

Artificial Intelligence - 65th Jubilee Some Examples and Opportunities

- IEEE student branch UFCB - July, 22th, 2021

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Summary

Background:

- Smart Cities
- IoT
- Machine Learning

Examples

- UAV/Drone Examples
- Self-Driving Car

Perspectives

PILE OF LINEAR ALGEBRA, THEN COLLECT THE ANSWERS ON THE OTHER SIDE. WHAT IF THE ANSWERS ARE WRONG?) JUST STIR THE PILE UNTIL THEY START LOOKING RIGHT.

THIS IS YOUR MACHINE LEARNING SYSTEM?

YUP! YOU POUR THE DATA INTO THIS BIG

Background



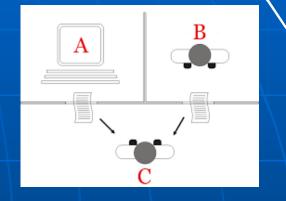
I PROPOSE to consider the question, 'Can machines think?'

This should begin with definitions of the meaning of the terms 'machine' and 'think'.

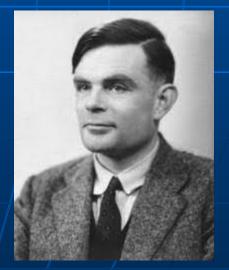
Instead of attempting such a definition I shall replace the question by another, which is closely related to it and is expressed in relatively unambiguous words.

The new form of the problem can be described in terms of a game which we call the **'imitation game'**.

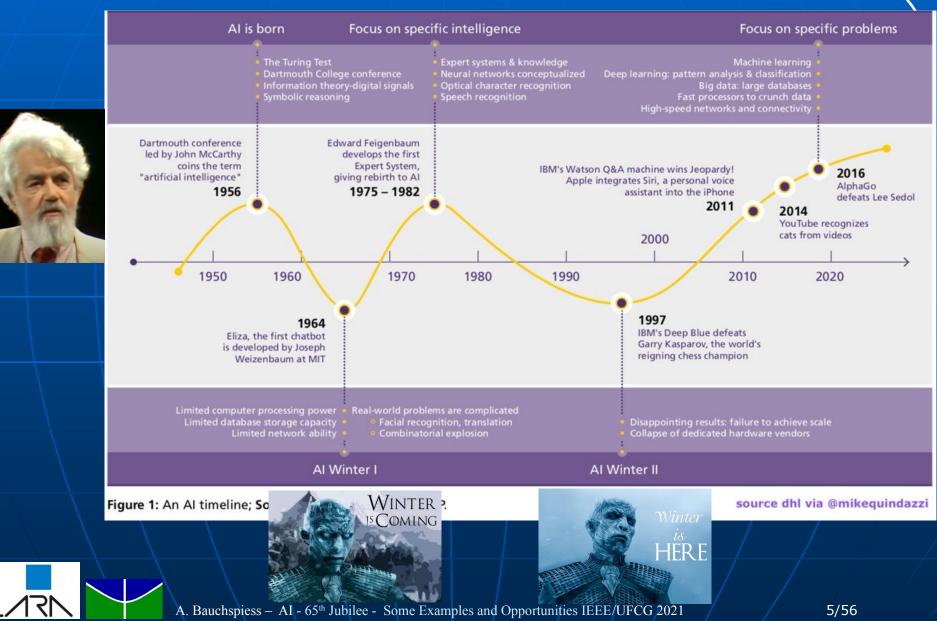
A. M. TURING, I.—COMPUTING MACHINERY AND INTELLIGENCE, Mind, Volume LIX, Issue 236, October 1950, Pages 433–460







Time Line - The 3rd AI Wave



Cities Evolution

City of neighbors → City of Strangers





André de Oliveira Bueno, Julho 2019 - Trilha Smart Cities - The Developer's Conference

The world's cities occupy just 3% of the Earth's land, but account for 60%-80% of energy consumption and 75% of carbon emissions. Prathombutr – Smart

Prathombutr – Smart Cities Development in Thailand https://www.nstda.or.th/nac/2019/images/seminar/26_Smartcity_passakorn.pdf

Future Smart City (?)

© Vincent Callebaut/Solent News

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@Pinterest 7/56

/Future Smart City (?)

LAR



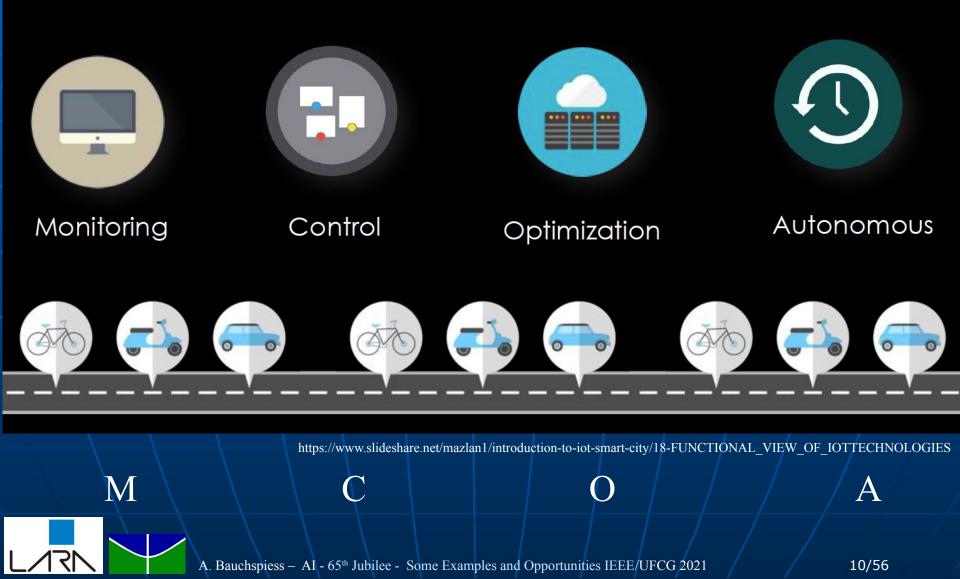
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Cyber-Physical Systems



THE 4 STAGES OF IOT MATURITY



Intelligent Systems - The Brain is the model !!

Build Neuron Synaptic Connections - Learning!



2 years to puberty

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Adult

From Natural Intelligence to Artificial Intelligence Ex. Dislexia?

I cnduo't byleiee taht I culod aulaclty uesdtannrd waht I was rdnaieg. Unisg the icndeblire pweor of the hmuan mnid, aocdcrnig to rseecrah at Cmabrigde Uinervtisy, it dseno't mttaer in waht oderr the lterets in a wrod are, the olny irpoamtnt tihng is taht the frsit and lsat ltteer be in the rhgit pclae. The rset can be a taotl mses and you can sitll raed it whoutit a pboerlm. Tihs is bucseae the huamn mnid deos not raed ervey ltteer by istlef, but the wrod as a wlohe. Aaznmig, huh? Yaeh and I awlyas tghhuot slelinpg was ipmorantt! See if yuor fdreins can raed tihs too.







Simpathic?



GRIMASSE STEHT KOPF

Auf den ersten Blick scheint das Foto von Margaret Thatcher nicht ungewöhnlich. Das ändert sich, wenn Sie das Bild auf den Kopf stellen. Der verblüffende Effekt tritt auf, weil Augen und Mund auf dem Foto um 180 Grad gedreht sind – und damit genau die Merkmale, auf die das Gesichtserkennungsprogramm des Hirns besonders sensibel anspricht.

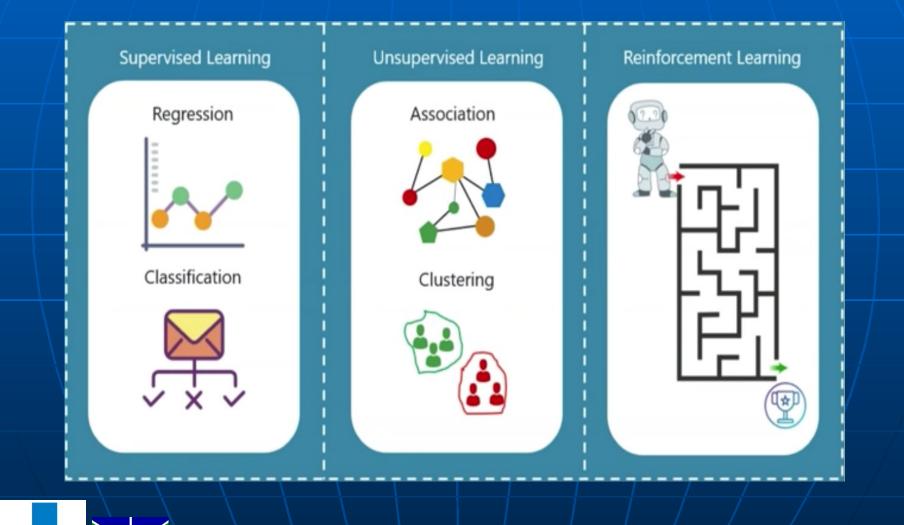
GRIMASSE STEHT KOPF

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PHO / AGENTUR FOCUS (L.); PERCEPTION (R.)

Antipathic?

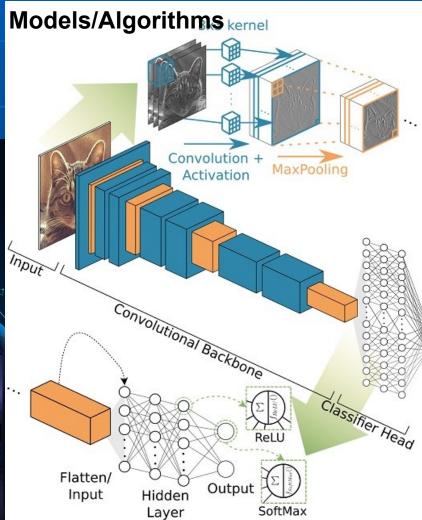
Machine Learning



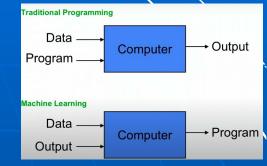
AI Enablers:

data processing algorithms





ML Algorithm "Tribes"



Technology

Production Rule System

Inverse Deduction

Backpropagation

Deep Learning

HMM

Graphical Model

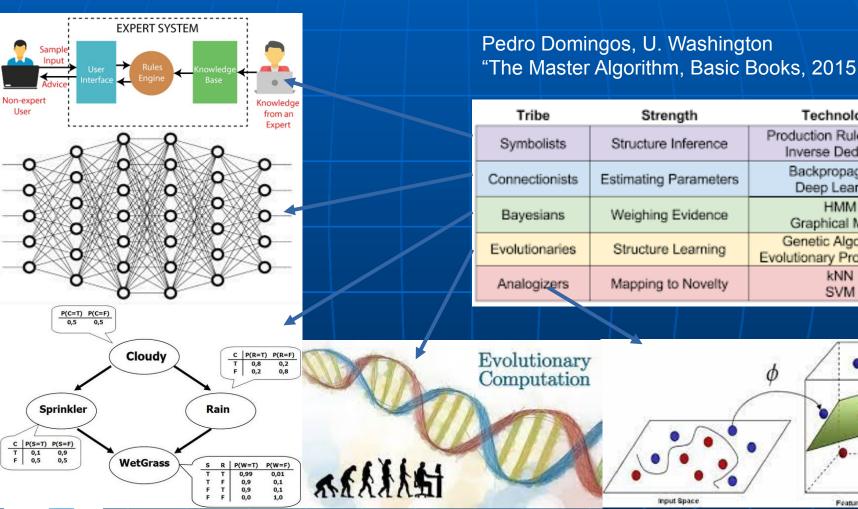
Genetic Algorithms

Evolutionary Programming

kNN

SVM

Ø



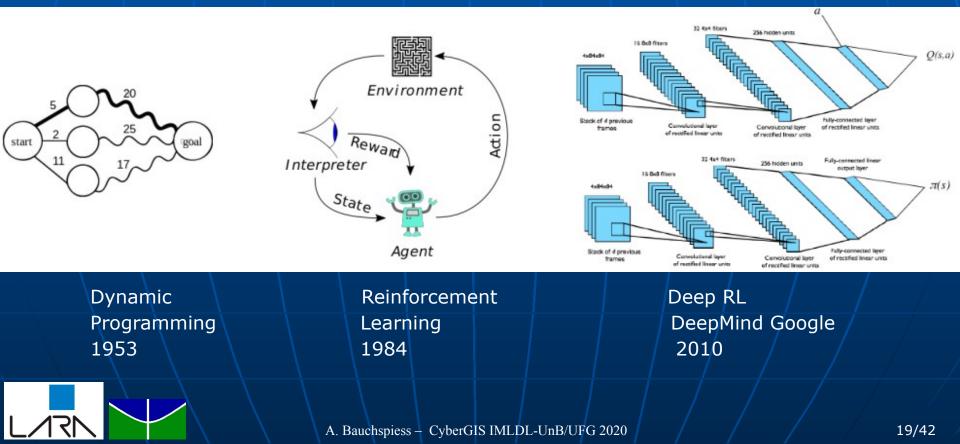
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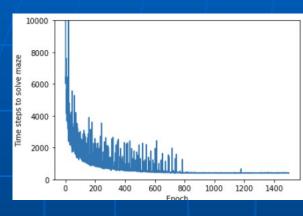
Feature Space

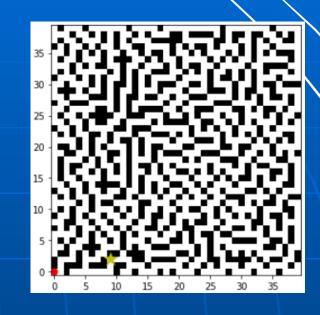
Reinforcement Learning

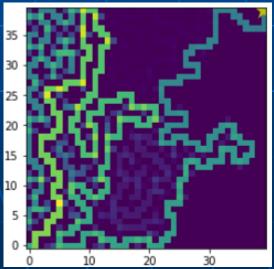
-Optimal Control -Trial & Error -Temporal Difference (max. future expected rewards)



Maze RL

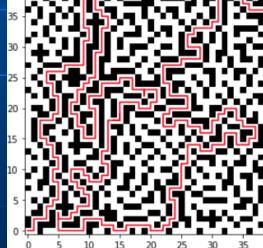






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env.treasure = (mx-1,my-1)



Time Line – AI != ML!

AIDMLDDL

ARTIFICIAL INTELLIGENCE

1970's

Engineering of making Intelligent Machines and Programs

1960's

1950's

MACHINE LEARNING

Ability to learn without being explicitly programmed

Learning based on Deep Neural Network

2010's

DEEP LEARNING

edu



2000's

2006's

1990's

1980's 🌔

2017's

2012's

The Deep Learning Superheros



Juergen Schmidhuber(?), Ian Goodfellow; François Chollet; Yann LeCunn, Andrew Ng,
LSTMGeoffrey Hinton,
BackProp.KL,etcLarry Page,
GoogleYoshua Bengio
GANLSTMGANKerasCNNGoogleBrainBackProp.KL,etcGoogleGAN

Examples



Visual Classification

CIFAR 10







CIFAR 100



bird

cat deer dog frog horse ship truck

Sklearn.load_digits

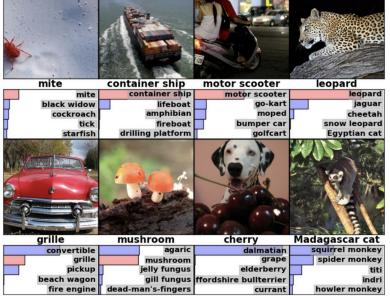
predict: 9 true: 3	predict: 8 true: 1	predict: 2 true: 1	predict: 9 true: 3	predict: 4 true: 4	
31		13.	3	4	
predict: 9	predict: 9 true: 3	predict: 9 true: 3	predict: 9 true: 5	predict: 2 true: 1	
true: 3					

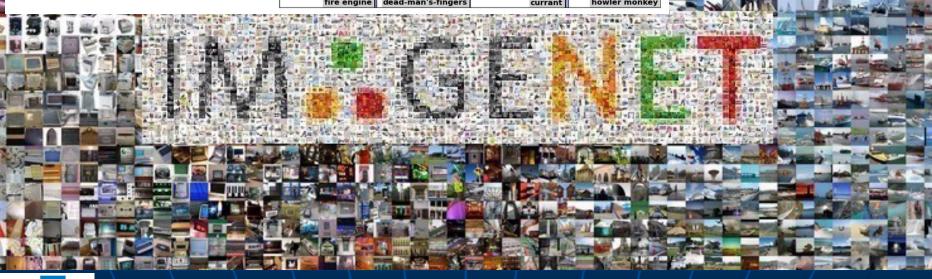
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ÍmageNet Challenge

IM GENET

- 1,000 object classes (categories).
- Images:
 - 1.2 M train
 - 100k test.



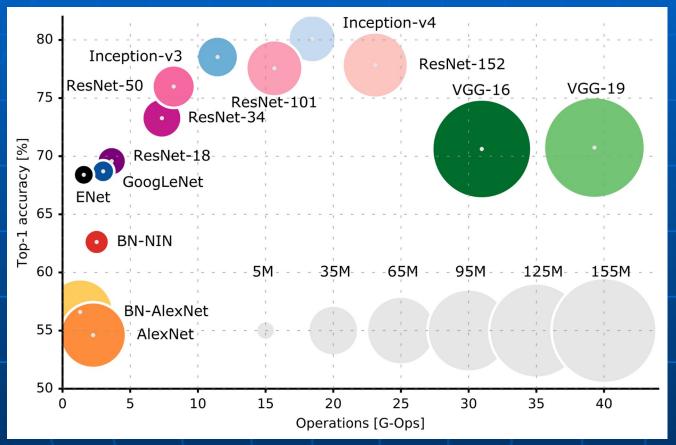




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ILSVRC 2018 Winner (ImageNet Large Scale Visual Recognition Competition)

Inception-v4 (Evolved from GoogLeNet, Merged with ResNet Idea)



The **Top-1 error** is the percentage of the time that the classifier did not give the correct class the **highest** score. The **Top-5 error** is the percentage of the time that the classifier did not include the correct class among its **top 5** guesses.

Network	Top-1 Error	Top-5 Error		
BN-Inception (Ioffe and Szegedy 2015)	25.2%	7.8%		
Inception-v3 (Szegedy et al. 2015b)	21.2%	5.6%		
Inception-ResNet-v1	21.3%	5.5%		
Inception-v4	20.0%	5.0%		
Inception-ResNet-v2	19.9%	4.9%		

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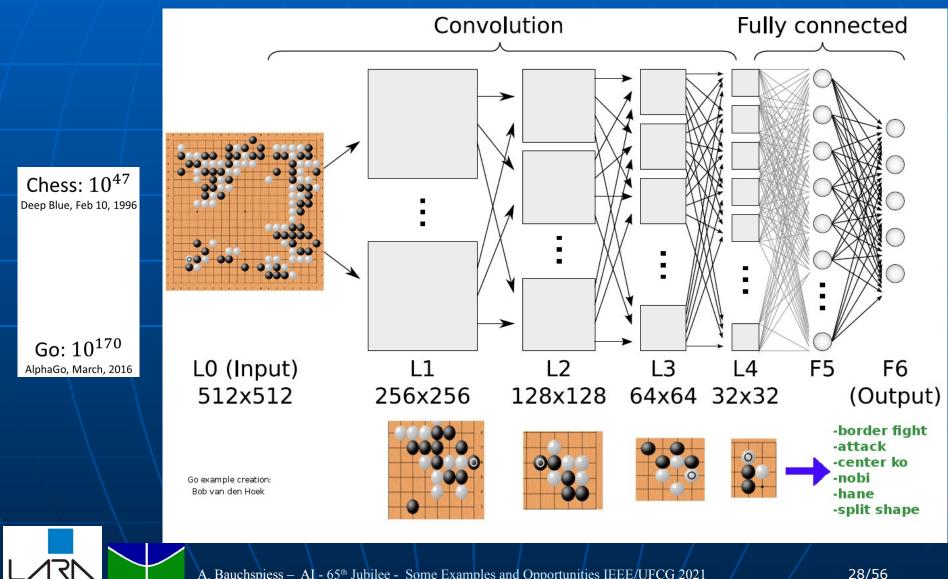
https://paperswithcode.com/Sota/image-classification-on-imagenet

Rank	Model	Top 1 🕇 Accuracy	Top 5 Accuracy	Number of params	Extra Training Data	Paper	Code	Result	Year	
1	ViT-G/14	90.45%		1843M	~	Scaling Vision Transformers		-2	2021	
2	ViT-MoE-15B (Every-2)	90.35%		14700M	~	Scaling Vision with Sparse Mixture of Experts		Ð	2021	
3	Meta Pseudo Labels (EfficientNet-L2)	90.2%	98.8%	480M	\checkmark	Meta Pseudo Labels	0	Ð	2021	
4	Meta Pseudo Labels (EfficientNet-B6-Wide)	90%	98.7%	390M	~	Meta Pseudo Labels	0	Ð	2021	
5	NFNet-F4+	89.2%		527M	~	High-Performance Large-Scale Image Recognition Without Normalization	0	Ð	2021	
		chemiage M			2012 2	Inception V2 SPPNetP Five Base + Five HiRes Wet 2013 2014 2015 20 0 Other models + Si d Some Examples EN	16 2017 tate-of-the-art	models	1 32x48d	1T-L (ResNet)

ViT-G/14

2021

Go



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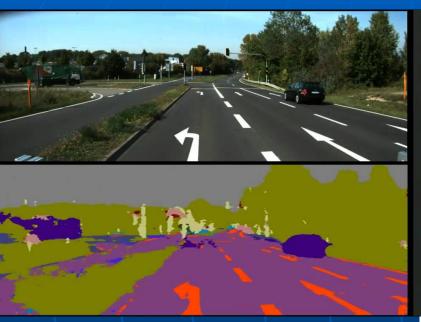
NGCAR

UDA



nttp\$://www.voutube.com/watch?v≠r14Ll3Jvcbw

RL – Examples: Self Driving Cars



Sky Building Pole Road Marking Road Pavement Tree Sign Symbol Fence Vehicle Pedestrian Bike



https://www.linkedin.com/pulse/machine-lea fundamentals-self-driving-cars-david-silver/

https://www.youtube.com/watch?v=kMMbW96nMW8

Deep Learning: Technology behind self-driving ca 6.194 visualizations Pub. 25/dec/2016



http://www.alphr.com/cars/1001713/practice-makes-perfect-driverless-cars-will-learn-from-

RL – Examples: Learn To Walk



Google's DeepMind AI Just Taught Itself To Walk - ... youtube.com



Another Break Through As Google's... mycomeup.com



Google's DeepMind Al Just Taught... highsnobiety.com



Google's DeepMind AI was Told to Teach Itself Ho... twistedsifter.com



Google's DeepMind AI Just Taught Its... luenymorell.com



Googles DeepMind AI just taught itself t... youtube.com



Watch: Google's AI Has Oddly Taught Itself To ... designtaxi.com



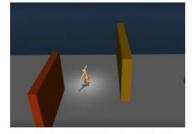
Google's DeepMind AI just taught itself to walk... gfycat.com



Google's DeepMind AI has taught itself to wal... home.bt.com



Google's DeepMind AI just taught itself to walk - C ...



Google's DeepMind AI has taught itself t... home.bt.com

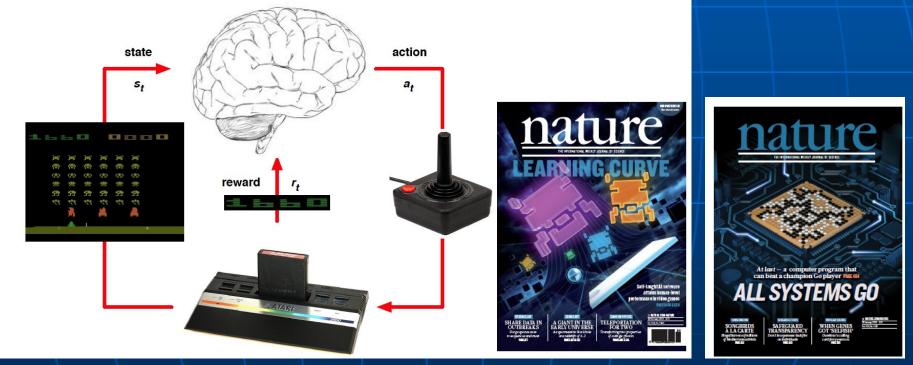


coub.com

Google's DeepMind AI Just Taught Itself to Walk 5.985.455 vis. 12/jul/2017 https://www.youtube.com/watch?v=gn4nRCC9TwQ

Deep Reinforcement Learning

Deep Reinforcement Learning in Atari



27 Fev 2015

28 jan 2016

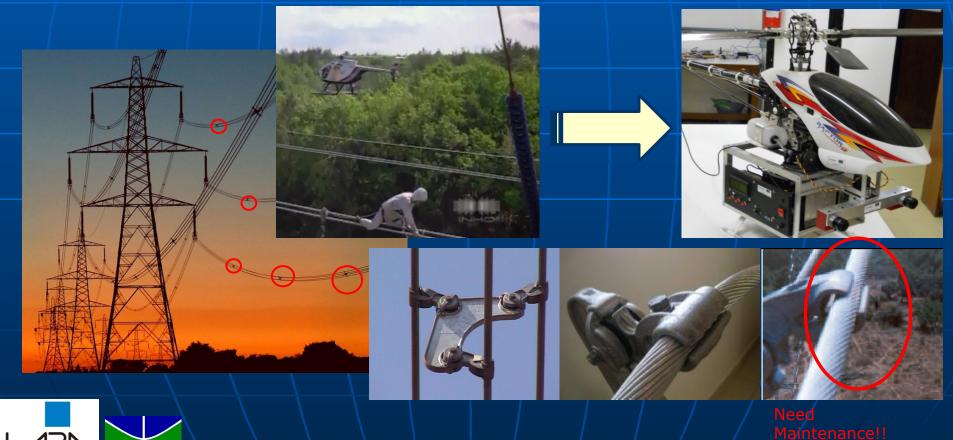


Adapted from: Deep Reinforcement learning – D. Silver, Google DeepMind, 2016 A. Bauchspiess – AI - 65th Jubilee - Some Examples and Opportunities IEEE/UFCG 2021

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Inspection of Transmission Lines

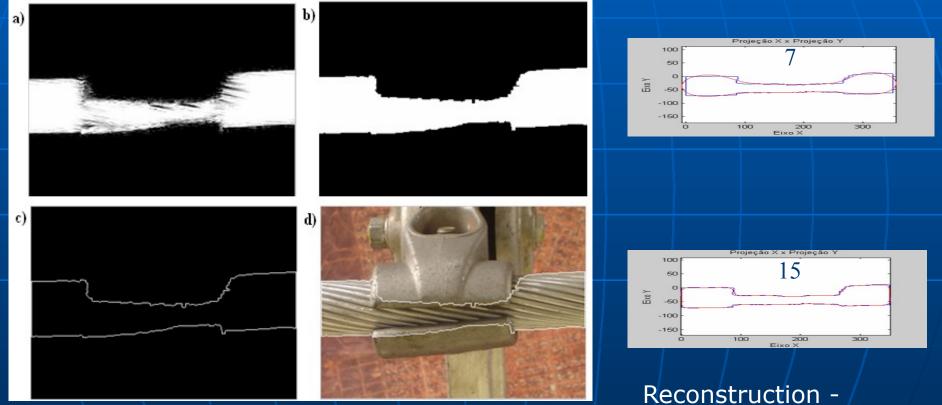
- Autonomous system visual inspection of electricity transmission lines
- Detection of flaws in the gripper of the line spacers



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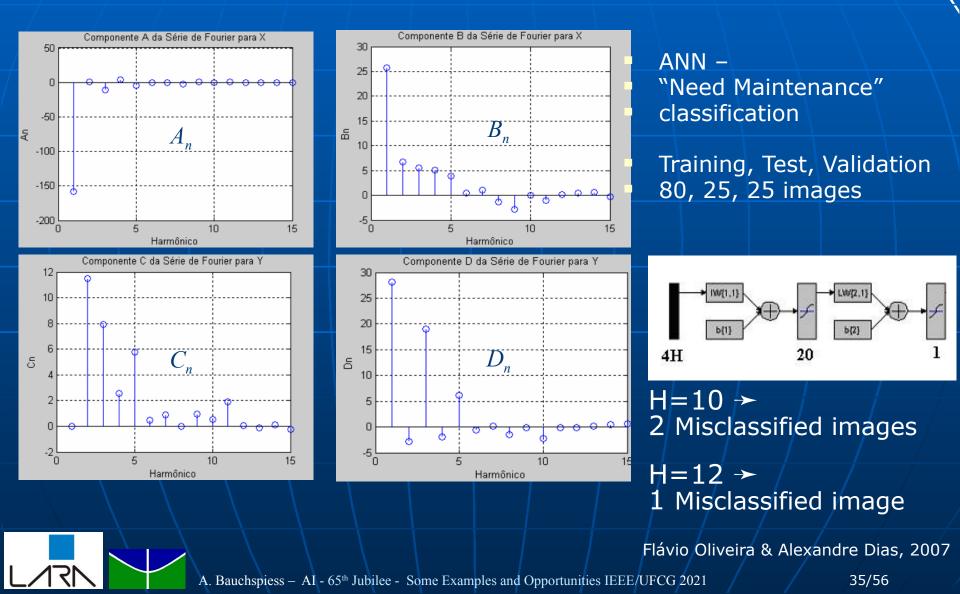
Gripped cable contour: FFT coefficients of directional chains



a) Gabor – b) Closing – c) Border – d)Image

Reconstruction -7 and 15 Harmonics

Gripped cable contour: FFT coefficients of directional chains

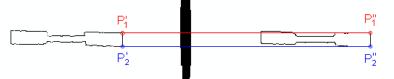


Gripper inspection with 3D reconstr.

- It is not possible to train an ANN for every position/orientation in the visual field of the VANT.
- ANN trained for a fixed point of view. Build 3D contour model Reproject 3D contour to ANN point of view Classify with ANN



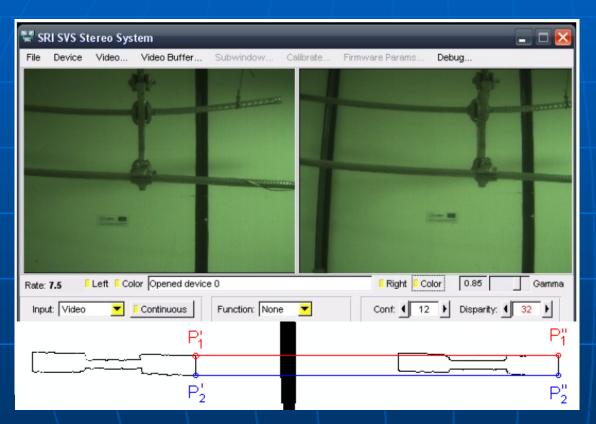
Different ROI's



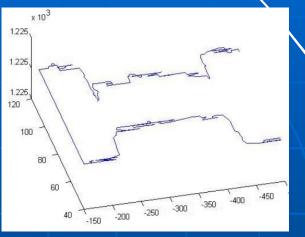
Correspondence -ROI contour in stereo pai

A. Bauchspiess - CyberGIS IMLDL-UnB/UFG 2021

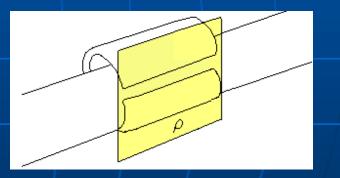
3D gripped cable



3D Reconstruction



ANN data bank Image plane



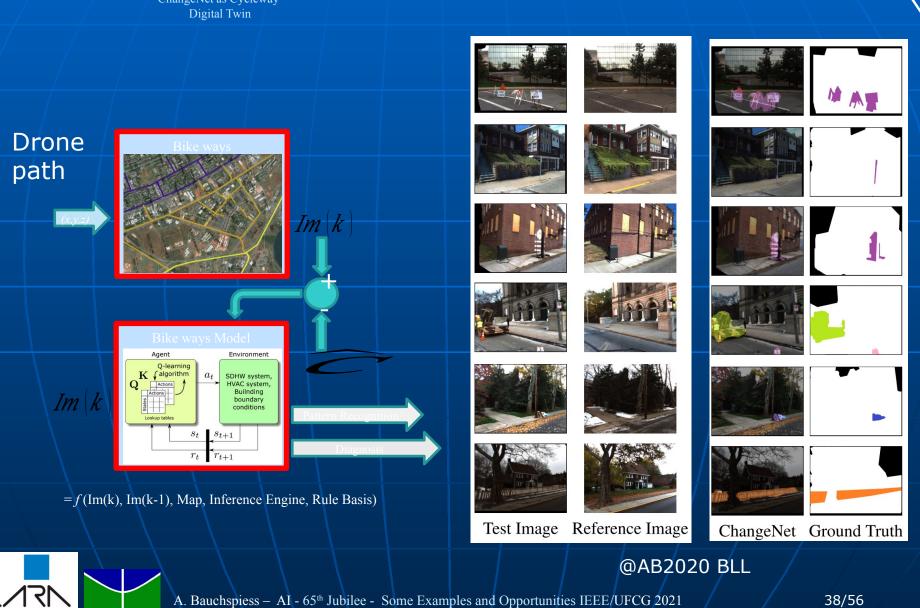
Reprojected contour for ANN

Results: 20 stereo pairs – 1 false pos., 1 false neg. Elder Oroski, 2011



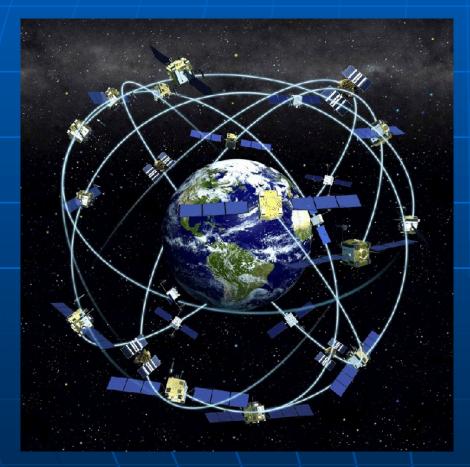


ChangeNet as Cycleway



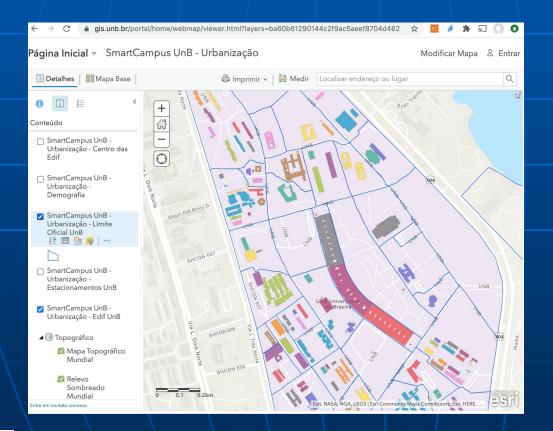
GPS + GIS

- Global Positioning System
- Geographical Information System





CPS - Cyber-Physical Systems





DRL Drone Bikeway Inspection Digital Twins SB Living Labs - ENE/ENC-UnB 2020



leitoria Un

Universidade de Brasilia

Campus Darcy Ribeir

BSAS - Bloco de Salas de Aula Si

Faculdade de réncias da Saúde...

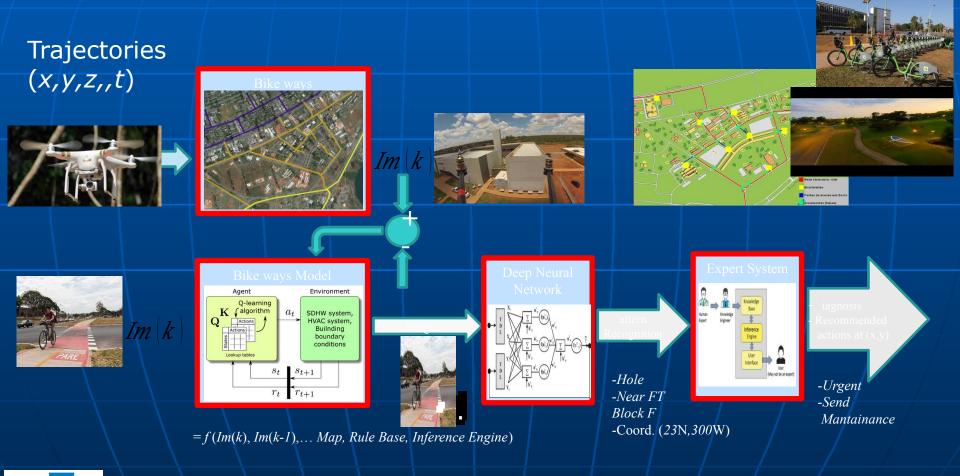




Some Examples and Opportunities IEEE/UFCG 2021

DRL Drone Bikeway Inspection Digital Twins BSB Living Labs - ENE/ENC-UnB 2020

Stored Info -Map -Registered Bikes



Semantic Segmentation





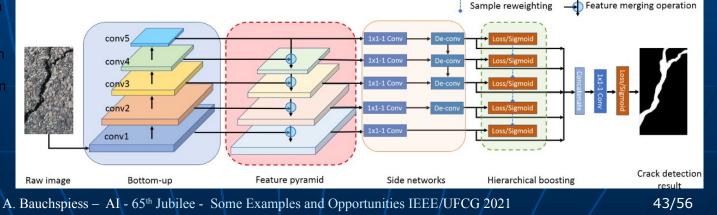




Christos Kyrkou, UDACITY SDCE Nanodegree Term 3 — Project 2: Advanced Deep Learning and Semantic Segmentation, https://ckyrkou.medium.com/

Thiago Rateke and Aldo von Wangenheim. Road surface detection and differentiation consideringsurface damages. 6 2020.

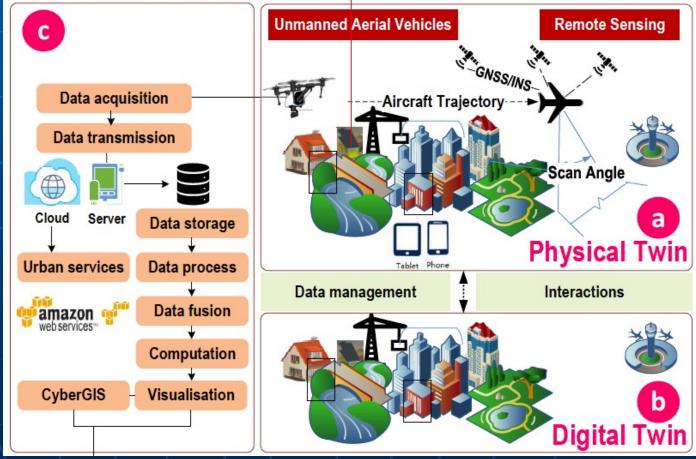
Gang Yang, Heng Chao Li, Wen Yang, Kun Fu, Yong Jian Sun, and William J. Emery. Unsupervised Change Detection of SAR Images Based on Variational Multivariate Gaussian Mixture Model and Shannon Entropy.IEEE Geoscience and Remote Sensing Letters, 16(5):826–830, 2019



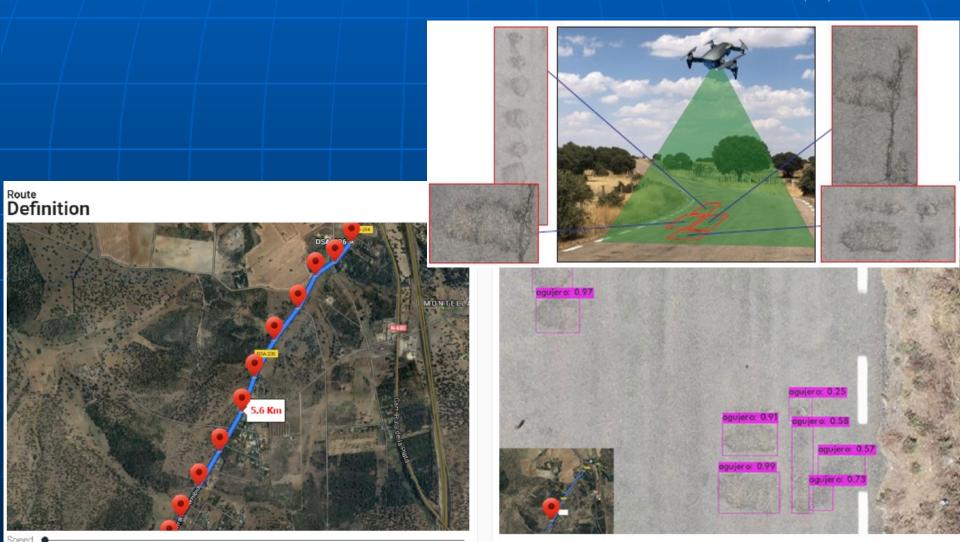
Ijgi Editorial – Shirowzhan, et al., 2020, 9, 240 Digital Twin and **CyberGIS** for Improving Connectivity and Measuring the Impact of Infrastructure Construction Planning in Smart Cities

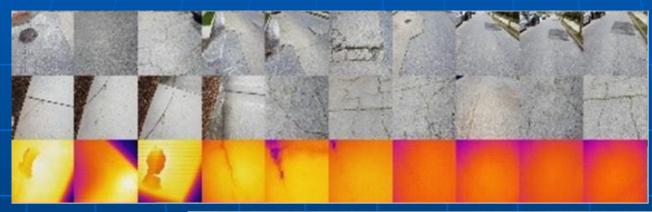


A 'digital representation' of a proposed building, located at Craik Avenue, Australia, Sydney.



An Architectural Multi-Agent System for a Pavement MonitoringSystem with Pothole Recognition in UAV Images L.A. Silva, H.S. San Blas, D.P. García, A.S.Mendes, and G.V. González. Sensors, 20(21), nov 2020.

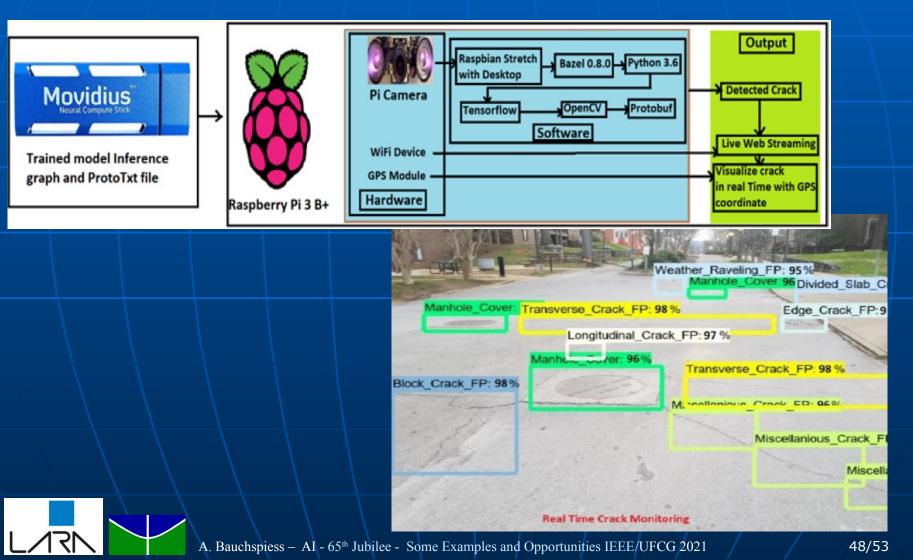












Models	Mean Average Precision	Real-time speed (FPS)
	(mAP)	
Faster R-CNN + inception V2	98%	0.5
Faster R-CNN + NasNet	94%	0.01
Faster R-CNN + ResNet101	97%	0.1
D. DOM & D. M. (101	070/	764.190 CP
R-FCN + ResNet101	87%	0.15
YOLO	26%	
YOLO	20%	
SSD + MobileNet V1	96%	13.8
	9070	
SSD + Inception V2	86%	3.6 (33.43.6P) (32.74.6P) (32.74.6P)
SSD + meepion v2		3.6 (3.43 (4) (3

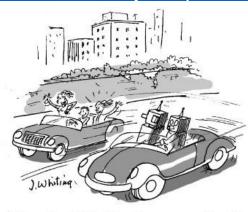
Perspectives





AI Opportunities
Deep Learning
Reinforcement Learning
Explanation Components

Challanges - AI with emotions - AI consciosness - ethics in AI - non-human intelligence - AGI (General, Strong AI)



"They shouldn't allow humans to drive!"

Learn to Drive: Self-Driving Car: >>1000 h Human ~ 20 h



Super-human in one task != Intelligent!!

The 10 most in-demand Jobs in AI - 2021

Machine Learning Engineer
 Deep Learning Engineer
 Senior Data Scientist
 Software Engineer
 Interns
 AI Specialist
 Robotics Engineer
 Full Stack Engineer
 Site Reliability Engineer
 Cybersecurity Specialist

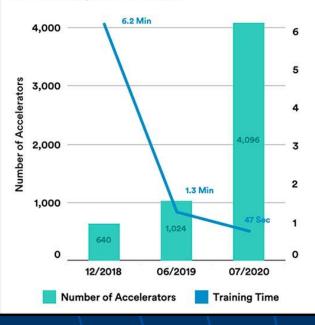


https://moneyinc.com/most-in-demand-jobs-ai-2021/

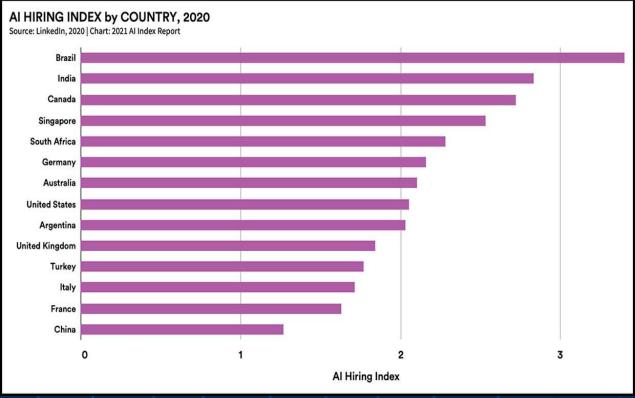
15 Graphs You Need to See to Understand AI in 2021 The 2021 AI Index provides insight into jobs, publications, diversity, and more

IMAGENET: TRAINING TIME and HARDWARE of the BEST SYSTEM

Source: MLPerf, 2020 | Chart: 2021 Al Index Report



https://spectrum.ieee.org/tech-talk/artificialintelligence/machine-learning/the-state-of-ai-in-15-graphs

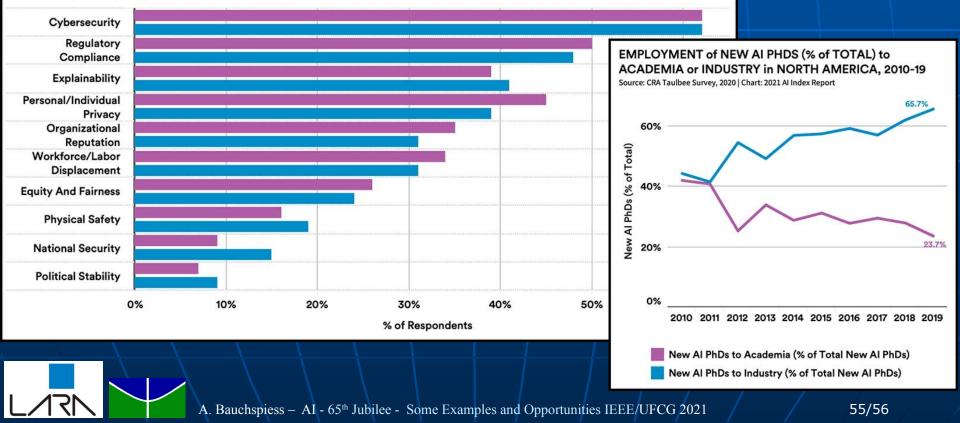


15 Graphs You Need to See to Understand AI in 2021 The 2021 AI Index provides insight into jobs, publications, diversity, and more

https://spectrum.ieee.org/tech-talk/artificialintelligence/machine-learning/the-state-of-ai-in-15-graphs

RISKS from ADOPTING AI THAT ORGANIZATIONS CONSIDER RELEVANT, 2020

Source: McKinsey & Company, 2020 | Chart: 2021 Al Index Report





Thank You!

 \bigcirc

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adolfobs@ene.unb.br

