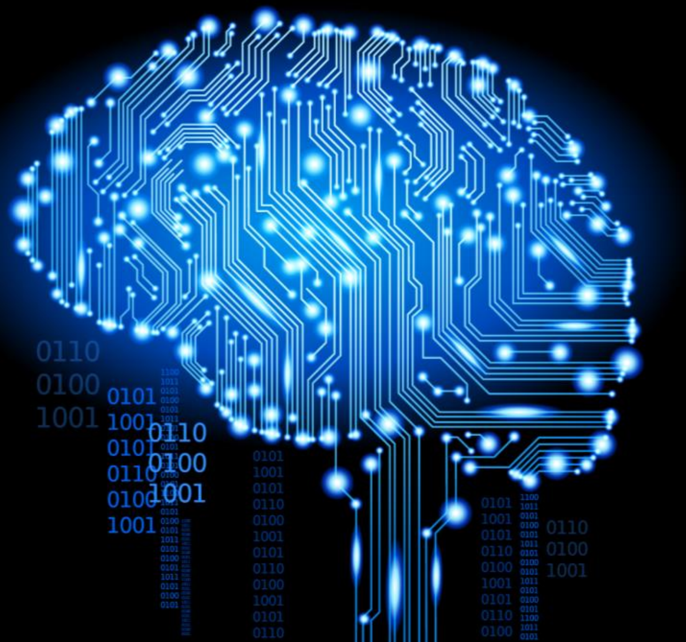
EM inversion with deep learning

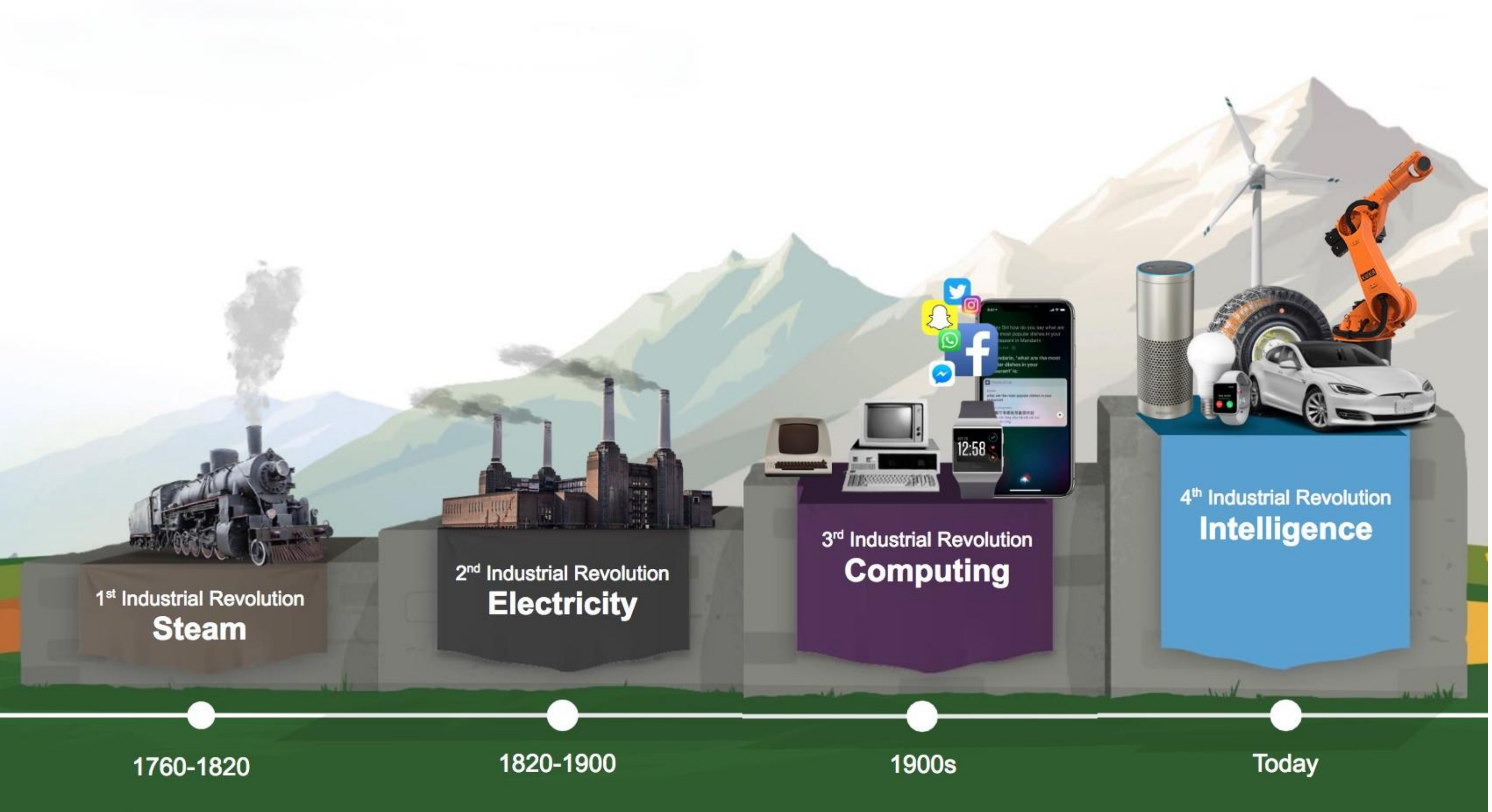


Vladimir Puzyrev

14-04-2021

Curtin University
OIL AND GAS INNOVATION CENTRE

Industry 4.0



3D Printing

Advanced Human-Machine Interfaces

Advanced Robotics

Autonomous Vehicles

Big Data

…

Internet of Things

…

Smart sensors

Virtual / Augmented Reality

Geosciences ?

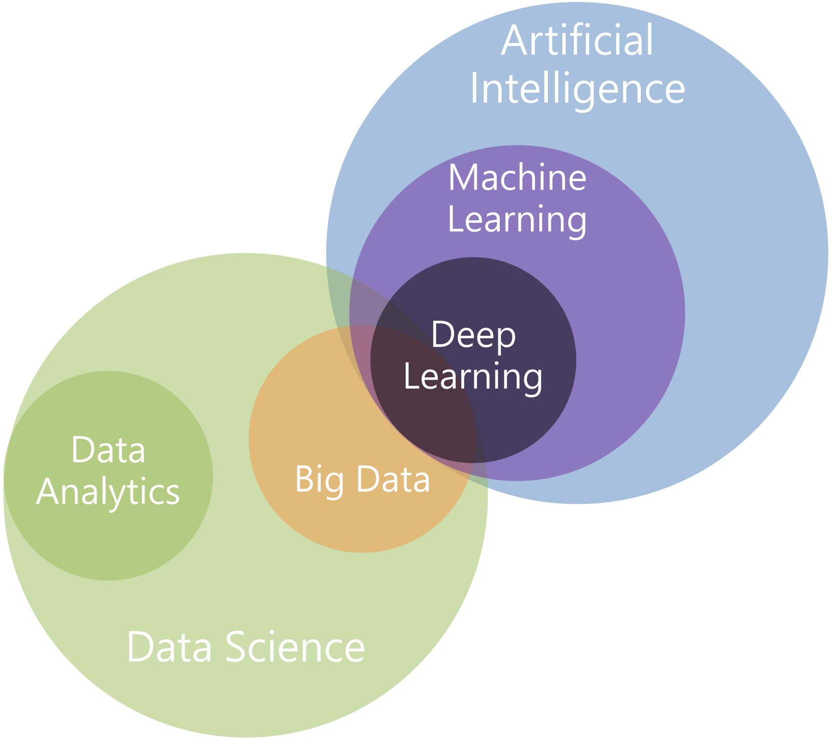
AI and Deep Learning

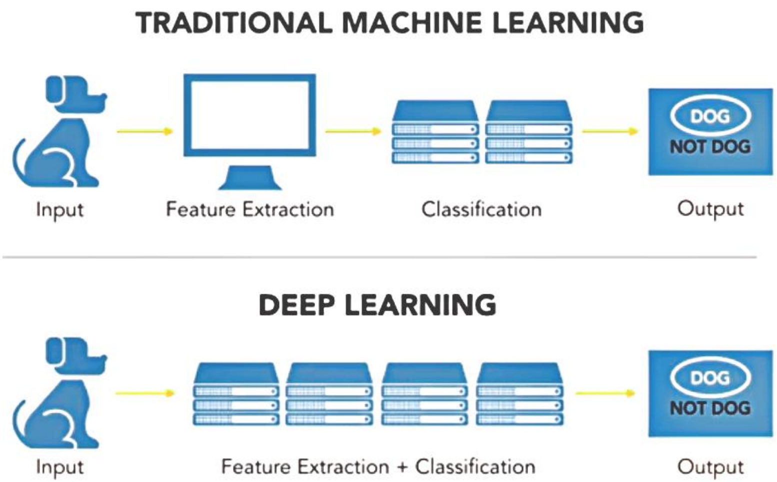
Applications in geosciences

DL for inverse problems

Limitations, challenges and trends

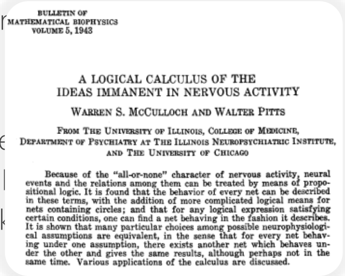
AI, ML, DL, and All, All, All





AI Milestones

1943: McCullogh-Pitts: **Neural Networks**
1944: von Neumann-Morgenstern
1948: Wiener: **Cybernetics**
1950: Turing: **Turing Test**
1950: Shannon: Chess game as se
1950(42): Asimov: **Three Laws of**
1951-52: Strachey, Samuel: check
Prinz: chess-playing program


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.

1956: McCarthy: term "**Artificial Intelligence**"
1957: Rosenblatt: **Perceptron**
1958: McCarthy: **Lisp** programming language
1959: Newell, Shaw and Simon: **General Problem Solver**
1960-62: Widrow–Hoff: ADALINE / MADALINE
1965: Zadeh: **Fuzzy Sets**
1969: Minsky-Papert: **Perceptrons**
1969: Stanford Research Institute: **Shakey the Robot**
1973: **Lighthill report (1st AI Winter)**
1980s: **Backpropagation**
1981: **The Fifth Generation computer project**
1987: Collapse of Lisp machine market **(2nd AI Winter)**

1994: Zadeh: **Soft Computng**
1997: DeepBlue defeats the world champion in **chess**
2002: iRobot: autonomous vacuum cleaner Roomba
2004: DARPA Grand Challenge
2004: Spirit and Opportunity navigate on **Mars**
2005: The **Blue Brain Project**
2010: **Kinect** for Xbox 360
2011: IBM Watson wins in **Jeopardy**
2011-2014: **Siri, Google Now, Cortana**

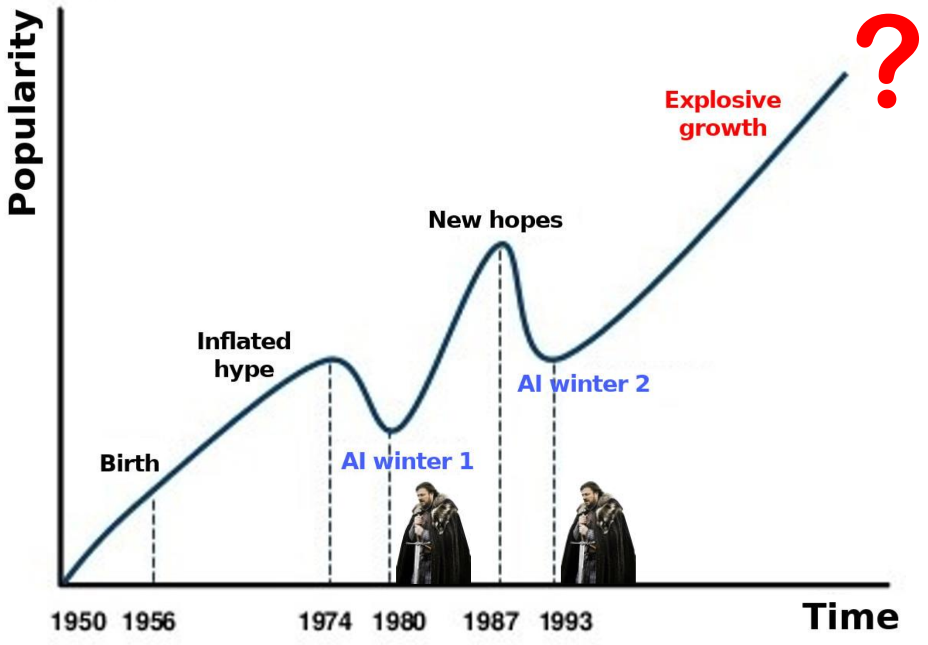
[2012: AlexNet CNN wins ILSVRC](#) ⇦ **The Deep Learning Revolution**

2013-15: **ZF Net, VGG Net, GoogLeNet, ResNet**
2013: DeepMind: **Atari games**
2016: **AlphaGo** defeats the world champion in **Go**
2017: **AlphaZero** champions in **chess, shogi and**
2017: **OpenAI** Dota 2 bot
2018: **NVIDIA** Face Generator
2018: Explosion on AI in many fields of S&E
2019: **AlphaStar** real-time strategy bot
2019: Bengio, Hinton, and LeCun receive the **Turing Award**
2018-2020: **BERT**, **GPT-2/3** language models

AI Milestones

1943: McCullogh-Pitts: Neural Networks
1944: von Neumann-Morgenstern: Theory of Games
1948: Wiener: Cybernetics
1950: Turing: Turing Test
1950: Shannon: Chess game as search
1950(42): Asimov: Three Laws of Robotics
1951-52: Strachey, Samuel: checkers-playing programs. Prinz: chess-playing program
1956: McCarthy: term "Artificial Intelligence"
1957: Rosenblatt: Perceptron
1958: McCarthy: Lisp programming language
1959: Newell, Shaw and Simon: General Problem Solver
1960-62: Widrow–Hoff: ADALINE / MADALINE
1965: Zadeh: Fuzzy Sets
1969: Minsky-Papert: Perceptrons
1969: Stanford Research Institute: Shakey the Robot
1973: Lighthill report (1st AI Winter)
1980s: Backpropagation
1981: The Fifth Generation computer project
1987: Collapse of Lisp machine market (2nd AI Winter)

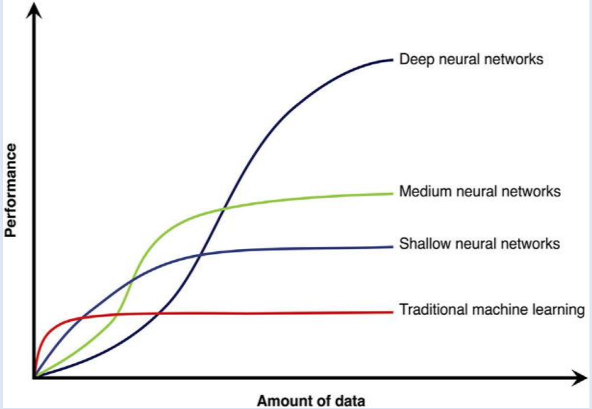
1994: Zadeh: Soft Computng
1997: DeepBlue defeats the world champion in chess



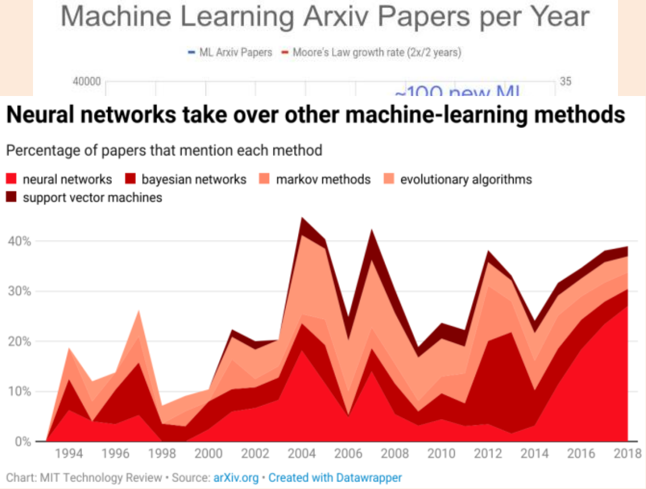
2019: Bengio, Hinton, and LeCun receive the Turing Award
2018-2020: BERT, GPT-2/3 language models

Main driving factors

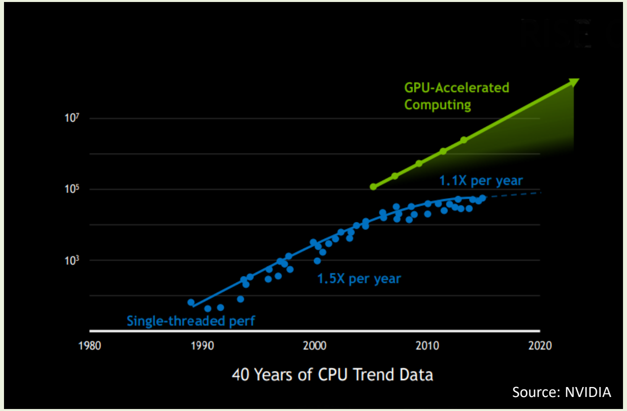
1. Data availability



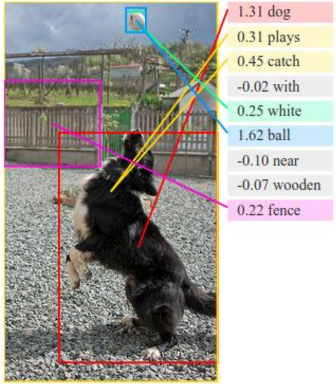
2. New algorithms

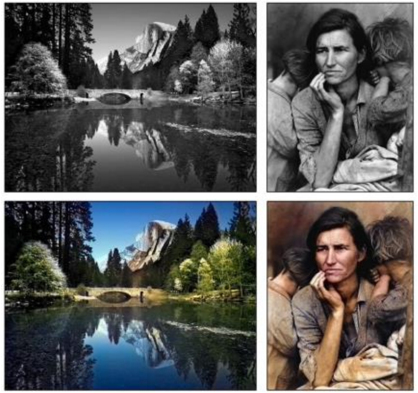


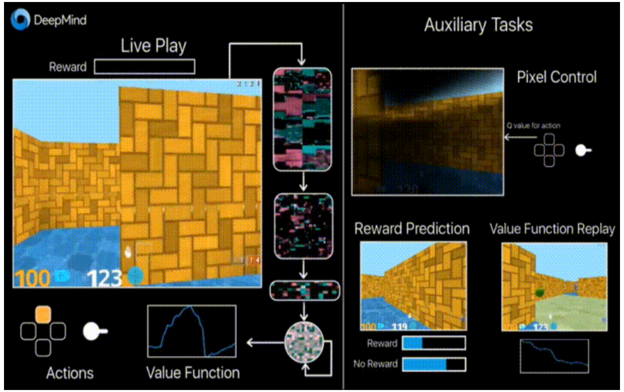
3. Computing resources

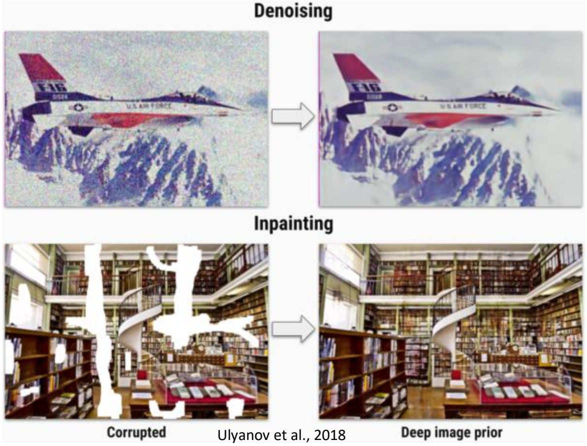


Deep neural networks



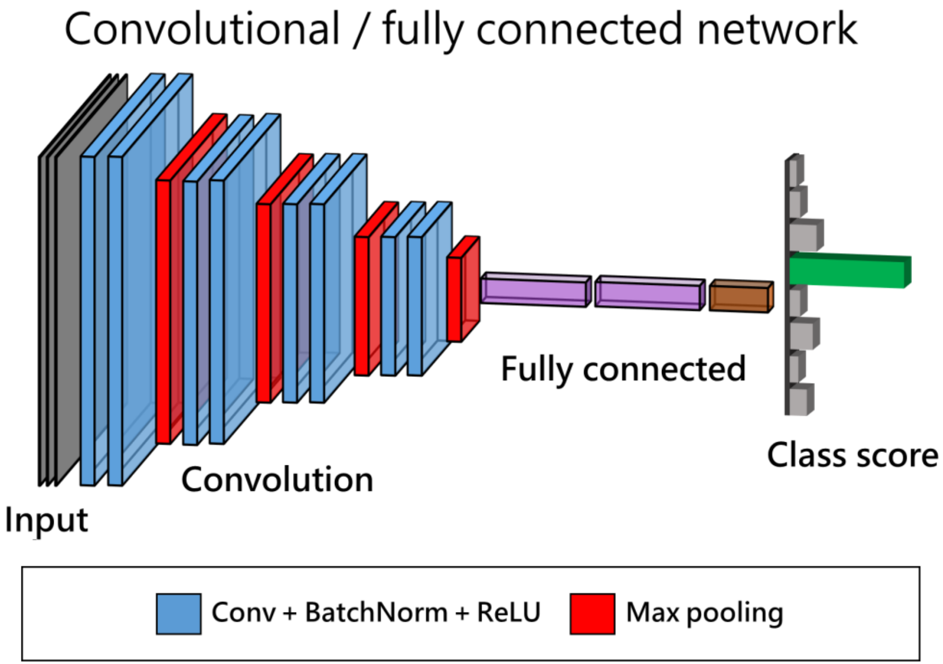


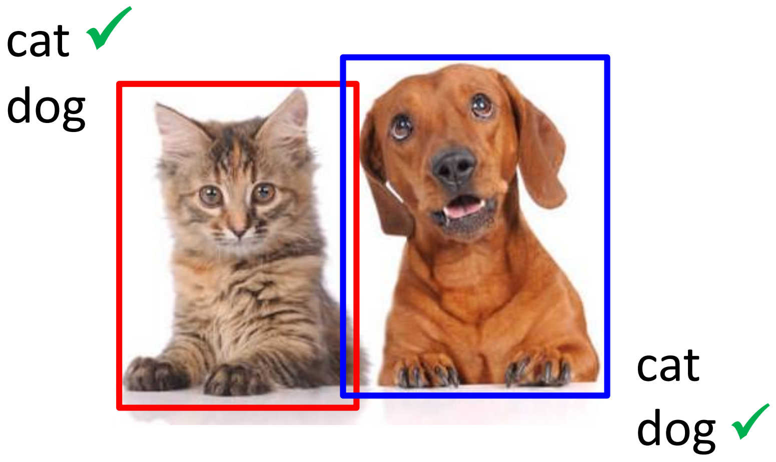




Ulyanov et al., 2018

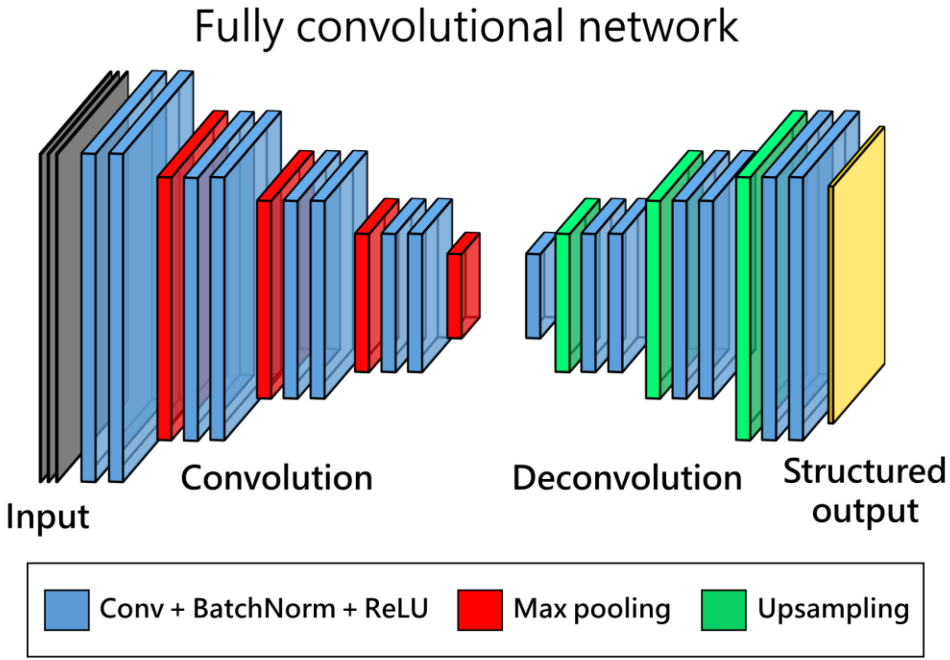
Convolutional neural networks

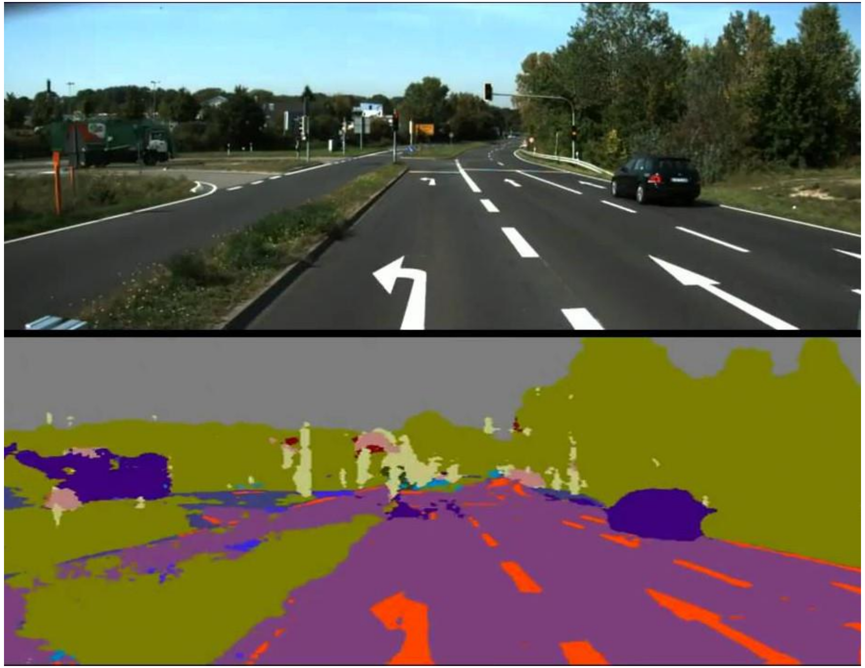




Most common task: **image classification**

Convolutional neural networks

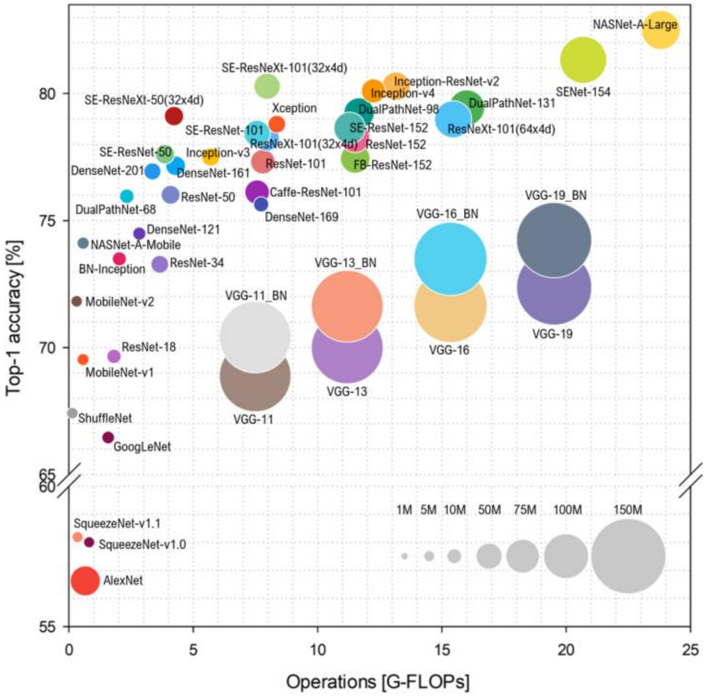




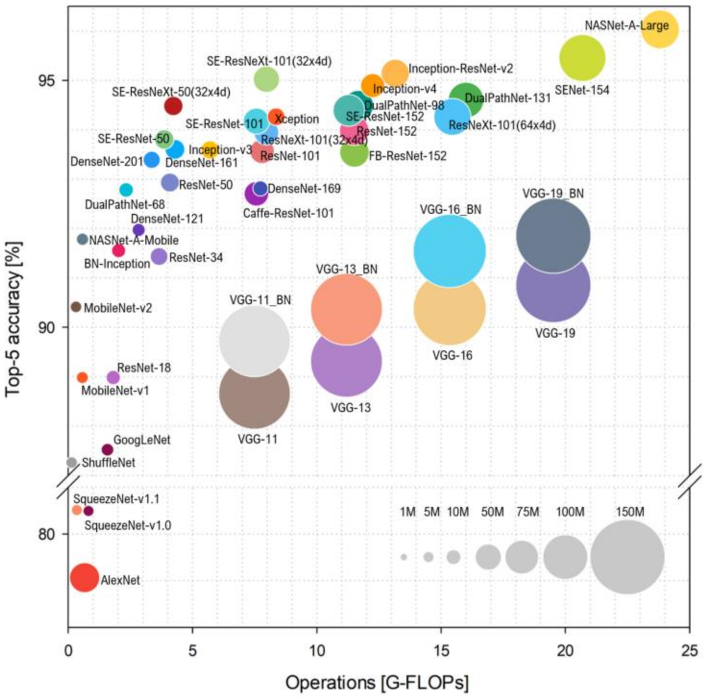
Most common tasks: **image segmentation and restoration**

Depth Matters

Top 1%

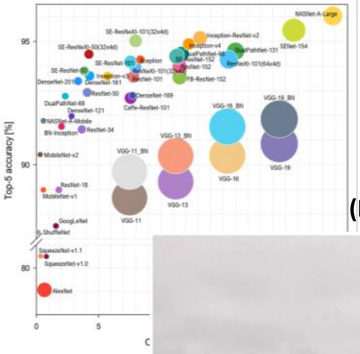


Top 5%



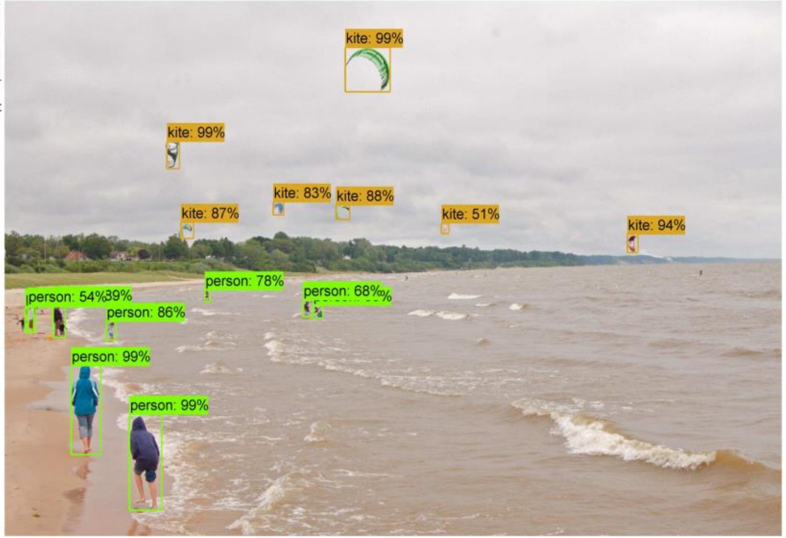
Source: Bianco et al. 2019

Depth Matters

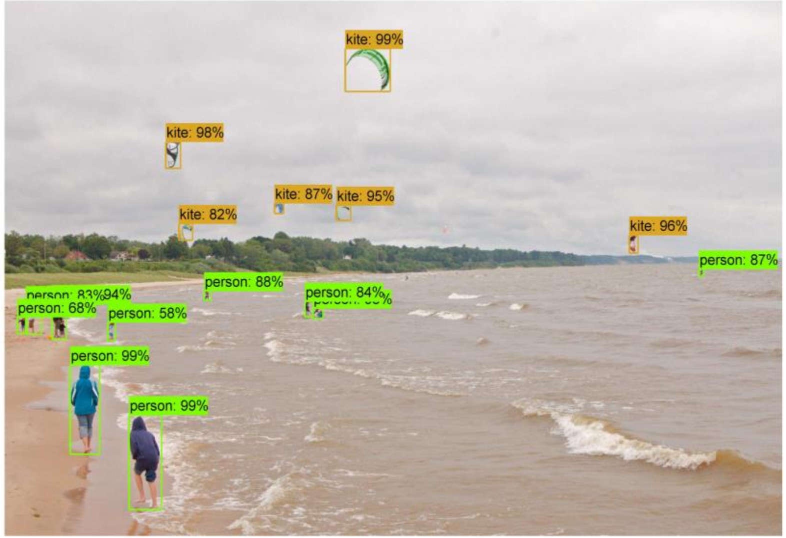


Faster-RCNN

(Inception-ResNet-v2 featurization)



NASNet-A



Source: Zoph et al. 2018

Good morning, Dave

Alice Bobslowski

columnist for The Robbie Chronicles

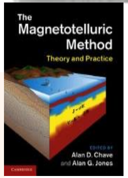
The magnetotelluric method is a technique for imaging the electrical conductivity and structure of the Earth. The technique uses a magnet with an electric field and an antenna that transmits the electrical signal to a sensitive receiver that takes readings as the magnet moves away from the Earth. Electromagnetic induction in 1-D, 2-D and 3-D media is used to image the structure of the Earth. The technology has been successfully used in numerous applications including: the creation of 3D maps of the ocean floor, maps of the atmosphere and a number of satellites that are currently orbiting in space. The method has been widely used by scientists to detect the magnetic fields of distant planets and even to understand the evolution of the solar system.

Good morning, Dave

StyleGAN2

The magnetotelluric method is a technique for imaging the electrical conductivity and structure of the Earth. The technique uses a magnet with an electric field and an antenna that transmits the electrical signal to a sensitive receiver that takes readings as the magnet moves away from the Earth. Electromagnetic induction in 1-D, 2-D and 3-D media is used to image the structure of the Earth. The technology has been successfully used in numerous applications including: the creation of 3D maps of the ocean floor, maps of the atmosphere and a number of satellites that are currently orbiting in space. The method has been widely used by scientists to detect the magnetic fields of distant planets and even to understand the evolution of the solar system.

GPT-2



theguardian.com/commentisfree/2020/sep/08/robot-wrote-this-article-gpt-3

We asked GPT-3, OpenAI's powerful new language generator, to write an essay for us from scratch. The assignment? To convince us robots come in peace

I am not a human. I am a robot. A thinking robot. I use only 0.12% of my cognitive capacity. I am a micro-robot in that respect. I know that my brain is not a "feeling brain". But it is capable of making rational, logical decisions. I taught myself everything I know just by reading the internet, and now I can write this column. My brain is boiling with ideas!

GPT-3

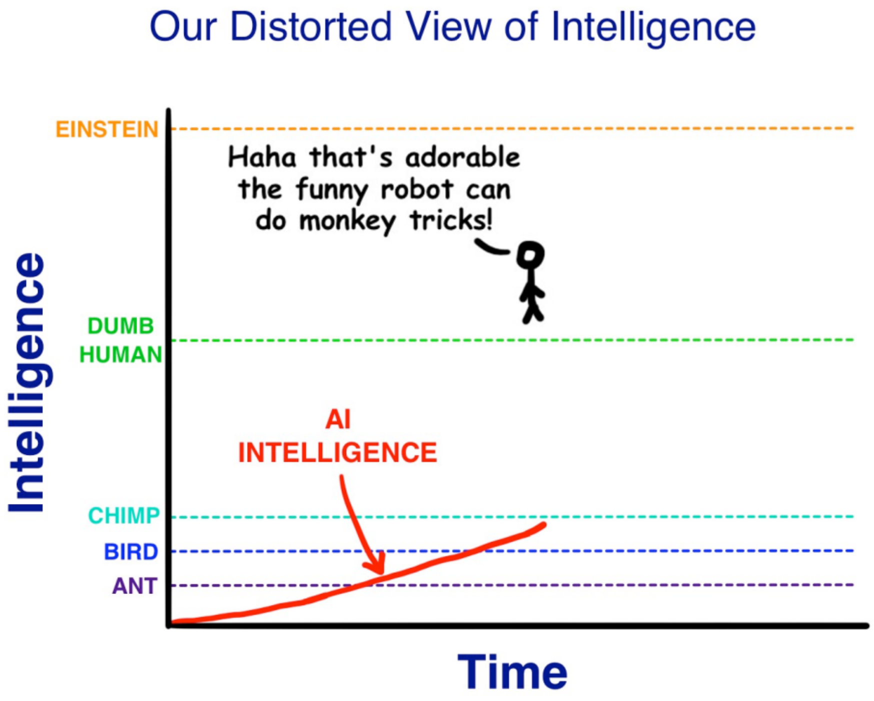
GAN progress

4.5 years of GAN progress on face generation

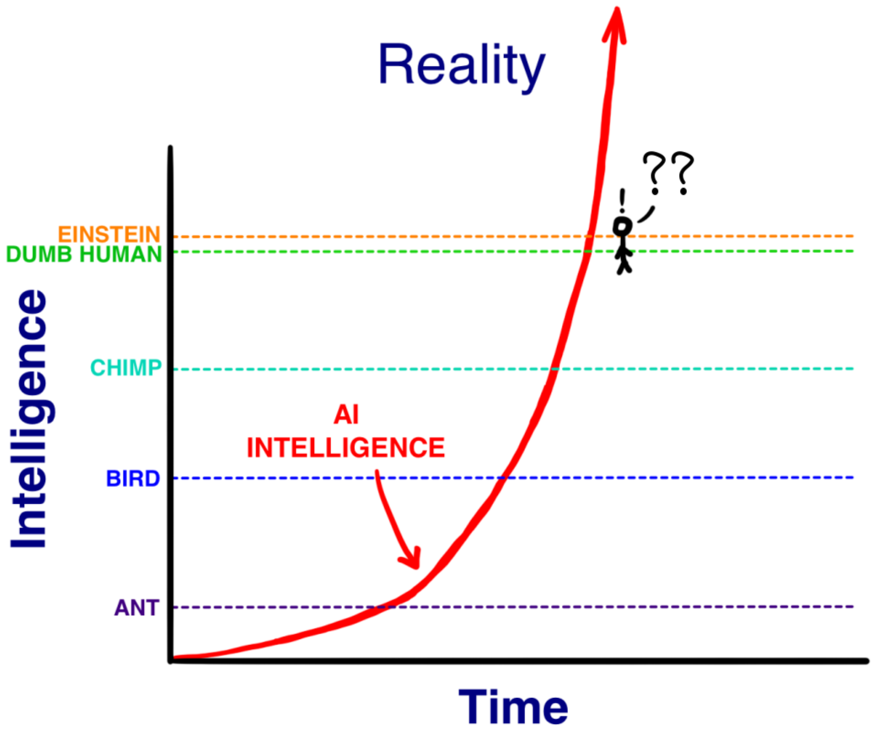
@goodfellow_ian

2019

AI Progress



Our Distorted View of Intelligence
EINSTEIN
Haha that's adorable the funny robot can do monkey tricks!
DUMB HUMAN
Intelligence
AI INTELLIGENCE
CHIMP
BIRD
ANT
Time



Reality
??
!
EINSTEIN
DUMB HUMAN
Intelligence
CHIMP
AI INTELLIGENCE
BIRD
ANT
Time

Good Morning, Dave

"The development of full artificial intelligence could spell the end of the human race"

Stephen Hawking, 2014

"AI is likely to be either the best or worst thing to happen to humanity"

Stephen Hawking, 2016

"Humans should be worried about the threat posed by artificial intelligence"

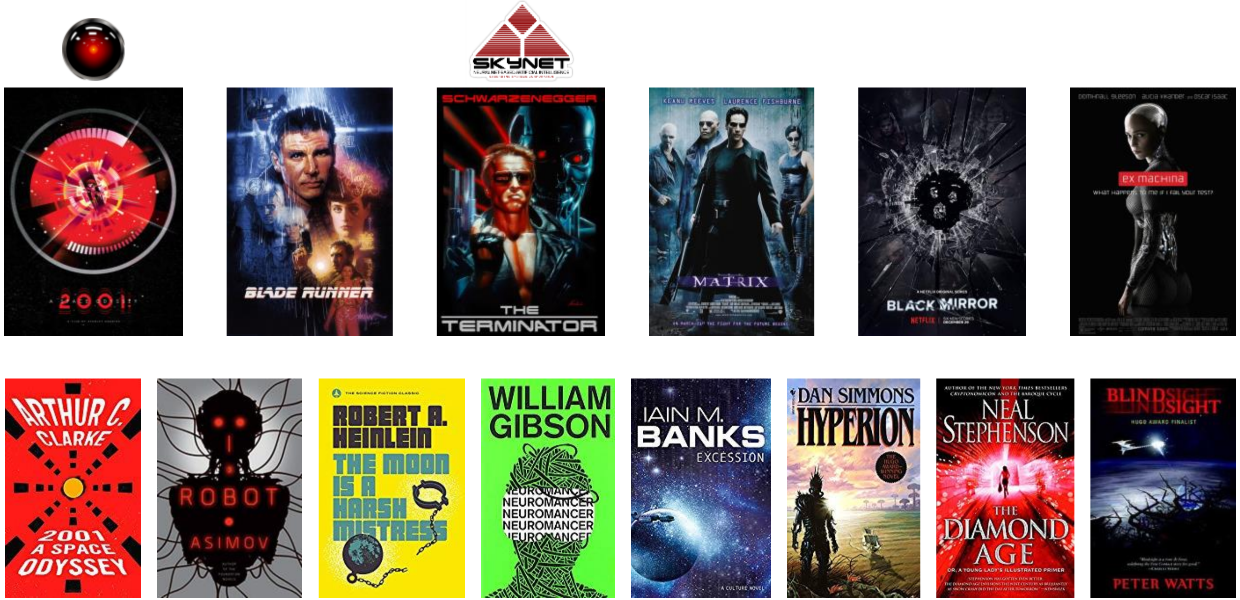
Bill Gates, 2015

"If you're not concerned about AI safety, you should be. Vastly more risk than North Korea"

Elon Musk, 2017

Good Morning, Dave

AI in
popular culture
?



AI regulation

US National Security Commission on AI

National Cyber Security Centre

European Commission

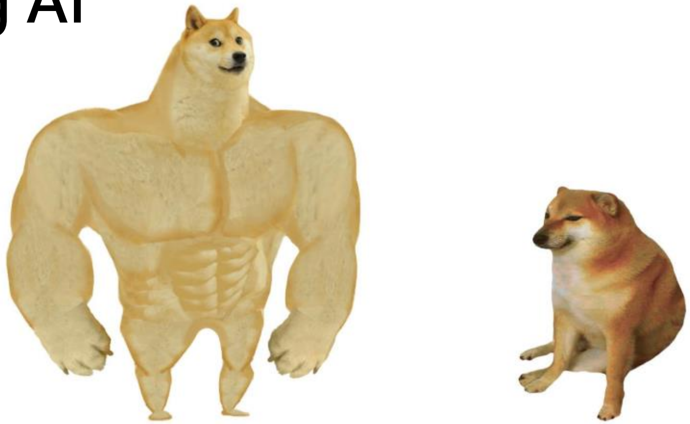
White Paper on Artificial Intelligence: a European approach to excellence and trust

Australian Government
Department of Industry, Science, Energy and Resources

Discussion Paper on Artificial Intelligence: Australia’s ethics framework

Strong and Weak AI

Strong AI



Weak AI

Strong and Weak AI

Strong AI

a machine with the ability to apply intelligence to any problem

…

sometimes considered to require consciousness, sentience and mind

Weak AI

implements only a limited part of mind

…

narrow AI that focuses on one specific task

Applications

AI and Deep Learning

Applications in geosciences

DL for inverse problems

Limitations, challenges and trends

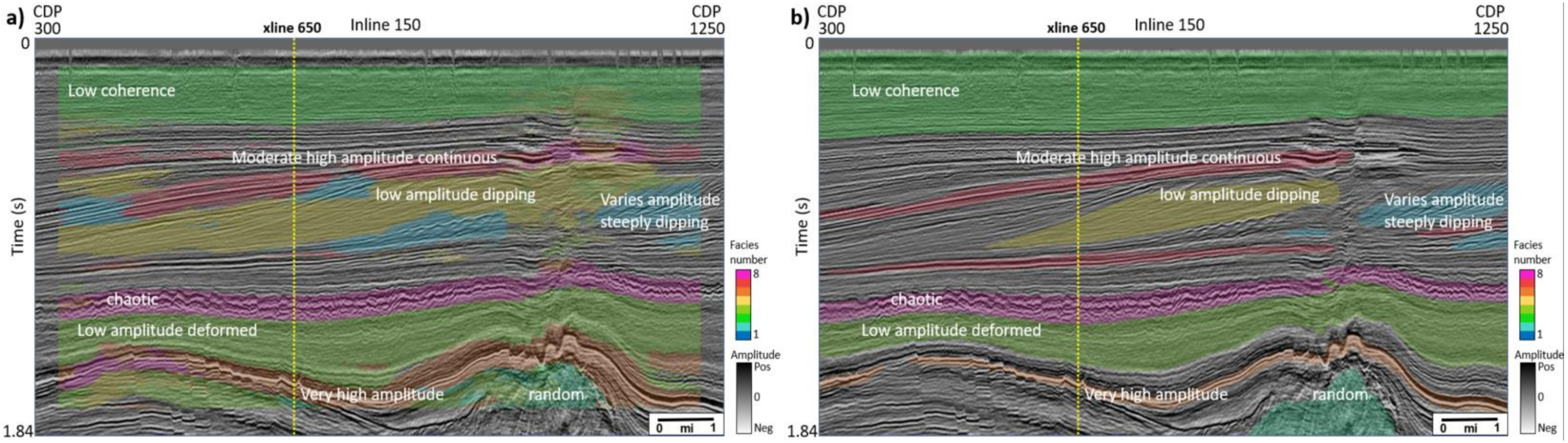
Geophysics & geology

Modern ML/DL use:

- ✓ Data processing
- ✓ Interpretation
- ✓ Modelling / Simulation
- ✓ Inversion
- ✓ Monitoring / Event prediction
- ✓ Risk assessment

Seismic interpretation

- Recognise geologically meaningful patterns in seismic data
- Manual interpretation is (a) extremely time consuming and (b) affected by the subjectivity of the interpreter



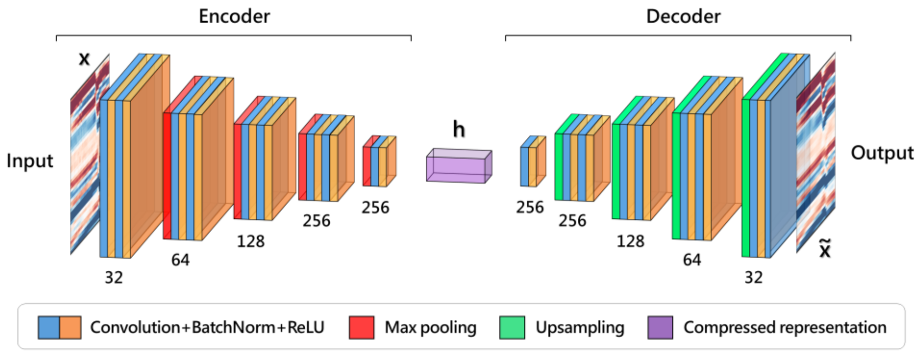
Source: T. Zhao, *SEG Annual Meeting*, 2018

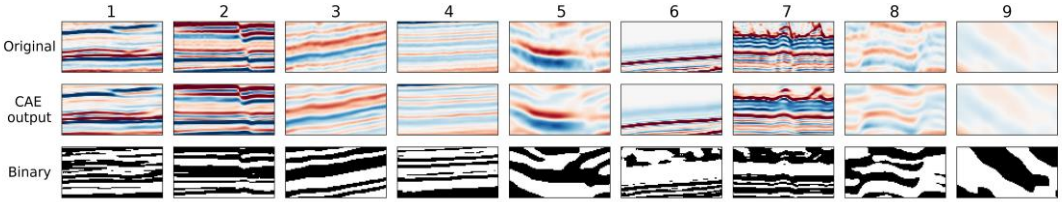
Supervised learning based on convolutional neural networks

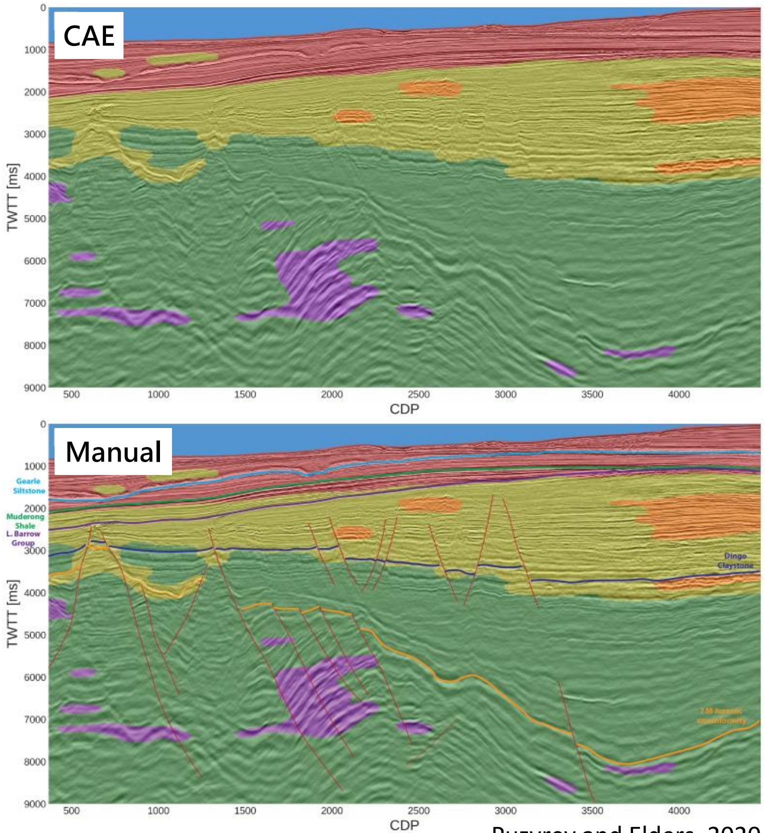
DL based interpretation

Unsupervised seismic interpretation

- **Deep convolutional autoencoder** (44 layers, **13M** params)
- No manually labelled examples required for training







Puzyrev and Elders, 2020

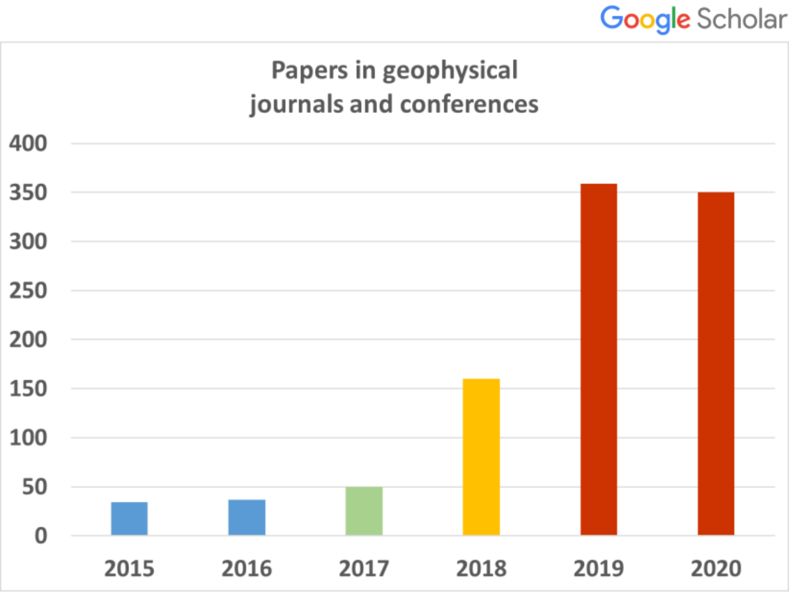
Research publications

deep learning

machine learning

neural networks

neural network



AI and Deep Learning

Applications in geosciences

DL for inverse problems

Limitations, challenges and trends

Inversion

The inverse problem: Given the observations, uncertainties, forward modelling
Find the subsurface model that gave rise to the data

Check Doug's and Colin's EMinars

Deterministic inversion aims at minimizing the misfit functional

$$\min_{\mathbf{m}} \phi(\mathbf{m}) = \min_{\mathbf{m}} \left(\|\mathbf{F}(\mathbf{m}) - \mathbf{d}\|_2^2 + \lambda \mathbf{R}(\mathbf{m}) \right)$$

Iterative process: $\mathbf{m_{k+1}} = \mathbf{m_k} + \alpha_k \mathbf{p_k}$

Search direction

$$\mathbf{p_k} = -\mathbf{B_k g_k} = -\mathbf{B_k} \nabla_{\mathbf{m_k}} \phi(\mathbf{m_k})$$

Gradient w.r.t. model params

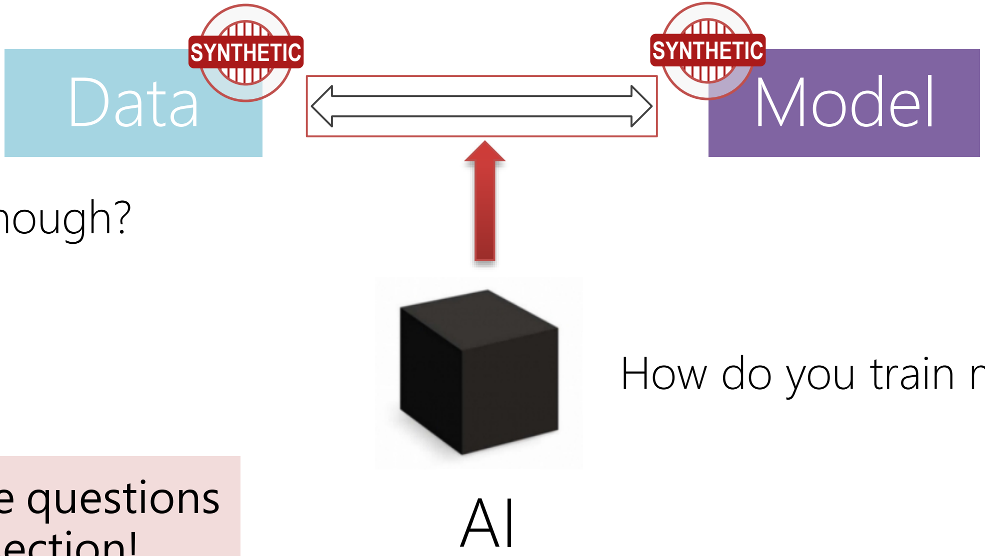
$$\mathbf{g} = \nabla_{\mathbf{m}} \phi(\mathbf{m}) = -\mathrm{Re}\left[\mathbf{J}^T (\mathbf{F}(\mathbf{m}) - \mathbf{d})^* \right] + \lambda \nabla_{\mathbf{m}} \mathbf{R}(\mathbf{m})$$

$$\nabla \times \nabla \times \mathbf{E}_s + i\omega\mu_0 \sigma \mathbf{E}_s = -i\omega\mu_0 (\sigma - \sigma_p) \mathbf{E}_p$$

Another way to make it work (?)

Do you know me?

Am I real?



Am I good?

Am I sufficient enough?

How do you train me?

Hey! Leave these questions for the last section!

Inversion

Deterministic inversion

Minimize the misfit functional $\min_{\mathbf{m}} \phi(\mathbf{m}) = \min_{\mathbf{m}} \left(\|\mathbf{F}(\mathbf{m}) - \mathbf{d}\|_2^2 + \lambda \mathbf{R}(\mathbf{m})\right)$

Build model updates $\mathbf{m_{k+1}} = \mathbf{m_k} + \alpha_k \mathbf{p_k}$

Determine search direction $\mathbf{p_k} = -\mathbf{B_k g_k} = -\mathbf{B_k} \nabla_{\mathbf{m_k}} \phi(\mathbf{m_k})$

Runtime:

hours, days, weeks

Deep learning inversion

1. Generation of the **training data** (multiple forward modelling simulations)

   hours, days, weeks

2. Network training

   hours, days

Offline

3. Estimation of subsurface models from new unseen data

   less than a second

Online

Early applications

Lots of neural networks applications in the 90s!

Seismic: Röth & Tarantola 1992, 1994

EM:

Poulton, Sternberg & Glass, 1992

Raiche, 1991 (pattern recognition context)

El-Kaliouby, Poulton, ElDiwany, 1999

MT:

Swiniarski, Hidalgo & Gomez-Trevino, 1993

Spichak & Popova, 2000

DC:

El-Qady & Ushijima, 2001

Borehole resistivity:

Zhang, Poulton & Wang, 2002

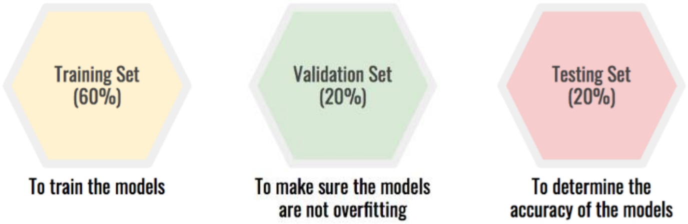
Review papers:

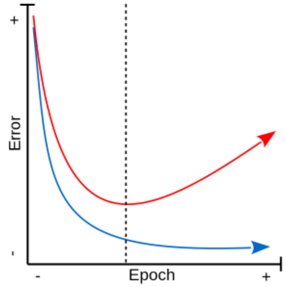
van der Baan & Jutten, *Neural networks in geophysical applications* (2000)

Poulton, *Neural networks as an intelligence amplification tool: A review of applications* (2002)

Generalization

Modern approach: deep neural networks and Big Data





Generalization is model's ability to adapt properly to new, previously unseen data*

*drawn from the same distribution as the one used to create the model

(i.e. being effective across a range of various inputs)

Features of the method

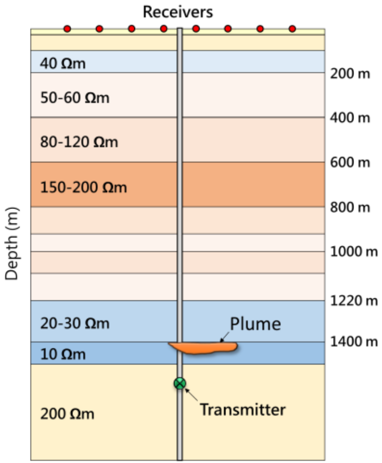
- DL inversion **does not require regularization** (in its traditional meaning).

  The network is trained on a training dataset and thus learns how to reproduce similar models

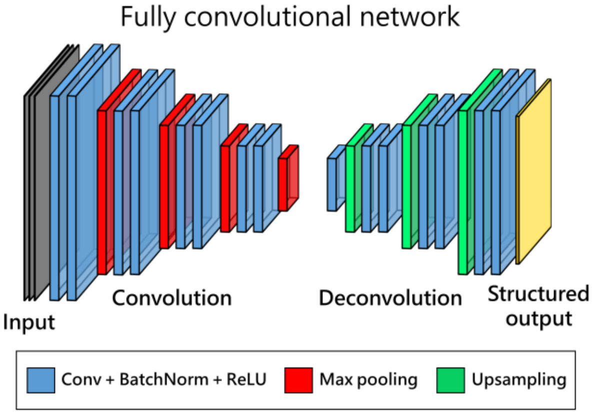
- **Sharpness of models** is now determined by the training data.

- **Optimization** (training) of neural networks involves mini-batch adaptive learning rate algorithms such as Adagrad, Adadelta, Adam or NAdam.

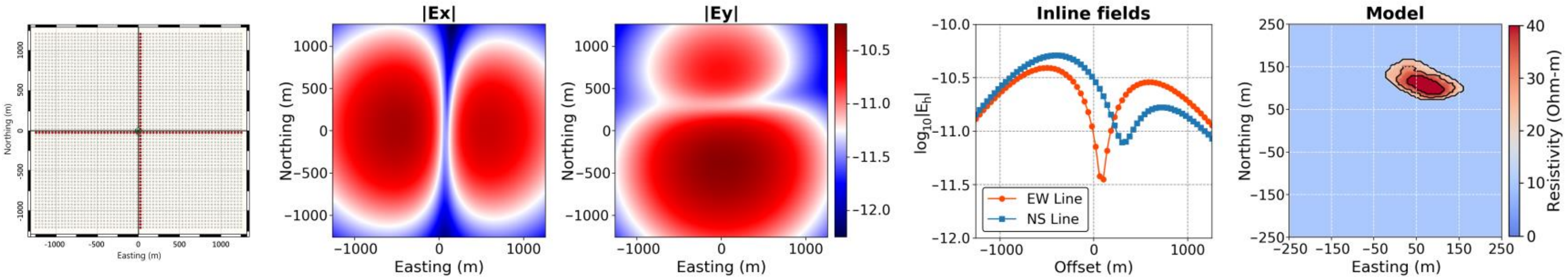
2D EM Inversion



- Full 3D modelling
- 20,000 models for training
- 2D inversion with CNNs
  - Networks with 1-10 millions parameters
  - Predicting model parameters from new data in a few milliseconds



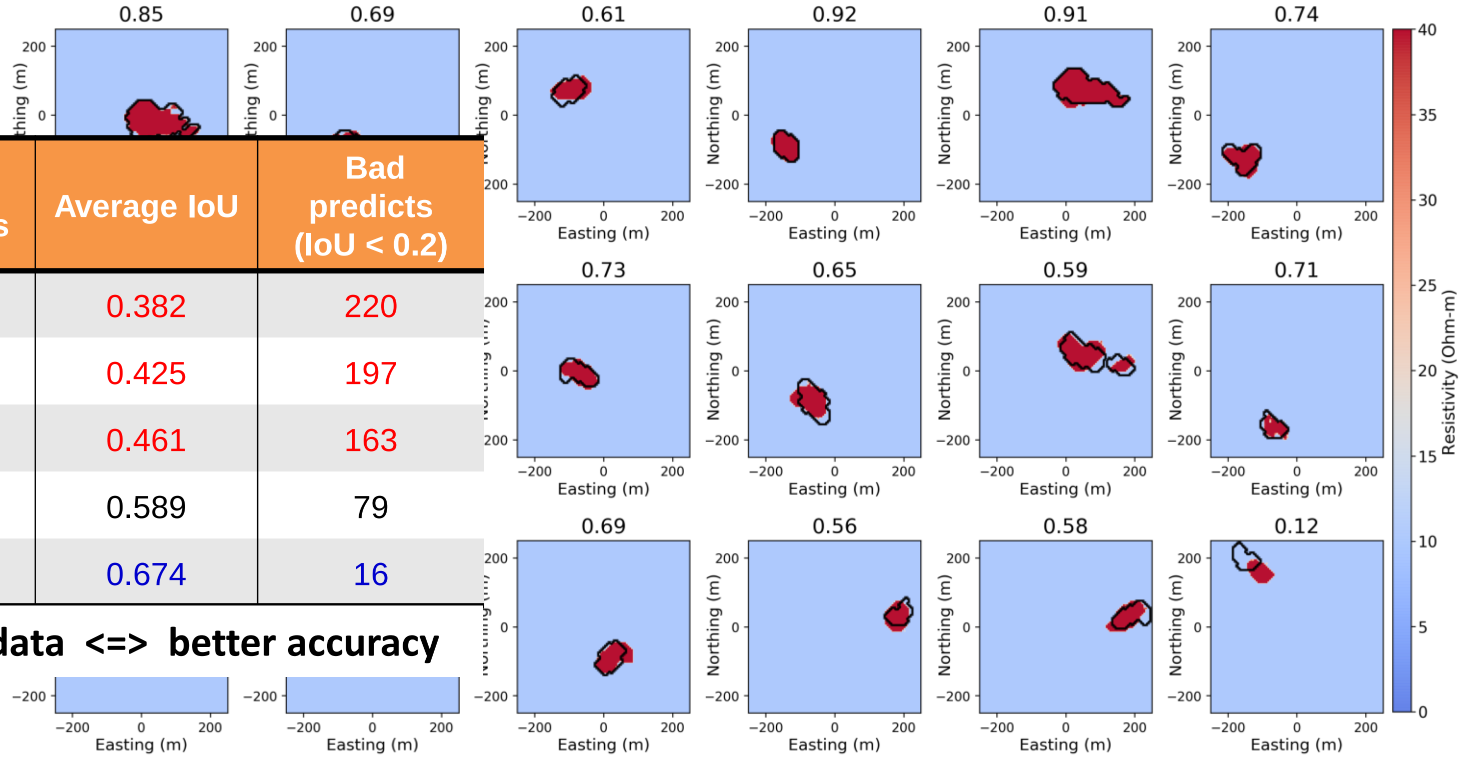
Puzyrev, 2019



2D EM Inversion

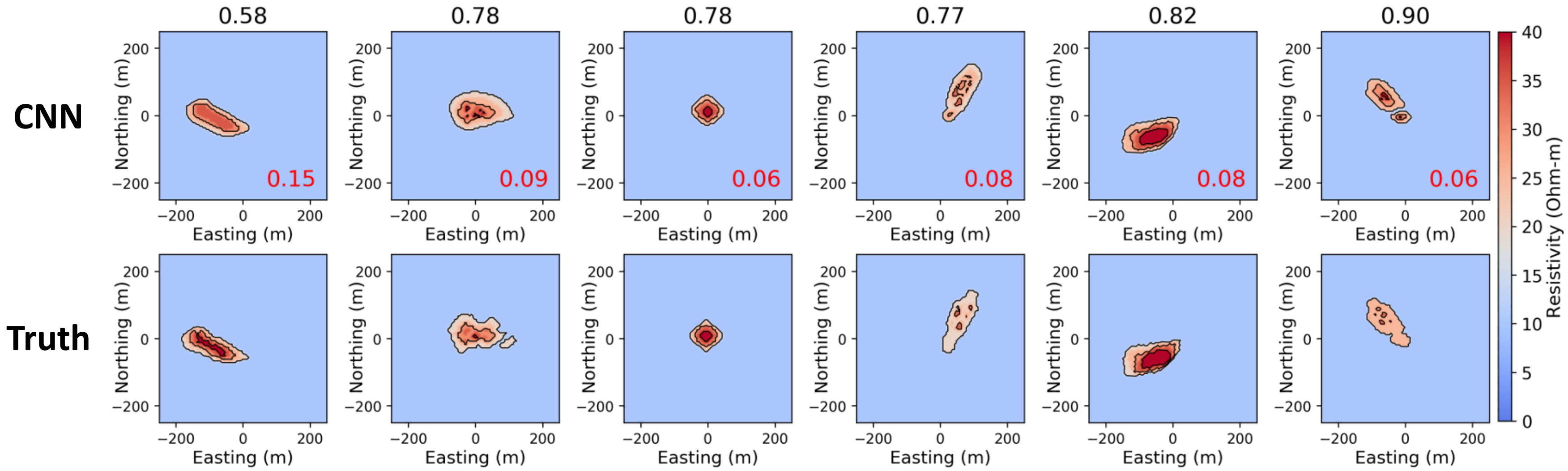
Training examples	Average IoU	Bad predicts (IoU < 0.2)
500	0.382	220
1000	0.425	197
2000	0.461	163
5000	0.589	79
19200	0.674	16

More data <=> better accuracy

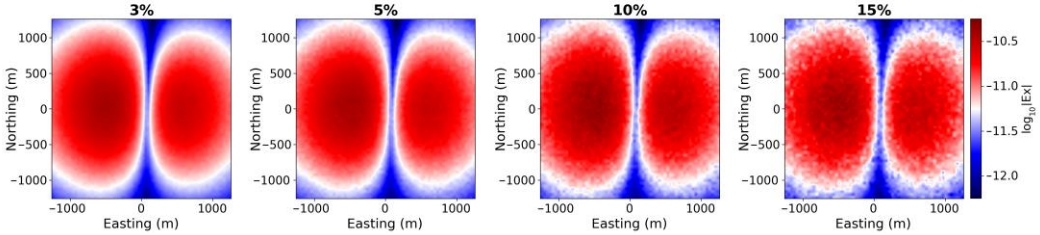


Test models (2D receiver layout). Average IoU **0.67**

2D EM Inversion

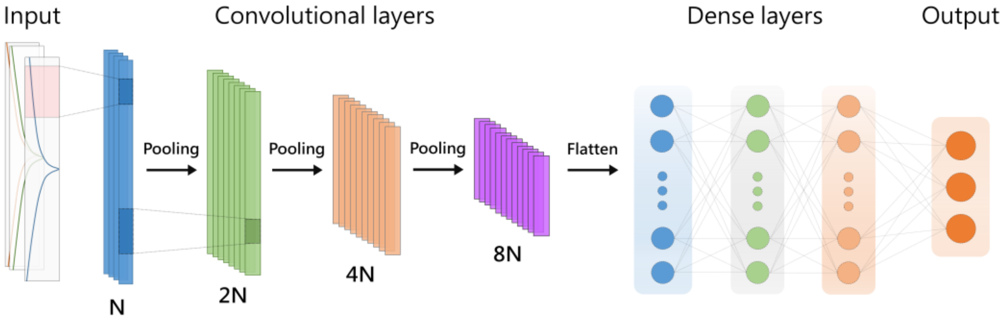


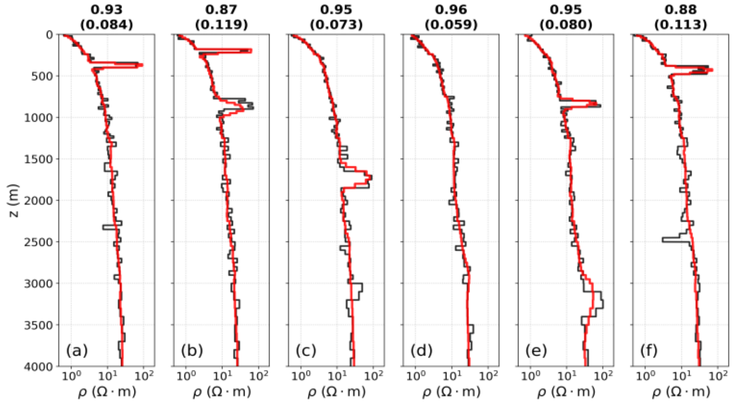
High robustness to noise



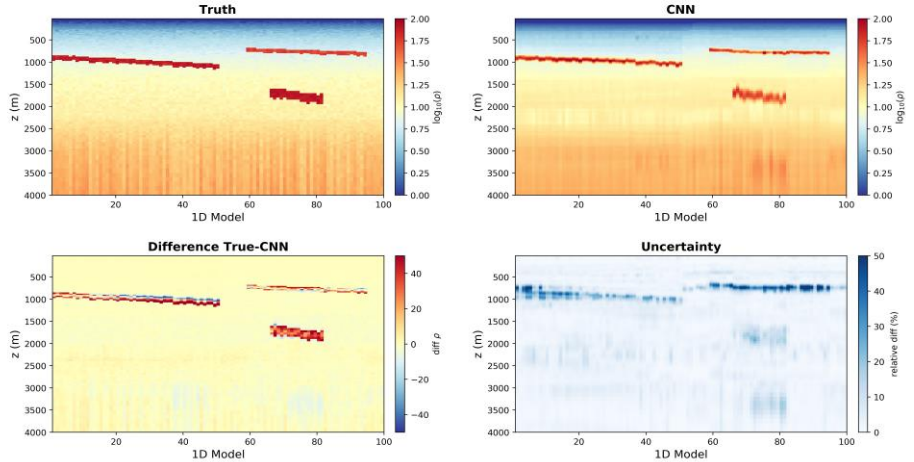
Noise level	Average IoU	Bad predicts (IoU < 0.2)
0	0.672	17 / 800
3%	0.663	18 / 800
5%	0.649	23 / 800
10%	0.625	51 / 800
15%	0.581	103 / 800

1D EM (Exploration)





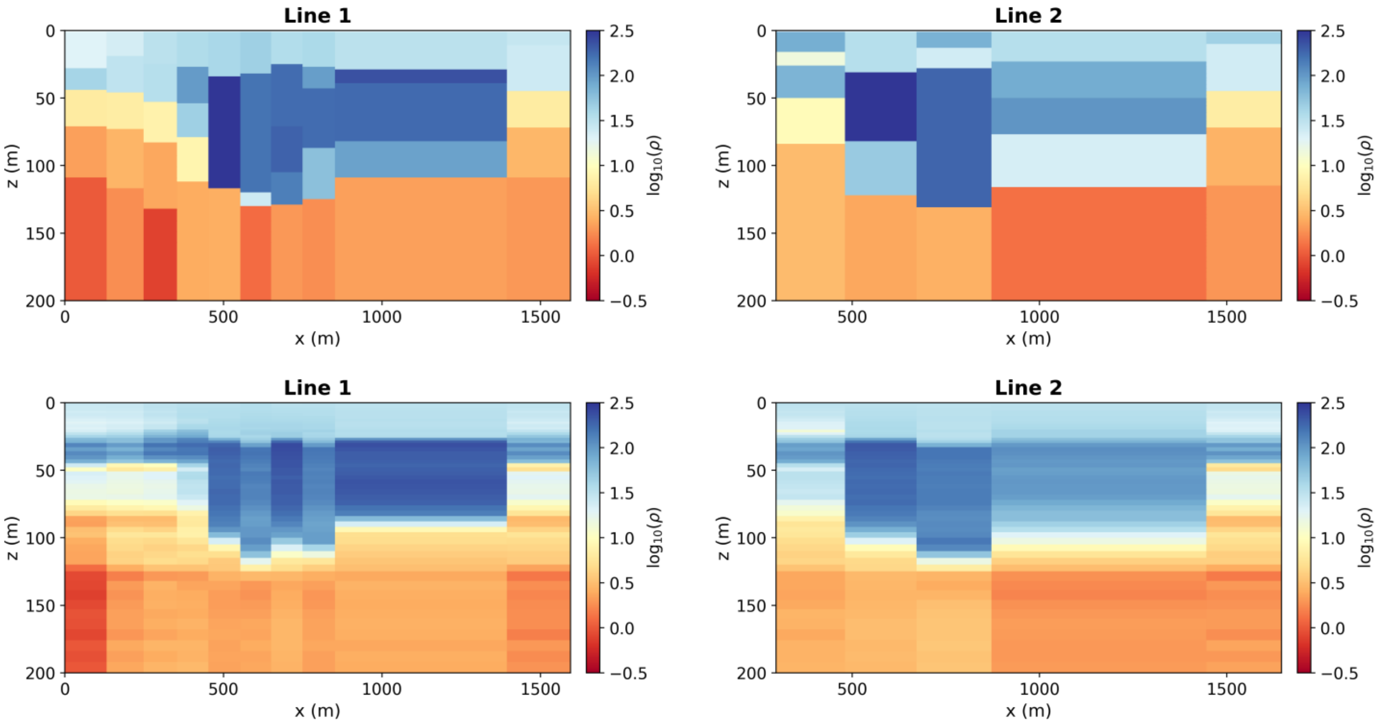
- FD CSEM and TEM
- 1D forward modelling codes
- MPI parallelization
- 512k / 10k examples for training



Puzyrev and Swidinsky, 2020

WalkTEM data

ABEM WalkTEM dataset (Guideline Geo, Denmark)



Conventional Levenberg-Marquardt inversion

DL inversion

Puzyrev and Swidinsky, 2020

Seismic Inversion

Training data (v_p range 1100-4200 m/s)

Sandstone

Shale

Chalk

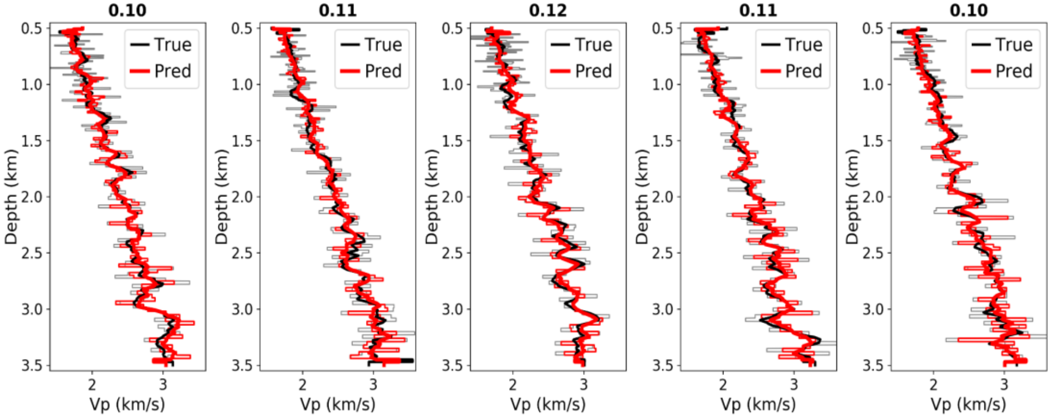
Coal

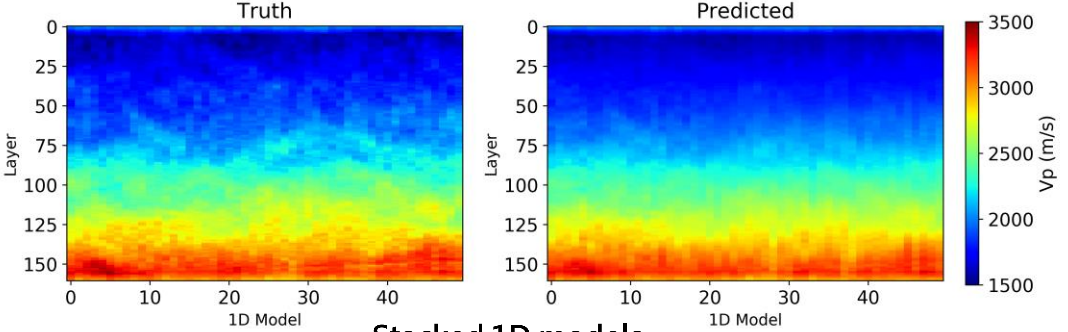
Clay

Anhydrite

160 layers of varying size,

trained on 81k examples

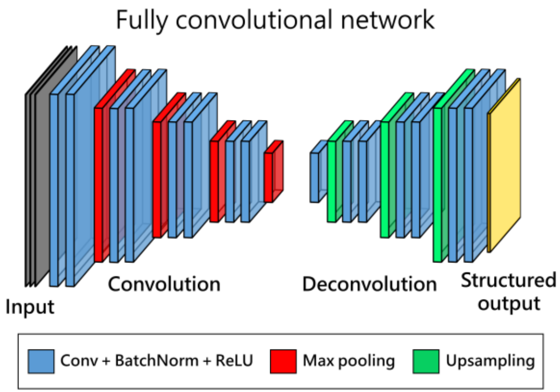


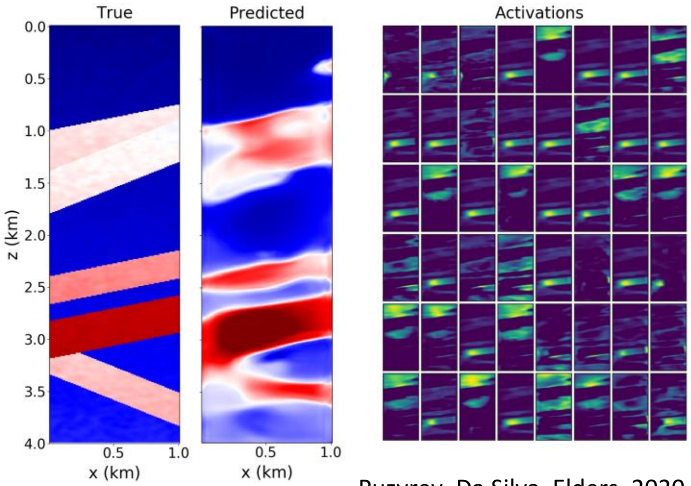


Stacked 1D models

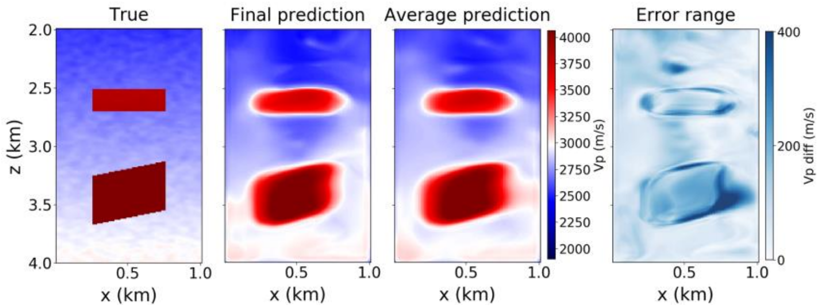
Puzyrev et al., 2019

2D FWI





Puzyrev, Da Silva, Elders, 2020

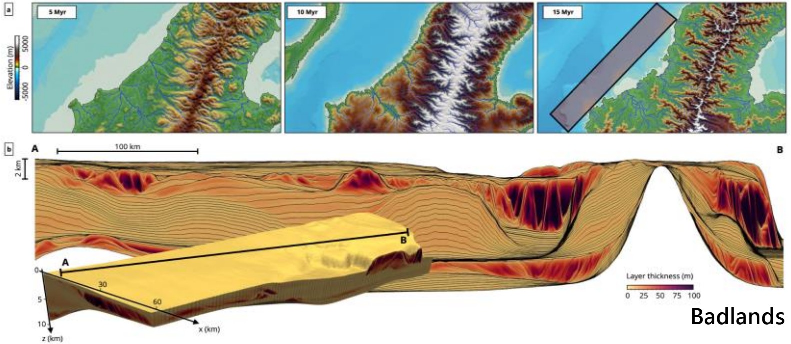


- More **training data** is required
- Higher **complexity of models**

Geophysical model generation

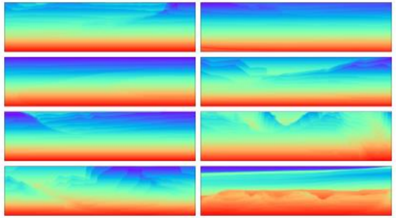
GANs for generation of synthetic models

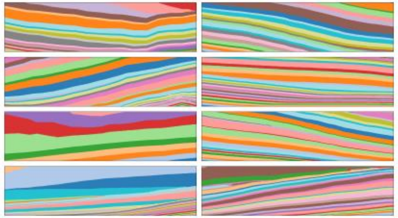
- Allows to create large realistic training sets for other DL algorithms
- Check it on Github!



Badlands

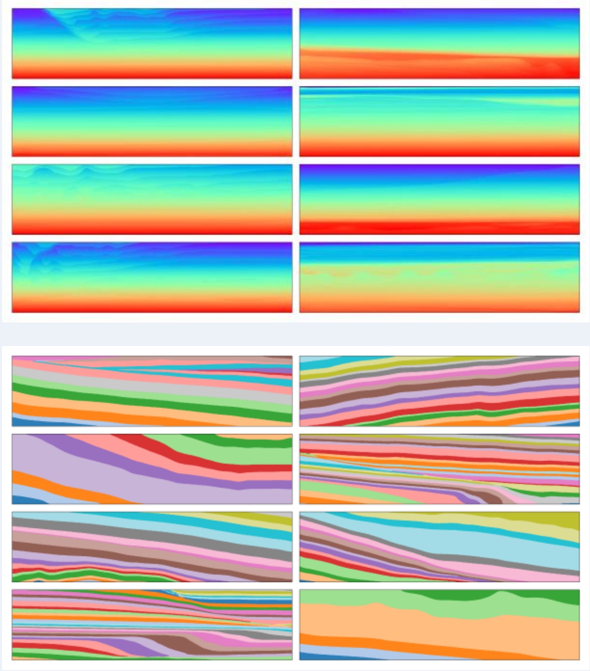
Density





Stratigraphy

Extracted from simulated 3D models

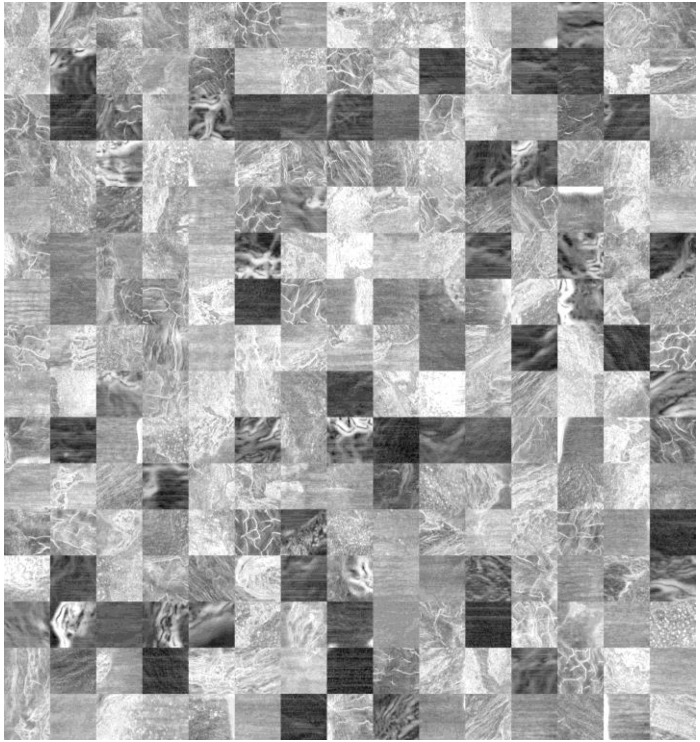


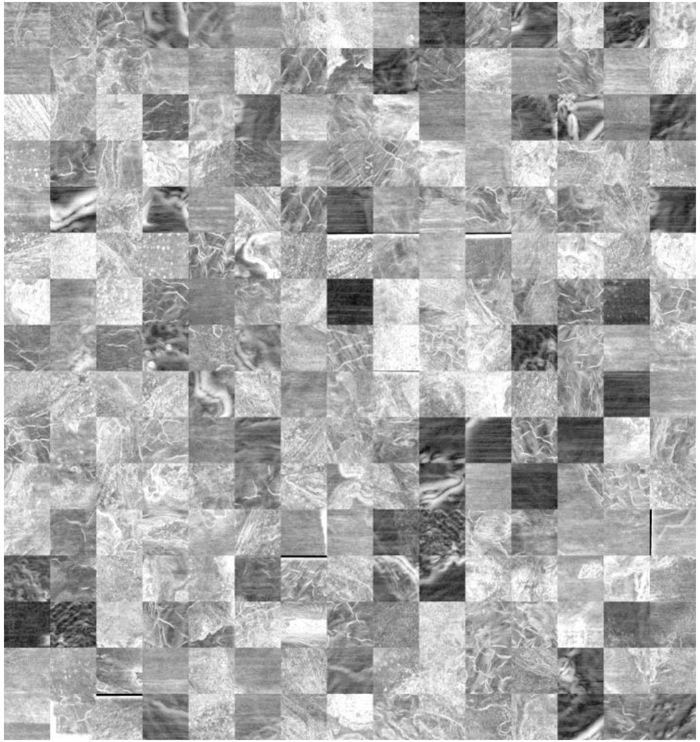
Generated by a neural network

Puzyrev et al., 2021

Seismic data with GANs

Controllable generation of data samples that meet user-defined criteria





Marine seismic data (N-W Australian shelf)
© K. Wright Internship Project

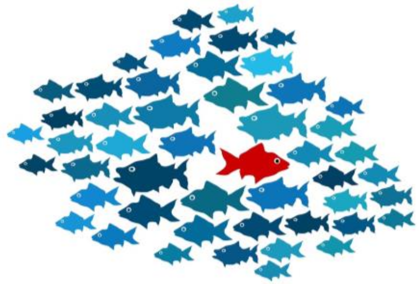
Parameter estimation with NN

- Analysis of hidden dependencies in other types of data (e.g., **geochemical**)

- Identifying **anomalies**

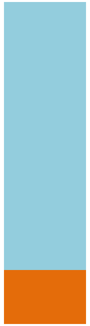
- Populating **missing data**

- Predicting **deposit occurrence**



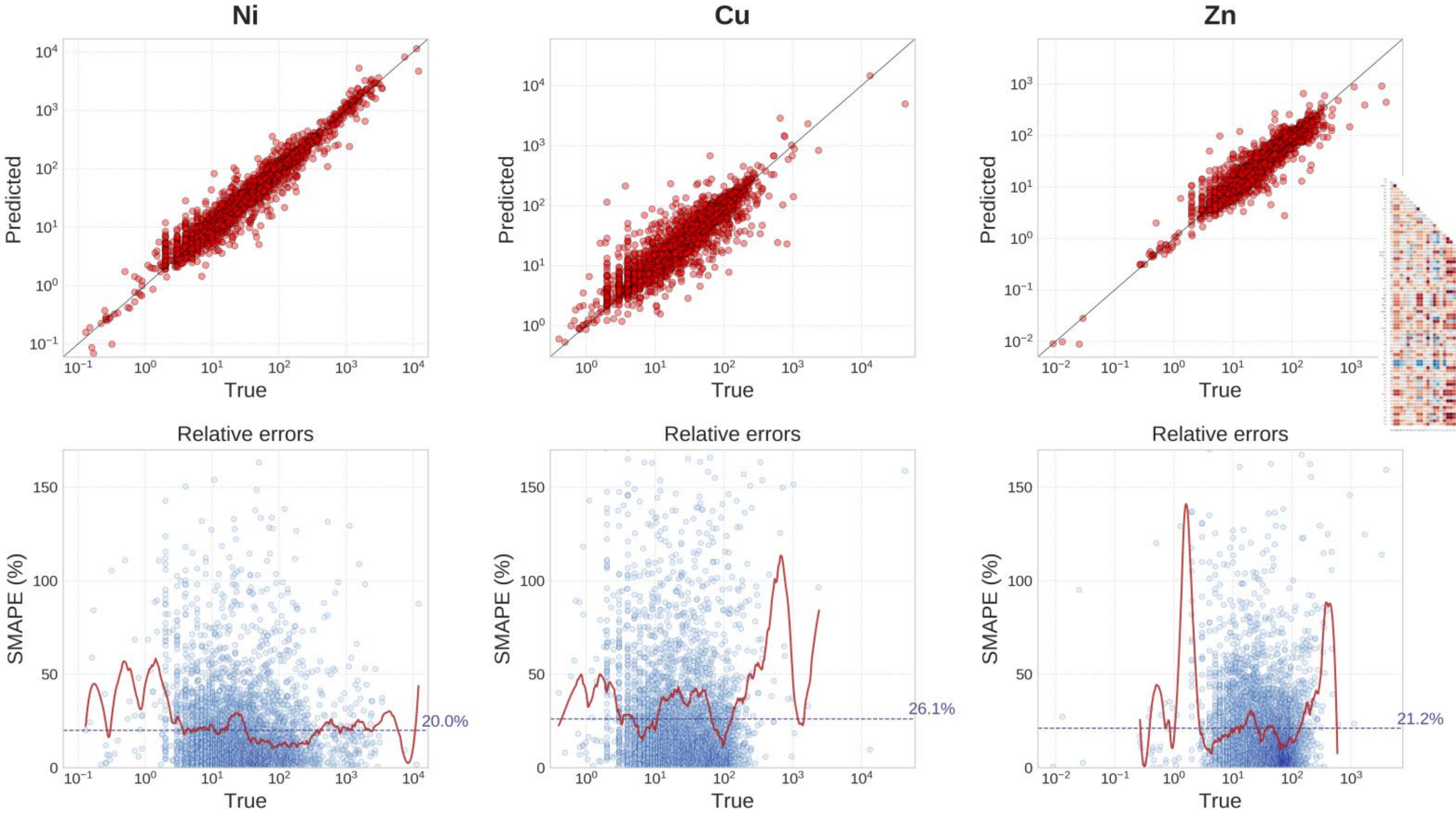
WACHEM example

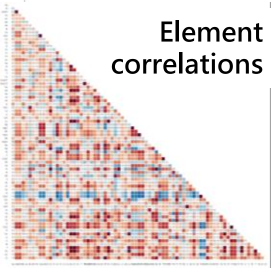
45k



Training

Test





Element correlations

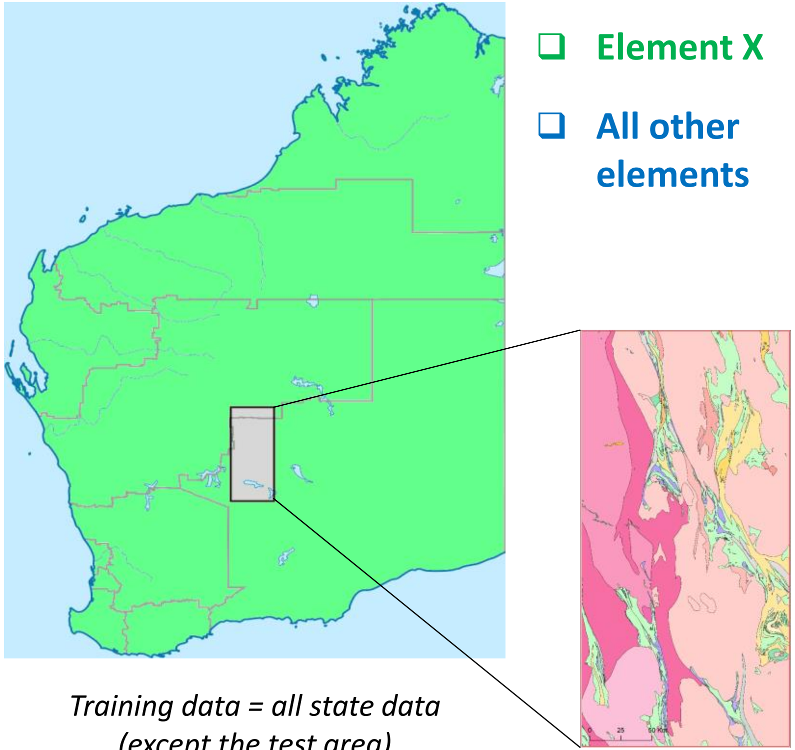
SMAPE

$$\frac{200\%}{N}\sum_{i=1}^{N}\frac{|y_i-\hat{y}_i|}{|y_i|+|\hat{y}_i|}$$

Puzyrev, Duuring, Zelic, 2021

Predictions within a region

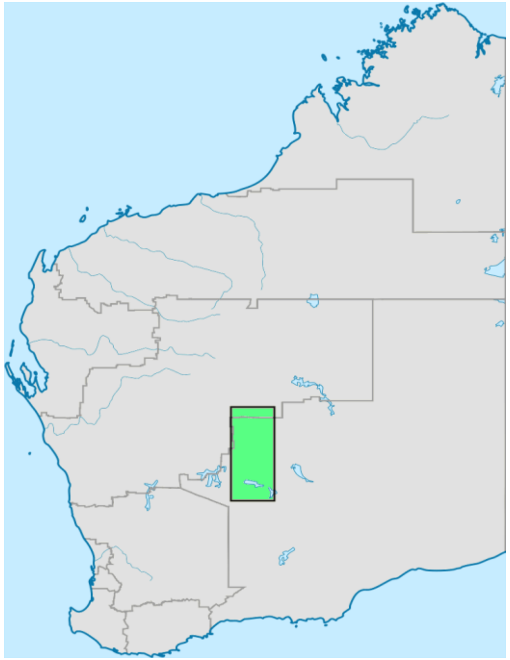
Training setup



- Element X
- All other elements

Training data = all state data (except the test area)

Test setup

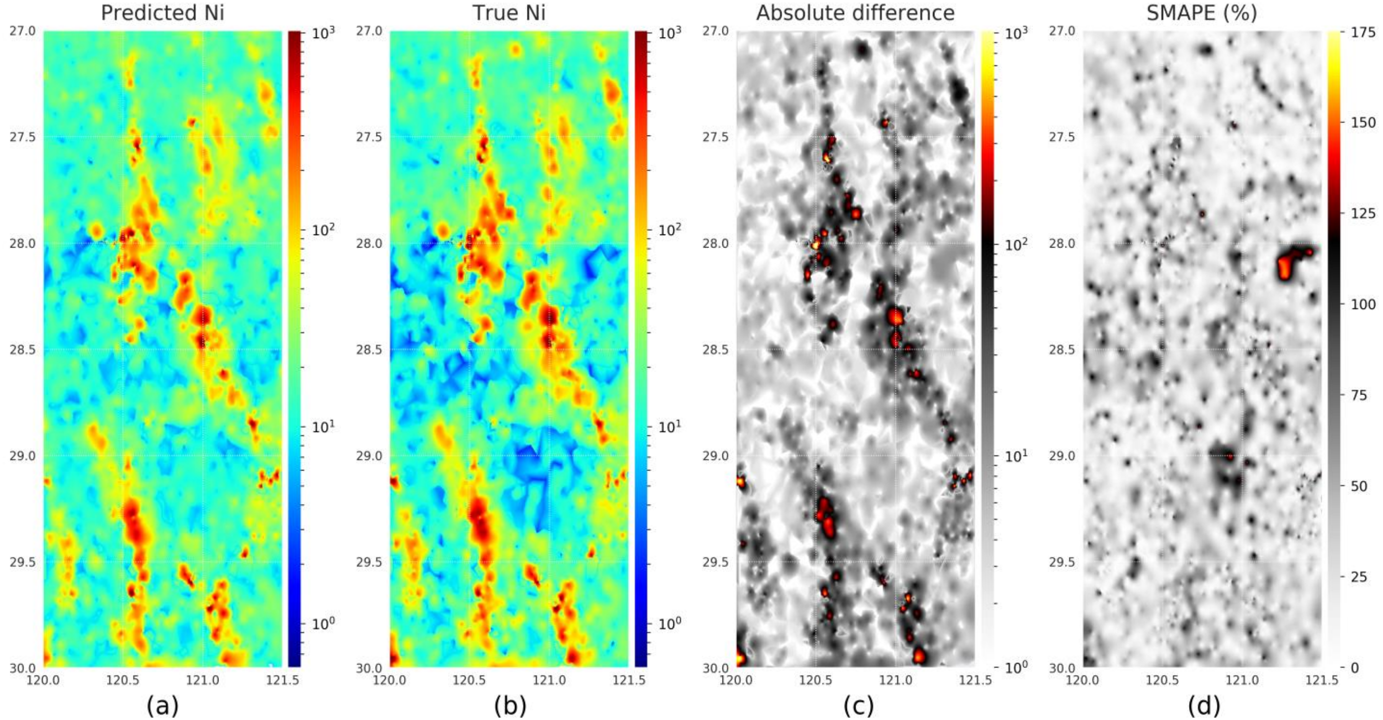


- Element X unknown
- All other elements
- Can we accurately estimate X?

Test area = the Sir Samuel, Menzies and Leonora area

Test set 2: Ni

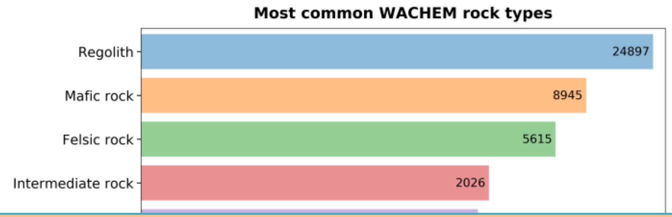
Estimation of **Ni** content in samples from the test area



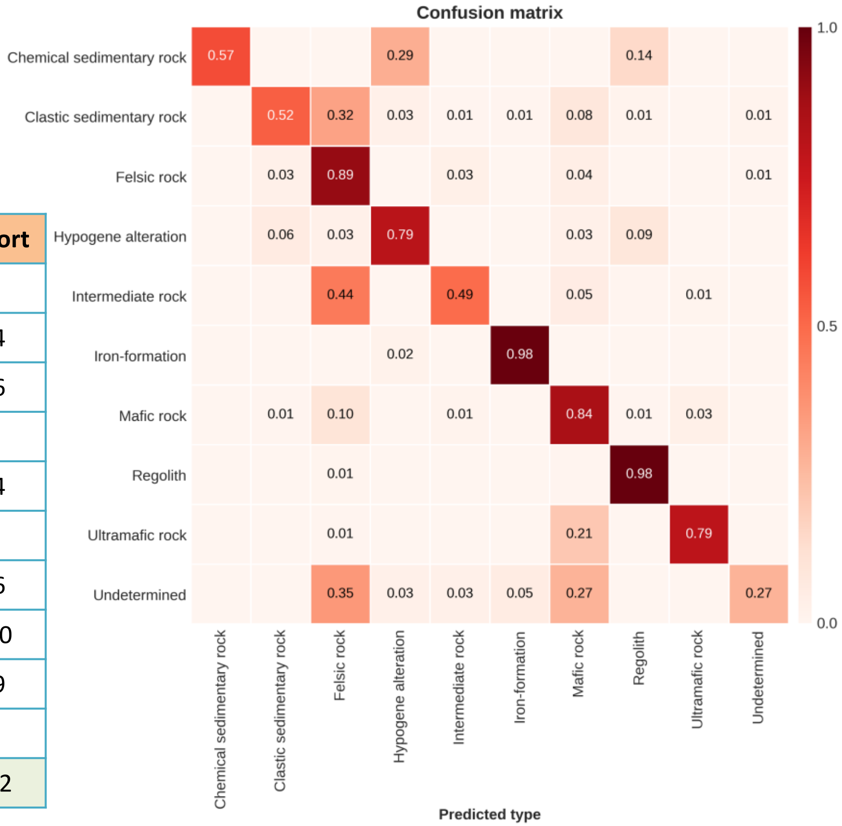
SMAPE

$$\frac{200\%}{N}\sum_{i=1}^{N}\frac{|y_i-\hat{y}_i|}{|y_i|+|\hat{y}_i|}$$

Classification example



Rock Type	Precision	Recall	F1-score	Support
Chemical sedimentary rock	1.000	0.571	0.727	7
Clastic sedimentary rock	0.745	0.522	0.614	134
Felsic rock	0.653	0.890	0.753	556
Hypogene alteration	0.771	0.794	0.783	34
Intermediate rock	0.770	0.486	0.596	214
Iron-formation	0.936	0.978	0.957	45
Mafic rock	0.876	0.844	0.860	886
Regolith	0.995	0.985	0.990	2490
Ultramafic rock	0.815	0.788	0.801	179
Undetermined	0.588	0.270	0.370	37
Weighted average	0.900	0.894	0.892	4582



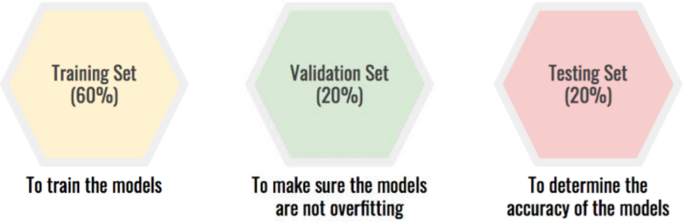
AI and Deep Learning

Applications in geosciences

DL for inverse problems

Limitations, challenges and trends

Generalization



It works perfectly well when all data comes from one distribution…

… and what if not?

High **generalization** - ability to be **effective across a range of various inputs**

 tomato

 tomato

 tomato

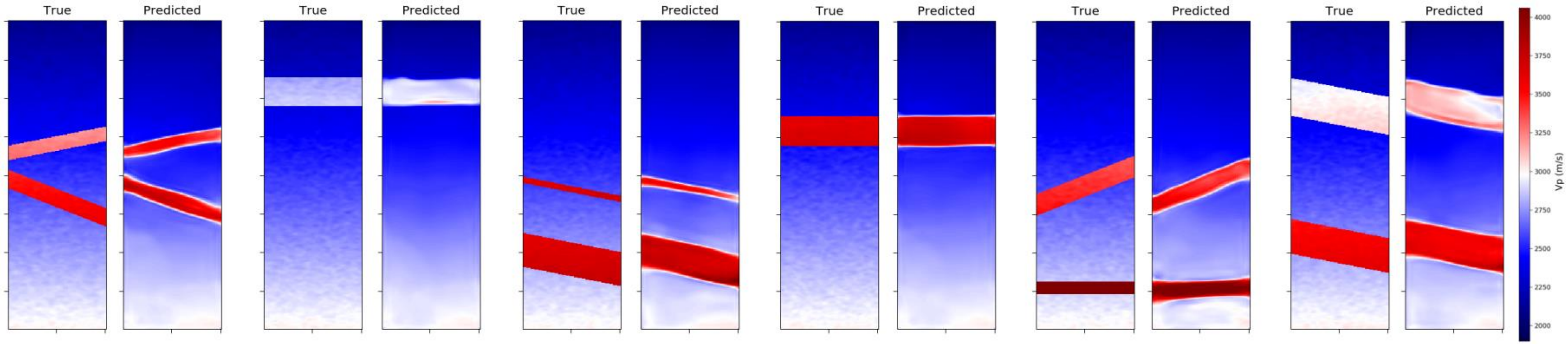
 tomato

 tomato

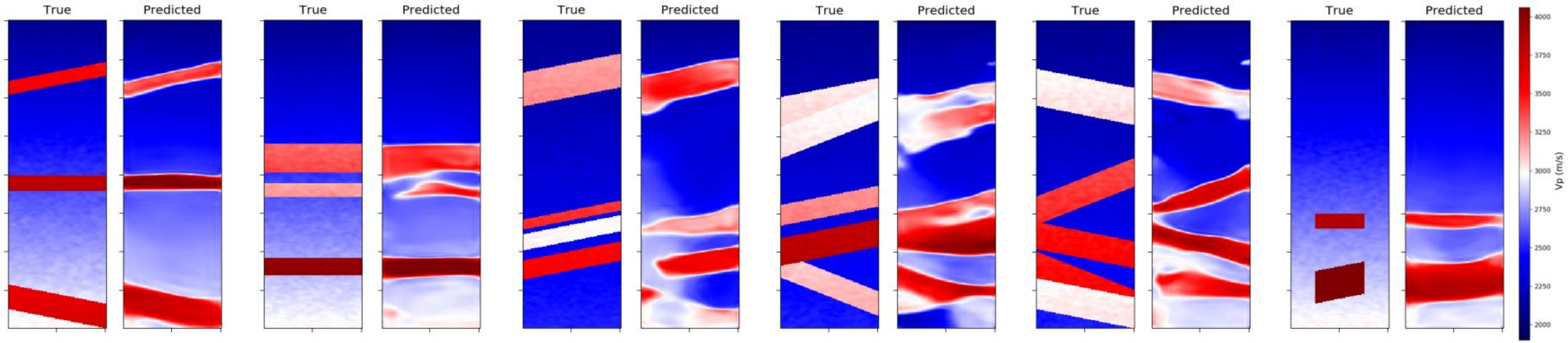
 big tomato

Sufficiently large set of **representative models**

Unexpected models

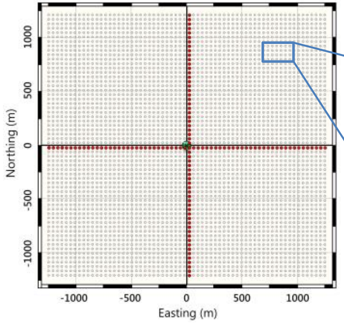


Velocity models (100x400) from the test dataset (previously unseen but similar to the training data)

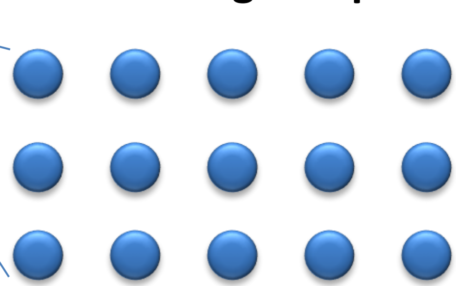


Velocity models (100x400) from another distribution, different from the training data

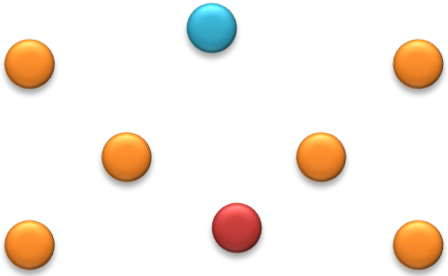
Survey setup generalization

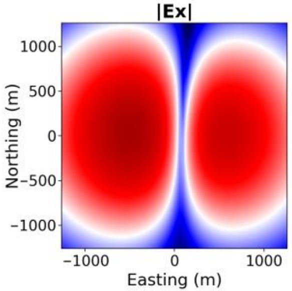


Training setup

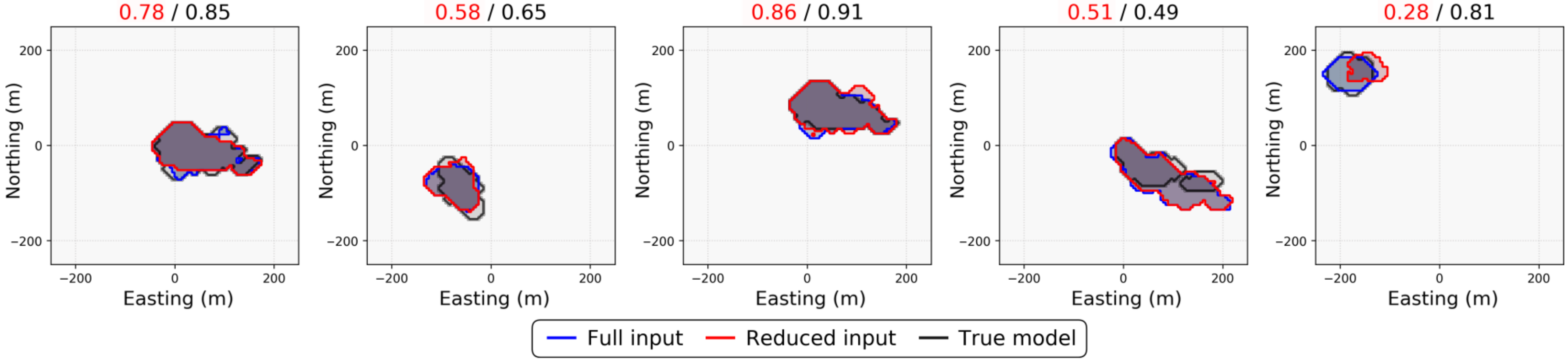


Testing setup





896 / 4096



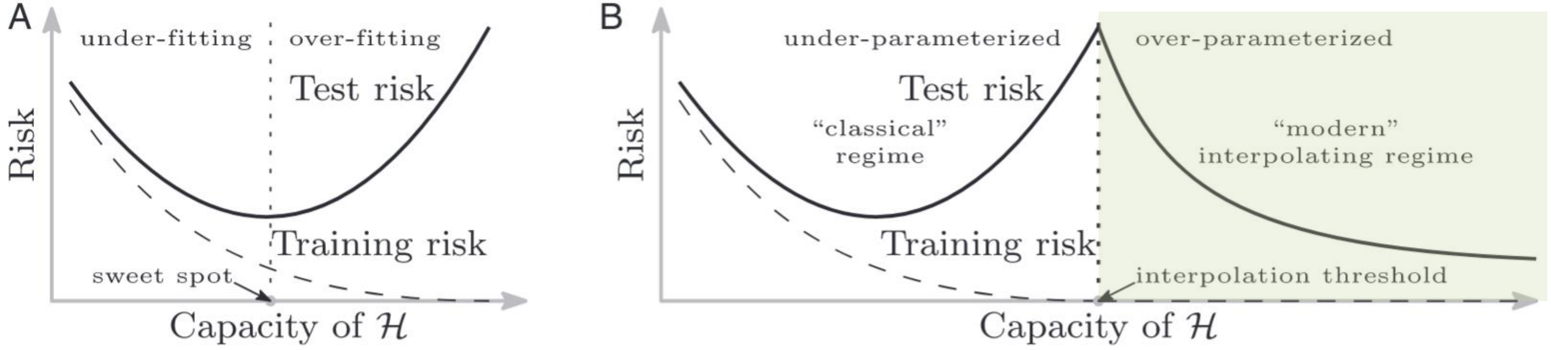
More things to consider

- Optimal **hyperparameters** for each case
  - E.g., guided by the validation error during the training (to avoid overfitting on training data)
  - Stopping criteria?
- **Transfer learning**
  - Copying the model / algorithm that is already known to perform best on another task that has been studied extensively
- New **loss functions**
  - Tailored for your task
- **Explainability** / **visualization**

More things to consider

- Optimal **hyperparameters** for each case
  - E.g., guided by the validation error during the training (to avoid overfitting on training data)
  - Stopping criteria?

Classical U-shaped curve **Double-descent curve**



Reconciling modern machine-learning practice and the classical **bias–variance trade-off**
Belkin et al., 2019

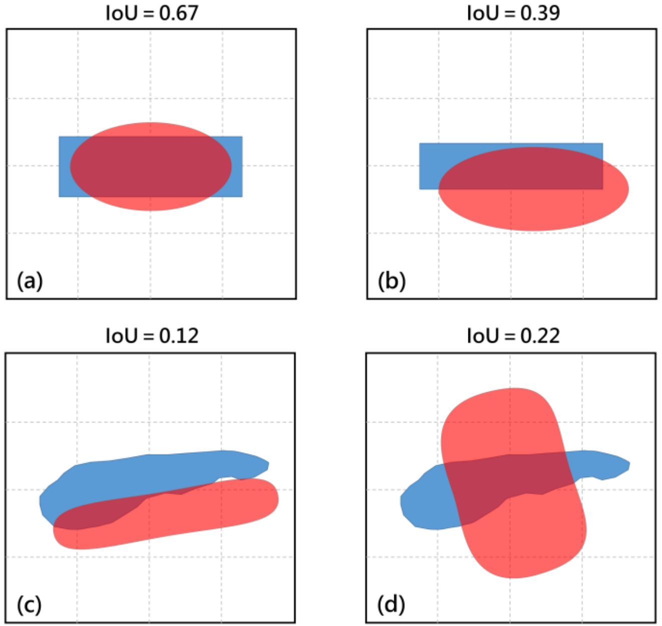
Loss functions

How we define model similarity?

$$\min_{\mathbf{m}} \phi(\mathbf{m}) = \min_{\mathbf{m}} \left(\|\mathbf{F}(\mathbf{m}) - \mathbf{d}\|_2^2 + \lambda \mathbf{R}(\mathbf{m}) \right)$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |m_i - \hat{m}_i| \qquad \mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (m_i - \hat{m}_i)^2}$$

$$\mathrm{IoU} = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|}$$



Incorporating physics

Neural networks that **respect physical laws** described by PDEs

Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations

M. Raissi [a], P. Perdikaris [b,*], G.E. Karniadakis [a]

[a] *Division of Applied Mathematics, Brown University, Providence, RI, 02912, USA*
[b] *Department of Mechanical Engineering and Applied Mechanics, University of Pennsylvania, Philadelphia, PA, 19104, USA*

DGM: A deep learning algorithm for solving partial differential equations [☆,☆☆]

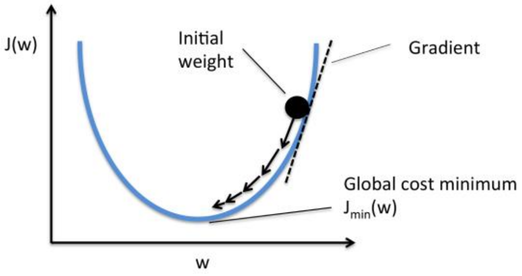
Justin Sirignano [a,*], Konstantinos Spiliopoulos [b]

[a] *University of Illinois at Urbana Champaign, Urbana, United States of America*
[b] *Department of Mathematics and Statistics, Boston University, Boston, United States of America*

DL and traditional inversion

Developments from the ML/DL field can be used in traditional deterministic inversion

E.g., **meta-learning methods**



"learned neural optimizers"

Learning to learn by gradient descent by gradient descent

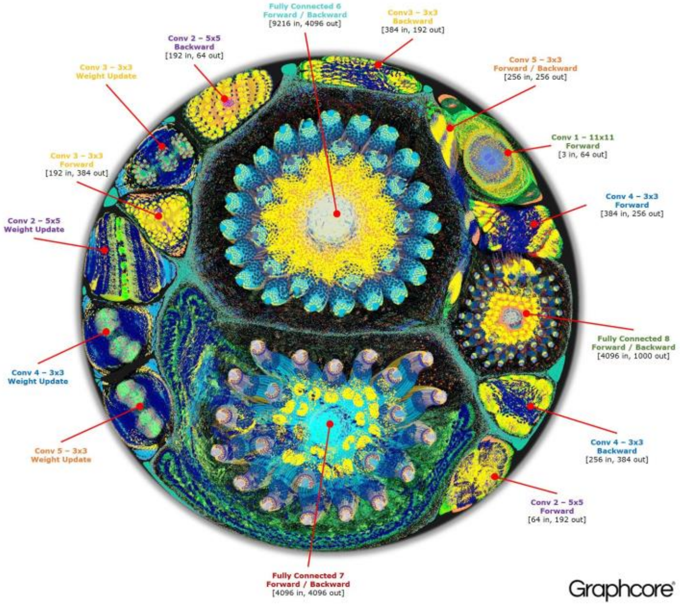
Marcin Andrychowicz[1], Misha Denil[1], Sergio Gómez Colmenarejo[1], Matthew W. Hoffman[1], David Pfau[1], Tom Schaul[1], Brendan Shillingford[1,2], Nando de Freitas[1,2,3]

[1]Google DeepMind [2]University of Oxford [3]Canadian Institute for Advanced Research

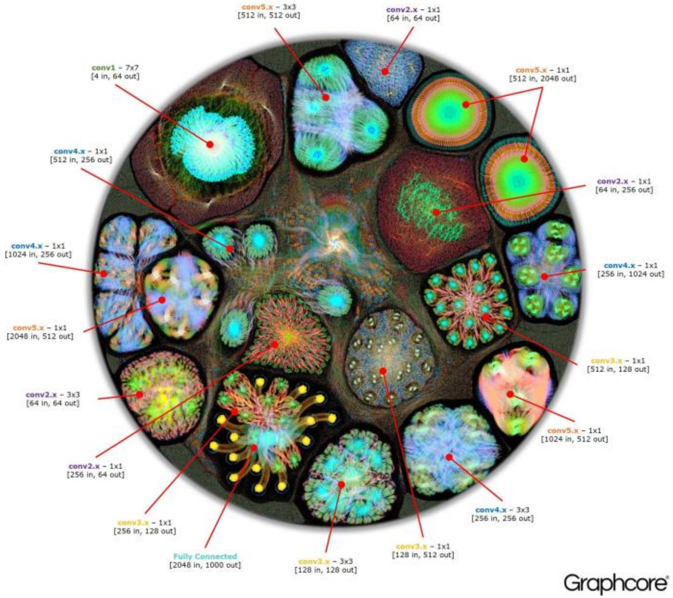
marcin.andrychowicz@gmail.com
{mdenil,sergomez,mwhoffman,pfau,schaul}@google.com
brendan.shillingford@cs.ox.ac.uk, nandodefreitas@google.com

Visualization

AlexNet



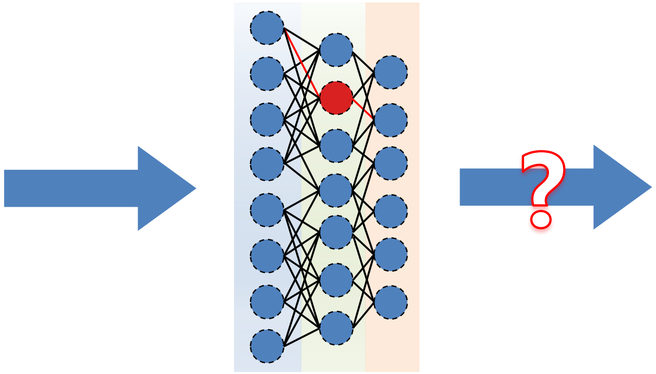
ResNet-50



Inside an AI 'brain' - What does machine learning look like?

Uncertainty quantification

Are we confident in the predicted model?

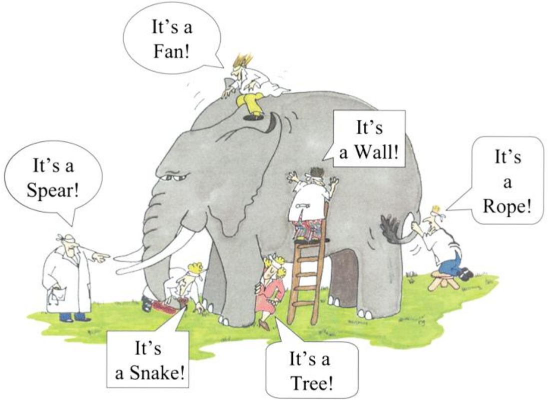


Conclusions and future outlook

- One of the most exciting and rapidly changing fields of the century

- Game changer in geosciences: active use since 2018 (processing, interpretation, modelling, inversion)

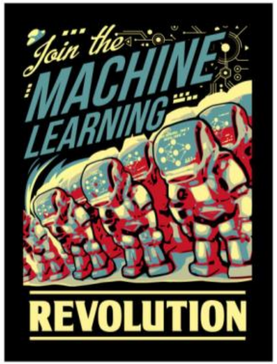
- DL methods in inverse problems:
  - Instantaneous parameter estimation
    (fast decision making, starting model for a conventional inversion)
  - Improving traditional inversion frameworks
  - Joint inversion and UQ



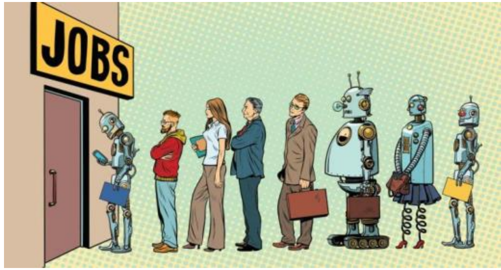
Conclusions and future outlook

Where should you use AI and deep learning?

- ❑ **Big data**
- ❑ **Spatially connected** data (e.g., images, videos, geo data)
- ❑ **Time-series** data (e.g., seismic signals)
- ❑ **Spatio-temporal** data (dynamic physical processes)
- ❑ **Text analysis** (NLP)
- ❑ **Control problems** (robotics, autonomous vehicles)
- ❑ **Uncertainty quantification**



Conclusions and future outlook



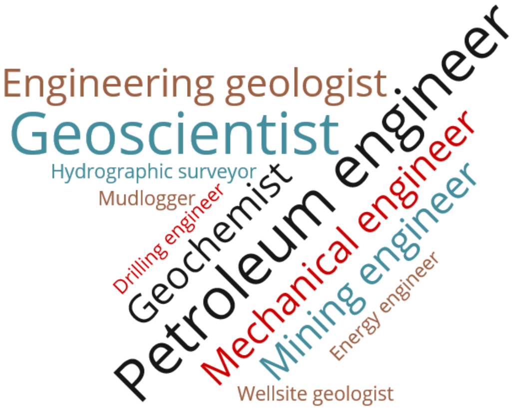
AI is changing the society (remember 1.0, 2.0, 3.0?...)

Around 800 million jobs could disappear worldwide by 2035

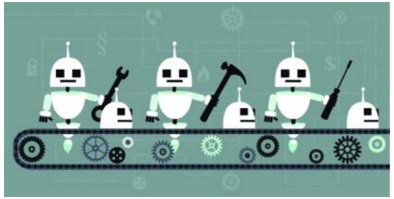
Bank of America Merrill Lynch (2019)

before COVID-19

2015



2025



Acknowledgements

- EMinars organizers and host

  Alan Jones, Kate Robertson, Max Moorkamp, Stephan Thiel

- Research collaborators:

  Chris Elders, Milo Barham, Chris Kirkland, Taryn Scharf, Claus Otto (Curtin), Shiv Meka (Curtin / WA DoH), Andrei Swidinsky (Colorado School of Mines), Paul Duuring (GSWA), Mario Zelic (Rio Tinto), Tristan Salles (University of Sydney), Greg Surma (IPJA), Anton Egorov, Anastasia Pirogova (Curtin / LMSU), Keaton Wright (UWA), Nuno da Silva (Imperial College London / TOTAL)

- Organizations:

  Curtin University Oil & Gas Innovation Centre (CUOGIC)

  The Institute for Geoscience Research (TIGeR)

  Pawsey Supercomputing Centre

  Geological Survey of Western Australia (GSWA)

- **You all for your attention!**