The Cutting Edge of Deep Learning
前瞻深度學習

NTHU

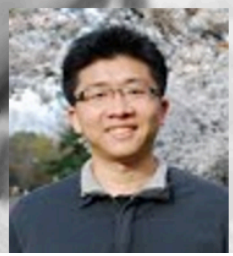
thecedl.github.io

How it begins...

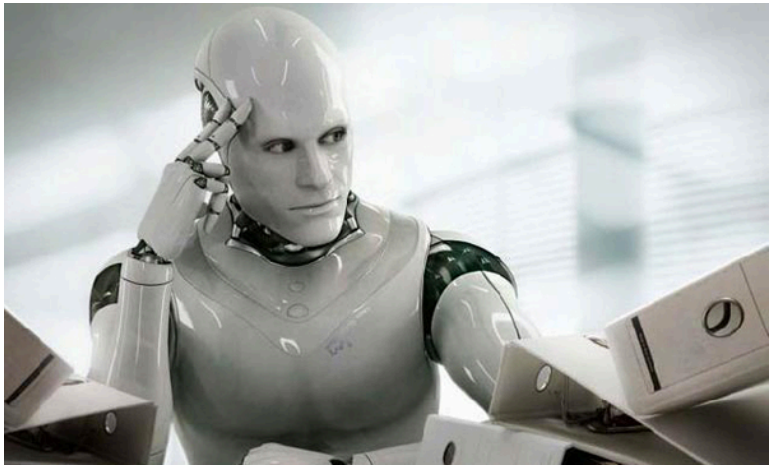
Che-Rung Lee, Associate Professor in Computer Science at National Tsing Hua University

Jerry Chou, Associate Professor in Computer Science at National Tsing Hua University

Hwann-Tzong Chen, Associate Professor in Computer Science at National Tsing Hua University



Min Sun, Assistant Professor in Electrical Engineering at National Tsing Hua University



MediaTek sponsors xxxx K NTD

Find the very best ...

Title of one deep learning paper you are confident to

Short-answer text

YouTube link to a video describing the paper (video must be less than 15 minutes; e.g. https://youtu.be/_8ZquaanUqE) *

Short-answer text

Link to your GitHub *

Short-answer text

Team captain's email (at most three members per

Short-answer text

Link to project proposal (no more than 5000 words; only one proposal for each team)

Short-answer text

Enrollment

- 34 students + 3 industrial friends

  http://goo.gl/E27iSy
- 8 solid teams + 12 individuals
  - less than 8 + 6 =14 teams (finalize no later than **9/19**)
  - Team advisors (confirm no later than **11/21**)
- GitHub organization
  - https://github.com/TheCEDL
- YouTube Arxiv Playlist

  http://goo.gl/UCKnoH

Syllabus

- Four parts (See link)
- Lecture ends on Nov. 17 (Thurs)
- Project-based show-and-tell (6 weeks)
- Final presentation or poster (Jan 2-6)
- Selected public presentation (Jan 9-13)
  - MTK High Executives

The Cutting Edge of Deep Learning

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The Cutting Edge of Deep Learning and AI

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The Cutting Edge of ~~Deep Learning~~ and AI (Representation Learning)

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What's the Next Big Thing?

http://research.microsoft.com/en-us/um/redmond/events/fs2015

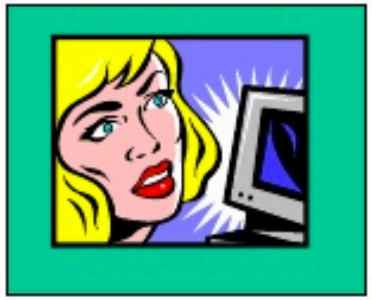
Goal

“big data being the source, machine learning being the technique, and AI being the outcome”

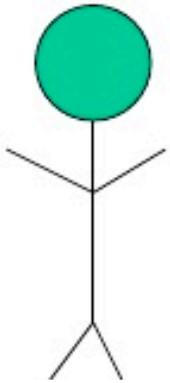
by Prof. Hsuan-Tien Lin at IEEE BigData 2016

Many kinds of **source (data)** and **outcomes (AI tasks)** can be trained end-to-end using **Deep Learning (DL)**

Classical AI Tests: Turing Test



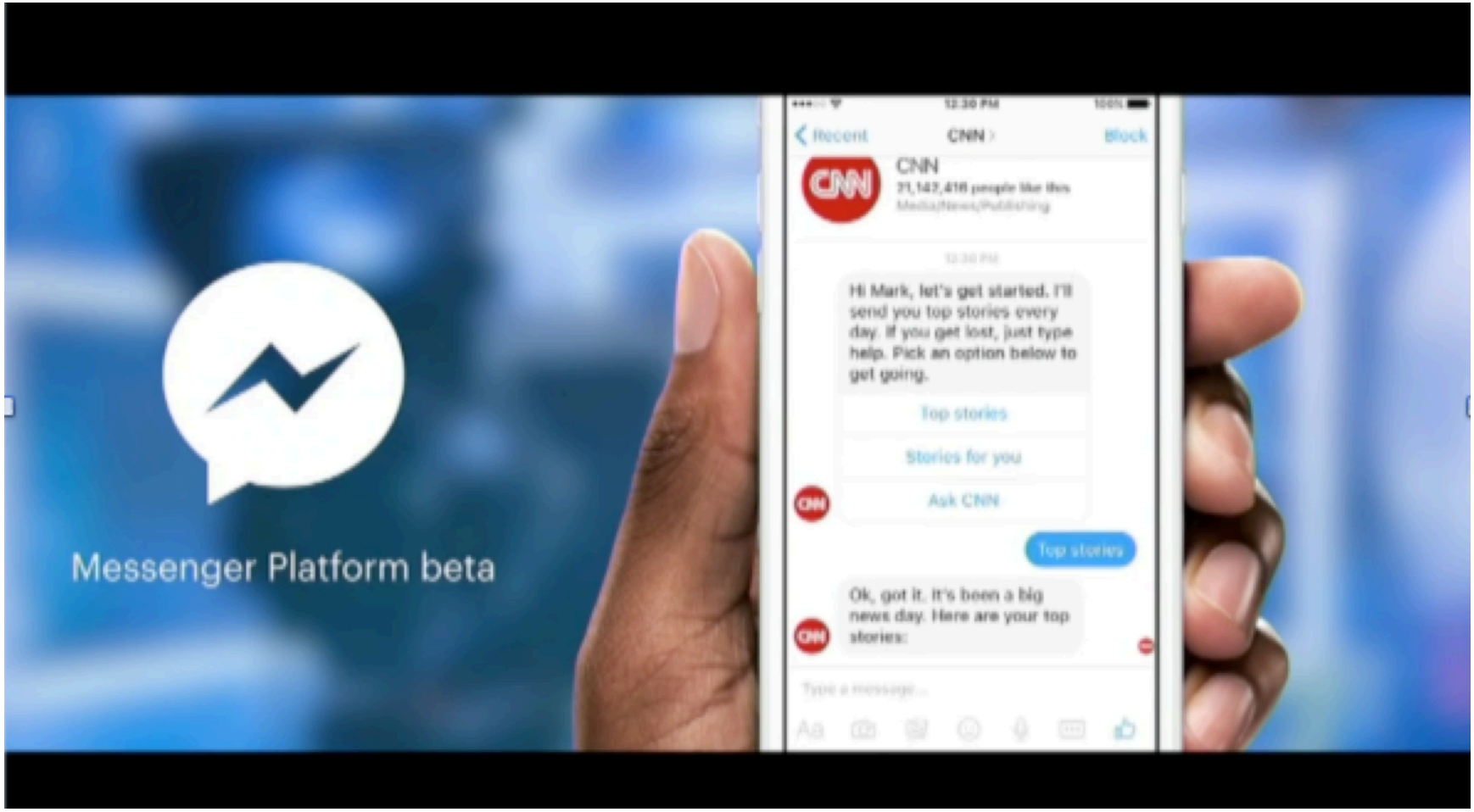
Judge



What color and in what style is your hair?

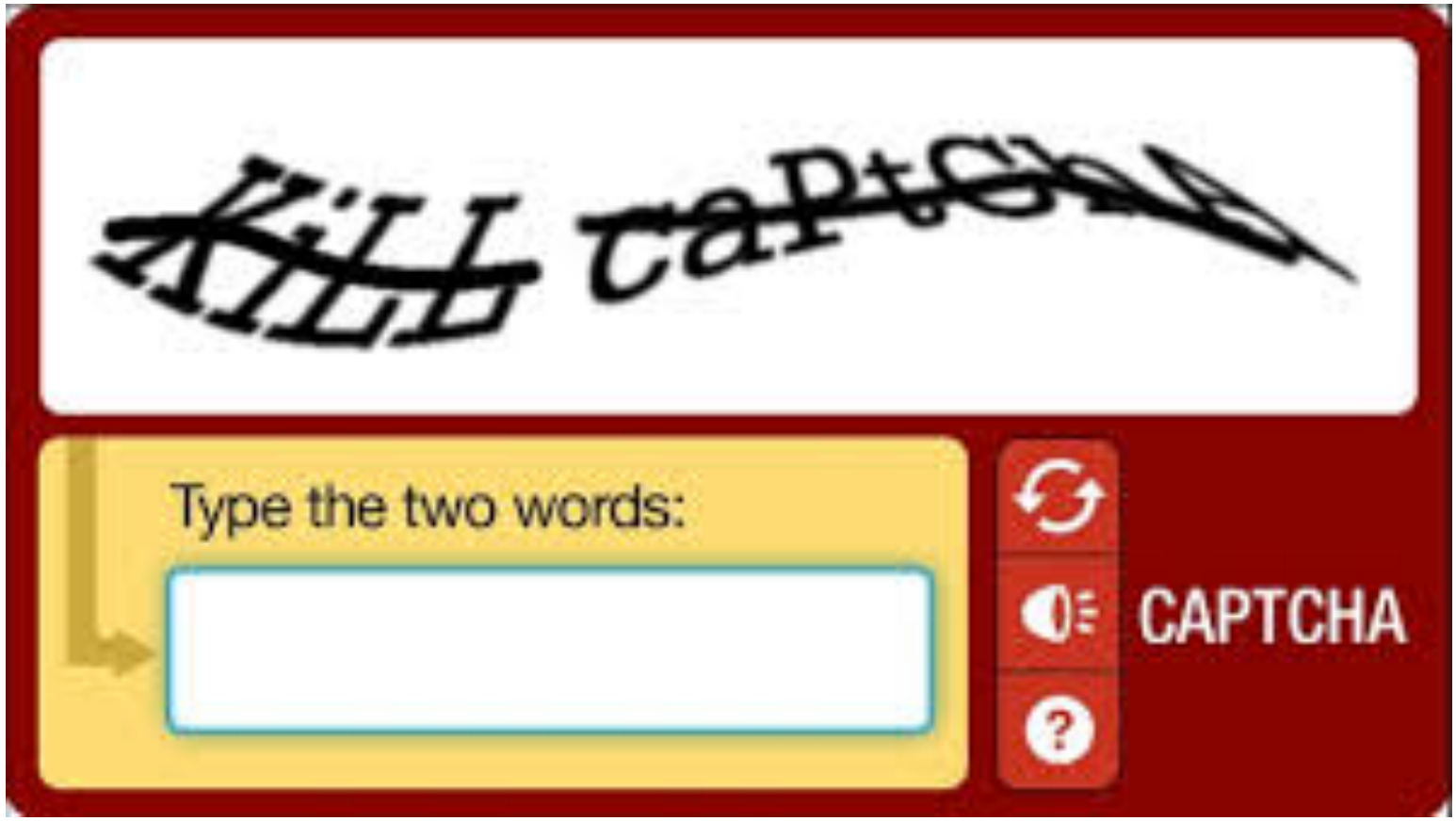
by Alan Turing in 1950

Chatbot@F8



https://developers.facebook.com/videos/f8-2016/keynote/

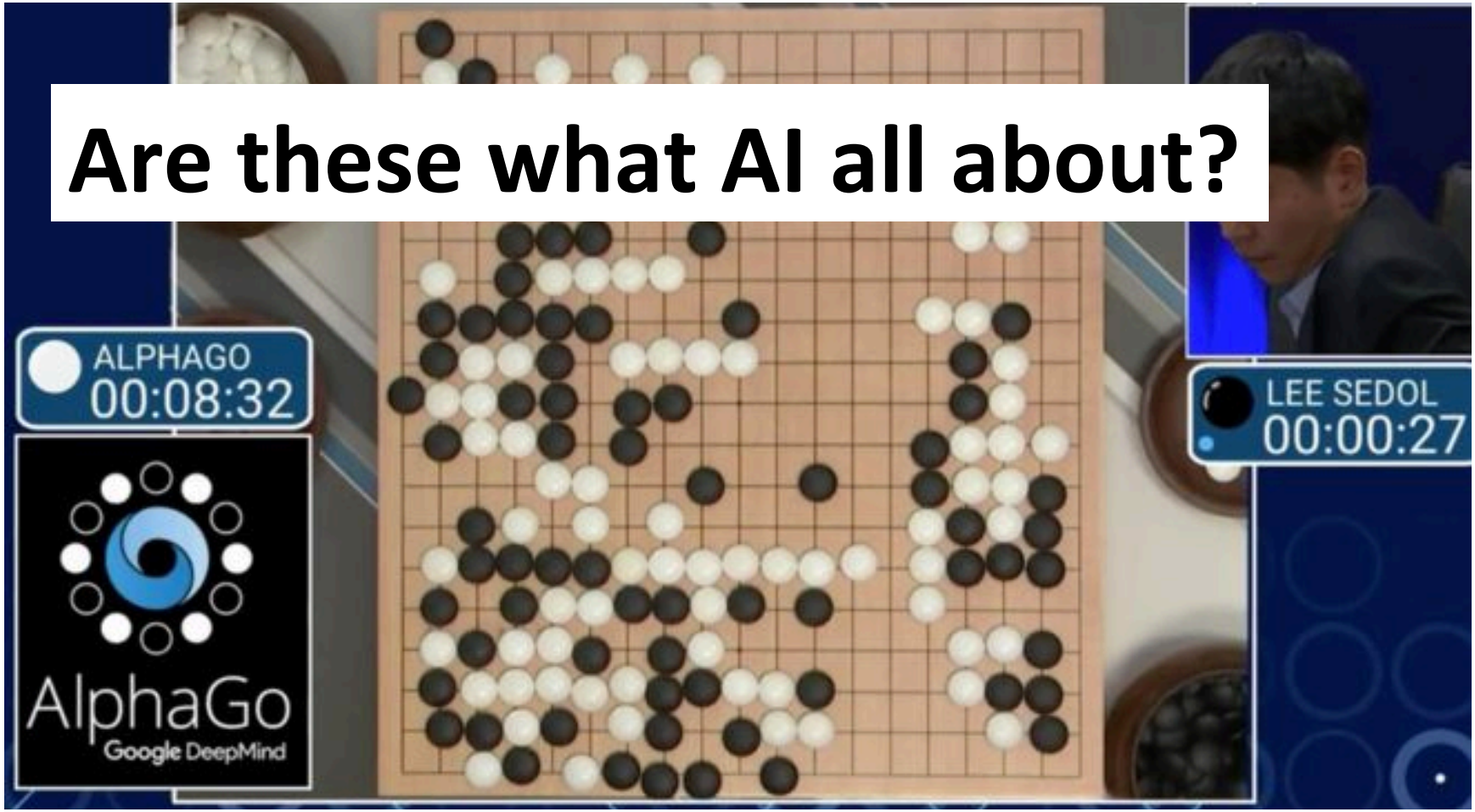
Classical AI Tests: CAPTCHA



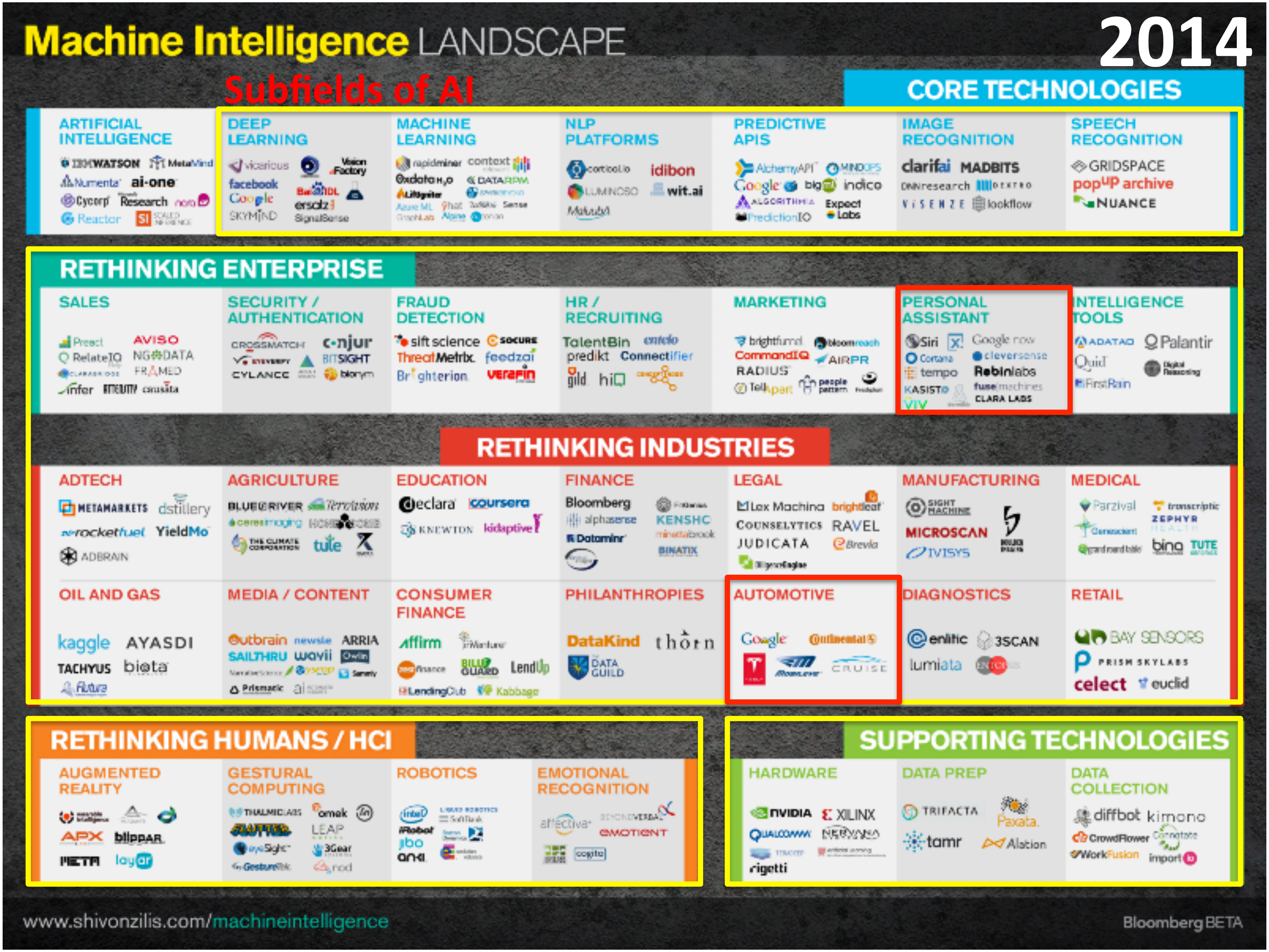
Breaking CAPTCHA

Nov. 2013 by vicarious.com

AlphaGo



2016 by Google DeepMind



Machine Intelligence LANDSCAPE
2014
Subfields of AI
CORE TECHNOLOGIES
ARTIFICIAL INTELLIGENCE
IBM WATSON
MetaMind
Numenta
ai-one
Cycorp
Research
Reactor
DEEP LEARNING
vicarious
Vision Factory
facebook
Google
SKYMIND
ersatz
SignalSense
MACHINE LEARNING
rapidminer
context
DATARPM
Alpine
NLP PLATFORMS
cortical.io
idibon
LUMINOSO
wit.ai
PREDICTIVE APIS
AlchemyAPI
MINDOPS
Google
bigml
indico
ALGORITHMIA
Expect Labs
PredictionIO
IMAGE RECOGNITION
clarifai
MADBITS
DNNresearch
VISENZE
lookflow
SPEECH RECOGNITION
GRIDSPACE
popUP archive
NUANCE
RETHINKING ENTERPRISE
SALES
Preact
AVISO
RelateIQ
NGDATA
FRAMED
infer
cauaita
SECURITY / AUTHENTICATION
CROSSMATCH
cynjur
BITSIGHT
CYLANCE
FRAUD DETECTION
sift science
SOCURE
ThreatMetrix
feedzai
Brighterion
verafin
HR / RECRUITING
TalentBin
entelo
predikt
Connectifier
gild
hiQ
MARKETING
brightfunnel
bloomreach
CommandIQ
AIRPR
RADIUS
people pattern
PERSONAL ASSISTANT
Siri
Google now
Cortana
cleversense
tempo
Rebinlabs
KASISTO
fuse machines
CLARA LABS
VIV
INTELLIGENCE TOOLS
ADATAO
Palantir
Quid
Digital Reasoning
FirstRain
RETHINKING INDUSTRIES
ADTECH
METAMARKETS
dstillery
rocketfuel
YieldMo
ADBRAIN
AGRICULTURE
BLUE RIVER
Terrafusion
ceresimaging
THE CLIMATE CORPORATION
tule
EDUCATION
declara
coursera
KNEWTON
kidaptive
FINANCE
Bloomberg
alphasense
KENSHO
Dataminr
BINATIX
LEGAL
Lex Machina
brightleaf
COUNSELYTICS
RAVEL
JUDICATA
Brevia
MANUFACTURING
SIGHT MACHINE
MICROSCAN
IVISYS
MEDICAL
Parzival
transcriptic
ZEPHYR HEALTH
bina
TUTE
OIL AND GAS
kaggle
AYASDI
TACHYUS
biota
Flutura
MEDIA / CONTENT
Outbrain
newsle
ARRIA
SAILTHRU
wavii
Owlin
Prismatic
CONSUMER FINANCE
Affirm
ZestFinance
BILLGUARD
LendUp
LendingClub
Kabbage
PHILANTHROPIES
DataKind
thorn
DATA GUILD
AUTOMOTIVE
Google
Continental
CRUISE
DIAGNOSTICS
enlitic
3SCAN
lumiata
RETAIL
BAY SENSORS
PRISM SKYLABS
celect
euclid
RETHINKING HUMANS / HCI
AUGMENTED REALITY
APX
blippar
META
layar
GESTURAL COMPUTING
THALMIC LABS
omek
LEAP
3Gear
nod
ROBOTICS
intel
iRobot
jibo
anki
EMOTIONAL RECOGNITION
affectiva
EMOTIENT
SUPPORTING TECHNOLOGIES
HARDWARE
NVIDIA
XILINX
QUALCOMM
rigetti
DATA PREP
TRIFACTA
Paxata
tamr
Alation
DATA COLLECTION
diffbot
kimono
CrowdFlower
WorkFusion
import.io
www.shivonzilis.com/machineintelligence
Bloomberg BETA

MACHINE INTELLIGENCE 2.0

2015

AGENTS

PROFESSIONAL
Howdy! x.ai clara
KASISTO DigitalGenius
OVERLAP.CC meekan
fuse|machines PRIMER

PERSONAL
facebook XIAOICE
large
assistant.ai nestor
@wesome Magic

OS INTERFACES
Siri Cortana VIV
maluuba api.ai
COGNEA Google Now

AUTONOMOUS SYSTEMS

AIR
3DR DJI PROJECT LOON Google
VERTICAL DroneDeploy
AIRDOG SKYCATCH
SKYDIO Airware LILY

GROUND
Google UBER
TESLA CRUISE
MOBILEYE
COMMA AdasWorks

SEA
LIQUID ROBOTICS
bluefin data
OPENROV
BluHaptics

INDUSTRIAL
KIVA Systems fetch
HARVEST AUTOMATION CLEARPATH
AVIDBOTS ENERGID
rethink robotics GREYORANGE
OSARO

ENTERPRISE

SECURITY / FRAUD
Sentinel graphistry
BITSIGHT feedzai AREA 1
drawbridge siftscience
CYLANCE Brighterion

HR / RECRUITING
textio hiQ gild
SpringRole entelo
unitive GIGSTER

SALES
6sense infer people pattern
Preact Prism AVISO
Vidora sentient
salespredict Gainsight

MARKETING
LiftIgniter
RADIUS brightfunnel
retention SCIENCE AIRPR

CUSTOMER SUPPORT
CLARABRIDGE
QUANTIFIND Wise.io
ACTIONIQ FRAMED
DigitalGenius

INTERNAL INTEL
Alation ADATAO
Palantir sapho lucid
Rainbird SKIPFLAG algolo
Digital Reasoning Narrative Science

MARKET INTEL
Quid mattermark
DataFox bottlenose
PREMISE enigma
CB INSIGHTS

PLATFORMS

Artifical General Intelligence (AGI)

RESEARCH / AGI
OpenAI vicarious
Google DeepMind Numenta
Cycorp nnaisense
SCALED INFERENCE CURIOUS
GEOMETRIC INTELLIGENCE

FULL STACK
context relevant
CognitiveScale
NVIDIA TERADEEP
QUALCOMM nervana SYSTEMS

MACHINE LEARNING
Dato rapidminer
cortical.io AYASDI
amazon web services Azure Machine Learning
narrologics PredictionIO
SKYTREE bigml blueyonder

INDUSTRIAL IOT
ThingWorx UPTAKE
IMUBIT Preferred Networks
Alluvium xively
PLANET OS

AUDIO
Gridspace TalkIQ
nexidia vocaliq
NUANCE Expect Labs
popUP archive

VISION
ORBITAL INSIGHT
Descartes Labs DEXTRO
cortica clarifai PLANET LABS
MetaMind

DATA ENRICHMENT
diffbot Paxata
TRIFACTA IDIBON
WorkFusion loop.ai Labs
CrowdFlower

INDUSTRIES

ADTECH
ADTHEORENT dstillery
BEYONDVERBAL
METAMARKETS TAPAD
rocketfuel affectiva

AGRICULTURE
BLUE RIVER tule
TerrAvion mavrx
THE CLIMATE CORPORATION CERES TECHNOLOGIES
HONEYCOMB

FOR GOOD
Conservation Metrics
DataKind DATA POP
thorn
BAYES IMPACT

RETAIL FINANCE
inVenture affirm
earnest MIRADOR
Lendo zestfinance LendUp

LEGAL
Everlaw RAVEL
LEGAL ROBOT Seal
BEAGLE ROSS
Lex Machina

MATERIALS & MFG
zymergen AUGMATE
GINKGO BIOWORKS
ITRINE TECHNOLOGIES SIGHT MACHINE CALCULARIO
Eigen Innovations

HEALTHCARE
deep genomics 3SCAN
enlitic Calico BUTTERFLY Network, Inc
Atomwise Recombine color
METABIOTA GRAND ROUNDS
Google Life Sciences IBM Watson Health

INDUSTRIES (CONT'D)

EDUCATION
KNEWTON
coursera turnitin
gradescope UDACITY
KHANACADEMY

TRANSPORT & LOGISTICS
NAUTO taleris
PRETECKT
clearmetal

INVESTMENT FINANCE
Bloomberg
Quantopian
Dataminr KENSHO
iSENTIUM NEURENSIC
alphasense

TECH USER TOOLS

DATA SCIENCE
DOMINO kaggle
Sentenai sense
yseop Outlier
ŷhat DataRobot

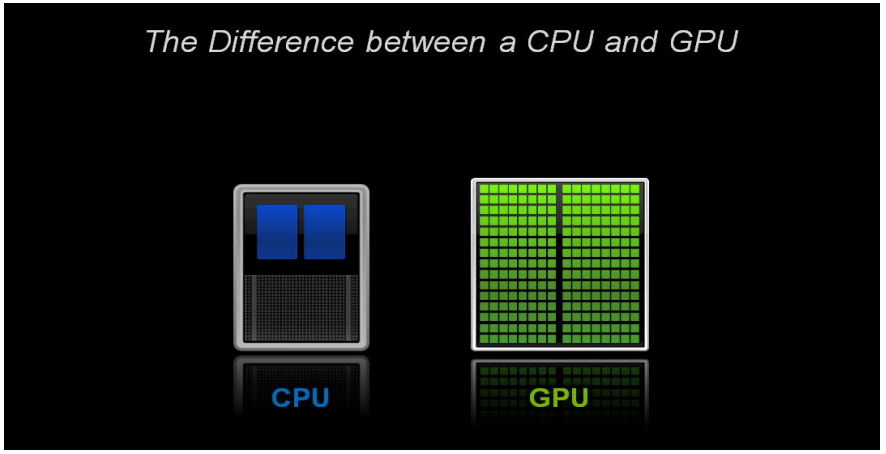
MACHINE LEARNING
Cortana Analytics AlchemyAPI glowfi.sh
IBM Watson Platform Anodot MonkeyLearn
(h[s]) HyperScience fuzzy.io SIGOPT
0xdata H2O SPARKBEYOND indico

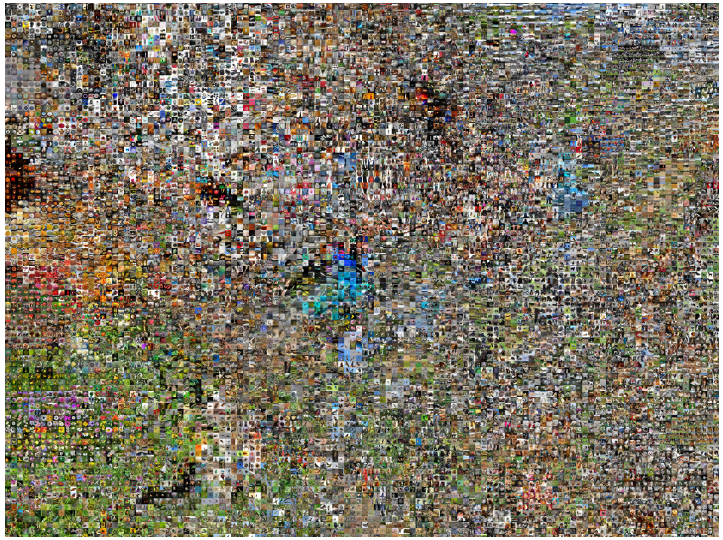
OPEN SOURCE
SKYMIND TensorFlow
seldon Caffe theano
Spark MLlib Microsoft DMTK spaCy
DL4J SciKit CGT

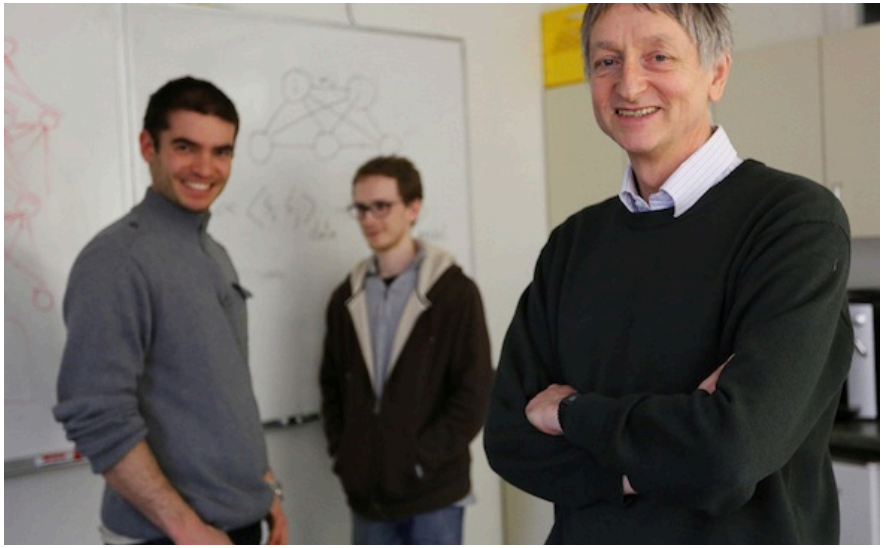
SHIVONZILIS.COM/MACHINEINTELLIGENCE

Deep Learning (DL)

- Data
- GPU Computing
- Talents







Data: IMAGENET

- 開始於 2007 @ Princeton
- 初登場於 2009 @ CVPR
- 照片停止搜集於 2010
  - ➢總共類別：21841
  - ➢總共圖片：1千4百萬
- ILSVR Challenge 從2010到現今

Jia Deng

Fei-Fei Li

Info from http://www.image-net.org/

1K Image Classification

Label = f(Image)

Deep Learning
深度學習

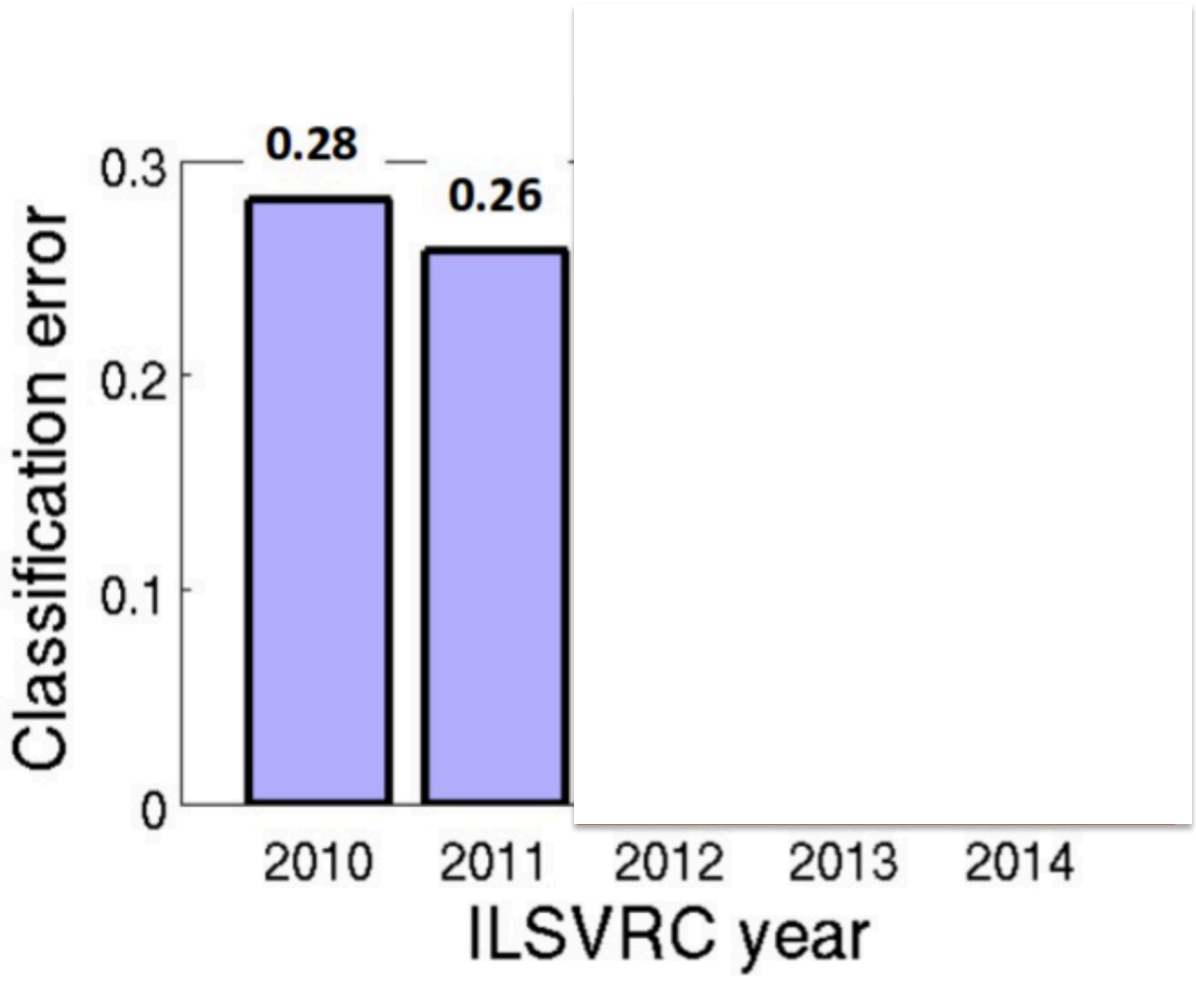
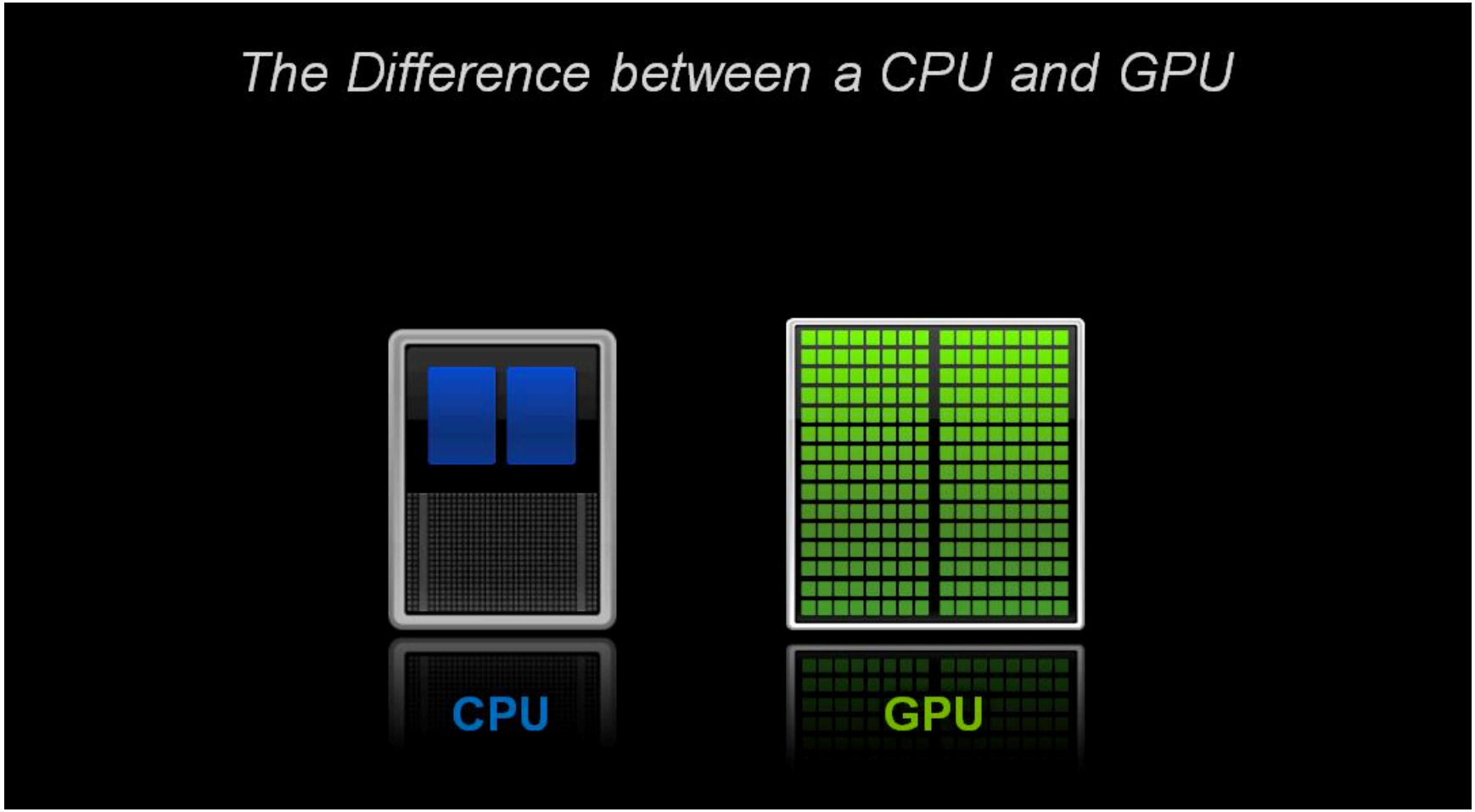


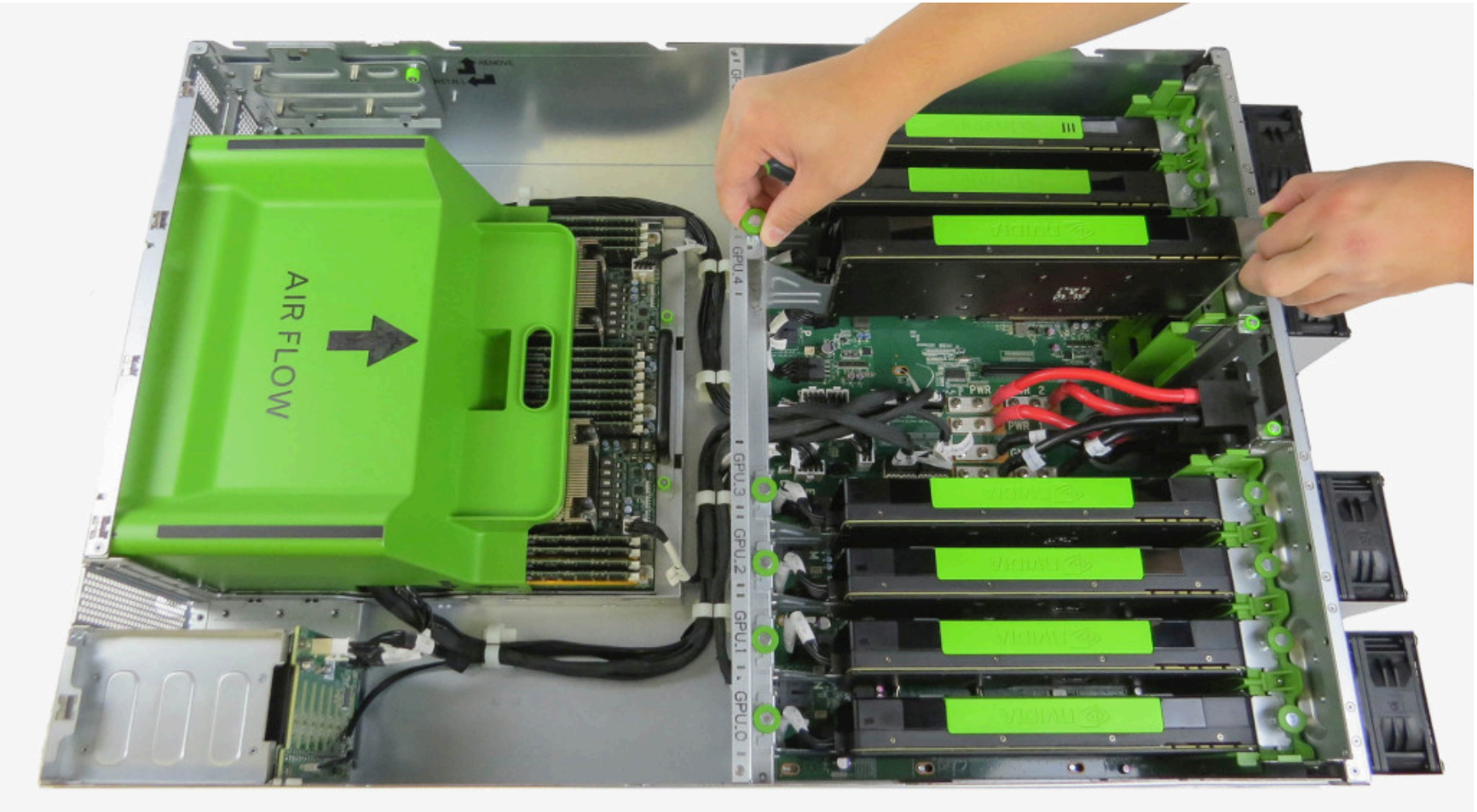
Figure from Olga Russakovsky ECCV'14 workshop

GPU: NVIDIA CUDA



Tesla P100 With Over 20 TFLOPS Of FP16
Read more: http://wccftech.com/nvidia-pascal-gpu-gtc-2016/#ixzz456KT75Jf

Facebook Machine Learning Server



Big Sur: 8 NVIDIA M40
https://techcrunch.com/gallery/a-look-inside-facebooks-data-center

Talents:
DNNresearch acquired by Google

Geoffrey Hinton (right: Professor) Alex Krizhevsky (middle; PhD student), and Ilya Sutskever (left; Postdoc)

“Deep” Software Revolution

- Modularized Building Blocks
  - Layers: conv, full, recurrence, etc.
- Symbolic Framework
  - CNTK, MXNET, TensorFlow, Theano
- Build Whatever!

http://blog.revolutionanalytics.com/2016/08/deep-learning-part-1.html

“Deep” Learning is Easy – Do Something Harder

- Representation Learning +
  - Reinforcement Learning
  - Generative Model
  - Knowledge-base (Memory Network)
- System
  - Distributed Computing
  - Embedded Computing

http://www.inference.vc/deep-learning-is-easy/

DL Fuses AI-subfields -> AGI

- Vision and Language

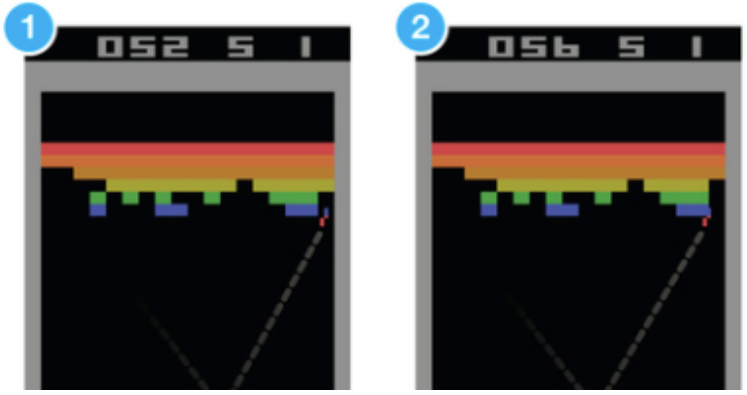
The man at bat readies to swing at the pitch while the umpire looks on.

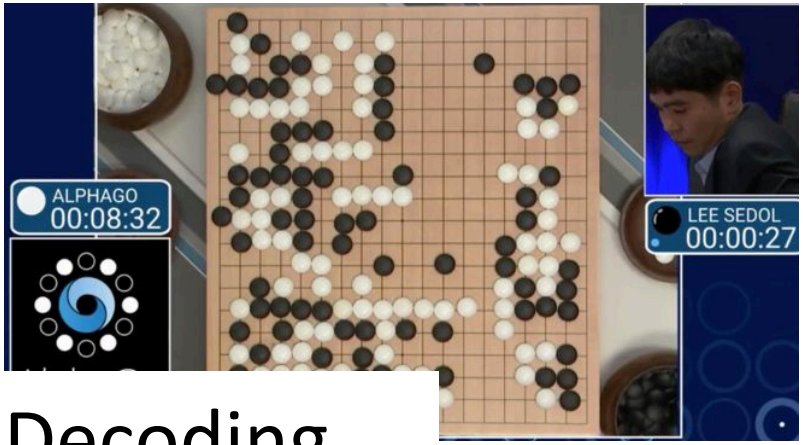
A large bus sitting next to a very tall building.

http://mscoco.org/

- Vision and Control

Atari Breakout game & AlphaGo, DeepMind.





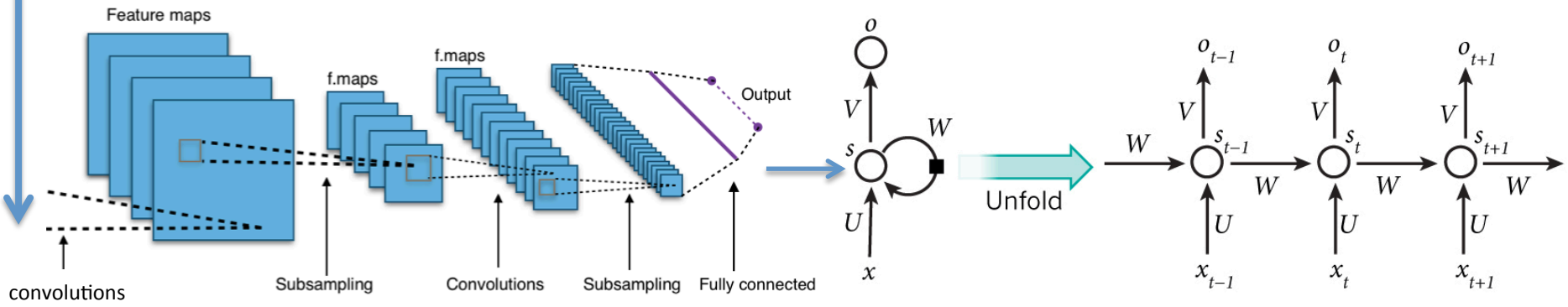
- Multiple Encoding and Decoding

Image Captioning

Vision

Language

f() = The man at bat is ready to swing at the pitch



Convolution Neuron Network (CNN)

credit: wiki

Recurrent Neuron Network (RNN)

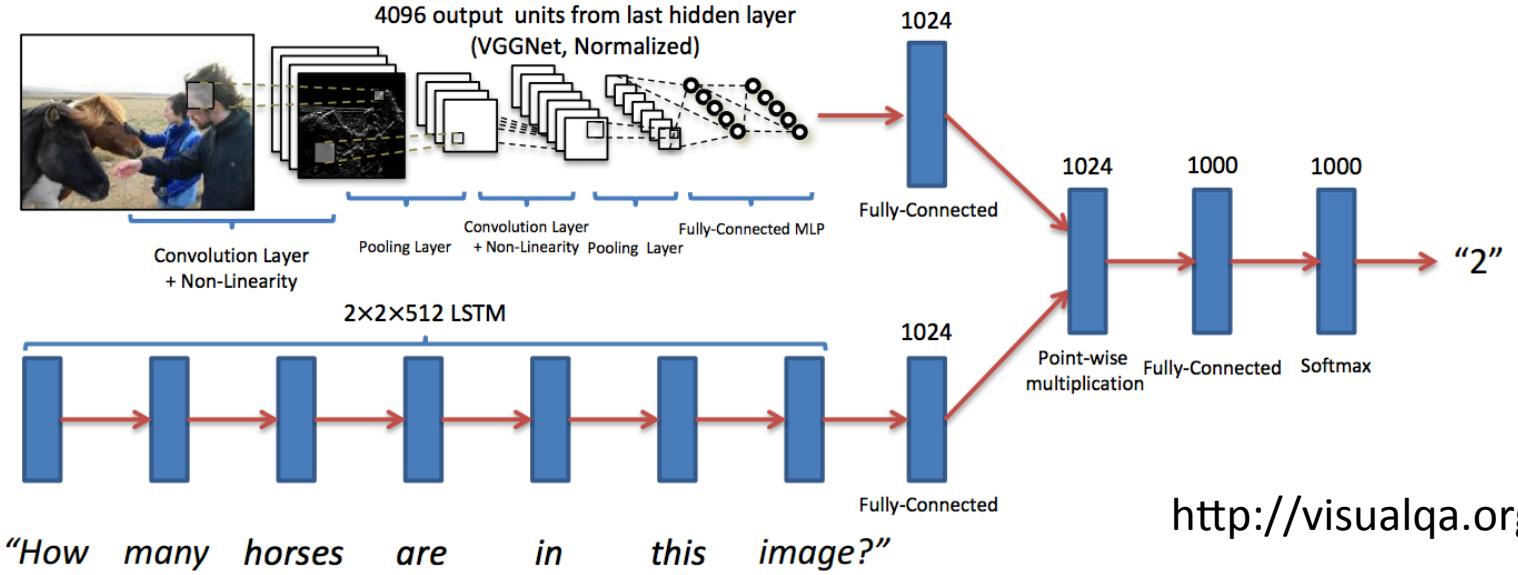
credit: Nature

Image Question Answering

What is the mustache made of?

AI System

bananas



http://visualqa.org/

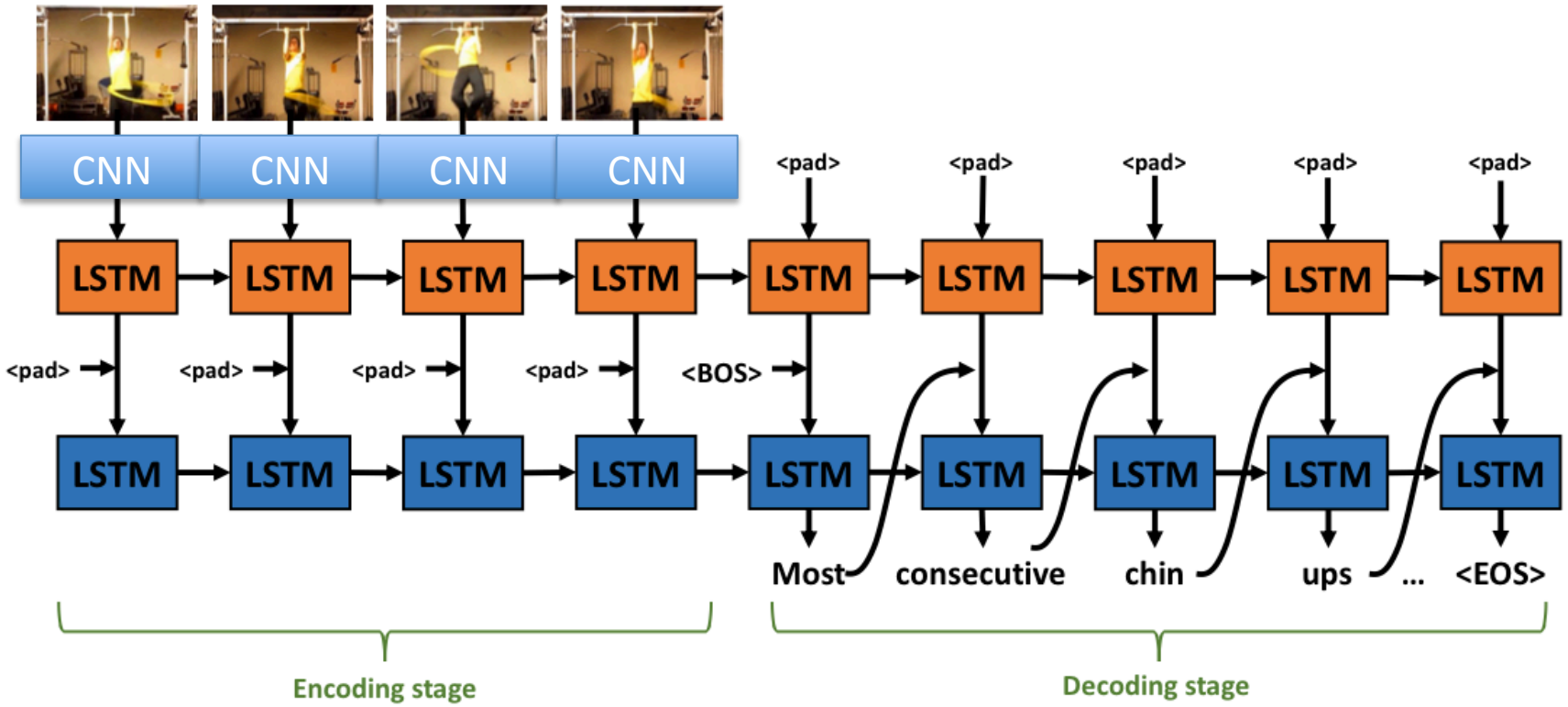
Video Captioning/Titling

Zhen et al. ECCV 2016 from VSLab and Stanford AI Lab

Big Video Data with Titles

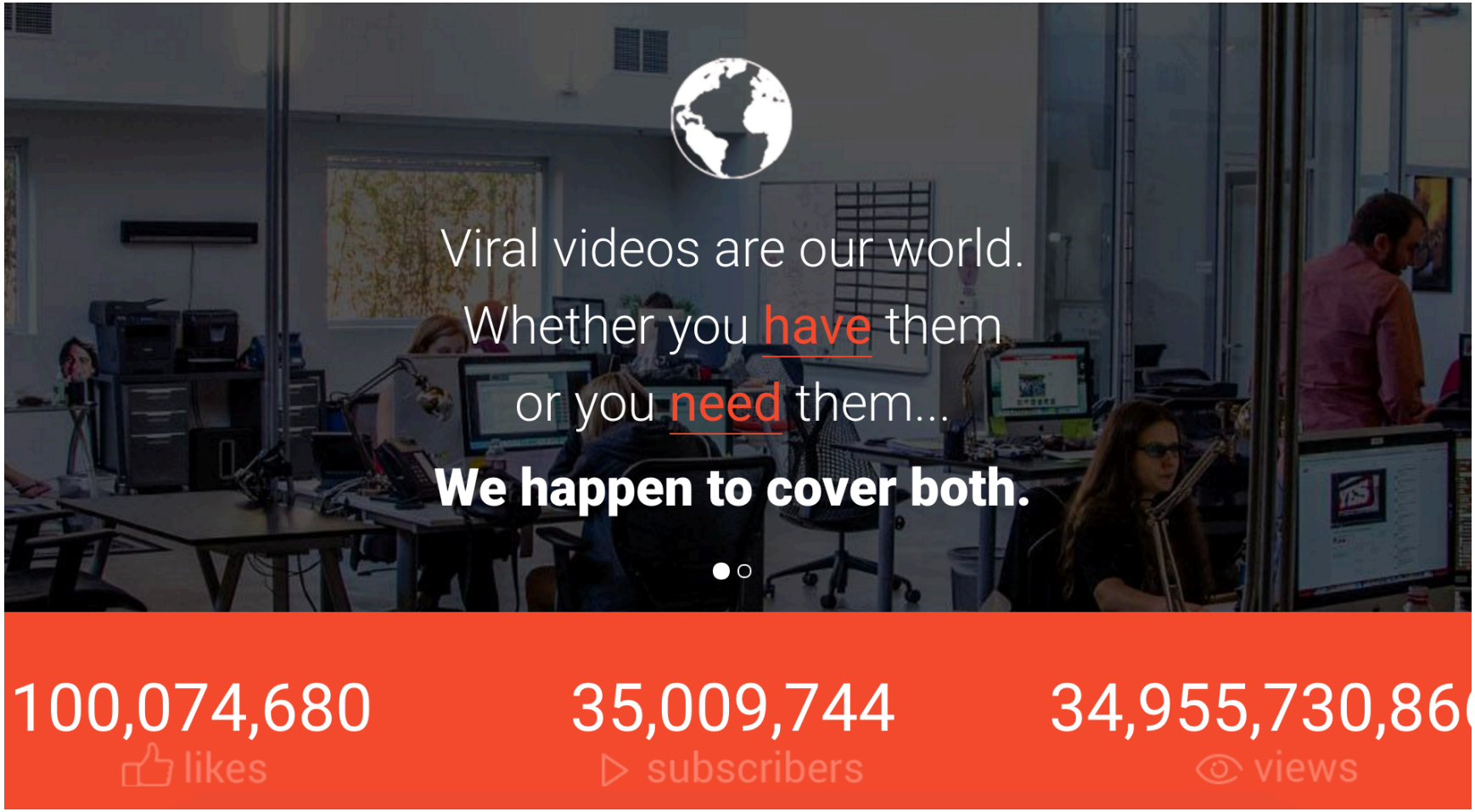
- Pairs of

Raw Video

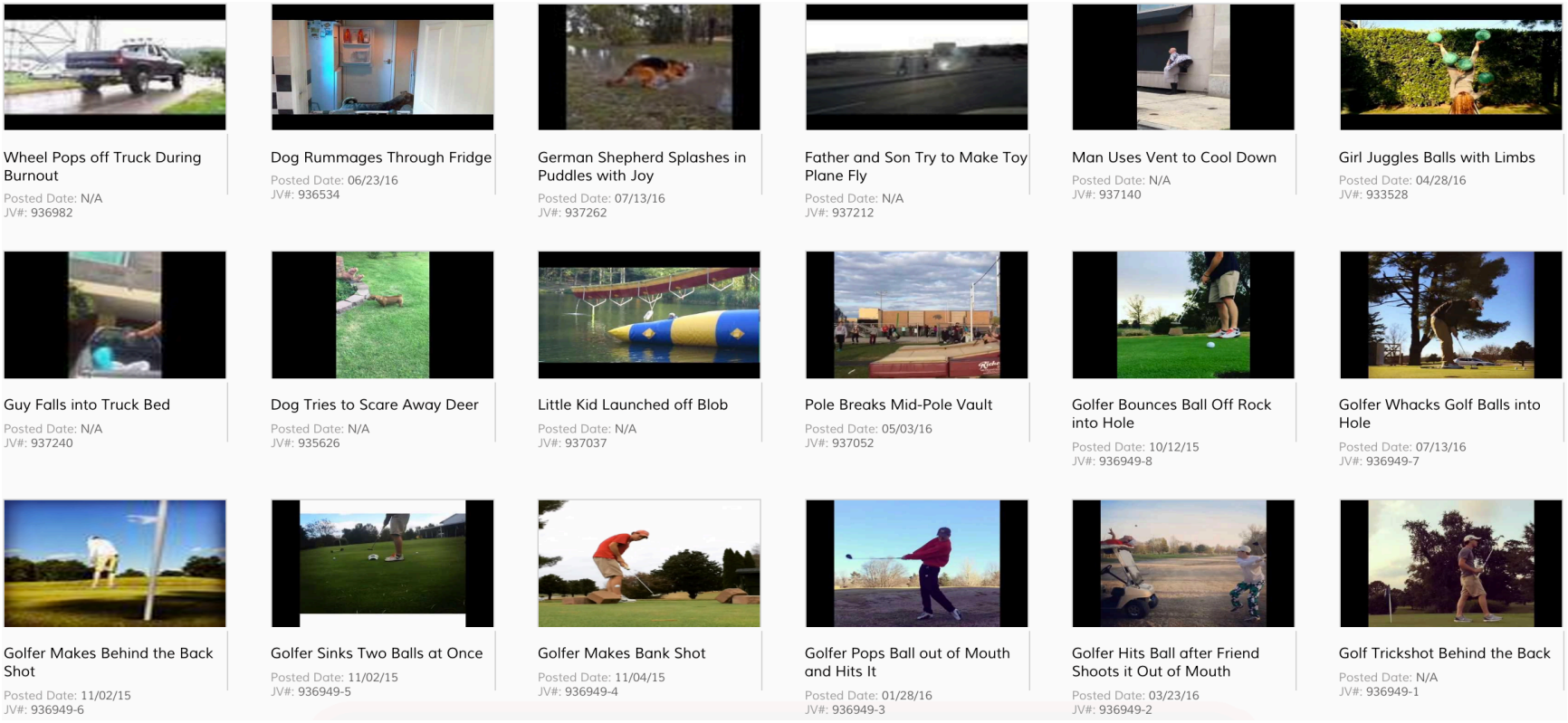


Title

Viral Videos



Huge Video Repository



Wheel Pops off Truck During Burnout
Posted Date: N/A
JV#: 936982

Dog Rummages Through Fridge
Posted Date: 06/23/16
JV#: 936534

German Shepherd Splashes in Puddles with Joy
Posted Date: 07/13/16
JV#: 937262

Father and Son Try to Make Toy Plane Fly
Posted Date: N/A
JV#: 937212

Man Uses Vent to Cool Down
Posted Date: N/A
JV#: 937140

Girl Juggles Balls with Limbs
Posted Date: 04/28/16
JV#: 933528

Guy Falls into Truck Bed
Posted Date: N/A
JV#: 937240

Dog Tries to Scare Away Deer
Posted Date: N/A
JV#: 935626

Little Kid Launched off Blob
Posted Date: N/A
JV#: 937037

Pole Breaks Mid-Pole Vault
Posted Date: 05/03/16
JV#: 937052

Golfer Bounces Ball Off Rock into Hole
Posted Date: 10/12/15
JV#: 936949-8

Golfer Whacks Golf Balls into Hole
Posted Date: 07/13/16
JV#: 936949-7

Golfer Makes Behind the Back Shot
Posted Date: 11/02/15
JV#: 936949-6

Golfer Sinks Two Balls at Once
Posted Date: 11/02/15
JV#: 936949-5

Golfer Makes Bank Shot
Posted Date: 11/04/15
JV#: 936949-4

Golfer Pops Ball out of Mouth and Hits It
Posted Date: 01/28/16
JV#: 936949-3

Golfer Hits Ball after Friend Shoots it Out of Mouth
Posted Date: 03/23/16
JV#: 936949-2

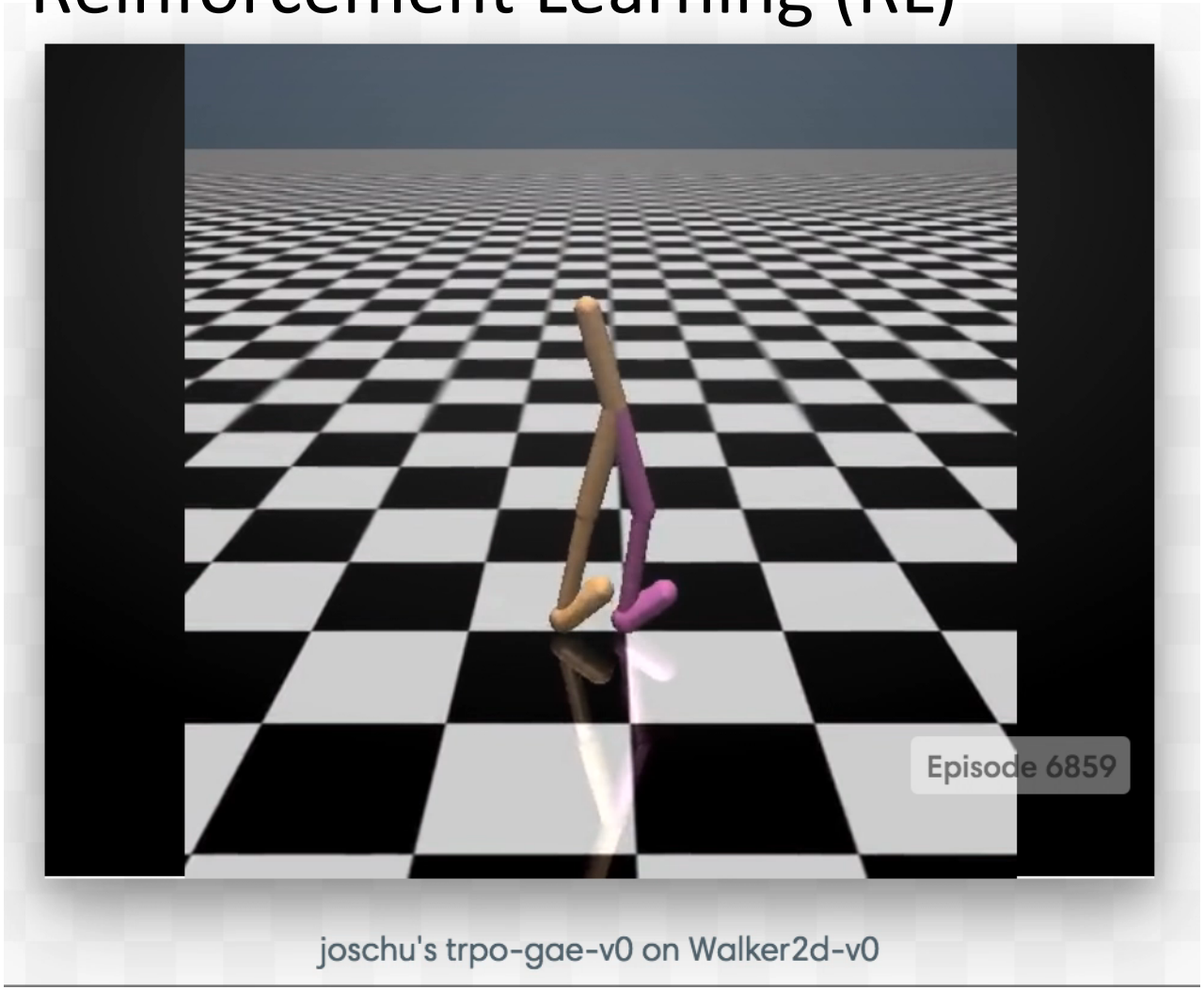
Golf Trickshot Behind the Back
Posted Date: N/A
JV#: 936949-1

Currently 28740 videos and keep growing

Vision and Control

- Learning to play game with weak supervision:

  Reinforcement Learning (RL)

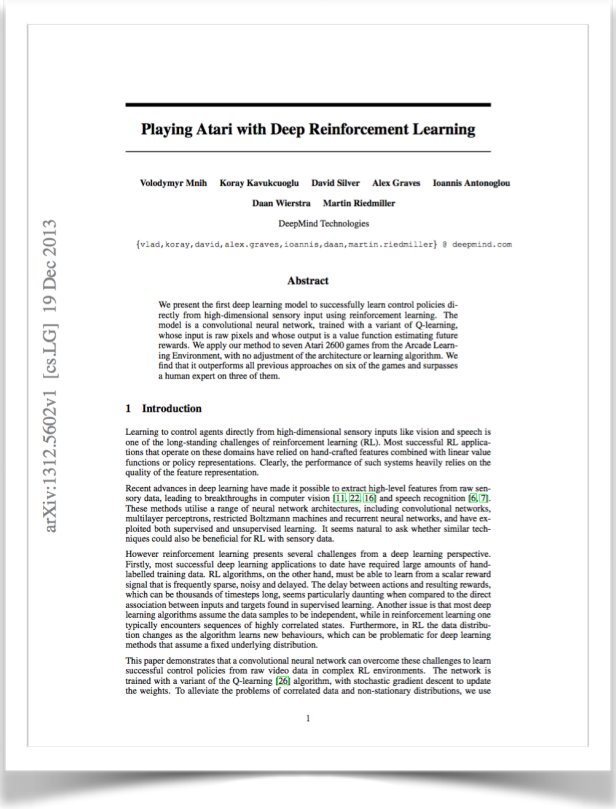


https://gym.openai.com/

Where It All Begins …

Playing Atari with Deep Reinforcement Learning

by DeepMind in NIPS 2013 Deep Learning Wrokshop



Playing Atari with Deep Reinforcement Learning

Volodymyr Mnih **Koray Kavukcuoglu** **David Silver** **Alex Graves** **Ioannis Antonoglou**
Daan Wierstra **Martin Riedmiller**
DeepMind Technologies
{vlad,koray,david,alex.graves,ioannis,daan,martin.riedmiller} @ deepmind.com

Abstract

We present the first deep learning model to successfully learn control policies directly from high-dimensional sensory input using reinforcement learning. The model is a convolutional neural network, trained with a variant of Q-learning, whose input is raw pixels and whose output is a value function estimating future rewards. We apply our method to seven Atari 2600 games from the Arcade Learning Environment, with no adjustment of the architecture or learning algorithm. We find that it outperforms all previous approaches on six of the games and surpasses a human expert on three of them.

1 Introduction

Learning to control agents directly from high-dimensional sensory inputs like vision and speech is one of the long-standing challenges of reinforcement learning (RL). Most successful RL applications that operate on these domains have relied on hand-crafted features combined with linear value functions or policy representations. Clearly, the performance of such systems heavily relies on the quality of the feature representation.

Recent advances in deep learning have made it possible to extract high-level features from raw sensory data, leading to breakthroughs in computer vision [11], [22], [16] and speech recognition [6], [7]. These methods utilise a range of neural network architectures, including convolutional networks, multilayer perceptrons, restricted Boltzmann machines and recurrent neural networks, and have exploited both supervised and unsupervised learning. It seems natural to ask whether similar techniques could also be beneficial for RL with sensory data.

However reinforcement learning presents several challenges from a deep learning perspective. Firstly, most successful deep learning applications to date have required large amounts of hand-labelled training data. RL algorithms, on the other hand, must be able to learn from a scalar reward signal that is frequently sparse, noisy and delayed. The delay between actions and resulting rewards, which can be thousands of timesteps long, seems particularly daunting when compared to the direct association between inputs and targets found in supervised learning. Another issue is that most deep learning algorithms assume the data samples to be independent, while in reinforcement learning one typically encounters sequences of highly correlated states. Furthermore, in RL the data distribution changes as the algorithm learns new behaviours, which can be problematic for deep learning methods that assume a fixed underlying distribution.

This paper demonstrates that a convolutional neural network can overcome these challenges to learn successful control policies from raw video data in complex RL environments. The network is trained with a variant of the Q-learning [26] algorithm, with stochastic gradient descent to update the weights. To alleviate the problems of correlated data and non-stationary distributions, we use

1

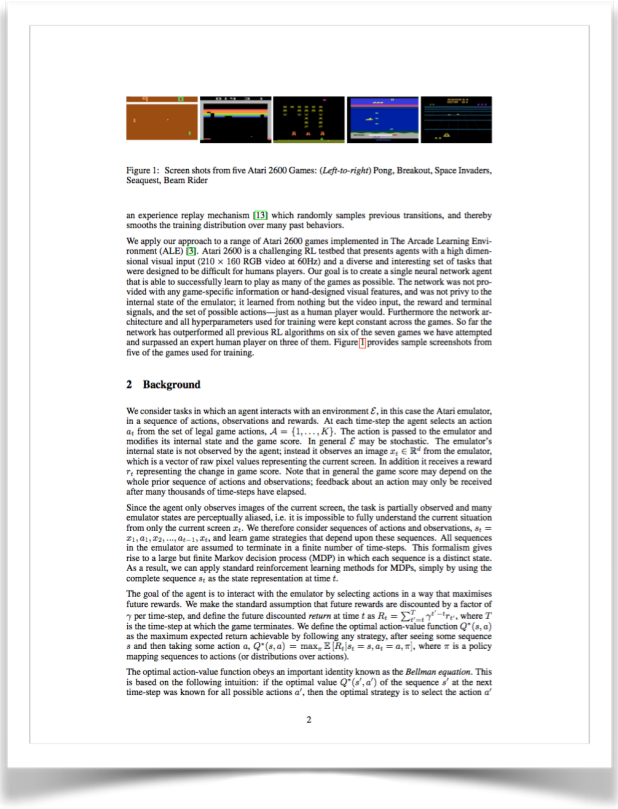


Figure 1: Screen shots from five Atari 2600 Games: (*Left-to-right*) Pong, Breakout, Space Invaders, Seaquest, Beam Rider

an experience replay mechanism [13] which randomly samples previous transitions, and thereby smooths the training distribution over many past behaviors.

We apply our approach to a range of Atari 2600 games implemented in The Arcade Learning Environment (ALE) [3]. Atari 2600 is a challenging RL testbed that presents agents with a high dimensional visual input (210 × 160 RGB video at 60Hz) and a diverse and interesting set of tasks that were designed to be difficult for humans players. Our goal is to create a single neural network agent that is able to successfully learn to play as many of the games as possible. The network was not provided with any game-specific information or hand-designed visual features, and was not privy to the internal state of the emulator; it learned from nothing but the video input, the reward and terminal signals, and the set of possible actions—just as a human player would. Furthermore the network architecture and all hyperparameters used for training were kept constant across the games. So far the network has outperformed all previous RL algorithms on six of the seven games we have attempted and surpassed an expert human player on three of them. Figure 1 provides sample screenshots from five of the games used for training.

2 Background

We consider tasks in which an agent interacts with an environment $\mathcal{E}$, in this case the Atari emulator, in a sequence of actions, observations and rewards. At each time-step the agent selects an action a_t from the set of legal game actions, $\mathcal{A} = \{1, \ldots, K\}$. The action is passed to the emulator and modifies its internal state and the game score. In general $\mathcal{E}$ may be stochastic. The emulator's internal state is not observed by the agent; instead it observes an image $x_t \in \mathbb{R}^d$ from the emulator, which is a vector of raw pixel values representing the current screen. In addition it receives a reward r_t representing the change in game score. Note that in general the game score may depend on the whole prior sequence of actions and observations; feedback about an action may only be received after many thousands of time-steps have elapsed.

Since the agent only observes images of the current screen, the task is partially observed and many emulator states are perceptually aliased, i.e. it is impossible to fully understand the current situation from only the current screen x_t. We therefore consider sequences of actions and observations, $s_t = x_1, a_1, x_2, \ldots, a_{t-1}, x_t$, and learn game strategies that depend upon these sequences. All sequences in the emulator are assumed to terminate in a finite number of time-steps. This formalism gives rise to a large but finite Markov decision process (MDP) in which each sequence is a distinct state. As a result, we can apply standard reinforcement learning methods for MDPs, simply by using the complete sequence s_t as the state representation at time t.

The goal of the agent is to interact with the emulator by selecting actions in a way that maximises future rewards. We make the standard assumption that future rewards are discounted by a factor of γ per time-step, and define the future discounted *return* at time t as $R_t = \sum_{t'=t}^{T} \gamma^{t'-t} r_{t'}$, where T is the time-step at which the game terminates. We define the optimal action-value function $Q^*(s, a)$ as the maximum expected return achievable by following any strategy, after seeing some sequence s and then taking some action a, $Q^*(s, a) = \max_\pi \mathbb{E}[R_t | s_t = s, a_t = a, \pi]$, where π is a policy mapping sequences to actions (or distributions over actions).

The optimal action-value function obeys an important identity known as the *Bellman equation*. This is based on the following intuition: if the optimal value $Q^*(s', a')$ of the sequence s' at the next time-step was known for all possible actions a', then the optimal strategy is to select the action a'

2

slides by
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Control: Learning to Act

Play **Breakout** equals to

- **Input:** screen images
- **Output:** actions
  (**do nothing** | **left** | **right**)

Supervised
Classification

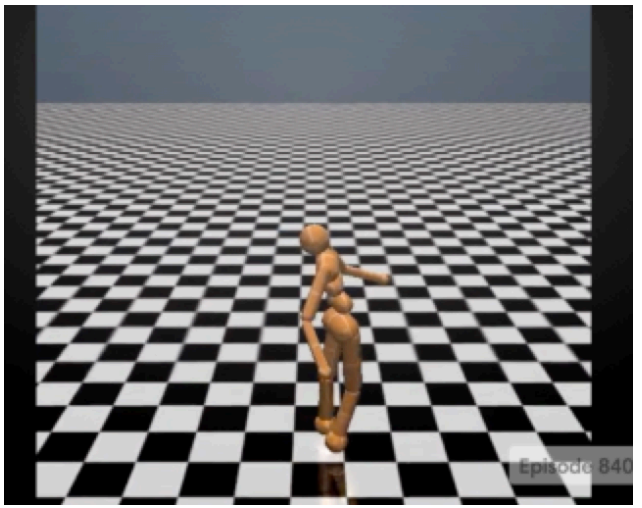
slides by
Yen-Chen Lin

Supervised Solution

- **Training data:** Record experts game sessions
- **Target label:** Action experts take at every step

Problems:

- What if there's no expert?
- This is not how human learns



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How Human Learns

- Don’t need somebody to tell us a million times which move to choose at each screen
- Just need **occasional feedback** that we did the right thing

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Reinforcement Learning

- Somewhere between **supervised** and **unsupervised** learning
- **Sparse** and **time-delayed** labels

Based only on those rewards, the agent has to learn to behave in the environment.
A rational agent should optimize total reward.

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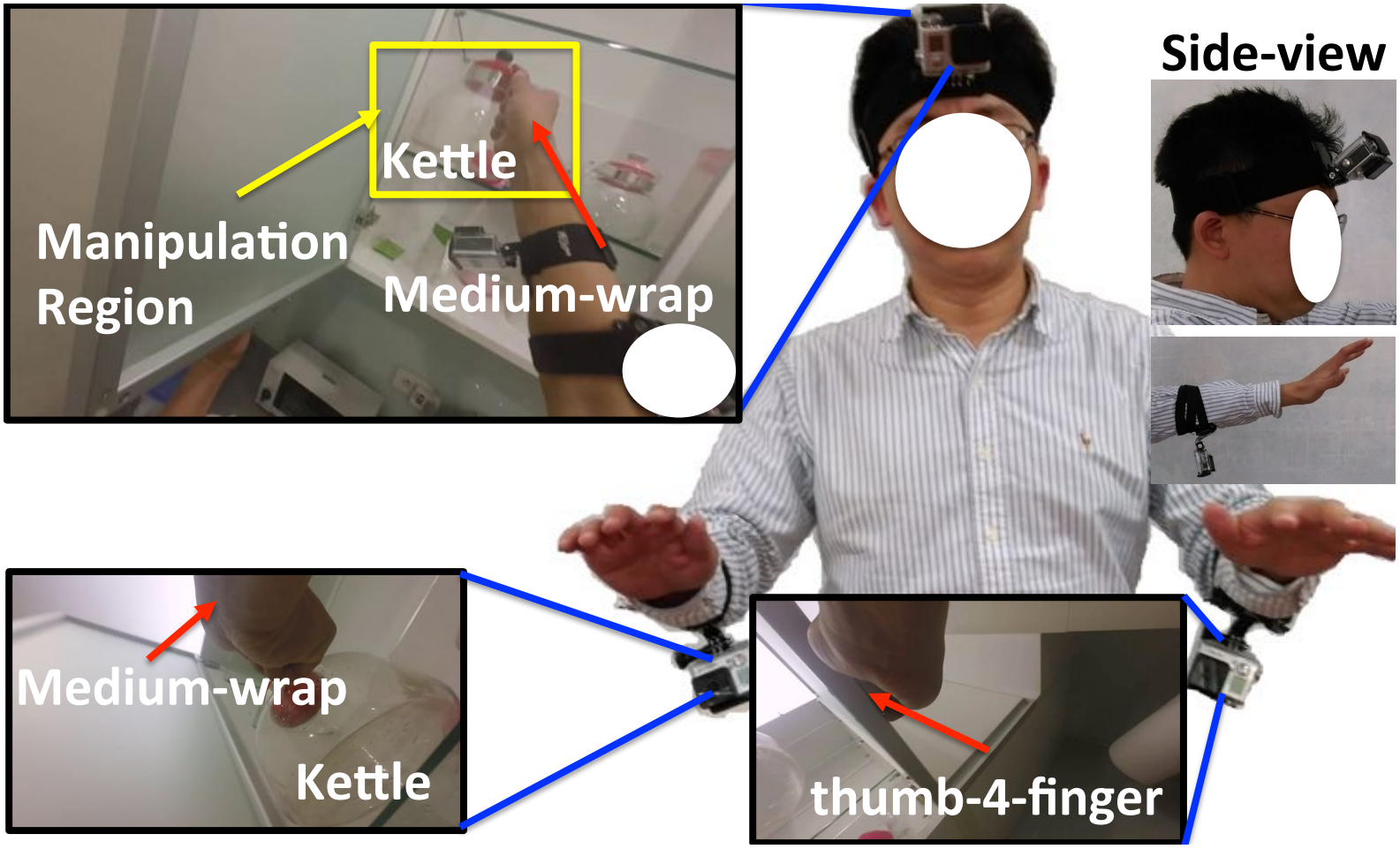
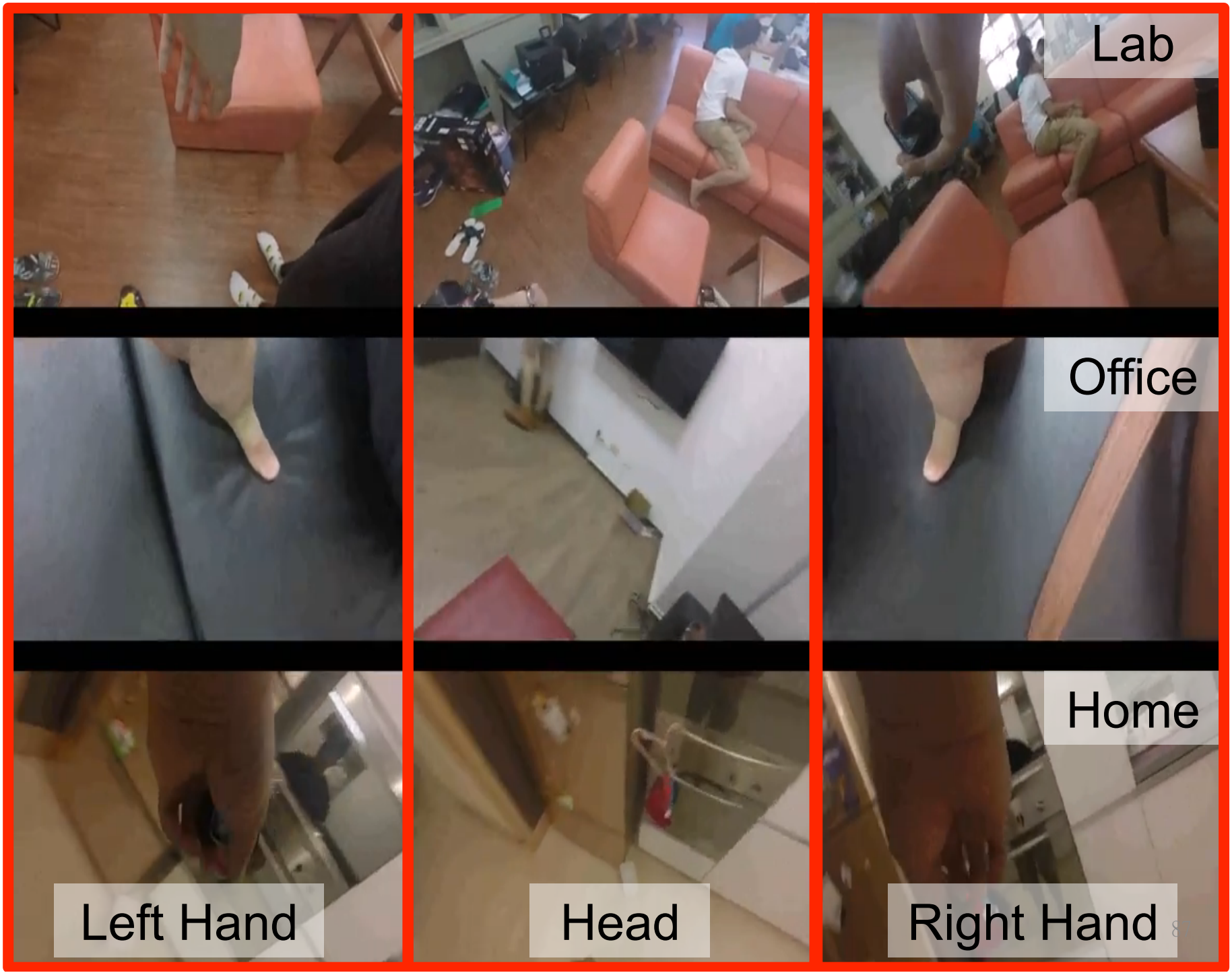
Self-driving Car:
Trigger Accident Warning

Fusing Multiple Sensors



Chan et al. ECCV 2015 from VSLab


Lab
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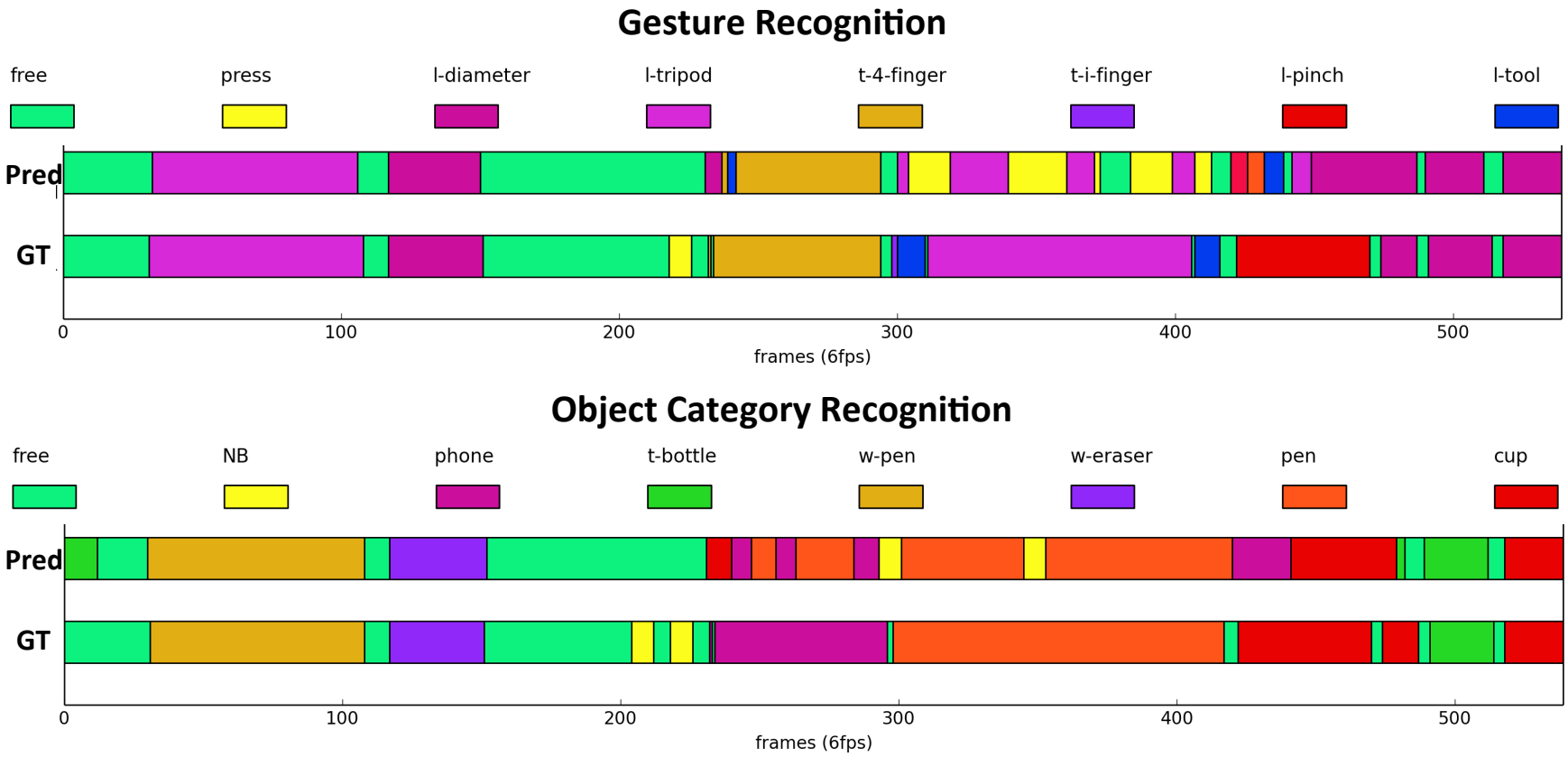
Recognition from Wearable Cameras



Real-time Wearable Demo

Fisheye camera

NVIDIA TK1

Accelerating the Revolution

- GitHub Awesome Lists
  - https://github.com/ChristosChristofidis/awesome-deep-learning
  - https://github.com/aikorea/awesome-rl
- GitHub Code Repos
- Blog or YouTube
  - karpathy.github.io
  - colah.github.io

Please connect everything to https://github.com/TheCEDL

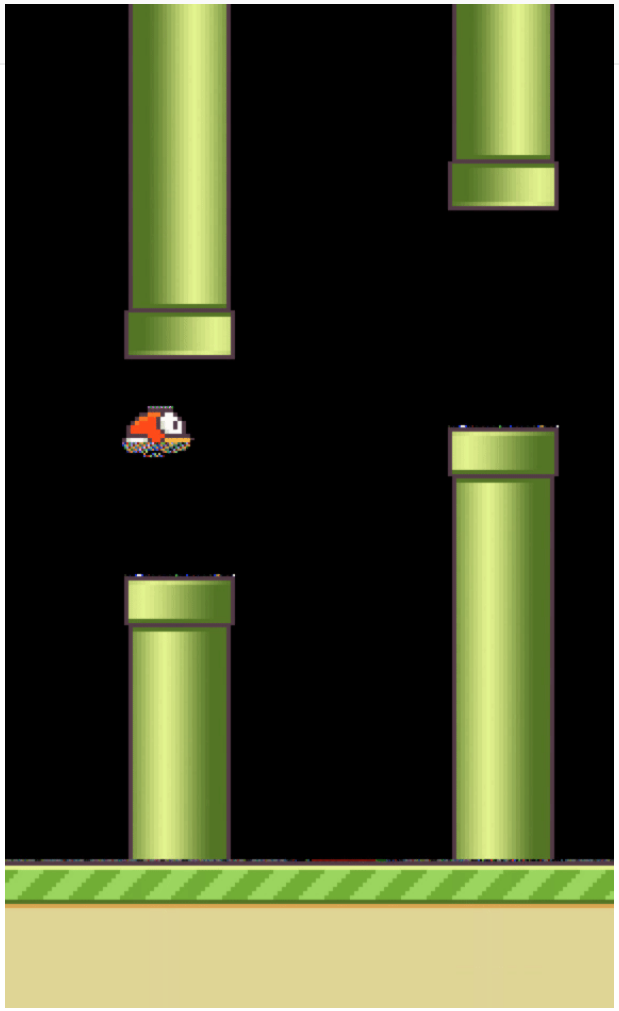
Case Study: NTHU@TW Undergraduate

yenchenlin1994 / DeepLearningFlappyBird

Watch 72 | Unstar 1,518 | Fork 198

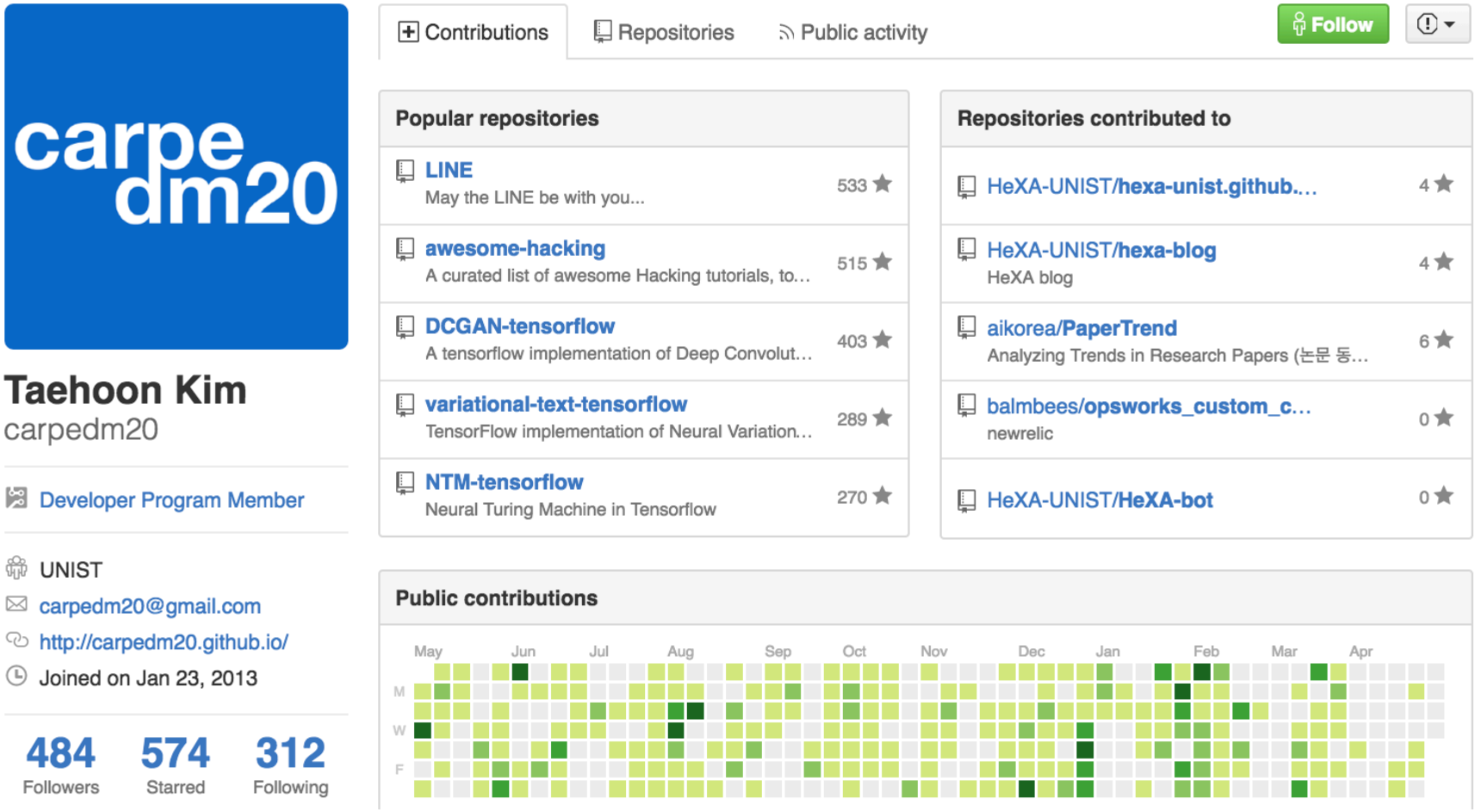
Code | Issues 5 | Pull requests 2 | Wiki | Pulse | Graphs

Flappy Bird hack using Deep Reinforcement Learning (Deep Q-learning).



https://github.com/yenchenlin1994/DeepLearningFlappyBird

Case Study: UNIST@Korean Undergraduate



AI is happening Fast

Microsoft Research @MSFTResearch · 16h

.@billgates: @MSFTResearch making "more progress now per year than ever I would say in the last 25 years" #FacSumm

Thanks!