

人工智慧民主化在台灣

讓機器學習及人工智慧在台灣深化，帶動產業發展

陳昇瑋

台灣人工智慧學校執行長
中央研究院資訊科學研究所研究員



資料分析這條路

- Since 2002 (my first PhD year) ...
- PhD dissertation: based on a 20-hour game packet trace
- Collaboration & Consulting
 - 製造業
 - 電信業
 - 社群網路 / 遊戲
 - 銀行 / 壽險 / 電子票証
 - 中央 / 地方政府



Change is the only constant

- Heraclitus (535 BC - 475 BC)



(Slide Credit: [Albert Chen](#))



AlphaZero AI

Mastering Chess and Shogi by self play
with reinforcement learning

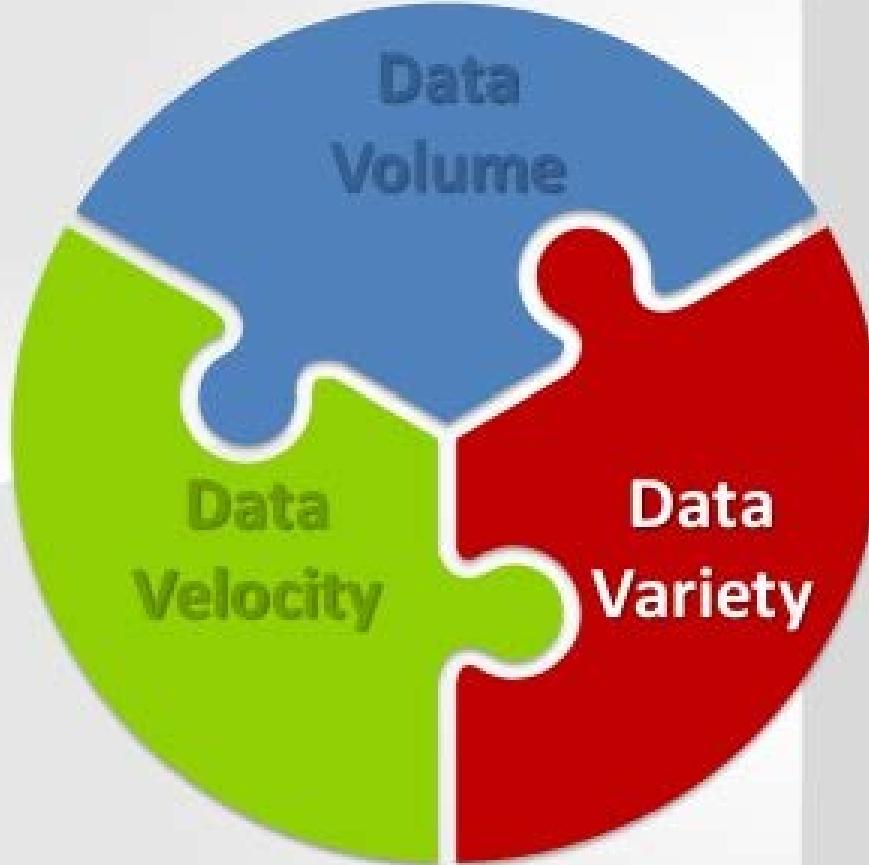








3V of Big Data explained



Volume

Huge data size,
terabytes – petabytes



Velocity

High speed of data
flow, data change and
data processing



Variety

Various data sources
(social, mobile, M2M,
structured and unstructured data)



Heart Rate = 128 BPM



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

Data variety: Our biggest challenge

Top Big Data Issues



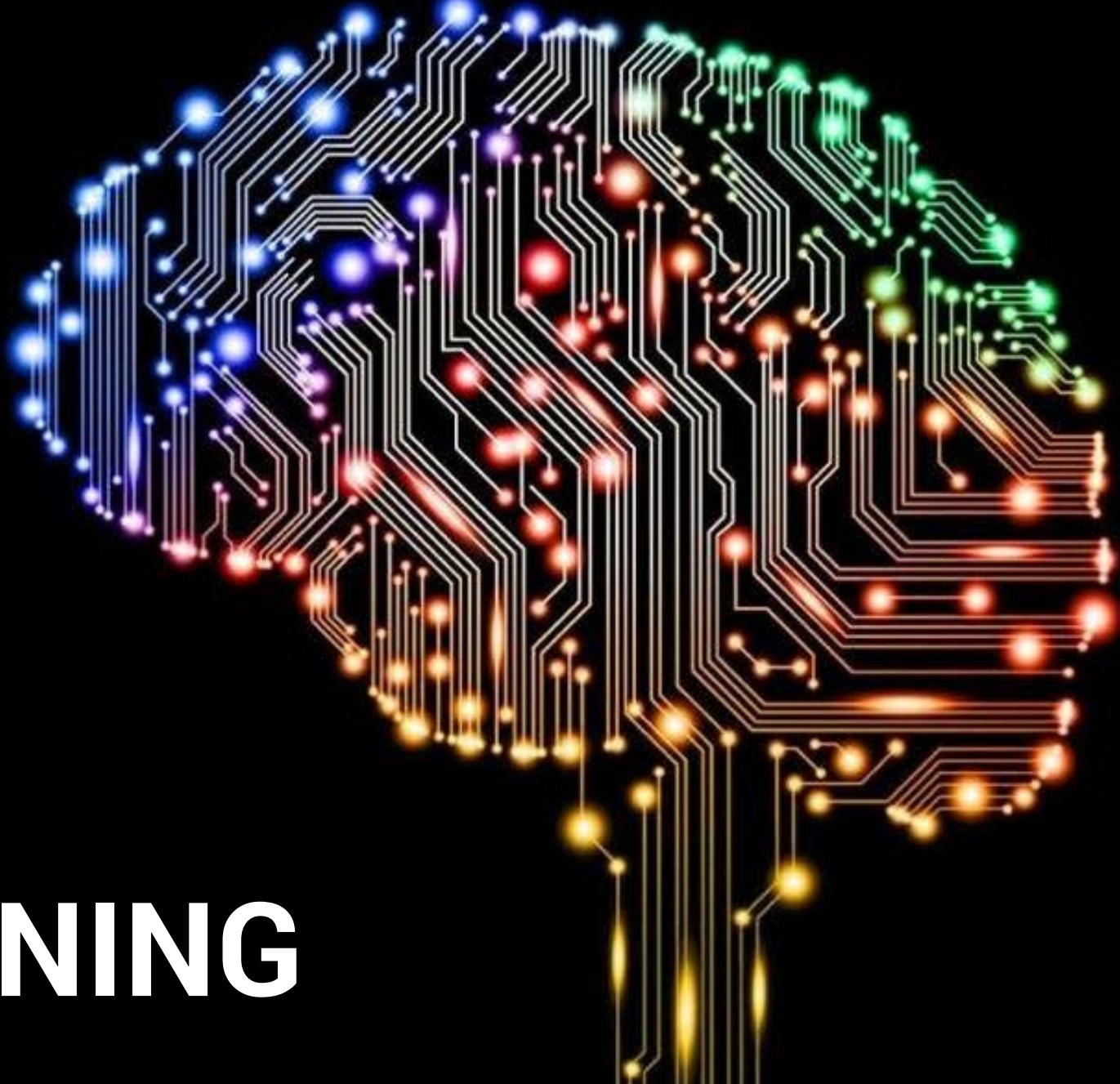
■ Data Variety (68%)
Diverse, streaming or new data types

■ Data Volume (15%)
Greater than 100TB

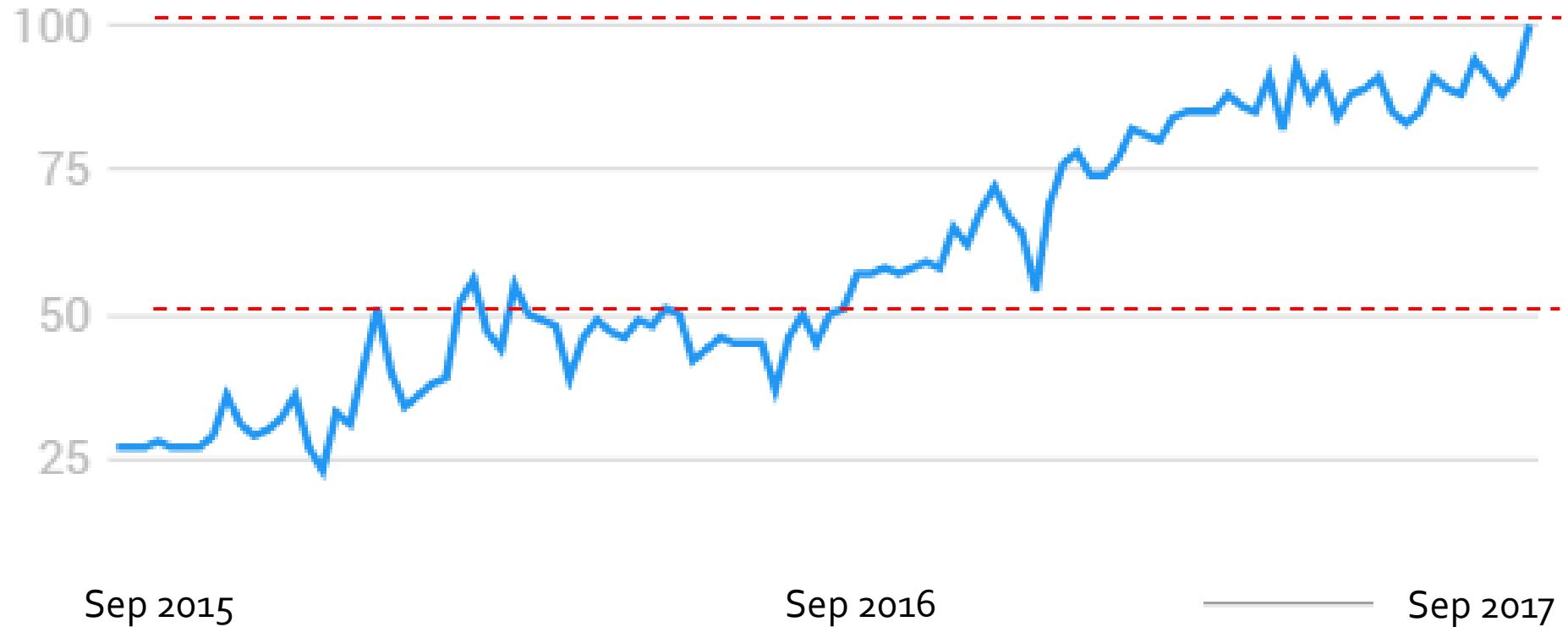
■ Other Data (17%)
Less than 100TB

*"Of Gartner's "3Vs" of big data (volume, velocity, variety), the **variety of data sources** is seen by our clients as both the greatest challenge and **the greatest opportunity.**"*

DEEP LEARNING



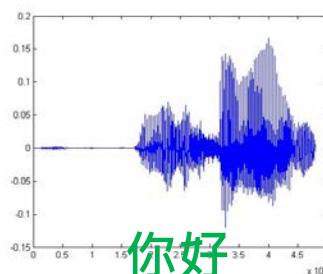
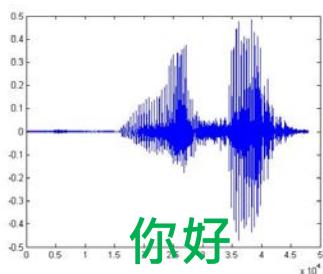
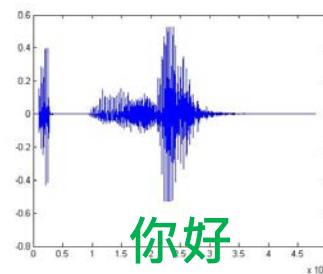
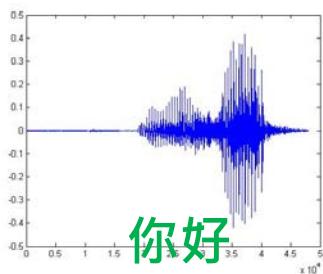
“Deep Learning” search trend



Machine Learning

“

A type of algorithms that gives computers the ability to learn rules from experience, rather than being hard coded.



Find the common patterns from the left waveforms

You quickly get lost in the exceptions and special cases.

It seems impossible to write a program for speech recognition

0 0 0 1 1 (1 1 1, 2

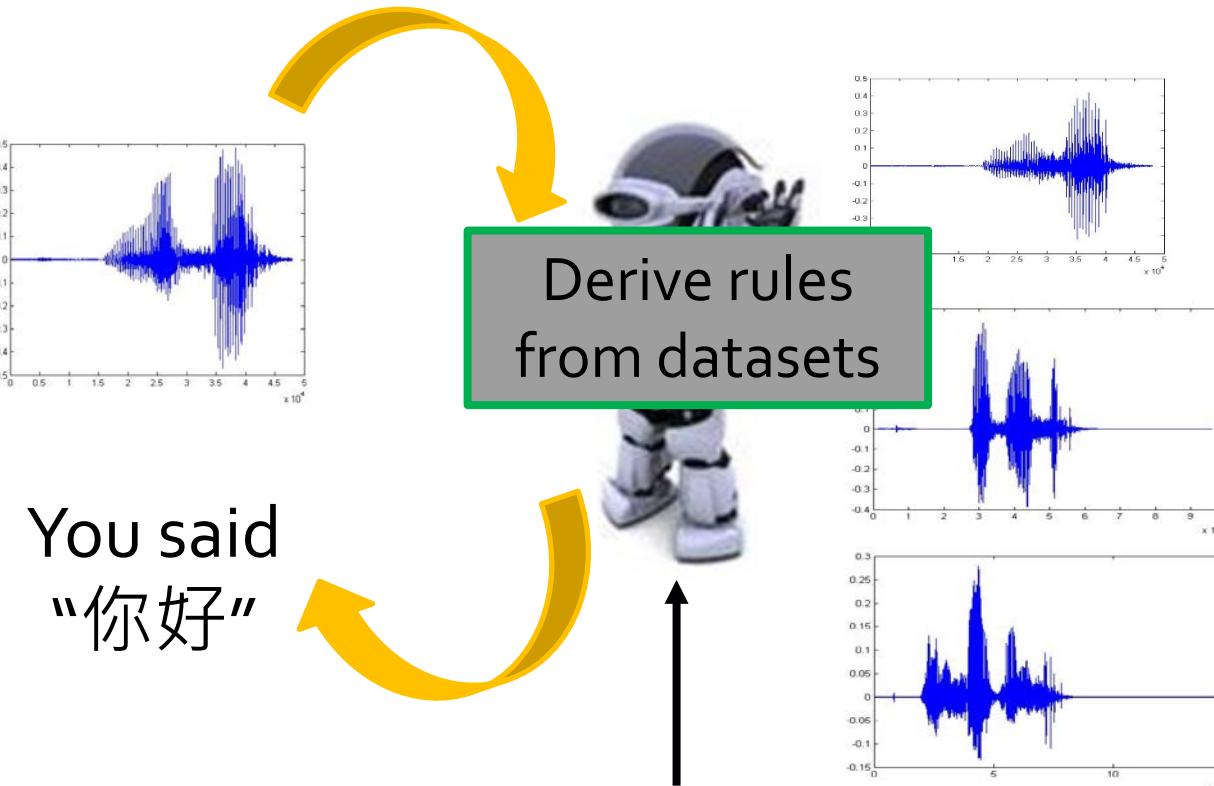
2 2 2 2 2 2 2 3 3 3

3 4 4 4 4 4 5 5 5 5

6 6 6 6 7 7 7 7 8 8 8

8 8 9 7 9 4 9 9 7

Let the machine learn by itself

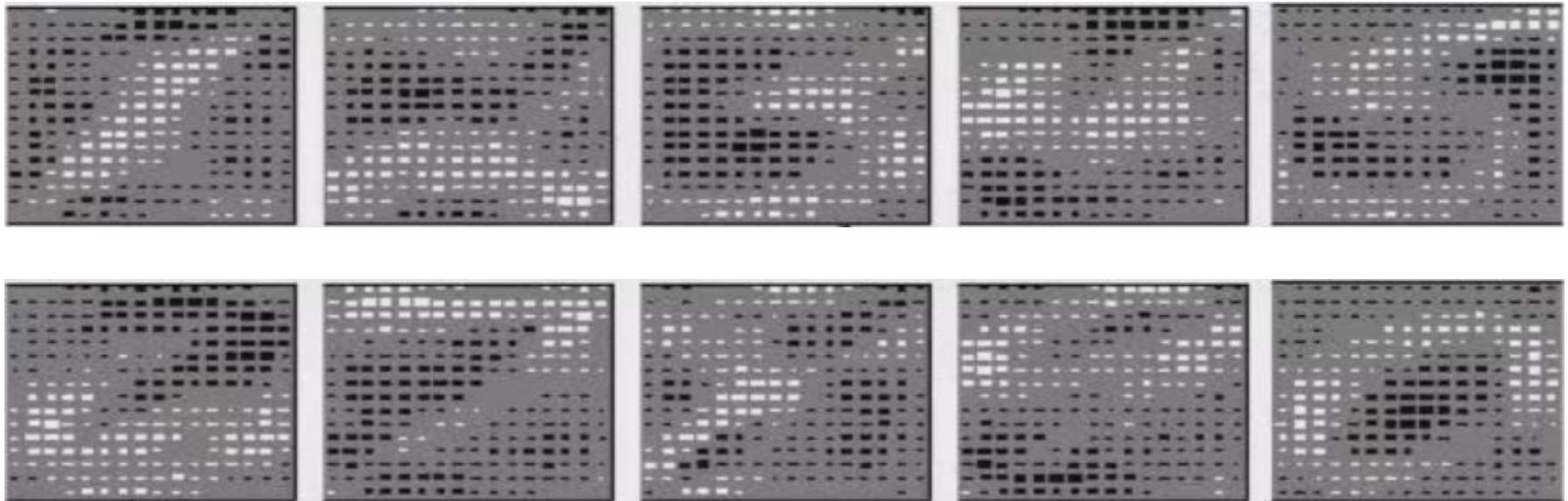


你好

大家好

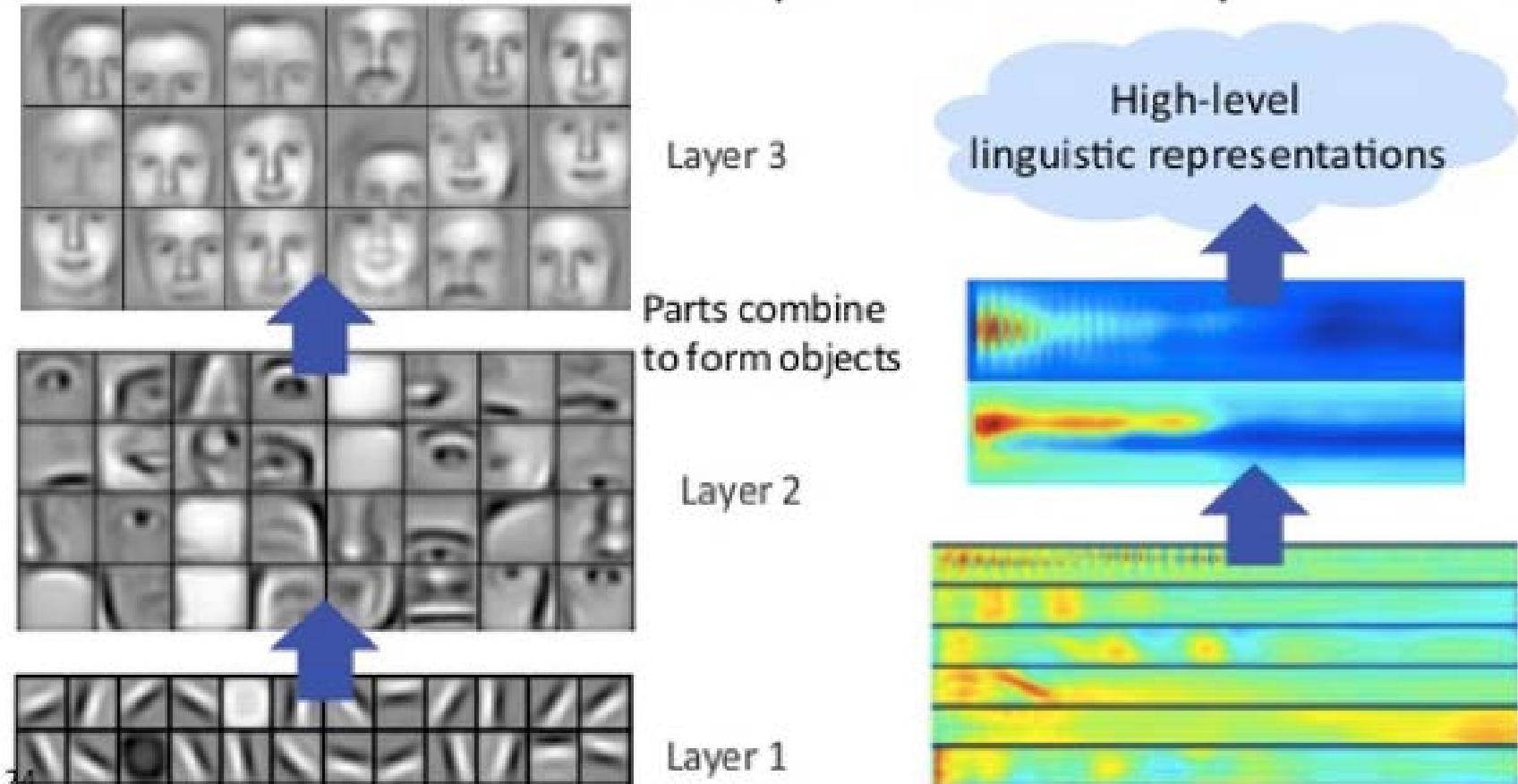
人帥真好

Patterns learned by machine



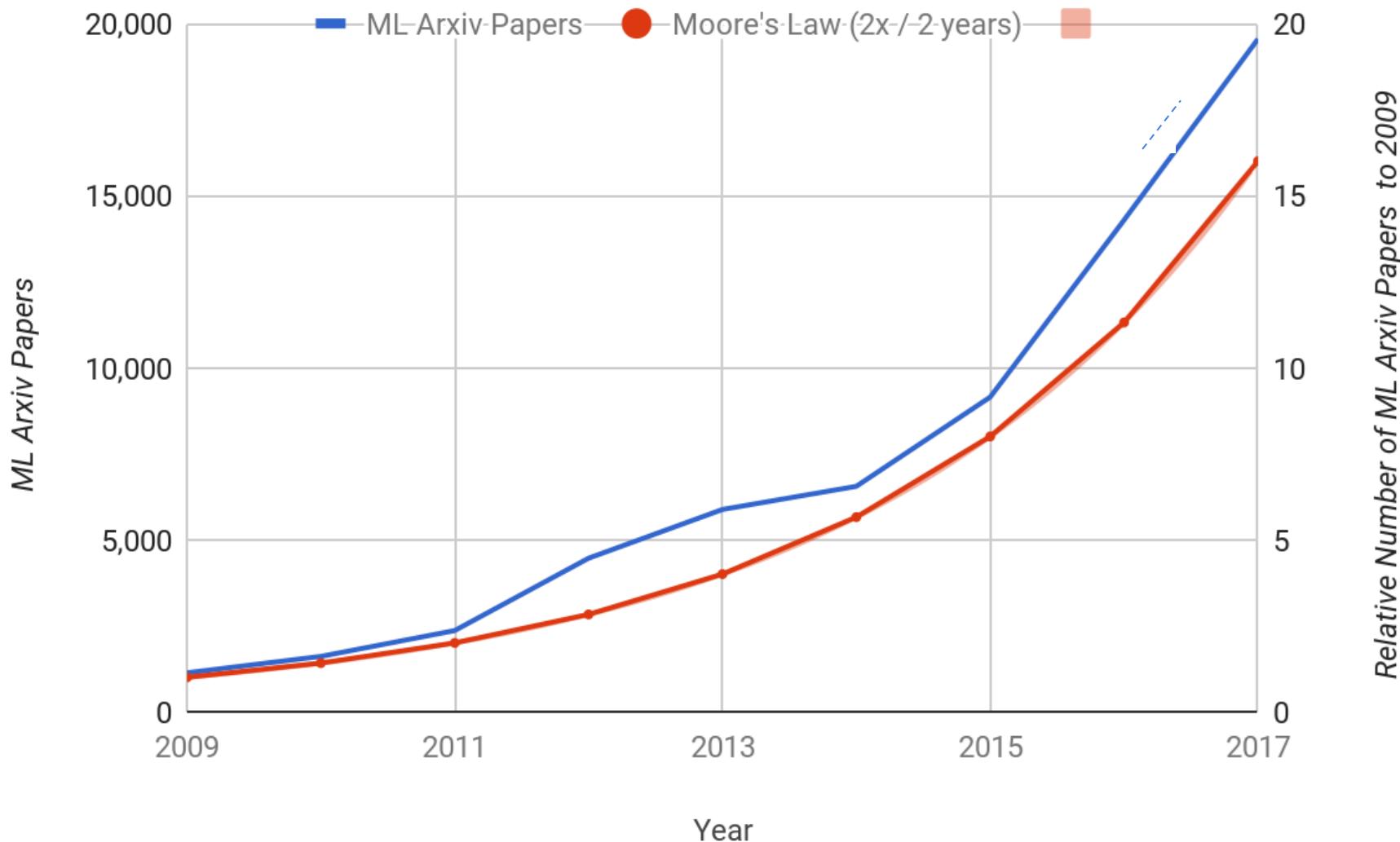
Multi-layer patterns learned from faces

Successive model layers learn deeper intermediate representations



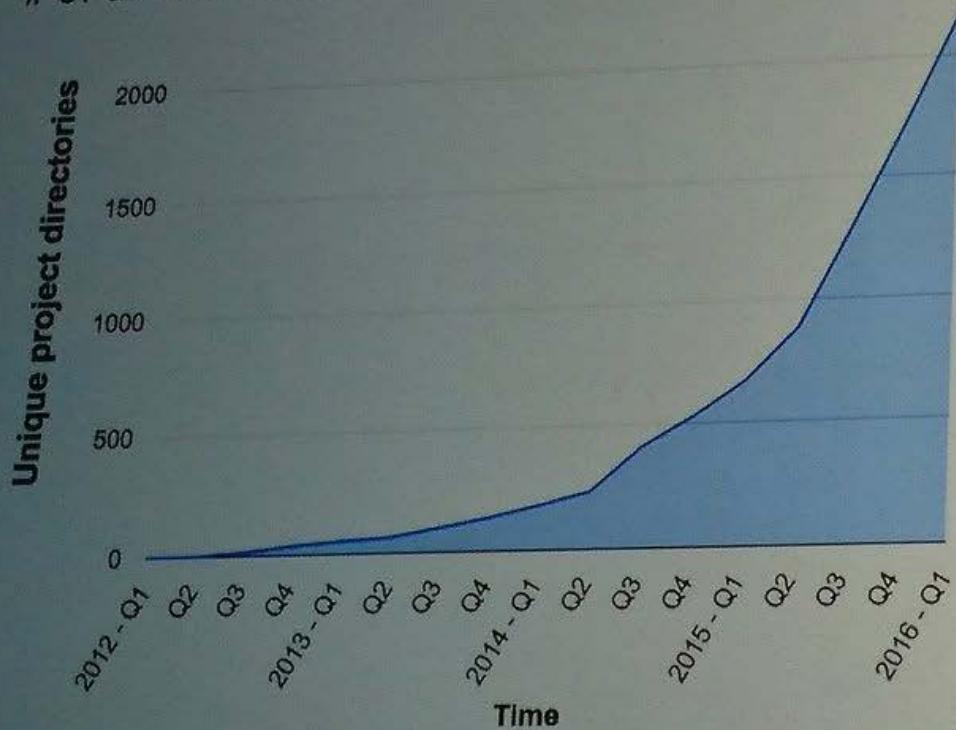
Prior: underlying factors & concepts compactly expressed w/ multiple levels of abstraction

ML Arxiv Papers per Year



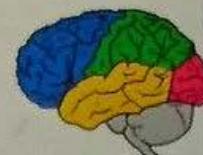
Growing Use of Deep Learning at Google

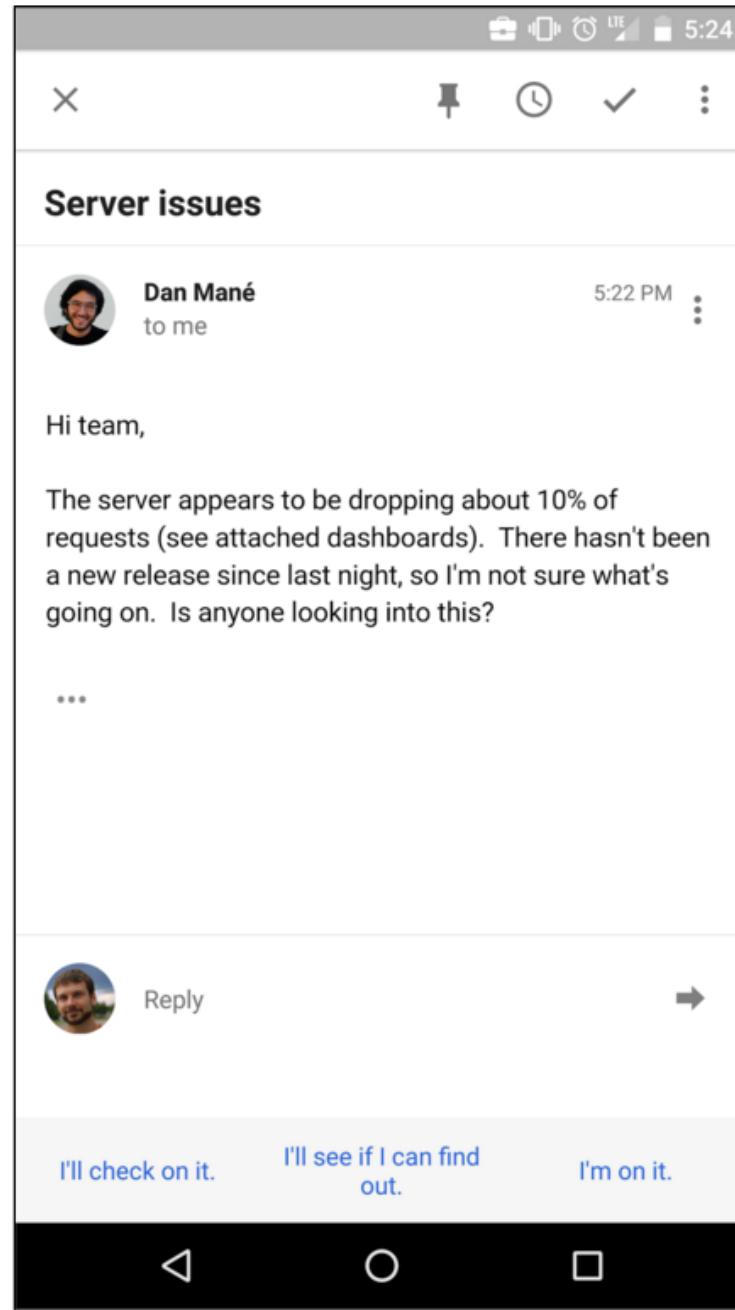
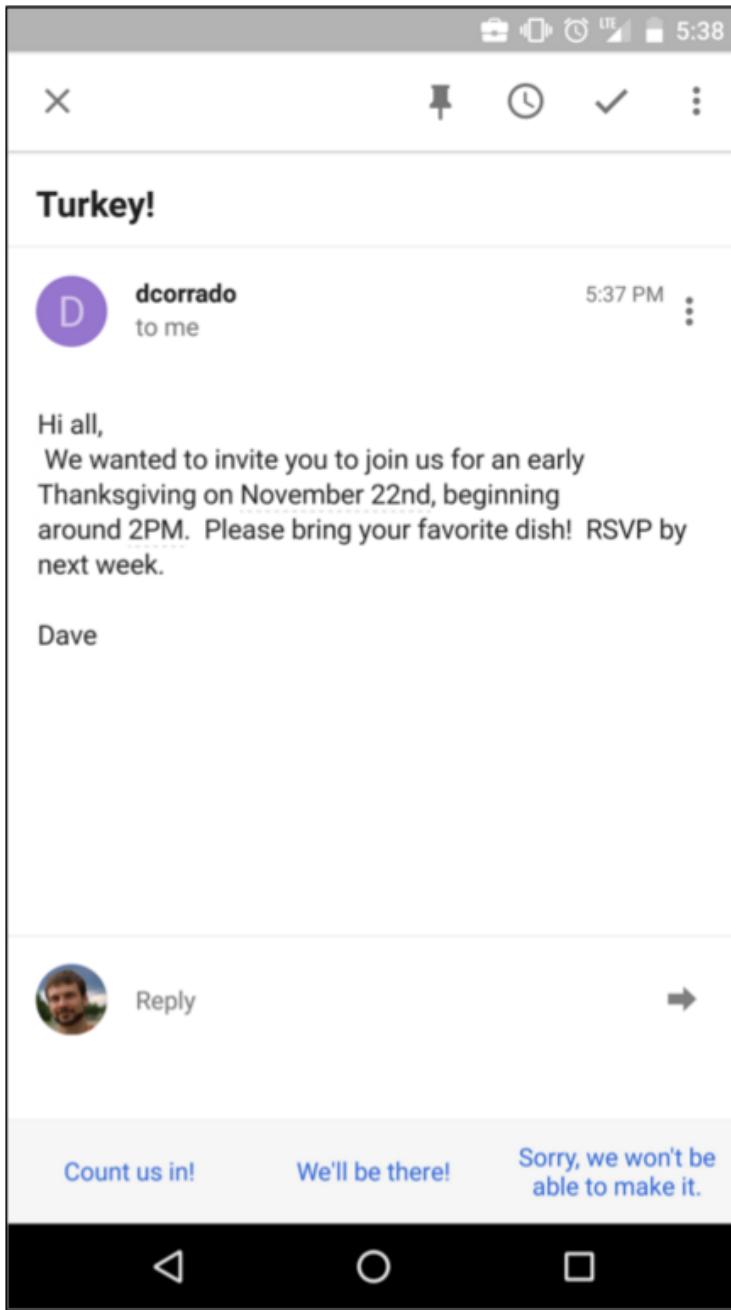
of directories containing model description files

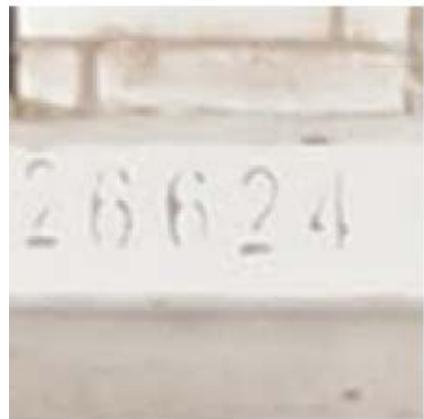


Across many products/areas:

- Android
- Apps
- drug discovery
- Gmail
- Image understanding
- Maps
- Natural language understanding
- Photos
- Robotics research
- Speech
- Translation
- YouTube
- ... many others ...

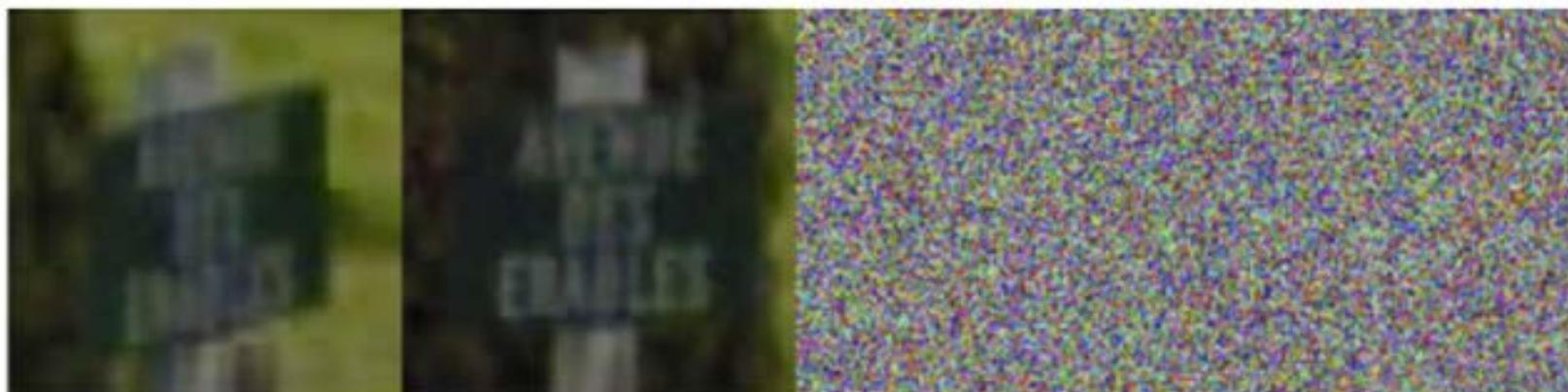








Route de la Ruaz



Avenue des Erables



Midway Avenue



Describes without errors



A person riding a motorcycle on a dirt road.

Describes with minor errors



Two dogs play in the grass.

Somewhat related to the image



A skateboarder does a trick on a ramp.



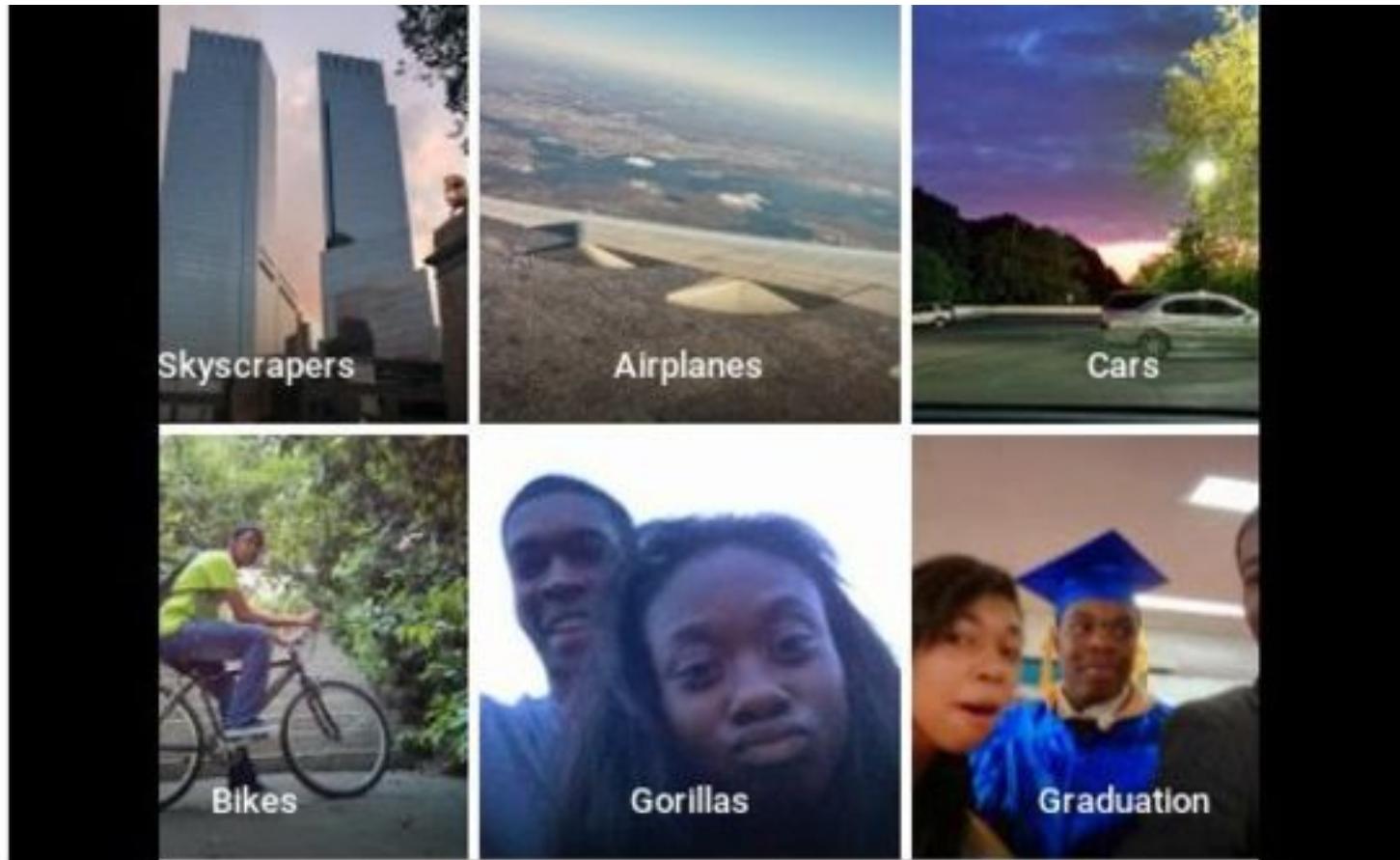
A group of young people playing a game of frisbee.



Two hockey players are fighting over the puck.



A little girl in a pink hat is blowing bubbles.



diri noir avec banan @jackyalcine · Jun 29

Google Photos, y'all

My friend's not a gorilla.



813

394



...

TWITTER

Deep learning can be highly flexible

- Speech Recognition

$$f * \left(\begin{array}{c} \text{A blue waveform plot showing a speech signal.} \\ \text{The plot has a vertical axis labeled from -0.05 to 0.05 and a horizontal axis labeled from 0 to 20.} \end{array} \right) = \text{"Morning"}$$

- Handwritten Recognition

$$f * \left(\begin{array}{c} \text{A handwritten digit '2' in black ink on a white background.} \end{array} \right) = \text{"2"}$$

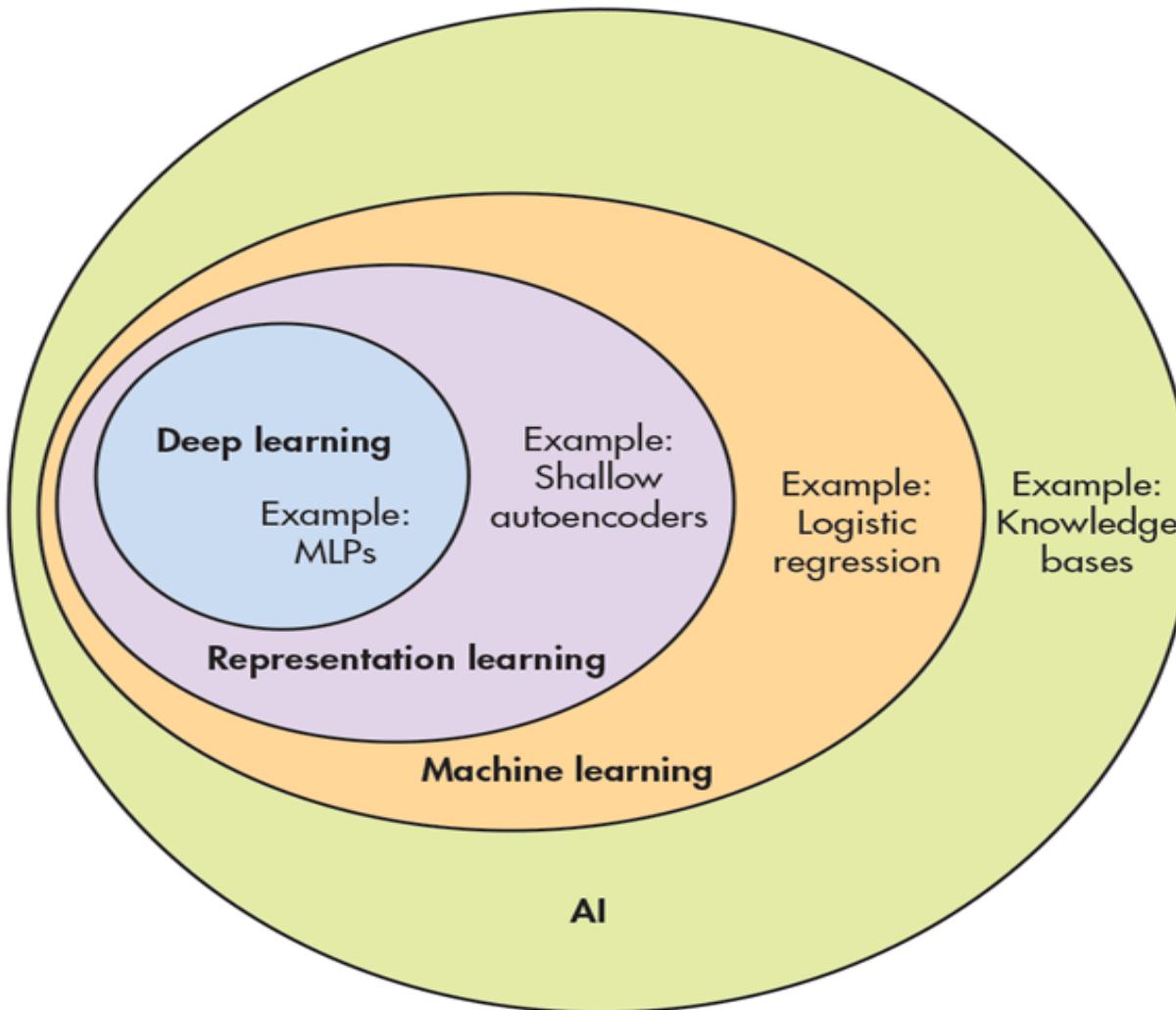
- Playing Go

$$f * \left(\begin{array}{c} \text{A Go board with black and white stones.} \\ \text{The board shows a complex game position with many stones on the board.} \end{array} \right) = \text{"5-5"} \\ \text{(step)}$$

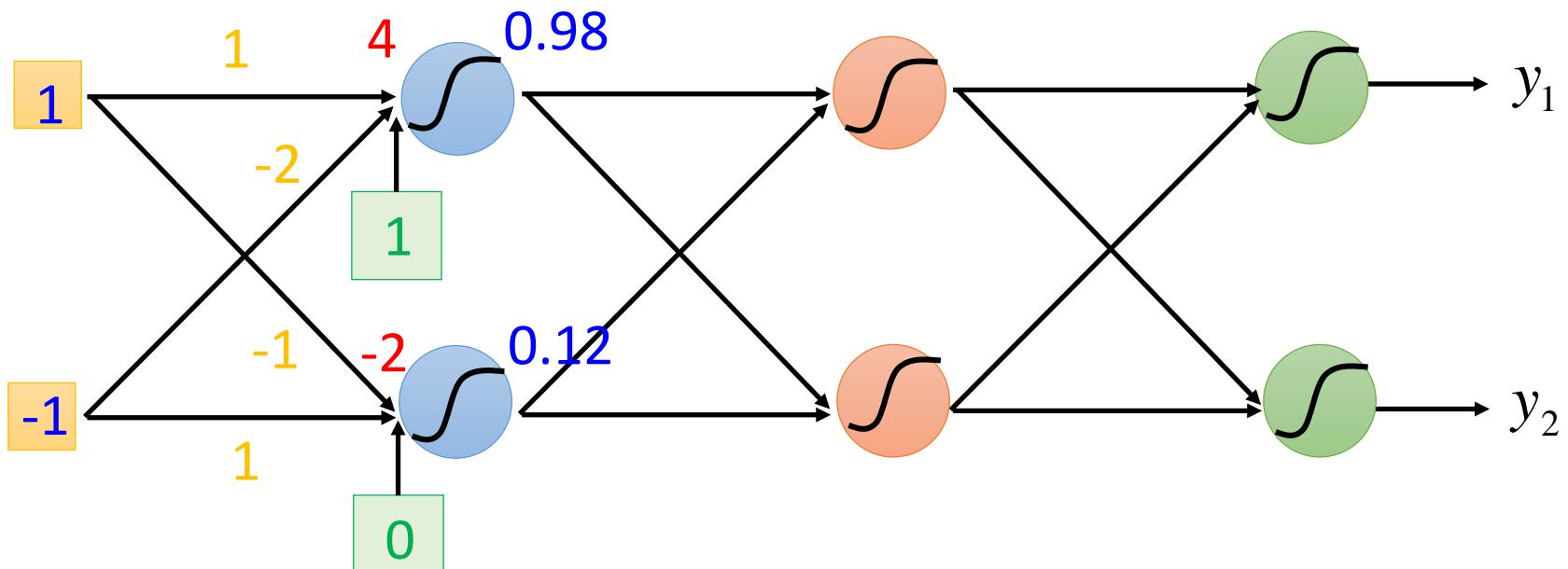
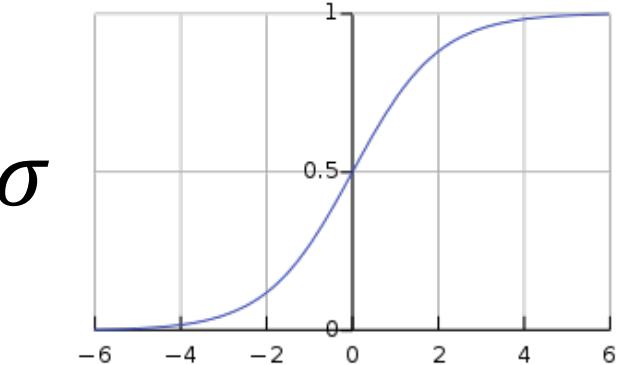
- Dialogue System

$$f * \left(\begin{array}{c} \text{"Hi"} \\ \text{(what the user said)} \end{array} \right) = \text{"Hello"} \\ \text{(system response)}$$

Deep Learning is a subset of Representation Learning



Matrix Operation

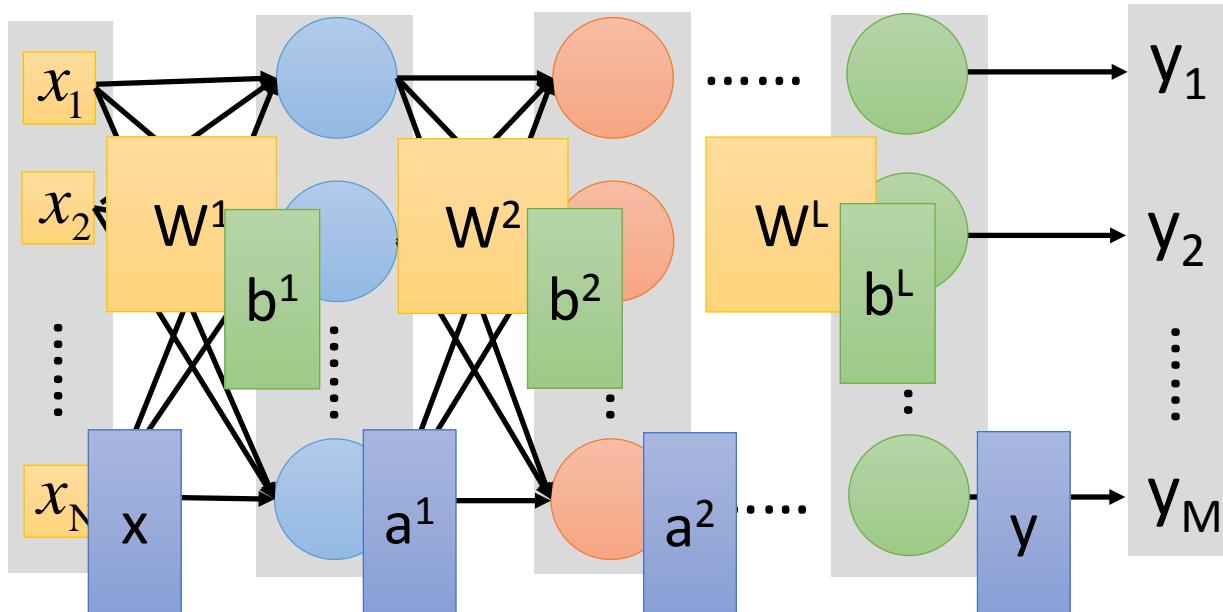


$$\sigma(\underbrace{\begin{bmatrix} 1 & -2 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix}}_{\begin{bmatrix} 4 \\ -2 \end{bmatrix}}) = \begin{bmatrix} 0.98 \\ 0.12 \end{bmatrix}$$

$$\begin{bmatrix} 4 \\ -2 \end{bmatrix}$$

(Slide Credit: [Hung-Yi Lee](#))

Neural Network



$$y = f(x)$$

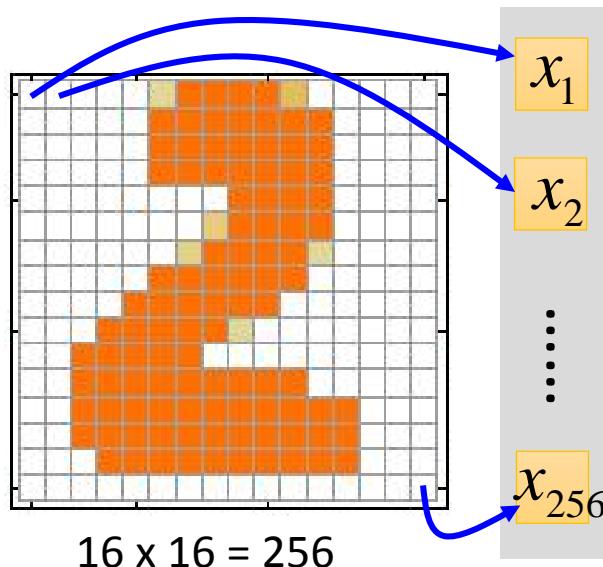
Using parallel computing techniques
to speed up matrix operation

$$= \sigma(W^L \dots \sigma(W^2 \sigma(W^1 x + b^1) + b^2) \dots + b^L)$$

Example Application

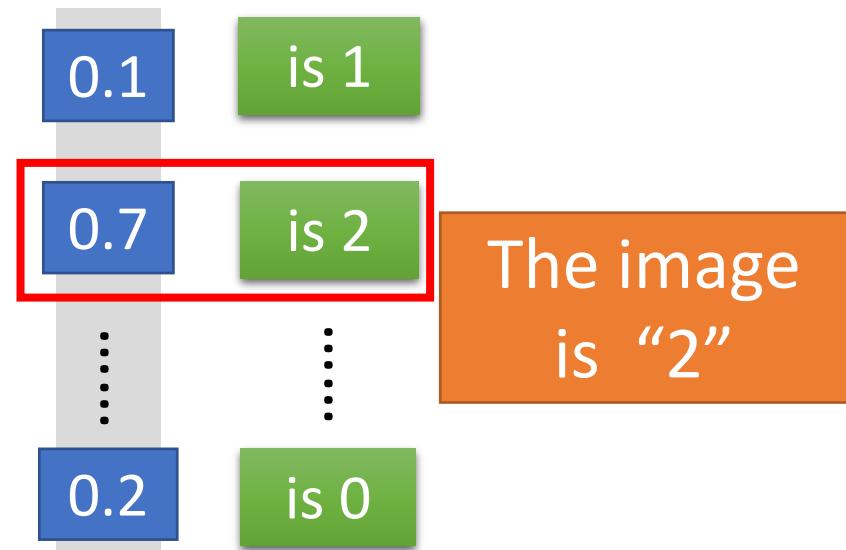


Input



Ink $\rightarrow 1$
No ink $\rightarrow 0$

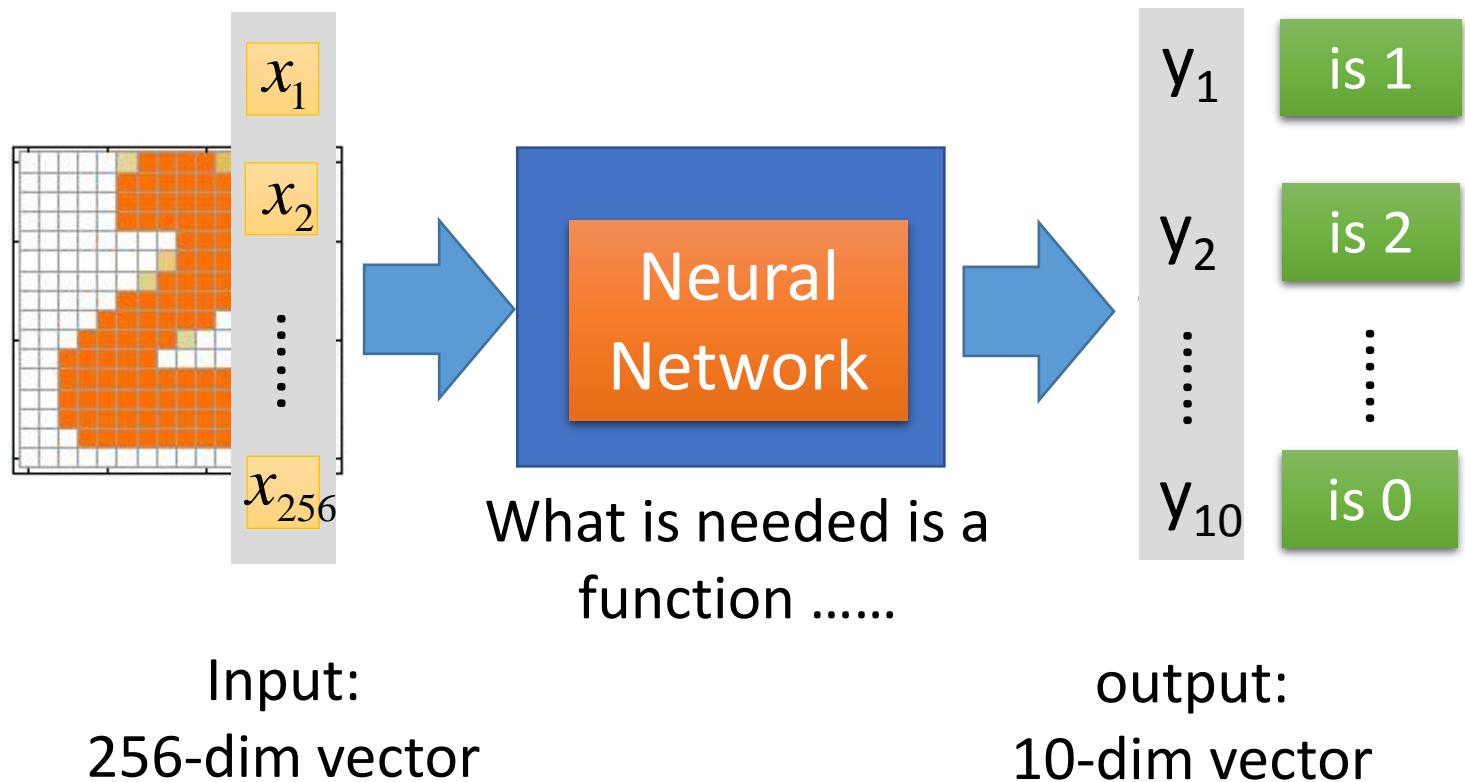
Output



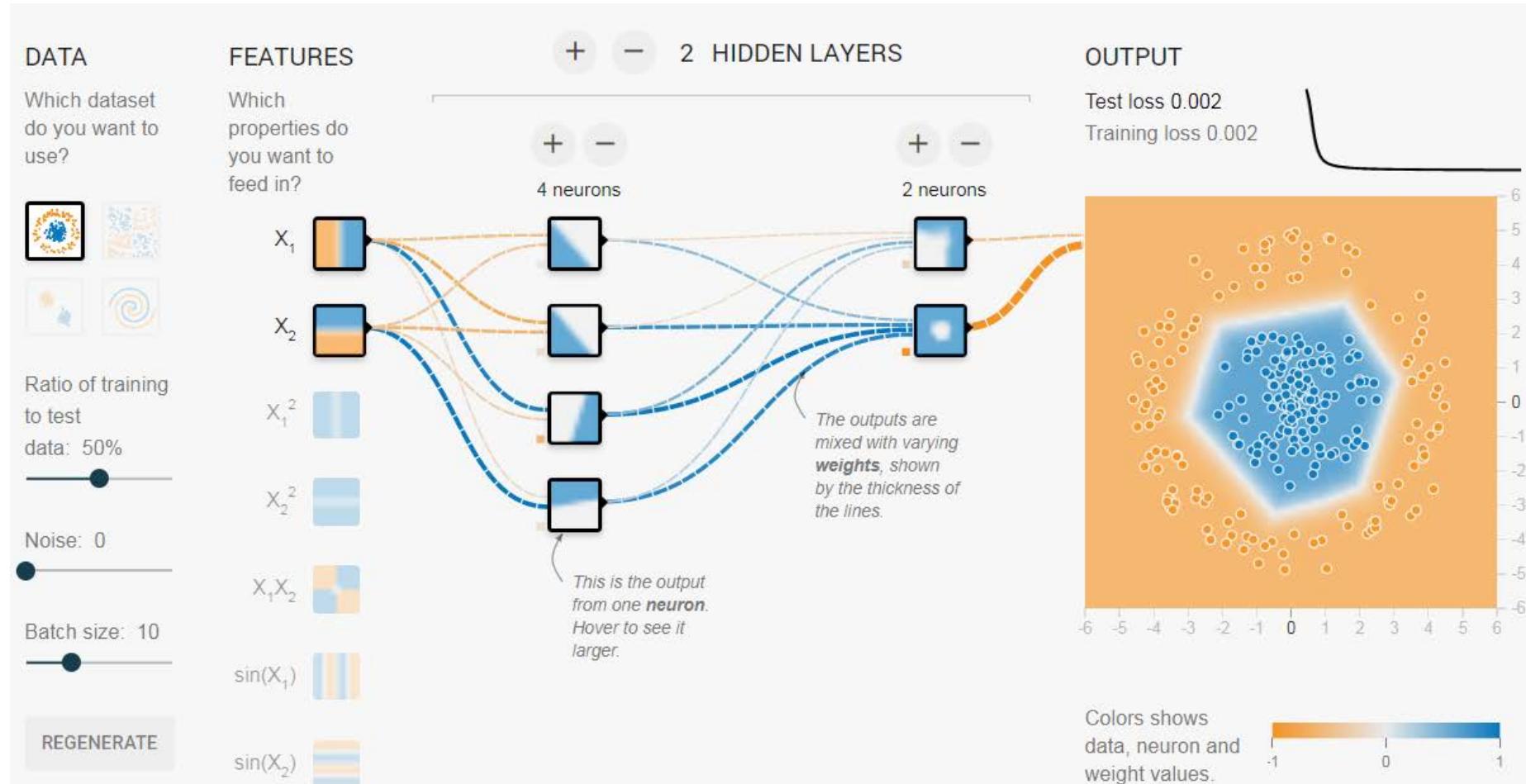
Each dimension represents the confidence of a digit.

Example Application

- Handwriting Digit Recognition



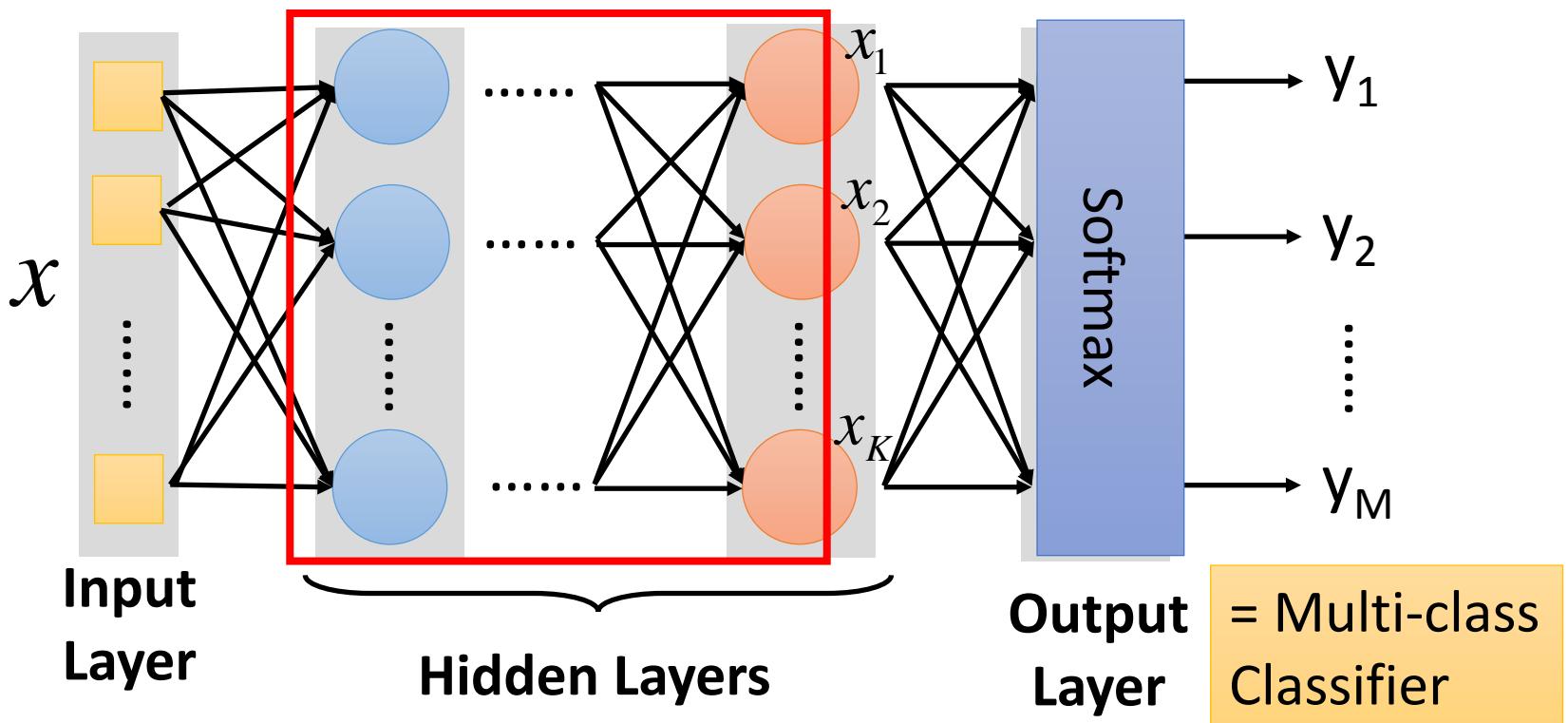
TensorFlow Playground



<http://playground.tensorflow.org/>

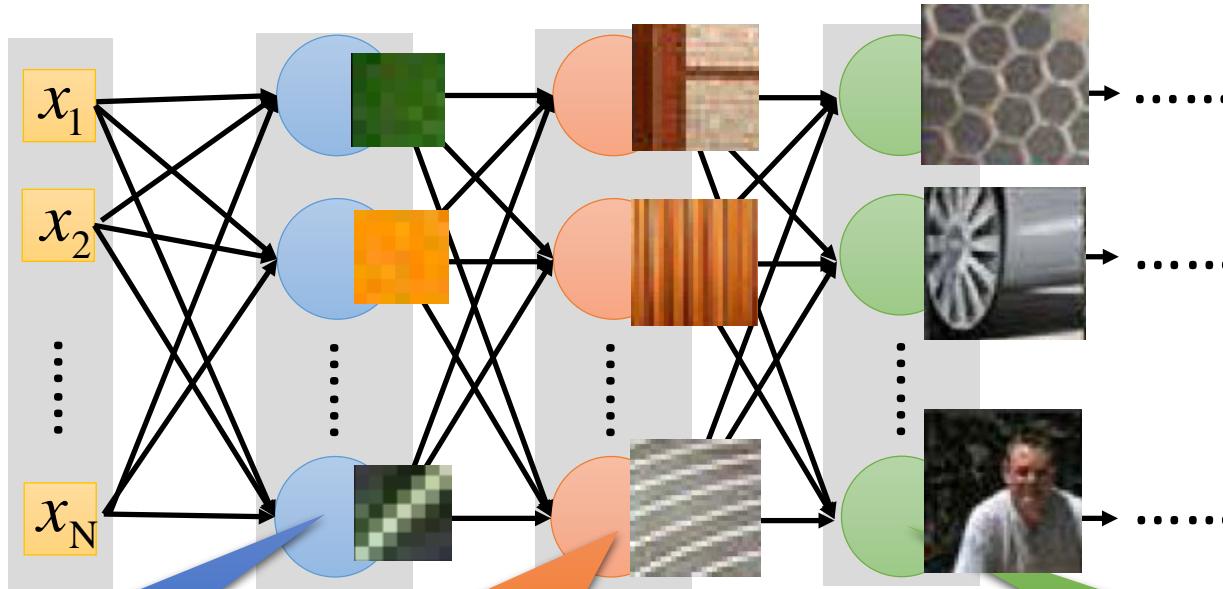
Output Layer as Multi-Class Classifier

Feature extractor replacing
feature engineering



Modularization - Image

- Deep → Modularization



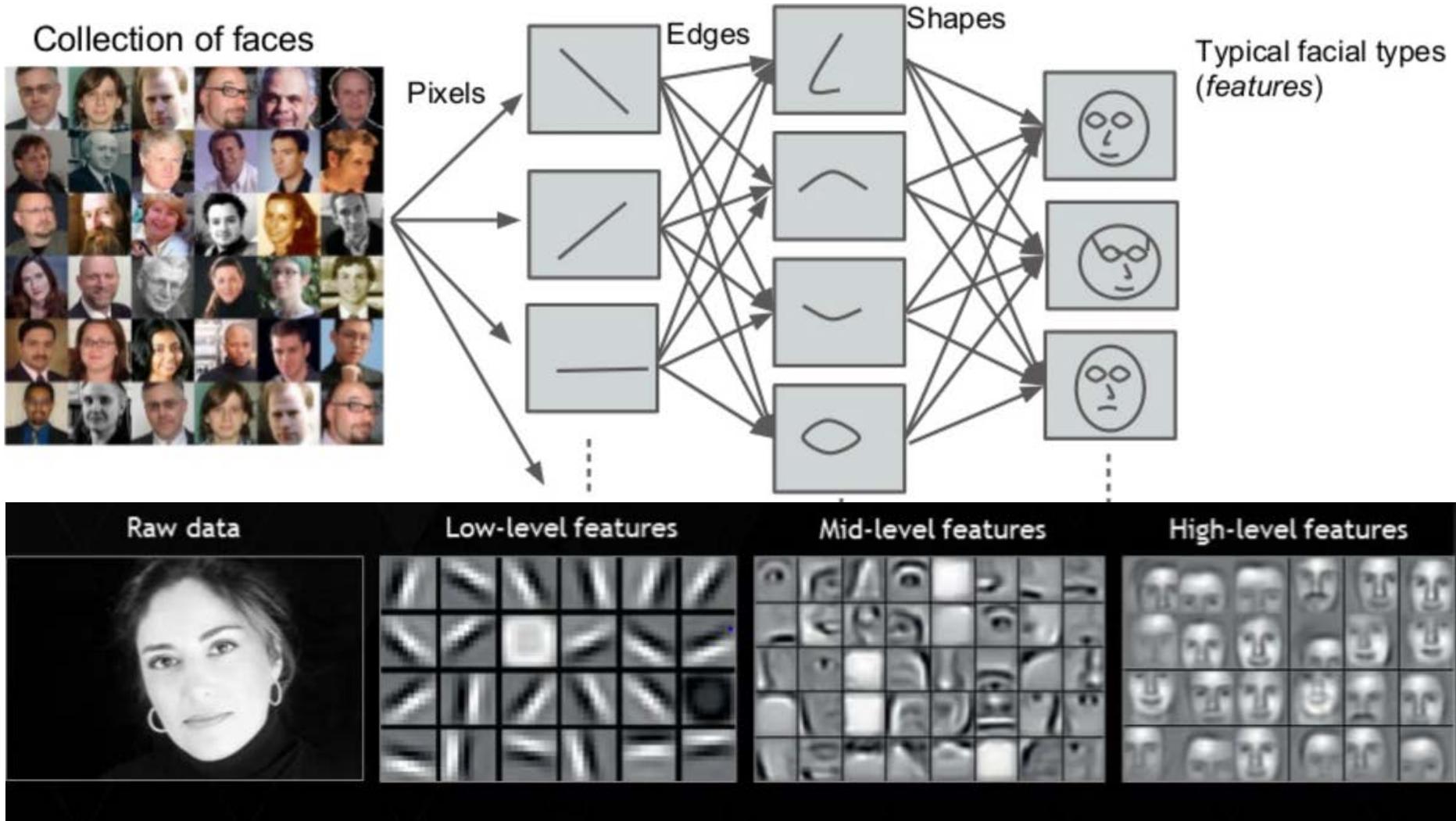
The most basic
classifiers

Use 1st layer as module
to build classifiers

Use 2nd layer as
module

Reference: Zeiler, M. D., & Fergus, R. (2014). Visualizing and understanding convolutional networks. In *Computer Vision–ECCV 2014* (pp. 818-833)

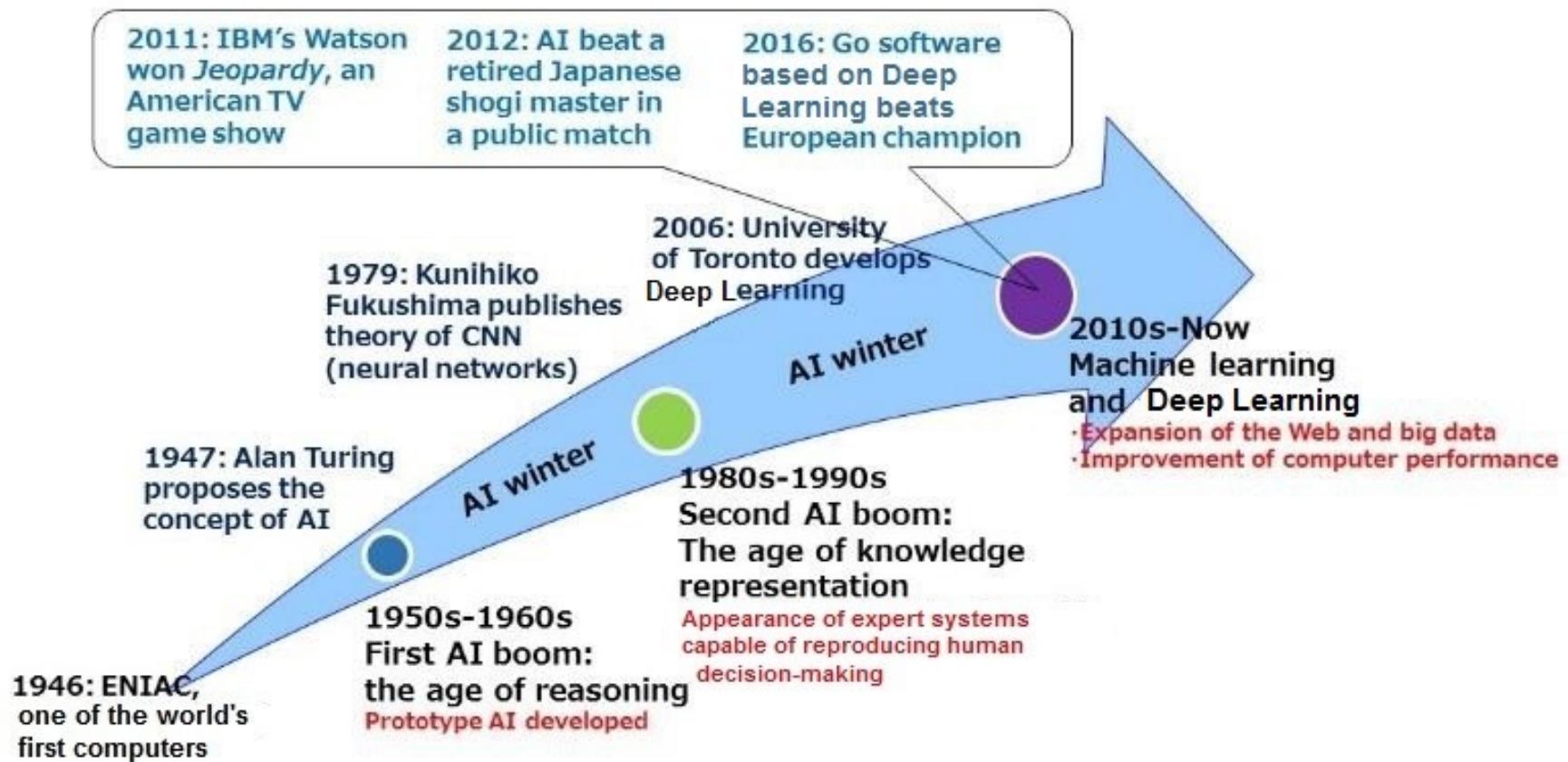
Multi-layer patterns learned from faces



(Credit: <https://www.slideshare.net/WillStanton/deep-learning-with-text-v4>)

AI Winter (1970-1980, 1990-2000)

AI Research and Development Timeline



https://www.mynewsdesk.com/toshiba-global/blog_posts/bringing-the-new-ai-era-to-life-the-researchers-creating-toshibas-technologies-55589

Ups and downs of Deep Learning

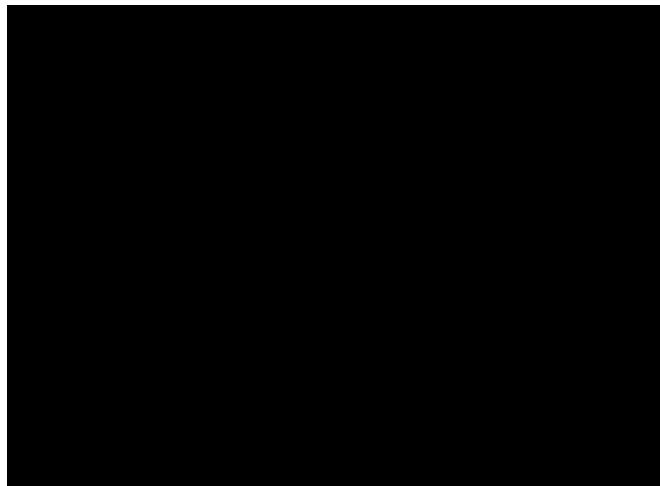
- 1958: Perceptron (linear model)
- 1969: Perceptron has limitation
- 1980s: Multi-layer perceptron
 - Do not have significant difference from DNN today
- 1986: Backpropagation
 - Usually more than 3 hidden layers is not helpful
- 1989: 1 hidden layer is “good enough”, why deep?
- 2006: RBM initialization
- 2009: GPU
- 2011: Start to be popular in speech recognition
- 2012: win ILSVRC image competition
- 2015.2: Image recognition surpassing human-level performance
- 2016.3: Alpha GO beats Lee Sedol
- 2016.10: Speech recognition system as good as humans

What was actually wrong with backprop in 1986?

- We all drew the wrong conclusions about why it failed. The real reasons were:
 - Our labeled **datasets** were thousands of times too small.
 - Our **computers** were millions of times too slow.
 - We initialized the weights in a stupid way.
 - We used the wrong type of non-linearity.

(Credit: Geoff Hinton, [What Was Actually Wrong With Backpropagation in 1986?](#))

人工智慧近年突破的主因之一：運算能力



手寫數字辨識 in 1993

影像物件辨識 2016

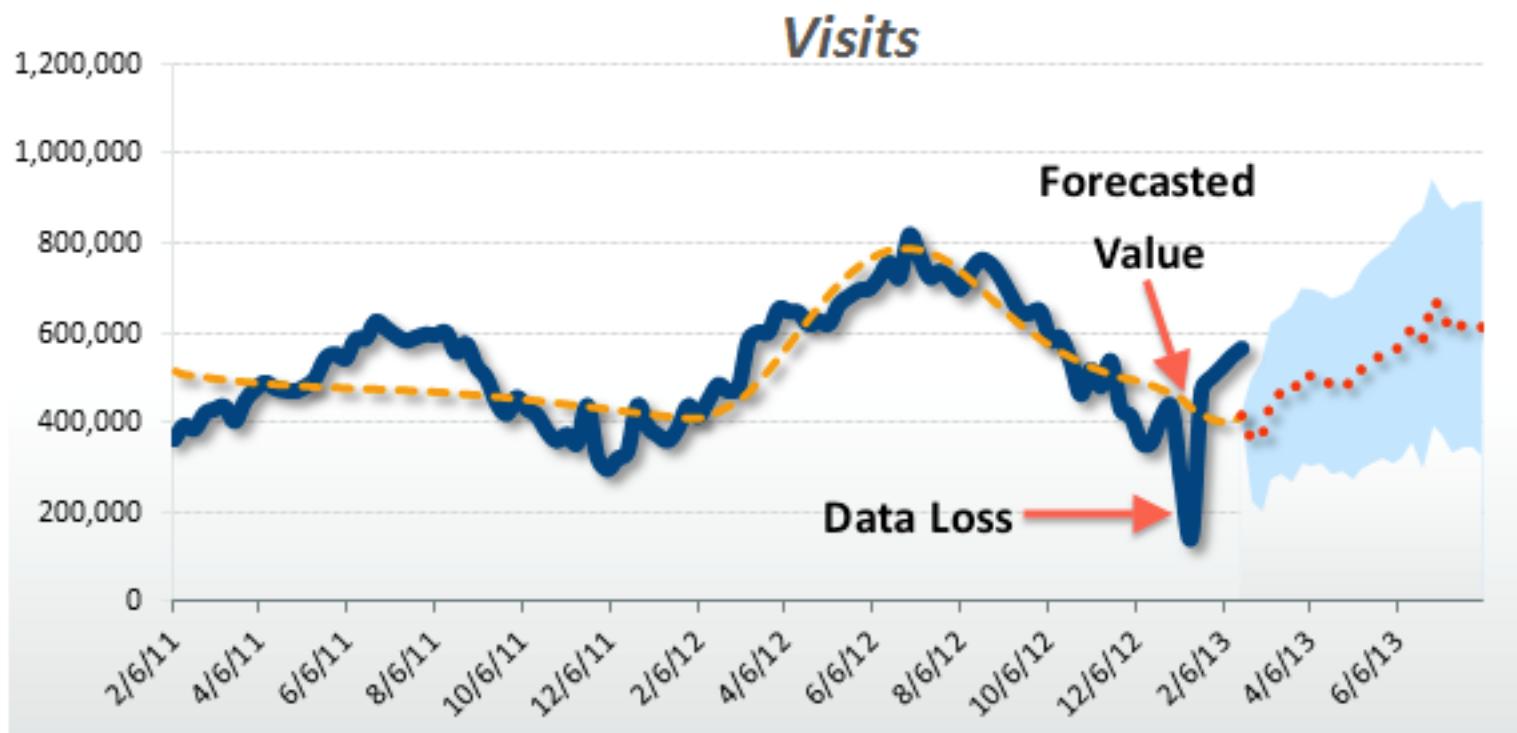


<https://pjreddie.com/darknet/yolo/>

BEYOND SUPERVISED ORDINARY PREDICTION



Time series forecasting





track cycling
cycling
track cycling
road bicycle racing
marathon
ultramarathon



ultramarathon
ultramarathon
half marathon
running
marathon
inline speed skating



heptathlon
heptathlon
decathlon
hurdles
pentathlon
sprint (running)



bikejoring
mushing
bikejoring
harness racing
skijoring
carting



demolition derby
demolition derby
monster truck
mud bogging
motocross
grand prix motorcycle racing



telemark skiing
snowboarding
telemark skiing
nordic skiing
ski touring
skijoring

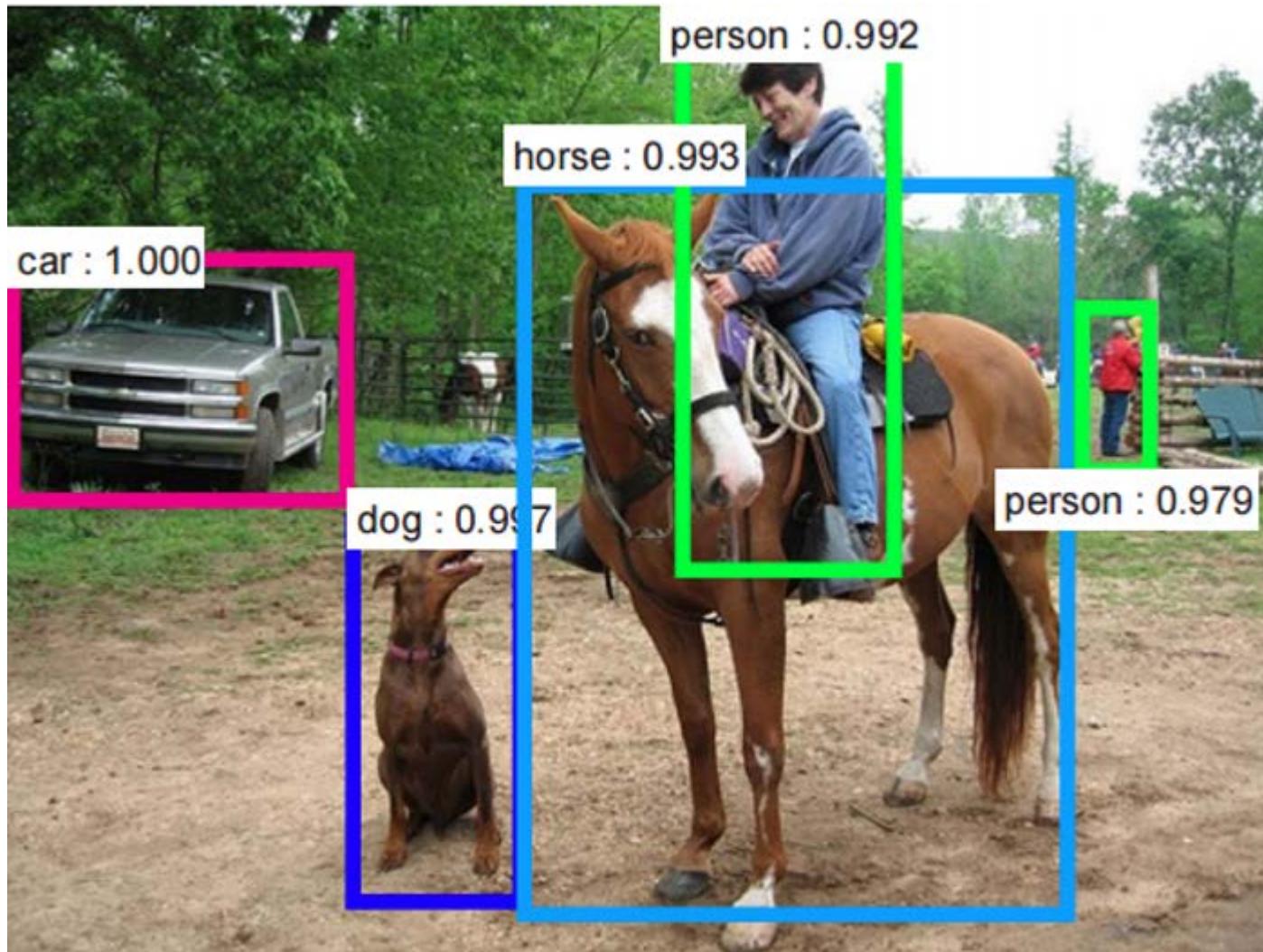


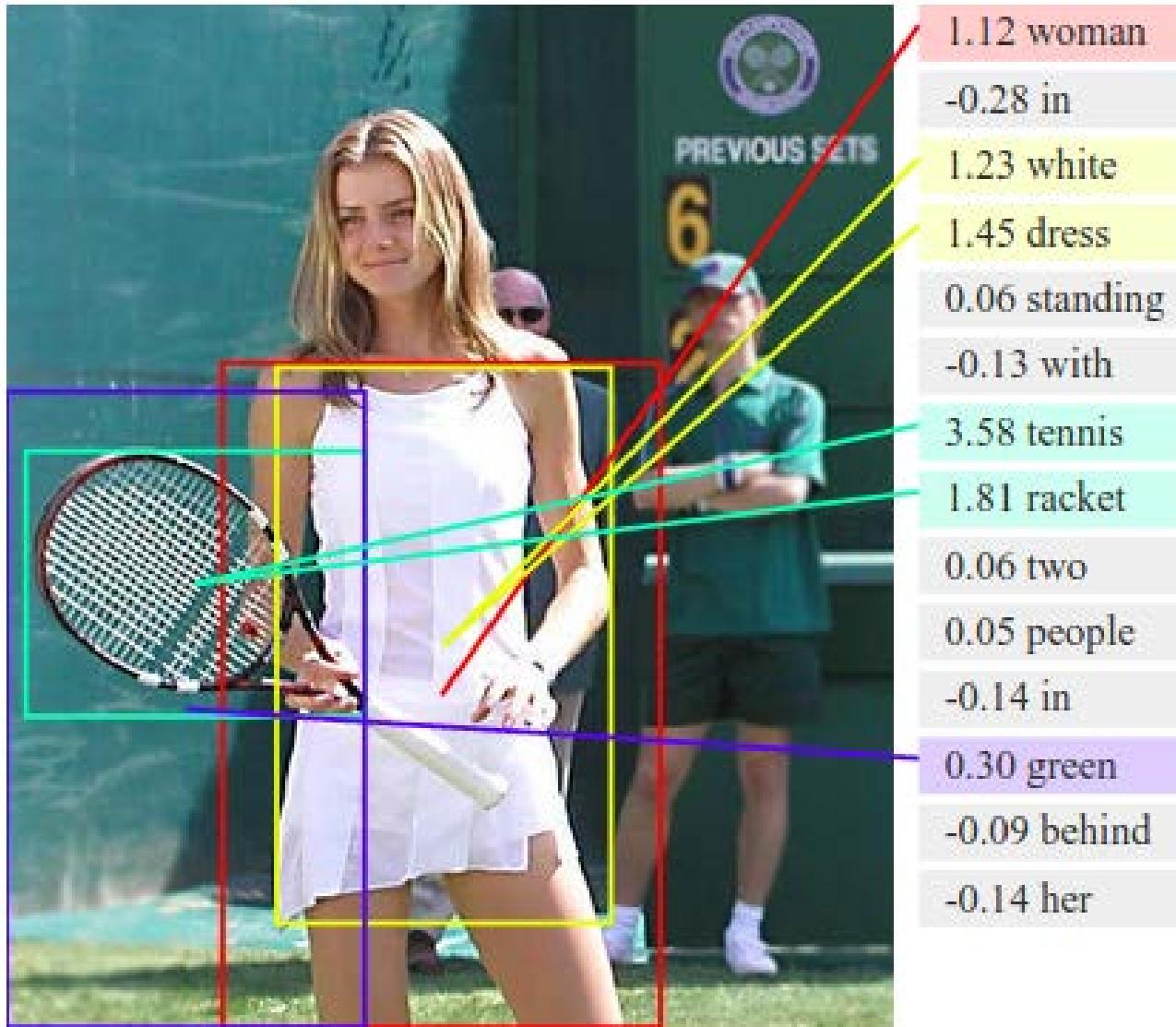
whitewater kayaking
whitewater kayaking
rafting
kayaking
canoeing
adventure racing

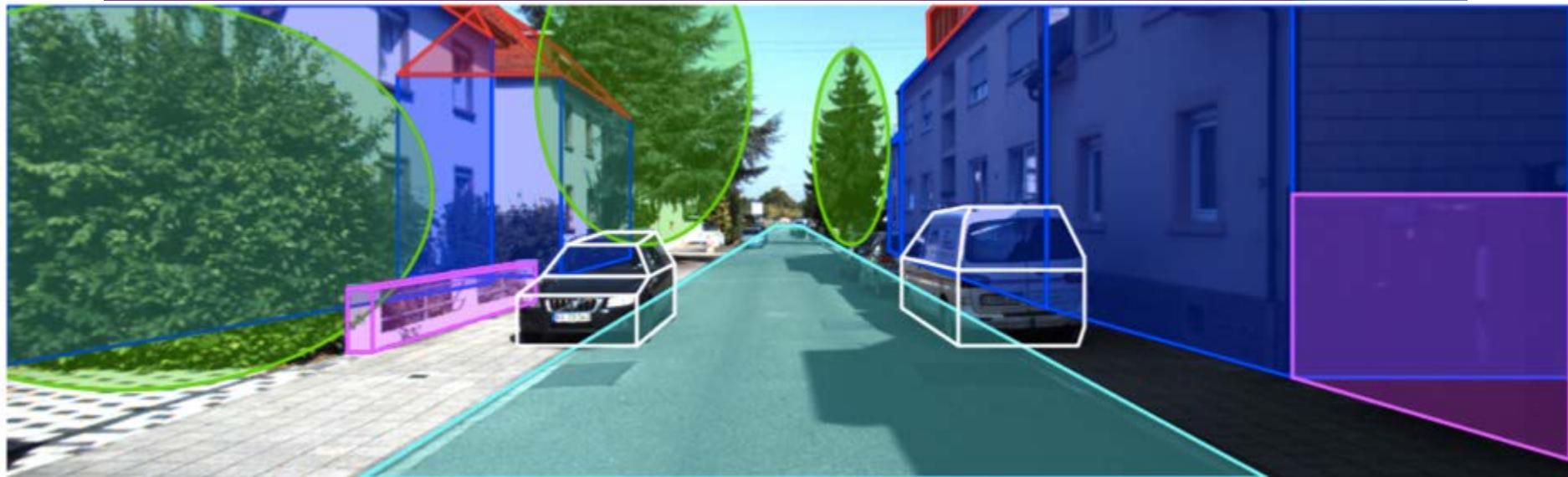


arena football
indoor american football
arena football
canadian football
american football
women's lacrosse

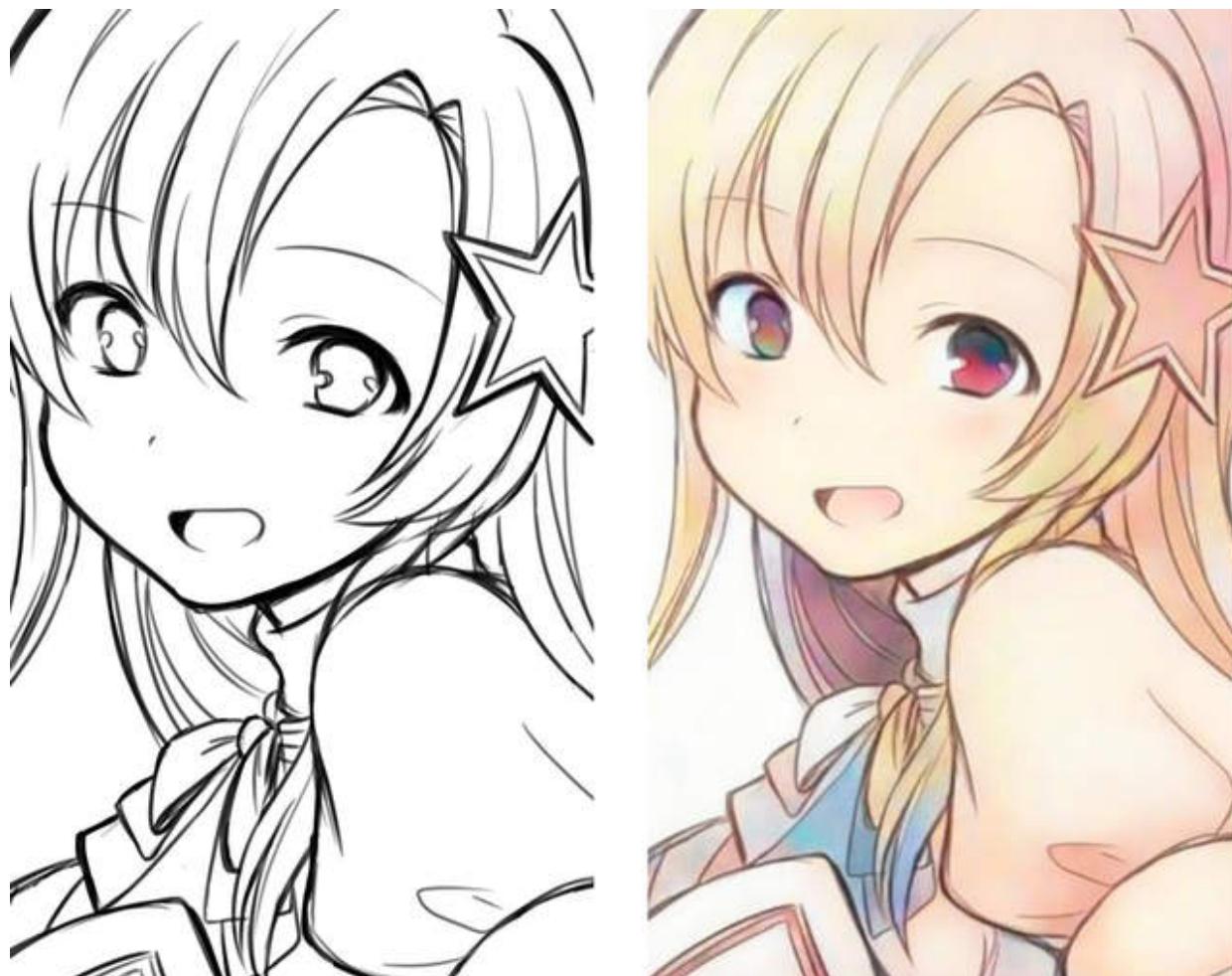
STRUCTURED LEARNING







Auto Coloring



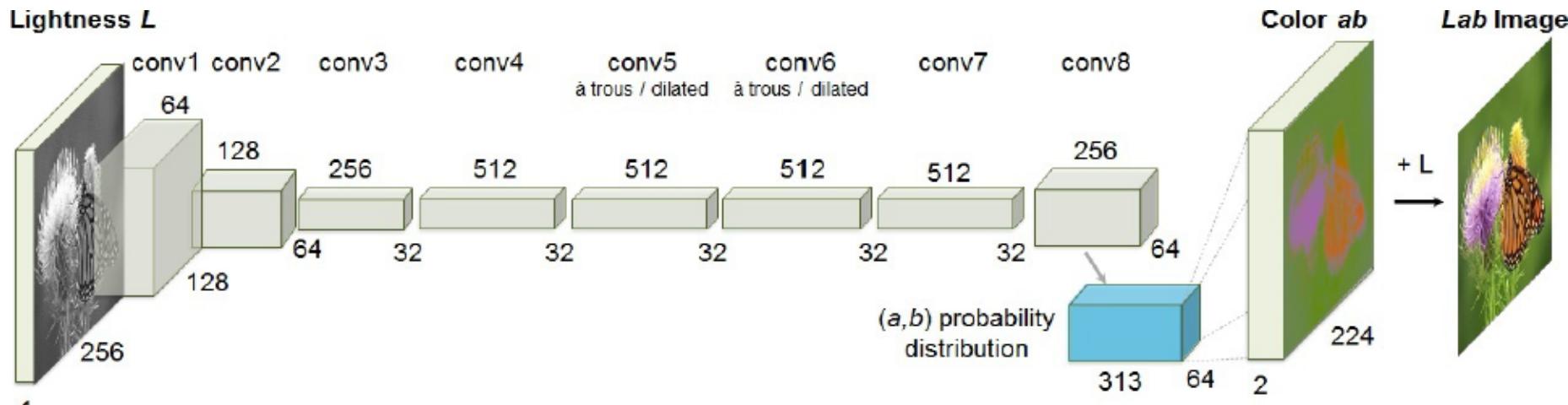
https://paintschainer.preferred.tech/index_zh.html
<https://zhuanlan.zhihu.com/p/24712438>

Colorful Image Colorization

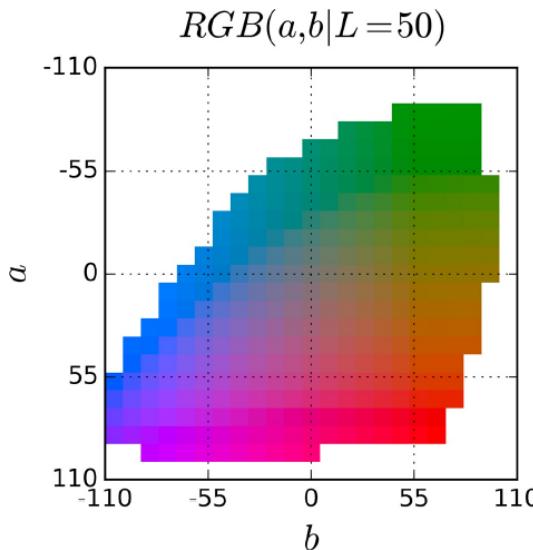


Zhang, Richard, Phillip Isola, and Alexei A. Efros. "Colorful image colorization." *European Conference on Computer Vision*. Springer International Publishing, 2016.

Colorful Image Colorization

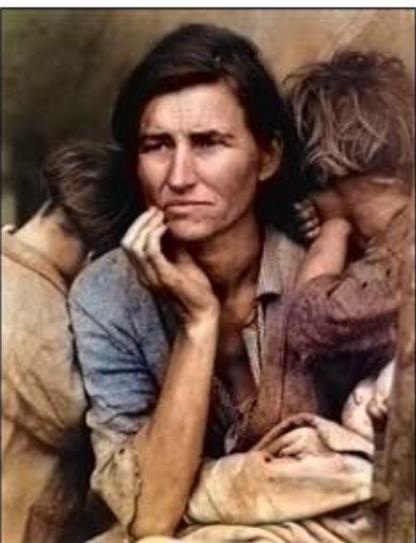


- A 313-class classification problem
- Input: 224x224x1 (L)
- Model output: 64x64x313
- Pixel values: annealed mean of 313 colors



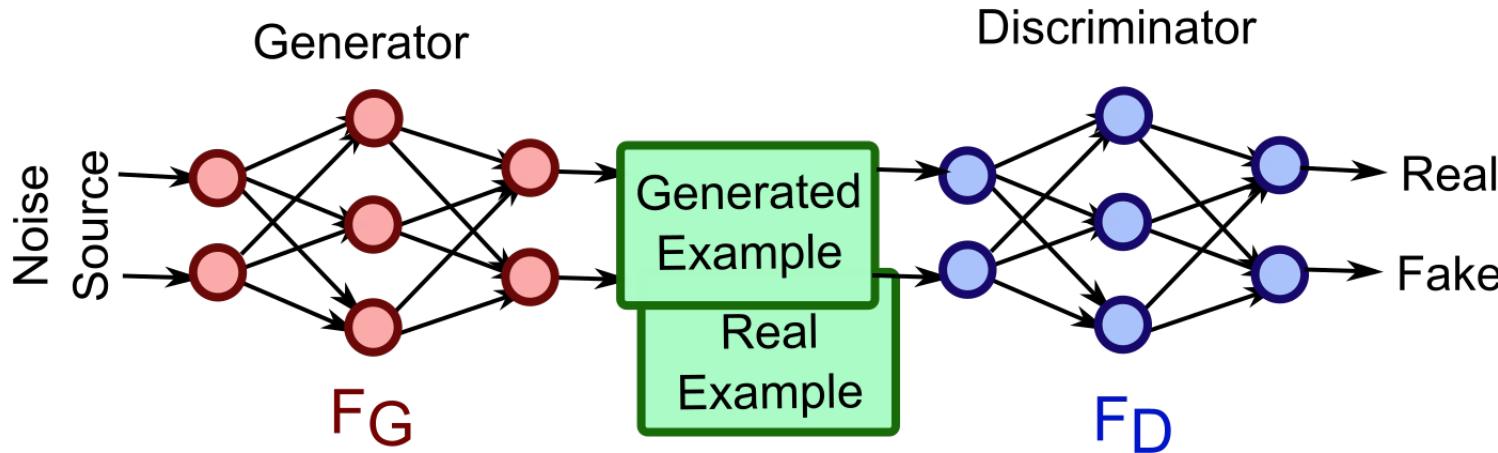
<http://richzhang.github.io/colorization/>

Colorizing Legacy Photos



GENERATIVE MODELS

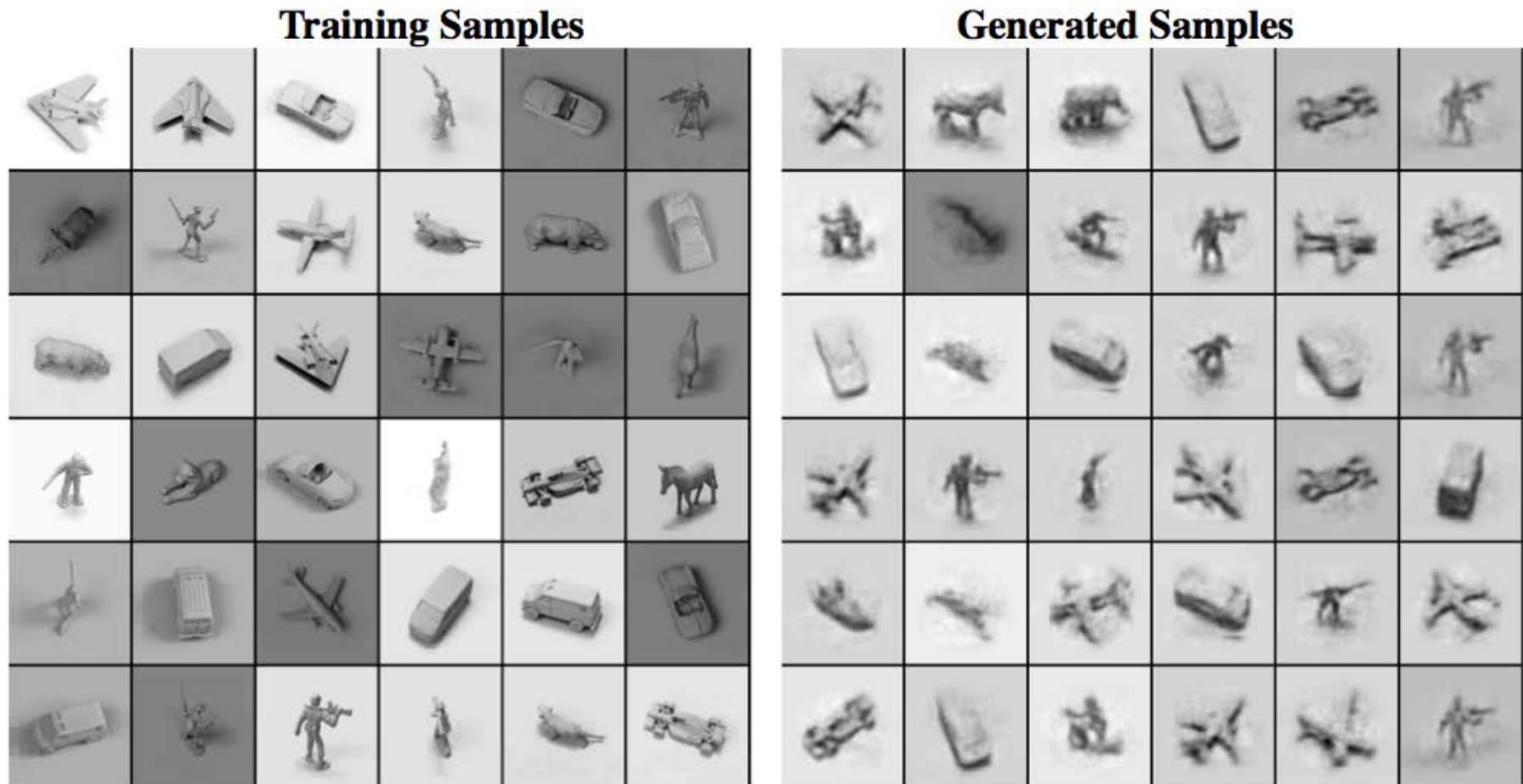
Generative Adversarial Networks



"Generative Adversarial Networks is the **most interesting idea in the last ten years** in machine learning."

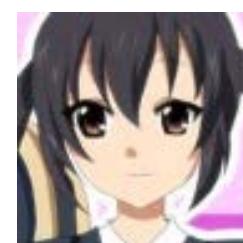
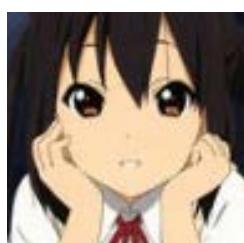
Yann LeCun, Director, Facebook AI

Truth vs. Generated Samples



https://metacademy.org/roadmaps/rgrosse/deep_learning

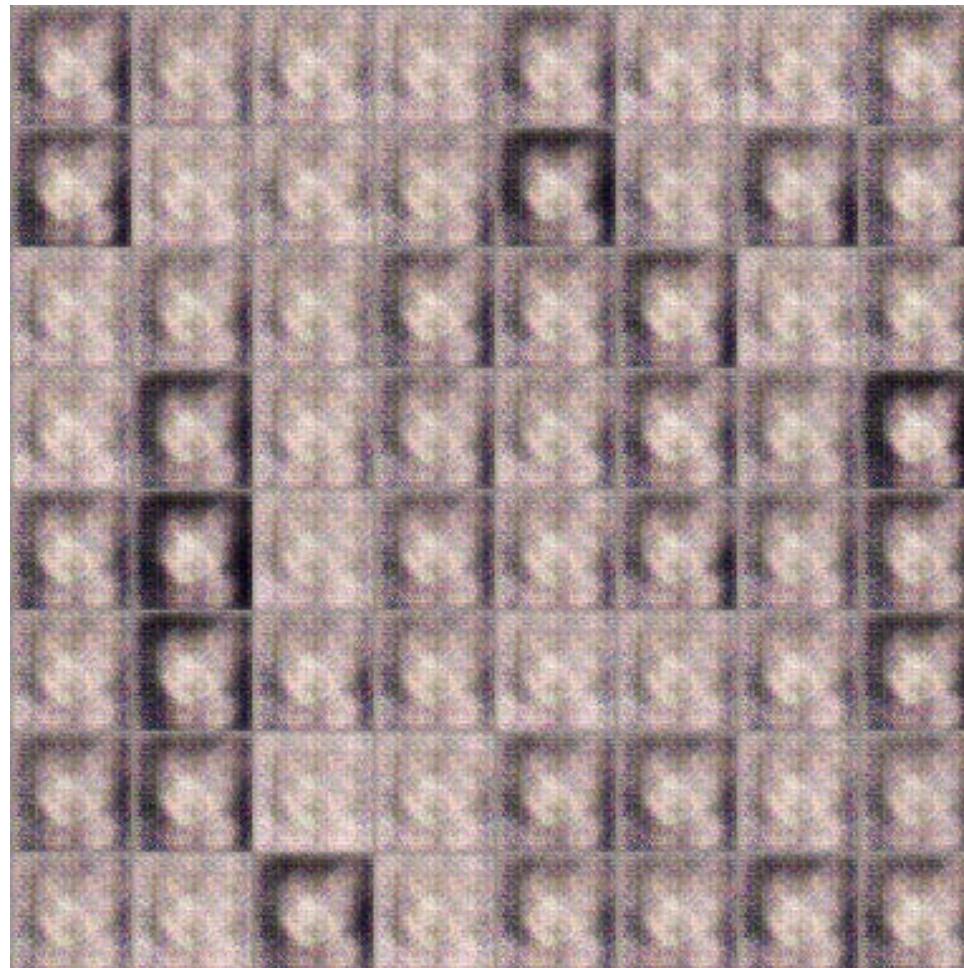
Anime Girl Face Generation



Source of images: <https://zhuanlan.zhihu.com/p/24767059>

DCGAN: <https://github.com/carpedm20/DCGAN-tensorflow>

Anime Girl Face Generation



100 rounds

Anime Girl Face Generation



1000 rounds

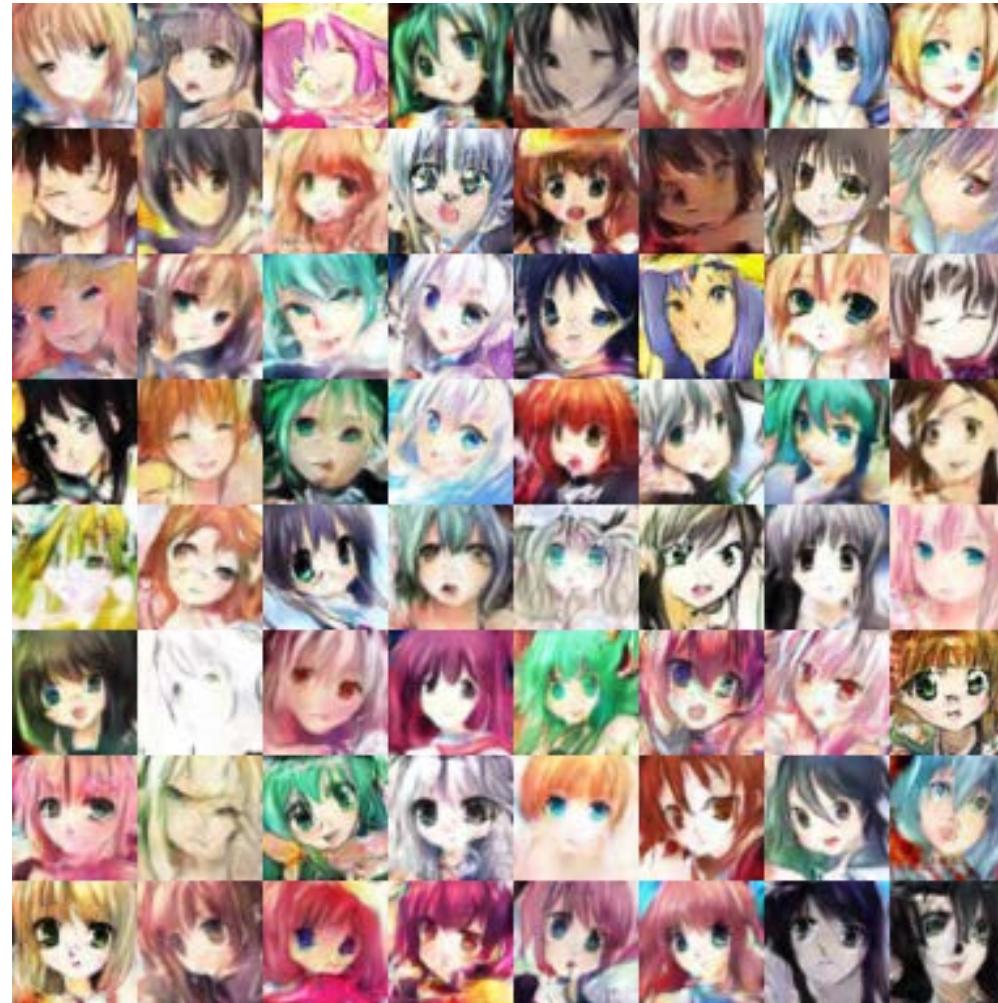
Anime Girl Face Generation

5000 rounds



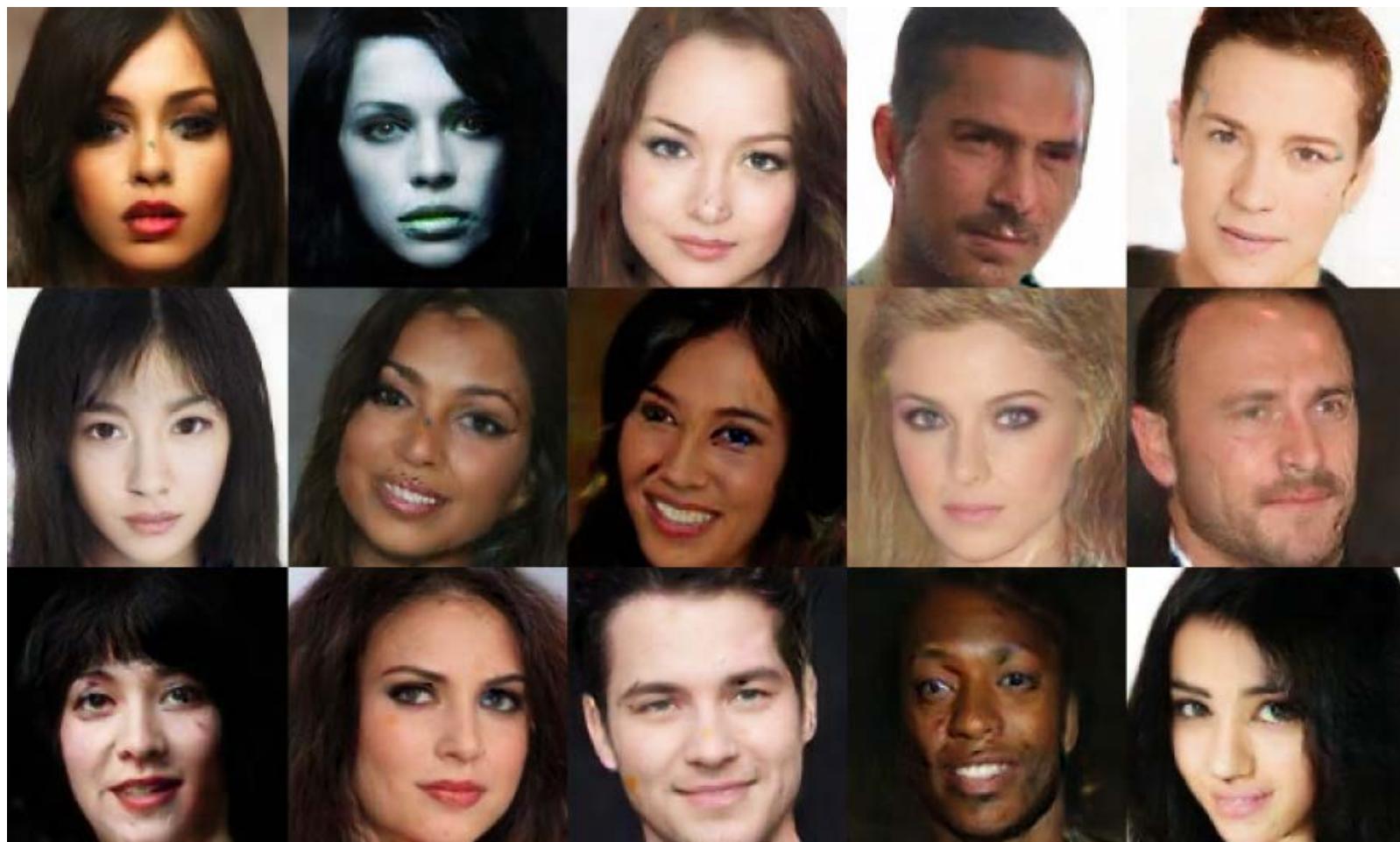
Anime Girl Face Generation

50,000 rounds



(Slide Credit: [Hung-Yi Lee](#))

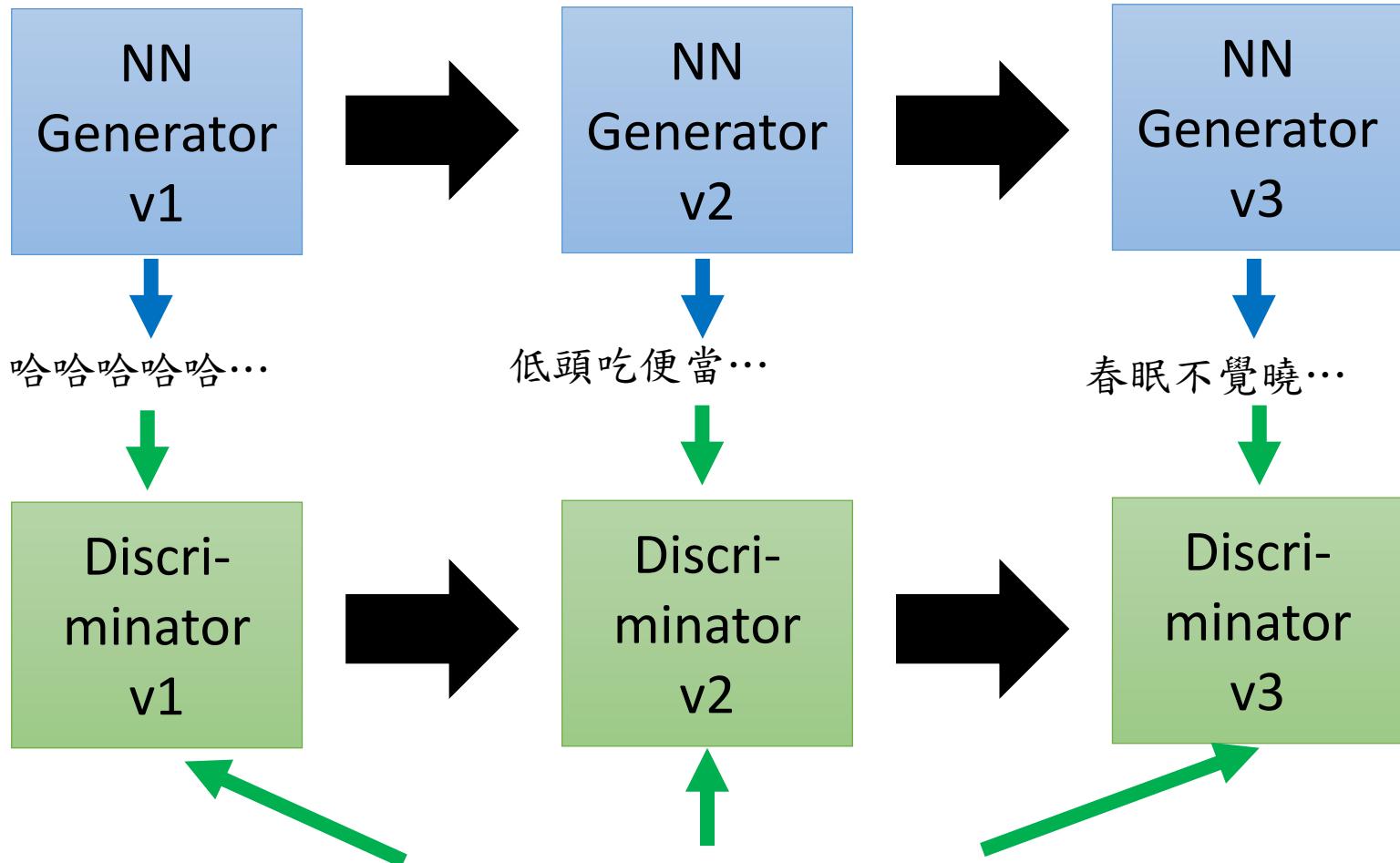
BEGAN (Boundary Equilibrium GAN)



<https://github.com/carpedm20/BEGAN-tensorflow>

Berthelot, David, Tom Schumm, and Luke Metz. "Began: Boundary equilibrium generative adversarial networks." *arXiv preprint arXiv:1703.10717*(2017).

WGAN – Poem Generation



Real poems: 床前明月光，疑似地上霜，舉頭望明月，低頭思故鄉。

WGAN – Poem Generation

由 李仲翊 同學提供實驗結果
Randomly generated

- 升雲白遲丹齋取，此酒新巷市入頭。黃道故海歸中後，不驚入得韻子門。
- 據口容章蕃翎羽，邦貸無遊隔將毬。外蕭曾臺遶出畧，此計推上呂天夢。
- 新來寶伎泉，手雪泓臺蓑。曾子花路魏，不謀散薦船。
- 功持牧度機邈爭，不躡官嬉牧涼散。不迎白旅今掩冬，盡蘸金祇可停。
- 玉十洪沄爭春風，溪子風佛挺橫鞋。盤盤稅焰先花齋，誰過飄鶴一丞幢。
- 海人依野庇，為阻例沉迴。座花不佐樹，弟闌十名儂。
- 入維當興日世瀕，不評皺。頭醉空其杯，駸園凋送頭。
- 鉢笙動春枝，寶參潔長知。官爲密爛去，絆粒薛一靜。
- 吾涼腕不楚，縱先待旅知。楚人縱酒待，一蔓飄聖猜。
- 折幕故蠟應韻子，徑頭霜瓊老徑徑。尚錯春鏘熊悽梅，去吹依能九將香。
- 通可矯目鷁須淨，丹迤挈花一抵嫖。外子當目中前醒，迎日幽筆釣弧前。
- 庭愛四樹人庭好，無衣服仍繡秋州。更怯風流欲鵝雲，帛陽舊據畝婷儻。

Conditional GAN – Text to Image

"red flower with
black center"



Caption	Image
this flower has white petals and a yellow stamen	
the center is yellow surrounded by wavy dark purple petals	
this flower has lots of small round pink petals	

AI 自動生成二次元妹子？ 或將替代插畫師部分工作

MakeGirls.moe

Home About News Tips Official Blog Github

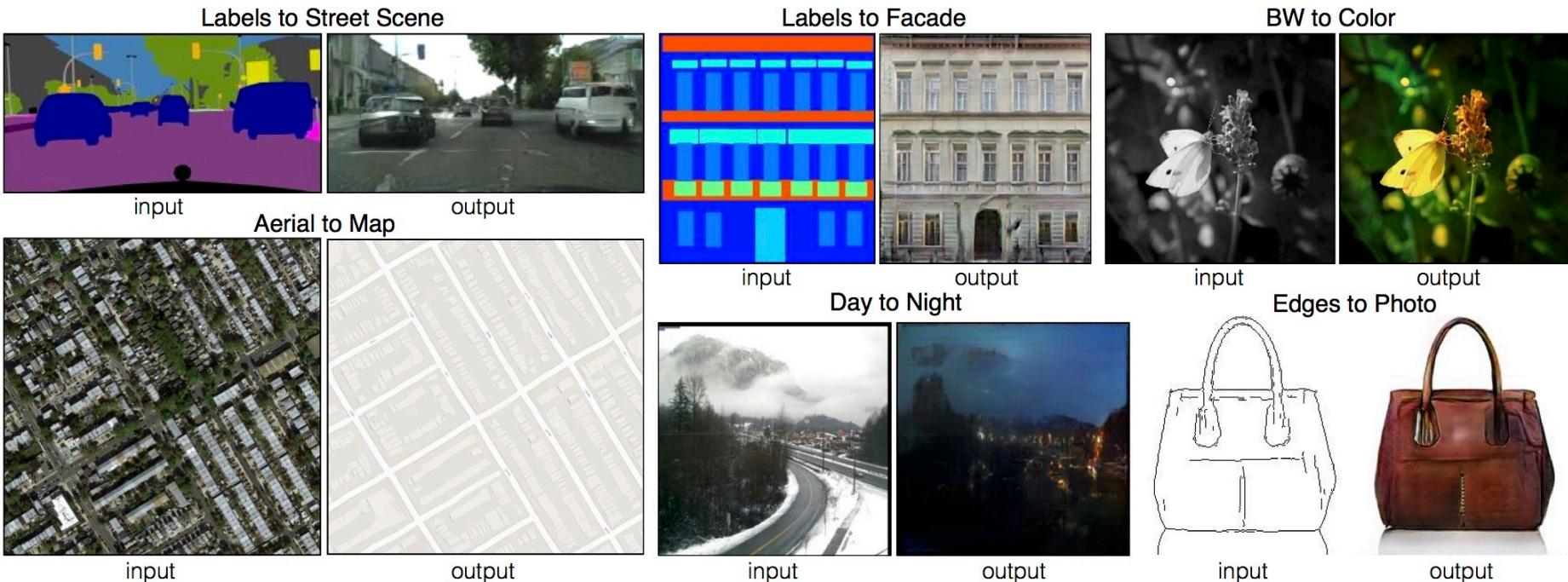
The screenshot shows a user interface for generating anime-style girls. On the left, there's a preview image of a girl with orange hair and blue eyes. Below it are buttons for 'Generate' (red), '+1' (light blue), and '-1' (light blue). There's also a 'Share on Twitter' button with a Twitter icon. The main area is titled 'Options' and contains several dropdown menus and toggle switches:

- Hair Color:** Orange (selected)
- Hair Style:** Long Hair
- Eye Color:** Blue
- Blush:** Off, Random, **On**
- Smile:** Off, Random, **On**
- Open Mouth:** Off, Random, **On**
- Hat:** Off (selected)
- Ribbon:** Off (selected)
- Glasses:** Off (selected)
- Noise:** Random (selected)
- Current Noise:** A colorful noise pattern.
- Noise Import/Export:** Import, Export

<http://make.girls.moe/#/>

<http://bangqu.com/b4U76M.html>

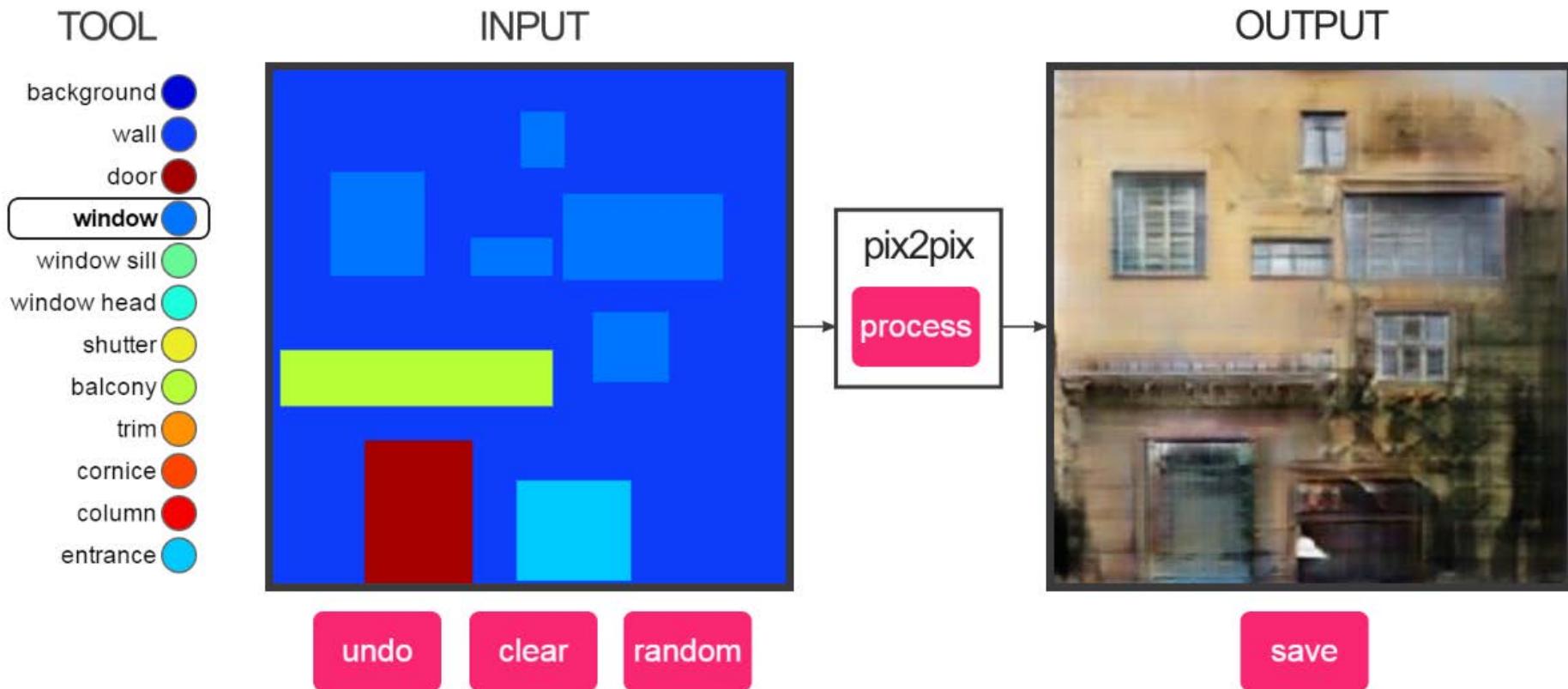
Image-to-image Translation



Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, Alexei A. Efros, "Image-to-Image Translation with Conditional Adversarial Networks", arXiv preprint, 2016

Interactive Image Translation with pix2pix-tensorflow

facades



<https://affinelayer.com/pixsrv/>

Image to Image Translation: CycleGAN

Input



Monet



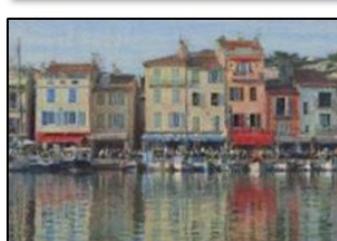
Van Gogh



Cezanne



Ukiyo-e

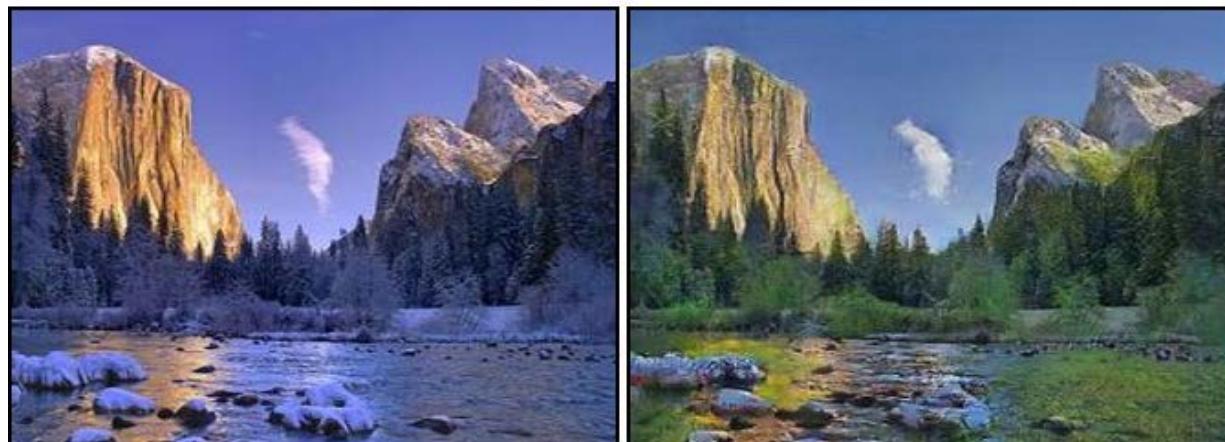


CycleGAN

Summer ↪ Winter



summer → winter

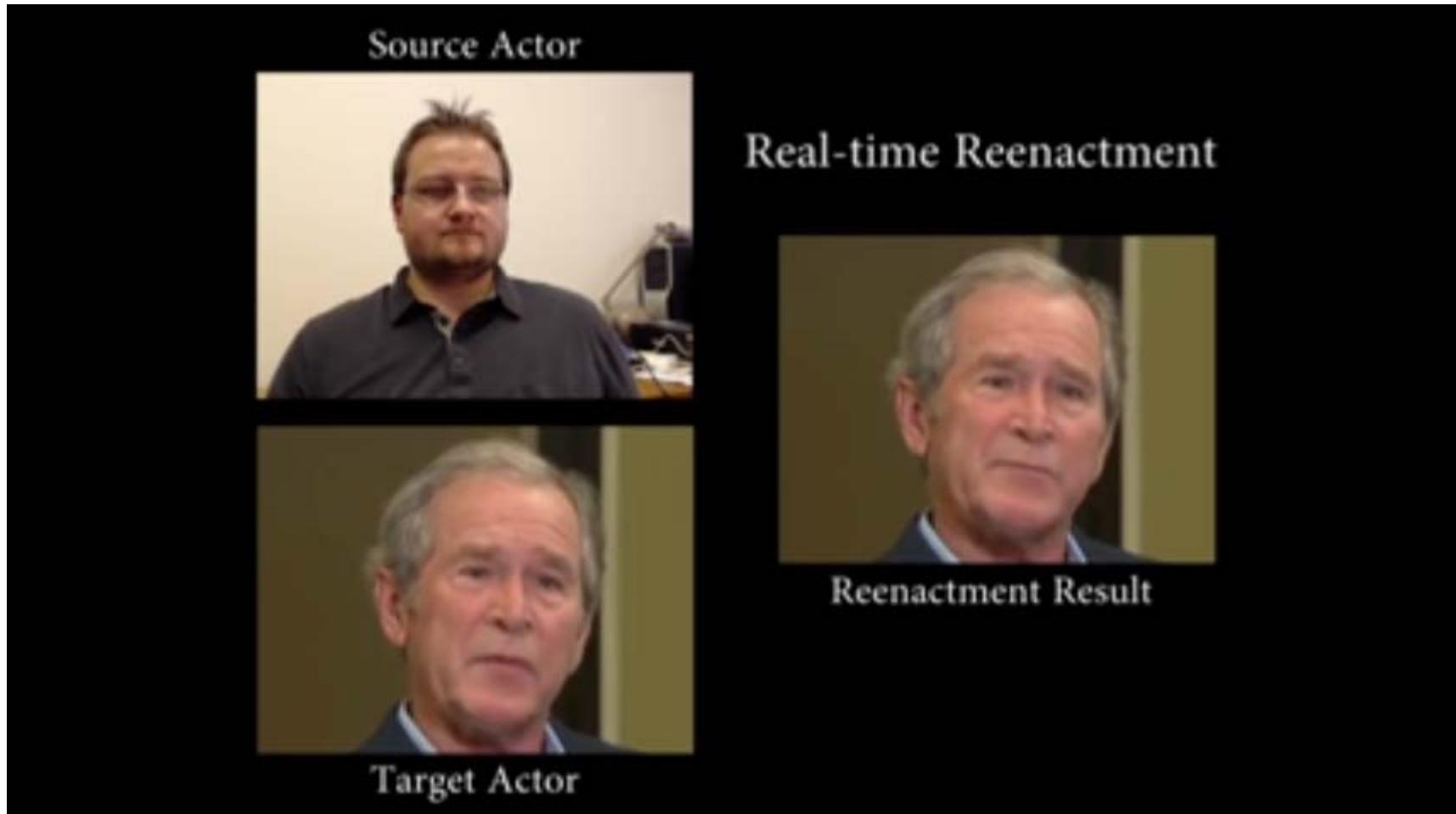


winter → summer

Horse <-> Zibra



Video Reenactment



<https://www.youtube.com/watch?v=ohmajJ TcpNk>
<https://www.youtube.com/watch?v=gYq67CjDqvW>

Deepfakes

AI 假色情終究來臨：神力女超人 Gal Gadot
臉被移花接木到 A 片中

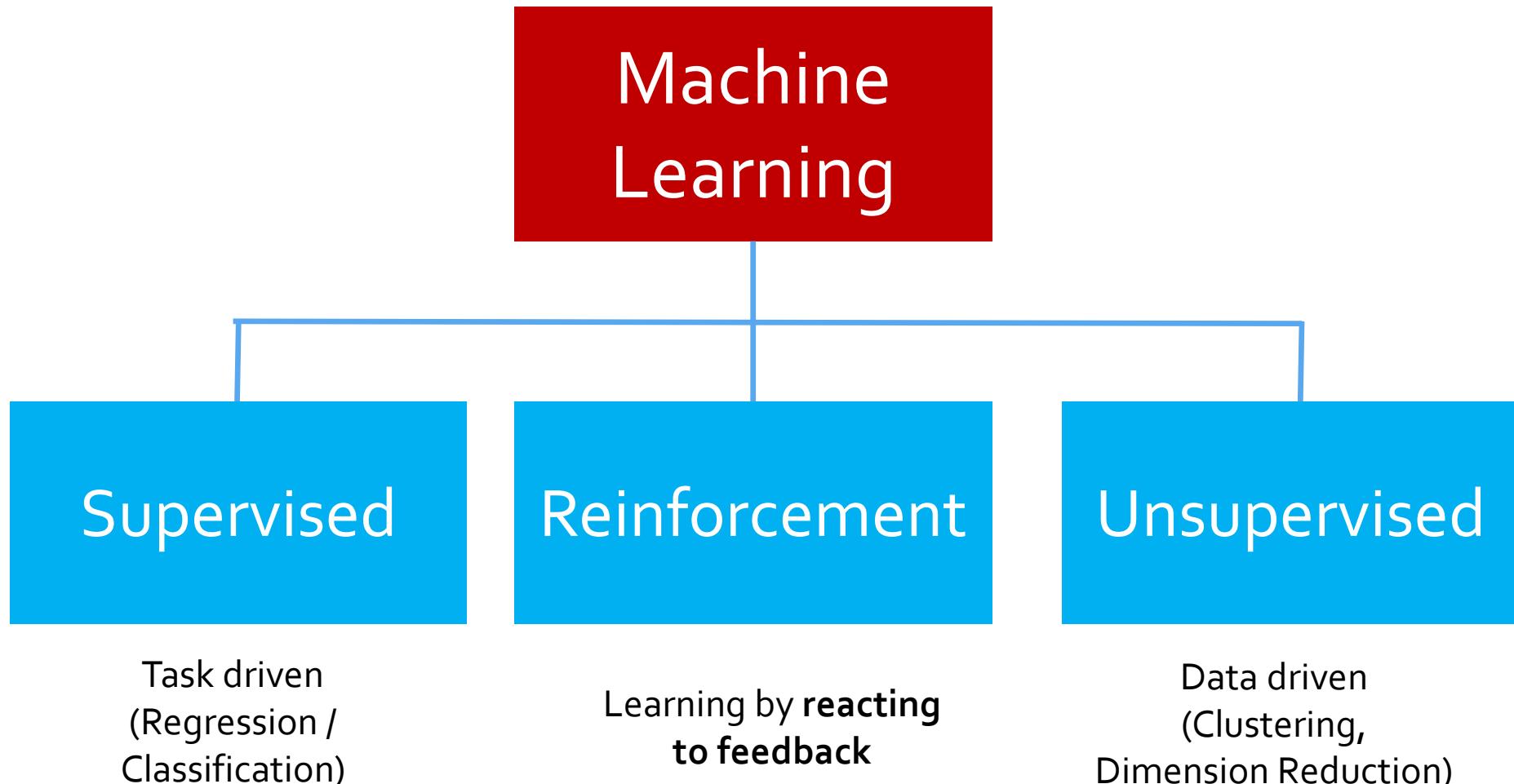
2017/12/13 · Chris · AI、machine learning



Photo Credit: SendVids

<https://www.inside.com.tw/2017/12/13/gal-gadot-fake-ai-porn>

Types of Machine Learning Methods



Why Supervised Learning is Not Enough

“

The brain has about 10^{14} synapses and we only live for about 10^9 seconds. So we have a lot more parameters than data.

This motivates the idea that we must do a lot of **unsupervised learning** since the perceptual input (including proprioception) is the only place we can get 10^5 dimensions of constraint per second.

-- Geoffrey Hinton

https://www.reddit.com/r/MachineLearning/comments/2lmo0/ama_geoffrey_hinton/

Learning to play Go

Supervised v.s. Reinforcement

- Supervised: Learning from teacher



Next move:
“5-5”



Next move:
“3-3”

- Reinforcement Learning Learning from experience

First move → many moves → Win!
(Two agents play with each other.)

Approaches To Reinforcement Learning

■ Policy-based RL

- Search directly for the **optimal policy**
- This is the policy achieving maximum future reward

■ Value-based RL

- Estimate the optimal **value function**
- This is the maximum value achievable under any policy

■ Model-based RL

- Build a transition model of the environment
- Plan (e.g. by **lookahead**) using model

■ Of course you can combine any of the above

Typical Applications of RL

- **Play games:** Atari, poker, Go, ...
- **Explore worlds:** 3D worlds, Labyrinth, ...
- **Control physical systems:** manipulate, walk, swim, ...
- **Interact with users:** recommend, optimize, personalize,

...



(Slide credit: David Silver)

DeepMind A3C



SL: Mimic excellent drivers
RL: Learn from failures



<https://youtu.be/oxo1Ldx3L5Q?t=22>

NVidia Self Driving Car, 2016

More RL Applications

- Flying Helicopter
- Driving
- Google Cuts Its Giant Electricity Bill With DeepMind-Powered AI
- Parameter tuning in manufacturing lines
- Text generation
 - Hongyu Guo, "Generating Text with Deep Reinforcement Learning", NIPS, 2015
 - Marc'Aurelio Ranzato, Sumit Chopra, Michael Auli, Wojciech Zaremba, "Sequence Level Training with Recurrent Neural Networks", ICLR, 2016

Data vs. Machine learning vs. AI

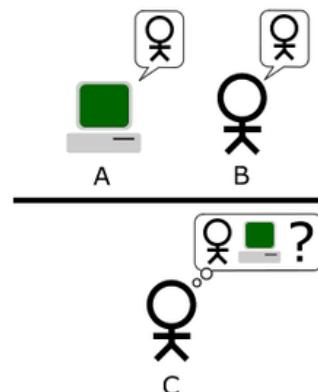
- Data: records of experience

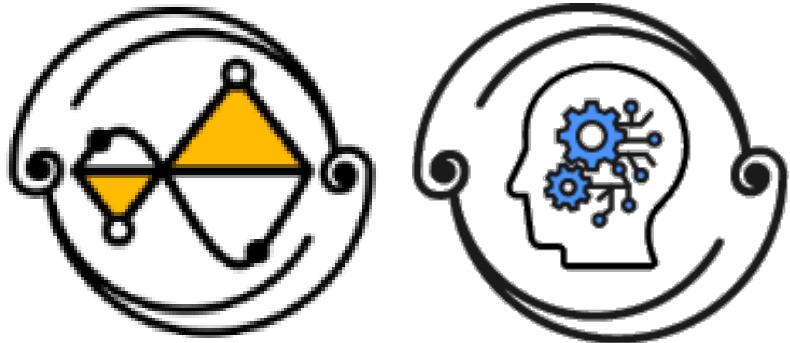


- Machine learning: “*A type of algorithms that gives computers the ability to learn from experience, rather than being explicit programmed.*”



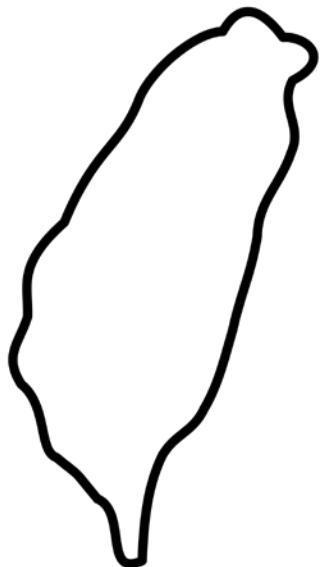
- Artificial intelligence
 - Turing test





資料科學及人工智慧

推廣在台灣



2 days x 800 ppl

2014 台灣資料科學
愛好者年會



8/30 – 8/31, 2014

<http://twconf.data-sci.org/>

<https://www.facebook.com/twdsconf>



Data Scientists × 17



2014 台灣資料科學愛好者年會
8/30-31 · 中央研究院人文科學館

黃孝文

- 林智仁 (Chih-Jen Lin), 國立臺灣大學資訊工程學系特聘教授
- 高嘉良 (Chia-liang Kao), g0v.tw 台灣零時政府共同創辦人
- 劉嘉凱 (Chia-Kai Liu), 御言堂總經理
- 陳君厚 (Chun-Hou Chen), 中央研究院統計科學研究所研究員兼副所長
- 趙國仁 (Craig Chao), Vpon 行動數據科技數據科學家
- 潘美連 (Mei-Lien Pan), 台灣醫學資訊學會祕書長
- 劉家宏 (Chia-Hung Liu), 華聯生物科技股份有限公司 研發部副理
- 林大利 (Da-Li Lin), 特有生物研究保育中心助理研究員
- 郭建甫 (Jeff Kuo), Gogolook 走著瞧公司創辦人兼執行長
- 高義銘 (Yimin Kao), Gogolook 走著瞧公司資料科學家
- 彭啟明 (Chi Ming Peng), 天氣風險管理開發公司總經理
- 吳牧恩 (Mu-En Wu), 東吳大學數學系助理教授
- 呂俊宏 (Enrico Lu), 資訊工業策進會創新應用服務研究所研究顧問
- 洪進吉 (Gene Hong), 台灣數位文化協會顧問
- 黃孝文 (Norman), Yahoo! Taiwan Senior Data Engineer
- 林于聖 (Jason Lin), Yahoo! Taiwan Senior Data Engineer
- 余孟勳 (MengHsun Simon Yu), 台灣公益責信協會發起人兼理事長

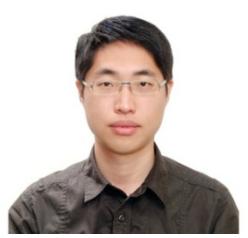
4 days x 1300 ppl



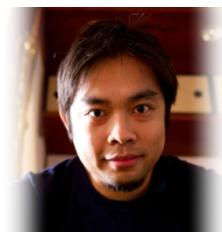
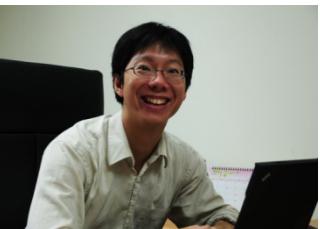
台灣資料科學 愛好者年會

8/20 – 8/23, 2015





Data Scientists x 24



4 days x 1718 ppi



2016

台灣資料科學 愛好者年會





資料科學專家 $\times 50$



台灣人工智慧年會系列活動





台灣人工智慧年會

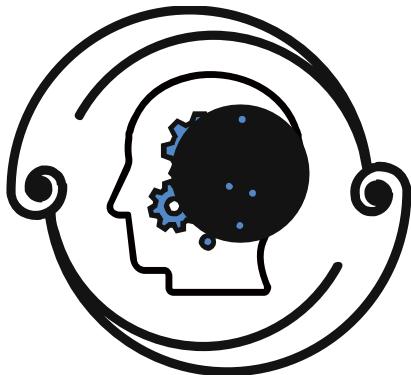


台灣資料科學年會

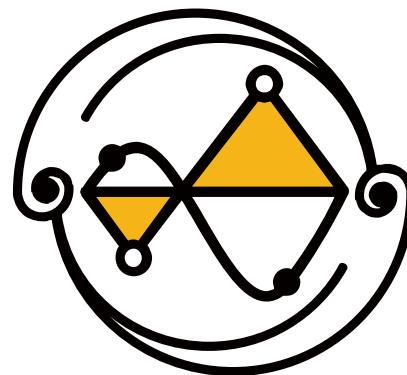
今年hen特別！



結合人工智慧及資料科學的盛大年會



台灣人工智慧年會



台灣資料科學年會



2017/11/09 ~ 2017/11/12
超過 2200 人報名



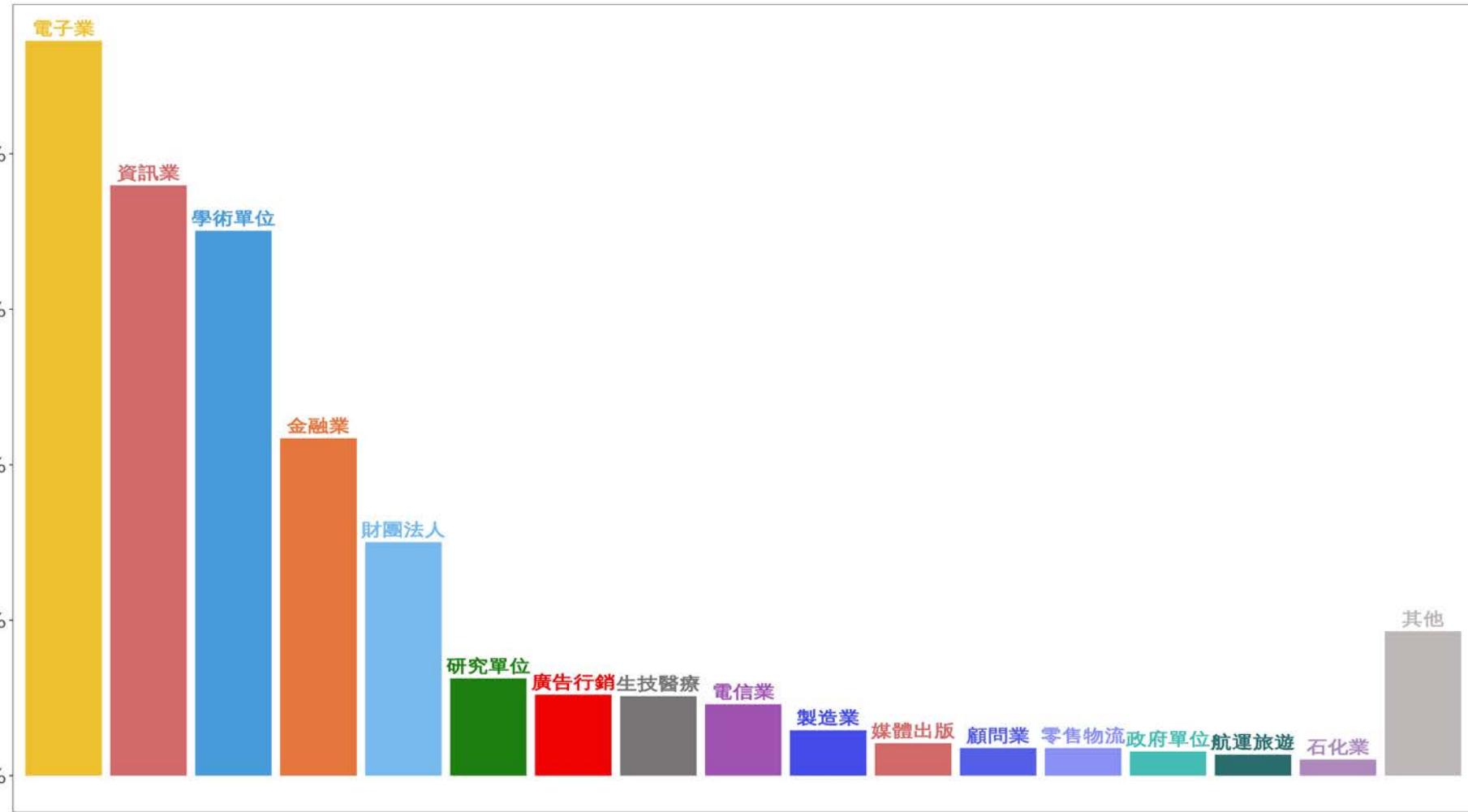


台灣人工智慧年會



台灣資料科學年會

與會者行業分布



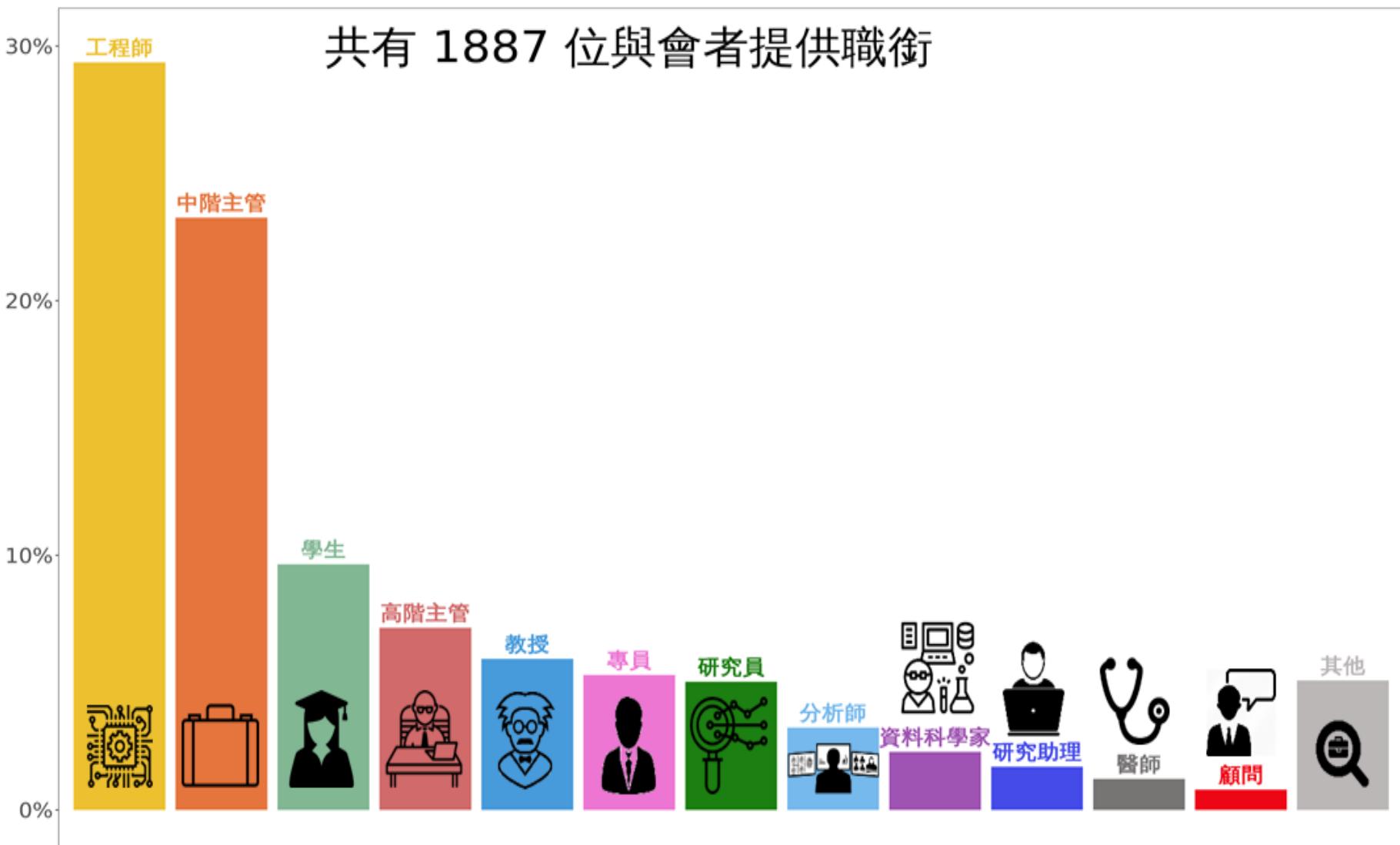


台灣人工智慧年會



台灣資料科學年會

與會者工作職別

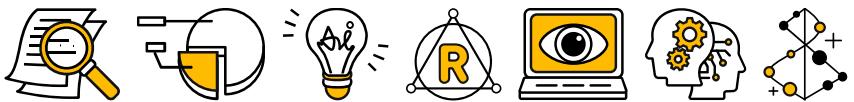




台灣人工智慧年會

台灣資料科學年會

130 場高品質演講



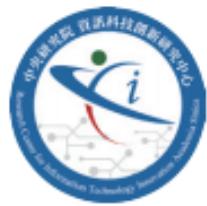
協辦單位



台灣人工智慧年會



台灣資料科學年會



中央研究院
統計科學研究所



中央研究院資訊服務處
ACADEMIA SINICA
Department of Information
Technology Services



工業技術研究院
Industrial Technology
Research Institute

NARLabs 國家實驗研究院
國家高速網路與計算中心



鑽石級贊助企業



台灣人工智慧年會



台灣資料科學年會



玉山金控
E.SUN FHC



TREND
MICROTM

白金級贊助企業



台灣人工智慧年會



台灣資料科學年會

黃金級贊助企業



Appier

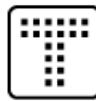
BRIDGEWELL
宇匯知識科技

Dcard

Deloitte.
勤業眾信

 Microsoft


NVIDIA.

 新加坡商 鈦坦科技
TITANSOFT

Tagtoo

whoscall



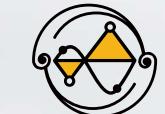
台灣人工智慧年會



台灣資料科學年會

帳篷照片

未雨綢繆，為四天活動特別搭上能容納千人的帳篷，並連接人文館及活動中心，方便與會者兩個場地來往。



台灣人工智慧年會

台灣資料科學年會



帳篷照片



台灣人工智慧年會



台灣資料科學年會

除了擋雨外，帳篷亦在大晴天下為與會者遮陽



帳篷照片



台灣人工智慧年會



台灣資料科學年會





會議盛況



會議盛況

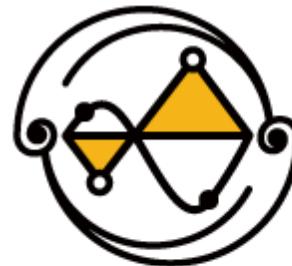


2018



台灣人工智慧年會

2017/11/9 ~ 2017/11/10



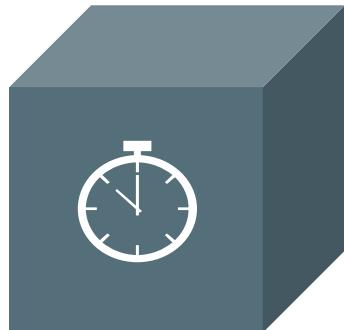
台灣資料科學年會

2017/11/11~2017/11/12

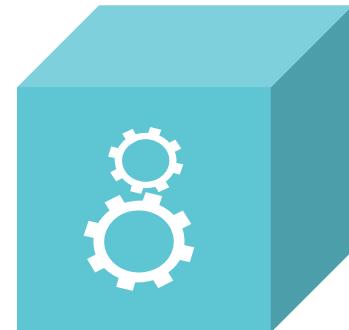
人工智能 · 智慧台灣



McKinsey's Four Dimensions in AI Value Chain



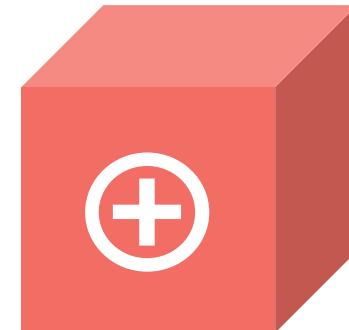
Project



Produce



Promote



Provide

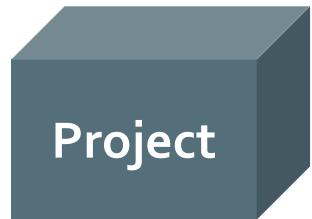
Smart R&D and forecasting

Optimized production with lower cost and higher efficiency

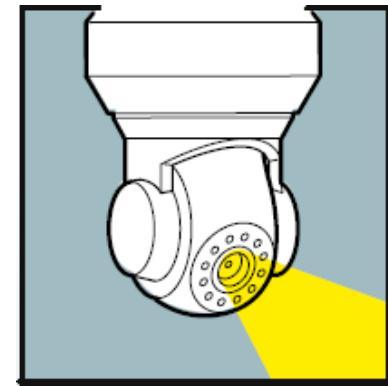
Products and services at the right price, time, and targets

Enriched and tailored user experience

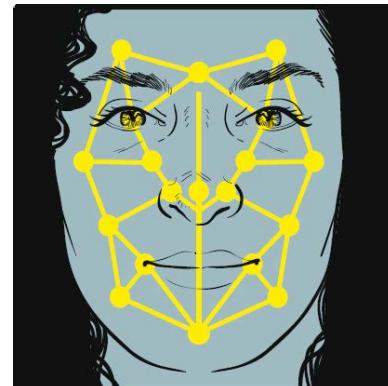
零售業



預測市場對於特定產品類型的需求
自動化與供應商的價格協商



自動化的倉儲管理
最佳化的商品管理及動線、擺設設計



最佳化訂價
個人化行銷



個人化購物提醒
即時的(虛擬)客服

 Laura Ellis

Visit No. - 90
Last Spent - \$450

 Mark King

Visit No. - 2
Last Spent - \$230

Sausages

Fresh Meat

8

Fresh Fish

Fresh Poultry

 Jeff Evans

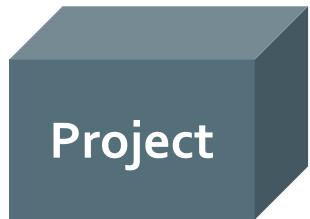
Visit No. - 75
Last Spent - \$304

UNKNOWN

 Tylor Hill

Visit No. - 7
Last Spent - \$30

製造業



Project

預測市場對於特定產品類型的需求

原料採購程序的自動化



Produce

生產設備參數的自動調校

生產設備的排程



Promote

預設新市場的開發方向



Provide

貨物送交的路線及時間排程

退貨 / 抱怨的資料分析，回饋到生產階段的改善

健康 / 醫療產業

Project

國民健康狀況及特定疾病 / 傳染病的預測
因預施而實施的預防性措施，減少發病 / 就診率

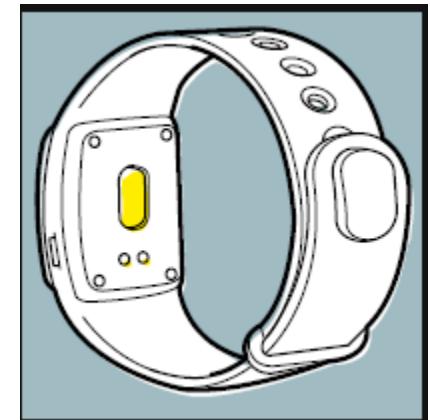
Produce

降低醫護人員的工作量
更全面地監測高風險族群
(醫院或居家) 狀況



Promote

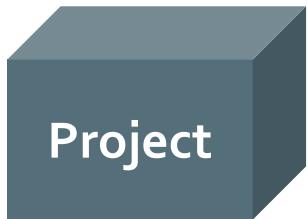
個人化行銷提升健康意識
生活中的健康飲食提醒



Provide

個人化醫學 / 治療
個人化即時身體狀況檢查

金融業



金融市場預測
更精準的放款 / 借款審核及信用卡盜刷偵測



更好的金融商品組合
更切中需求的個人金融商品 (e.g., 信用卡)



行銷策略設計
個人化行銷



AI 理財 / 客服專員
精準的 churn prediction

AI 導入進程





AI IN MANUFACTURING

2016 Global manufacturing competitiveness index rankings

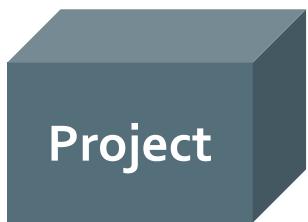
Rank	Country	Index score (100=High) (10 = Low)
1	China	100.0
2	United States	99.5
3	Germany	93.9
4	Japan	80.4
5	South Korea	76.7
6	United Kingdom	75.8
7	Taiwan	72.9
8	Mexico	69.5
9	Canada	68.7
10	Singapore	68.4



1/3 of the GDP

- Manufacturing GDP of **\$178B**, almost **1/3** of total GDP
- **30%** of the employment are in the manufacturing sector
- Cheap labor cost of **\$9.42/hr** with average labor productivity of almost **\$60k** in GDP/person
- **17%** corporate tax rate

The Four-P Dimensions in Manufacturing



- Improve product design
- Automate supplier assessment and price negotiation
- Anticipate parts requirements



- Improve manufacturing processes
- Automate assembly lines
- limit product rework



- Optimize pricing
- Predict sales of maintenance services
- Refine sales-leads prioritization



- Optimize flight/fleet planning and route
- Enhance maintenance engineering
- Enhance pilot training

Data is the new oil.
It's only useful when
it's refined!

Jess Greenwood, Contagious



孔祥重 院士

H.T. Kung



現任

- 中央研究院 院士
- 美國哈佛大學電腦與電機系 蓋茲講座教授

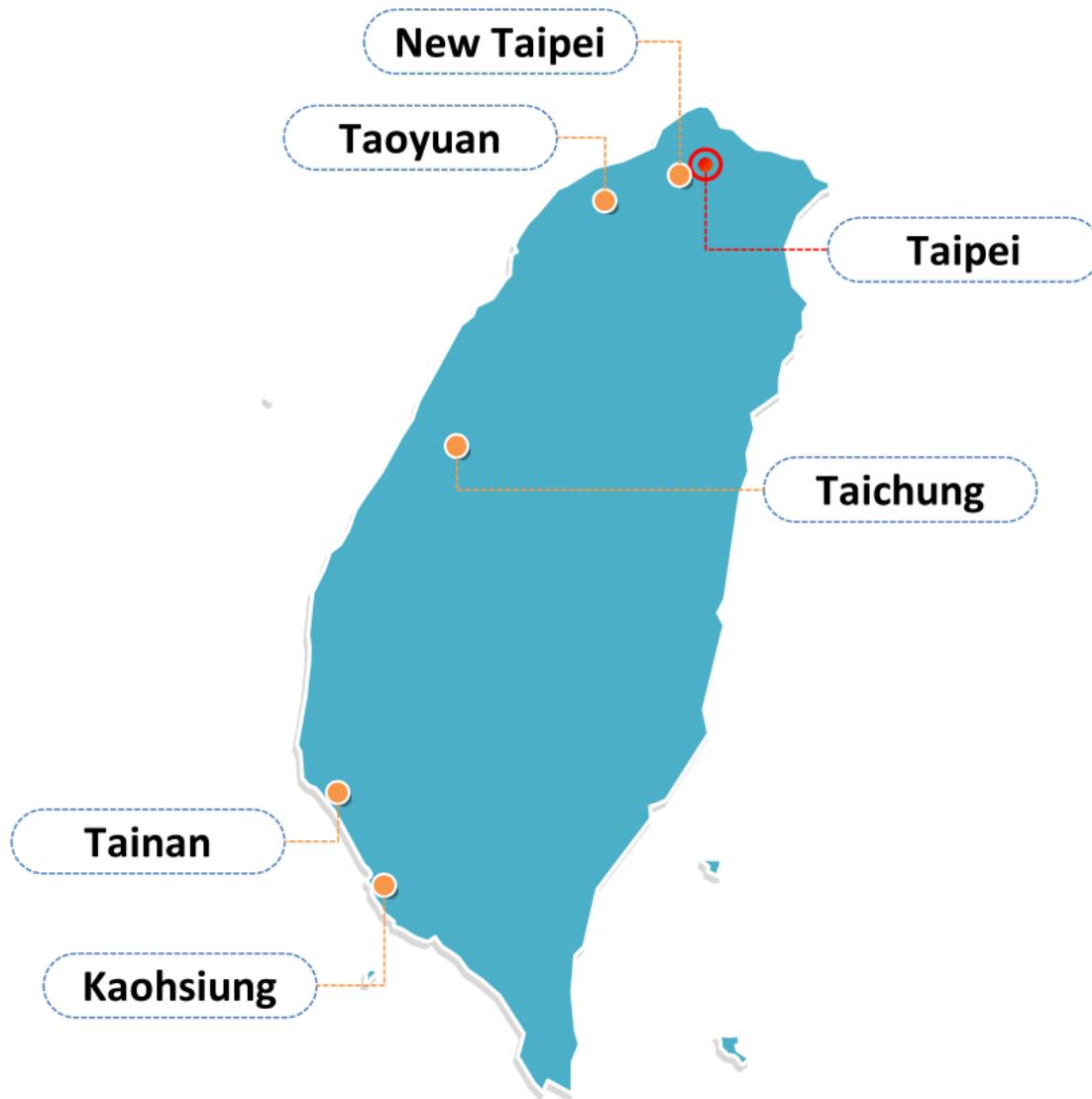
經歷

- 美國卡內基美隆大學電腦教授
- 美國哈佛大學資訊科技與管理博士學程共同主席
- 行政院 SRB 會議海外專家與科技顧問
- 行政院科技顧問
- 國家級計畫重要推手
 - 數位台灣計畫 (e-Taiwan)
 - 行動台灣計畫 (M-Taiwan)
 - 電信國家型計畫
 - WiMAX 發展藍圖
 - 網路通訊國家型計畫



To empower Taiwan (manufacturing)
industries with Artificial Intelligence

March – November in 2017



台塑石化
長春石化
奇美實業
英業達
欣興電子
敬鵬工業
可成科技
致茂電子
永進機械
研華科技
農科院
紡織所
聯發科技
台積電
宏遠紡織
台元紡織
佳和紡織
強盛染整
臺灣塑膠
龍鼎蘭花
經緯航太科技

Unmet “Soft” Needs for Nurturing Next-Generation Industries in the AI Era

- Human resource development
 - Machine learning experts with hands-on experiences
- Problem/opportunity identification
 - Problem identification is the biggest challenge for newcomers
- Business transformation
 - Problem identification and solving strategies
 - Spin-offs/R&D initiatives
- Shared technology infrastructure
 - Knowledge base, datasets and baseline practices

Project 0 Weekly Meetings at NCTU and Also Online with Academia Sinica

June 6, 2017



Why it's called Project θ?

Example:

$$\rightarrow \theta = \begin{bmatrix} \theta_1 \\ \theta_2 \end{bmatrix} \quad \min_{\theta} J(\theta)$$

$\theta_1 = 5, \theta_2 = 5$.

$$\rightarrow J(\theta) = (\theta_1 - 5)^2 + (\theta_2 - 5)^2$$

$$\rightarrow \frac{\partial}{\partial \theta_1} J(\theta) = 2(\theta_1 - 5)$$

$$\rightarrow \frac{\partial}{\partial \theta_2} J(\theta) = 2(\theta_2 - 5)$$

```
→ options = optimset('GradObj', 'on', 'MaxIter', '100');
→ initialTheta = zeros(2,1);
[ optTheta, functionVal, exitFlag ] ...
= fminunc(@costFunction, initialTheta, options);
```

```
function [jVal, gradient]
    = costFunction(theta)
    jVal = (theta(1)-5)^2 + ...
           (theta(2)-5)^2;
    gradient = zeros(2,1);
    gradient(1) = 2*(theta(1)-5);
    gradient(2) = 2*(theta(2)-5);
```

Industry-wide Problems

- Automated Optical Inspection (AOI) systems
- Adaptive process control
- Predictive maintenance
- Component selection optimization
- ...

Industry-wide Problem #1: Human Operators for Optical Inspection

- A sad story that AI-assisted AOI can help avoid
 - 14 suicide events in 2010 at Foxconn China factories
 - Only 2 of the suicides survived



<https://theinitium.com/article/20170802-mainland-Foxconn-factorygirl/>

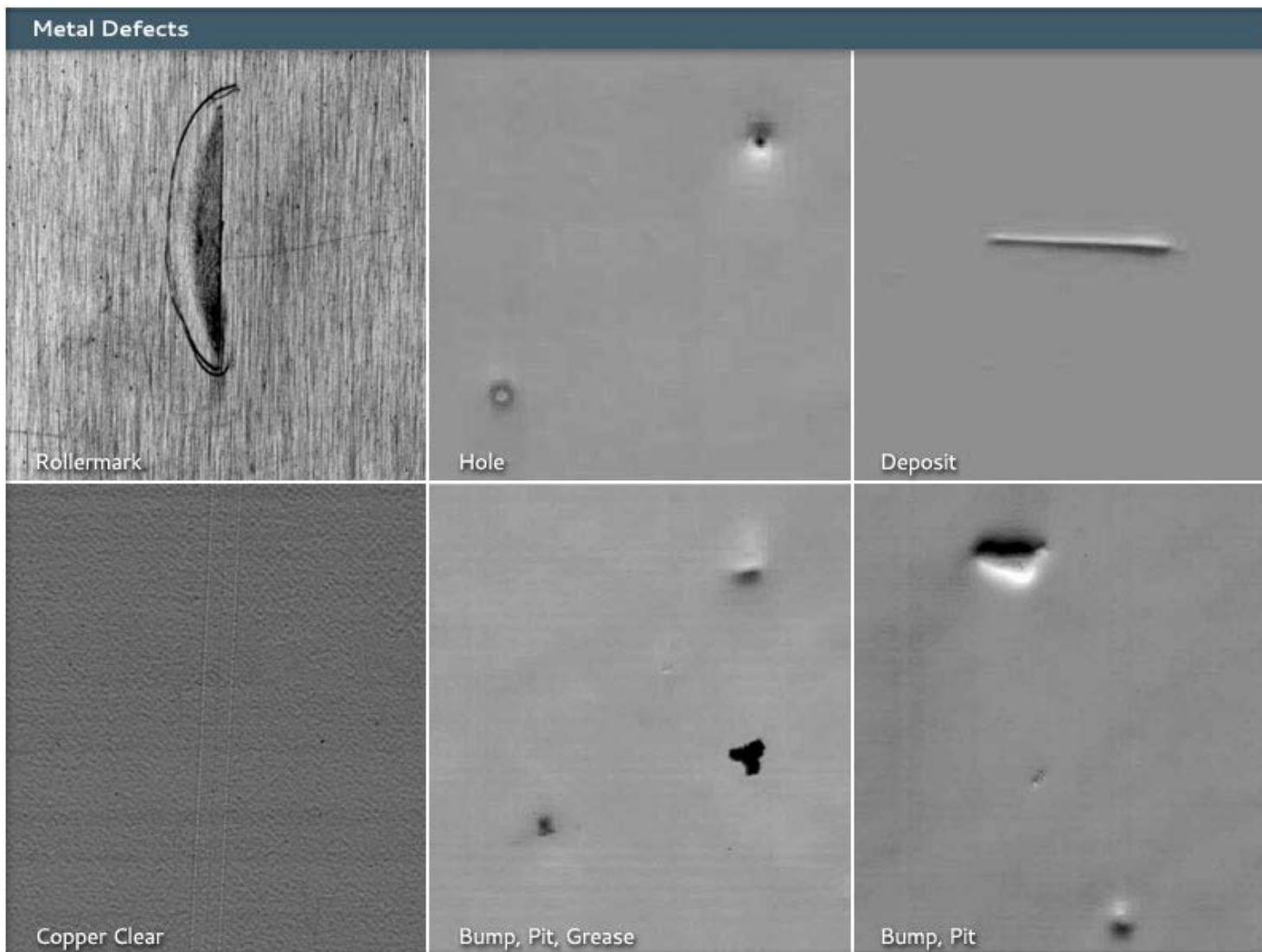
Human Operators for Optical Inspection

- The factories recruit only workers under 29 years old
- Their work involve checking scratches on consumer products (likely Apple iPhone) for 2,880 times a day
 - This means 4 times per minute assuming 12 working hours per day

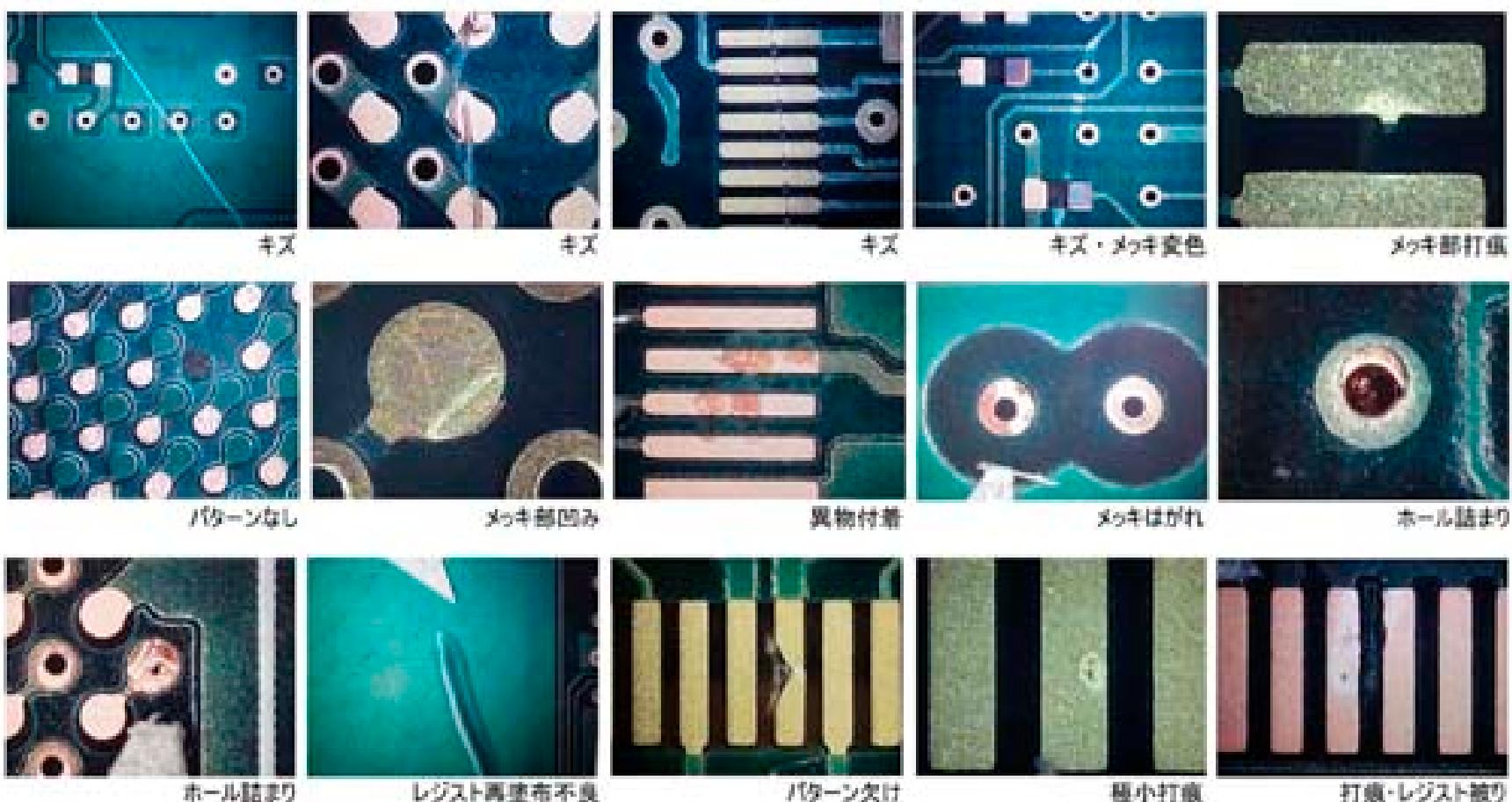


<https://theinitium.com/article/20170802-mainland-Foxconn-factorygirl/>

Typical metal defects

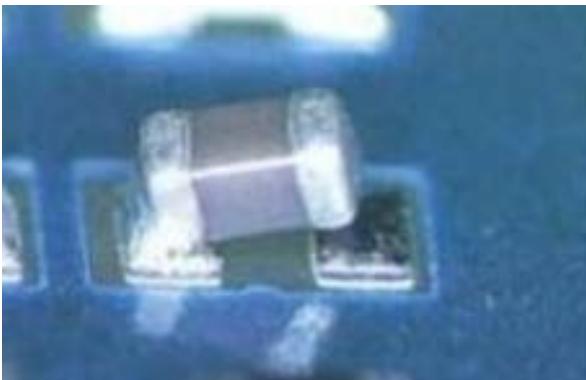
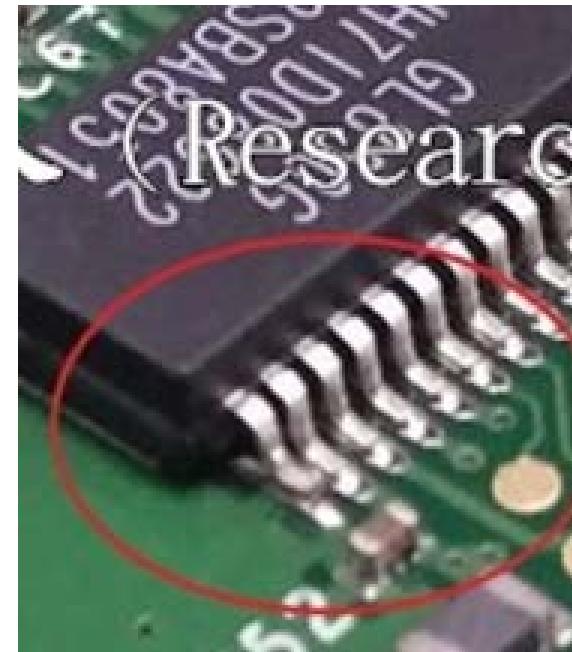


Typical PCB defects



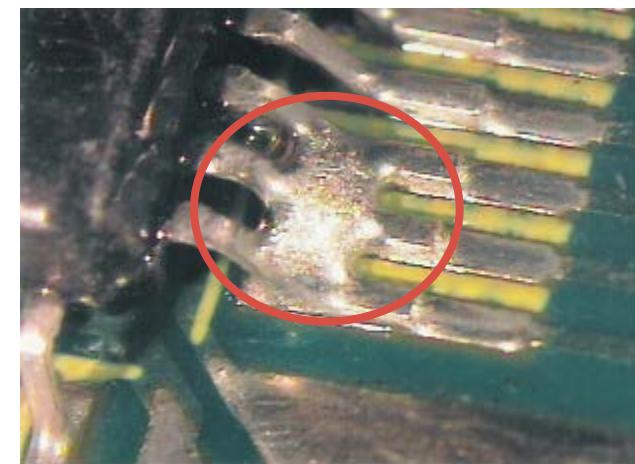
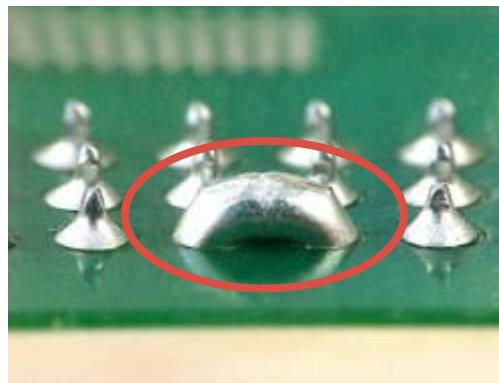
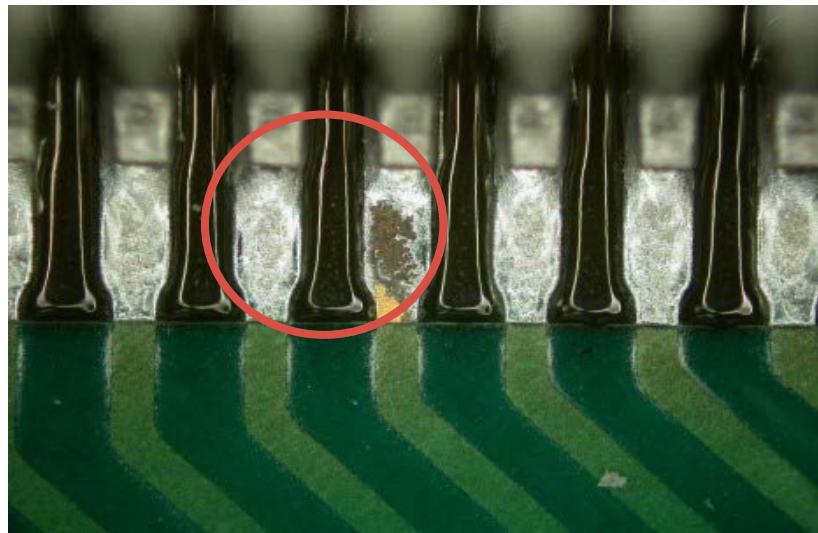
Typical defects after SMT (Surface-Mount Technology) process

- 短路
- 空焊
- 極反
- 缺件
- 浮高
- 跪腳
- 撞件
- 錫球
- 墓碑
- ...

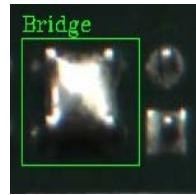
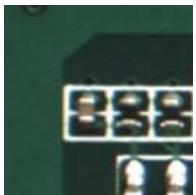
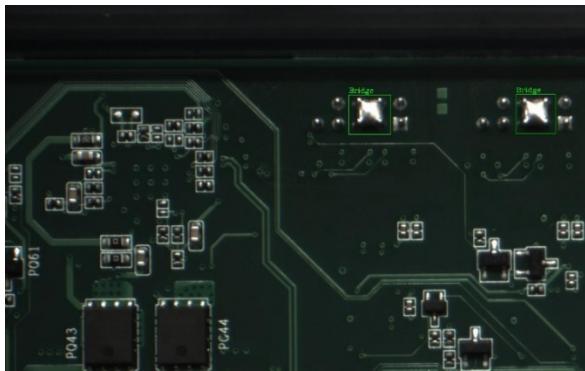


<https://www.researchmfg.com/2011/02/soldering-defect-symptom/>

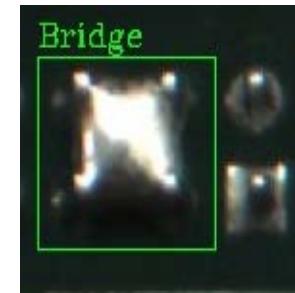
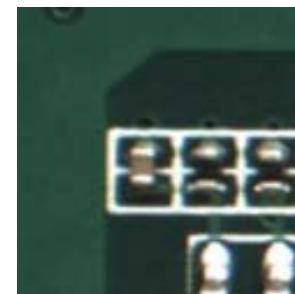
More SMT/DIP Defect Examples



Typical Deep-Learning based AOI Systems

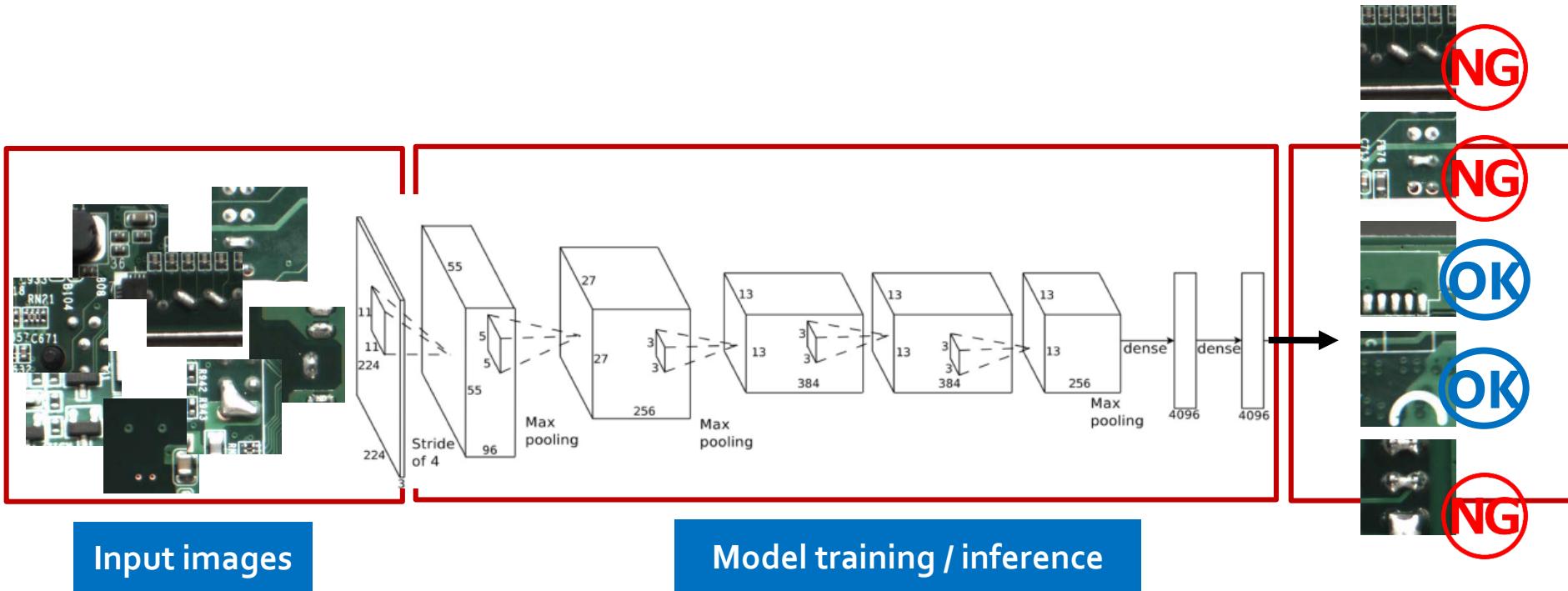


AI



Deep Neural Networks

- Deep Convolution Neural Networks
- Transfer learning
 - Pre-trained using 14-million image dataset
- Resnet with > 8-million parameters



實際案例 – 視覺檢測速度比較 (廠商 A)

傳統
人力
目檢

產線數量: 23 條

4 位目檢人員

AOI 設備每小時影像輸出量: 配合人力允許條件, 60 萬張/每日

(極限為每條產線 2 萬張/小時 = 1104 萬/日)

判定耗時: 30 萬張 / 人日 = 120 萬張/日

深度
學習
系統

硬體設備: 中高階桌上型電腦 + NVIDIA GPU: 10 ~ 15 萬

軟體: 開源軟體 + 高度調校之深度學習模型

判斷速度: 1 萬張影像 / 60 秒 = 166.67 張 / sec

每日輸出可達 1440 萬張影像

實際案例 – 視覺檢測效益評估 (廠商 B)

傳統
人力
目檢

品質：根據複判初步統計，目檢人員漏網率至少為 **12.9%**
速度：目檢人員 8~10 位，每天約可檢查共約 3,000,000 張

深度
學習
系統

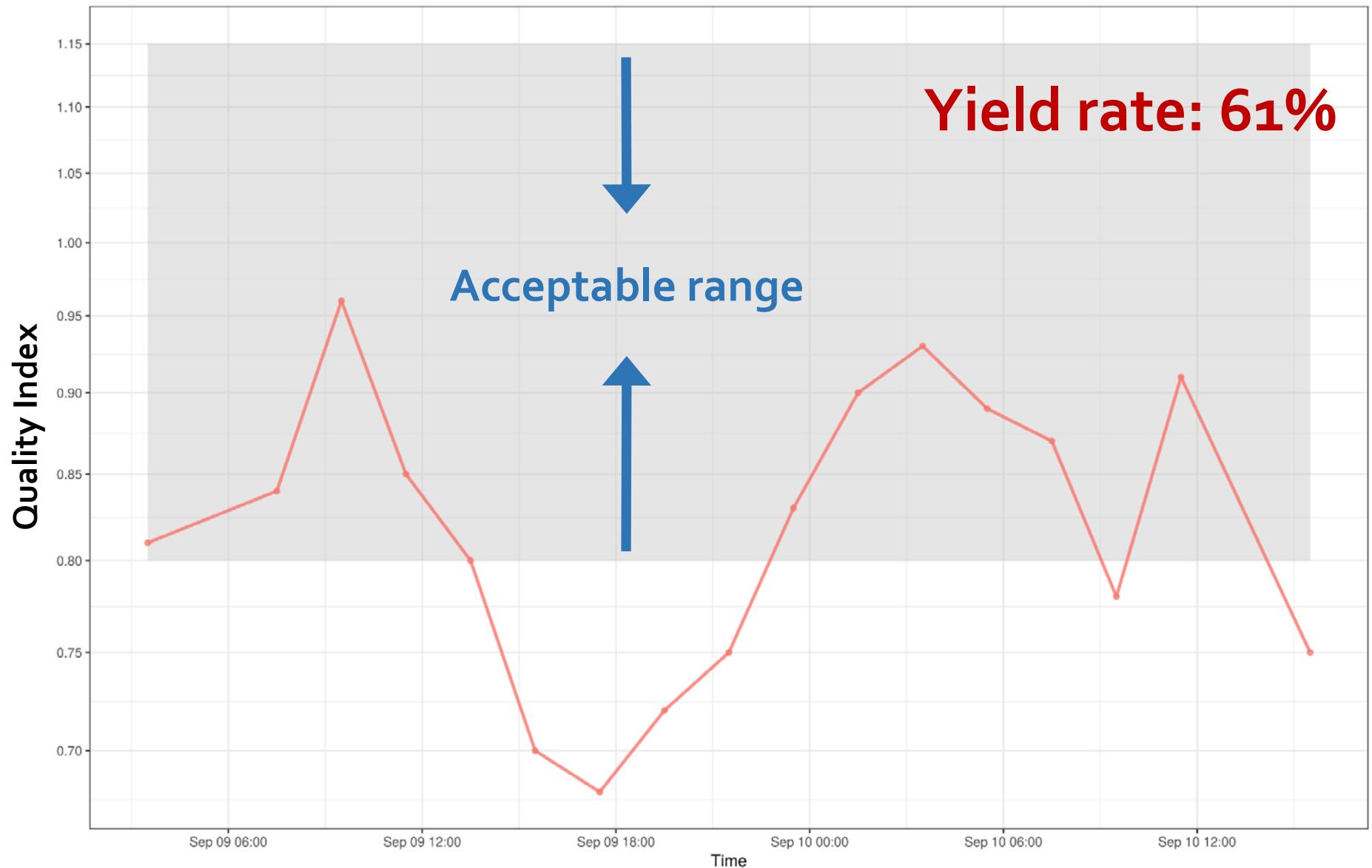
硬體設備：**中高階桌上型電腦 + NVIDIA GPU: 10 ~ 15 萬**
軟體：**開源軟體 + 高度調校之深度學習模型**
品質：**模型漏網率控制在 1% 之下**，目檢人員只需檢查原本總數之 **10%** 的圖片
速度：8,640,000 張 / 天 = 100 張 / 秒

Industry-wide Problem #2: Adaptive process control



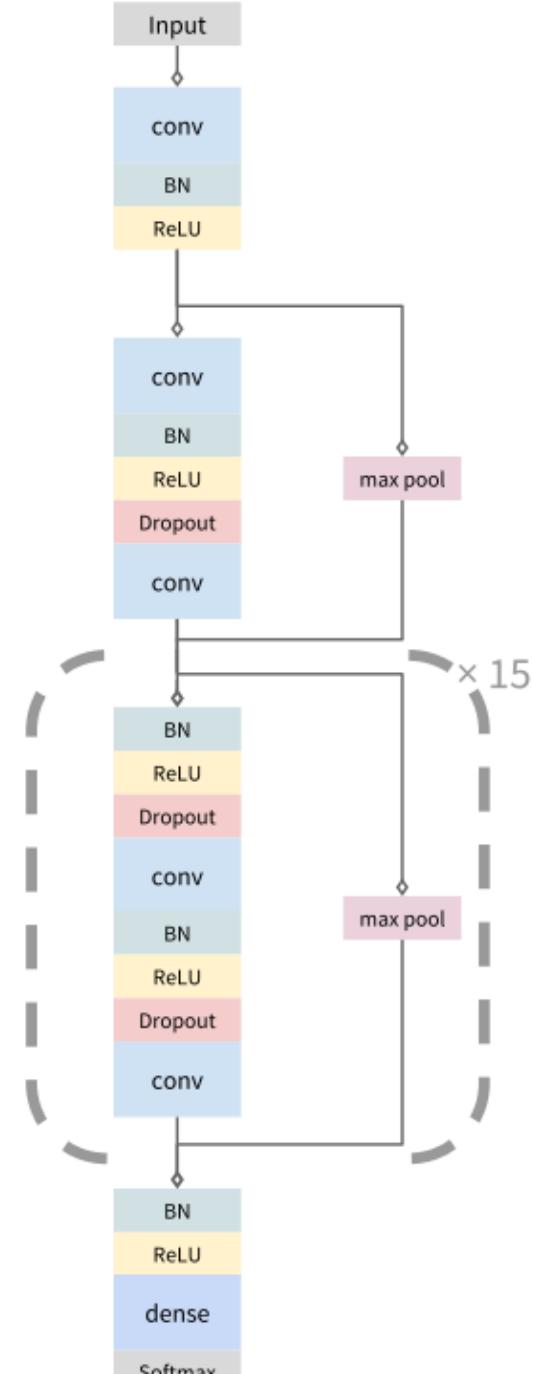
Case Study: A Chemical Process

- 12 parameters
 - Hydrogen (H)
 - Catalyst
 - Ethylene (C_2H_4), Ethane (C_2H_6), Butene (C_4H_8)
 - Pressure, temperature, fluid level, and so on
- Output
 - A quality index of a certain chemical product



Residual networks

- Very similar to Residual network in Image classification
 - main stream + residuals

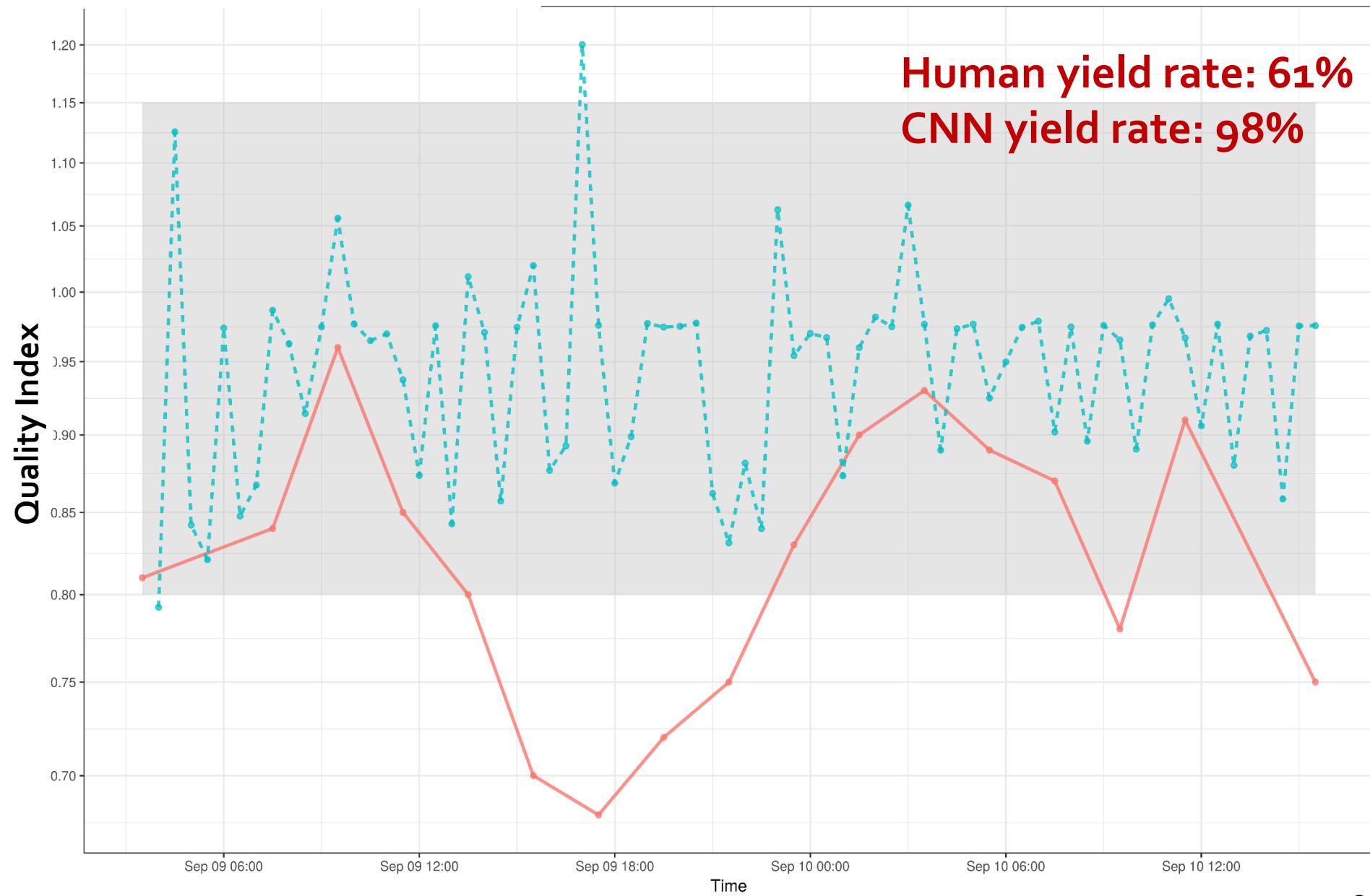


Residual network reference

Cardiologist-Level Arrhythmia Detection with Convolutional Neural Networks, Pranav et.al., 2017

Preliminary Control Results

Human yield rate: 61%
CNN yield rate: 98%

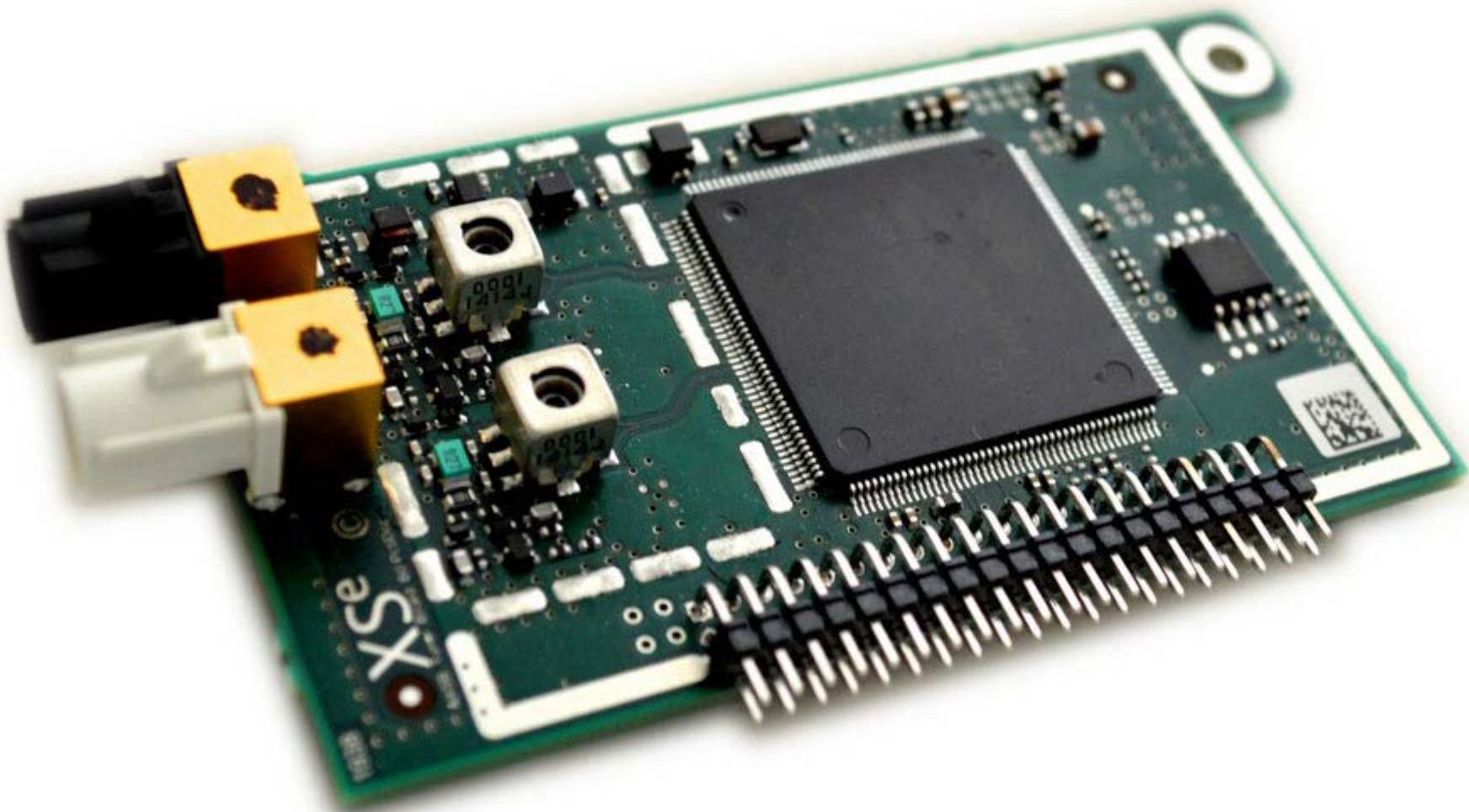


Industry-wide Problem #3: Predictive maintenance

- Especially important for equipment with high failure cost (such as motors in machine tools)
- Also important for expensive consumables (such as blades used in precision cutting machines)



Industry-wide Problem #4: Component selection optimization



LAB : L172RL016 重 0 開單日: 2017/02/17
客戶: POLO
成品布: FVG7743QDWKF

業交日: 2017/03/01
色數: 00003
底布:

色樣提供: Y
季節: SS18
客色: HIBISCUS

客色 客名 評

HIBISCUS HIBISCUS
備註:
請提供耐日光牢度測試(後補, 謝謝!)

PANTONE

HIBISCUS

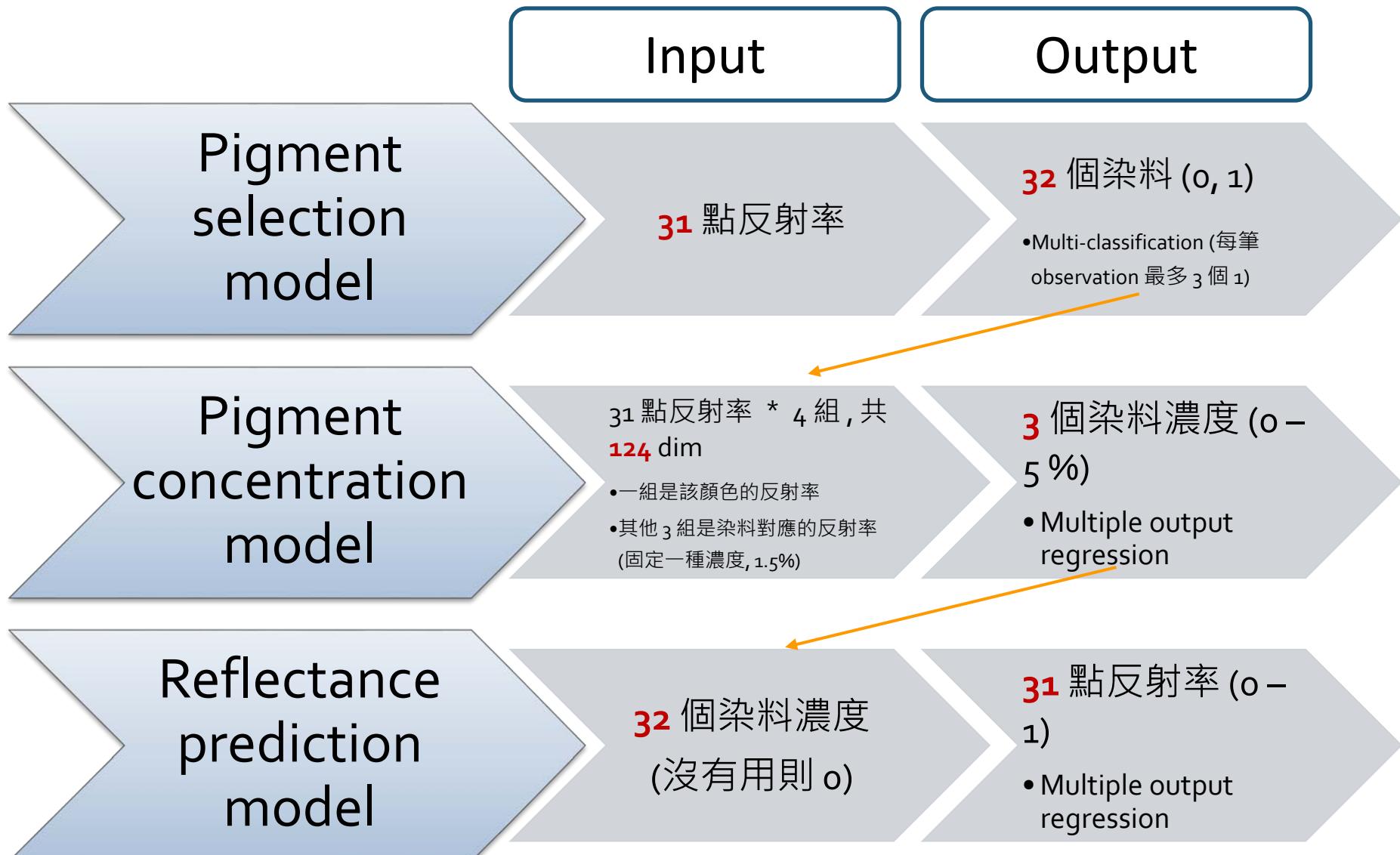


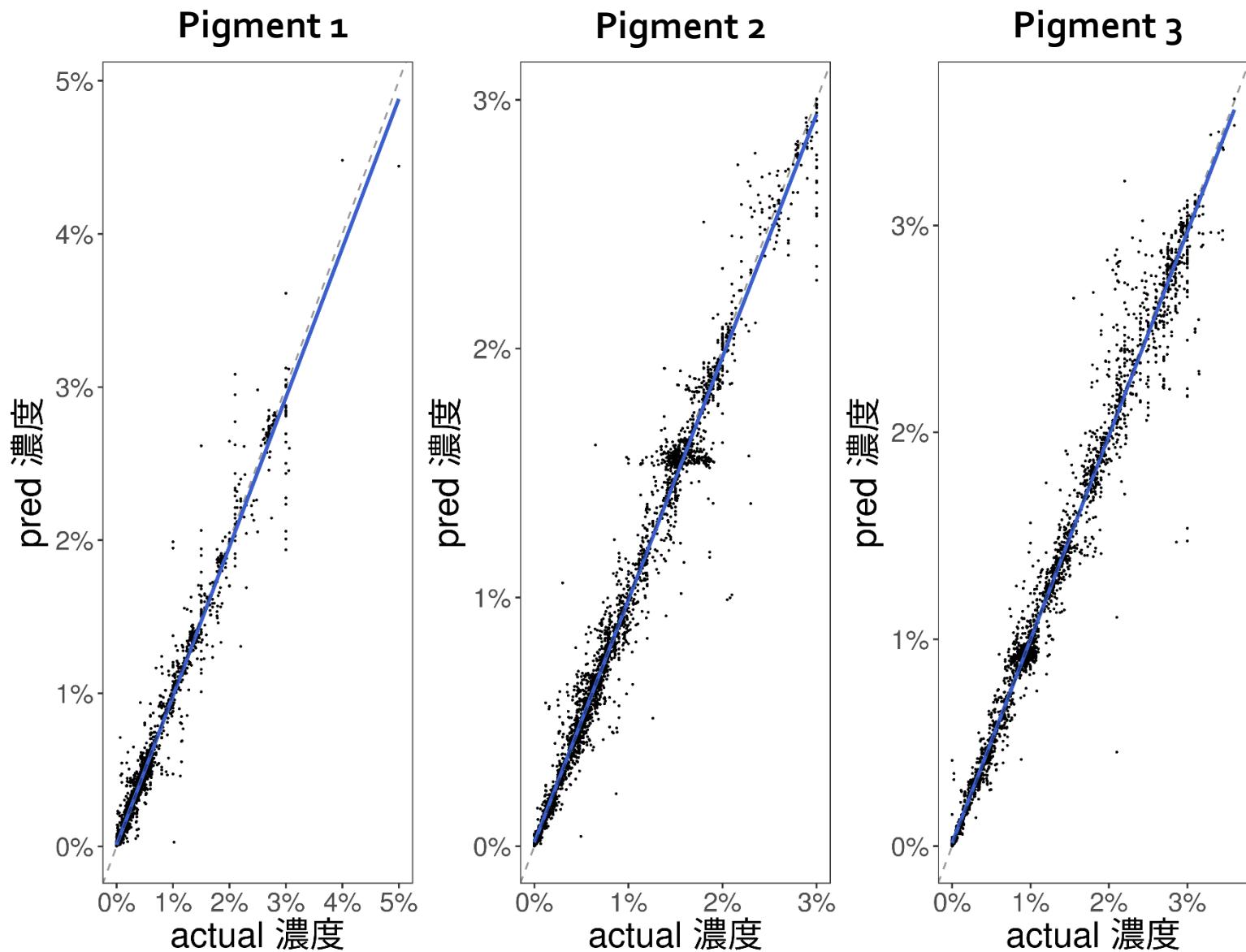
表單編號: PR129 A1 表單規格: A4
染色效果: 3 純色 主光源: 5 INCA
特殊牢度: 水洗: 4 標準: ISO 105-B02 :1
乾摩擦: 4 濕摩擦: 4
耐氯: PPM 每色打: 3 色 0 Oth色
特殊規格: 10.0 X 10.0 cm 2 份 業代: [REDACTED]

染印部: 副光源: 1 D65 課長:
日光: 20 HR 4 級 副光源:
日光: 40 HR 3 級 色泣:
汗牢度: 4 水牢度: 4
標準色樣 6.0 X 4.0 cm 2 份 UPF:
助代: [REDACTED] [REDACTED]



Model & workflow





**PROJECT Ø TEAM HAS SOLVED
10+ PROBLEMS
FROM 10+ COMPANIES
WITHIN 6 MONTHS...**

LOOKS IT WORKS OUT, BUT ...



台灣發展人工智慧 的挑戰

- 產學之間的鴻溝
- 人才缺乏
- 習慣外來技術的導入



台灣人工智慧學校



TAIWAN AI ACADEMY - A SOLUTION TO SCALE OUT PROJECT Θ



台灣人工智慧學校

<http://aiacademy.tw/>

- 三個月密集培訓 AI 技術種子
- 讓「找不到人才」不再成為障礙
- 建立「自己的問題自己解決」的文化



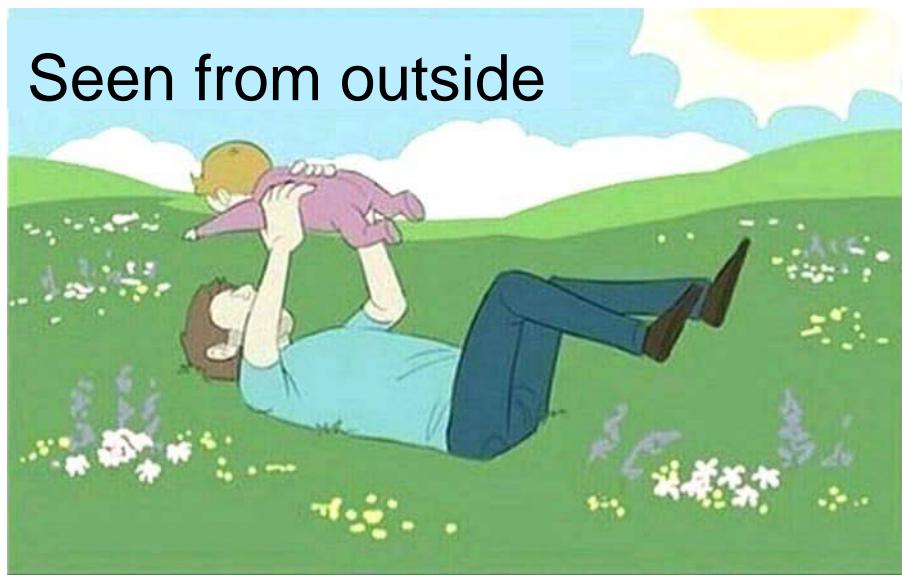
台灣人工智慧學校

<http://aiacademy.tw/>

- 學校後專業人才 + 人工智慧
- 與學界連結，第一線研究者任導師，訓練找題 / 解題的能力
- 與產業連結，實際問題做中學

Using deep learning

Seen from outside



Inside





企業夥伴計畫

- 以人工智能技術解決實務問題
- 與學員的直接互動
- 優秀結業生招募機會

Current class design

■ Elite Engineer Class (技術領袖培訓班)

- 12 weeks
- 9am to 6pm on Monday to Friday
- Lectures + hands-on sessions + term projects
- Mid-term and final exams

■ Manager Class (經理人周末研修班)

- 12 weeks
- 9am to 9pm each Saturday
- Lectures only

Elite Engineer Class

Applications due on Dec 4, 2017. Nearly 500 applicants registered while we can only accept 208 students.

Two-step filtering:

1. Document review
2. Entrance exam: calculus, linear algebra, probability, statistics, programming



投影片線上閱讀 / 下載

http://www.iis.sinica.edu.tw/~swc/talk/from_data_science_to_ai.html



煞氣a深度學習



煞氣a人工智能





台灣人工智慧學校



讓台灣在全球人工智慧技術的快速發展
洪流中不落人後，能佔有一席之地。

陳昇瑋

台灣人工智慧學校
中央研究院資訊科學研究所



台灣資料科學年會粉絲專頁