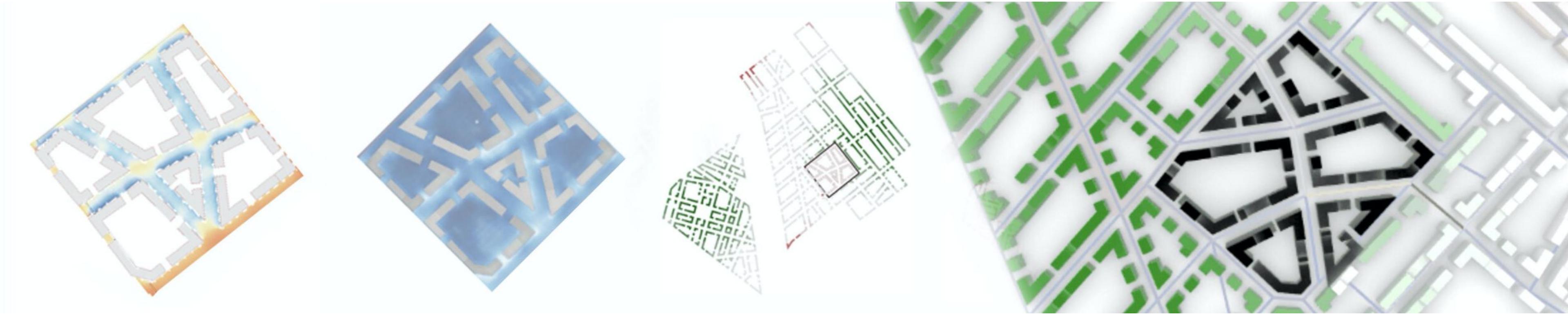
Artificial Intelligence for resilient urban planning



Team

Angelos Chronis

Nariddh Khean

Serjoscha Düring

Diellza Elshani

CIL CITY INTELLIGENCE LAB

Introduction & Workshop structure

CIL CITY INTELLIGENCE LAB

Workshop structure

What is a Hackathon?

A guiding topic and technologies

Brainstorming & Idea finding

Pitch your ideas!

Team up around pitches!

HACK!*

Present your project to the world**!

*project and prototype development **workshop

Workshop structure

What is a Hack?

A prototype of a digital solution for a well defined problem In the realm of urban planning or the AEC industry

Workshop structure

What is a Hack?

An online platform for...

An App for..

A grasshopper plugin for

A tool that uses dimensionality reduction and clustering to communicate results and trade-offs associated to urban performance simulation

Using ML to speed up the optimal placement of amenities

Use ML agents to plan walk-ways that anticipate shortcut behavior

Use RL to find the right trade-off between lock-down measures and damage to local economy

A prototype of a digital solution for a well defined problem In the realm of urban planning or the AEC industry

Microclimate simulations are too slow!

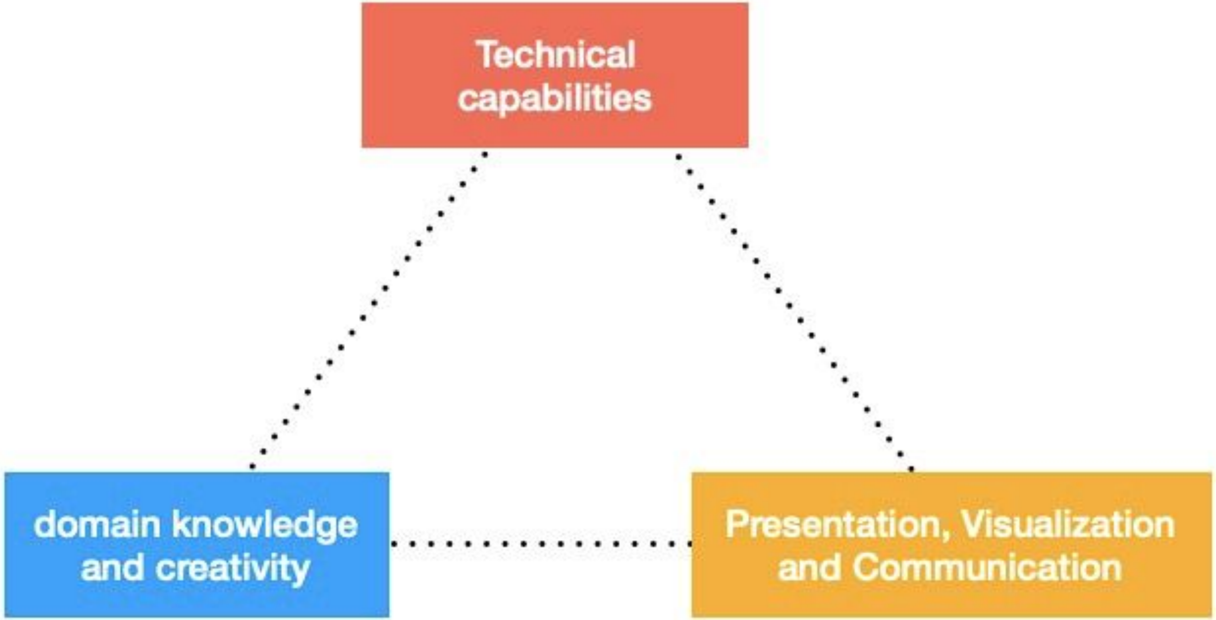
Citizens don't understand the complexity of urban pans

Results of multi-objective optimization processes are too complicated to read

How can we rapidly test different urban morphology types for a site?

Workshop structure

Teaming up



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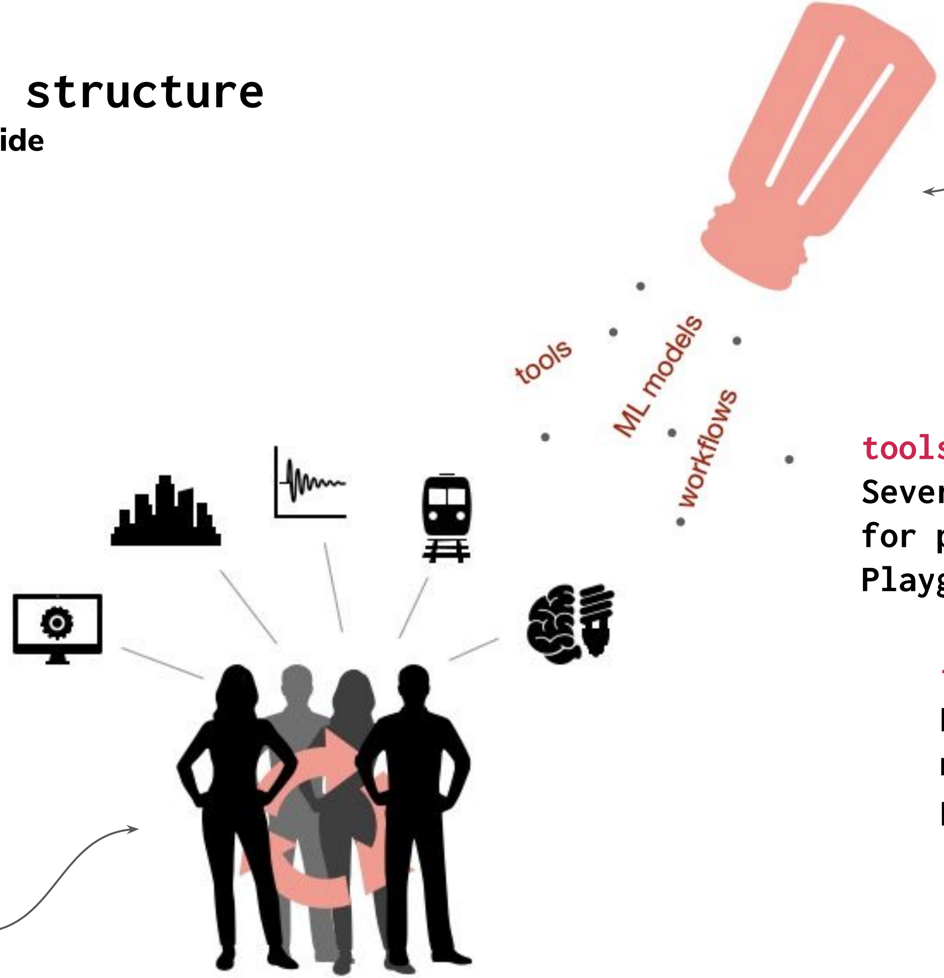
Workshop structure

What we provide



workshop

you

Inputs and lectures

Lectures on AI, ML and their application within the AEC Industry

tools & data

Several ML models and workflows for python and Grasshopper + Playground city model

topic

Develop prototypes of tools and methods to improve urban planning and design practice

Workshop structure

What we expect

Cool projects

With creative implementation of AI algorithms fused with the expertise coming from within your teams

Scope of project

- Projects should be doable in within the given timeframe.
- They can be focused on very particular problems.
- The use and integration of ML in workflows is the focus of the workshop

Active participation, teamwork and fun

- Exchange and communicate through Slack, Zoom, Google Drive, Miro etc.

Strong final presentation

Workshop structure
Schedule

Day 1 (Sun 28th)

Name
Talk: Intro
Exercise: Ice Breaker
Talk: Intro to CIL
Talk: Intro to AI
Break
Talk: Workshop Topics and Tools
Break
Exercise: Group Forming

Day 2 (Mon 29th)

Name
Talk: Intro
Talk: Intro to Computer Vision
Demo: Semantic Segmentation
Demo: Style Transfer
Demo: pix2pix in GH
Demo: DQL in GH
Talk: Summary
Break
Exercise: Project Work
Presentation: Refined Pitches

Day 3 (Wed 1st)

Name
Talk: Intro
Talk: Visualisation Techniques
Exercise: Project Work
Presentation: Sitreps

Day 4 (Fri 3rd)

Name
Presentations
Official Close
Break
Open Discussion (Optional)

Workshop structure
Schedule

Day 1 (Sun 28th)

Name	Room	Time (GMT)	Description
Talk: Intro	Webinar	10:00 - 10:15	The workshop structure, introduction to Hackathons, expectations and deliverables
Exercise: Ice Breaker	Webinar	10:15 - 10:45	"A picture a person"
Talk: Intro to CIL	Webinar	10:45 - 11:00	Who we are and what we do
Talk: Intro to AI	Webinar	11:00 - 11:45	Scope, history, heuristics
Break	break	11:45 - 11:55	-
Talk: Workshop Topics and Tools	Webinar	11:55 - 12:40	ML Models, sample problems, playground city model
Break	break	12:40 - 12:45	-
Exercise: Group Forming	Meeting	12:45 - 14:00	Brainstorming, algorithmic groups, idea finding and pitching

Introduction to AI

Introduction to ~~AI~~ ML

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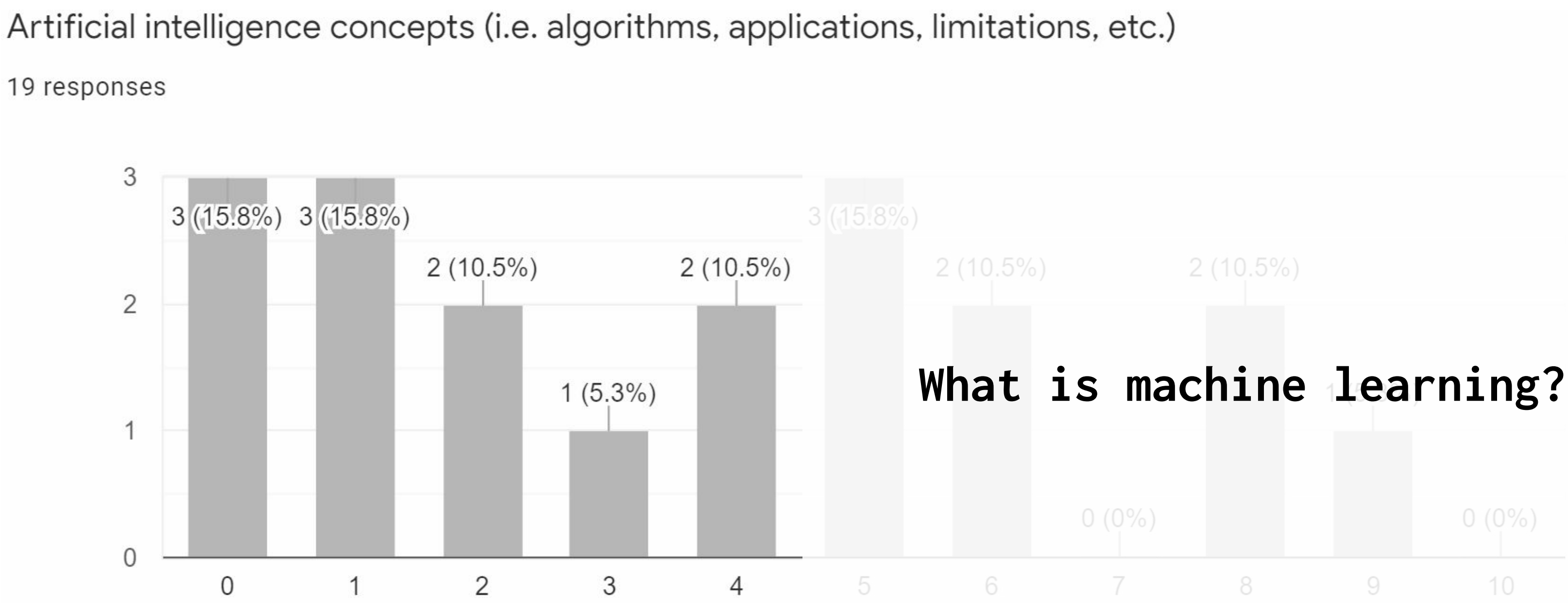
Fundamentals of Machine Learning

NOT EVERYONE CAN BE A 9



What is machine learning?

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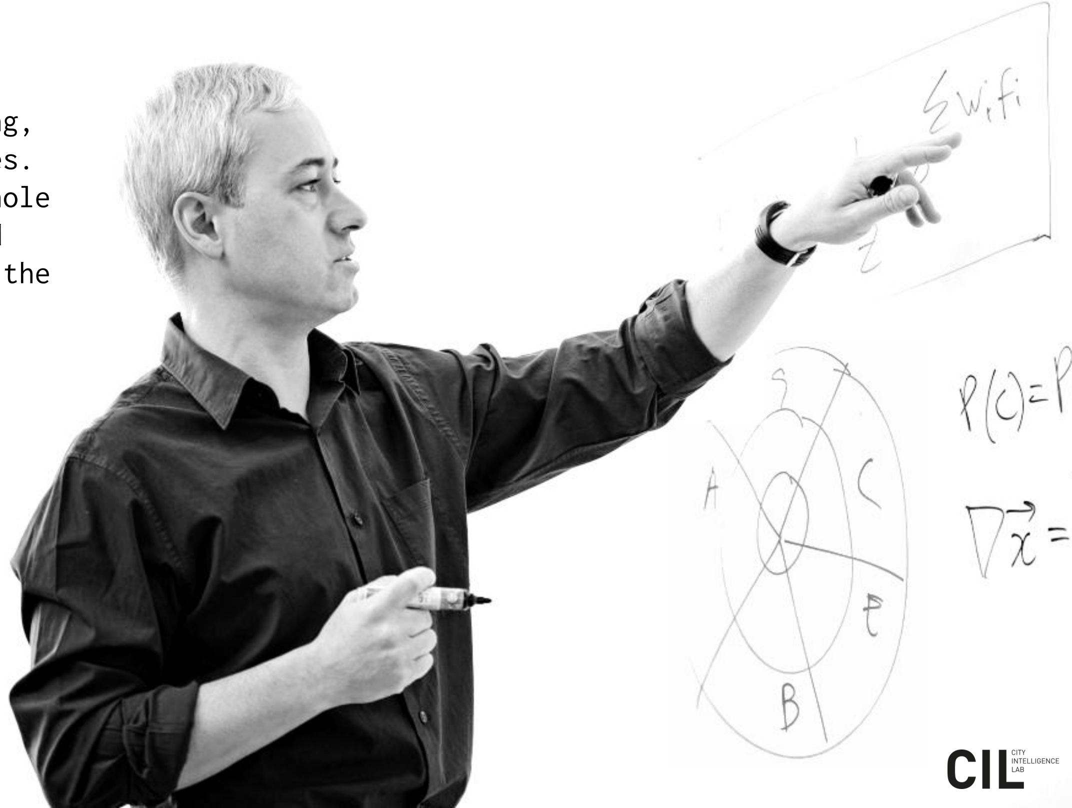
Fundamentals of Machine Learning
THREE SCHOOLS ACROSS FIVE TRIBES

**“Machine learning is the scientific method...
... on steroids.”**

“... It follows the same process of generating, testing, and discarding or refining hypotheses. But while a scientist may spend his or her whole life coming up with and testing a few hundred hypotheses, a machine learning system can do the same in a fraction of a second..."

“Machine learning automates discovery.”

[3]



Fundamentals of Machine Learning

THREE SCHOOLS ACROSS FIVE TRIBES

multi-instance learning

semi-supervised learning

self-supervised learning

supervised learning

unsupervised learning

multi-task learning

reinforcement learning

inductive learning

active learning

online learning

deductive learning

ensemble learning

transfer learning

transductive learning

Fundamentals of Machine Learning
THREE SCHOOLS ACROSS FIVE TRIBES

*Supervised learning is the machine learning task of learning a function that **maps an input to an output** based on example input-output pairs.*

*Unsupervised learning is a type of machine learning that **looks for previously undetected patterns** in a data set with no pre-existing labels and with a minimum of human supervision.*

supervised learning

unsupervised learning

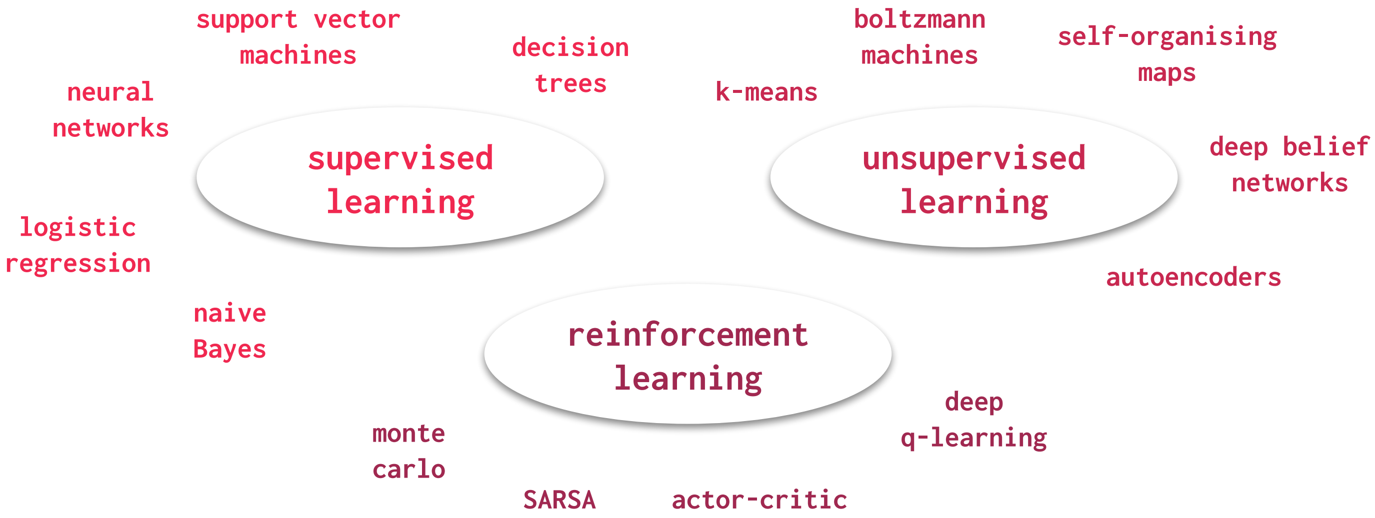
reinforcement learning

*Reinforcement learning is an area of machine learning concerned with **how software agents ought to take actions in an environment** in order to maximize the notion of cumulative reward.*

[5, 6, 7]

Fundamentals of Machine Learning

THREE SCHOOLS ACROSS FIVE TRIBES



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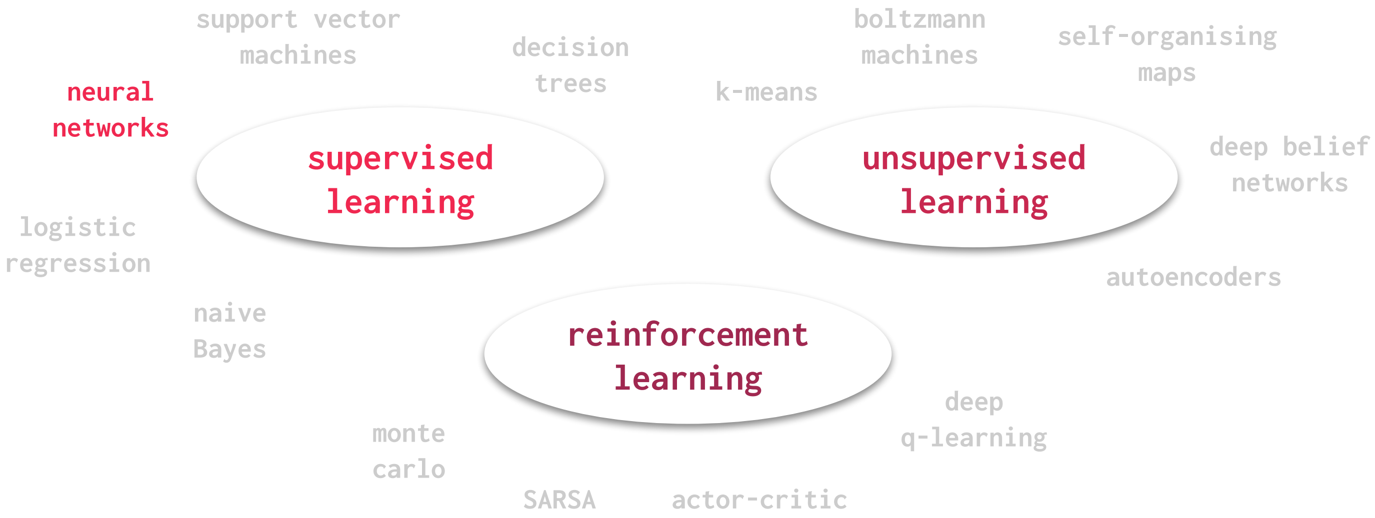
THREE SCHOOLS ACROSS FIVE TRIBES



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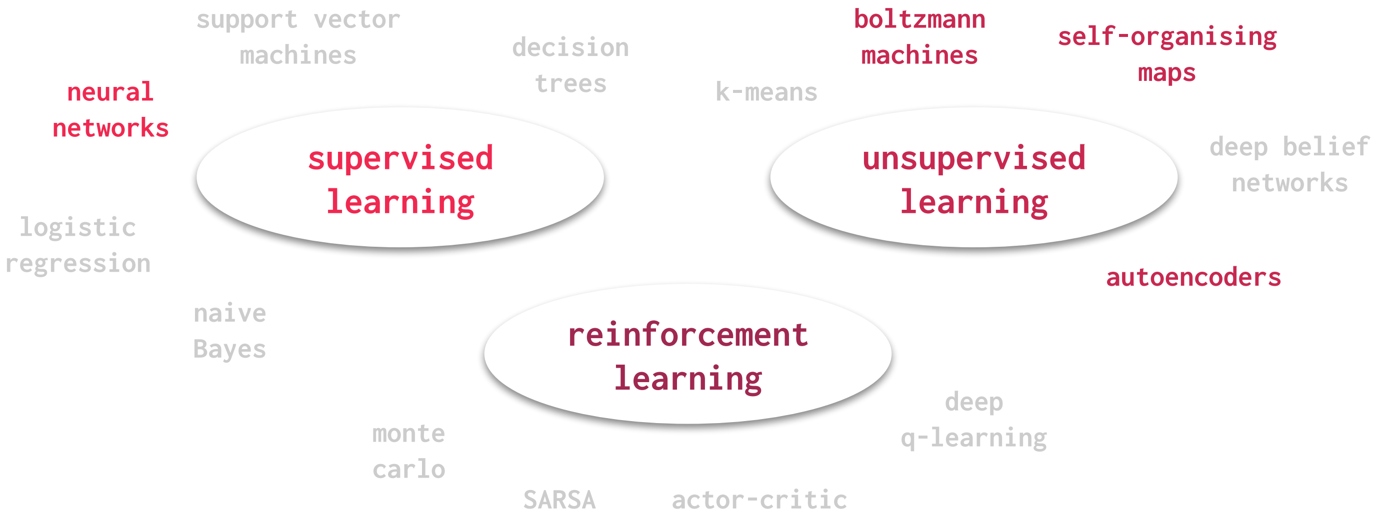
Fundamentals of Machine Learning
THREE SCHOOLS ACROSS FIVE TRIBES



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Fundamentals of Machine Learning

THREE SCHOOLS ACROSS FIVE TRIBES

multi-instance learning

Supervised learning is the machine learning task of learning a function that ***maps an input*** *...* ***output*** *based on example input-output pa...*

Unsupe... ...ning is a type of machine ... that ... ...iously undetected ... pre-existing ... human supervision.

semi-supervised learning

self-supervised learning

support vector machines

decision trees

k-means

maps

neural networks

supervised learning

unsupervised learning

deep belief networks

logistic regression

multi-task learning

naive Bayes

autoencoders

reinforcement learning

inductive learning

active learning

online learning

deep q-learning

deductive learning

monte carlo

SARSA

actor-critic

ensemble learning

transductive learning

transfer learning

... learning is an area of machine ... concerned with ***how software agents*** *...* ***actions in an environment*** *in order to maximize the notion of cumulative reward.*

Fundamentals of Machine Learning
THREE SCHOOLS ACROSS FIVE TRIBES

finding correlation
between input and output

supervised learning

discovering patterns
between different inputs

unsupervised learning

reinforcement learning

developing behaviour of
agent in environment

Fundamentals of Machine Learning

THREE SCHOOLS ACROSS FIVE TRIBES

1. I have a dataset, where each building in a city is a datapoint. For each datapoint, there is information such as building height, GFA, architect, building use, cost to build, and so on. My objective: find similar buildings to one specific building. Which school of machine learning should I use?

supervised learning

unsupervised learning

reinforcement learning

Fundamentals of Machine Learning

THREE SCHOOLS ACROSS FIVE TRIBES

2. I want to give control of a smart building to an algorithm, so that it can intelligently control the air conditioning and the windows. That said, I will still allow the occupants of the building to take control and go against the algorithm if they see fit. I don’t have any data, but will place sensors around to collect data overtime, and also record the actions of occupants in relation to the sensed data. Which school of machine learning should I use?

supervised learning

unsupervised learning

reinforcement learning

Fundamentals of Machine Learning

THREE SCHOOLS ACROSS FIVE TRIBES

3. I want to measure the occupancy of an office's bathroom, as well as making sure that there is no graffiti and other illicit activities happening in the place of privacy. I want to use camera footage and image recognition to classify what the user is doing inside the stall. Which school of machine learning should I use?

supervised learning

unsupervised learning

reinforcement learning

Fundamentals of Machine Learning

THREE SCHOOLS ACROSS FIVE TRIBES

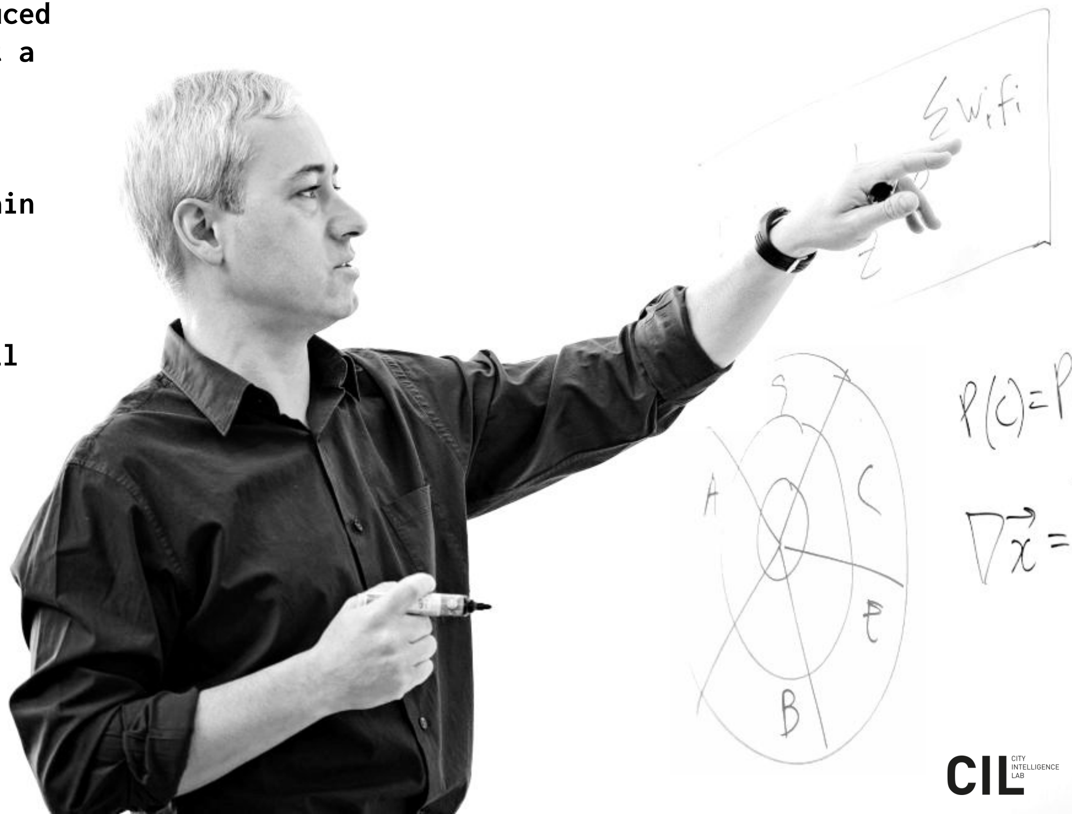
“For symbolists, all intelligence can be reduced to manipulating symbols, in the same way that a mathematician solves equations by replace expressions with other expressions.

“For connectionists, learning is what the brain does, and so what we need to do is reverse engineer it.

“Evolutionaries believe that the mother of all learning is natural selection.

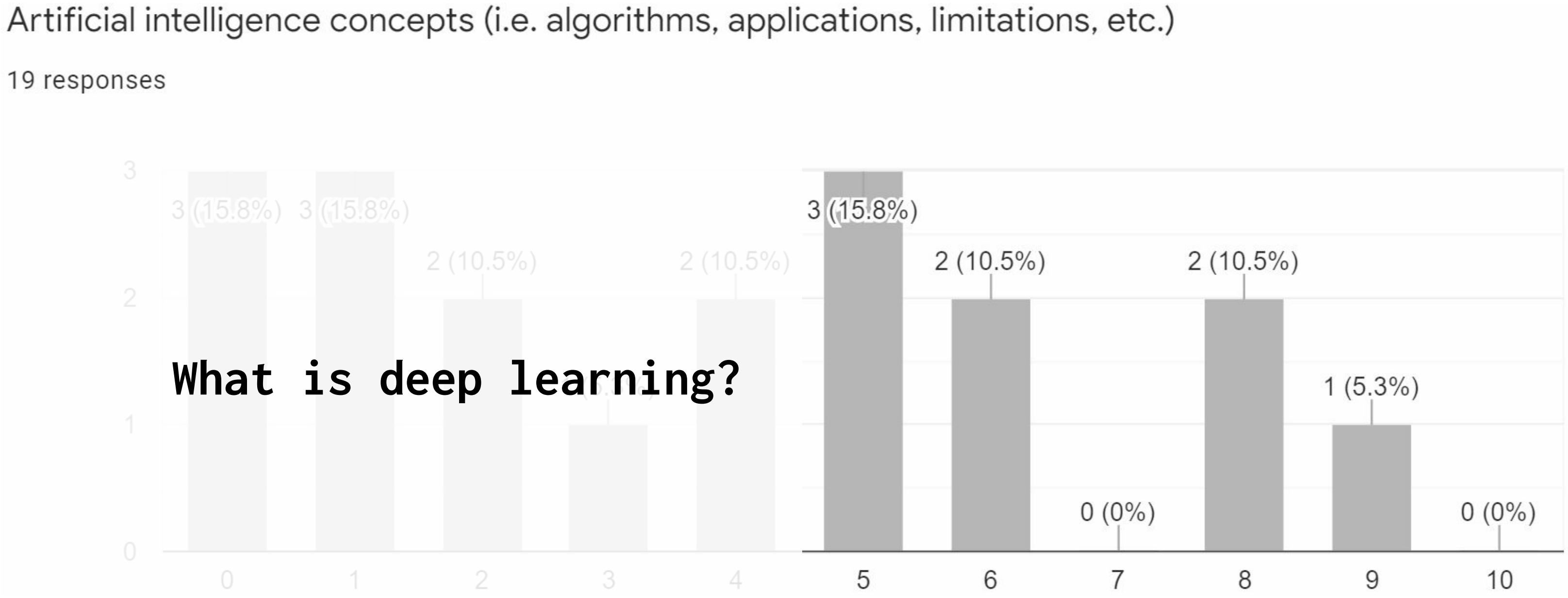
“Bayesians are concerned above all with uncertainty.

“For analogisers, the key to learning is recognizing similarities between situations and thereby inferring other similarities.”



Fundamentals of Machine Learning

MACHINE VS DEEP LEARNING



What is deep learning?

Fundamentals of Machine Learning

TRIUMPHS OF DEEP LEARNING

1943: Neural Networks

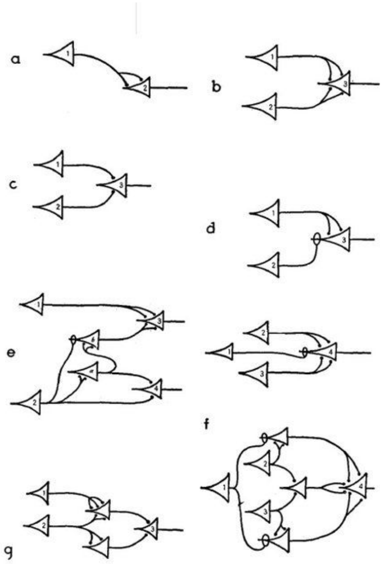
BULLETIN OF
MATHEMATICAL BIOPHYSICS
VOLUME 5, 1943

A LOGICAL CALCULUS OF THE IDEAS IMMANENT IN NERVOUS ACTIVITY

WARREN S. MCCULLOCH AND WALTER PITTS

FROM THE UNIVERSITY OF ILLINOIS, COLLEGE OF MEDICINE, DEPARTMENT OF PSYCHIATRY AT THE ILLINOIS NEUROPSYCHIATRIC INSTITUTE, AND THE UNIVERSITY OF CHICAGO

Because of the "all-or-none" character of nervous activity, neural events and the relations among them can be treated by means of propositional logic. It is found that the behavior of every net can be described in these terms, with the addition of more complicated logical means for nets containing circles; and that for any logical expression satisfying certain conditions, one can find a net behaving in the fashion it describes. It is shown that many particular choices among possible neurophysiological assumptions are equivalent, in the sense that for every net behaving under one assumption, there exists another net which behaves under the other and gives the same results, although perhaps not in the same time. Various applications of the calculus are discussed.



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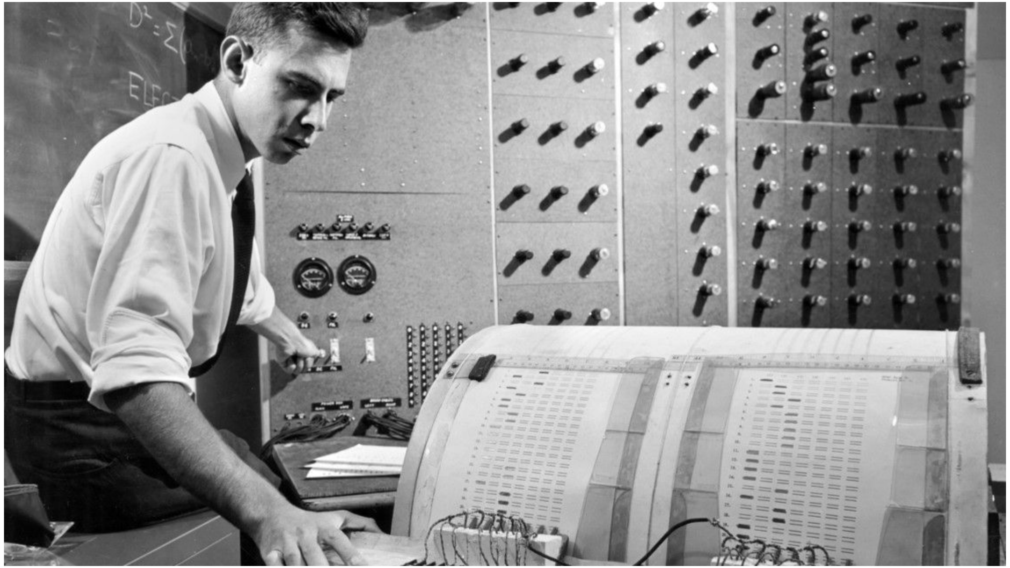
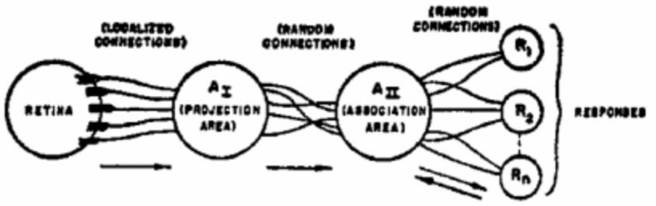
TRIUMPHS OF DEEP LEARNING

1957-62: Perceptrons





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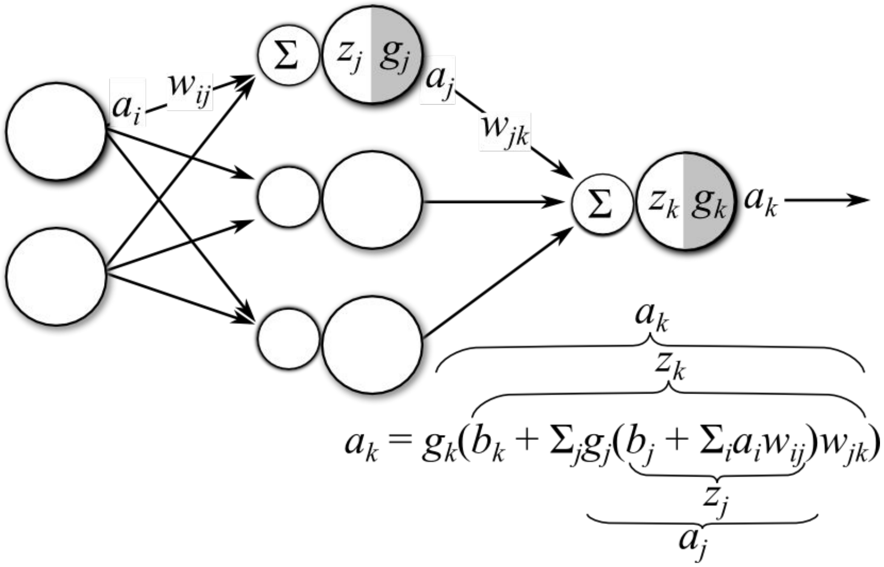
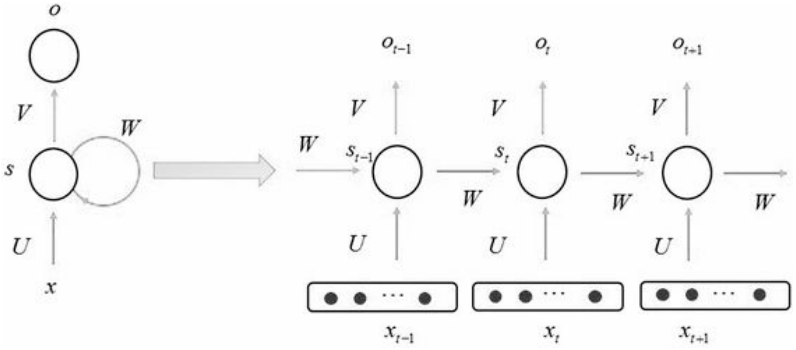
TRIUMPHS OF DEEP LEARNING

1970-86: Backpropagation and Recurrent Neural Networks (RNN)





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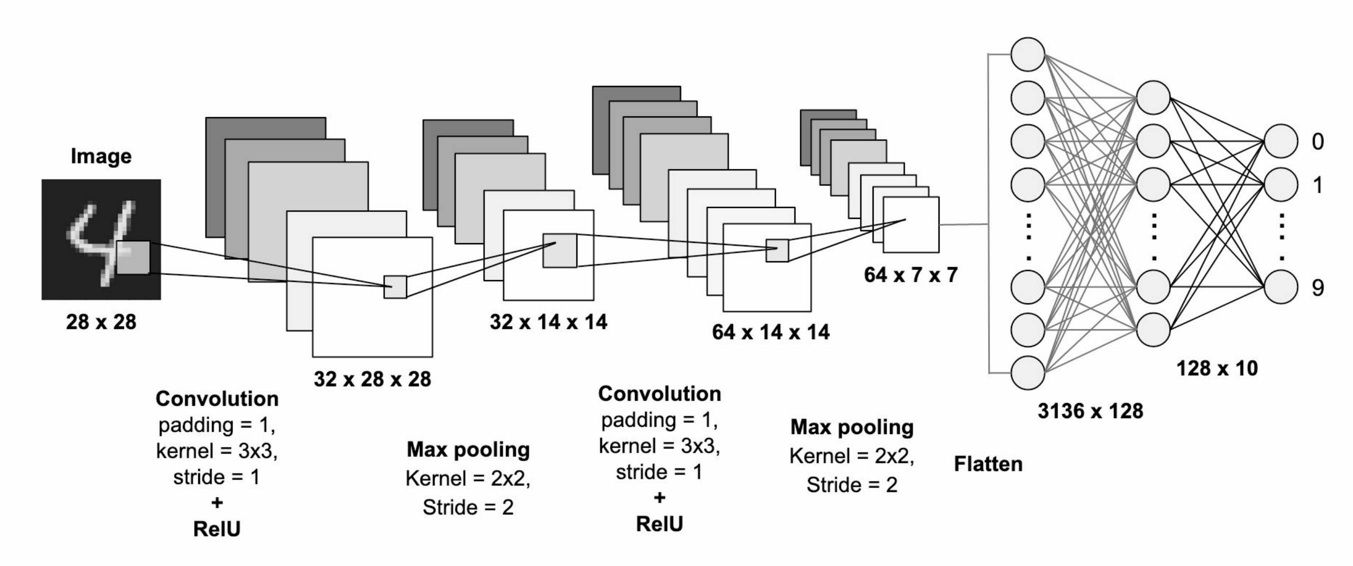
TRIUMPHS OF DEEP LEARNING

1979-98: Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM)



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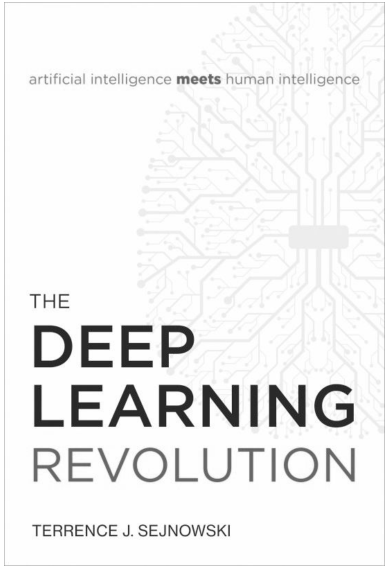
TRIUMPHS OF DEEP LEARNING

2006: “Deep Learning”



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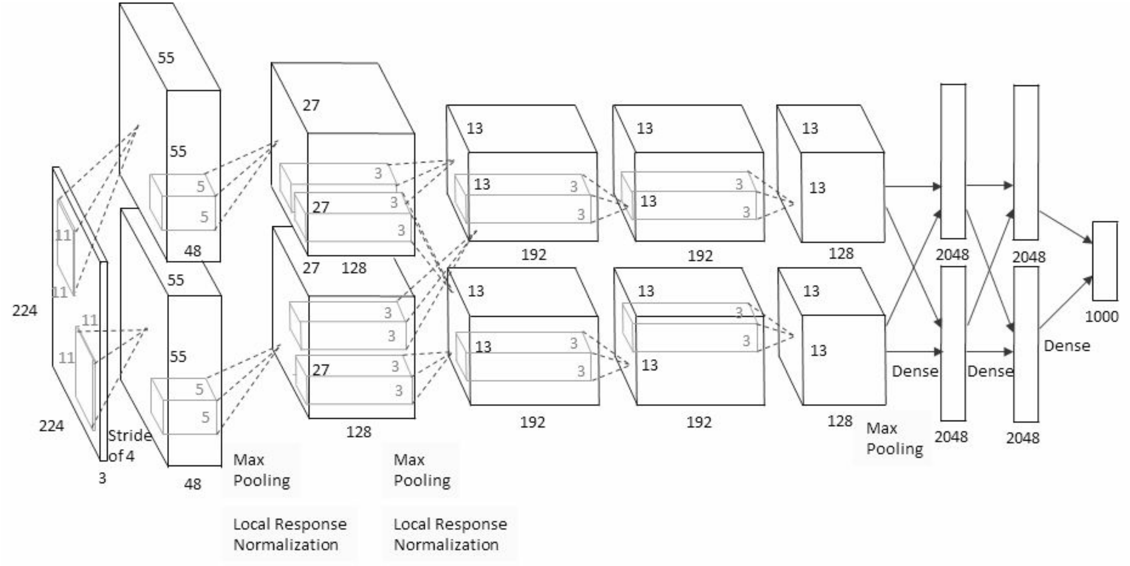
TRIUMPHS OF DEEP LEARNING

2009: ImageNet and AlexNet



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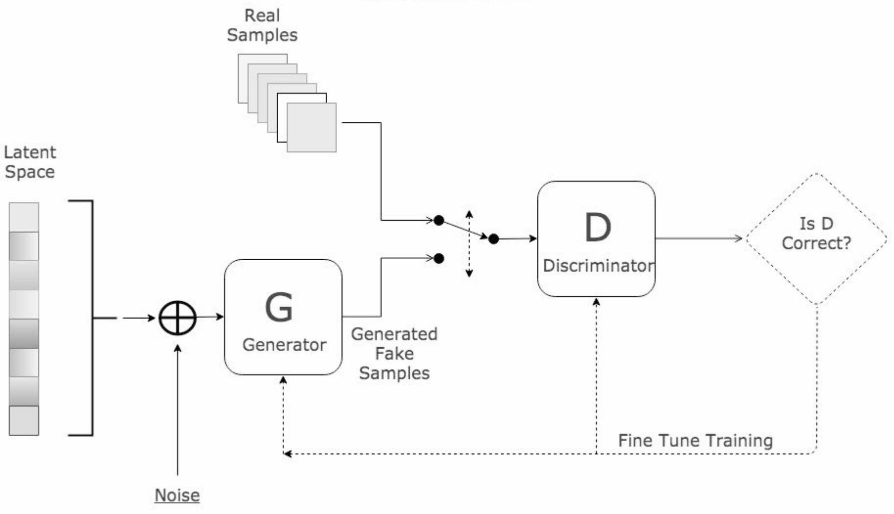
TRIUMPHS OF DEEP LEARNING

2014: Generative Adversarial Networks (GAN)



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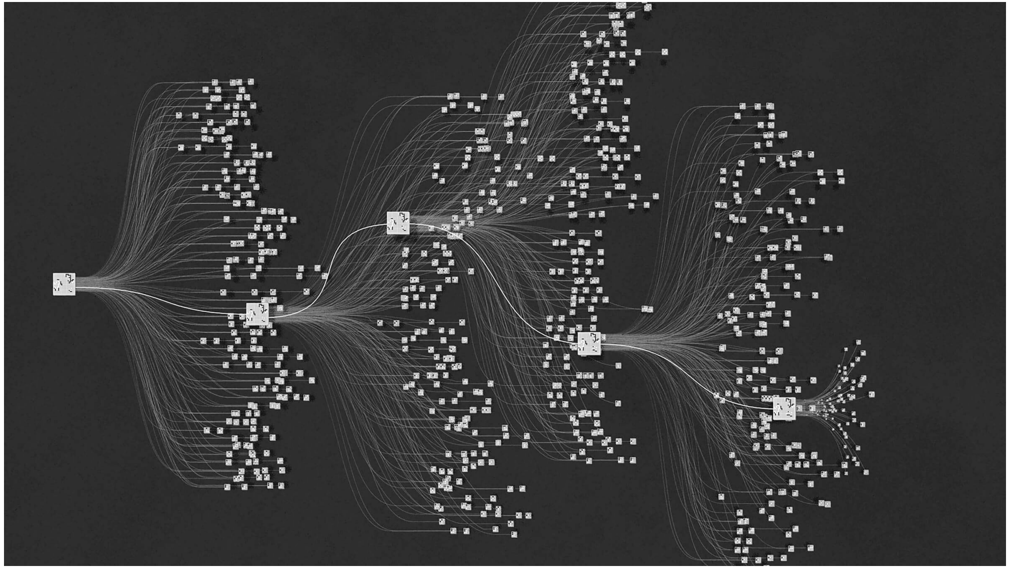
TRIUMPHS OF DEEP LEARNING

2016-17: Reinforcement Learning and AlphaGo



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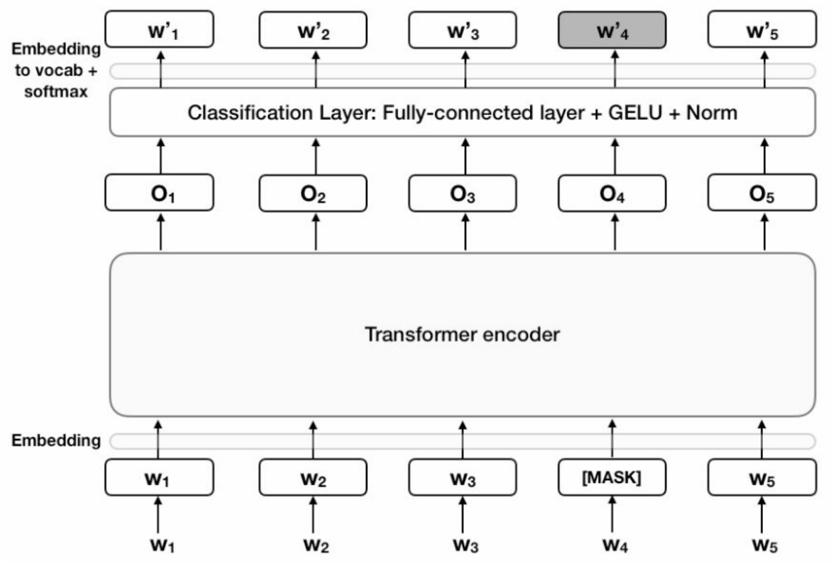
TRIUMPHS OF DEEP LEARNING

2017-19: Transformers and Bidirectional Encoder Representations from Transformers (BERT)



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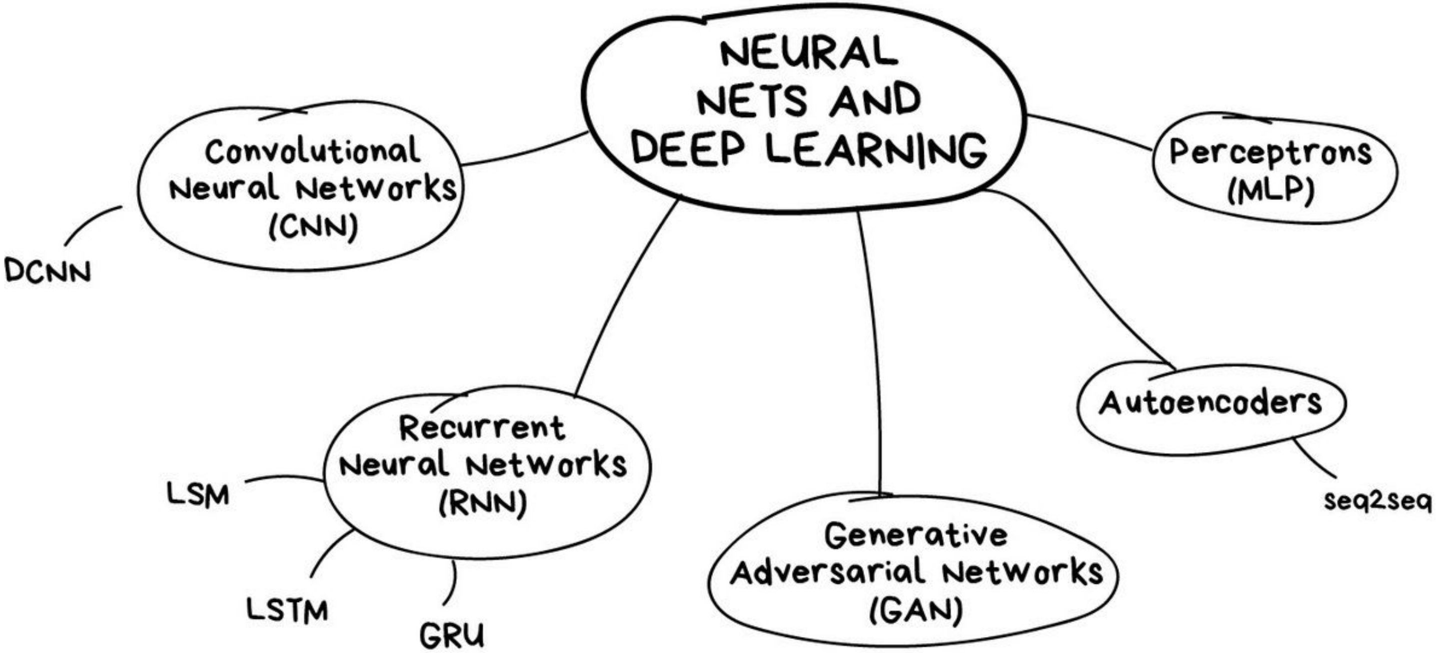
KEY DEEP LEARNING METHODS



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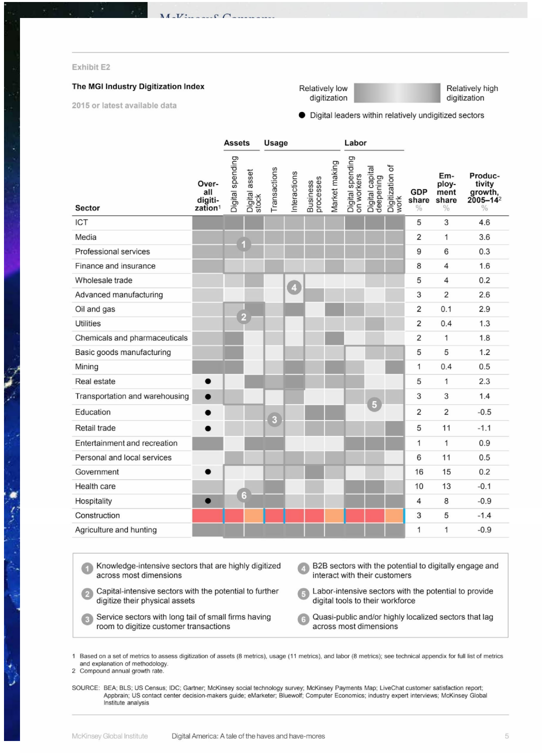
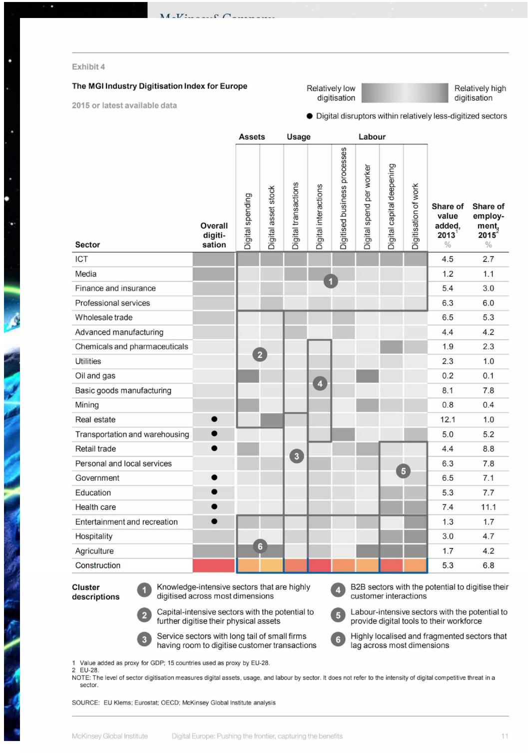
DEEP LEARNING IN THE BUILT ENVIRONMENT





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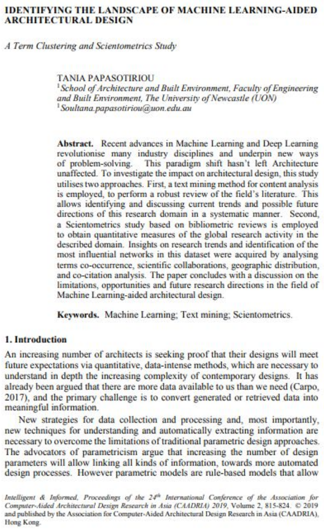


IDENTIFYING THE LANDSCAPE OF MACHINE LEARNING-AIDED ARCHITECTURAL DESIGN

A Term Clustering and Scientometrics Study

TANIA PAPASOTIRIOU
[1]*School of Architecture and Built Environment, Faculty of Engineering and Built Environment, The University of Newcastle (UON)*
[1]*Soultana.papasotiriou@uon.edu.au*

Abstract. Recent advances in Machine Learning and Deep Learning revolutionise many industry disciplines and underpin new ways of problem-solving. This paradigm shift hasn't left Architecture unaffected. To investigate the impact on architectural design, this study utilises two approaches. First, a text mining method for content analysis is employed, to perform a robust review of the field's literature. This allows identifying and discussing current trends and possible future directions of this research domain in a systematic manner. Second, a Scientometrics study based on bibliometric reviews is employed to obtain quantitative measures of the global research activity in the described domain. Insights on research trends and identification of the most influential networks in this dataset were acquired by analysing terms co-occurrence, scientific collaborations, geographic distribution, and co-citation analysis. The paper concludes with a discussion on the limitations, opportunities and future research directions in the field of Machine Learning-aided architectural design.

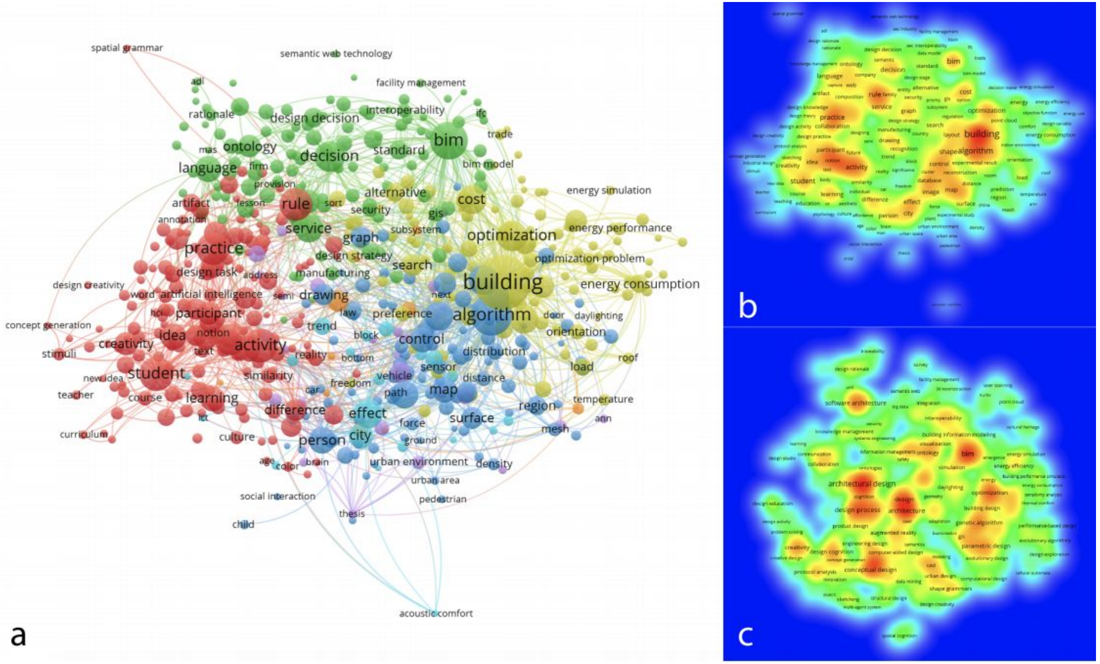
Keywords. Machine Learning; Text mining; Scientometrics.

1. Introduction

An increasing number of architects is seeking proof that their designs will meet future expectations via quantitative, data-intense methods, which are necessary to understand in depth the increasing complexity of contemporary designs. It has already been argued that there are more data available to us than we need (Carpo, 2017), and the primary challenge is to convert generated or retrieved data into meaningful information.

New strategies for data collection and processing and, most importantly, new techniques for understanding and automatically extracting information are necessary to overcome the limitations of traditional parametric design approaches. The advocators of parametricism argue that increasing the number of design parameters will allow linking all kinds of information, towards more automated design processes. However parametric models are rule-based models that allow

Intelligent & Informed, Proceedings of the 24th International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA) 2019, Volume 2, 815-824. © 2019 and published by the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA), Hong Kong.



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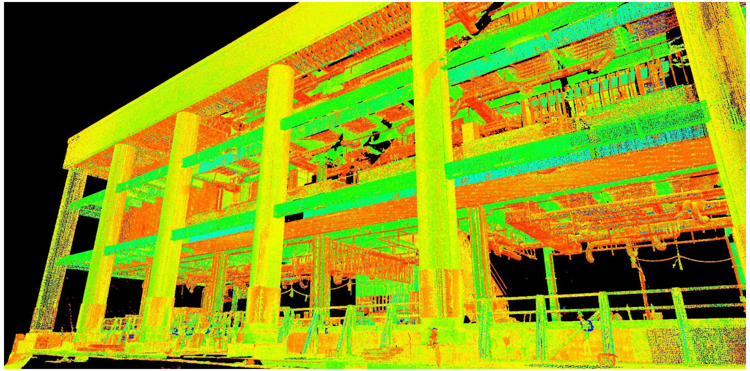

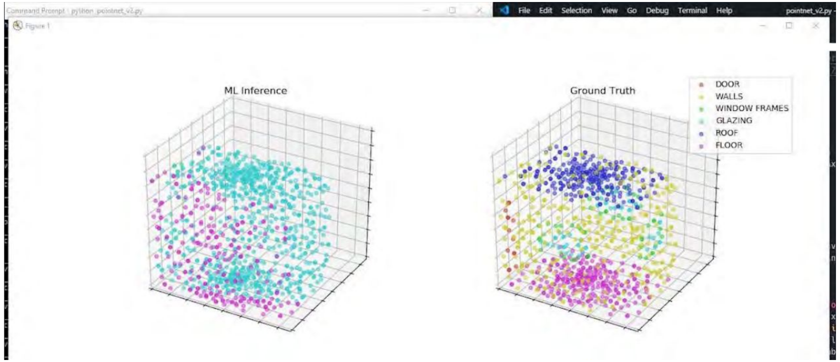

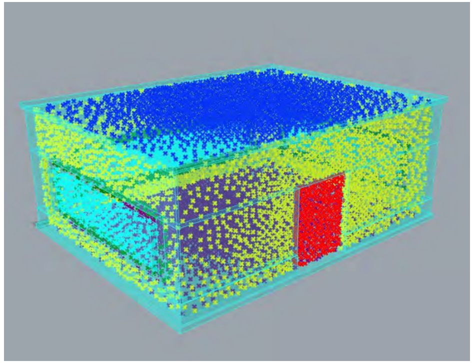

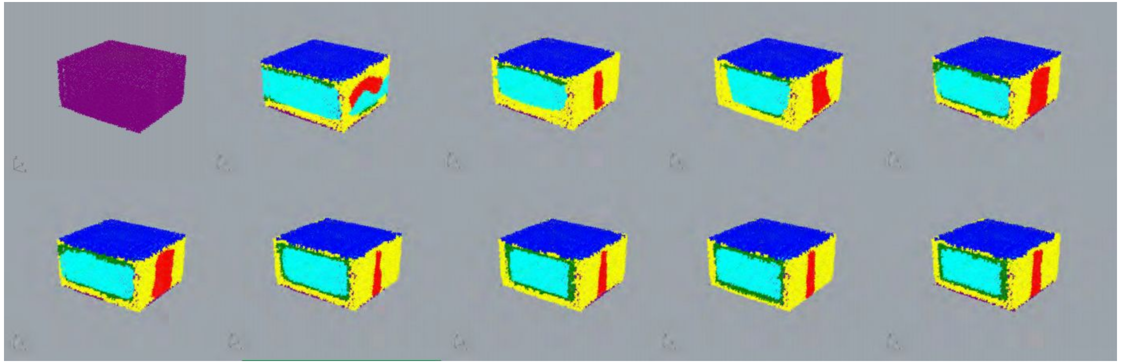

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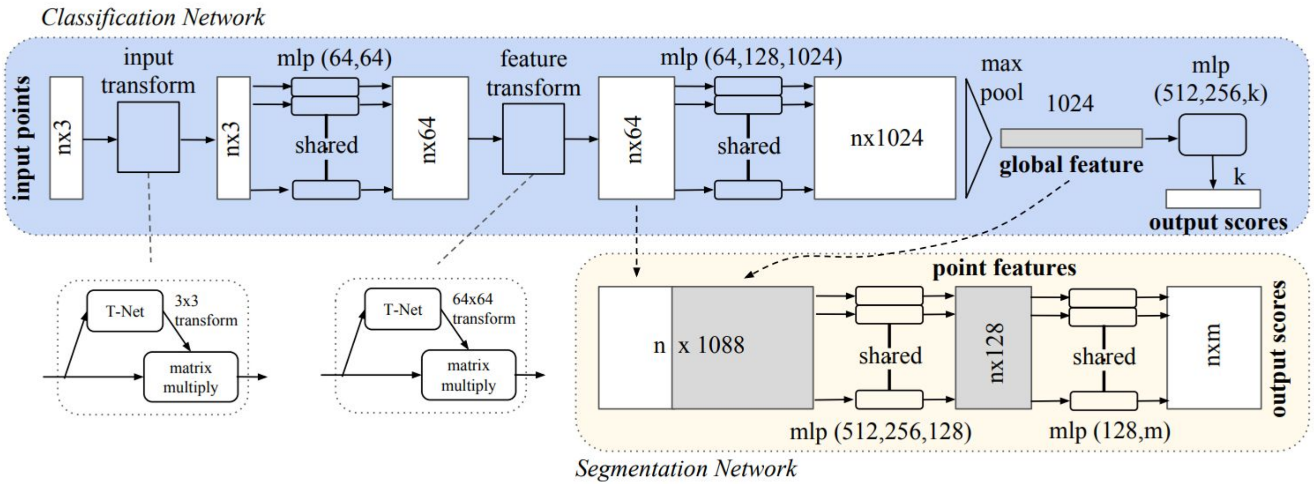

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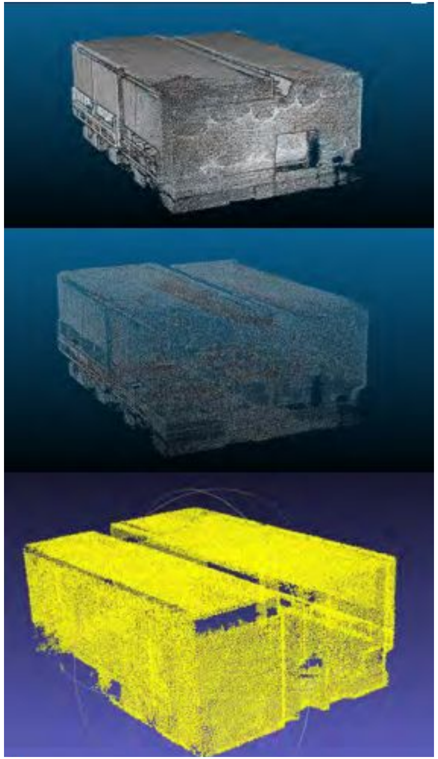

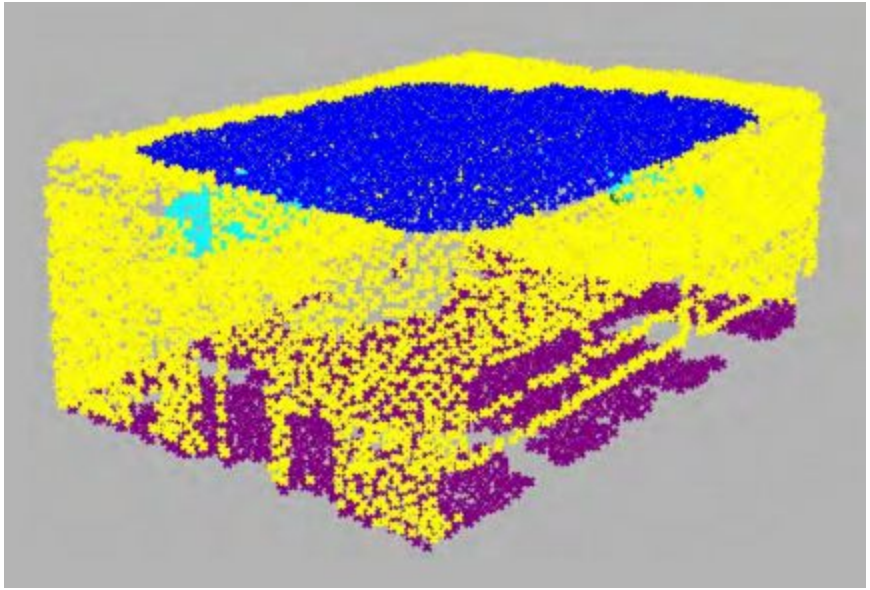

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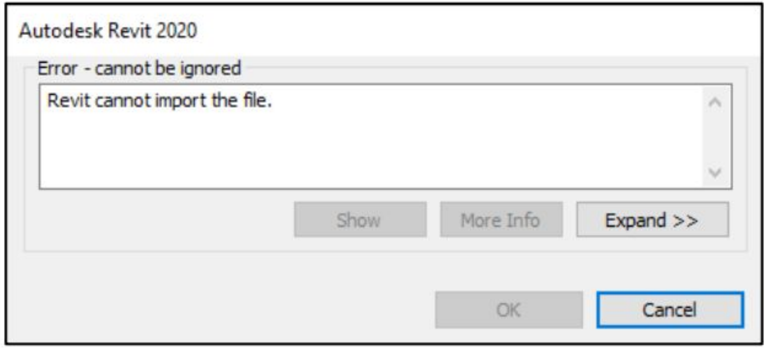

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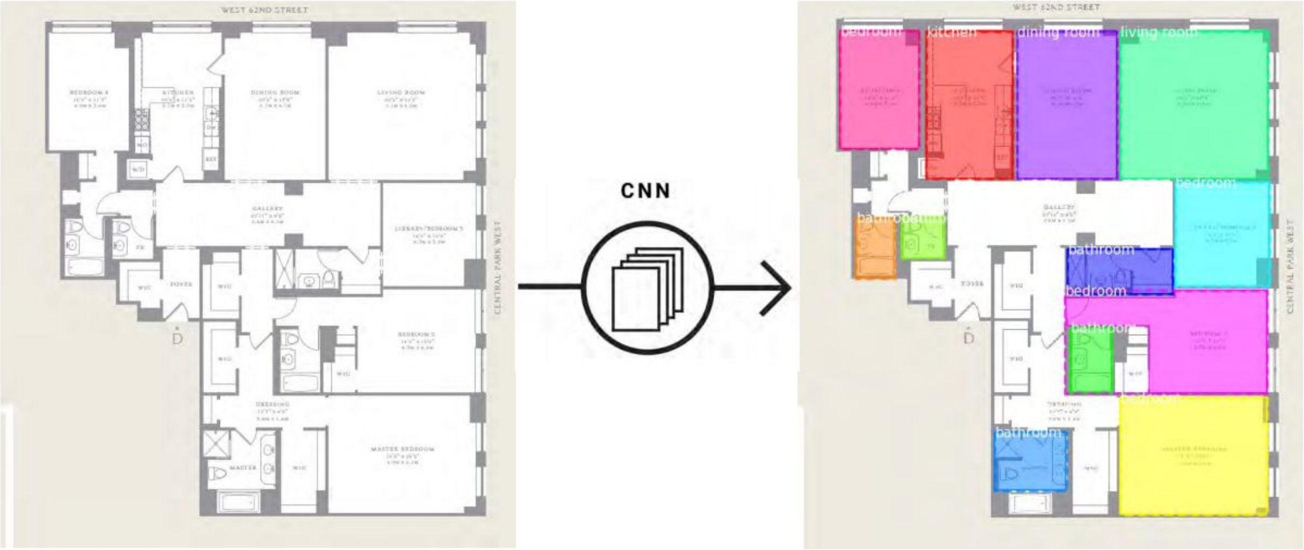

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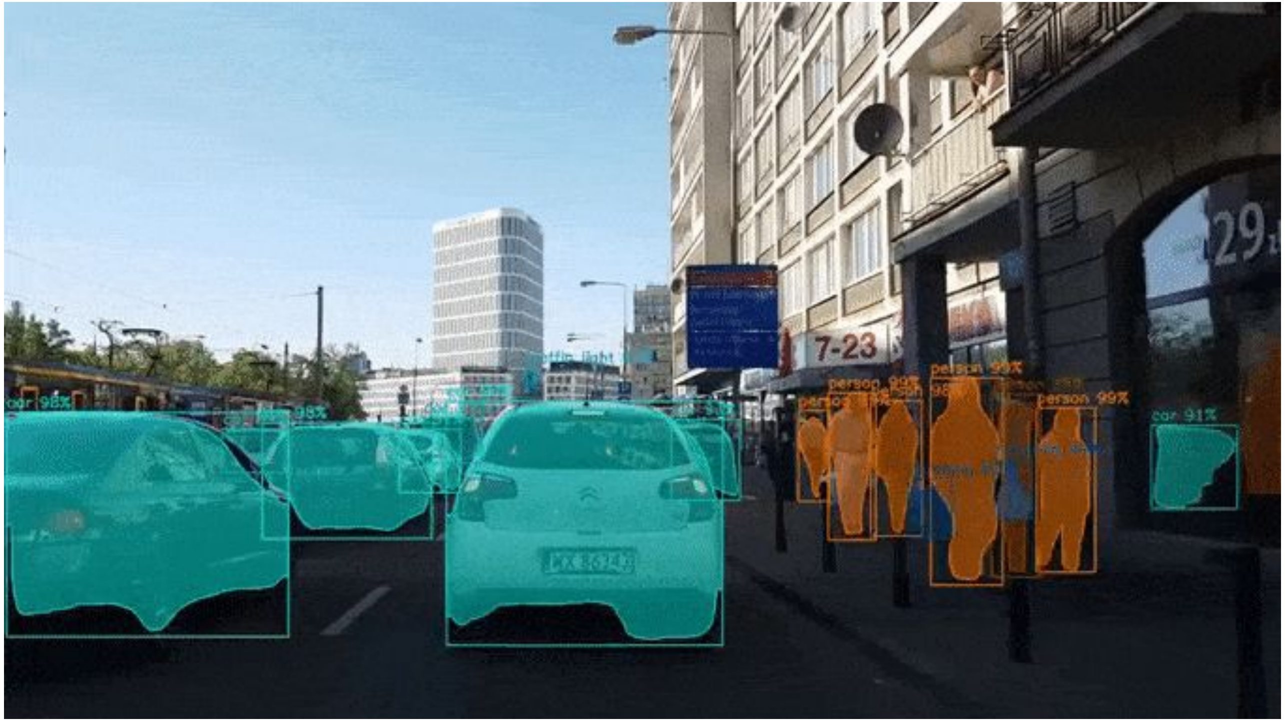

https://github.com/matterport/Mask_RCNN

Fundamentals of Machine Learning
DEEP LEARNING IN THE BUILT ENVIRONMENT

Fundamentals of Machine Learning

DEEP LEARNING IN THE BUILT ENVIRONMENT

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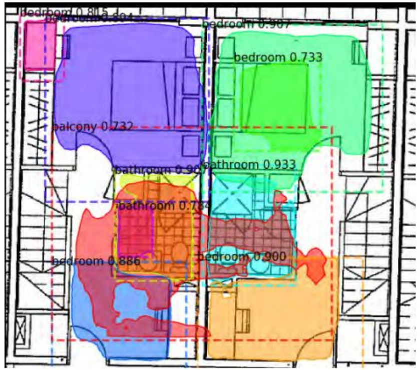

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Fundamentals of Machine Learning
DEEP LEARNING IN THE BUILT ENVIRONMENT

- Using a camera attached to a robot to traverse concrete tunnels, checking for cracks.

- Predicting the usage of bike sharing schemes and times of load.

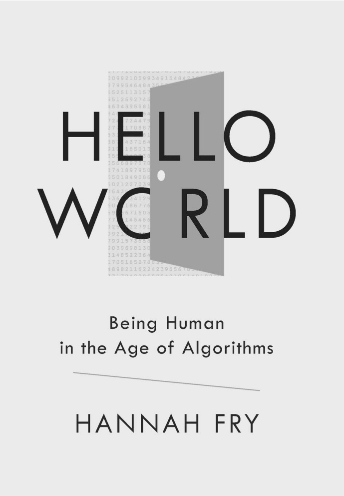
- Question and answering system for fire code regulation search.

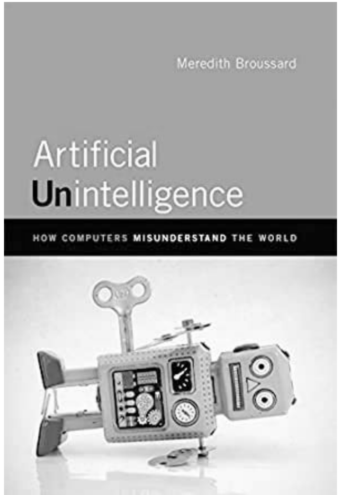
- Realtime geotechnical analysis for on-site drilling.

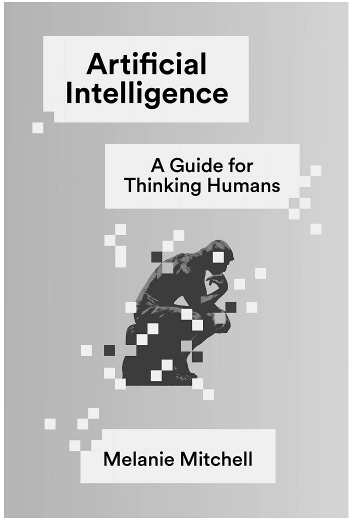
- Predicting the locations and likelihood of traffic accidents.

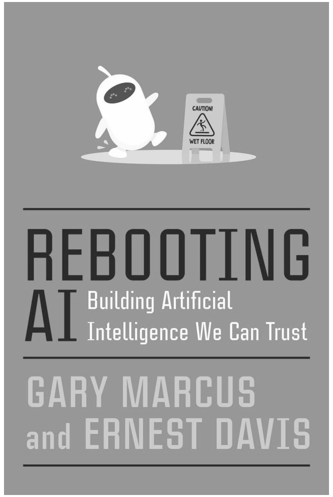
Fundamentals of Machine Learning

NOT A SILVER BULLET

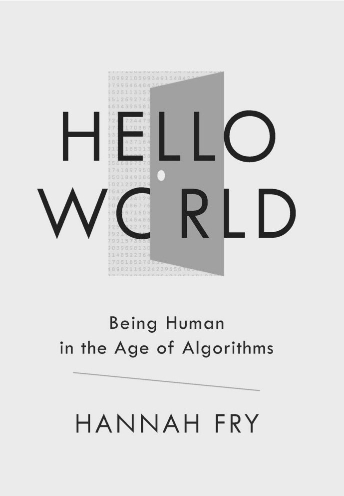




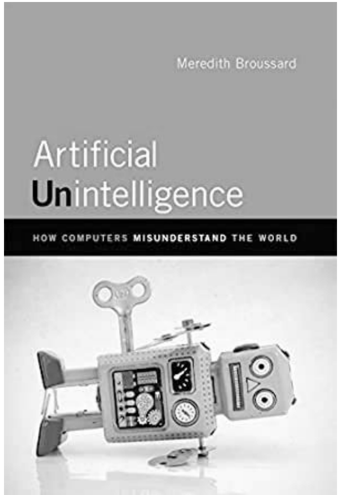




Fundamentals of Machine Learning
NOT A SILVER BULLET



"Just because a computer says something doesn't make it so."



"Technochauvinism"

Machine Bias

There's software used across the country to predict future criminals. And it's biased against blacks.

by Julia Angwin, Jeff Larson, Surya Mattu and Lauren Kirchner, ProPublica

May 23, 2016

ON A SPRING AFTERNOON IN 2014, Brisha Borden was running late to pick up her god-sister from school when she spotted an unlocked kid's blue Huffy bicycle and a silver Razor scooter. Borden and a friend grabbed the bike and scooter and tried to ride them down the street in the Fort Lauderdale suburb of Coral Springs.

Just as the 18-year-old girls were realizing they were too big for the tiny conveyances — which belonged to a 6-year-old boy — a woman came running after them saying, "That's my kid's stuff." Borden and her friend immediately dropped the bike and scooter and walked away.

But it was too late — a neighbor who witnessed the heist had already called the police.

Fundamentals of Machine Learning
SUMMARY

- Supervised learning is used to correlate input to output.
- Unsupervised learning is used to find patterns in datasets.
- Reinforcement learning is used discover behaviours from rewards and punishments.
- Deep learning is a subset of machine learning that is defined by the algorithms, inspired by biological neural networks.
- Just because a computer says something, doesn’t make it so.
- The outcomes are biased because reality is biased.