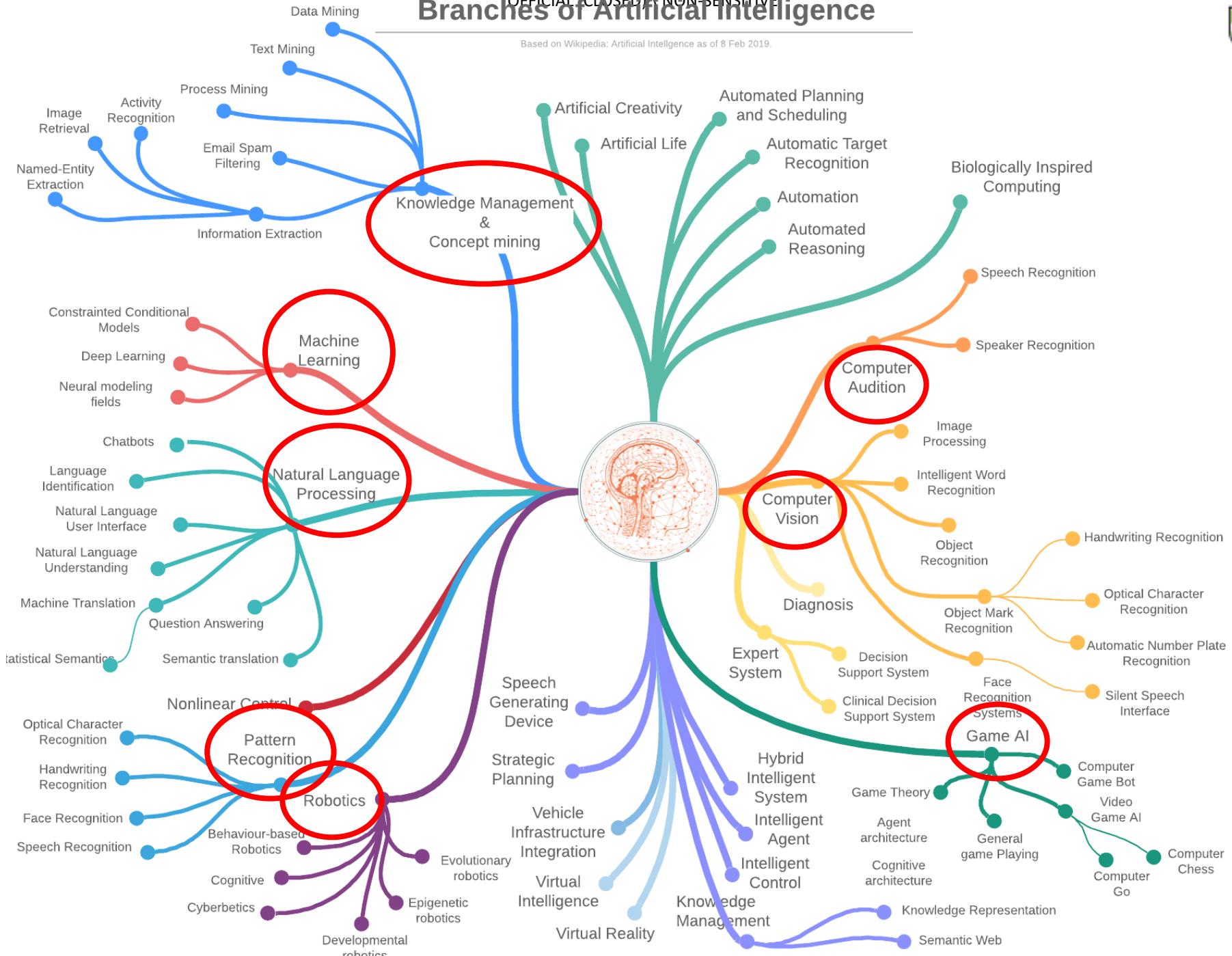


If I'm a self-driving car: At a yellow light, brake or accelerate?
For a robot vacuum: Keep vacuuming, or go back to the charging station?



OFFICIAL (CLOSED) & NON-SENSITIVE Branches of Artificial Intelligence

Based on Wikipedia: Artificial Intelligence as of 8 Feb 2019.





Machine Learning Example

- Suppose you wanted to identify fraudulent credit card transactions.
- You could define features to be:
 - Transaction time
 - Transaction amount
 - Transaction location
 - Category of purchase
- The algorithm could learn what feature combinations suggest unusual activity.





Machine Learning Limitations

- Suppose you wanted to determine if an image is of a cat or a dog.
- What features would you use?
- This is where **Deep Learning** can come in.



Dog and cat recognition

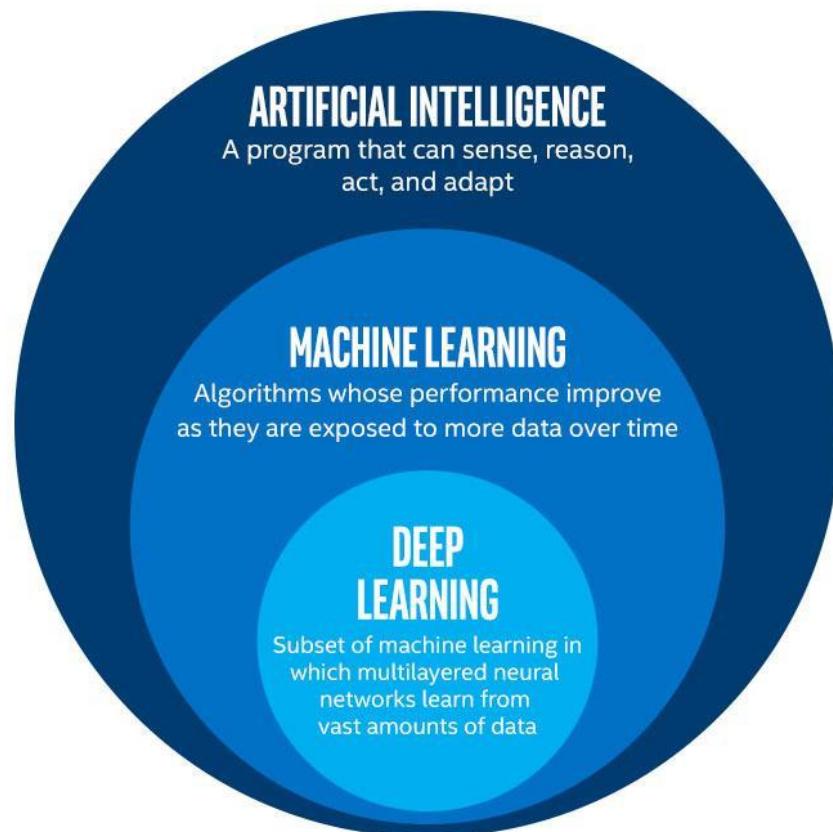


What is deep learning?

Deep Learning

“Machine learning that involves using very complicated models called “deep neural networks”.”
(Intel)

Models determine best representation of original data; in classic machine learning, humans must do this.

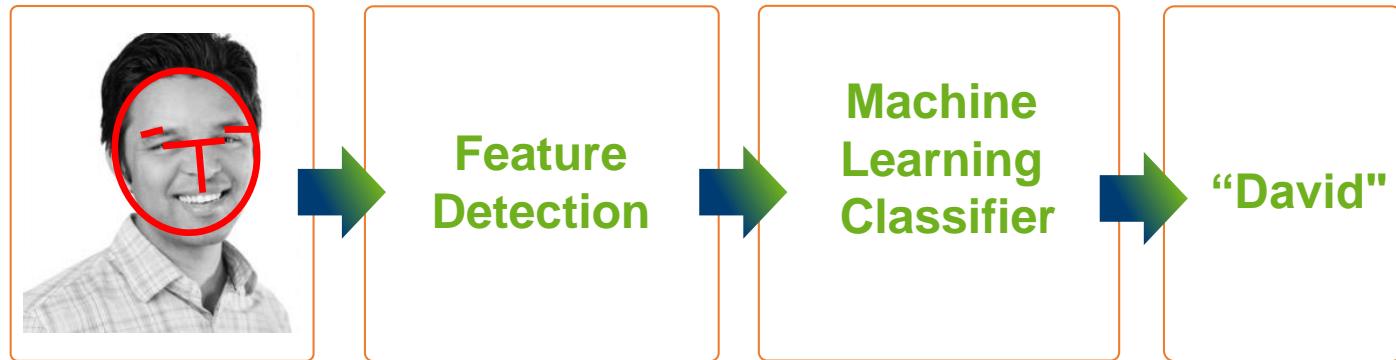




Deep Learning Example

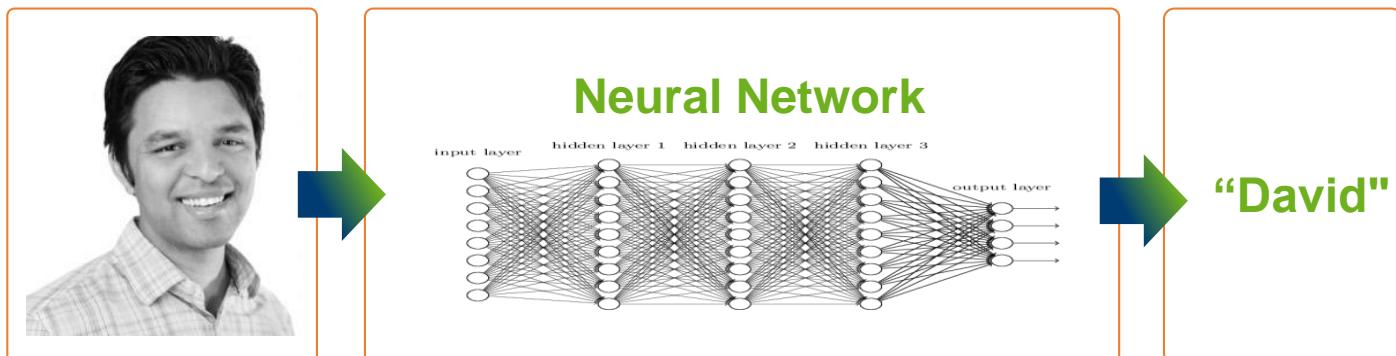
Classic Machine Learning

Step 1: Determine features.
Step 2: Feed them through model.



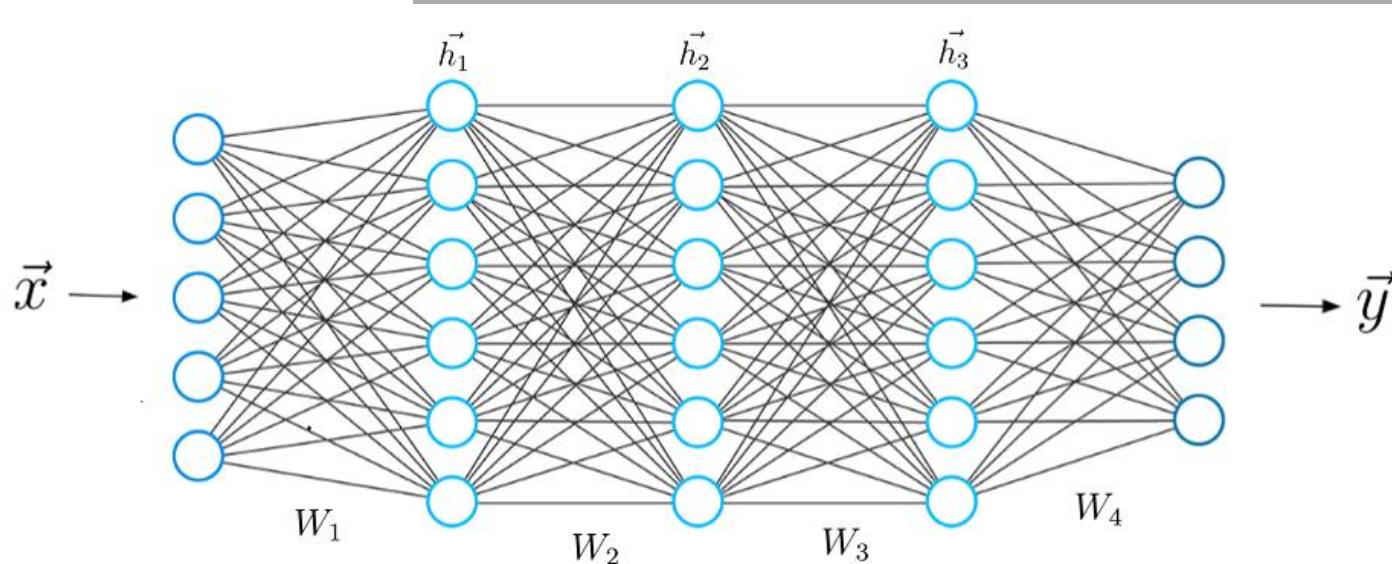
Deep Learning

Steps 1 and 2 are combined into 1 step.

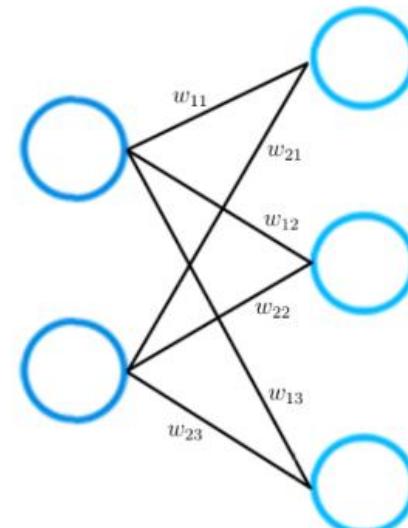




Neural Networks

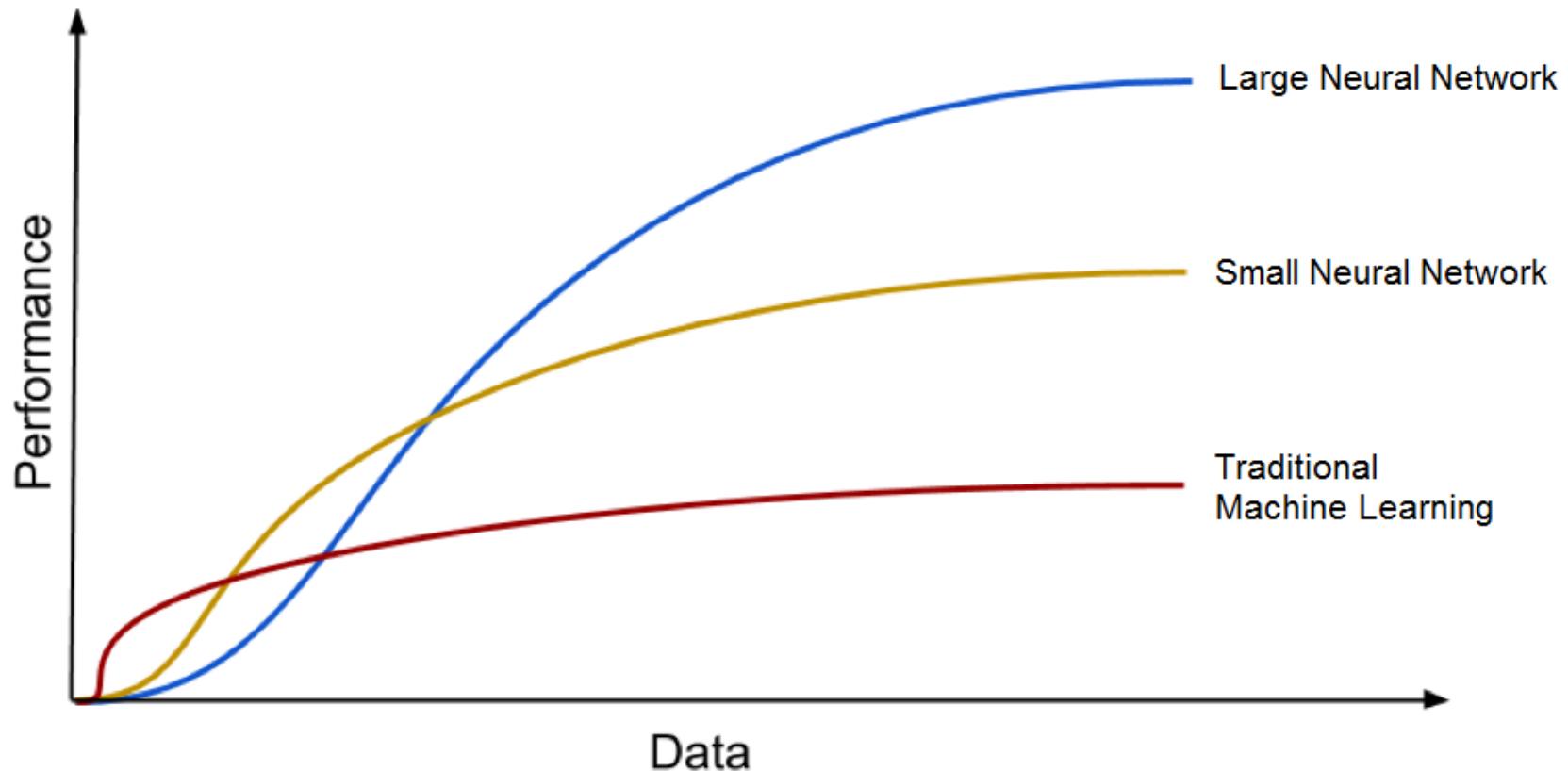


The challenge in training a neural networks is finding a set of weights the give the most accurate output.





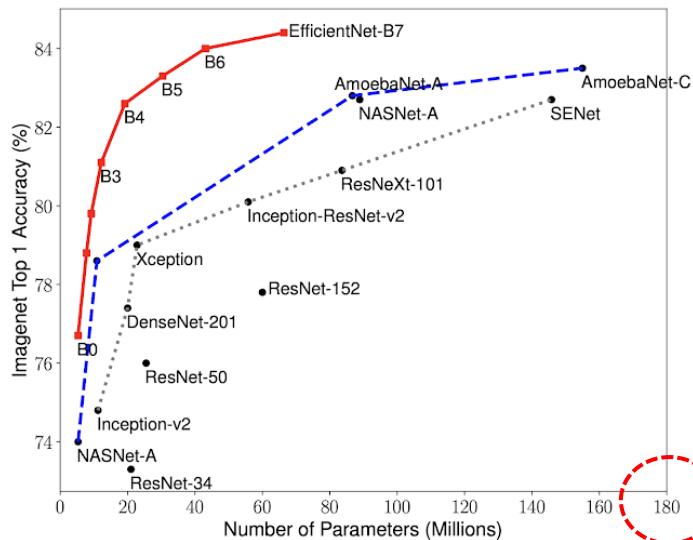
Performance



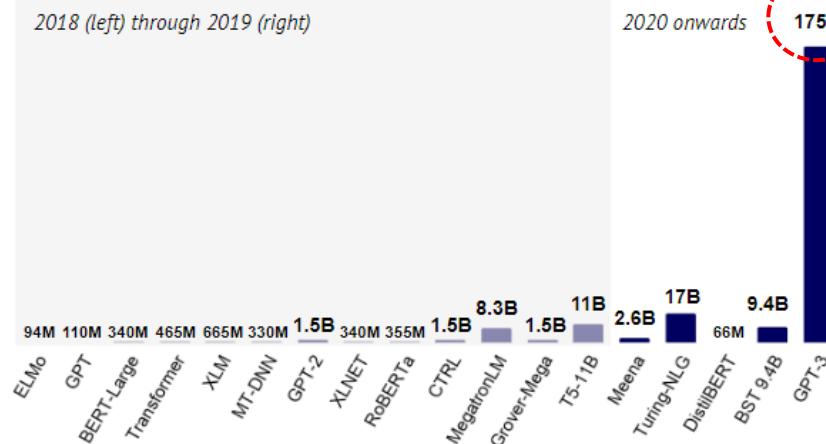
Deep Learning Algorithms get better with the increasing amount of data.



Size



► Huge models, large companies and massive training costs dominate the hottest area of AI today, NLP.



Note: The number of parameters indicates how many different coefficients the algorithm optimizes during the training process.



Deep Learning in Action

bit.ly/google_teachable

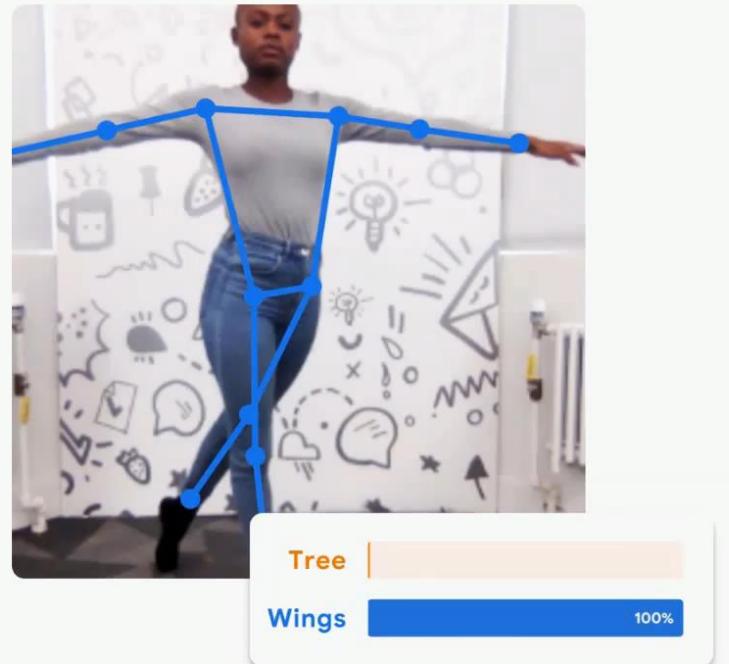
Teachable Machine



Train a computer to recognize your own images, sounds, & poses.

A fast, easy way to create machine learning models for your sites, apps, and more – no expertise or coding required.

Get Started



ml⁶

p5.js

Coral



node
js



Optional Activity



15 Mins Break

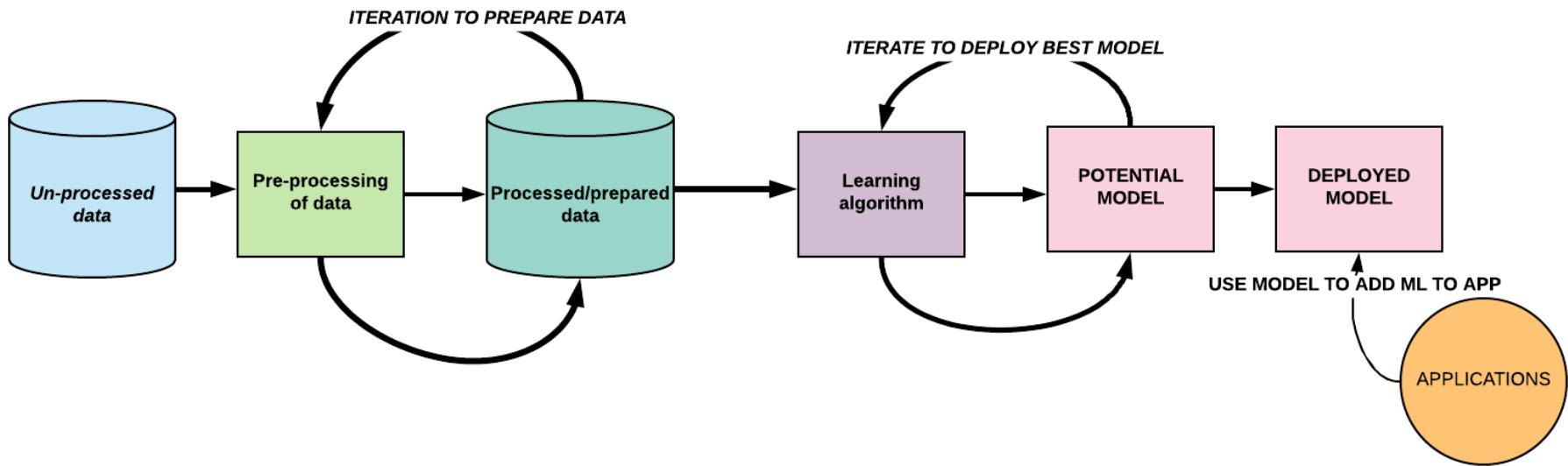


bit.ly/top10_2020





Machine Learning workflow

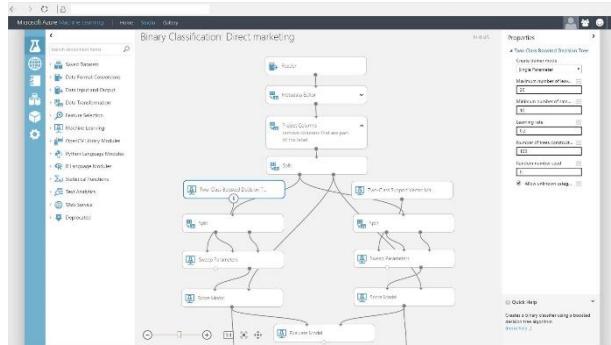


Ref: <https://cloudacademy.com/blog/what-is-azure-machine-learning/>

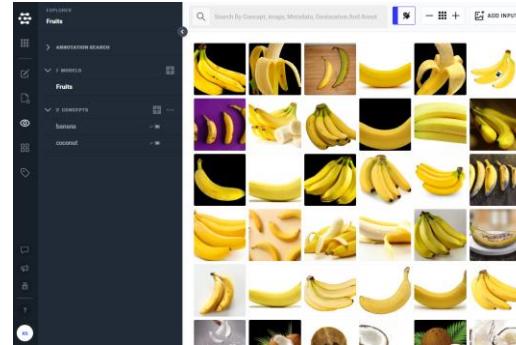


Code-Free Machine Learning tools

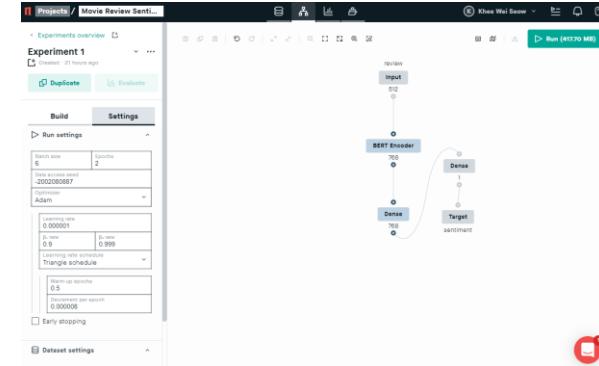
Microsoft Azure
Machine Learning Studio
(Classic)



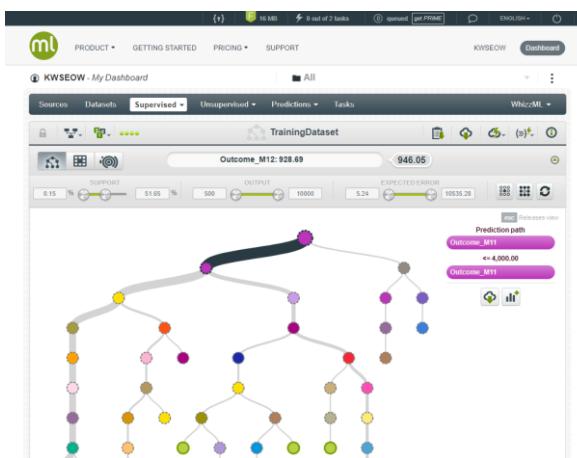
Clarifai



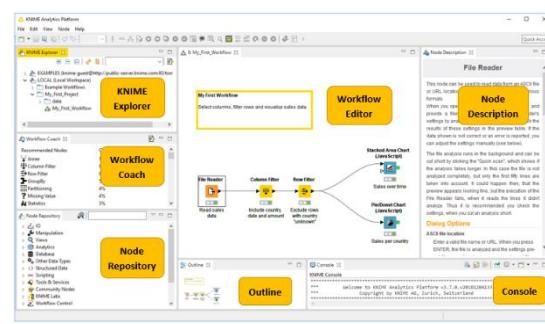
Peltarion



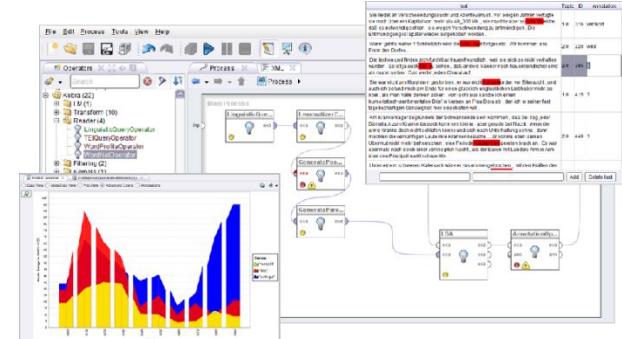
bigml



KNIME



Rapidminer





Activity 1 – First Machine Learning with Azure

- Automobile Price Prediction

Given some features of a car, e.g. engine capacity, no of doors, horsepower, predict the selling price



Step 1:
Watch and listen to the instructor's demonstration



30 mins

symboling	normalized_msr	make	fuel-type	aspiration	num-of-drivewheels	body-style	drive-wheel	engine-loc	wheel-base	length	width	height	curb-weight	engine-type	num-of-cyl	engine-size	fuel-system	bore	stroke
3 ?	1.0	alfa-romeo	gas	std	two	convertible	rwd	front	88.6	168.8	64.1	48.8	2548	dohc	four	130	mpfi	3.47	2.68
3 ?	1.0	alfa-romeo	gas	std	two	convertible	rwd	front	88.6	168.8	64.1	48.8	2548	dohc	four	130	mpfi	3.47	2.68
1 ?	1.0	alfa-romeo	gas	std	two	hatchback	rwd	front	94.5	171.2	65.5	52.4	2823	ohcv	six	152	mpfi	2.68	3.47
2	164	audi	gas	std	four	sedan	fwd	front	99.8	176.6	66.2	54.3	2373	ohc	four	109	mpfi	3.19	3.4
2	164	audi	gas	std	four	sedan	4wd	front	99.4	176.6	66.4	54.3	2824	dohc	five	136	mpfi	3.19	3.4
2 ?	audi	gas	std	two	sedan	fwd	front	99.8	177.3	66.3	53.1	2507	ohc	five	136	mpfi	3.19	3.4	
1	158	audi	gas	std	four	sedan	fwd	front	105.8	192.7	71.4	55.7	2844	ohc	five	136	mpfi	3.19	3.4
1 ?	audi	gas	std	four	wagon	fwd	front	105.8	192.7	71.4	55.7	2954	ohc	five	136	mpfi	3.19	3.4	
1	158	audi	gas	turbo	four	sedan	fwd	front	105.8	192.7	71.4	55.9	3058	ohc	five	131	mpfi	3.13	3.4
0 ?	audi	gas	turbo	two	hatchback	4wd	front	99.5	178.2	67.9	52	3053	ohc	five	131	mpfi	3.13	3.4	
2	192	bmw	gas	std	two	sedan	rwd	front	101.2	176.8	64.8	54.3	2395	ohc	four	108	mpfi	3.5	2.8
0	192	bmw	gas	std	four	sedan	rwd	front	101.2	176.8	64.8	54.3	2395	ohc	four	108	mpfi	3.5	2.8
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0	198	bmw	gas	std	four	sedan	rwd	front	103.5	189	66.9	55.7	3055	ohc	six	164	mpfi	3.21	3.3
1 ?	bmw	gas	std	four	sedan	rwd	front	103.5	189	66.9	55.7	3230	ohc	six	209	mpfi	3.62	3.39	
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1	98	chevrolet	gas	std	two	hatchback	fwd	front	94.5	155.9	63.6	52	1874	ohc	four	90	2bbl	3.03	3.11
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1	101	honda	gas	std	two	hatchback	fwd	front	93.7	150	64	52.6	1837	ohc	four	79	1bbl	2.91	3.07
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0 ?	isuzu	gas	std	four	sedan	rwd	front	94.3	170.7	61.8	53.5	2337	ohc	four	111	2bbl	3.31	3.23	
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1	104	mazda	gas	std	two	hatchback	fwd	front	93.1	159.1	64.2	54.1	1890	ohc	four	91	2bbl	3.03	3.15
1	104	mazda	gas	std	two	hatchback	fwd	front	93.1	159.1	64.2	54.1	1900	ohc	four	91	2bbl	3.03	3.15
1	113	mazda	gas	std	four	sedan	fwd	front	93.1	166.8	64.2	54.1	1945	ohc	four	91	2bbl	3.03	3.15
1	124	mazda	gas	std	four	sedan	fwd	front	93.1	166.8	64.2	54.1	1950	ohc	four	91	2bbl	3.03	3.15
3	150	mazda	gas	std	two	hatchback	rwd	front	95.3	169	65.7	49.6	2380	rotor	two	70	4bbl	?	?
3	150	mazda	gas	std	two	hatchback	rwd	front	95.3	169	65.7	49.6	2385	rotor	two	70	4bbl	?	?
3	150	mazda	gas	std	two	hatchback	rwd	front	95.3	169	65.7	49.6	2500	rotor	two	80	mpfi	?	?
1	129	mazda	gas	std	two	hatchback	fwd	front	98.8	177.8	66.5	53.7	2385	ohc	four	122	2bbl	3.39	3.39
1	129	mazda	gas	std	two	hatchback	fwd	front	98.8	177.8	66.5	53.7	2386	ohc	four	122	2bbl	3.39	3.39
0	115	mazda	gas	std	four	sedan	fwd	front	98.8	177.8	66.5	55.5	2410	ohc	four	122	2bbl	3.39	3.39
0	115	mazda	diesel	std	?	sedan	fwd	front	98.8	177.8	66.5	55.5	2443	ohc	four	122	idi	3.39	3.39

30 mins

Individual Activity

45 mins



60 mins Lunch Break

Some interesting videos

<https://www.youtube.com/watch?v=bmNaLtC6vkU>

https://www.youtube.com/watch?v=Nnf8P5A_saE

LUNCH BREAK





Recap

Machine Learning in ML Studio

Anomaly Detection

- One-class Support Vector Machine
- Principal Component Analysis-based Anomaly Detection
- Time Series Anomaly Detection*

Classification

Two-class Classification

- Averaged Perceptron
- Bayes Point Machine
- Boosted Decision Tree
- Decision Forest
- Decision Jungle
- Logistic Regression
- Neural Network
- Support Vector Machine

Multi-class Classification

- Decision Forest
- Decision Jungle
- Logistic Regression
- Neural Network
- One-vs-all

Clustering

- K-means Clustering

Recommendation

- Matchbox Recommender

Regression

- Bayesian Linear Regression
- Boosted Decision Tree
- Decision Forest
- Fast Forest Quantile Regression
- Linear Regression
- Neural Network Regression
- Ordinal Regression
- Poisson Regression

Statistical Functions

- Descriptive Statistics
- Hypothesis Testing T-Test
- Linear Correlation
- Probability Function Evaluation

Text Analytics

- Feature Hashing
- Named Entity Recognition
- Vowpal Wabbit

Computer Vision

- OpenCV Library

<https://studio.azureml.net>

Guest Access Workspace: Free trial access without logging in.

Free Workspace: Free persisted access, no Azure subscription needed.

Standard Workspace: Full access with SLA under an Azure subscription.

Cross browser drag & drop ML workflow designer.
Zero installation needed.

Import Data

Preprocess

Unlimited Extensibility

- R Script Module
- Python Script Module
- Custom Module
- Jupyter Notebook

Built-in ML Algorithms

Split Data

Train Model

Score Model

Training Experiment

One-click Operationalization

Predictive Experiment

Make Prediction with Elastic APIs

- Request-Response Service (RRS)
- Batch Execution Service (BES)
- Retraining API

Data Source

- Azure Blob Storage
- Azure SQL DB
- Azure SQL DW*
- Azure Table
- Desktop Direct Upload
- Hadoop Hive Query
- Manual Data Entry
- OData Feed
- On-prem SQL Server*
- Web URL (HTTP)

Data Format

- ARFF
- CSV
- SVMLight
- TSV
- Excel
- ZIP

Data Preparation

- Clean Missing Data
- Clip Outliers
- Edit Metadata
- Feature Selection
- Filter
- Learning with Counts
- Normalize Data
- Partition and Sample
- Principal Component Analysis
- Quantize Data
- SQLite Transformation
- Synthetic Minority Oversampling Technique

Enterprise Grade Cloud Service

- SLA: 99.95% Guaranteed Up-time
- Azure AD Authentication
- Compute at Large Scale
- Multi-geo Availability
- Regulatory Compliance*

Community

- Gallery (<http://gallery.azureml.net>)
- Samples & Templates
- Workspace Sharing and Collaboration
- Live Chat & MSDN Forum Support

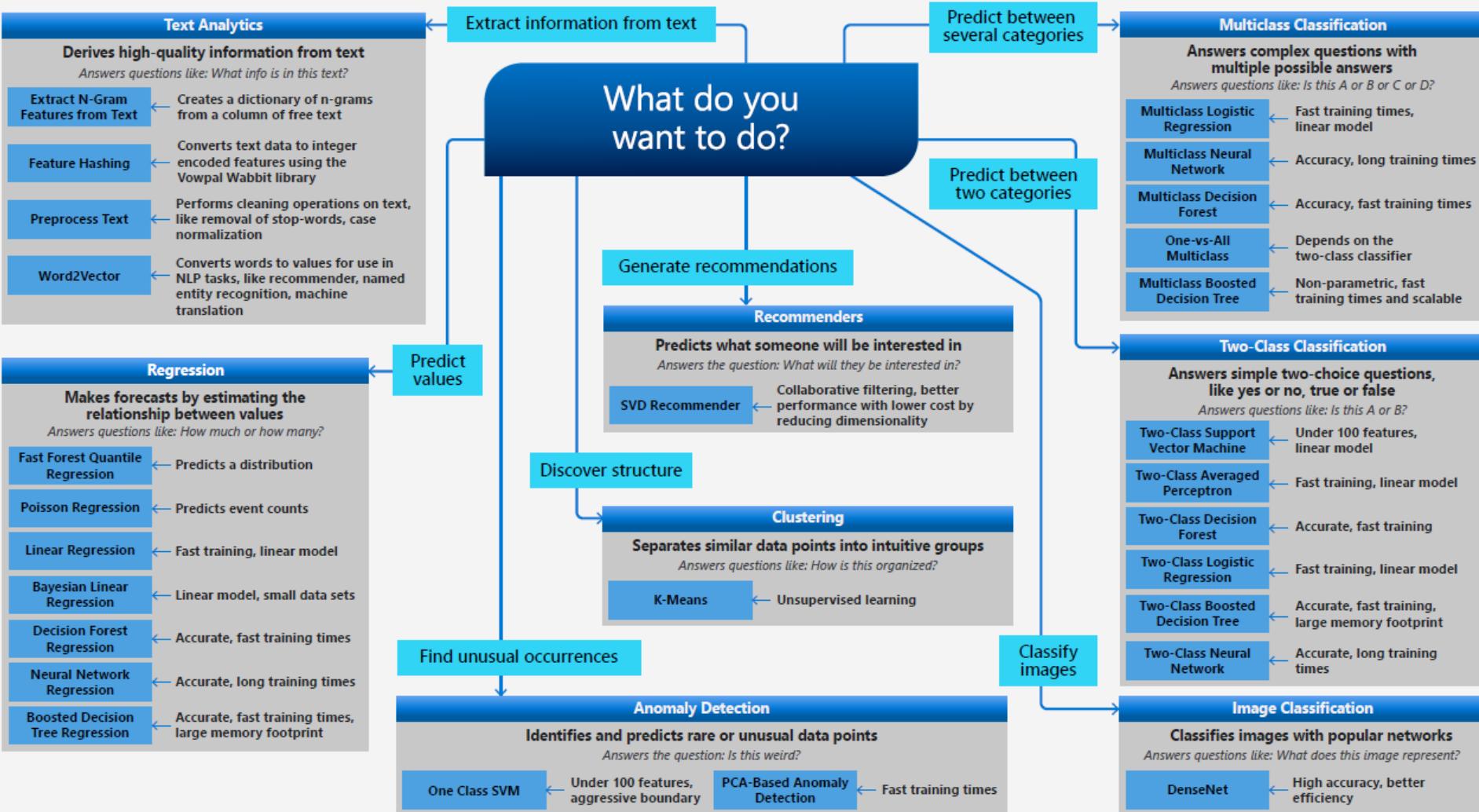
* Feature Coming Soon



Azure ML Algorithm Cheat Sheet

Microsoft Azure Machine Learning Algorithm Cheat Sheet

This cheat sheet helps you choose the best machine learning algorithm for your predictive analytics solution. Your decision is driven by both the nature of your data and the goal you want to achieve with your data.





Activity 2

- Deploying your experiment as a Web Service & Make Prediction using Excel

	A	B	C	D	E	F	G	H	I	J
1	symboling	normalized make	fuel-type	aspiration	num-of-doors	body-style	drive-wheel	engine-location	wheel-base	length
2	3	1 alfa-romero	gas	std	two	convertible rwd	front		88.6	
3	3	1 alfa-romero	gas	std	two	convertible rwd	front		88.6	
4	1	1 alfa-romero	gas	std	two	hatchback rwd	front		94.5	
5	2	164 audi	gas	std	four	sedan fwd	front		99.8	
6	2	164 audi	gas	std	four	sedan 4wd	front		99.4	
7										
8										
9										
10	make	body-style	wheel-base	engine-size	horsepower	peak-rpm	highway-mpg	price		Scored Labels
11	alfa-romero	convertible		88.6	130	111	5000	27	13495	13498.476
12	alfa-romero	convertible		88.6	130	111	5000	27	16500	13498.476
13	alfa-romero	hatchback		94.5	152	154	5000	26	16500	14329.816
14	audi	sedan		99.8	109	102	5500	30	13950	15696.502
15	audi	sedan		99.4	136	115	5500	22	17450	17161.153
16										

Azure Machine Learning interface showing the experiment setup:

- VIEW SCHEMA**: Shows the schema of the input data.
- PREDICT**: Shows the prediction interface where input data is selected from Sheet1!A1:Z6 and checked for headers.
- INPUT**: Input is set to Sheet1!A1:Z6 and checked for headers. An option to use sample data is available.
- OUTPUT**: Output is set to Sheet1!A10 and checked for headers.
- PREDICT**: Predict button is shown with an option to auto-predict.
- ERRORS**: Shows any errors related to the prediction process.

Predicting will override existing values. This can't be undone. Got it!

Step 1:
Watch and listen to the instructor's demonstration



15 mins

Step 2:
Work through the activities

Individual Activity



45 mins

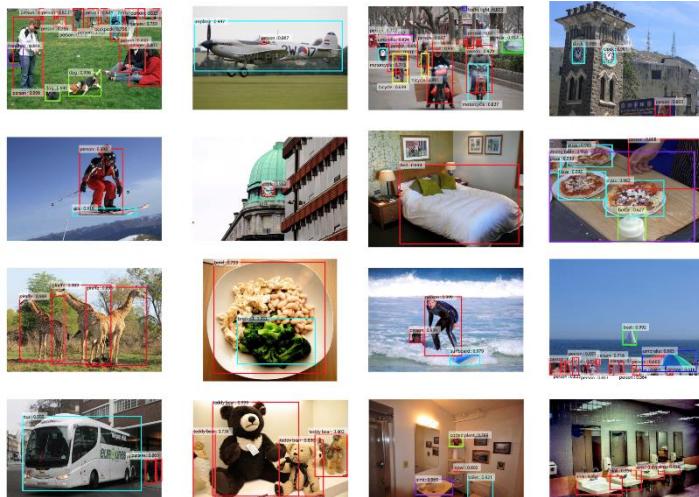
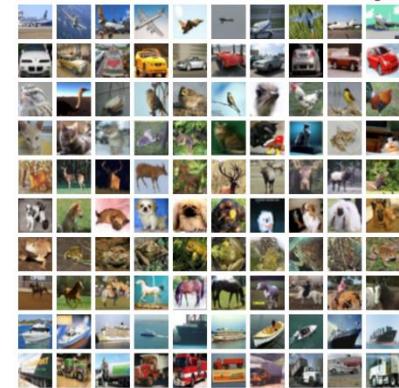


Applications of Computer Vision

- Image Classification
- Image Classification With Localization
- Object Detection
- Object Segmentation



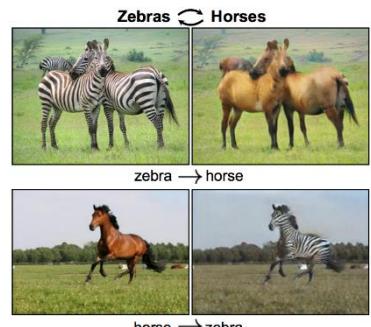
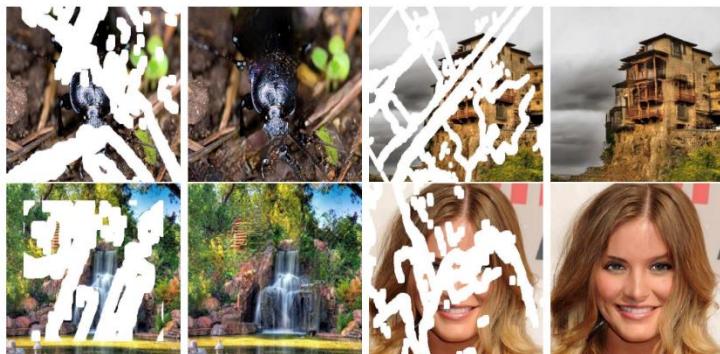
airplane
automobile
bird
cat
deer
dog
frog
horse
ship
truck





Applications of Computer Vision

- Image Style Transfer
- Image Colorization
- Image Reconstruction
- Image Super-Resolution
- Image Synthesis
- Other Problems





Transfer Learning



Humans have an inherent ability to transfer knowledge across tasks.

What we acquire as knowledge while learning about one task, we utilize in the same way to solve related tasks.

The more related the tasks, the easier it is for us to transfer, or cross-utilize our knowledge.

Some simple examples would be,

- * Know how to ride a motorbike → Learn how to ride a car
- * Know how to play classic piano → Learn how to play jazz piano

- Models are difficult to train from scratch
 - Huge datasets (like ImageNet)
 - Long number of training iterations
 - Very heavy computing machinery
 - Time experimenting to get hyper-parameters just right

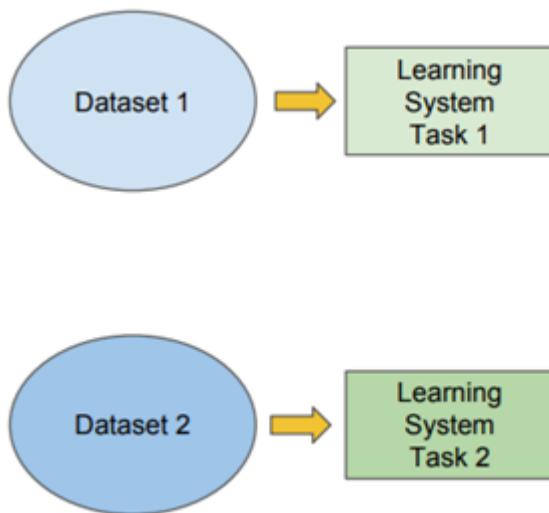


Transfer Learning

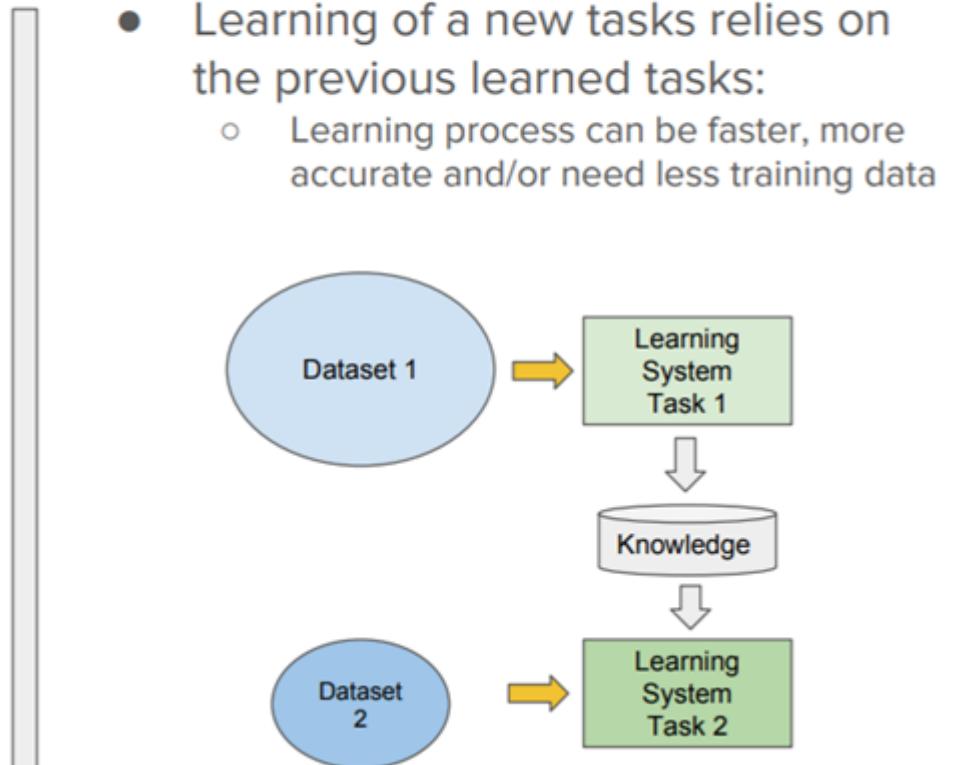
Traditional ML

vs Transfer Learning

- Isolated, single task learning:
 - Knowledge is not retained or accumulated. Learning is performed w.o. considering past learned knowledge in other tasks

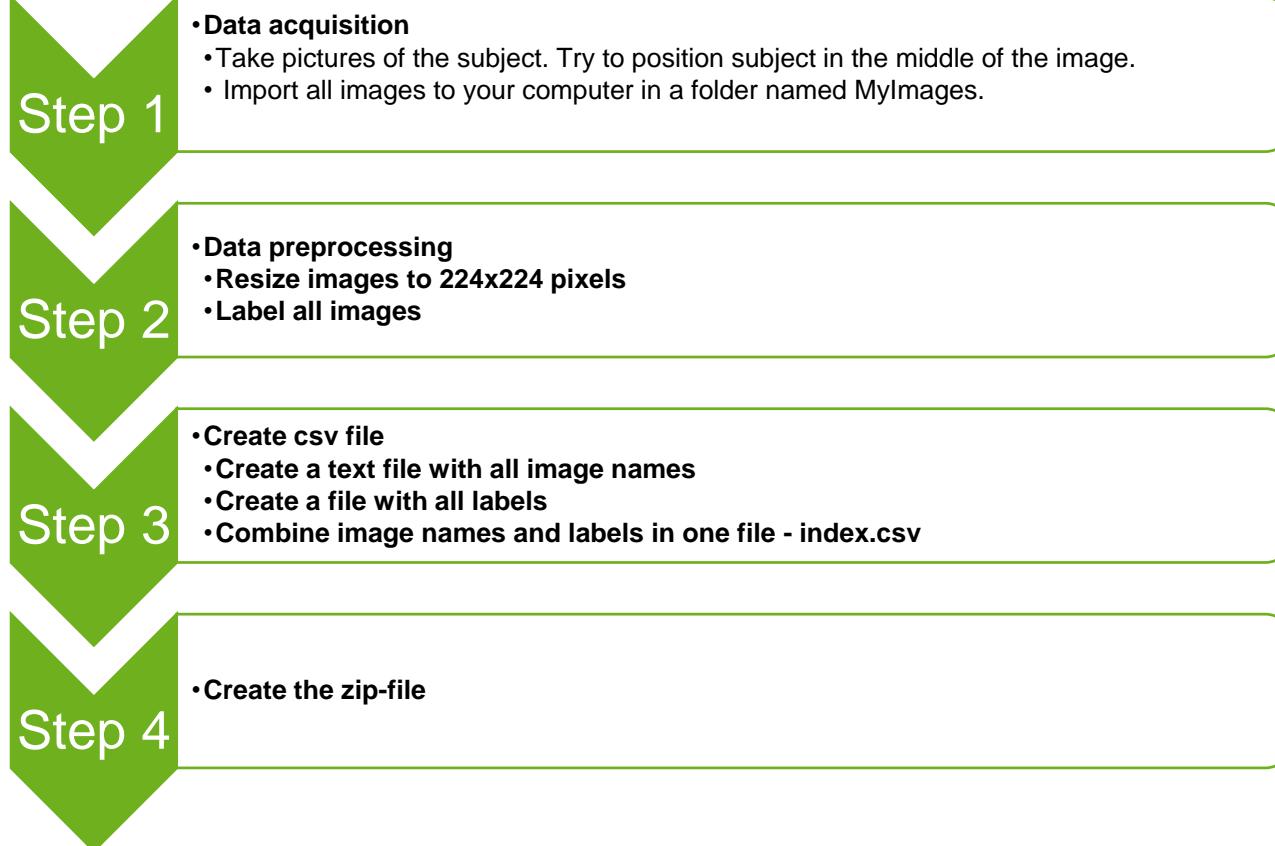


- Learning of a new tasks relies on the previous learned tasks:
 - Learning process can be faster, more accurate and/or need less training data





Creating a new dataset





Example

The diagram illustrates the structure of a car damage dataset. It shows a file tree, a CSV metadata table, and a preview of the images.

File Tree:

- <> Dataset > Car damage dataset >
- Name
- image (highlighted with a red dashed box)
- test_images
- index.csv (highlighted with a red dashed box)
- metadata.json

A green arrow points from the 'image' folder in the file tree to the 'image' column in the CSV table.

CSV Metadata Table:

A1	A	B	C
1	image	class	subset
2	image/0.jpeg	unknown	T
3	image/1.jpeg	head_lamp	T
4	image/2.jpeg	door_scratch	T
5	image/3.jpeg	head_lamp	T
6	image/4.jpeg	unknown	T
7	image/5.jpeg	unknown	T
8	image/6.jpeg	glass_shatter	T

Image Preview:

Dataset > Car damage dataset > image

- Search image
- 0.jpeg
- 1.jpeg
- 2.jpeg
- 3.jpeg
- 4.jpeg
- 5.jpeg
- 6.jpeg
- 7.jpeg
- 8.jpeg
- 9.jpeg
- 10.jpeg
- 11.jpeg
- 12.jpeg
- 13.jpeg
- 14.jpeg
- 15.jpeg
- 16.jpeg
- 17.jpeg



Activity 3 – Car Damage Classifier

A close-up photograph of a car's headlight that has been shattered into many pieces.	A photograph of a car's rear right light assembly, which appears to be broken or severely damaged.	A photograph of a car's side window that has been shattered, showing a large hole and broken glass shards.	A photograph of a car's white door panel with a visible horizontal scratch.
A photograph of a car's white door panel with a prominent dent.	A photograph of a dark-colored car's front bumper that has been dented.	A photograph of a white car's side bumper with a visible scratch.	A photograph of a silver SUV parked in a showroom setting.

Step 1:
Watch and listen to the
instructor's demonstration



20 mins

Step 2:
- Do on your own



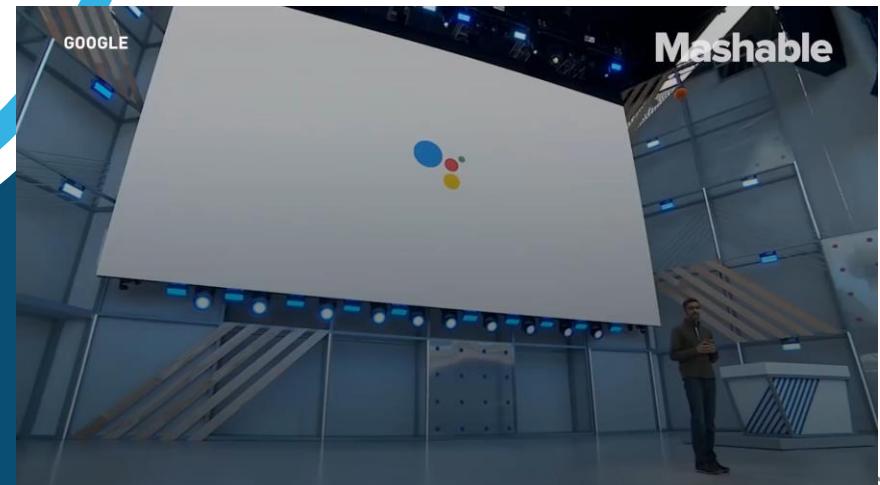
40 mins

Individual Activity



15 Mins Break

bit.ly/google_duplex2019





Natural Language Processing

- Search Autocorrect and Autocomplete
- Language Translator
- **Social Media Monitoring**
- Chatbots
- **Survey Analysis**
- Targeted Advertising
- Hiring and Recruitment
- Voice Assistants
- Grammar Checkers
- Email Filtering





Dataset

review	sentiment
Encoding Text	Encoding Binary Positive class positive
1 Hubert Selby Jr. gave us the book "Requiem For A Dream" and co-wrote the screenplay to Aronofsky's movie of it. That movie succeeded on every level by delivering an intimate, and unbiased portrait of the horrors of the characters lives and the vices that destroyed them. "Last Exit To Brooklyn" still has the vice and the multiple characters living sad lives, but it hardly does them the same justice Aronofsky did. The film seems laughably anti-gay at times. Especially when in the film homosexuality equals death. One gay character gets stoned, is launched skyward by a speeding car, and lands dead on the pavement. Another is crucified and still more are simply beat up. Another exaggerated piece of shock value, that might actually hav...	negative
2 There are very few performers today who can keep me captivated throughout an entire film just by their presence. One of those few is Judy Davis, who has built a successful career out of creating characters that are headstrong in attitude but very vulnerable at heart. She takes roles that most other performers would treat melodramatically and adds a fiery, deeply emotional intensity that pulls attention away from everything else on the screen. Her skills are well displayed in "High Tide," a film that matches her up a second time with director Gillian Armstrong, who gave Davis her first major success with "My Brilliant Career." In that film, Davis played a young woman who was determined to make it in the world, despite the suffocat...	positive
3 C'mon guys some previous reviewers have nearly written a novel commenting on this episode. It's just an old 60's TV show ! This episode of Star Trek is notable	negative

Information

Creator

Review, Sentiment

Rows

25 000

Size

13 MB

Categories

Text, Classification



Activity 4 - Creating a Sentiment Analyser



About this dataset

This dataset contains textual movie reviews from IMDB users, together with the rating (simplified as positive or negative) that the user gave to the movie.

Inspiration

Use this dataset to predict a simple positive or negative category from paragraph-sized text data.

Step 1:

Watch and listen to the instructor's demonstration



20 mins

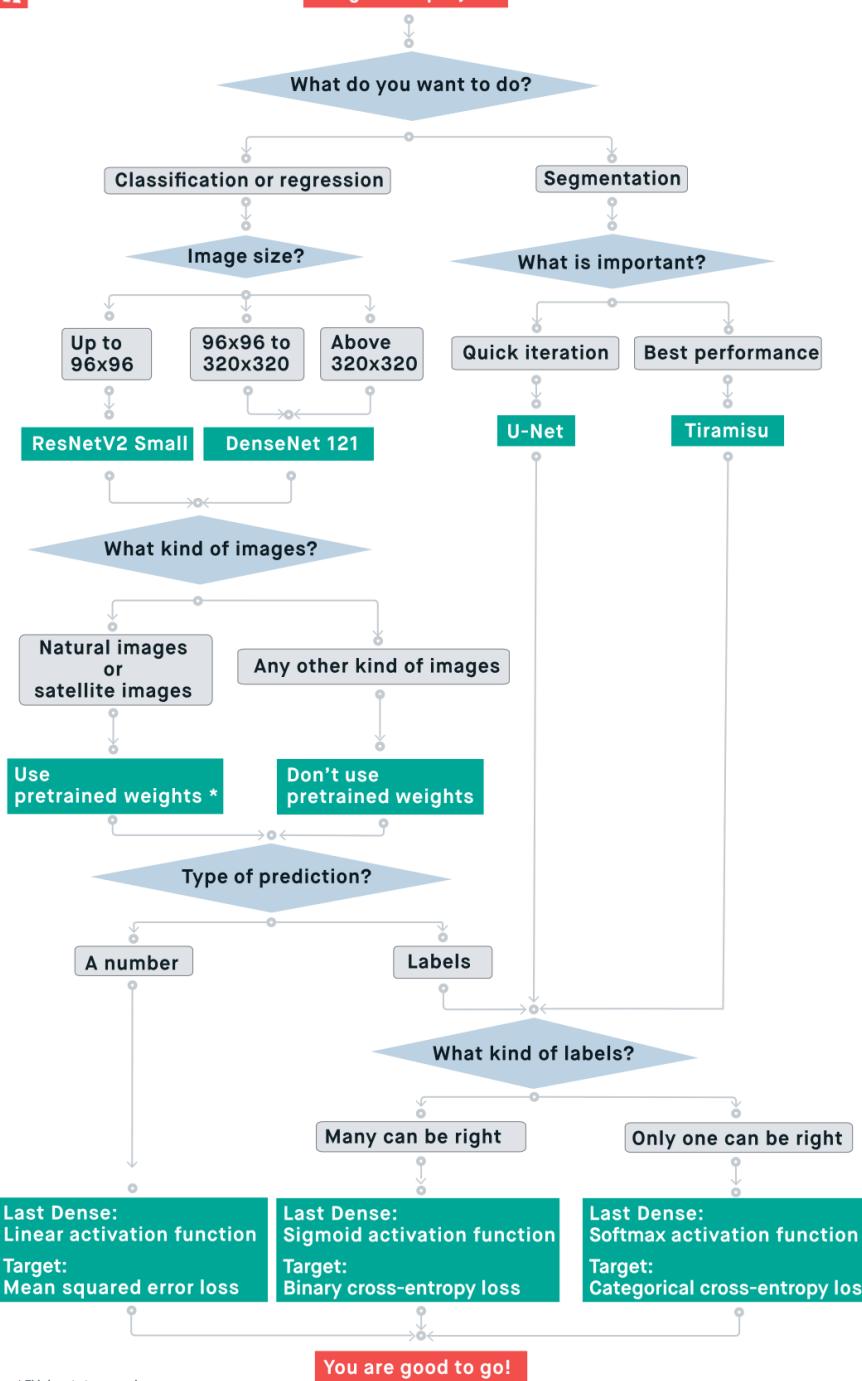
Step 2:

- Do on your own



40 mins

Individual Activity



Cheatsheet

<https://peltarion.com/knowledge-center/documentation/cheat-sheets>



Linking Them Together

App Development

Top 9 No-Code Web App Development Tools that May Compete with Bubble

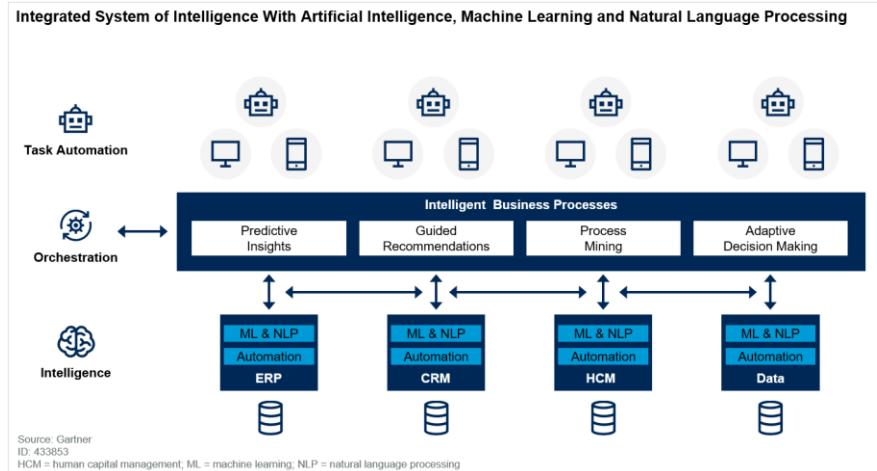
We're here to prove that "building the best product" is possible not only with Bubble.

Discover the 5 most powerful *Bubble* alternatives in the comparison table below to decide which one fits you best. Find more detailed information about the other *Bubble.io* alternatives after the table.

The screenshot shows the Bubble UI Builder interface. On the left, there's a sidebar with various tools like Design, Data, Styles, Plugins, and Settings. The main workspace displays a mobile application screen with a "GET STARTED" button. A modal window titled "Button GET STARTED" is open, showing settings for the button's appearance, conditional logic, and transitions. The "Appearance" tab is selected, showing options for style (Primary Button), tooltip text, and width percentages. The "Conditional" tab shows a dropdown menu for "Start/Edit workflow". The "Transitions" tab shows a preview of the button's movement. At the bottom of the workspace, there's a section titled "UI Elements" with a collection of building blocks.

<https://uibakery.io/bubble-alternatives>

RPA



Adobe Acrobat
Document

<https://www.youtube.com/watch?v=FV8IM9SIFQ8> 51



When to use Machine Learning

- **What are our most pressing problems right now?**
 - Just like any other tool in business, AI should be viewed as a tool that can help make your organization more effective, profitable or streamlined
- **What parts of our business generate revenue but currently have low profit margins?**
 - These revenue streams could provide fertile ground for automation and acceleration via AI.
- **Where would we like to cut costs?**
 - Review your costs and pinpoint the ones you'd like to reduce. AI can help you better understand what generates costs and identify areas that could be optimized or changed to reduce them.
- **Where do we make a high percentage of errors in our work?**
 - A well-trained AI model has the capacity to perform with far less margin of error than humans
- **What work do our employees do that they don't particularly like?**
 - If it's repetitive or annoying for a human to do, there might be a component of the task better done by AI.



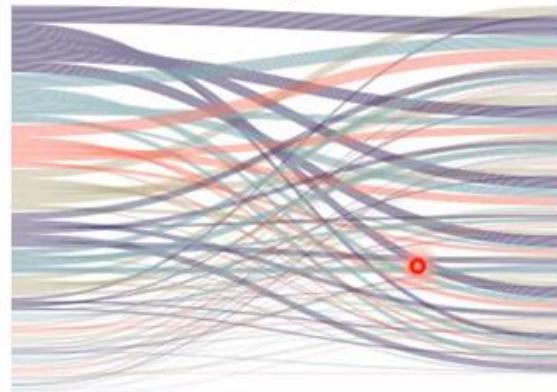
Some easy readings

THE
ESSENTIAL
AI HANDBOOK
FOR
LEADERS

FOREWORD BY MARCUS WALLEMBERG

AT THE END OF THE DAY it is not technology that creates success; it is people. It is leaders that take the right decisions based on the most accurate data, insights and their ability to work with the best people. It is the ones who do this faster than the competition that will succeed.

ALGORITHMIKA
2020 state of enterprise machine learning



O'REILLY®

**AI Adoption in
the Enterprise
2020**

Roger Magoulas & Steve Swoyer

RADAR REPORT



Datasets and Data Prep

GitHub

<https://kwseow.github.io/>

kaggle

<https://www.kaggle.com/datasets>

Google
Dataset Search Beta

<https://datasetsearch.research.google.com/>



<https://www.kdnuggets.com/datasets/index.html>



Microsoft



roboflow



Dataset and Data Prep

- Datasets
 - <http://kwseow.github.io>
 - <https://datasetsearch.research.google.com/>
 - <https://www.kaggle.com/>
- Data prep
 - Excel
 - Tableau Prep
 - Power BI



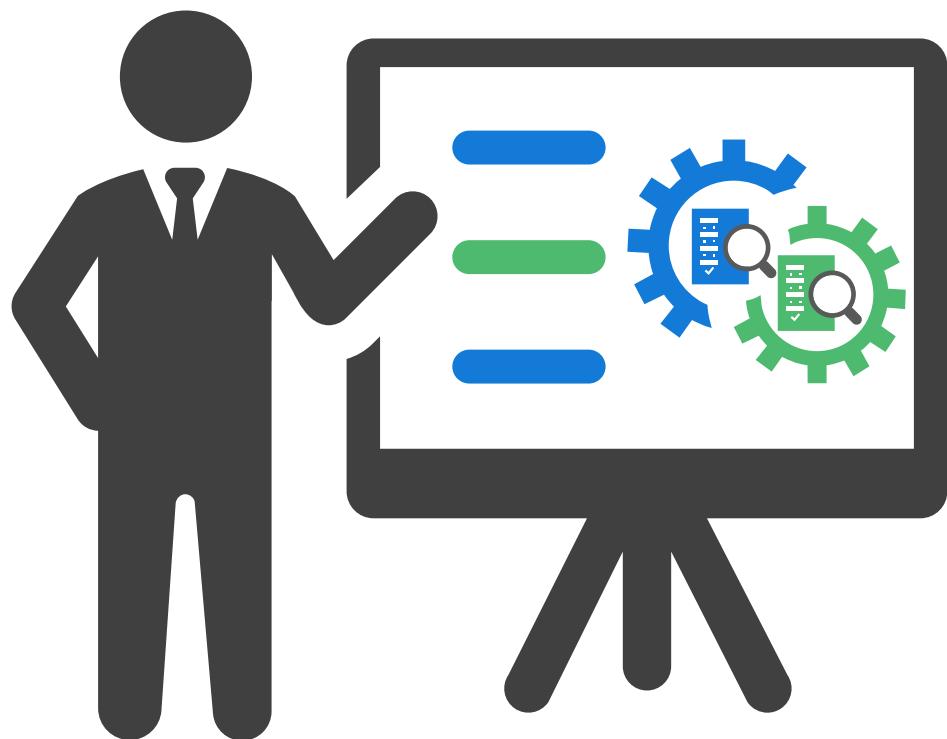
Survey

<https://bit.ly/3fVYxaF>





Summary



Email
zack_toh@rp.edu.sg

Telegram
[@zacktohsh](https://t.me/zacktohsh)

Source code:

57



Thank you