



# The Machine Learning (ML) Hub @ KAUST

Prof. Bernard Ghanem

# The ML Hub Organizers



**Prof. Panagiotis Kalnis**  
CS, ECRC



**Prof. Marco Canini**  
CS, ECRC



**Prof. Peter Richtarik**  
CS, AMCS, STAT, VCC



**Prof. Bernard Ghanem**  
EE, CS, STAT, VCC

# The Machine Learning Hub

ML @ KAUST



[ml.kaust.edu.sa](http://ml.kaust.edu.sa)

## ARTIFICIAL INTELLIGENCE

A program that can sense, reason, act, and adapt

## MACHINE LEARNING

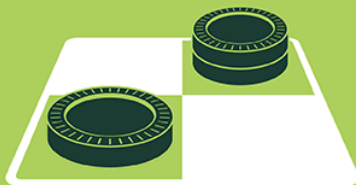
Algorithms whose performance improve as they are exposed to more data over time

## DEEP LEARNING

Subset of machine learning in which multilayered neural networks learn from vast amounts of data

## ARTIFICIAL INTELLIGENCE

Early artificial intelligence stirs excitement.



## MACHINE LEARNING

Machine learning begins to flourish.



## DEEP LEARNING

Deep learning breakthroughs drive AI boom.



1950's

1960's

1970's

1980's

1990's

2000's

2010's

# Google CEO: A.I. is more important than fire or electricity

Catherine Clifford | 12:56 PM ET Thu, 1 Feb 2018



Beck Diefenbach | Reuters

Google CEO Sundar Pichai takes the stage during the presentation of new Google hardware in San Francisco on Oct. 4, 2016.



# AI skills reign supreme in the fastest-growing jobs of the year

Six out of the 15 top emerging jobs in 2018 were related to artificial intelligence, according to LinkedIn.

By Macy Bayern | December 13, 2018, 6:07 AM PST

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## The big takeaways for tech leaders:

- *AI has a prominent presence on the emerging jobs list, making up six of the 15 fastest-growing jobs of the year. — LinkedIn, 2018*
- *The top five emerging jobs of 2018 include blockchain developer, machine learning engineer, application sales executive, machine learning specialist, and professional medical representative. — LinkedIn, 2018*

# Trump administration unveils order to prioritize and promote AI

3 MIN READ



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WASHINGTON (Reuters) - U.S. President Donald Trump on Monday signed an executive order asking federal government agencies to dedicate more resources and investment into research, promotion and training on artificial intelligence, known as AI.



# AI Index Report 2018 (aiindex.org)

**Our Mission is to ground the conversation about AI in data.**

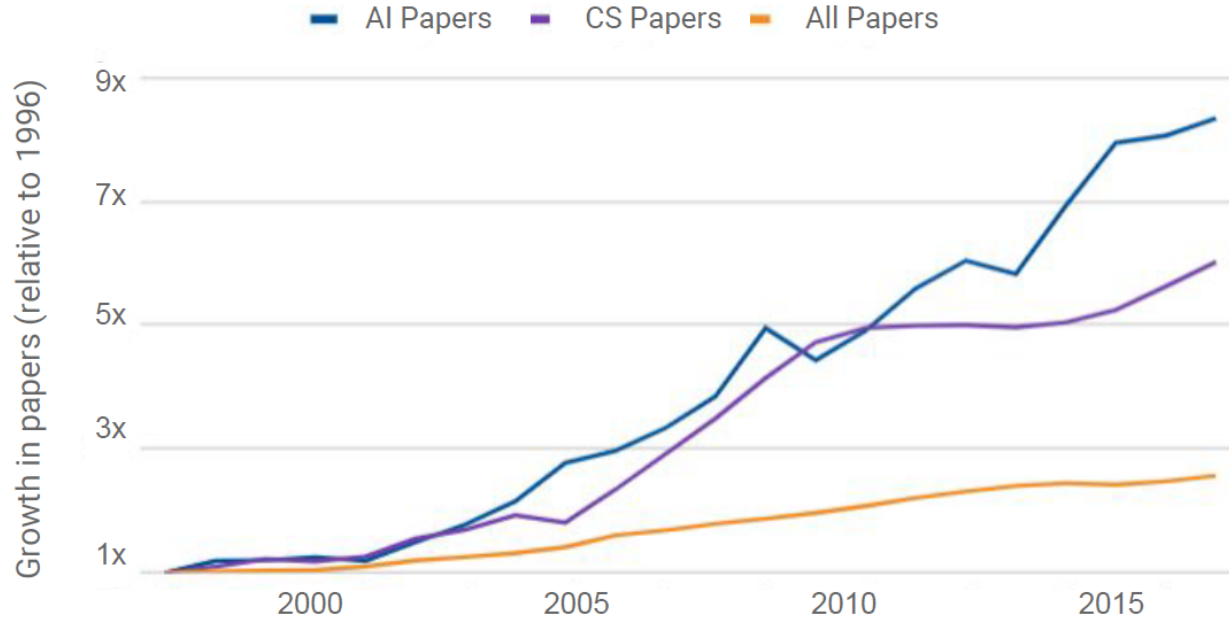
The AI Index is an effort to track, collate, distill, and visualize data relating to artificial intelligence. It aspires to be a comprehensive resource of data and analysis for policymakers, researchers, executives, journalists, and the general public to develop intuitions about the complex field of AI.



# Impact of AI on Research

Growth of annually published papers by topic (1996–2017)

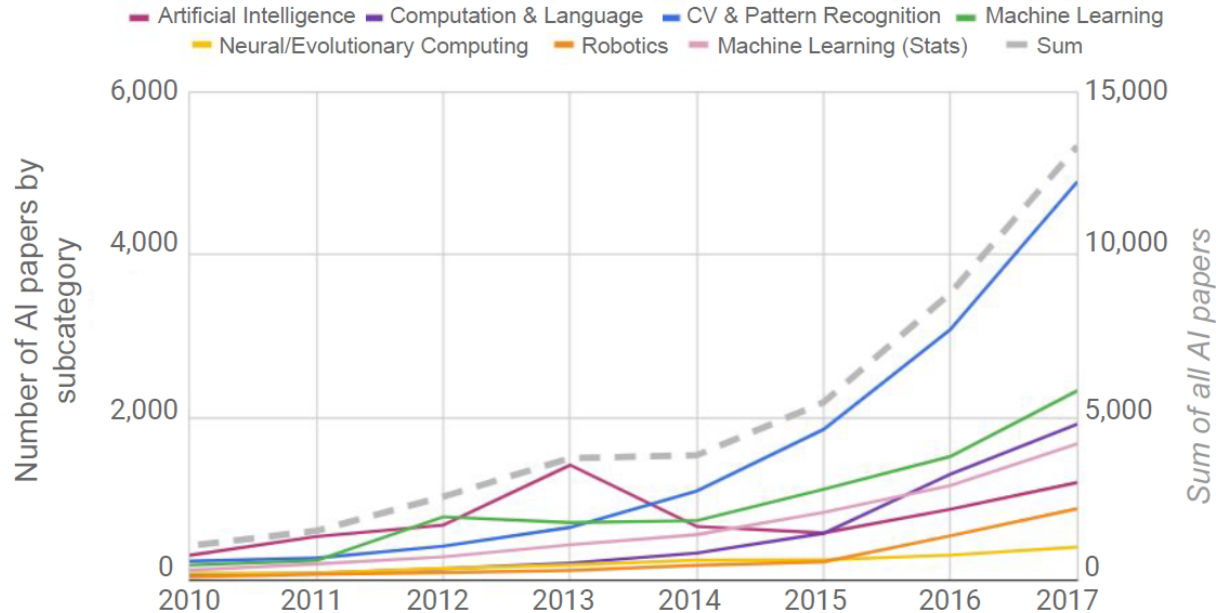
Source: Scopus



# Impact of AI on Research

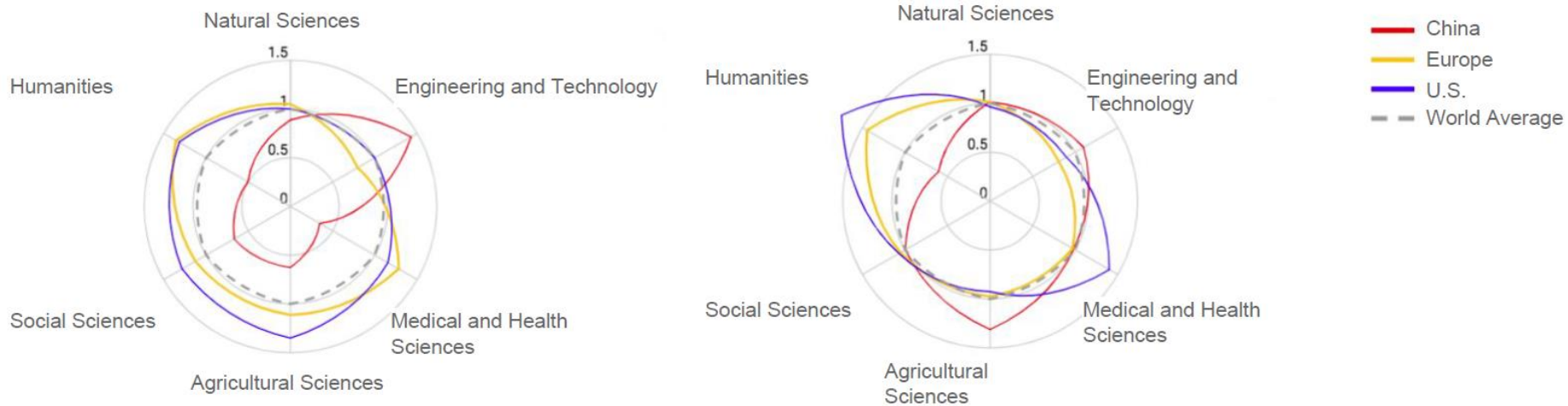
Number of AI papers on arXiv by subcategory (2010–2017)

Source: arXiv



# Impact of AI on Research (interdisciplinary)

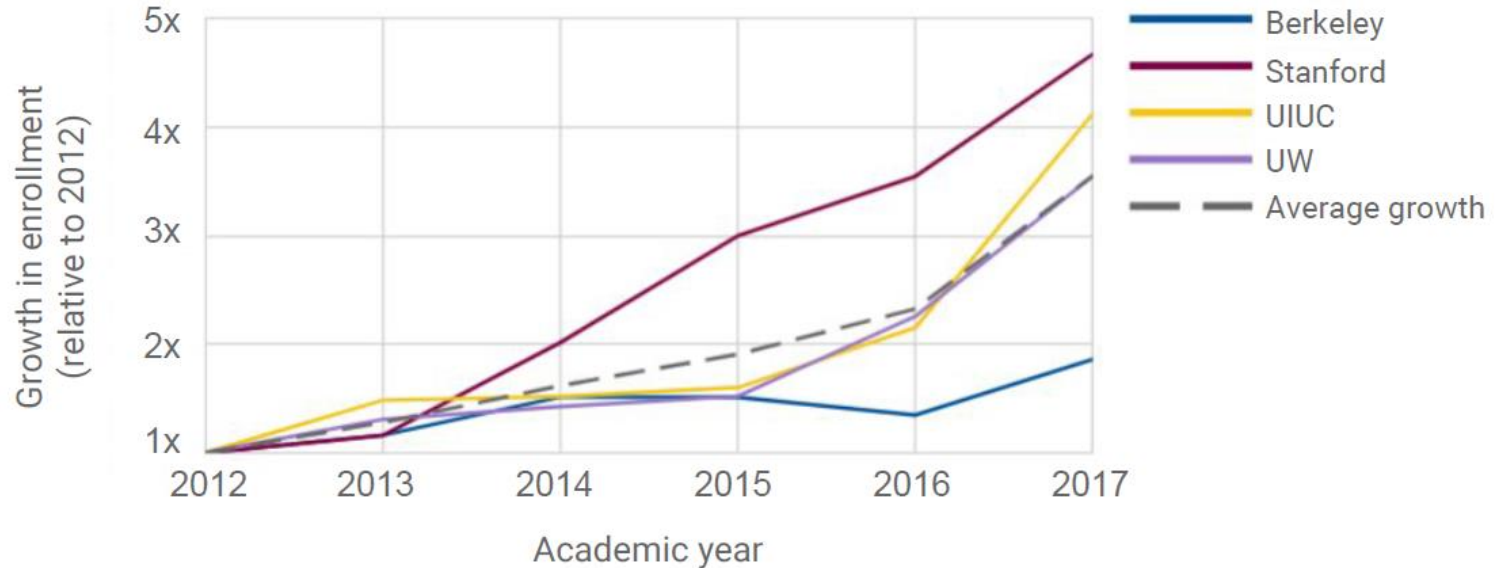
## Relative Activity Focus by Region and AI Research Sector in 2000 and 2017



# Impact of AI on Education/Training

Growth in introductory AI course enrollment (2012–2017)

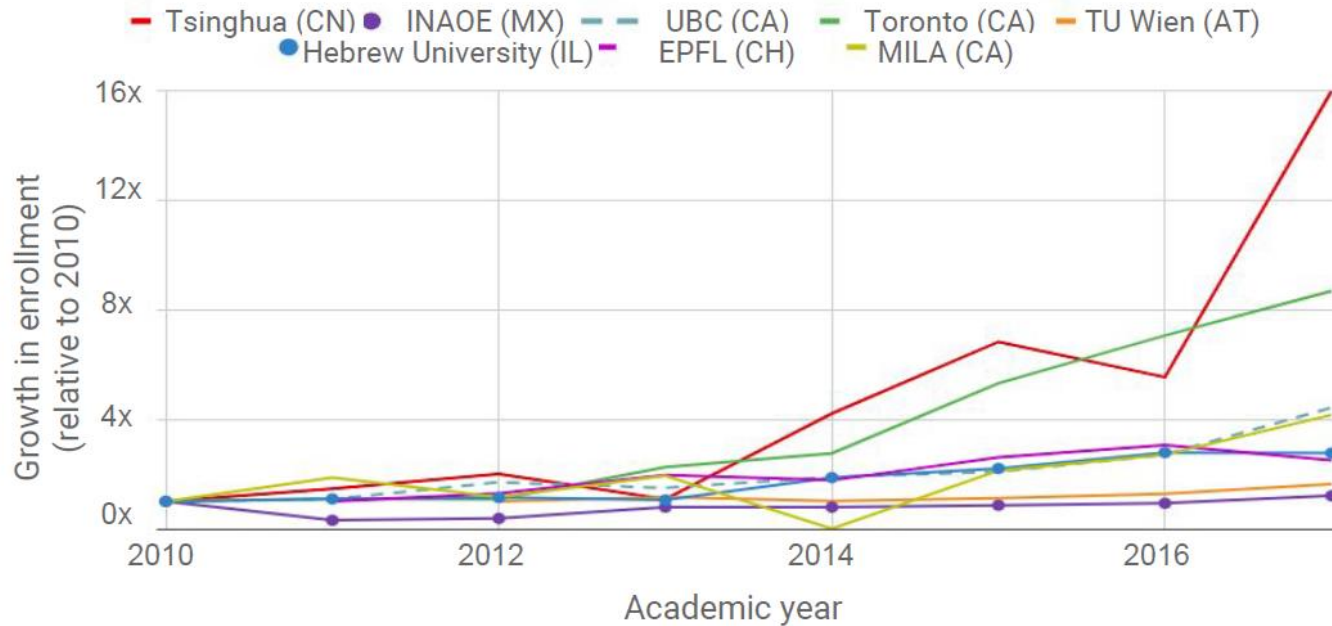
Source: University provided data



# Impact of AI on Education/Training

Growth of AI+ML course enrollment — Non-U.S. (2010–2017)

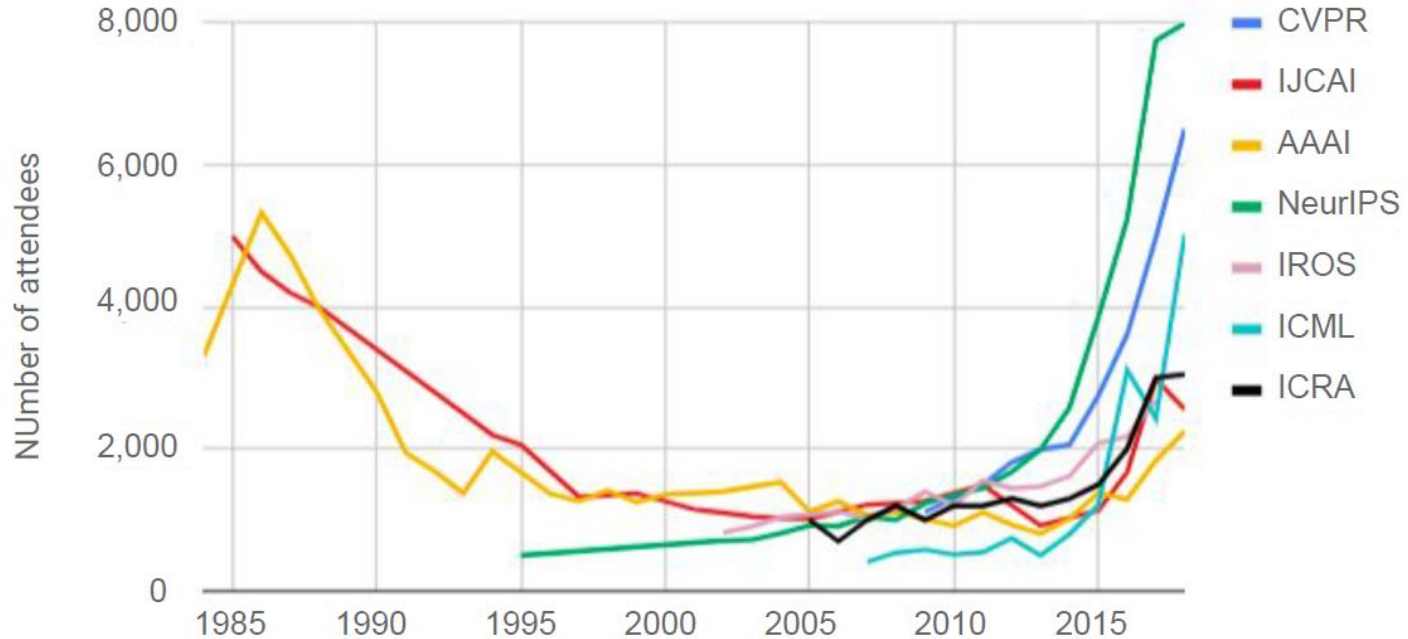
Source: University provided data



# Impact of AI on Education/Training

Attendance at large conferences (1984–2018)

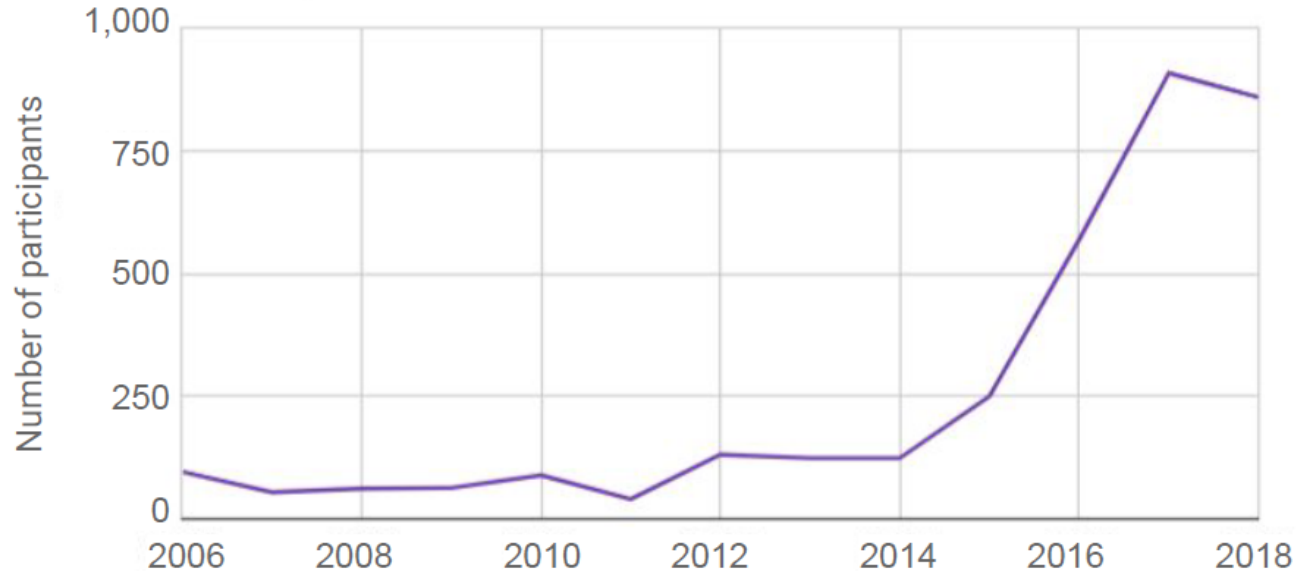
Source: Conference provided data



# Impact of AI on Education/Training

WiML workshop registration (2006–2018)

Source: WiML

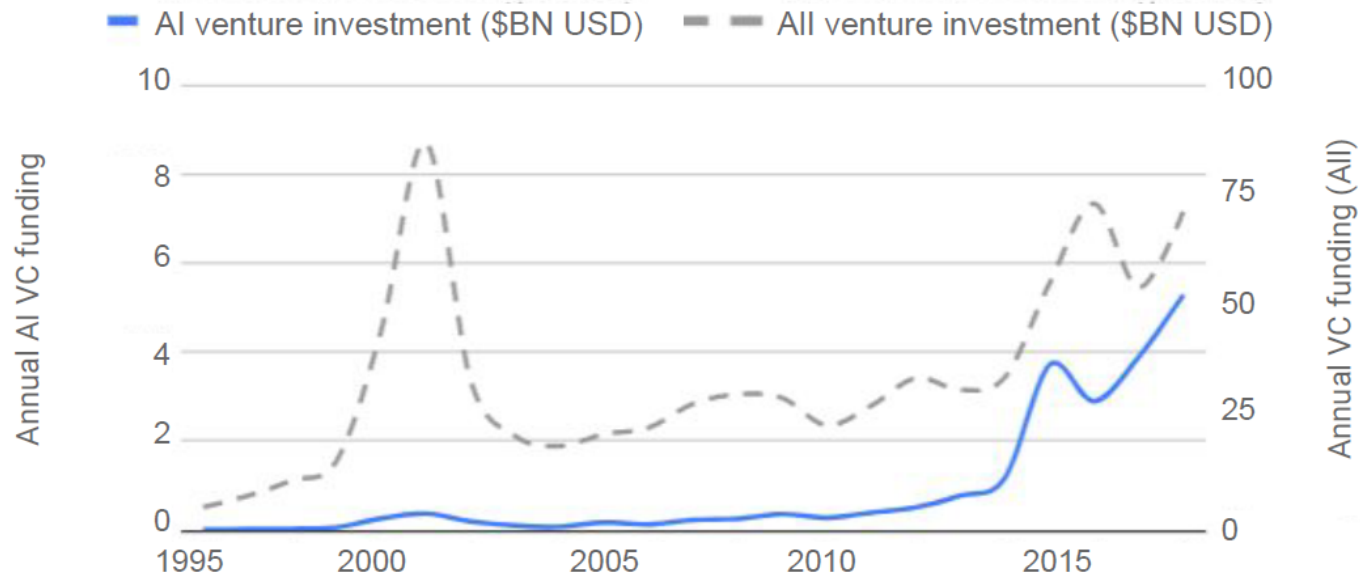




# Impact of AI on IED/Jobs

Annual VC funding of AI startups (U.S., 1995 – 2017)

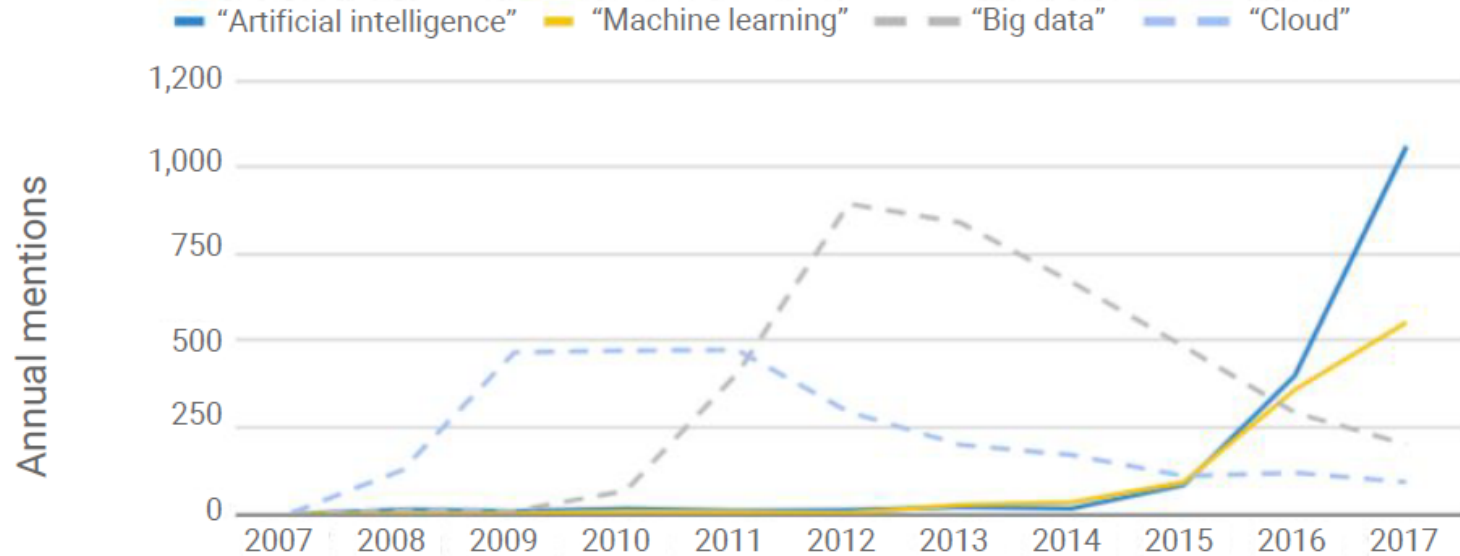
Source: Sand Hill Econometrics



# Impact of AI on IED/Jobs

## Company earnings calls mentions – IT companies (2007–2017)

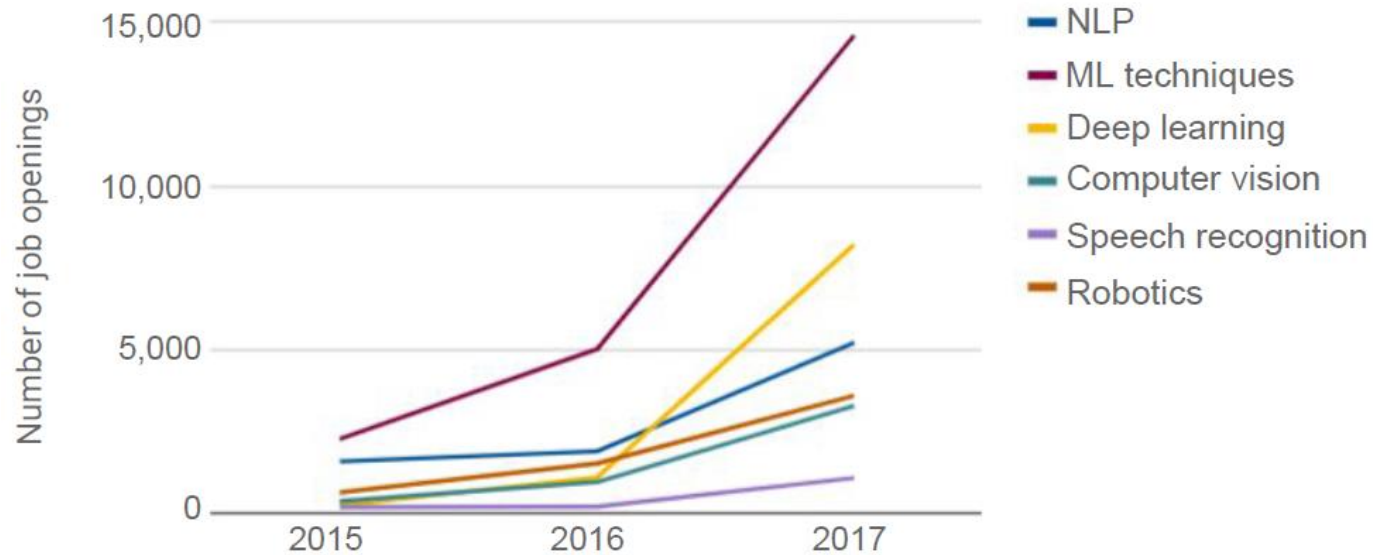
Source: Prattle



# Impact of AI on IED/Jobs

Job openings by AI skills required (2015 – 2017)

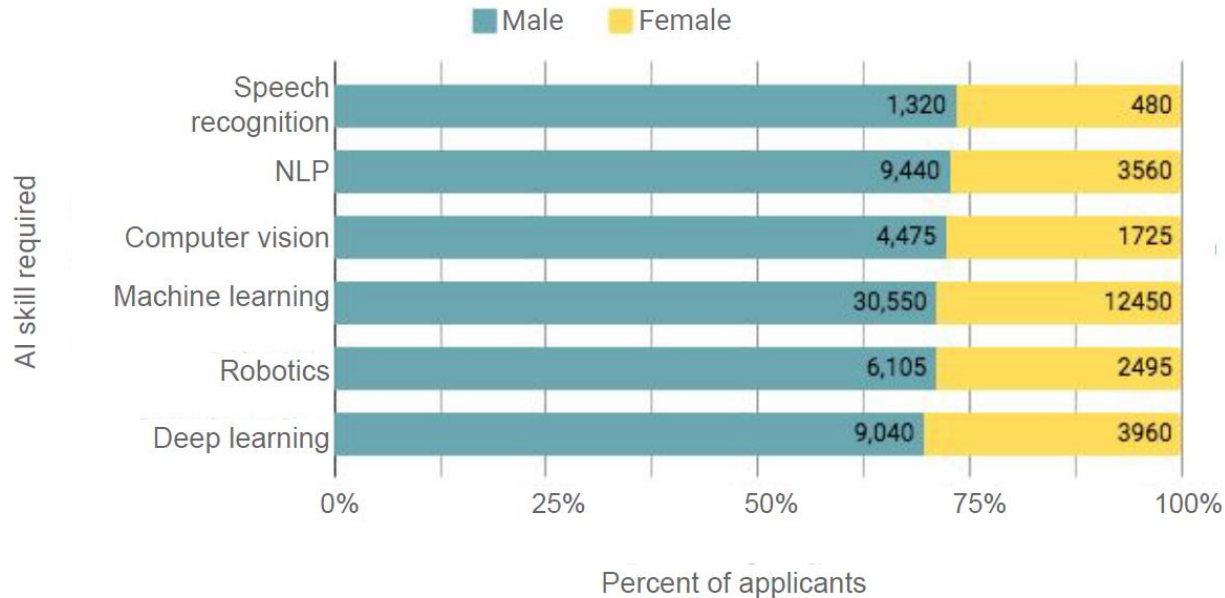
Source: Monster.com



# Impact of AI on IED/Jobs

Job applicants by gender (2017)

Source: Gartner TalentNeuron



# Why has AI/ML been so impactful?

## Perfect “storm”

- Large-scale data
- Tools (e.g. deep networks)
- Mathematical foundations
- Hardware/Software systems (e.g. GPUs, TensorFlow)
- Applications and industry adoption

# Where is KAUST in all this?

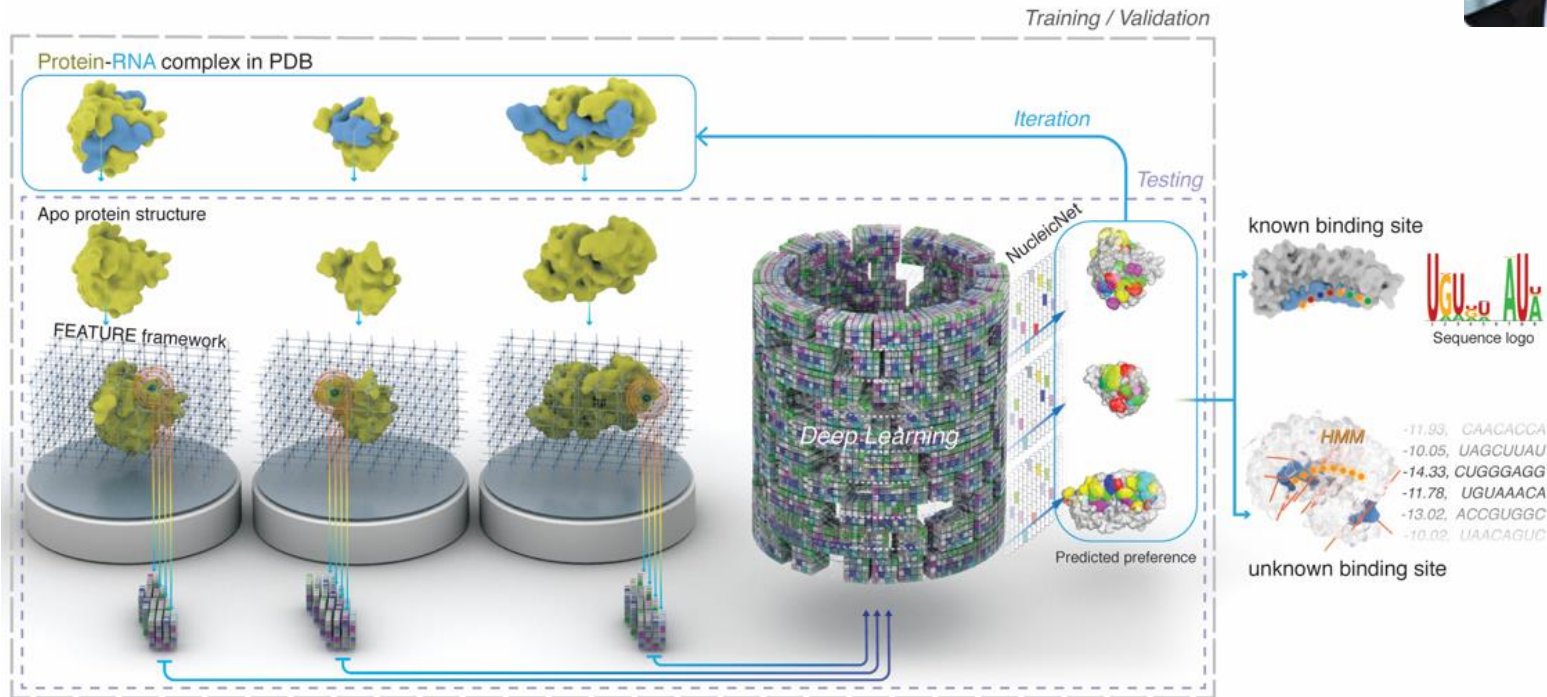


Conference & Journal Ranking in: Computer Science / AI & Pattern Recognition

Rank	Conference (Full Name)	Short Name	H5-Index
1	IEEE Conference on Computer Vision and Pattern Recognition	★ CVPR	112.00
2	IEEE Transactions on Pattern Analysis and Machine Intelligence	★ TPAMI	101.00
3	Expert Systems with Applications	Expert Syst. Appl.	59.00
4	International Journal of Computer Vision	★ IJCV	58.00
5	IEEE International Conference on Robotics and Automation	★ ICRA	58.00
6	International Conference on Computer Vision	★ ICCV	58.00
7	International Conference on Machine Learning	★ ICML	56.00
8	Annual Conference on Neural Information Processing Systems	★ NIPS	51.00
9	Journal of Machine Learning Research	★ JMLR	49.00
10	Annual Meeting of the Association for Computational Linguistics	ACL	48.00
11	IEEE Transactions on Audio, Speech, and Language Processing	TASLP	46.00
12	Conference on Empirical Methods in Natural Language Processing	EMNLP	45.00
13	AAAI Conference on Artificial Intelligence	★ AAAI	44.00
14	IEEE Transactions on Fuzzy Systems	TFS	44.00
15	Decision Support Systems	DSS	43.00
16	Neurocomputing		39.00
17	IEEE Transactions on Evolutionary Computation	TEVC	38.00
18	Pattern Recognition Letters	PRL	37.00
19	Autonomous Agents and Multi-Agent Systems	AAMAS	36.00
20	International Joint Conference on Artificial Intelligence	★ IJCAI	35.00

<https://aminer.org/ranks/conf>

# Predicting Binding Specificity of RNA Constituents





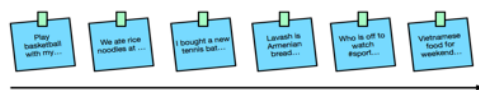
# Learn to Profile Users in Social Media



**Input:** A stream of tweets generated across the time

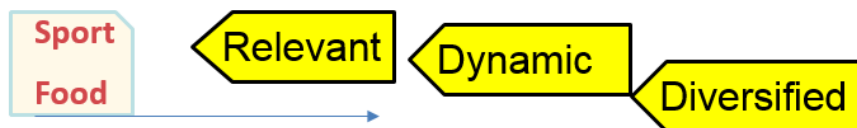


Twitter Users



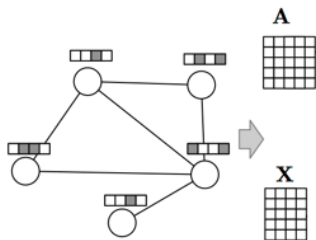
Tweets over time

**Output:** A set of **keywords** to profile the user at different point in time



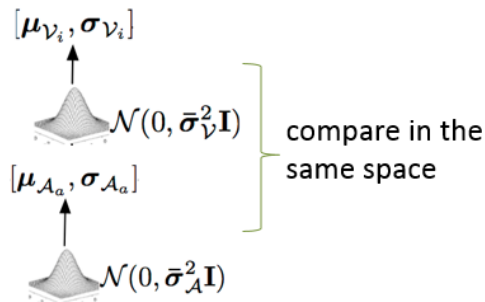
Tags over time

**Input:** Attributed Network  $G^t$



**Output:**

- **user** representation
- **attribute** (e.g., keyword) representation



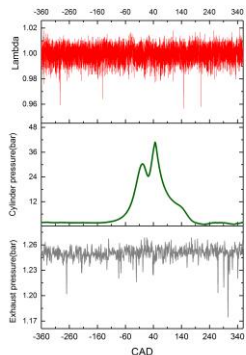
**Two papers published at**  
[SIGKDD 2018, WSDM 2019]

# Prediction of preignition events in spark ignited engines using deep learning

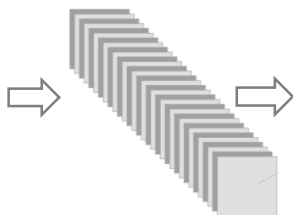


- Pre-ignition is defined as ignition of the fuel/air mixture prior to spark plug firing
- Highly stochastic event that can lead to engine destruction
- We developed a deep learning model to predict preignition early in the engine cycle to avoid damage.

Multivariate time-series data



Supervised Binary Classification Problem

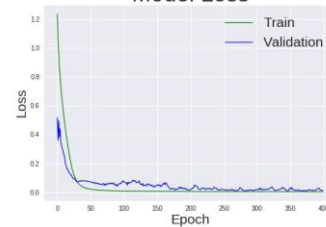


CNN layers

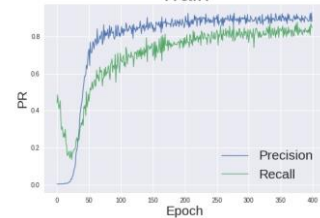
Hard  
Negative  
Mining

Output

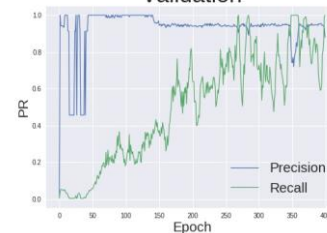
Model Loss



Train



Validation



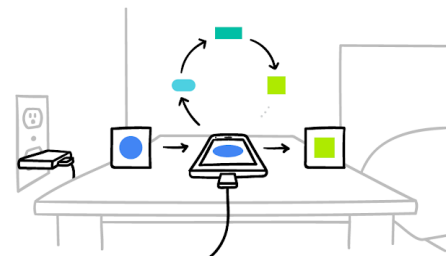
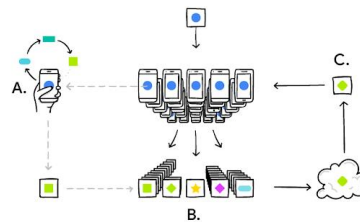
# Federated Learning

**TASK:** Train machine learning models on millions of mobile devices without sharing private data

Collaboration with 

Downloaded by 1bn+ Android users

Horizon 2020 call dedicated to FL



[Forbes](#)  
[The Verge](#)  
[Quartz](#)  
[TechRepublic](#)  
[ZDNet](#)  
[Computer Business Review](#)  
[Motherboard Vice](#)  
[Infoworld](#)  
[Silicon.co.uk](#)  
[Venturebeat](#)  
[Engadget](#)  
[Tech Narratives](#)  
[GadgetHacks](#)  
[BGR](#)  
[AndroidAuthority](#)  
[AndroidHeadlines](#)  
[Tom's Guide](#)  
[Digital Trends](#)  
[The Exponential View](#)  
[vvc4t](#)  
[9to5Google](#)

The CEO of Google, Sundar Pichai, said (May 2017):

“... We continue to set the pace in machine learning and AI research. We introduced a new technique for training deep neural networks on mobile devices called **Federated Learning**. This technique enables people to run a shared machine learning model, while keeping the underlying data stored locally on mobile phones...”

NIPS 2016

## FEDERATED LEARNING: STRATEGIES FOR IMPROVING COMMUNICATION EFFICIENCY

Jakob Konecny, H. Brendan McElhiney, Felix X. Yu, Anand Theerthi Suresh & David Bacon  
Google

Peter Richtarik  
School of Mathematics and Statistics, University of Edinburgh, Edinburgh, Scotland

### ABSTRACT

Federated Learning is a machine learning setting where the goal is to train a high-quality centralized model while training data remains distributed across a large number of clients each with unshareable and relatively slow network connections. We consider training algorithms for this setting where each round, each client locally optimizes an update to the central model based on its local data, and communicates this update to a central server, where the client-side updates are aggregated to compute a global model. The typical focus in this setting are model updates, and communication efficiency is of the utmost importance.

In this paper, we propose two ways to reduce the network communication cost: structured updates, where we directly share an update from a selected subset of parameters; and distributed updates, where we share a full model update and then compress it using a combination of quantization, randomization, and subsampling before sending it to the server. Subsequently, we both evaluate and compare these methods, where the proposed methods can reduce the communication cost by two orders of magnitude.

### 1 INTRODUCTION

As datasets grow larger and models more complex, training machine learning models increasingly requires distributing the optimization of model parameters over multiple machines. Existing machine learning algorithms are designed for highly centralized environments, such as data centers where the data is distributed among machines in a balanced and i.i.d. fashion, and high throughput networks are available.

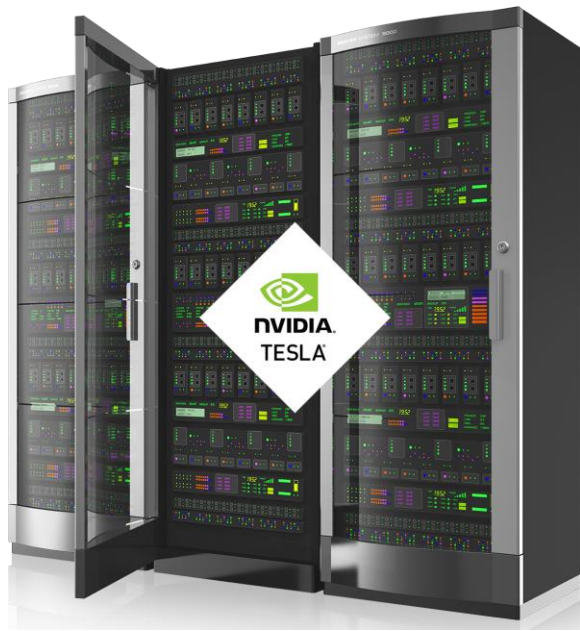
Recently, Federated Learning and related decentralized approaches (McElhiney & Bacon, 2017; Konecny et al., 2016; McElhiney et al., 2017; Suresh & Bacon, 2017) have been proposed as an alternative setting, a shared global model is trained under the coordination of a central server, from a collection of participating devices. The participating devices themselves are typically large, as devices are often slow to update network connections. A typical scenario is training of Federated Learning when the training data comes from users' interaction with mobile applications. Federated Learning enables mobile phones to collaboratively learn a shared predictive model while keeping all the training data on device, decoupling the ability to do machine learning from the need to store the data in the cloud. The training data is kept locally on users' mobile devices, and the devices do not need to make complicated connections to their local data in order to update a global model. This approach also has the advantage of making predictions on mobile devices, so keeping model training on the device also allows better control over confidential information.

Work performed while also affiliated with University of Edinburgh.

Train models right on the device.  
Better for everyone (individually.)

<https://ai.googleblog.com/2017/04/federated-learning-collaborative.html>

# Scale ML to 1000's of GPUs

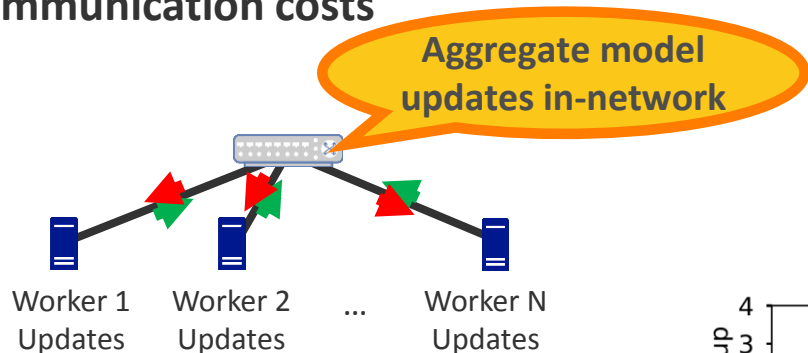


- Accelerate training
  - Minimize communication
  - Use very large mini-batch sizes
  - Split a single model in multiple GPUs
- Accelerate Serving (inference)
  - Many instances of the same model
  - Exploit common computation paths
- ML for scientific data

# Scaling Distributed ML with In-Network Aggregation



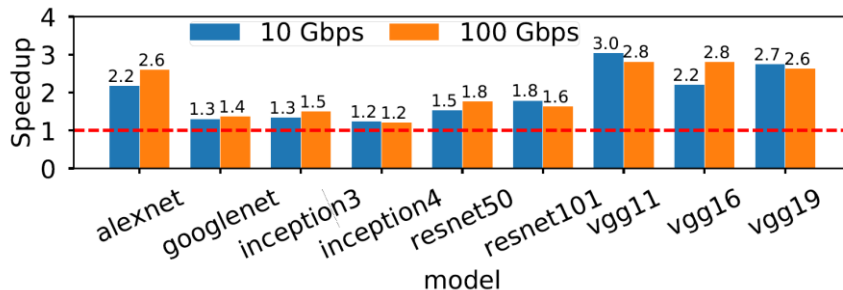
Distributed ML training scales poorly due to communication costs



Key idea: co-design ML and networking to maximize communication efficiency

Designed and built **SwitchML**

Workers stream model updates to a **6.4 Tbps programmable switch** that aggregates and redistributes combined parameters



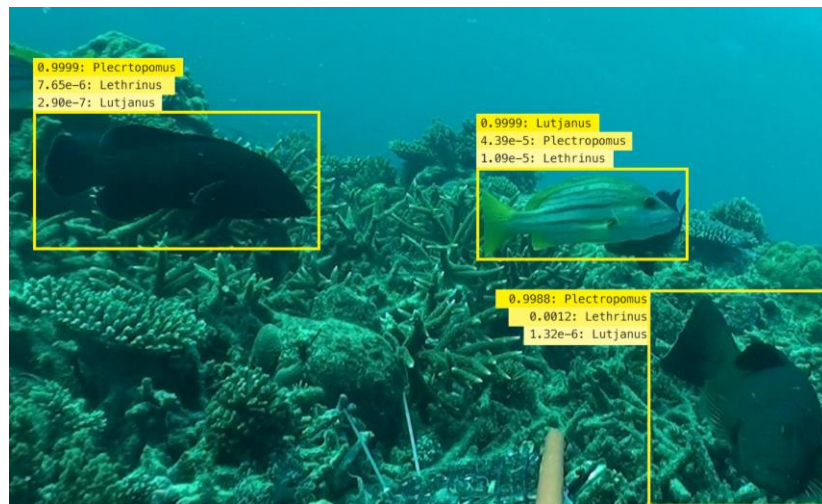
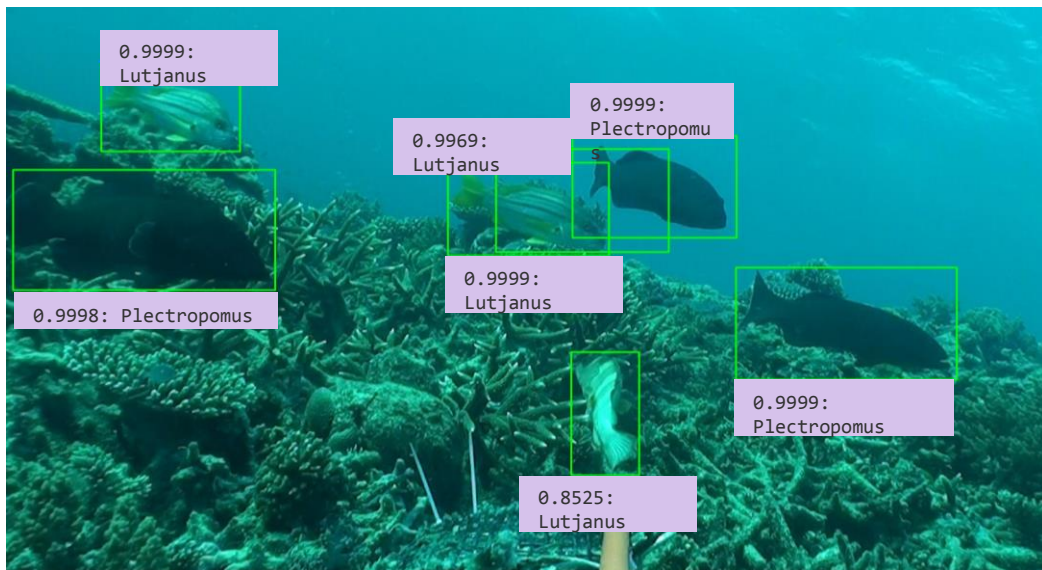
**SwitchML speeds up training by up to 300%**

A KAUST collaboration with





# Fish Species Classification Underwater

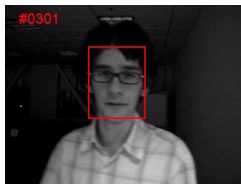


# Tools and Foundations for Understanding Images and Videos



## Video Understanding

- Activity Detection
- Efficient Search
- Object Tracking



**ACTIVITYNET**

## Vision for Automation

- Sim4CV
- Transfer Learning
- Applications

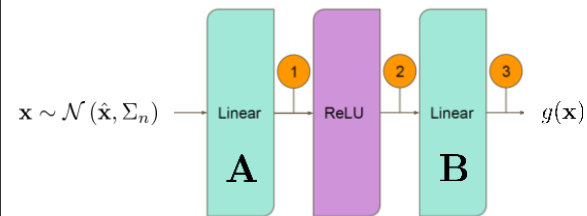
DRIVING



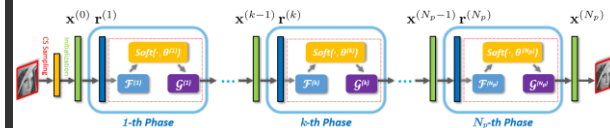
Our controller

## Fundamentals

- Optimization for CV&ML (sparse, low-rank, integer)
- Deep DNN Understanding



$$\min_{\mathbf{x}} f(\mathbf{x}) \quad \text{s.t. } \mathbf{x} \in \{1, -1\}^n; \mathbf{x} \in \Omega$$





# Large-Scale Activity Detection



HOME PEOPLE CHALLENGE PROGRAM DATES EVALUATION CONTACT



## Challenge Description

### Challenge Introduction

We are proud to announce that this year the challenge will host six diverse tasks which aim to push the limits of semantic visual understanding of videos as well as bridging visual content with human captions. These out of the seven tasks are based on the *ActivityNet* dataset, which was introduced in CVPR 2015 and organized hierarchically in a semantic taxonomy. These tasks focus on trace evidence of activities in time in the form of proposals, class labels, and captions.

In this installment of the challenge, we will host three guest tasks which enrich the understanding of visual information in videos. These tasks focus on complementary aspects of the activity recognition problem at large scale and involve challenging and recently compiled activity/action datasets, including *Kinetics* (Google DeepMind), *AVA* (Berkeley and Google), and *Moments in Time* (MIT and IBM Research).

### ActivityNet Tasks



TASK 1

#### Temporal Action Proposals (ActivityNet)

This task is intended to evaluate the ability of algorithms to generate high quality action proposals. The goal is to produce a set of candidate temporal segments that are likely to contain a human action.

DETAILS



TASK 2

#### Temporal Action Localization (ActivityNet)

This task is intended to evaluate the ability of algorithms to temporally localize activities in untrimmed video sequences. Here, videos can contain more than one activity instance, and multiple activity categories can appear in the video.

DETAILS



TASK 3

#### Dense-Captioning Events in Videos (ActivityNet Captions)

This task involves both detecting and describing events in a video. For this task, participants will use the ActivityNet Captions dataset, a new large-scale benchmark for dense-captioning events.

DETAILS

### Guest Tasks



TASK A

#### Trimmed Activity Recognition (Kinetics)

This task is intended to evaluate the ability of algorithms to recognize activities in trimmed video sequences. Here, videos contain a single activity, and all the clips have a standard duration of ten seconds. For this task, participants will use the Kinetics dataset, a large-scale benchmark for trimmed action classification.

DETAILS



TASK B

#### Spatio-temporal Action Localization (AVA)

This task is intended to evaluate the ability of algorithms to localize human actions in space and time. Each labeled video segment can contain multiple subjects, each performing potentially multiple actions. The goal is to identify these subjects and actions over continuous 15-minute video clips extracted from movies. For this task, participants will use the new AVA atomic visual actions dataset.

DETAILS



TASK C

#### Trimmed Event Recognition (Moments in Time)

This task is intended to evaluate the ability of algorithms to classify events in trimmed 3-second videos. Here, videos contain a single activity, and all clips have a standard duration of 3 seconds. There will be two tracks. The first track will use the Moments in Time dataset, a new large-scale dataset for video understanding, which has 800K videos in the training set. For the second track, participants will use the Moments in Time Mini dataset, a subset of Moments in Time with 100K videos provided in the training set.

DETAILS



pole vault



diving



washing dishes



baseball throw



Key  
Detection  
Ground-truth  
Time

(Background  
is sped up)

Sponsors:  DeepMind  Google AI

facebook

ActivityNet: A Large-Scale Video Benchmark for Human Activity Understanding [CVPR'15] [Google Faculty Research Award (only one from SA)]

# Natural Genomics Circuits - are complicated - we explore foundational research on Machine Intelligence and Causal Reasoning to facilitate Scientific Discoveries from our Single-Cell Genomics Experiments



[Home](#) > [News](#) > Developing an AI system that thinks like a scientist

## Developing an AI system that thinks like a scientist

Feb 03, 2019 Research



EMAIL



FACEBOOK




LINKEDIN




TWITTER





nature  
machine intelligence

nature video  
Publicerad den 7 jan. 2019

Causal Deconvolution by Algorithmic Generative Models  
Hector Zenil, Narsis A. Kiani, Allan A. Zea and Jesper Tegnér  
Nature Machine Intelligence, January 7th 2019

  
LEARN MORE

  
WATCH MORE



Remodelling machine learning: An AI that thinks like a scientist

- **Technically: Approximating uncomputable Mathematics, in a Church-Turing sense, to create an ORACLE**

- <https://github.com/allgebrist/Causal-Deconvolution-of-Networks/>
- <https://www.youtube.com/watch?v=rkmz7DAA-f8&feature=youtu.be>

# 1 Strategic Goal – RESEARCH

"It is my desire that KAUST becomes one of the world's great institutions of research." King Abdullah

## Update of our Pillars

WATER



ENVIRONMENT



ENERGY



FOOD / HEALTH



DIGITAL



## Where we are

Recognized as a rich international University with high quality faculty and facilities

- High quality faculty (9 Highly Cited Researchers)
- High impact (Mat Sci, Chemistry, Biology, Energy...)
- Strong, stable research budget
- High level of external grants (e.g. Gates Found.)
- Top facilities (Core Labs & equipment)
- High quality research staff

## Opportunities/Challenges

Evolving environment: science & KSA

- Catalyzing KSA economy
- Aligning with national priorities, e.g. Vision 2030, knowledge economy
- Complacency, risk averse?
- Clarifying funding models & strategies

## STRATEGIC INITIATIVES

- 1.1 New research priorities (AI/ML, cybersecurity, robotics) through (cluster) faculty hires, new centers and new partnerships
- 1.2 Identification of additional priority areas based on global trends, subcritical strength, cross-cutting, chances to excel
- 1.3 Additional pillars: Food / Health – emerging scientific trend and national demand  
Digital – great opportunities & cross-cutting
- 1.4 Review of Research Centers: role, structure, creation, sunset, new \$ for IED activities
- 1.5 Review of funding modalities: baseline, internal competitive grants, Centers

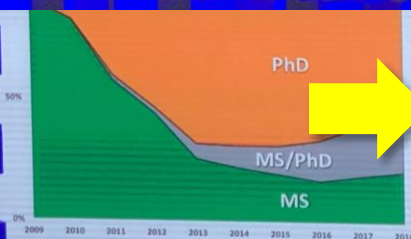
...entists, engineers and technologists."

King Abdullah

## Opportunities/Challenges

Entrepreneurship below potential  
Adapt to Saudi job market

- Gap between Saudi job market and our offerings
- Missing out on online platform
- Need more entrepreneurship, management, and soft skills
- Not fully a 21<sup>st</sup> century digital univ.



- 2.1 Require exposure to innovation & entrepreneurship of all students
- 2.2 New Division/Institute on Innovation and Entrepreneurship – future Business School?
- 2.3 New degrees/Prof Masters/MOOCs (AI, Data Sci, Cybersecurity, Bio-Eng, HealthTech...)
- 2.4 Create a Center for Teaching & Learning (to improve pedagogy for faculty & future grads)
- 2.5 Establish undergrad partnership/joint degrees with other Saudi institutions?

# The ML Hub Offerings

## One-stop-shop for AI/ML on campus

- regular seminars and activities
  - invited speakers (academic & industry)
  - new research and trends in the areas
  - participation events (e.g. hackathon)



# The ML Hub Offerings

## One-stop-shop for AI/ML on campus

- network of AI/ML enthusiasts and experts
  - mentorship and consulting
  - brainstorming and collaboration
  - vehicle for disseminating information (e.g. news, research, job opportunities, etc.)

# The ML Hub Offerings

## One-stop-shop for AI/ML on campus

- hands-on tutorials and workshops
  - practical starters
  - various levels of AI/ML competence and use
  - hardware and software awareness

# The ML Hub Offerings

## One-stop-shop for AI/ML on campus

- the AI/ML KAUST window to the world
  - aggregation of our work in the field
  - showcase our growing position in these areas



# What's coming up next?

- **Sci-Café: AI**
  - February 20<sup>th</sup>
- **Hub Seminar (Prof. Zheng Qu, HKU)**
  - March 20<sup>th</sup>

# The Machine Learning Hub

## ML @ KAUST



**Webpage:** [ml.kaust.edu.sa](http://ml.kaust.edu.sa)

**Twitter:** @kaustMLhub

**Slack:** [the-ml-hub.slack.com](https://the-ml-hub.slack.com)