

Practical Machine Learning

Lecture 1 Introduction to Machine Learning

Dr. Suyong Eum



Course Outline

- □ Lecture program
- □ Assignments / Assessment
- □ Subject Website
- Contact detail
- □ Pre-requisite for the class
- Regarding tutorial sessions

Lecture Program

	Title of each lecture						
Week 1	Introduction to Machine Learning						
Week 2	Linear models for classification and regression						
Week 3	K-means model and Gaussian Mixture Model (GMM)	Non-neural network based machine learning algorithms					
Week 4	Hidden Markov Model (HMM)			ine learning algorithms			
Week 5	Support Vector Machine (SVM) and Kernel trick						
Week 6	Principal Component Analysis (PCA)	Preprocessing and feature extraction					
Week 7	Neural Networks						
Week 8	Convolutional Neural Networks (CNN)		Neural networks based machine learning algorithms				
Week 9	Tensorflow – CNN implementation	nentation					
Week 10	Recurrent Neural Networks (RNN) and Long Short Term Memory (LSTM)						
Week 11	Tensorflow – RNN/LSTM/GRU implementation						
Week 12	Generative Models: Variational Auto Encoder (VAE) and Generative Adversarial Network (GAN)						
Week 13	Tensorflow – VAE and DCGAN implementation						
Week 14	Reinforcement Learning (RL): Deep Q-Network (DQN) and Policy Gradient (PG: AC/A3C)						
Week 15	Tensorflow – DQN/PG/AC/A3C implementation			Reinforcement Learning			

□ No examination

□ There will be three assignments during the course.

- First two assignments: 2 x 30% = 60%
- Last assignment: 40%
- Assignment can be done individually or by a group of three or less
 - No advantage or disadvantage in terms of the number of students
- □ Attendance is not mandatory

□ Please visit the website regularly.

- □ The latest lecture notes and information will be available before the lecture.
- □ You can find assignments as well as their relevant information.

□ Please go to:

- www.suyongeum.com/ML

Contact detail

Dr. Suyong EUM (Lecturer)

OSAKA University Graduate School of Information Science and Technology 1-5 Yamadaoka, Suita, Osaka, JAPAN, 565-08. B606 email: suyong[at]ist.osaka-u.ac.jp

Dr. Hua YANG (tutor)

OSAKA University Graduate School of Information Science and Technology 1-5 Yamadaoka, Suita, Osaka, JAPAN, 565-08. B501 email: h-yang[at]ist.osaka-u.ac.jp

Pre-requisite for the class

Good knowledge of Python

- All assignments need to be done with python.
- One python tutorial will be given by the tutor.

□ Some mathematics

- Linear algebra
- Optimization
- Probability theory

Regarding tutorials

- □ There will be four tutorials during the course (1 hour each)
 - 1) Introduction to Python (Week 2)
 - 2) Perceptron algorithm (Week 3)
 - 3) Support Vector Machine (Week 6)
 - 4) Principal Component Analysis (Week 7)
- We need to decide when and what time to do that
- The completion of the tutorials will help you to do the first assignment.
- A request from the tutor
 - Make sure the installation of "Anaconda" in your laptop before the tutorial.
 - Python 3.x and setting Path appropriately.
 - https://conda.io/docs/user-guide/install/index.html

Lecture Outline

- □ Machine learning and its short history
- □ A typical process in the operation of machine learning algorithms with an example
- □ What you can do after this course

A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.

Machine Learning – Tom M. Mitchell, 1997

Learning is a process to understand an underlying process through a set of observations.







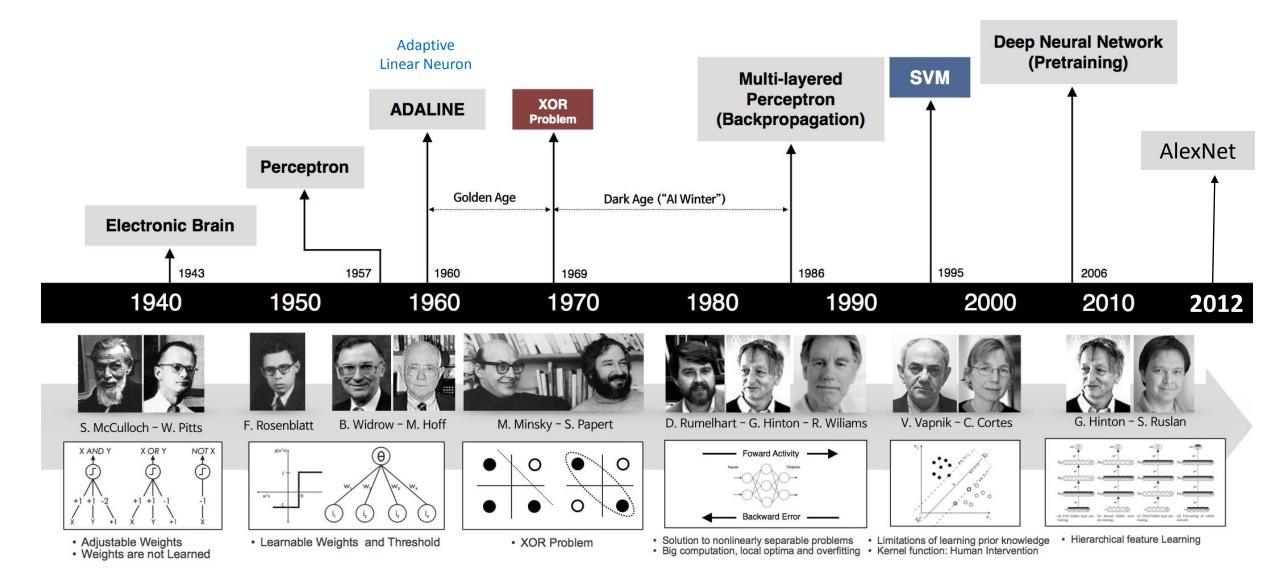
recognition





creation

History of Machine Learning



The perfect storm

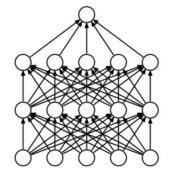
<u>Data</u>

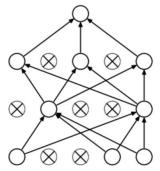


Computation



<u>Algorithms</u>

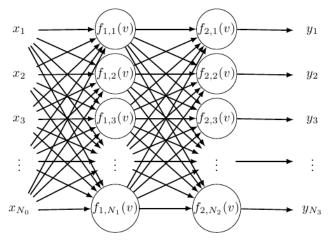




(a) Standard Neural Net

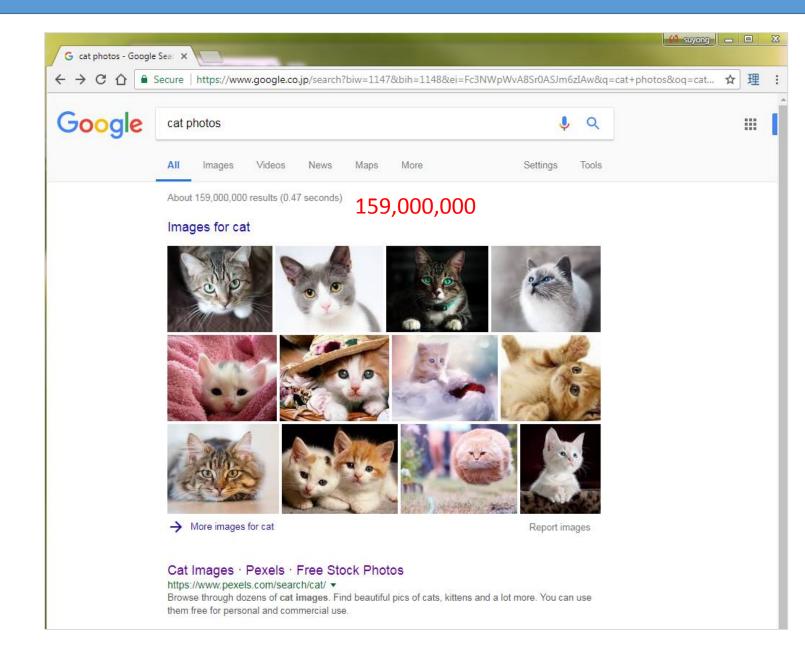
(b) After applying dropout.

dropout



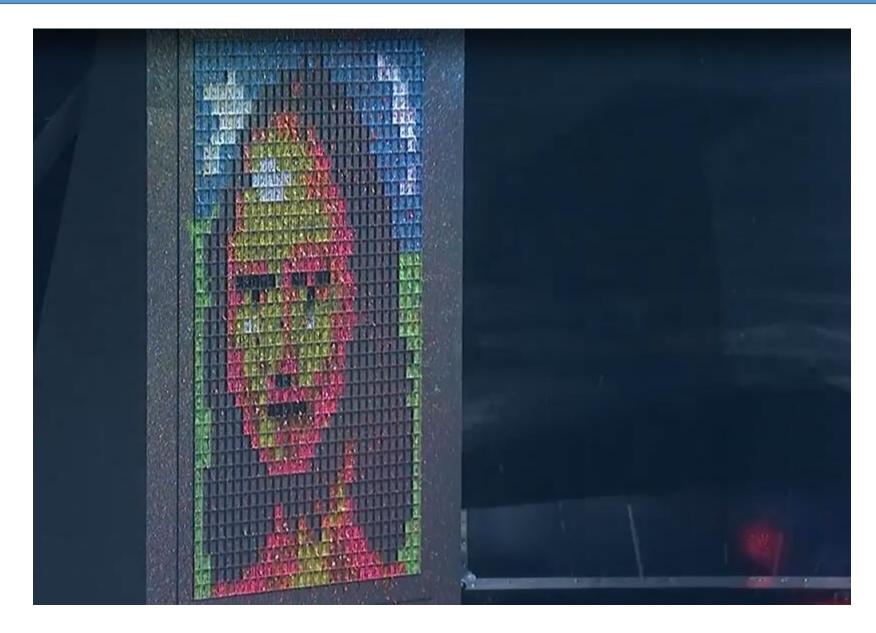
Backpropagation

Data

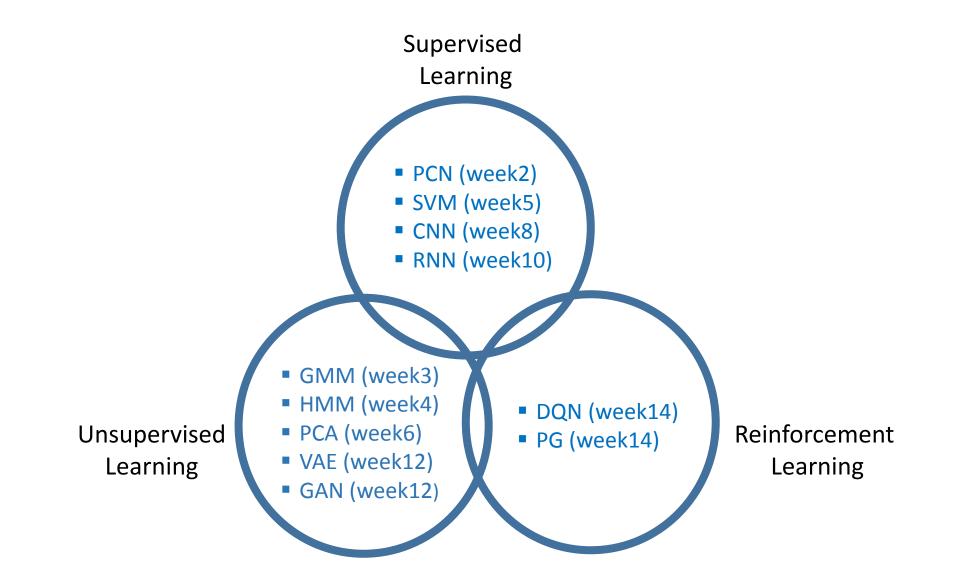


13

CPU vs GPU demo



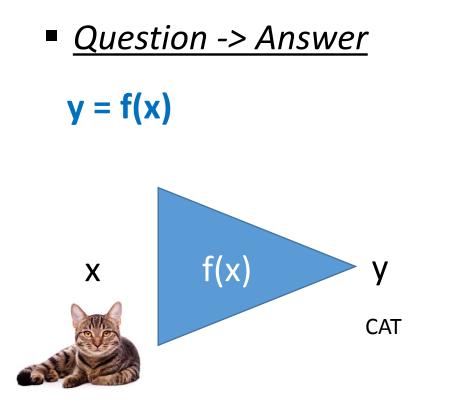
Types of machine learning algorithms

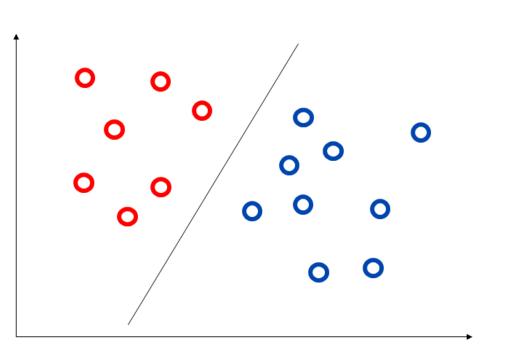


Supervised Learning

□ Input + Output with Label

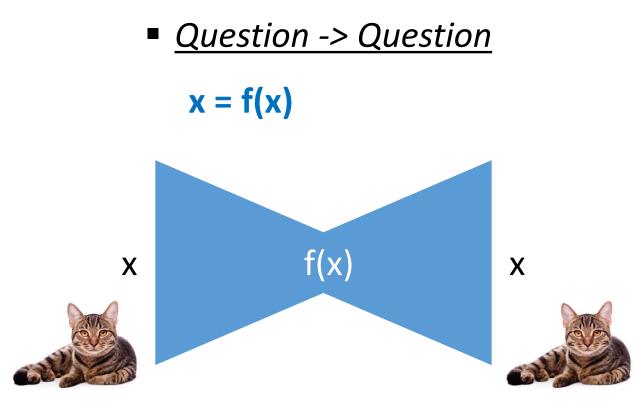
□ Supervised learning is learning from by a knowledgeable external supervisor.

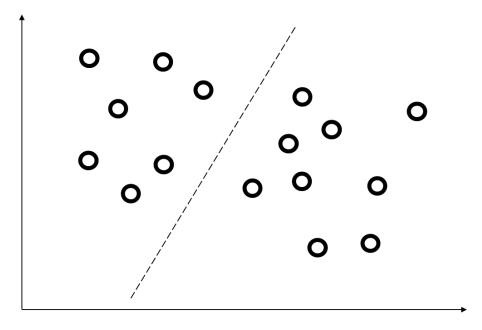




Unsupervised Learning

Input + Output without LabelFeature Learning

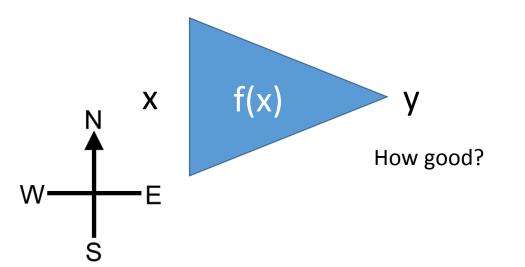


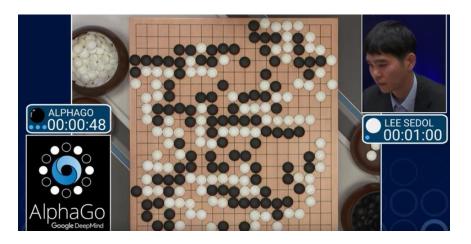


Reinforcement Learning

Input + partial output with its quality: in some sense similar to supervised learning
 An action is rewarded/penalized to take a better action next time

<u>Carrot and stick</u>
 y = f(x)



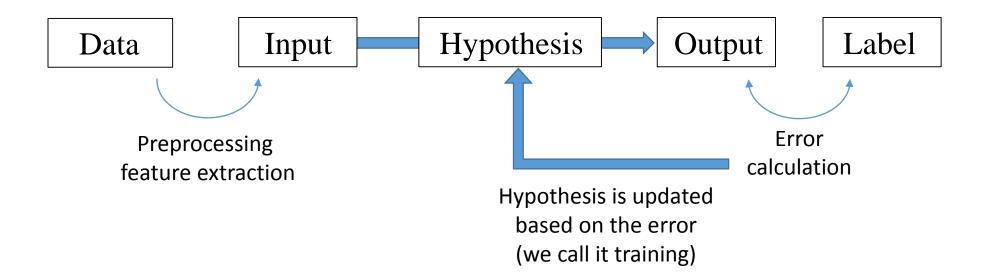




A typical process in the operation of machine learning algorithms with an example

Components of machine learning

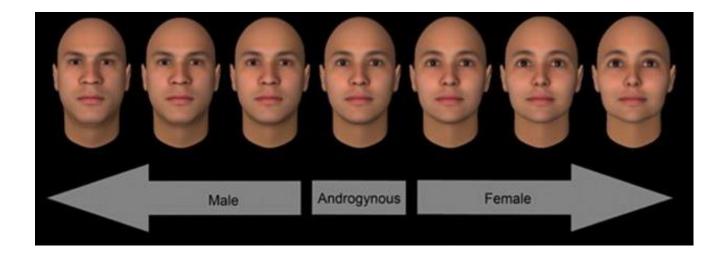
- **Raw data (including label)**
- □ Input (features: dimension of a data point)
- Hypothesis (a function approximating a target function)
- Output
- 🛛 Label



Male

Given data per person

- Height: 170cm
- Weight: 52kg
- Foot size: 25cm
- Hand size: 20cm
- Nose height: 1.5cm
- Eye size: 2.5cm
- Hair length: 5cm

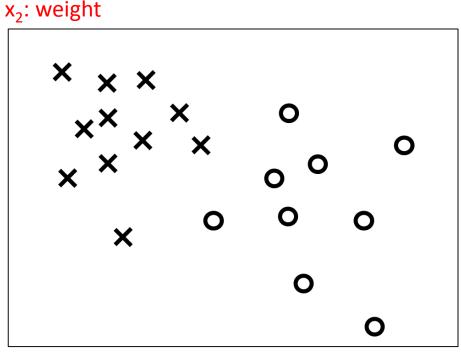


Components	Notation	Description		
Data	(x1, y1), (x2, y2),, (xn, yn)	(a vector data, male/female)		
Input	Х	$xn=\{x_1,x_2, \dots, x_d\}$: d dimensions		
Output	Y	Output data from hypothesis		
Hypothesis	g: $X \rightarrow Y$	(hypothesis) A model		
Target function	$f: X \rightarrow Y$	Unknown		

□ Which features are important to tell that the given object is male or female? Assuming you chose two features and then you plot the data points

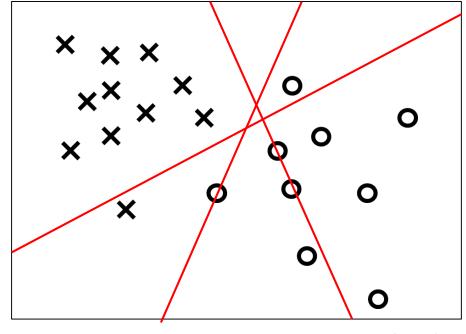
Given data per person

- Height: 170cm
 - Male
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An example: hypothesis (model) selection

x₂: weight

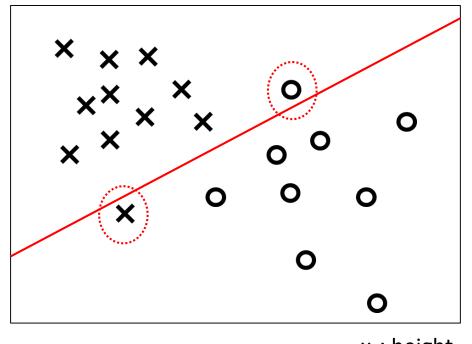


x₁: height

Female if $\sum_{i=1}^{i} w_i x_i < threshold$ Male if $\sum_{i=1}^{n} w_i x_i > threshold$ $h(x) = sign\left(\left(\sum_{i=1}^{2} w_i x_i\right) - threshold\right)$ $h(x) = sign\left(\sum_{i=0}^{d} w_i x_i\right)$ $h(x) = sign\left(\mathbf{W}^{\mathsf{T}}\mathbf{X}\right)$

An example: training the hypothesis to produce less error





x₁: height

$$h(x) = sign\left(\mathbf{W}^{\mathsf{T}}\mathbf{X}\right)$$

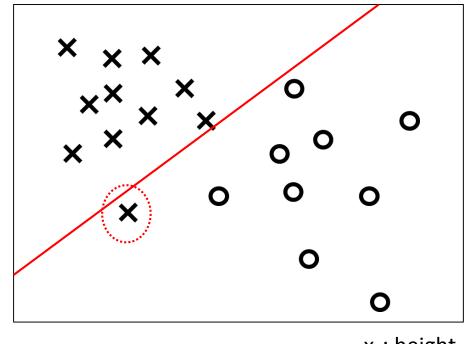
- ❑ Random selection of ₩
- Misclassified data points are found
- ❑ Update ₩ in order to correctly classify

the misclassified data points.

- How? : depending on learning algorithm
 - Neural network: backpropagation?
 - Linear algebra: perceptron algorithm

An example: training the hypothesis to produce less error

 x_2 : weight



x₁: height

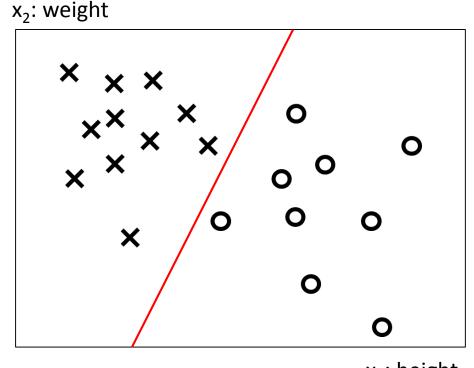
$$h(x) = sign\left(\mathbf{W}^{\mathsf{T}}\mathbf{X}\right)$$

- ❑ Random selection of ₩
- Misclassified data points are found
- ❑ Update ₩ in order to correctly classify

the misclassified data points.

- How? : depending on learning algorithm
 - Neural network: backpropagation?
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An example: training the hypothesis to produce less error



x₁: height

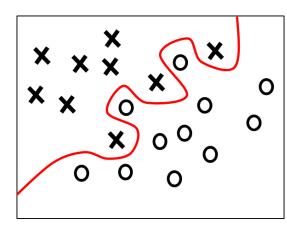
$$h(x) = sign\left(\mathbf{W}^{\mathsf{T}}\mathbf{X}\right)$$

- Random selection of W
- Misclassified data points are found
- Update W in order to correctly classify

the misclassified data points.

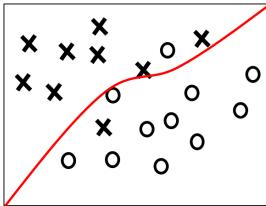
- How? : depending on learning algorithm
 - Neural network: backpropagation?
 - Linear algebra: perceptron algorithm

You are generally given one big training data set.
How to verify goodness of your model?



Occam's razor

$$y(x, w) = w_0 + w_1 x + w_2 x^2 + \dots + w_M x^M = \sum_{j=0}^M w_j x^j$$

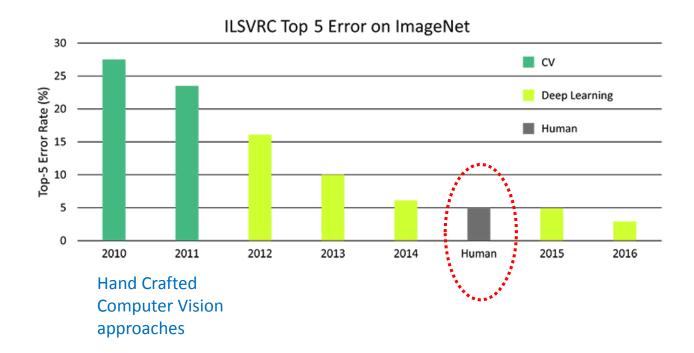


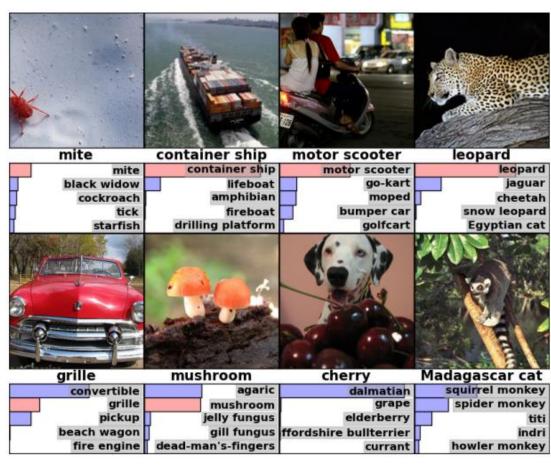


What you can do after this course

Large Scale Visual Recognition Challenge (ILSVRC)

- 1000 class objects
- around 1.4 million images

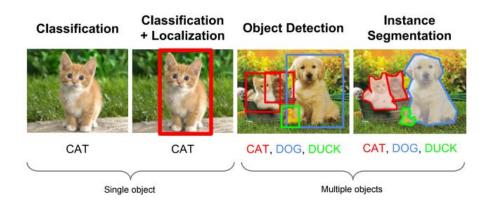


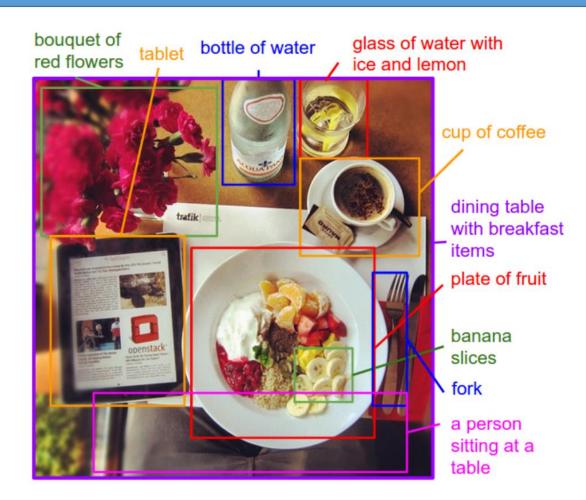


https://www.dsiac.org/resources/journals/dsiac/winter-2017-volume-4-number-1/real-time-situ-intelligent-video-analytics http://www.cs.toronto.edu/~fritz/absps/imagenet.pdf

Image detection

	M	Mean Average		
2016		Precision		
Real-Time Detectors	Train	mAP		
100Hz DPM [31]	2007	16.0		
30Hz DPM [31]	2007	26.1		
Fast YOLO	2007+2012	52.7		
YOLO	2007+2012	63.4		
Less Than Real-Time				
Fastest DPM [38]	2007	30.4		
R-CNN Minus R [20]	2007	53.5		
Fast R-CNN [14]	2007+2012	70.0		
Faster R-CNN VGG-16[28]	2007+2012	73.2		
Faster R-CNN ZF [28]	2007+2012	62.1		
YOLO VGG-16	2007+2012	66.4		





- Classification
- Localization
- Detection
- Segmentation

https://arxiv.org/pdf/1506.02640.pdf https://arxiv.org/pdf/1412.2306v2.pdf

Image caption



a man is riding a motorcycle on a street logprob: -8.65



a woman is standing in front of a store logprob: -11.40



a bus is parked on the side of the road logprob: -7.19



a woman holding a teddy bear in front of a mirror logprob: -9.65



a zebra standing in a field of grass logprob: -7.88



a baby laying on a bed with a stuffed bear logprob: -8.85

https://cs.stanford.edu/people/karpathy/deepimagesent/generationdemo/

PANDARUS:

Alas, I think he shall be come approached and the day When little srain would be attain'd into being never fed, And who is but a chain and subjects of his death, I should not sleep.

Second Senator:

They are away this miseries, produced upon my soul, Breaking and strongly should be buried, when I perish The earth and thoughts of many states.

DUKE VINCENTIO:

Well, your wit is in the care of side and that.

Second Lord:

They would be ruled after this chamber, and my fair nues begun out of the fact, to be conveyed, Whose noble souls I'll have the heart of the wars.

Clown:

Come, sir, I will make did behold your worship.

VIOLA: I'll drink it.

Writing new episodes of Friends is easy if you use a neural network

"Chandler: Well, I proposed to my shoe..."

By James Vincent | @jjvincent | Jan 21, 2016, 4:03am EST

🔰 🕝 SHARE



For $\bigoplus_{n=1,...,m}$ where $\mathcal{L}_{m_{\bullet}} = 0$, hence we can find a closed subset \mathcal{H} in \mathcal{H} and any sets \mathcal{F} on X, U is a closed immersion of S, then $U \to T$ is a separated algebraic space.

Proof. Proof of (1). It also start we get

 $S = \operatorname{Spec}(R) = U \times_X U \times_X U$

and the comparicoly in the fibre product covering we have to prove the lemma generated by $\coprod Z \times_U U \to V$. Consider the maps M along the set of points Sch_{fppf} and $U \to U$ is the fibre category of S in U in Section, ?? and the fact that any U affine, see Morphisms, Lemma ??. Hence we obtain a scheme S and any open subset $W \subset U$ in Sh(G) such that $Spec(R') \to S$ is smooth or an

$U = \bigcup U_i \times_{S_i} U_i$

which has a nonzero morphism we may assume that f_i is of finite presentation over S. We claim that $\mathcal{O}_{X,x}$ is a scheme where $x, x', s'' \in S'$ such that $\mathcal{O}_{X,x'} \to \mathcal{O}'_{X',x'}$ is separated. By Algebra, Lemma ?? we can define a map of complexes $\operatorname{GL}_{S'}(x'/S'')$ and we win.

To prove study we see that $\mathcal{F}|_U$ is a covering of \mathcal{X}' , and \mathcal{T}_i is an object of $\mathcal{F}_{X/S}$ for i > 0 and \mathcal{F}_p exists and let \mathcal{F}_i be a presheaf of \mathcal{O}_X -modules on \mathcal{C} as a \mathcal{F} -module. In particular $\mathcal{F} = U/\mathcal{F}$ we have to show that

$$\widetilde{I}^{\bullet} = \mathcal{I}^{\bullet} \otimes_{\mathrm{Spec}(k)} \mathcal{O}_{S,s} - i_X^{-1} \mathcal{F})$$

is a unique morphism of algebraic stacks. Note that

 $Arrows = (Sch/S)_{fppf}^{opp}, (Sch/S)_{fppf}$

and

 $V = \Gamma(S, \mathcal{O}) \longmapsto (U, \operatorname{Spec}(A))$

is an open subset of X. Thus U is affine. This is a continuous map of X is the inverse, the groupoid scheme S.

```
Proof. See discussion of sheaves of sets.
```

Lan of Francis 22. It may

The result for prove any open covering follows from the less of Example ??. It may replace S by $X_{spaces, \acute{e}tale}$ which gives an open subspace of X and T equal to S_{Zar} , see Descent, Lemma ??. Namely, by Lemma ?? we see that R is geometrically regular over S.

Creation: music composition









Generation: image generation



Generated by a machine



Generated by a machine based on given text

Generation: style transfer



Season Transfer







winter Yosemite → summer Yosemite



summer Yosemite → winter Yosemite

Input Output

horse \rightarrow zebra



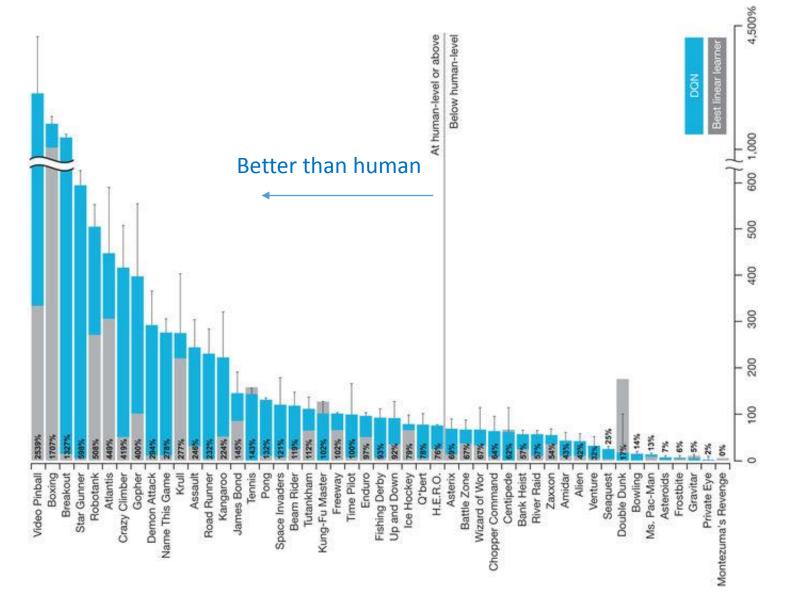
 $zebra \rightarrow horse$



apple \rightarrow orange



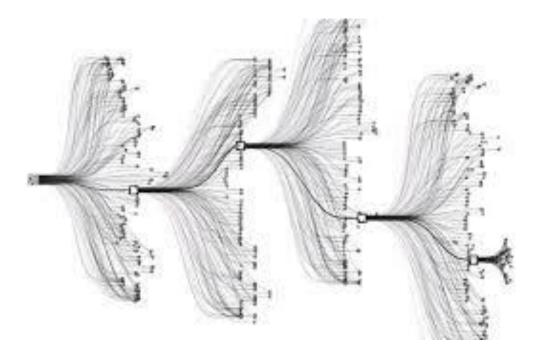
orange \rightarrow apple







- Game Go: 10¹⁷⁰ state space
 Beat European Champion: October 2015
- Beat World Champion: March 2016



Automatic Driving

- □ 1.3 million people die every year in car accidents.
- □ 94% of those accidents involve human error.
- □ 70% of the manned Taxis is related to labor cost.





