Introduction to Big Data & ML in Remote Sensing

Greg Tsagkatakis

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ICS – FORTH

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Who am I?

- BSc & MSc Electronics and Computer Engineering at the University of Crete, Greece (2005, 2007)
- Ph.D. Imaging Science, Rochester Institute of Technology, NY (2011)
- Research associate with Signal Processing Lab at the Foundation for Research and Technology – Hellas (FORTH)
- Marie-Curie fellowship with Prof. Mahta Moghaddam, Electrical and Computer Engineering, USC
- Assistant Professor at the Computer Science Department, University of Crete, Greece
- Research interest: (deep) machine learning for big scientific data analysis


United Kingdom
Denmark
Ireland
Poland
Belarus
Germany
Ukraine
Austria
France
Romania
Italy
Spain
Portugal
Greece
Türkiye
Tunisia
Morocco

FORTH

FORTH

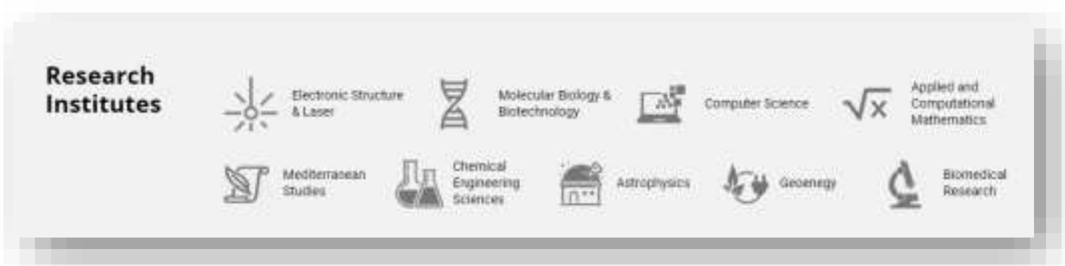
ICS + 8 Institutes

SPL + 7 Labs

2006

4 Researchers/Academics (permanent)
1 Postdoctoral Researchers
12 Postgraduate Students
2 Research Engineers

> 9M€ (PI/co-PI in EU & national projects)



Collaborators

Panos Tsakalides
Head of the Signal Processing lab

Mahta Moghaddam
Head of Microwave Systems, Sensors, and Imaging Lab

Jean-Luc Starck
Head of the CosmoStat lab
French Alternative Energies and Atomic Energy Commission

Funding

CALCHAS

Computational Intelligence for Multi-Source Remote Sensing Data Analytics

MARIE CURIE ACTIONS

European Commission

Horizon 2020
European Union funding
for Research & Innovation

TITAN

ARTIFICIAL INTELLIGENCE
IN ASTROPHYSICS

European Commission

RESEARCH EXECUTIVE AGENCY

esa

NASA

Overview

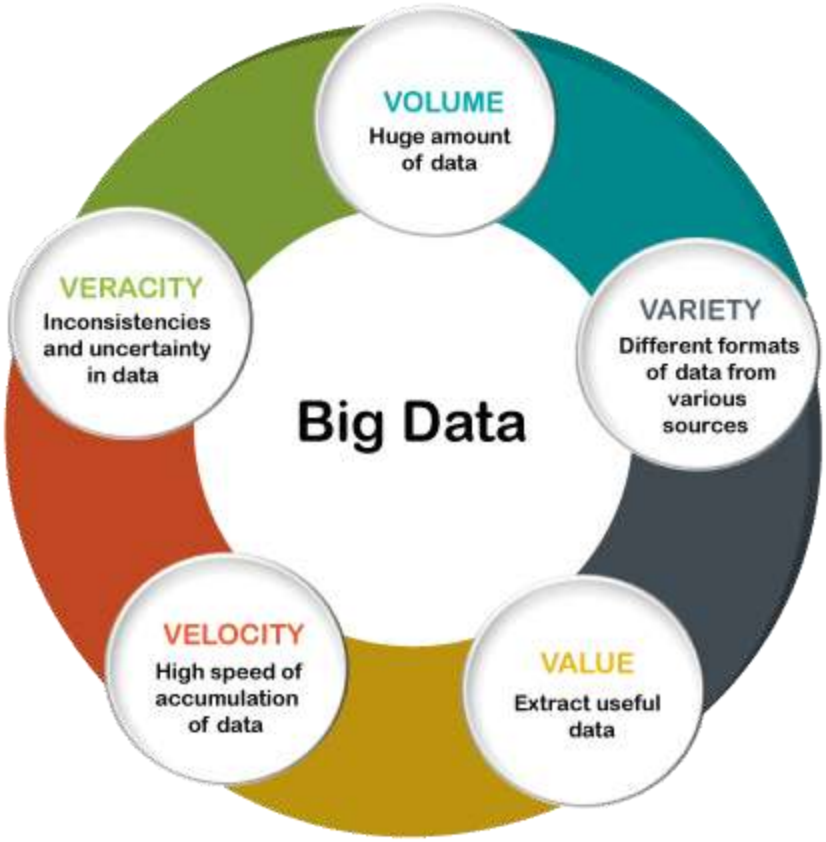
Introduction
- Motivation
- Introduction to Deep Learning (DL)

Discriminative models
- Classification
- Hands-on

Generative models and inverse problems
- Enhancement
- Hands-on

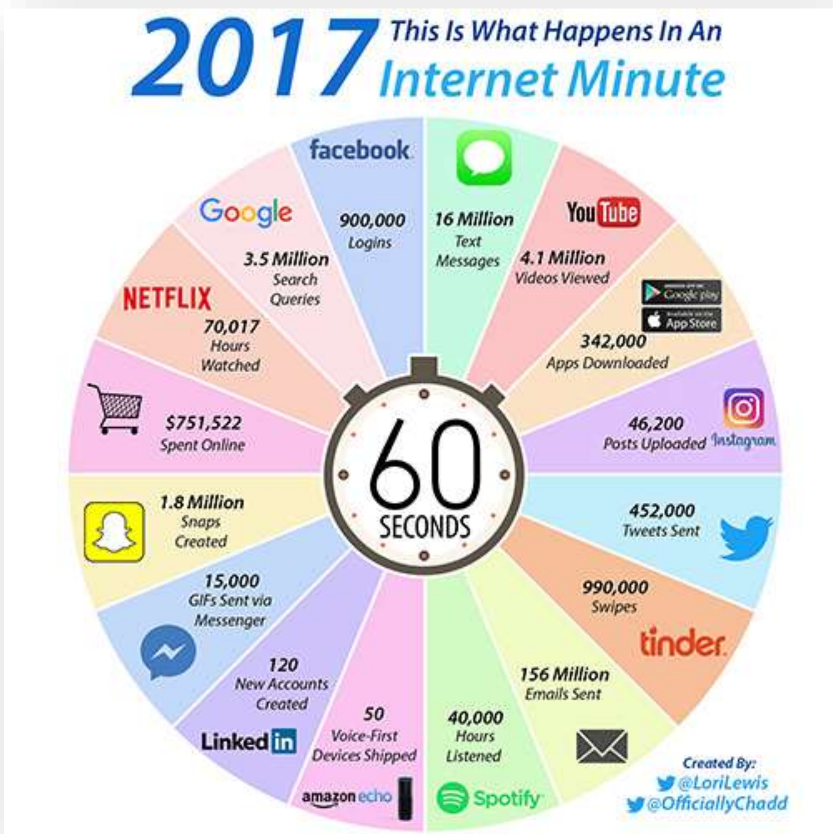
Other topics

Big Data



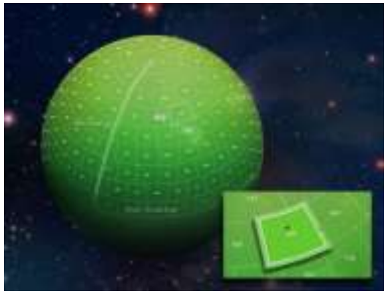
VOLUME
Huge amount of data
VARIETY
Different formats of data from various sources
VALUE
Extract useful data
VELOCITY
High speed of accumulation of data
VERACITY
Inconsistencies and uncertainty in data
Big Data

The Big Data era

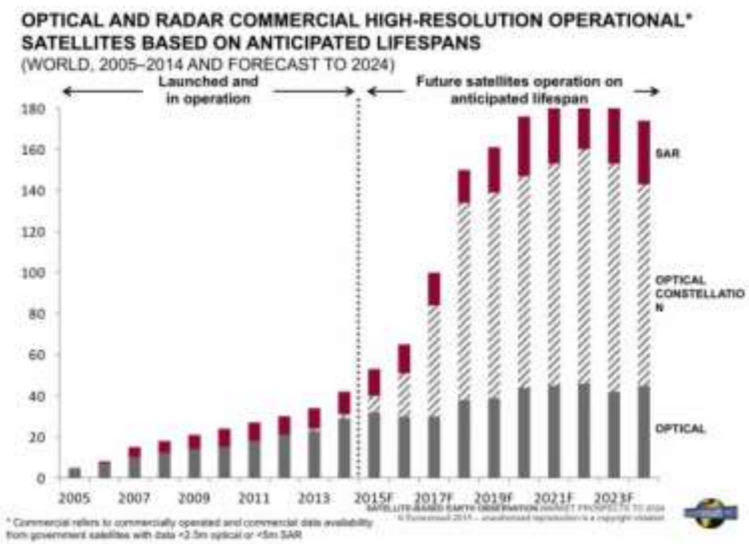


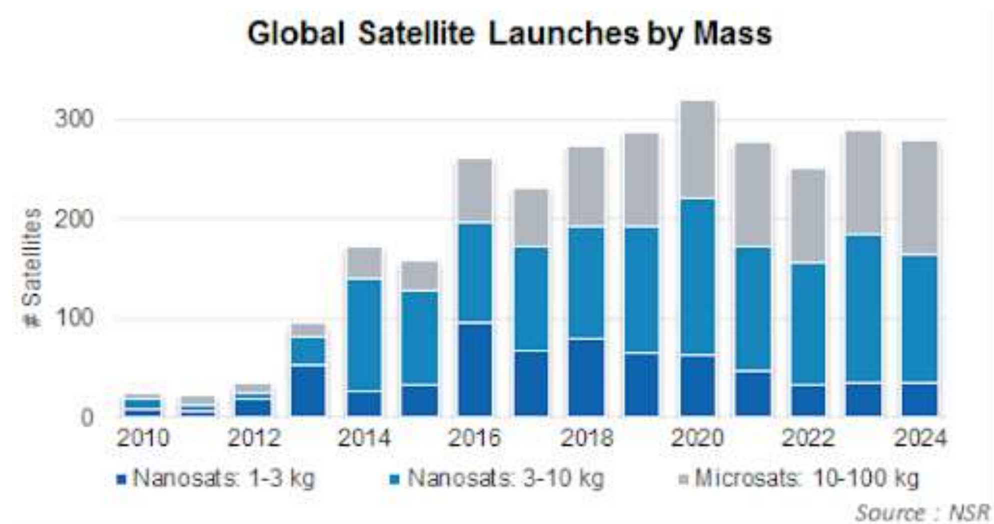
Big Data in Astrophysics

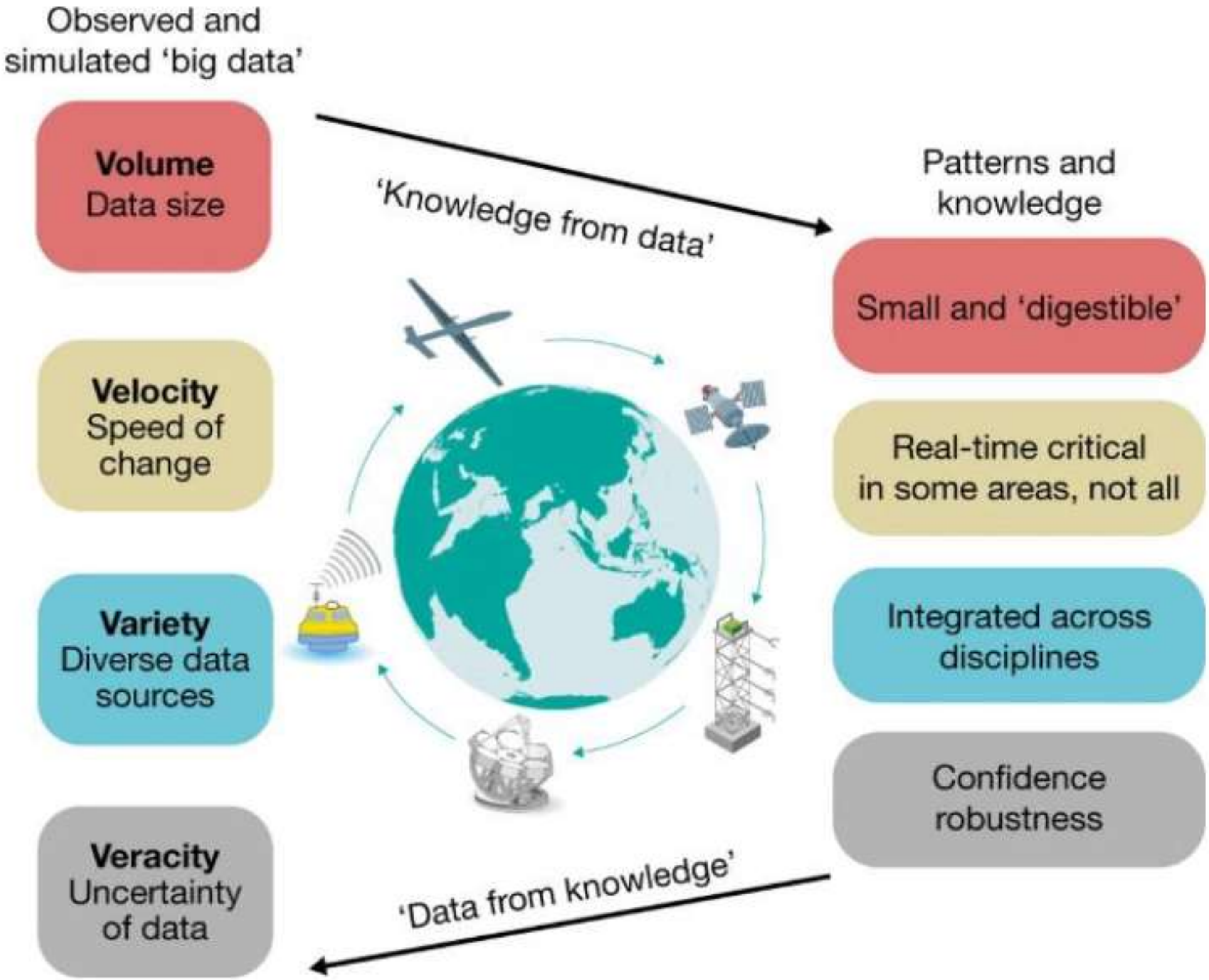
Sky Survey Project	Volume	Velocity	Variety
The Palomar Digital Sky Survey	3 PB		
Sloan Digital Sky Survey (SDSS)	50 TB	200 GB per day	Images, redshifts
Large Synoptic Survey Telescope (LSST)	~ 200 PB	10 TB per day	Images, catalogs
Square Kilometer Array (SKA)	~ 4.6 EB	150 TB per day	Images, redshifts



Big Data in Earth Observation





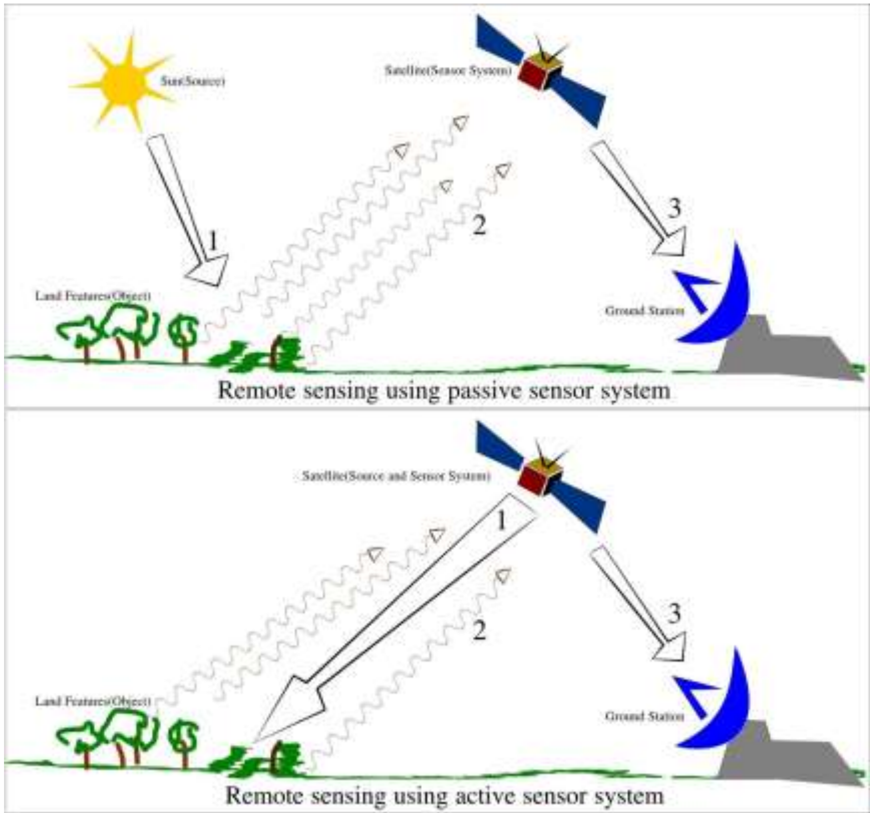


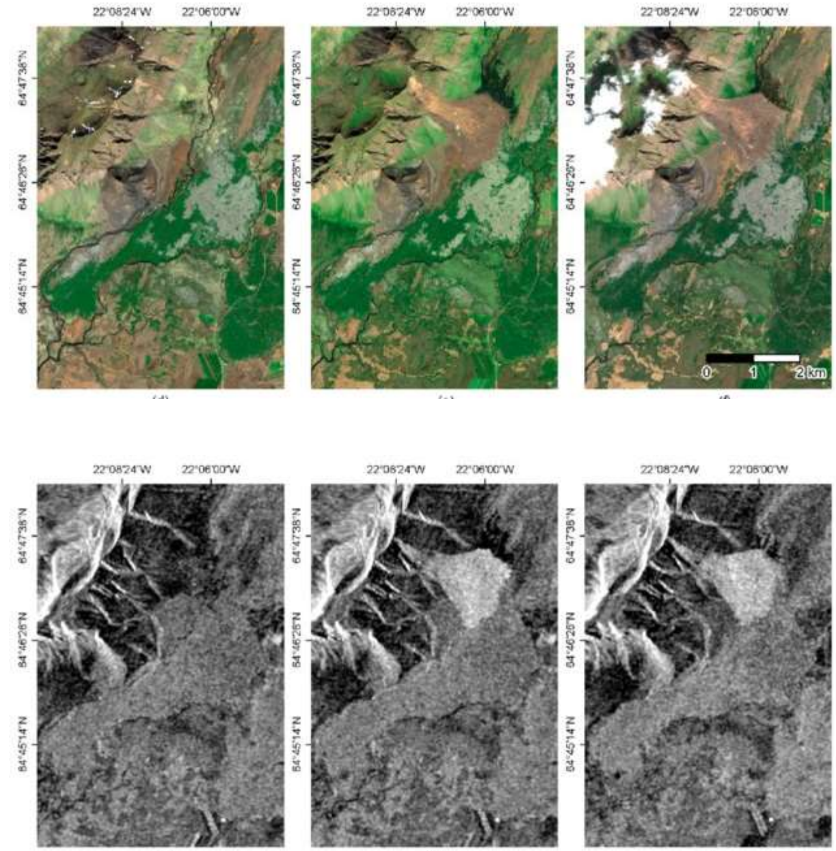
Reichstein et al. (2019). https://doi.org/10.1038/s41586-019-0912-1

Types of Earth Observation data

- Active vs Passive imaging
- Color -> Multispectral -> Hyperspectral
- Global coverage vs tasked
- Private vs public/institutional
- Historical vs modern

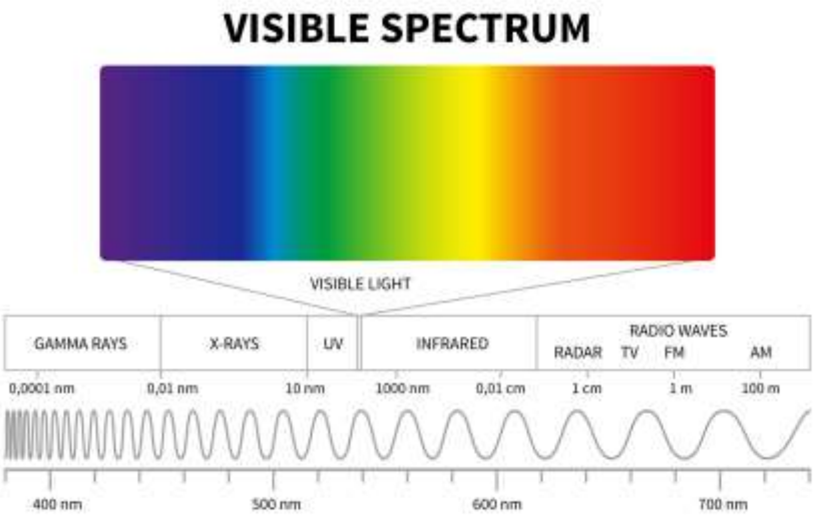
Active vs Passive sensing

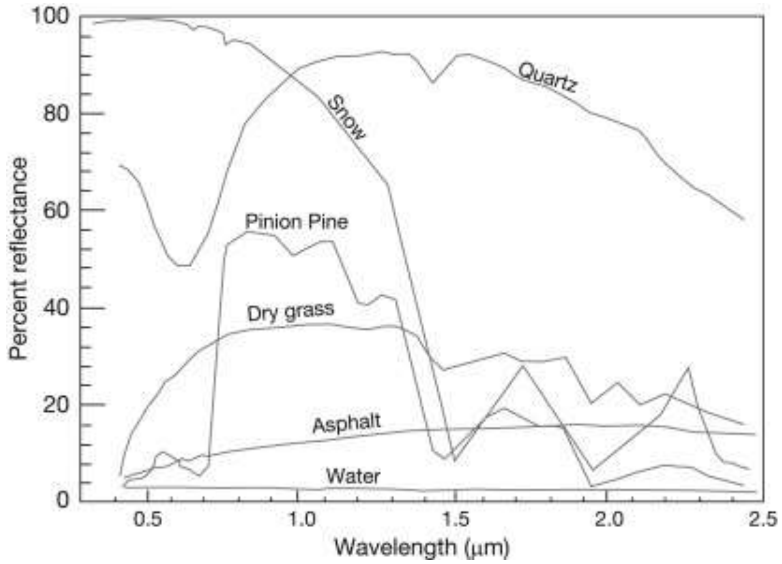




https://en.wikipedia.org/wiki/Remote_sensing

EM spectrum

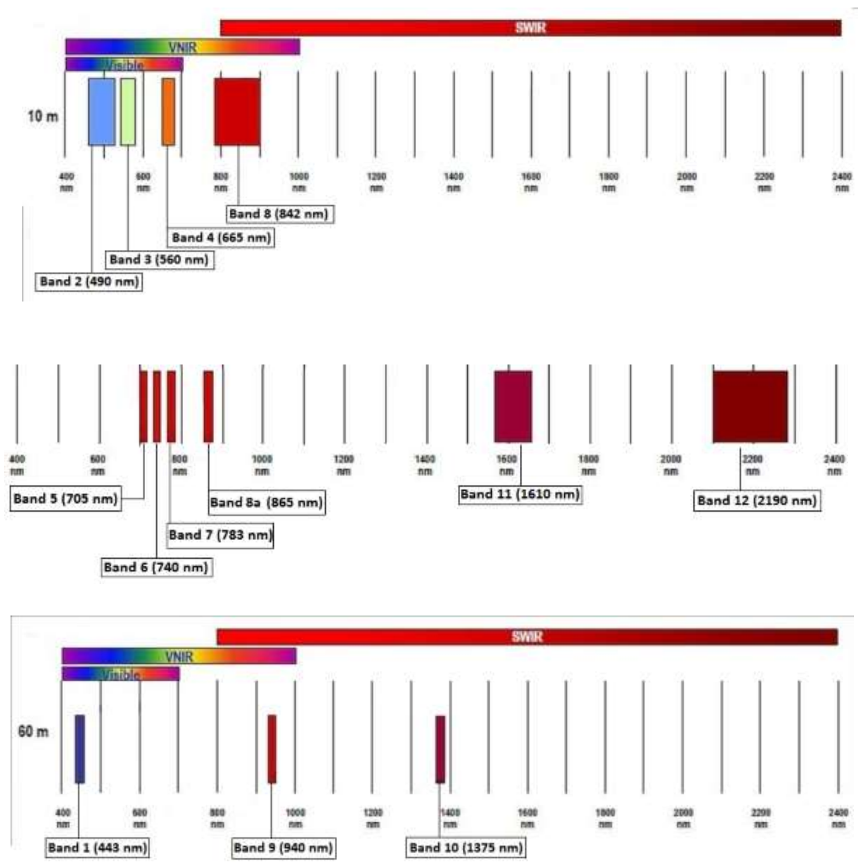

VISIBLE SPECTRUM
VISIBLE LIGHT
GAMMA RAYS
X-RAYS
UV
INFRARED
RADIO WAVES
RADAR
TV
FM
AM
0,0001 nm
0,01 nm
10 nm
1000 nm
0,01 cm
1 cm
1 m
100 m
400 nm
500 nm
600 nm
700 nm


Percent reflectance
100
80
60
40
20
0
0.5
1.0
1.5
2.0
2.5
Wavelength (μm)
Quartz
Snow
Pinion Pine
Dry grass
Asphalt
Water

ESA Sentinel 2

- Optical (Multispectral) imaging
- Global coverage
- Open-access

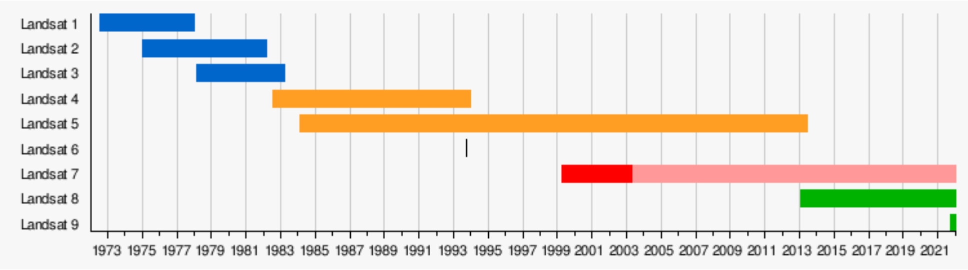
Spatial Resolution	10/20/60m
Spectral Resolution	13 bands
Swath	290km
Revisit	5-days



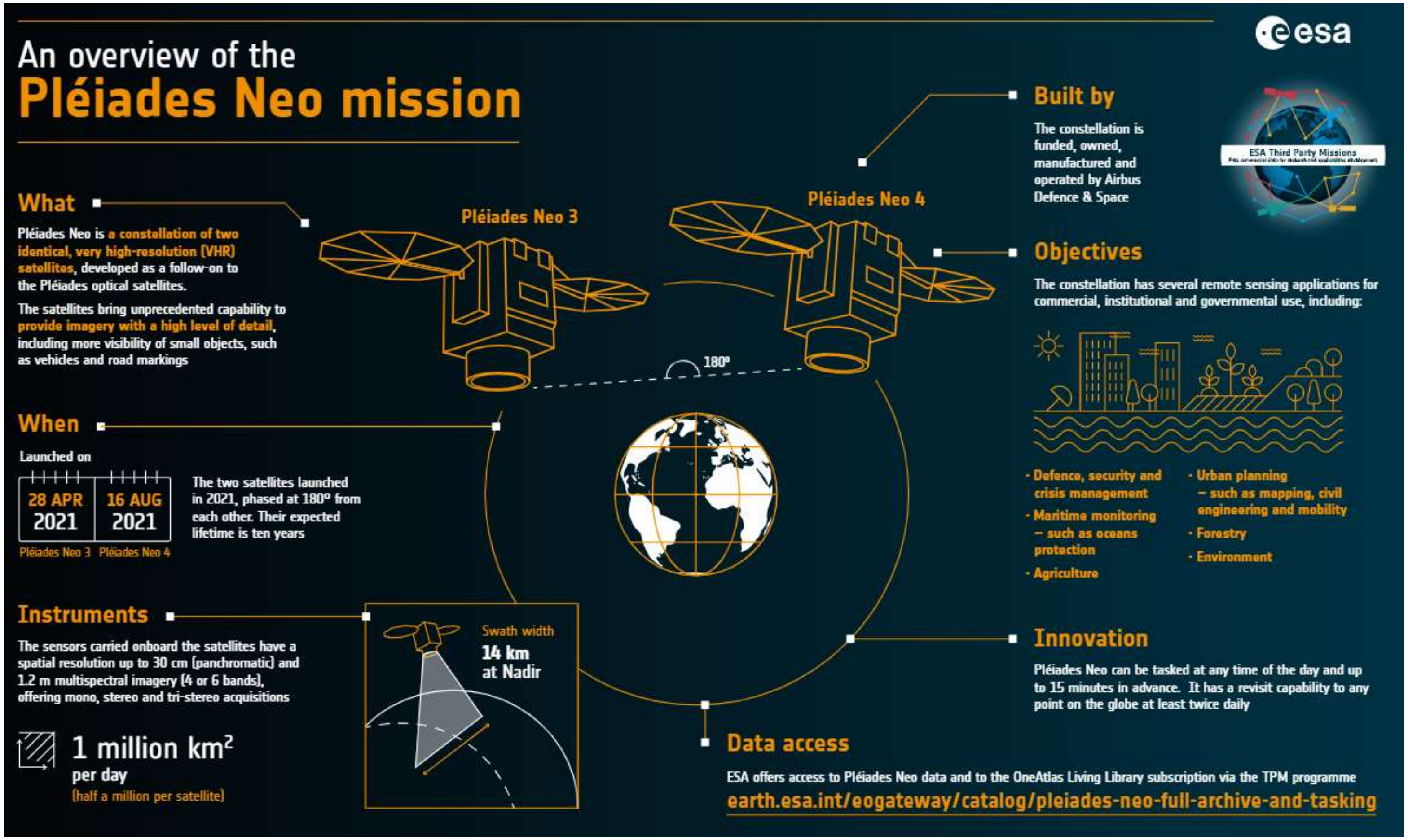
NASA Landsat 7/8/9

- Optical (Multispectral) imaging
- Global coverage
- Open-access

Spatial Resolution	15/30/100m
Spectral Resolution	11 bands
Swath	185km
Revisit	16-days



Private



An overview of the
Pléiades Neo mission
esa
What
Pléiades Neo is a constellation of two identical, very high-resolution (VHR) satellites, developed as a follow-on to the Pléiades optical satellites.
The satellites bring unprecedented capability to provide imagery with a high level of detail, including more visibility of small objects, such as vehicles and road markings
Pléiades Neo 3
Pléiades Neo 4
180°
Built by
The constellation is funded, owned, manufactured and operated by Airbus Defence & Space
ESA Third Party Missions
Objectives
The constellation has several remote sensing applications for commercial, institutional and governmental use, including:
· Defence, security and crisis management
· Maritime monitoring – such as oceans protection
· Agriculture
· Urban planning – such as mapping, civil engineering and mobility
· Forestry
· Environment
When
Launched on
28 APR 2021
16 AUG 2021
Pléiades Neo 3
Pléiades Neo 4
The two satellites launched in 2021, phased at 180° from each other. Their expected lifetime is ten years
Instruments
The sensors carried onboard the satellites have a spatial resolution up to 30 cm (panchromatic) and 1.2 m multispectral imagery (4 or 6 bands), offering mono, stereo and tri-stereo acquisitions
1 million km²
per day
(half a million per satellite)
Swath width
14 km
at Nadir
Innovation
Pléiades Neo can be tasked at any time of the day and up to 15 minutes in advance. It has a revisit capability to any point on the globe at least twice daily
Data access
ESA offers access to Pléiades Neo data and to the OneAtlas Living Library subscription via the TPM programme
earth.esa.int/eogateway/catalog/pleiades-neo-full-archive-and-tasking

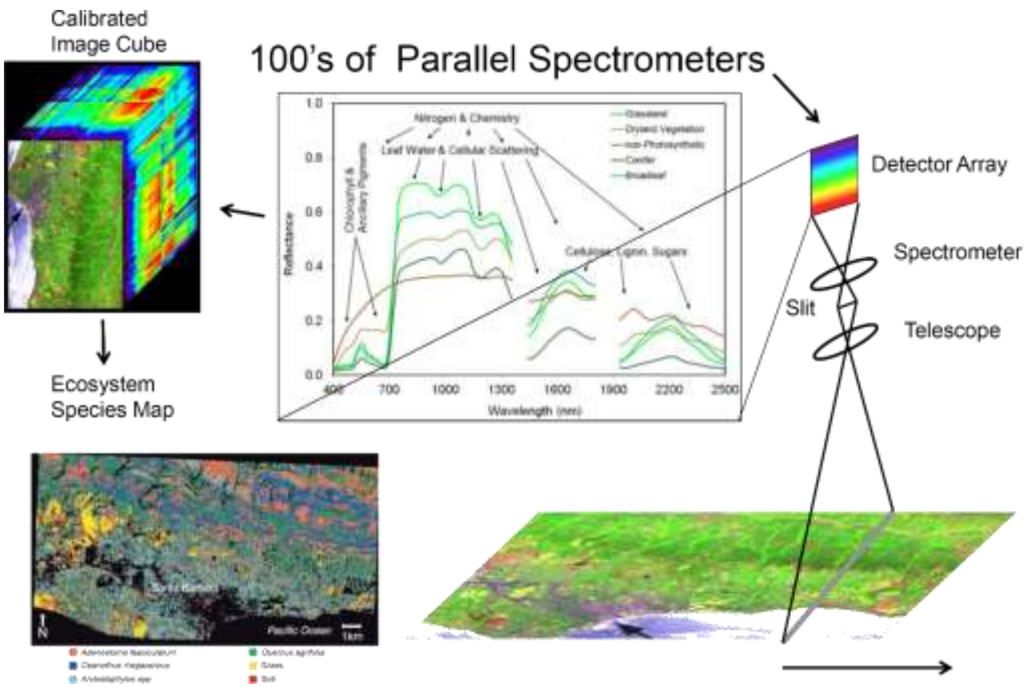
MODIS

Terra & Aqua Moderate Resolution Imaging Spectroradiometer

Orbit:	705 km, 10:30am descending node (Terra) or 1:30p.m. ascending node (Aqua), sun-synchronous, near-polar, circular
Visit	1-2 days
Swath Dimensions:	2330km (cross track) by 10km (along track at nadir)
Spatial Resolution:	250m (bands 1-2) 500m (bands 3-7) 1000m (bands 8-36)
Wavebands:	36 bands: 1-19 from 405 to 2155nm 20-36 from 3.66 to 14.28 microns
Design Life:	6 years
Duration:	Operational

AVIRIS & AVIRIS-NG

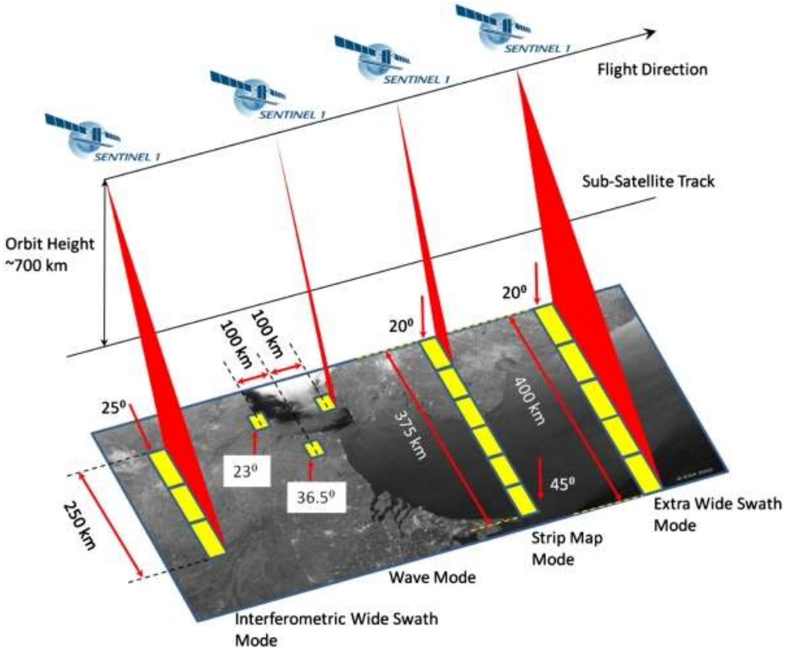
Airborne Visible/Infrared Imaging Spectrometer

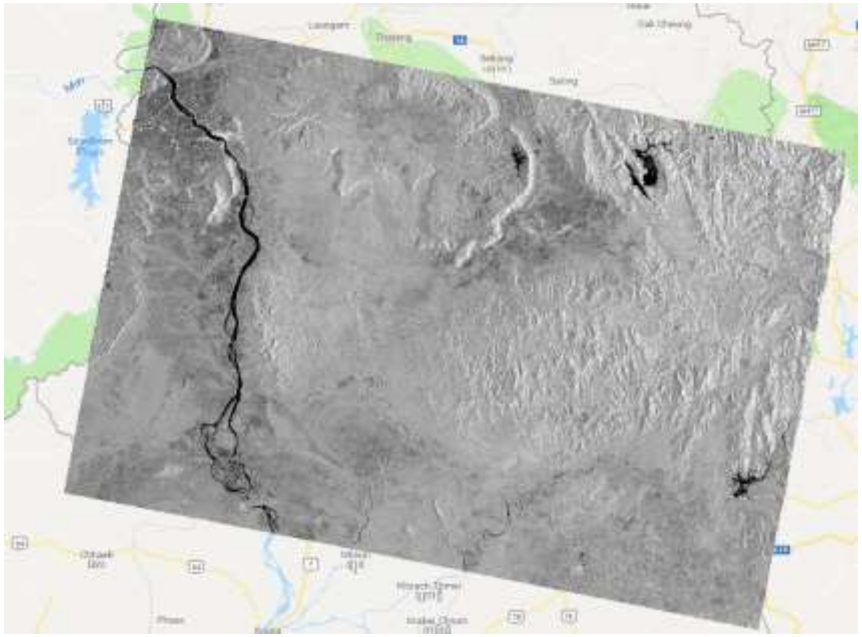


ESA Sentinel-1

ESA Sentinel 1 A/B

- C-band radar (5.405 GHz, 4 polarizations)
- 6 days revisit





NASA SMAP mission

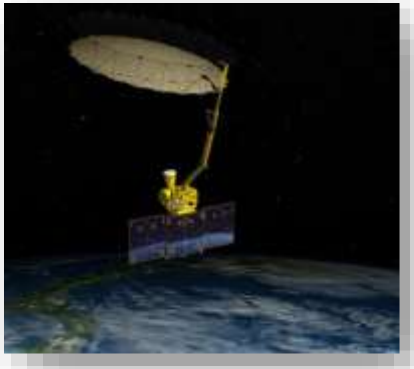
Soil Moisture Active Passive (SMAP) satellite

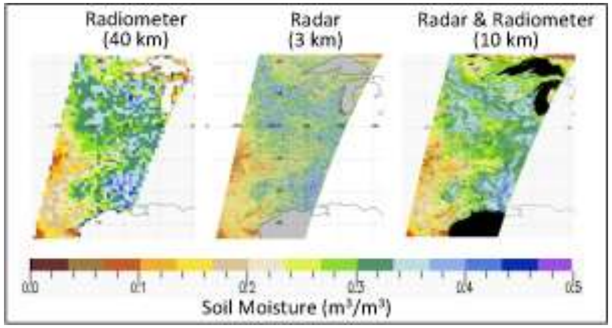
Objective: global soil moisture every 2-3 days

Operational since April 2015

Instruments @ L-band (1.2 GHz , 1.41 GHz) :

- Radar (active): spatial resolution 3km, high SM uncertainty
- Radiometer (passive): spatial resolution 36km, low SM uncertainty
- Combined: 9km, accuracy 0.04 cm^3/cm^3

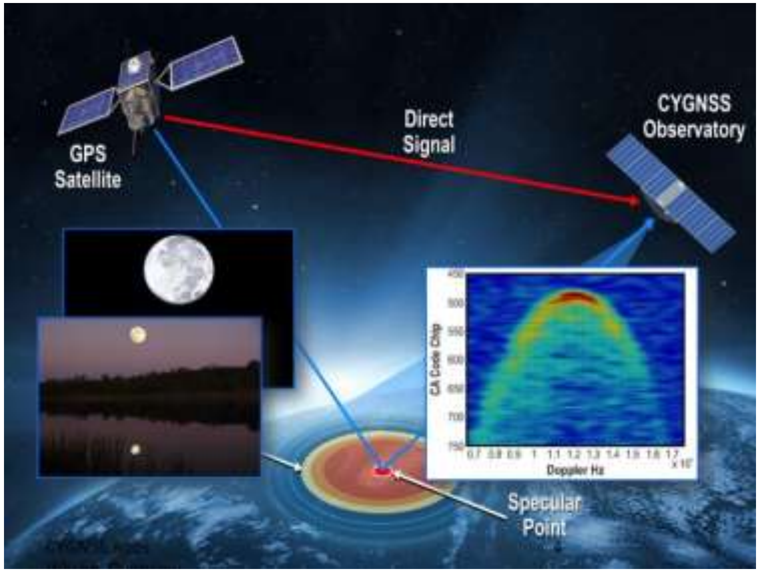




Challenge: Radar failed after 3 months of operation

NASA CYGNSS

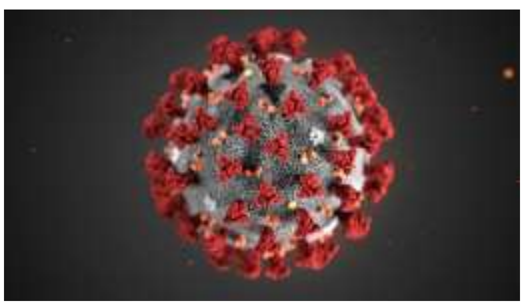
- Cyclone Global Navigation Satellite System: 8 satellites in LEO (500 km altitude) at 35° orbit inclination
- Primary objective: Sensing sea level wind speed in tropical cyclones
- Application in Surface Soil Moisture



https://spaceflight101.com/cygnss/

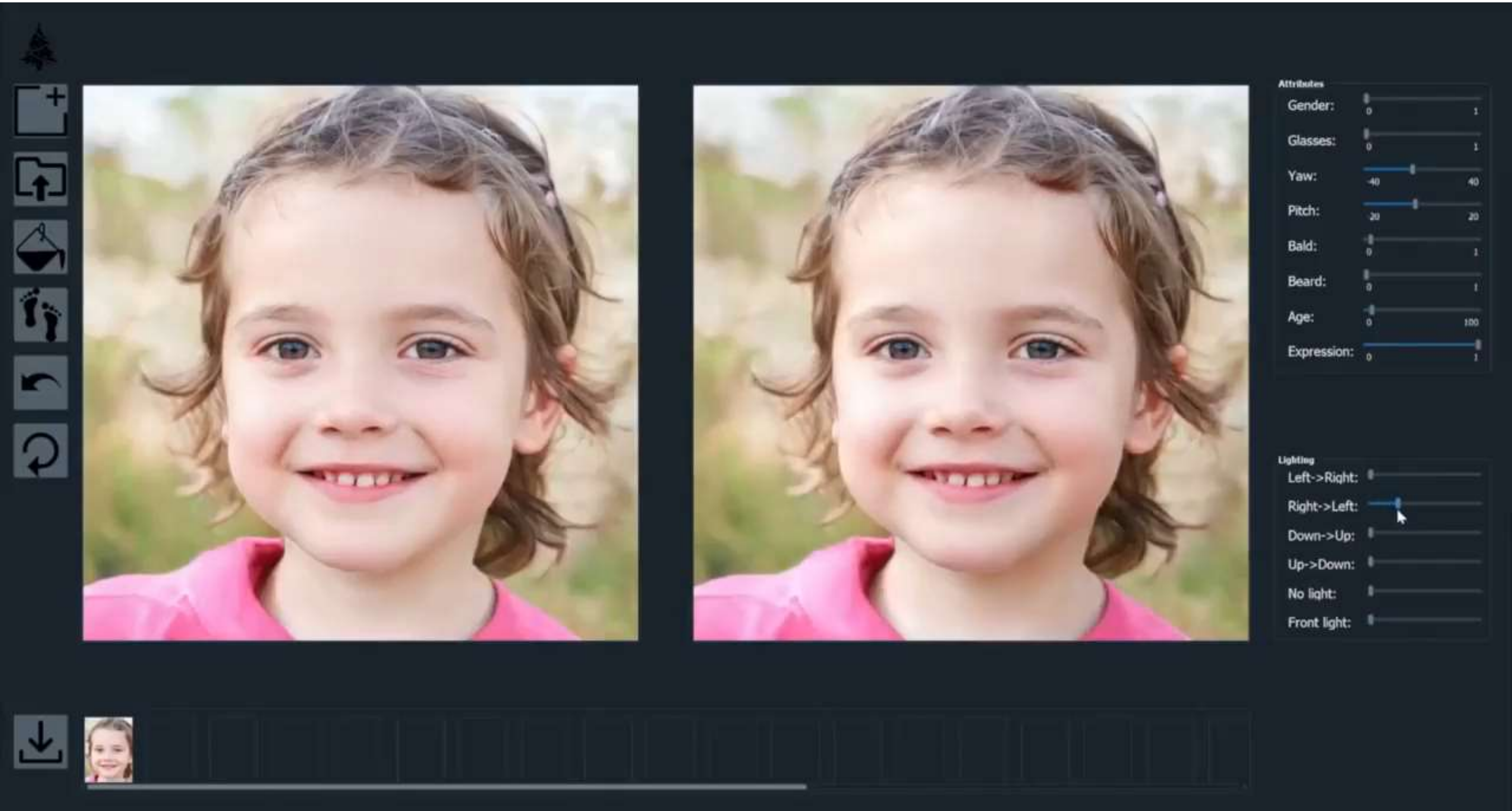
Advances in Machine Learning

Artificial intelligence-created medicine to be used on humans for first time, BBC news, 30/1/2020



Coronavirus: Can AI Make A Difference? Forbes, 2/2/2020

https://www.bbc.co.uk/sounds/play/m000dsc4



Source: [Abdal et al. 2020]

2023

D Make a song about a programmer and someone who isn't a programmer.

Here is a sample song about a programmer and someone who isn't a programmer:

Verse 1:
Programmer, programmer, sitting at the screen
Typing code all day, living in a dream
Creating apps and websites, making them just right
A master of technology, always up to date

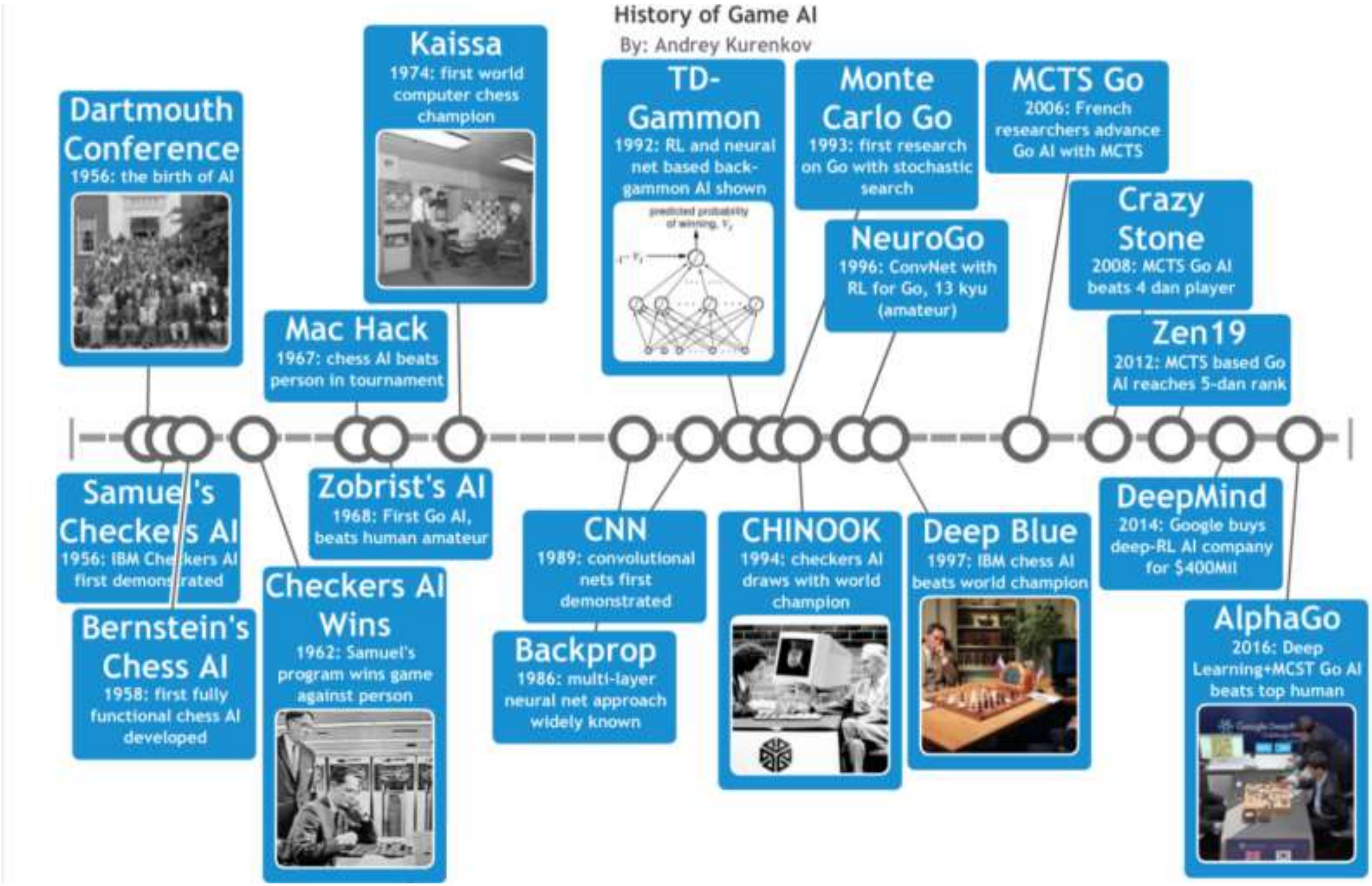
Chorus:
Programmer, programmer, so smart and so bright
Always coding away, day and night

Verse 2:
Non-programmer, non-programmer, not a clue
About the world of code, what it can

DALL·E 2

"An astronaut riding a horse in a photorealistic style"

Brief history of ML/AI



Types of ML

Supervised learning

- Classification
- Regression

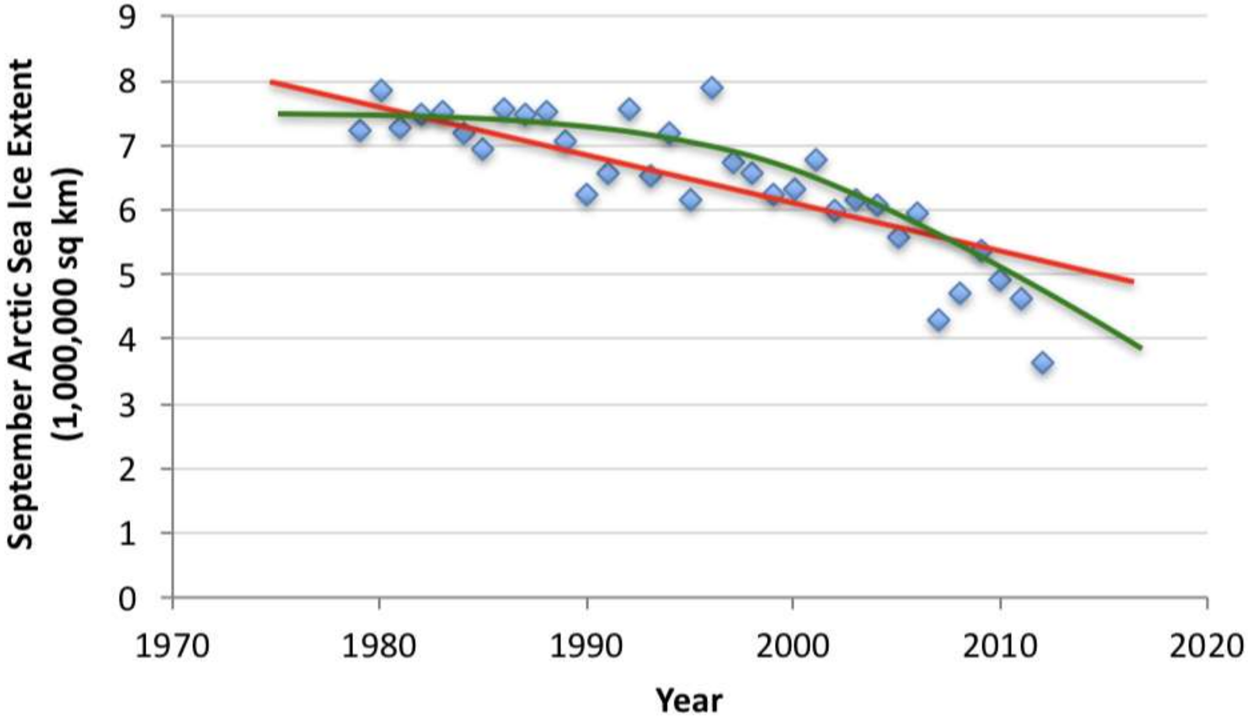
Unsupervised learning

- Clustering
- Generative models
- Inverse problems

Reinforcement learning

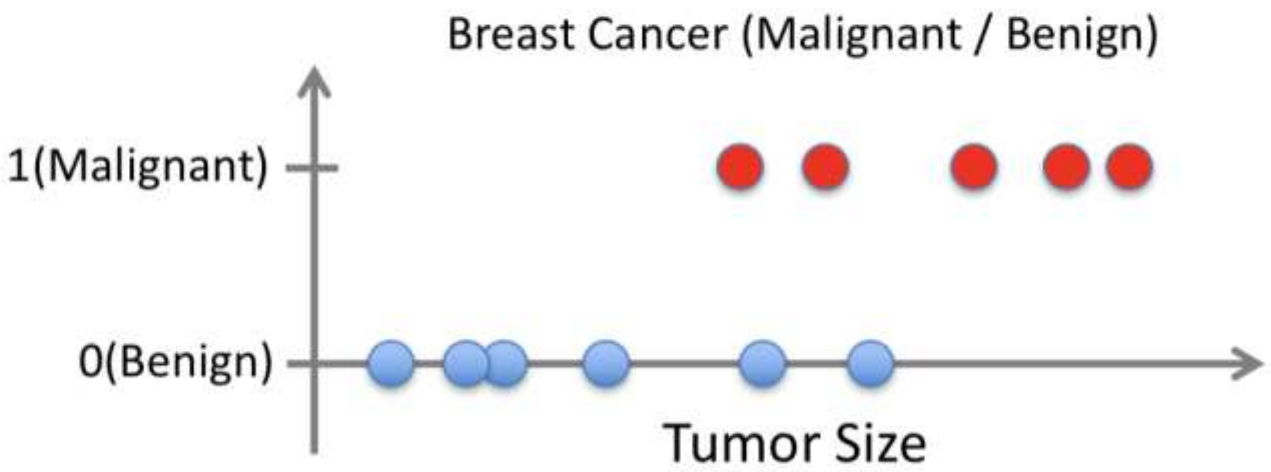
Supervised Learning: Regression

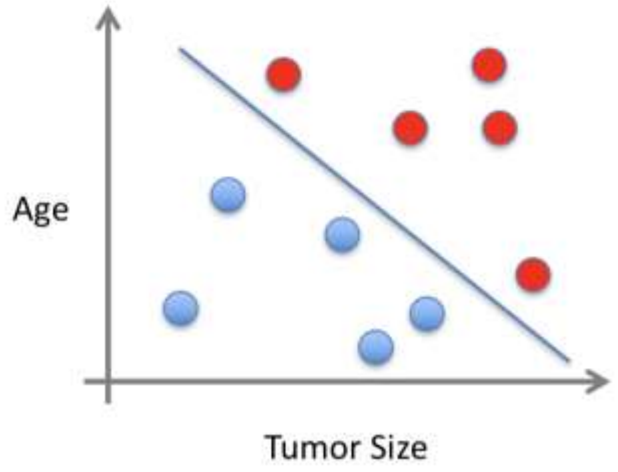
Given $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$: Learn a function $f(x)$ to predict real-valued y given x



Supervised Learning: Classification

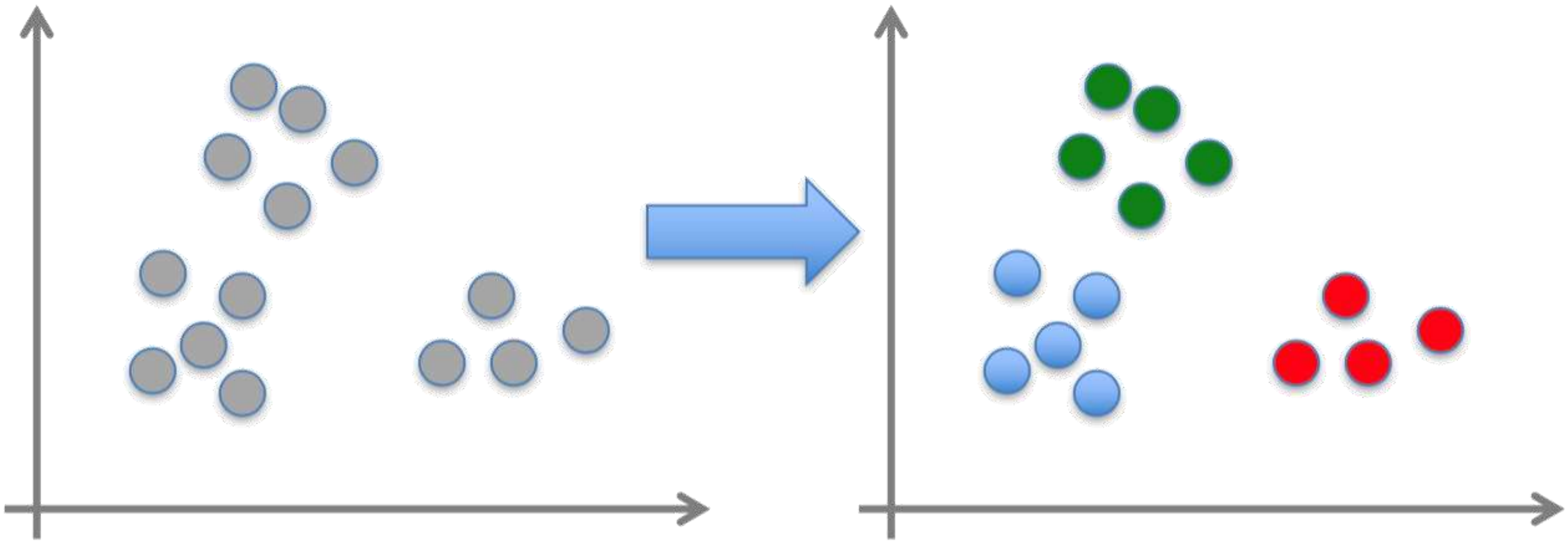
Given $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$: Learn a function $f(x)$ to predict categorical y given x





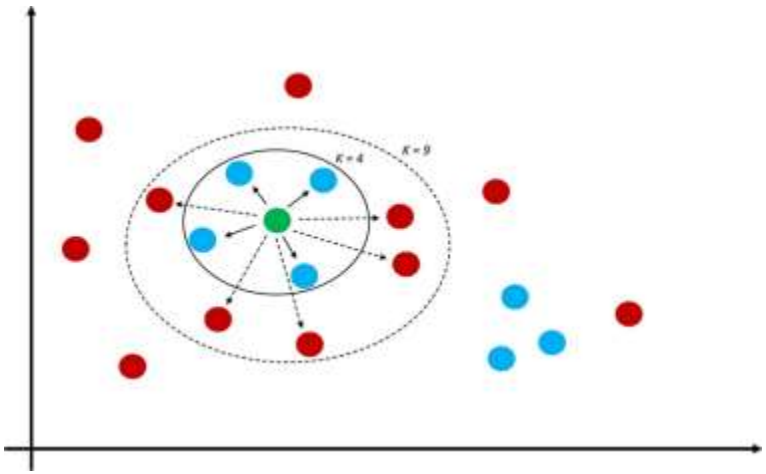
Unsupervised Learning

- Given x_1, x_2, ..., x_n (without labels)
- Output hidden structure behind the x's
  - E.g., clustering



KNN classification

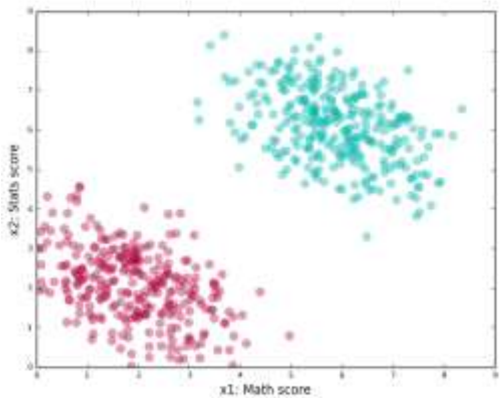
<u>Use neighbors to infer class</u>

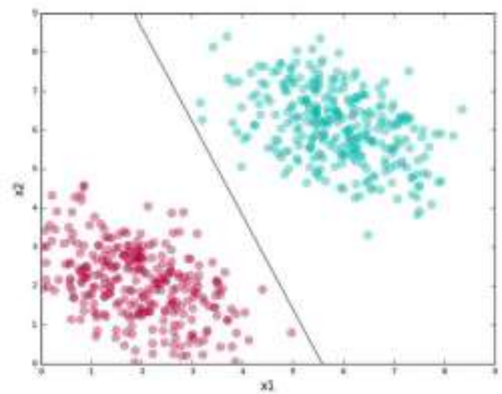


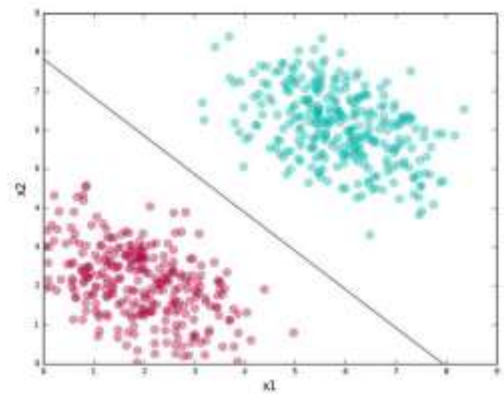
Challenges

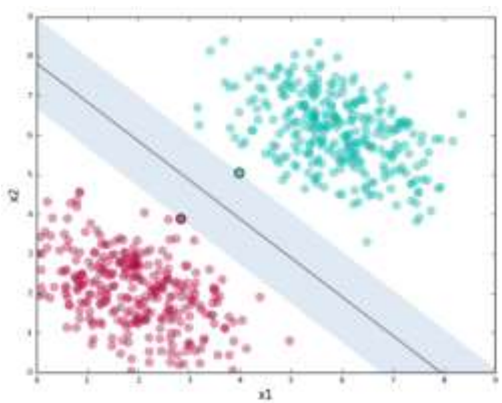
- ➢Preprocessing & Feature extraction
- ➢Impact of dimensionality
- ➢Sensitivity to the value of k
- ➢Real-time application

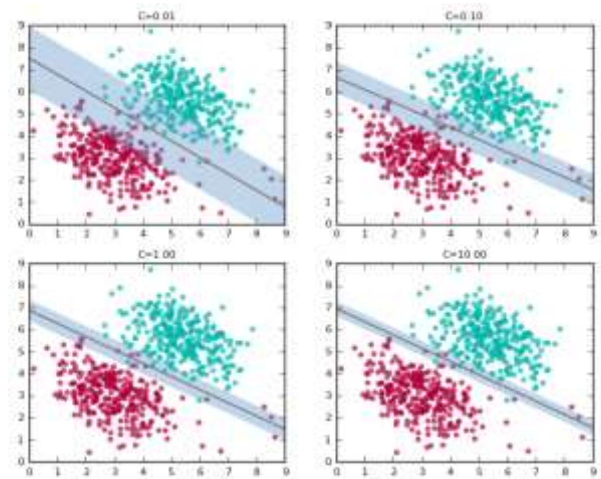
SVM





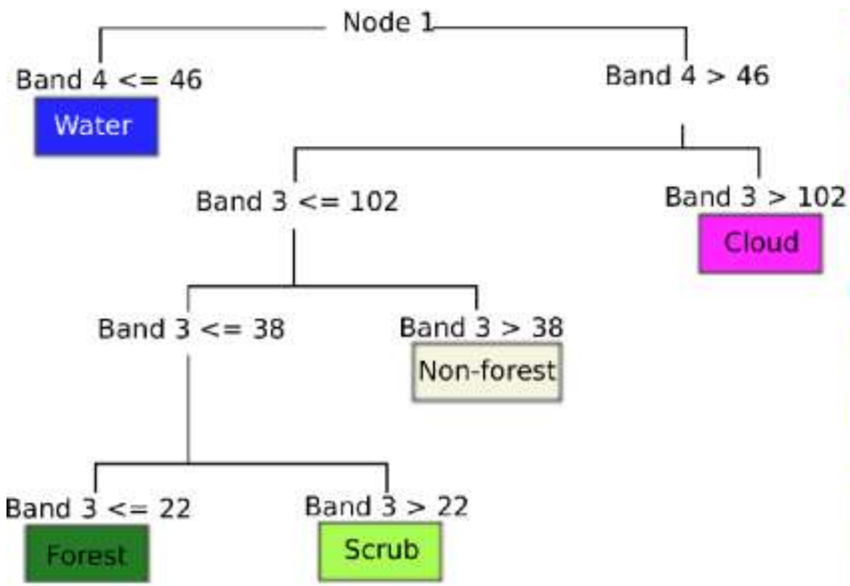


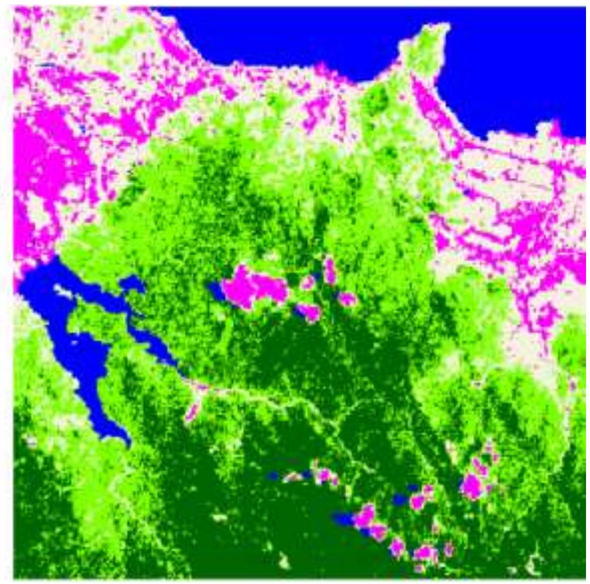




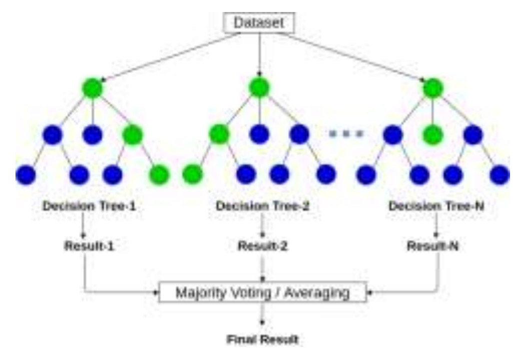
https://medium.com/cube-dev/support-vector-machines-tutorial-c1618e635e93

Trees & Forests

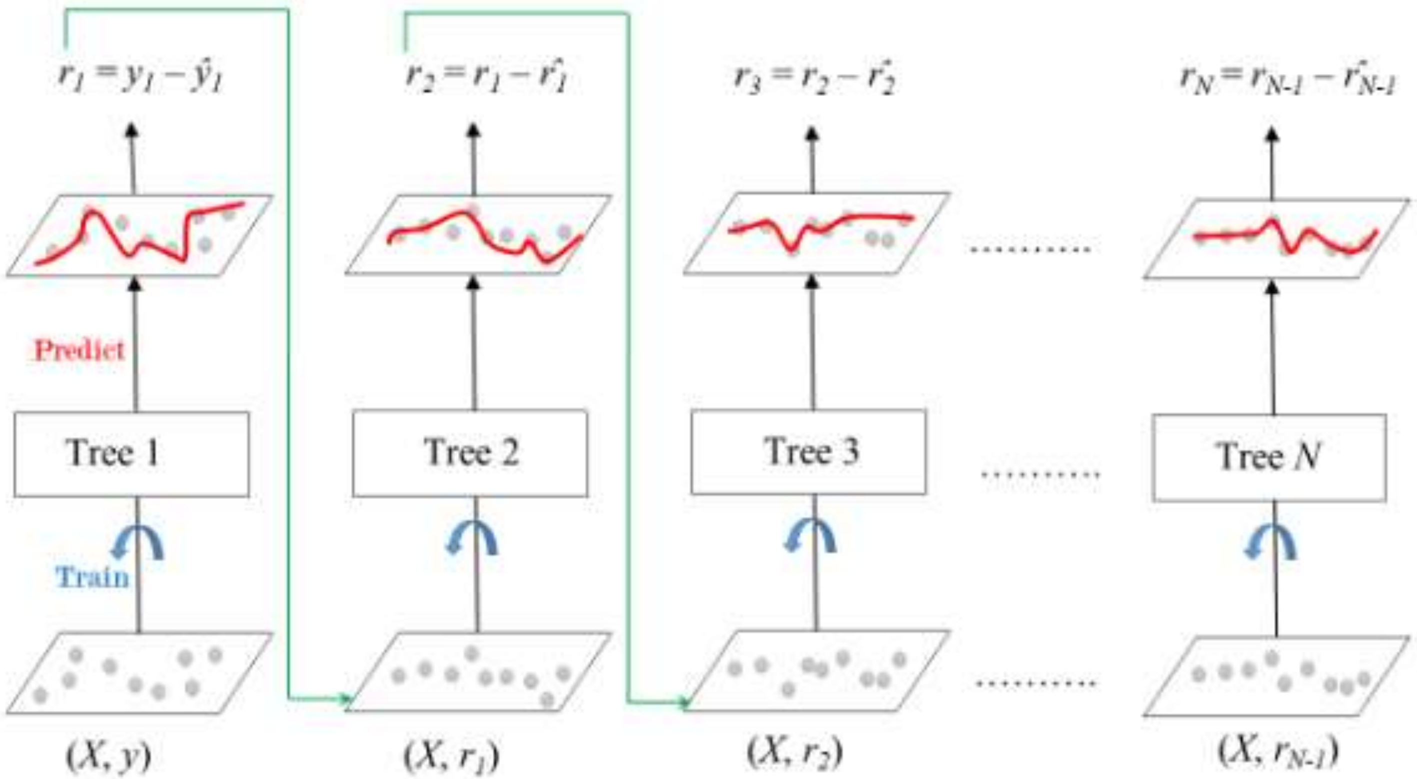




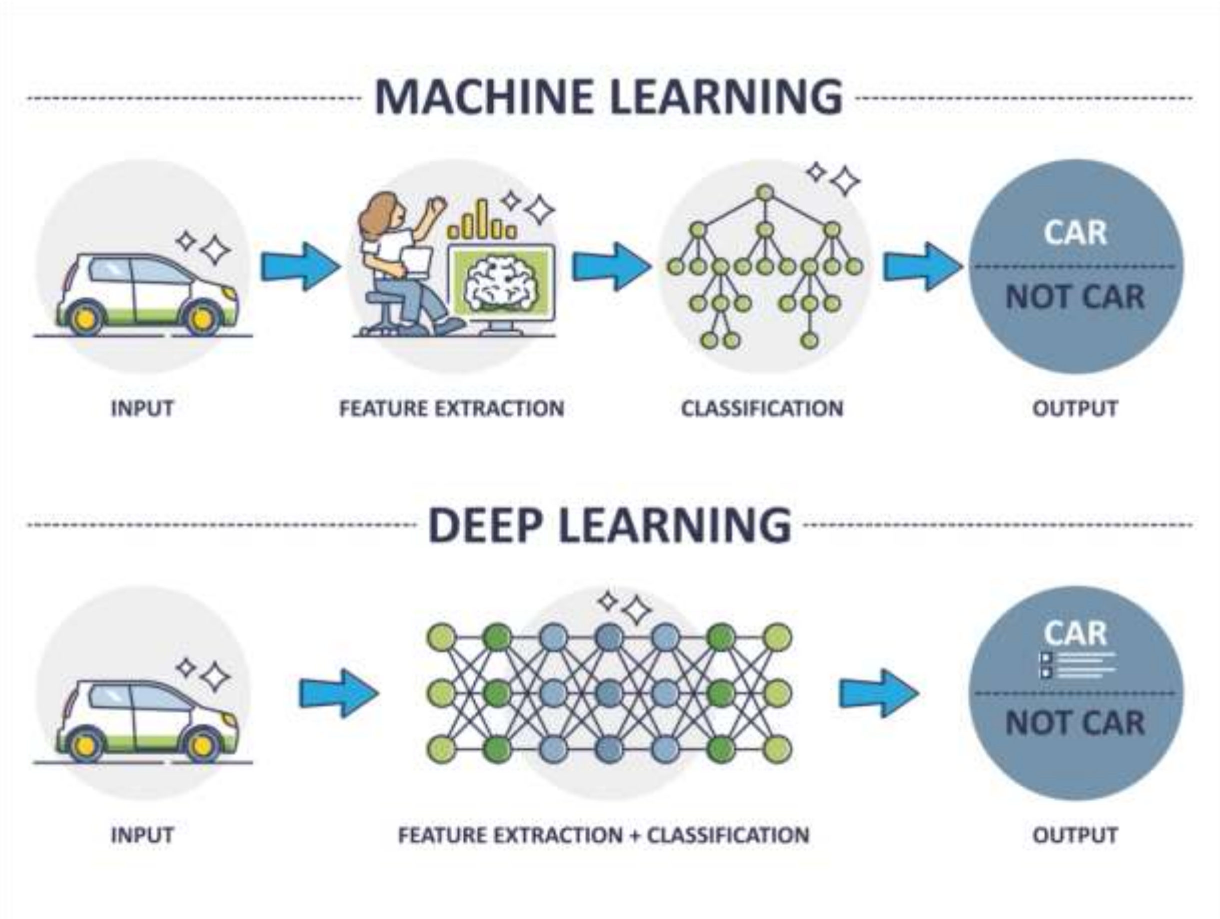
Random Forests : An algorithm for image classification and generation of continuous fields data sets



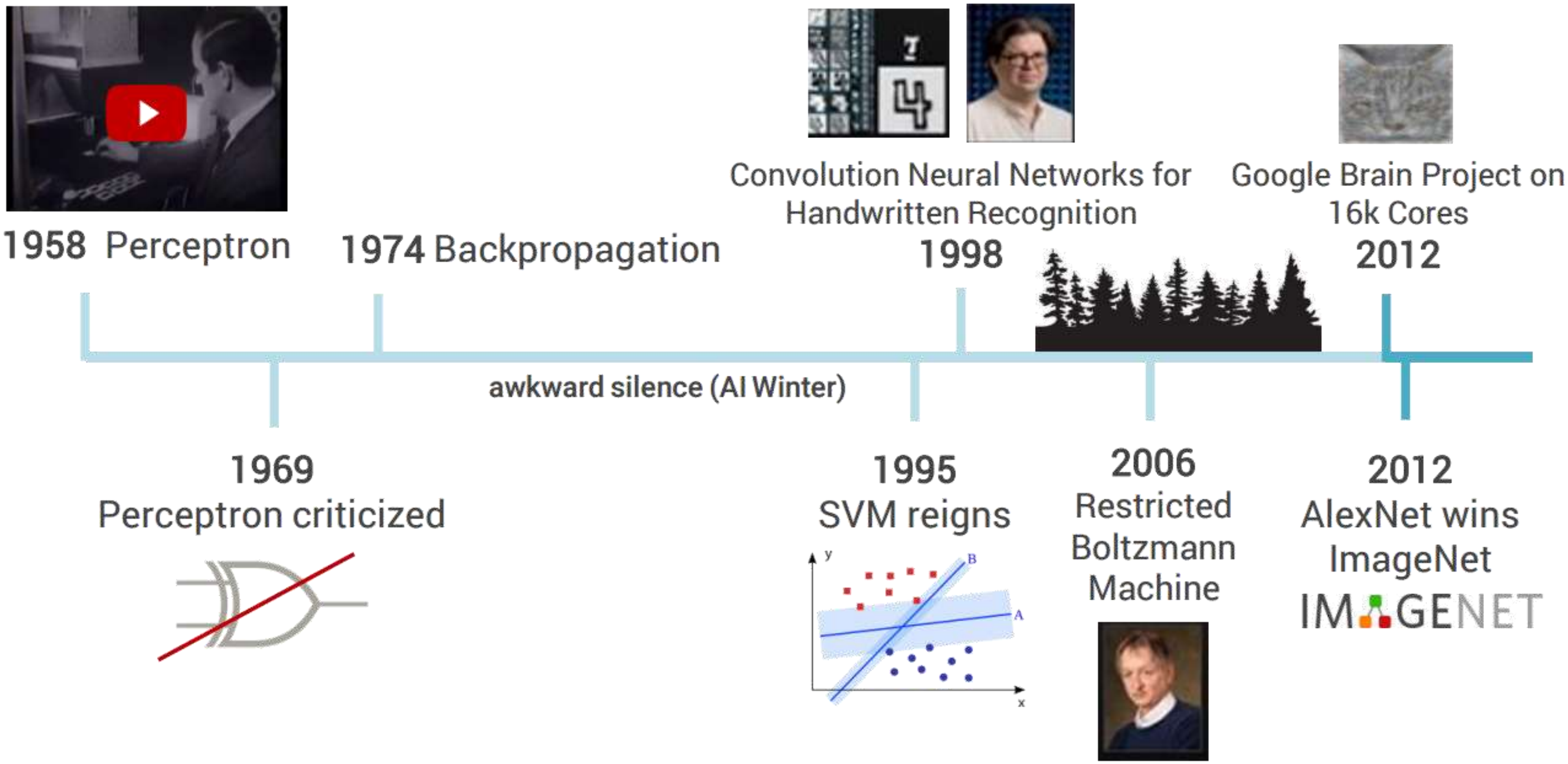
Gradient boosting



Deep Learning

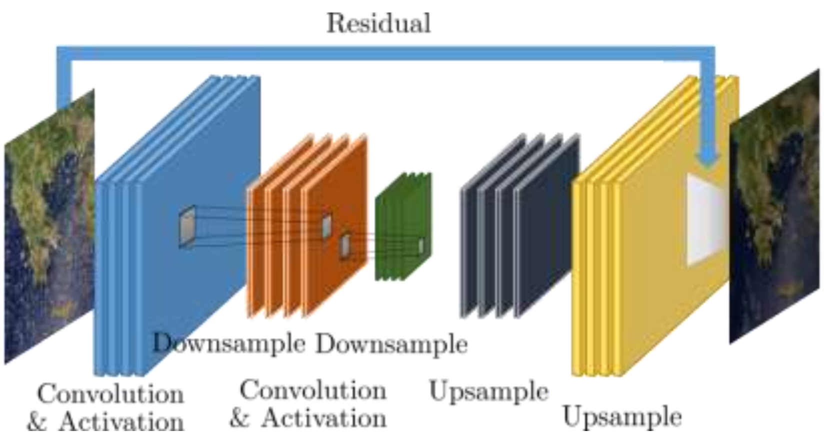


Brief history of DL

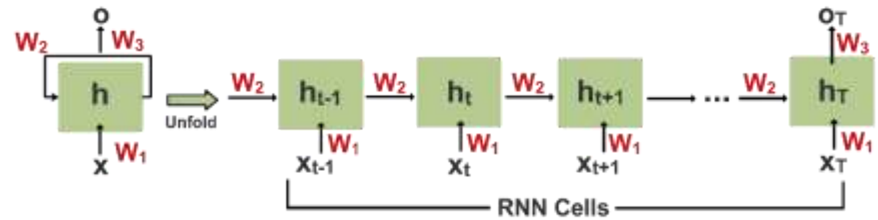


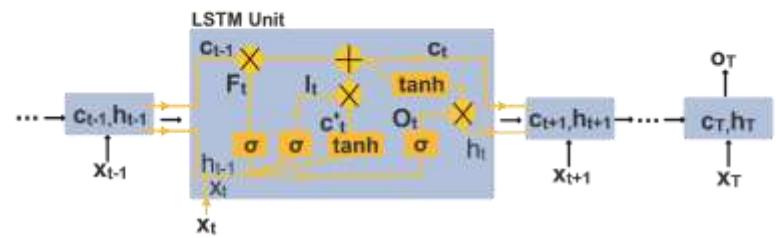
State-of-the-art

CNNs



RNN/LSTMs





Transformers

Applications in RS

Land Use/Land Cover Classification	Infrastructure Monitoring
Object Detection	Oceanographic Features Analysis
Change Detection	Species Distribution Modelling
Weather and Climate Prediction	Iceberg Detection
Agricultural Crop Yield Prediction	Forest Fire Detection
Disaster Damage Assessment	Sea Pollution Monitoring
Vegetation and Biomass Estimation	Earthquake Damage Assessment
Urban Planning and Development	Flood Mapping and Assessment
Surface Water Mapping	Atmosphere Gas Concentration
Soil and Land Degradation Assessment	Marine Traffic Monitoring

Scene classification - Aerial

$$x \in \mathbb{R}^{m \times m \times 3} \to y \in \{0, 1, 2, \cdots k\}$$

AID: A Benchmark Dataset for Performance Evaluation of Aerial Scene Classification

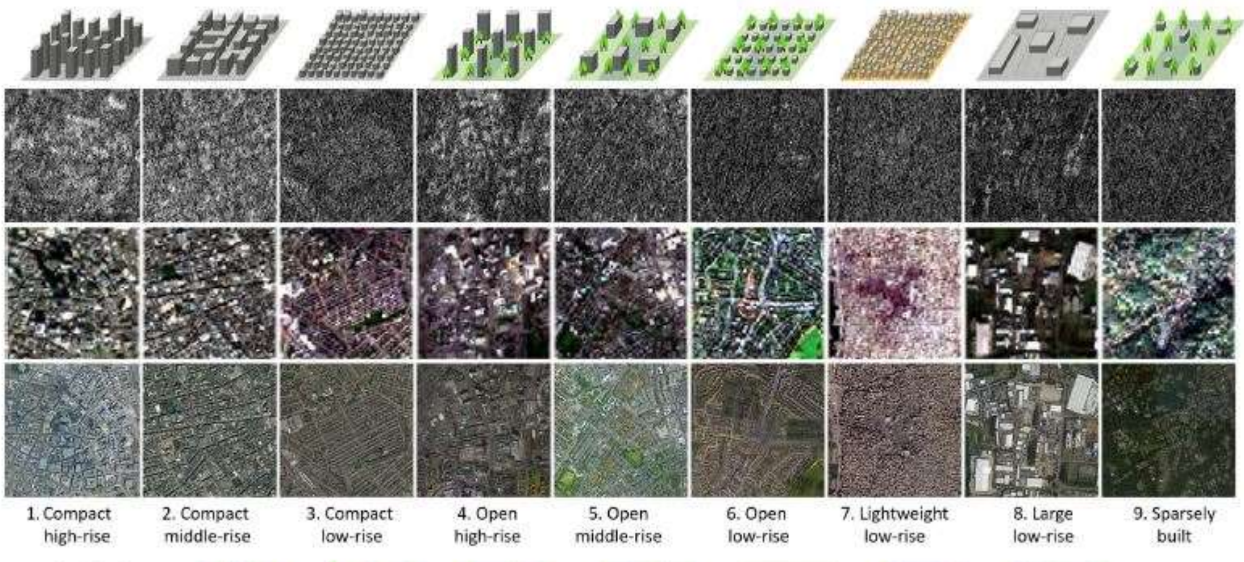
EUROSAT

- A land use / land cover classification on Sentinel-2 satellite images.
- Each sample is 64x64 pixels and is associated with one out of 10 classes.

$$x \in \mathbb{R}^{m \times m \times 12} \rightarrow y \in \{0, 1, 2, \cdots k\}$$

So2SAT LCZ42

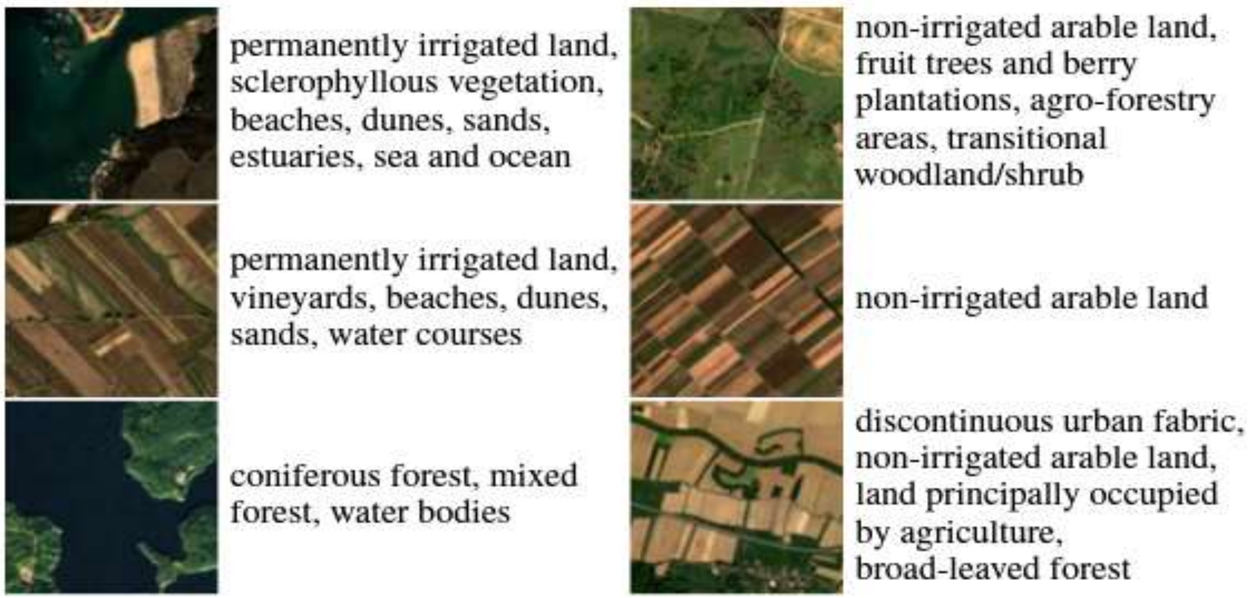
- Co-registered SAR (Sentinel 1) and multispectral (Sentinel 2) patches
- Local climate zones (LCZ) over 42 cities across different regions.
- Each sample is 32x32 pixels and is associated with one out of 17 classes



$$x_1 \in \mathbb{R}^{m \times m \times 12}, x_2 \in \mathbb{R}^{m \times m \times 2} \to y \in \{0, 1, 2, \cdots k\}$$

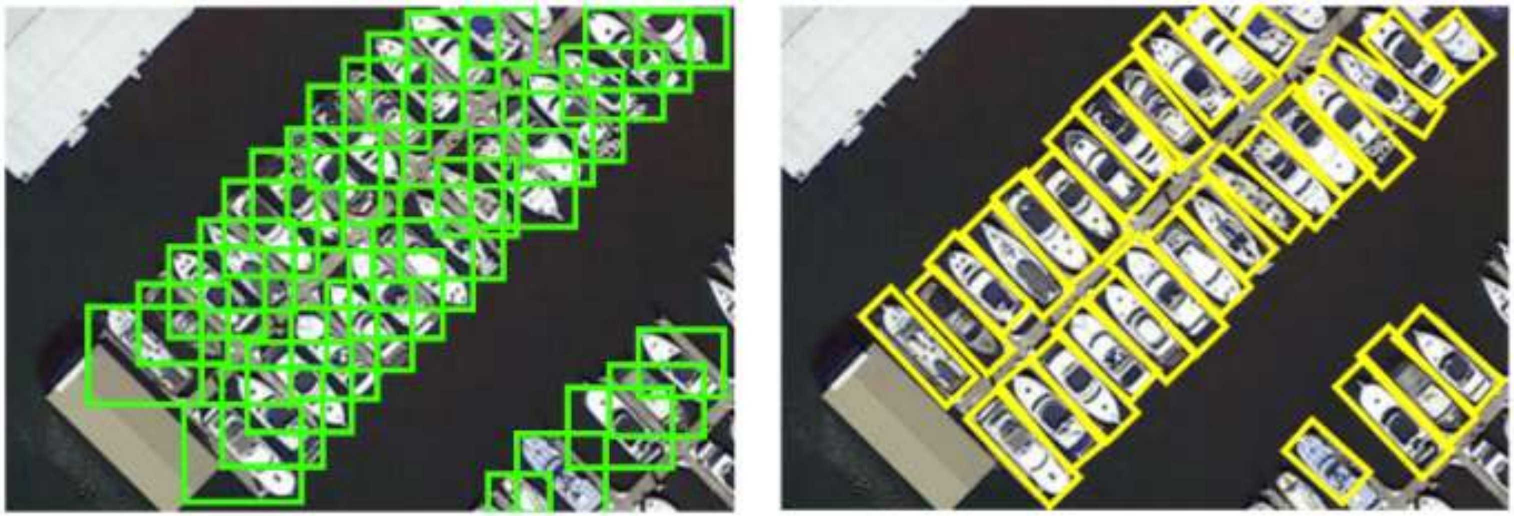
BigEarthNet

- 590,326 Sentinel-2 image patches
- Each patch is associated with multiple labels (43 imbalanced labels).
- Each example is 120x120 pixels at 10 m (atmospherically corrected).
- Annotation based on L3-hierarchy of Corine Land Cover (CLC) 2018.



$$x \in \mathbb{R}^{m \times m \times 12} \rightarrow y \in \{0\}, \{0,1\}, \cdots, \{1,2\}, \cdots \{1,7,k\}$$

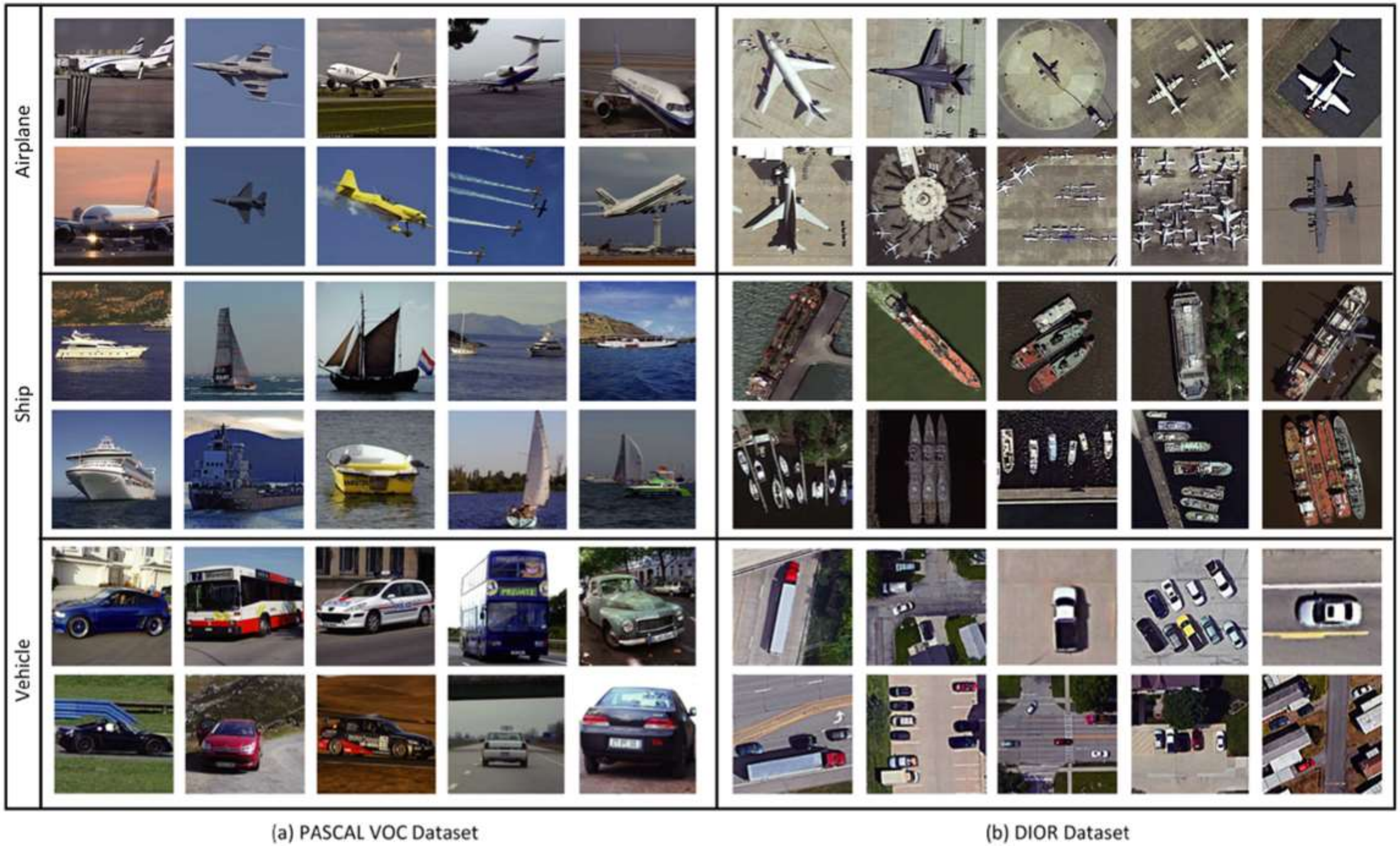
Object detection



(a) Horizontal object detection. (b) Rotated object detection.

$$x \in \mathbb{R}^{m \times m \times 12} \rightarrow \{BB_1, C_1\}, \cdots, \{BB_n, C_n\}$$

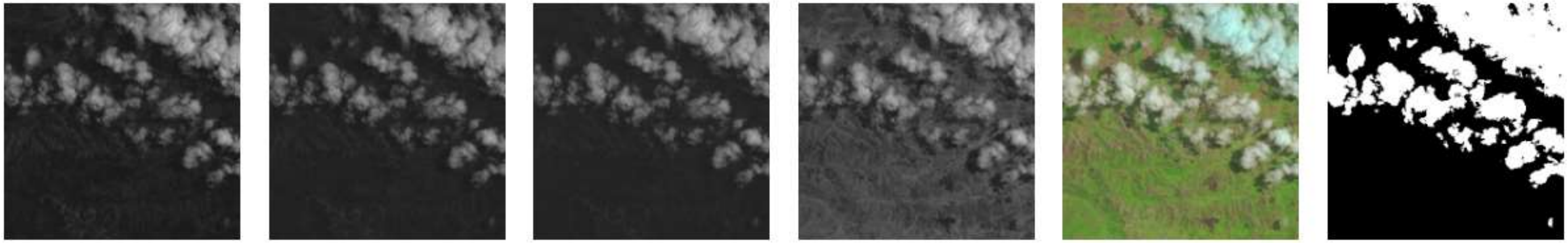
Object detection



Object detection in optical remote sensing images: A survey and a new benchmark

Cloud detection

- 38 Landsat 8 scene images
- 8400 patches for training and 9201 patches for testing.



Red Green Blue NIR False color Ground truth

Object/target recognition

- Snow cover

- Active fire

- Oil spills

- Floating plastic litter (distribution)

- Solar PV parks

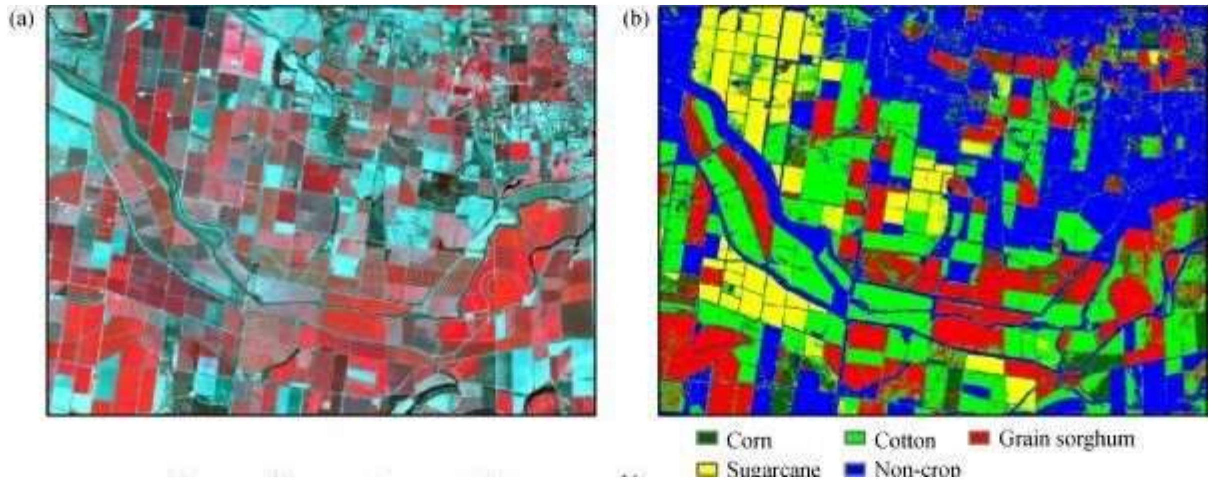
- Volcanic eruption

Image segmentation

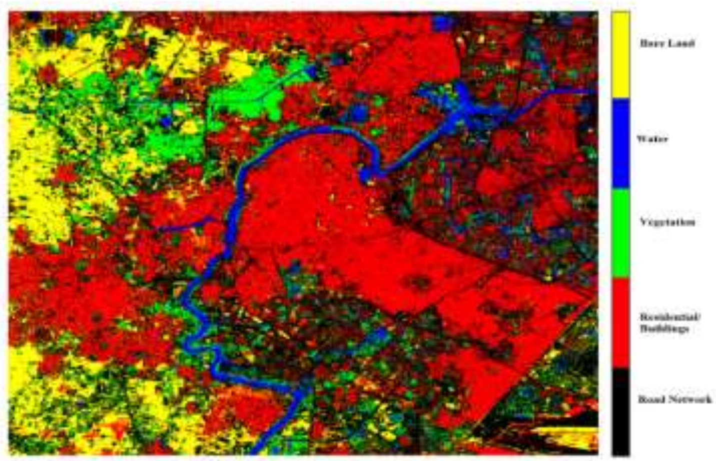
$$x \in \mathbb{R}^{m \times m \times 3} \to y \in \mathbb{Z}_k^{m \times m}$$

Land classification

Crop type



Land cover



Change detection

Given two instances -> find changes

Challenges

- Atmospheric conditions
- Resolution
- Modality
- Lack of ground truth

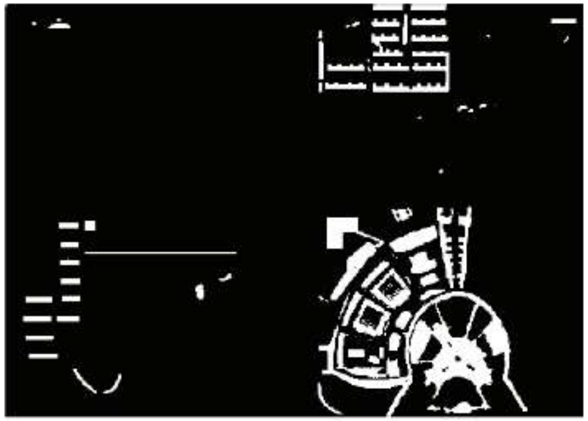


Image denoising

$$\xrightarrow[+n]{\mathcal{F}}$$

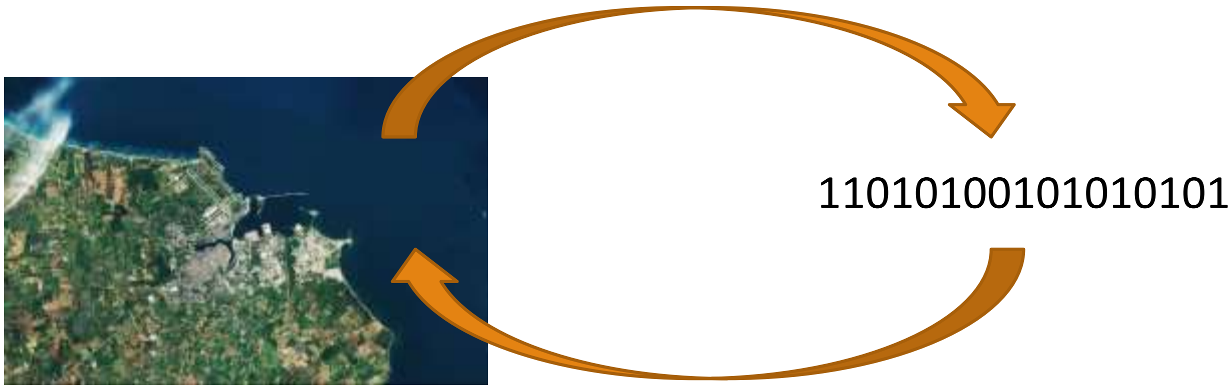
$$x \in \mathbb{R}^{m \times m \times b} \rightarrow y \in \mathbb{R}^{m \times m \times b}$$

Image Super-Resolution

$$\xrightarrow[\times k]{\mathcal{F}}$$

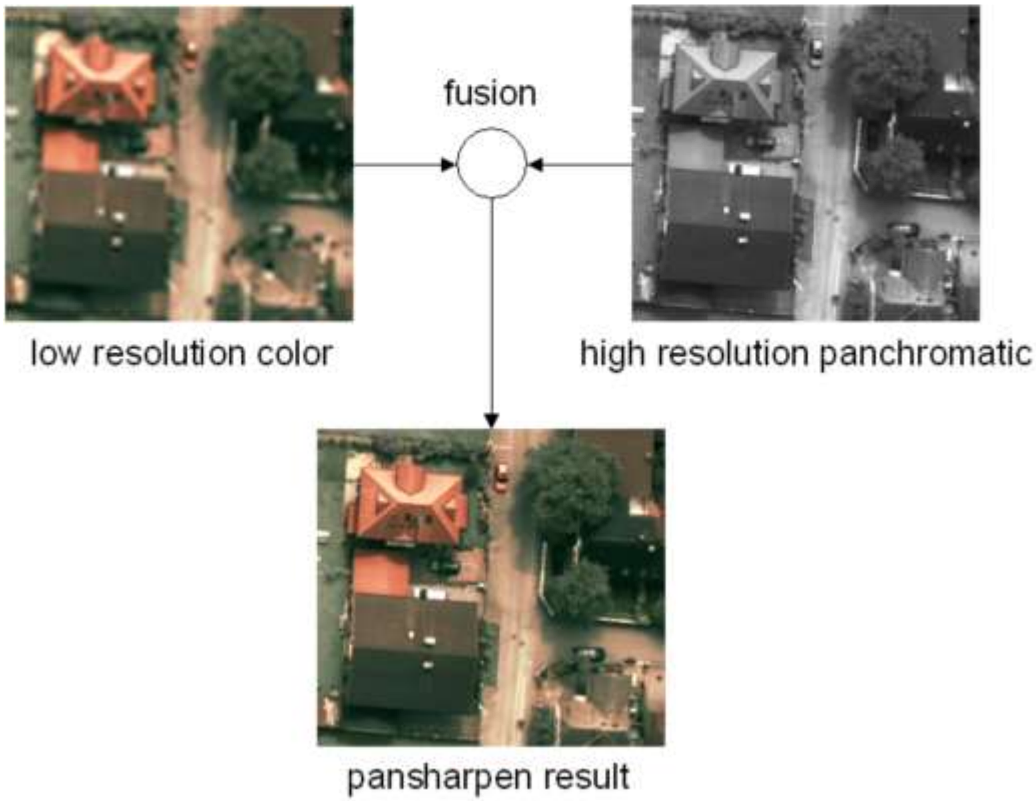
$$x \in \mathbb{R}^{m \times m \times b} \rightarrow y \in \mathbb{R}^{km \times km \times b}$$

Image compression



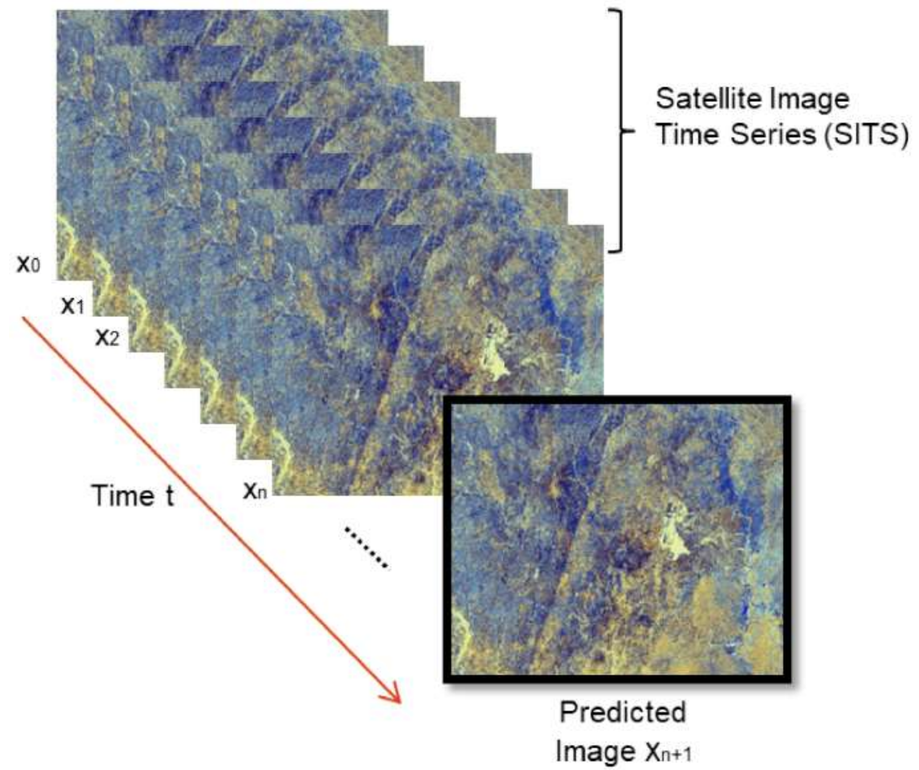
$$x \in \mathbb{R}^{m \times m \times b} \rightarrow y \in \{00011101010101101010101 \cdots\}$$

Fusion



$$\{x_1 \in \mathbb{R}^{m\times m\times b}, x_2 \in \mathbb{R}^{n\times n\times 1}\} \rightarrow y \in \mathbb{R}^{n\times n\times b}$$

Forecasting



$$x \in \mathbb{R}^{m \times m \times t} \rightarrow y \in \mathbb{R}^{m \times m}$$

Data sources

In-situ

+ High quality

+ High temporal resolution

- Localized

Remote Sensing

+ Global coverage

+ Moderate temporal resolution

- Coarse-resolution

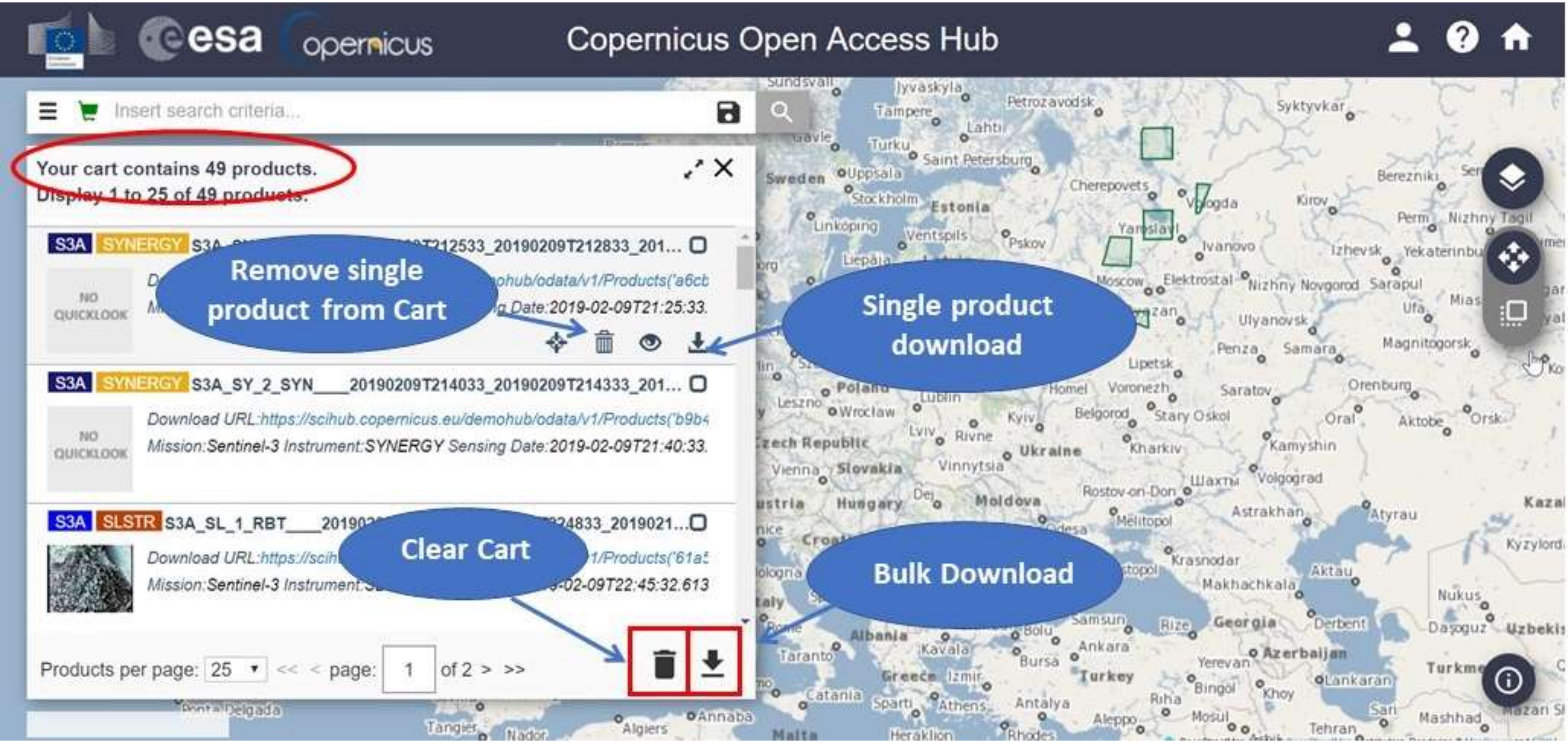
Numerical models

+ Capture physical laws

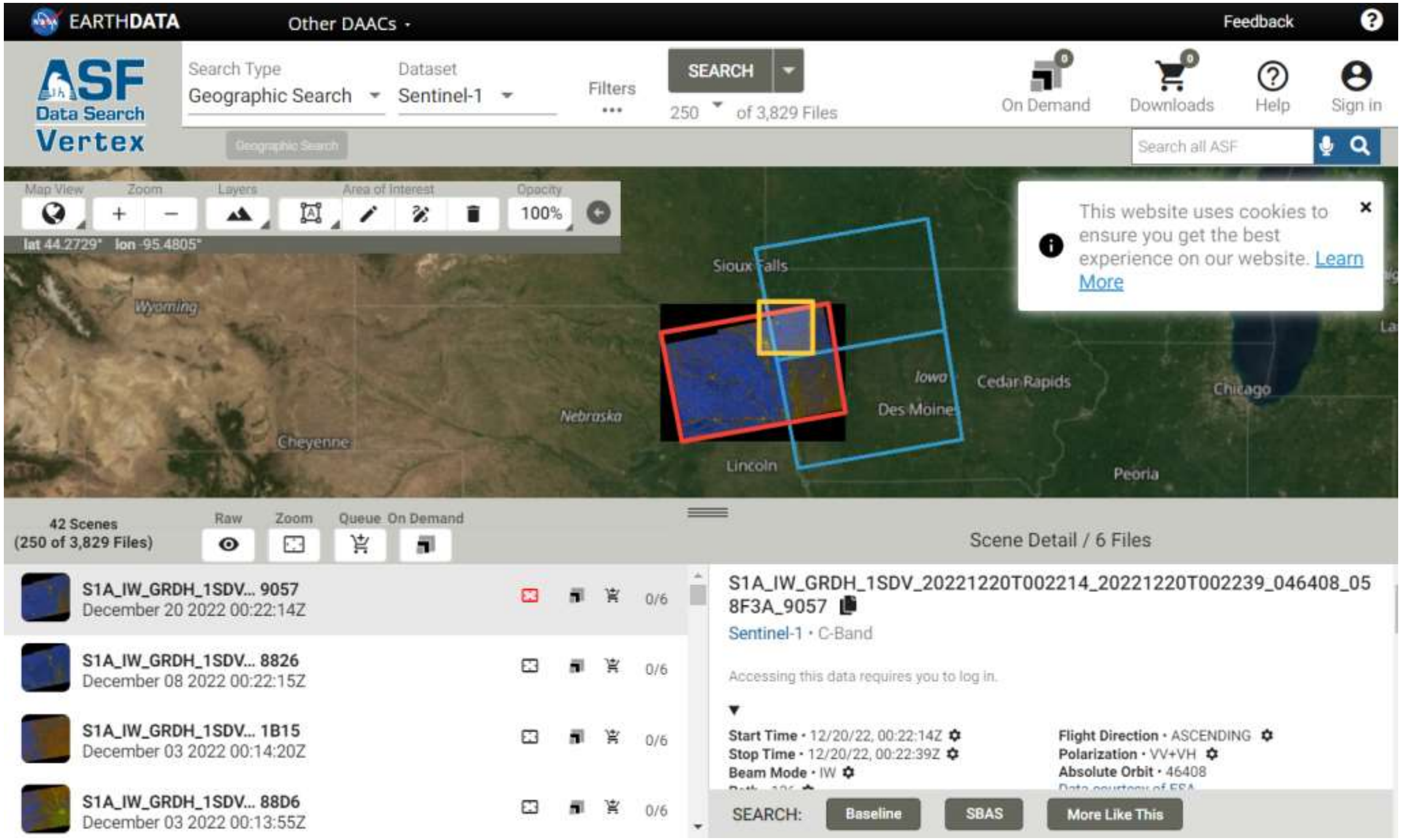
+ Flexible spatial/temporal resolution

- Expensive

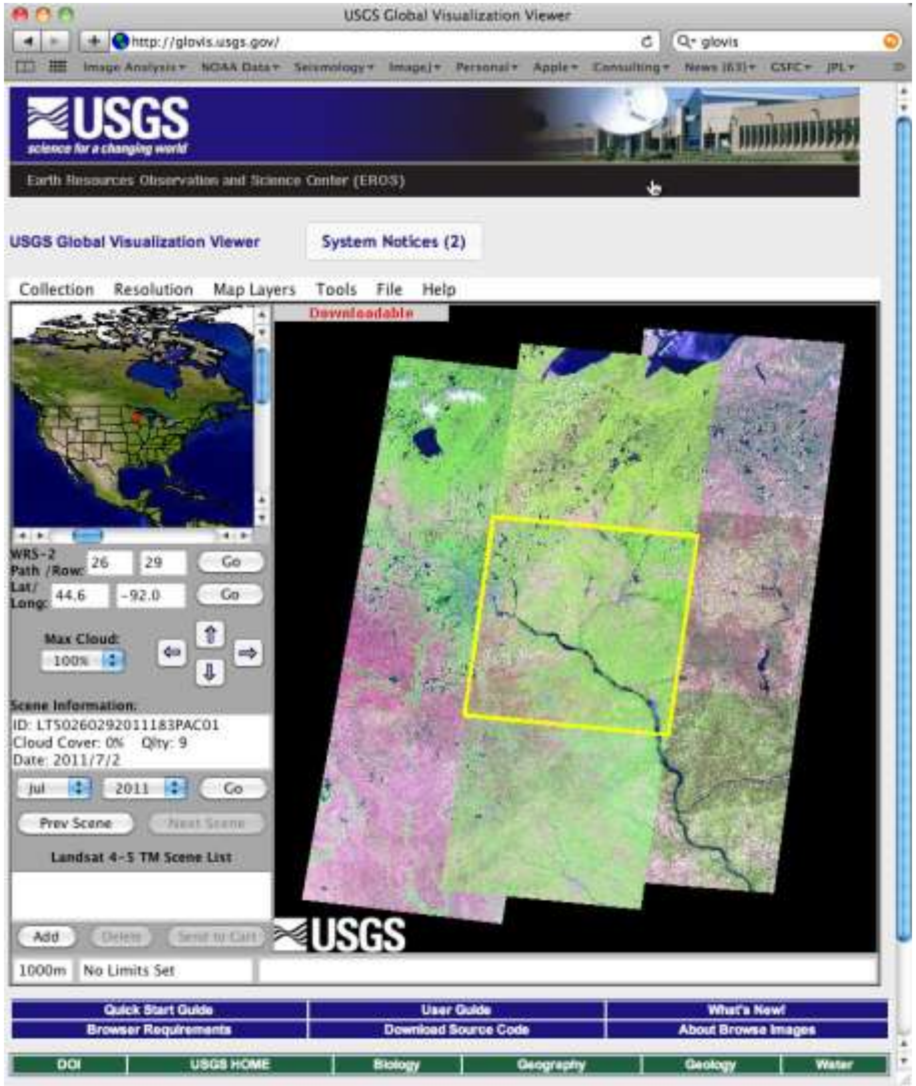
Copernicus data



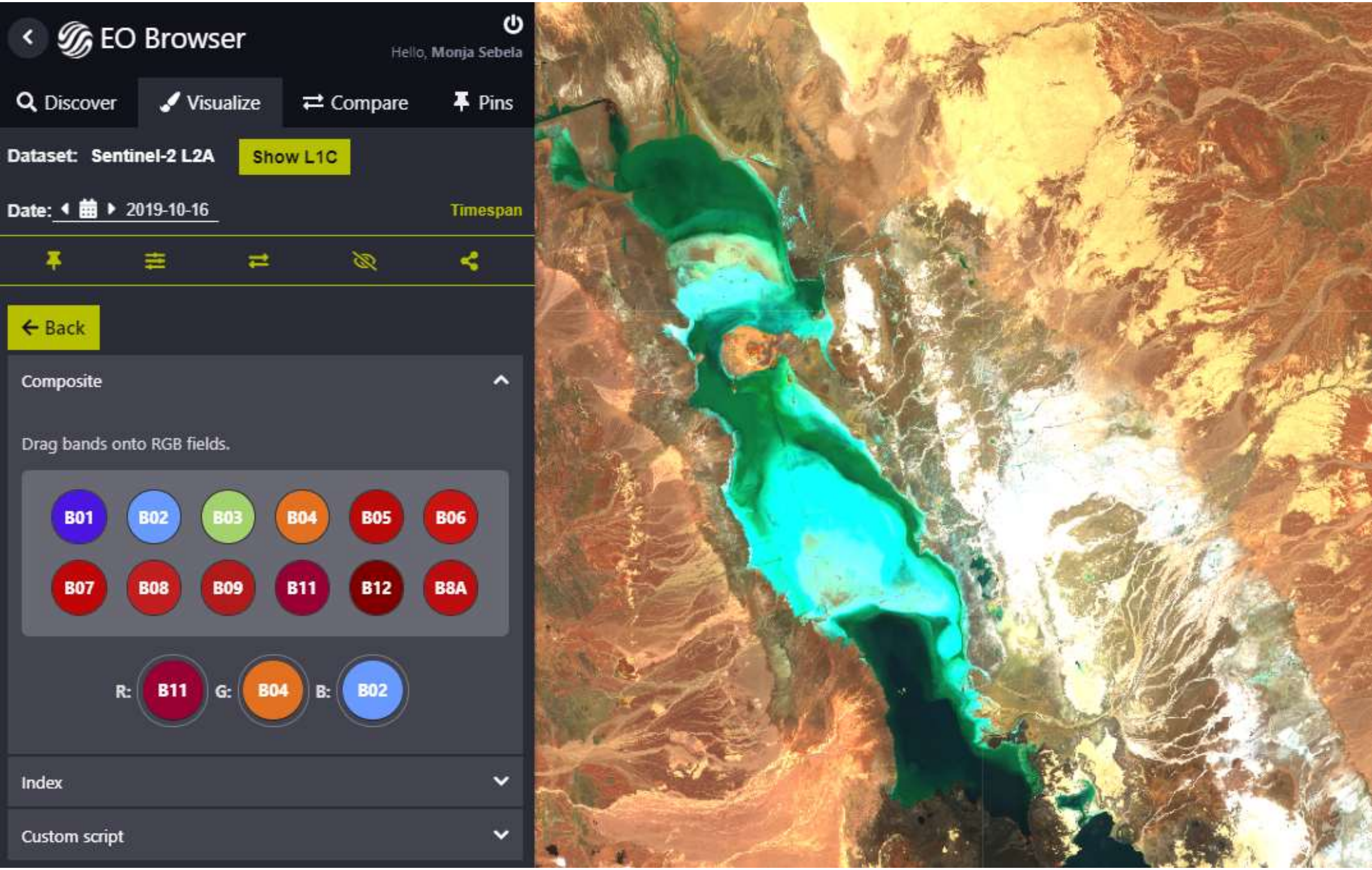
Alaska Satellite Facility

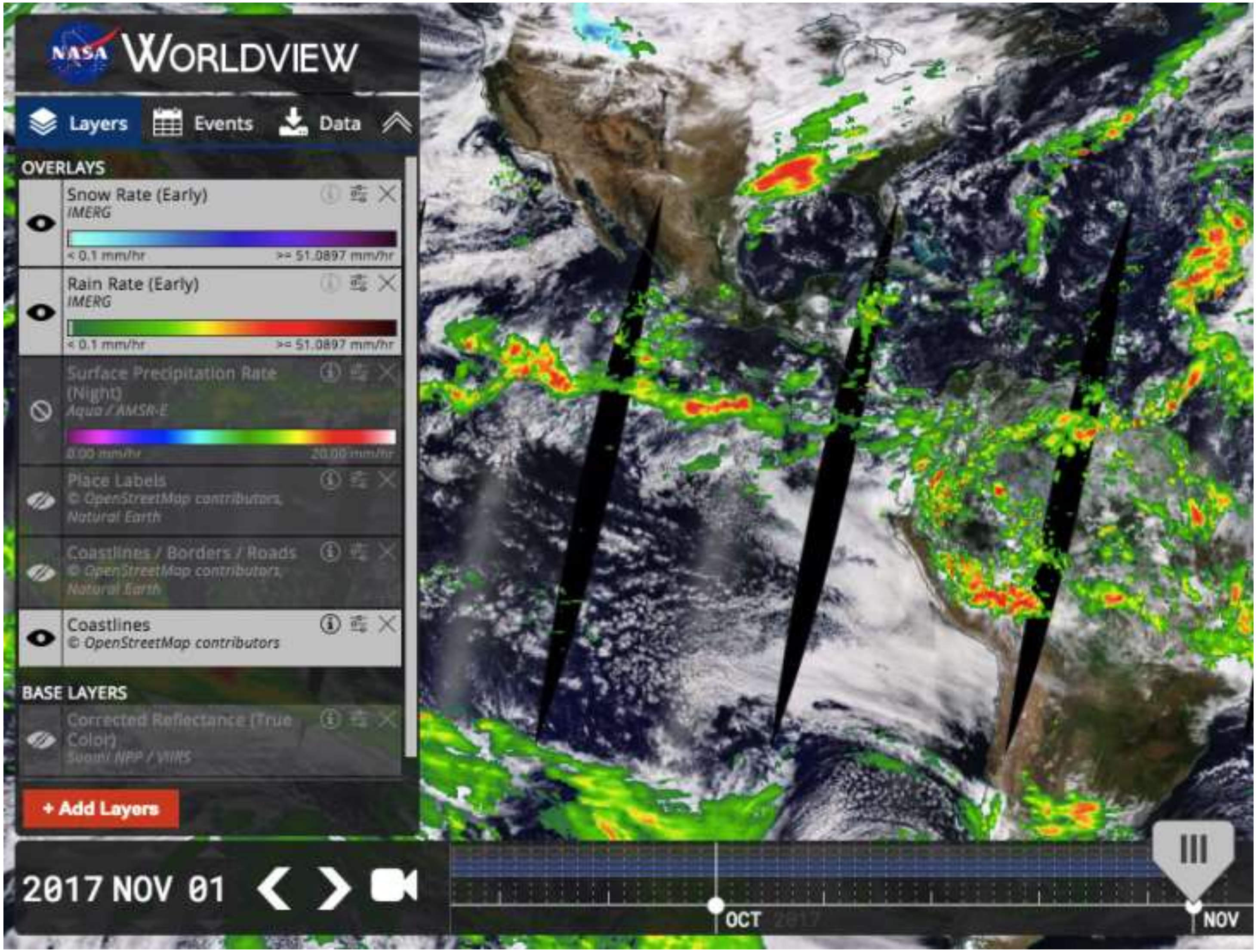


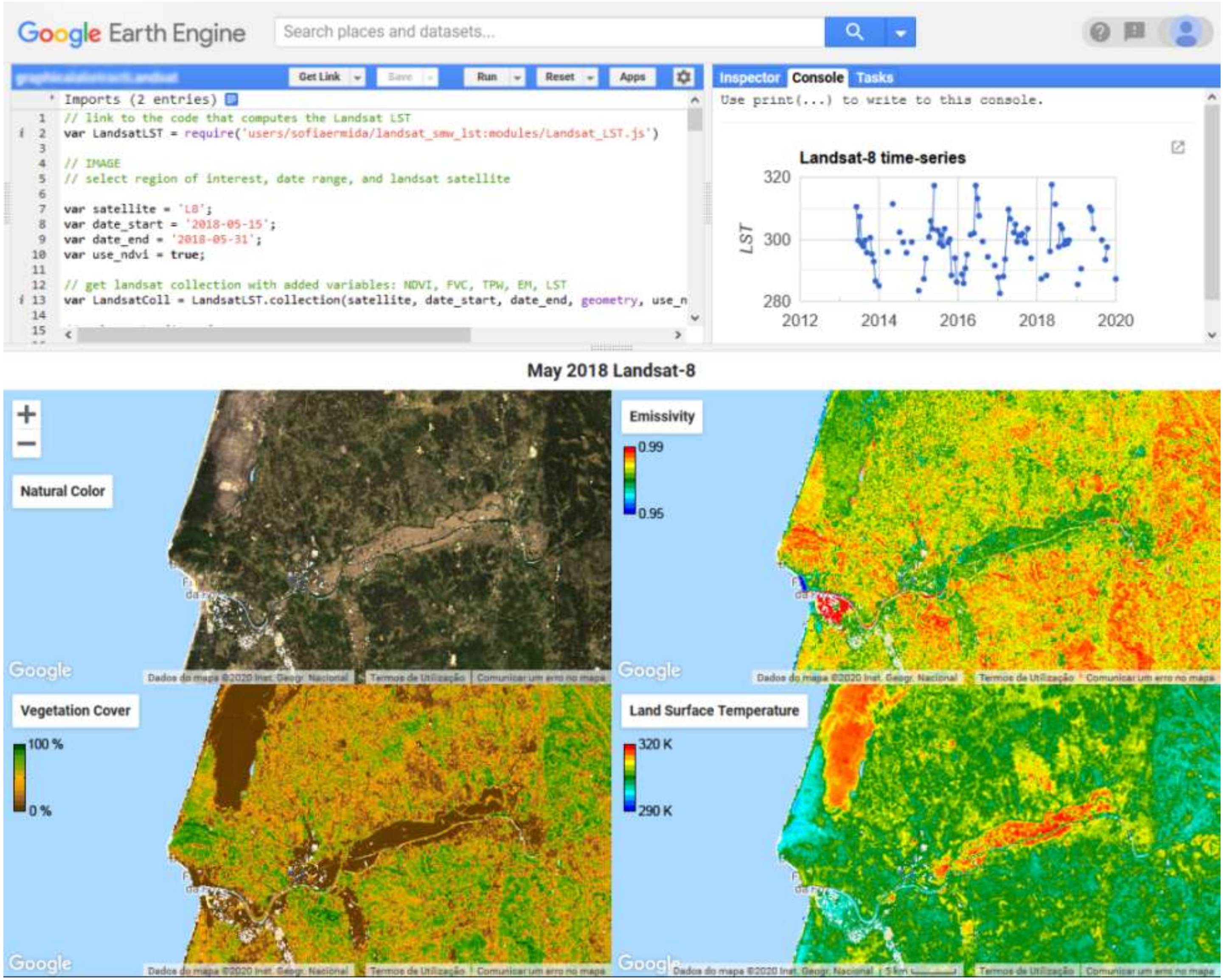
USGS



USGS Global Visualization Viewer
http://glovis.usgs.gov/
USGS
science for a changing world
Earth Resources Observation and Science Center (EROS)
USGS Global Visualization Viewer
System Notices (2)
Collection Resolution Map Layers Tools File Help
Downloadable
WRS-2 Path /Row: 26 29 Go
Lat/ Long: 44.6 -92.0 Go
Max Cloud: 100%
Scene Information:
ID: LT50260292011183PAC01
Cloud Cover: 0% Qlty: 9
Date: 2011/7/2
Jul 2011 Go
Prev Scene Next Scene
Landsat 4-5 TM Scene List
Add Delete Send to Cart
1000m No Limits Set
Quick Start Guide
User Guide
What's New!
Browser Requirements
Download Source Code
About Browse Images
DOI USGS HOME Biology Geography Geology Water


EO Browser
Hello, Monja Sebela
Discover
Visualize
Compare
Pins
Dataset: Sentinel-2 L2A
Show L1C
Date: 2019-10-16
Timespan
Back
Composite
Drag bands onto RGB fields.
B01 B02 B03 B04 B05 B06
B07 B08 B09 B11 B12 B8A
R: B11 G: B04 B: B02
Index
Custom script


WORLDVIEW
Layers
Events
Data
OVERLAYS
Snow Rate (Early)
IMERG
< 0.1 mm/hr
>= 51.0897 mm/hr
Rain Rate (Early)
IMERG
< 0.1 mm/hr
>= 51.0897 mm/hr
Surface Precipitation Rate (Night)
Aqua / AMSR-E
Place Labels
© OpenStreetMap contributors, Natural Earth
Coastlines / Borders / Roads
© OpenStreetMap contributors, Natural Earth
Coastlines
© OpenStreetMap contributors
BASE LAYERS
Corrected Reflectance (True Color)
Suomi NPP / VIIRS
+ Add Layers
2017 NOV 01
OCT
NOV


Google Earth Engine
Search places and datasets...
Get Link
Save
Run
Reset
Apps
Inspector
Console
Tasks
Imports (2 entries)
// link to the code that computes the Landsat LST
var LandsatLST = require('users/sofiaermida/landsat_smw_lst:modules/Landsat_LST.js')
// IMAGE
// select region of interest, date range, and landsat satellite
var satellite = 'L8';
var date_start = '2018-05-15';
var date_end = '2018-05-31';
var use_ndvi = true;
// get landsat collection with added variables: NDVI, FVC, TPW, EM, LST
var LandsatColl = LandsatLST.collection(satellite, date_start, date_end, geometry, use_n
Use print(...) to write to this console.
Landsat-8 time-series
LST
320
300
280
2012
2014
2016
2018
2020
May 2018 Landsat-8
Natural Color
Emissivity
0.99
0.95
Vegetation Cover
100 %
0 %
Land Surface Temperature
320 K
290 K
Google

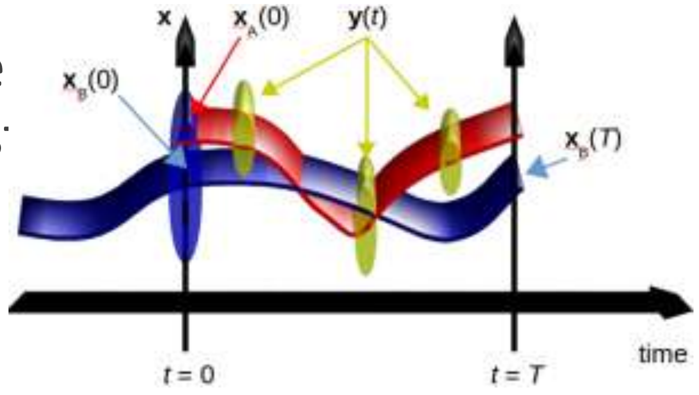
Data assimilation

Challenges

- Free running model will drift from reality (modelling approximations, unknown processes acting, and uncertain initial conditions).

Approach

Data Assimilation: fusion of differe
to estimate possible states of a sys



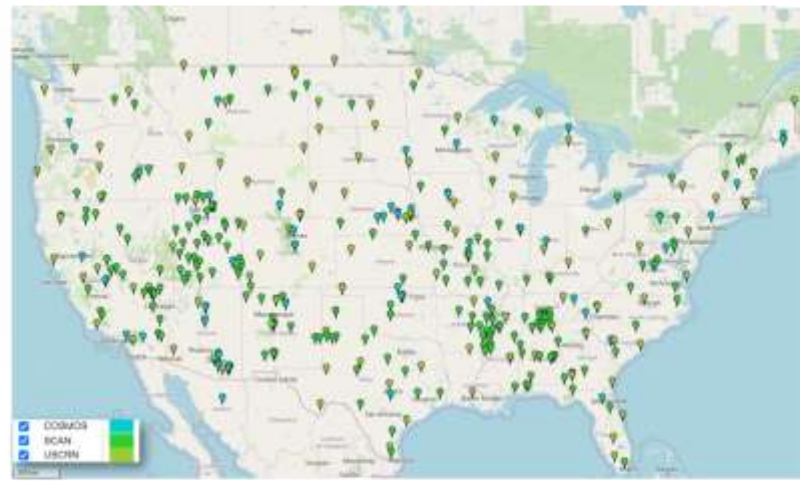
- Sparse observations
- Measurements error
- Indirect sensing

https://research.reading.ac.uk/met-darc/aboutus/what-is-data-assimilation/

In-situ sensor network

The International Soil Moisture Network (ISMN)

Variable name	Abbreviation	Units	Measurement depth* (m)	Variable with depth?	No. of time series (stations)
Soil moisture	sm	$m^3\,m^{-3}$	0.00–2.10	Y	10 610 (2822)
Soil suction	su	kPa	0.04–0.75	Y	73 (18)
Soil temperature	ts	°C	0.00–2.03	Y	8113 (1629)
Air temperature	ta	°C	2.00–12.00	Y	1292 (1234)
Surface temperature	tsf	°C	0.00–0.00	N	126 (126)
Precipitation	*p*	mm	0.00–2.00	N	759 (700)
Snow depth	sd	mm	0.00	N	562 (555)
Snow water equivalent	sweq	mm	0.00	N	507 (427)

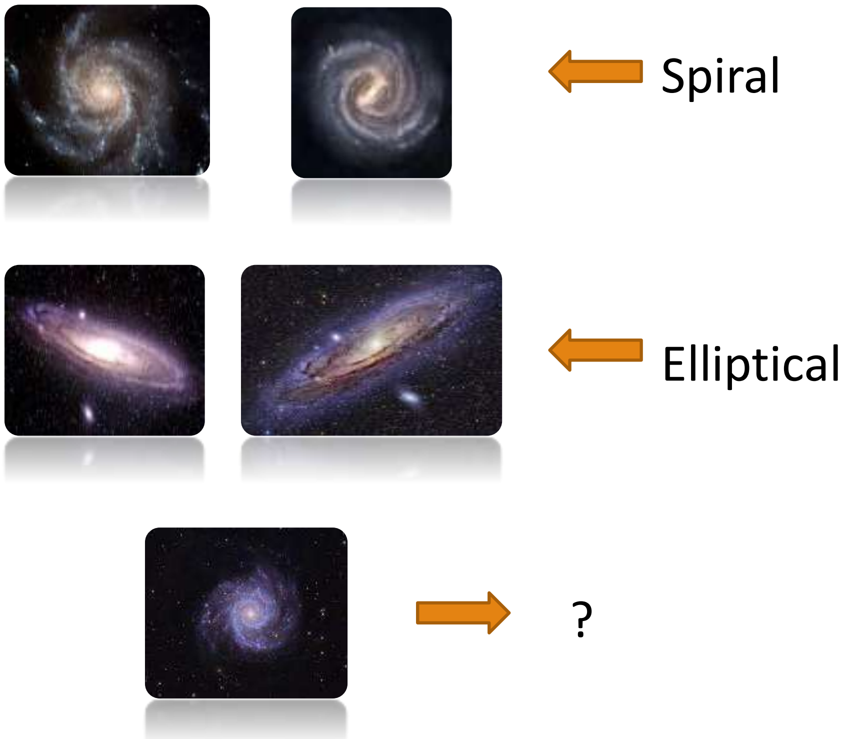


- Harmonization
- Quality Control
- Sparse locations

Supervised Learning

Data
Labels

Model
Prediction



Exploiting prior knowledge

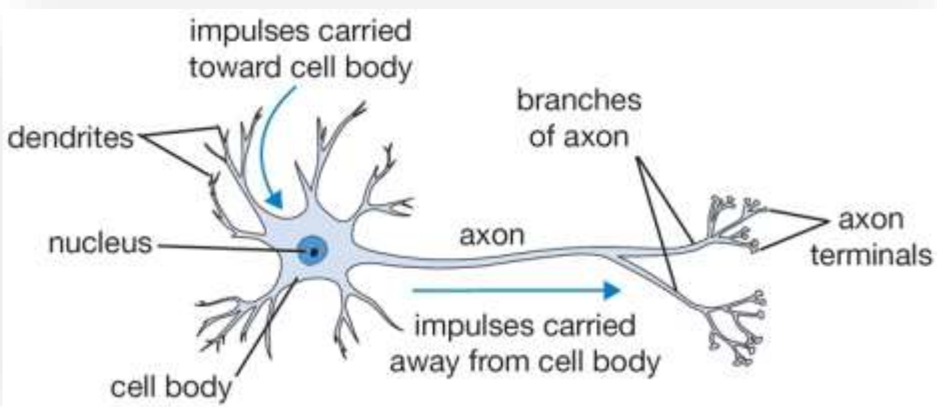
- Expert users
- Crowdsourcing
- Other instruments
- Time

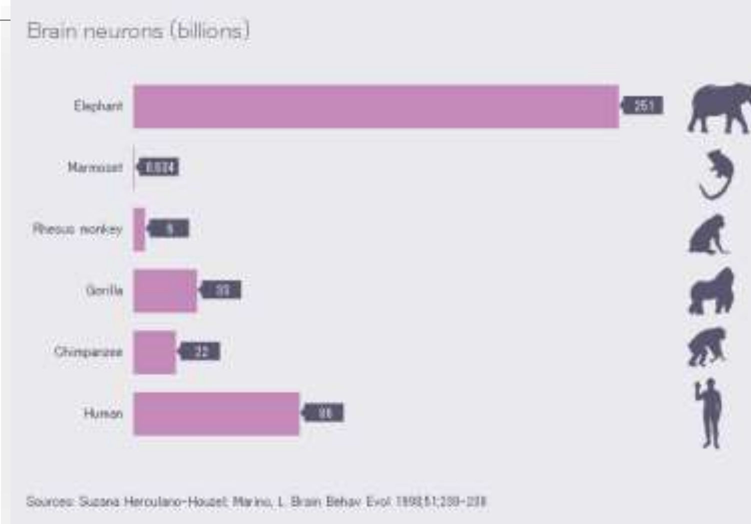
Artificial Neural Networks (ANN)

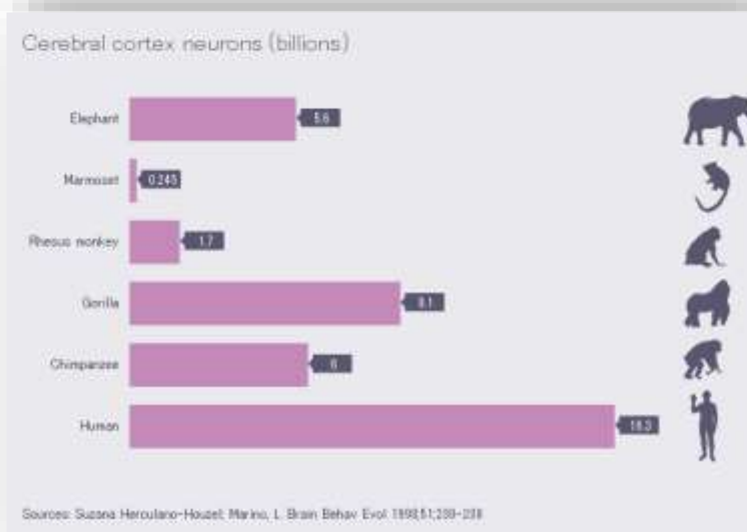
aka **Deep Learning**

Inspiration from brain

- 86Billion neurons
- 10^{14}-10^{15} synapses

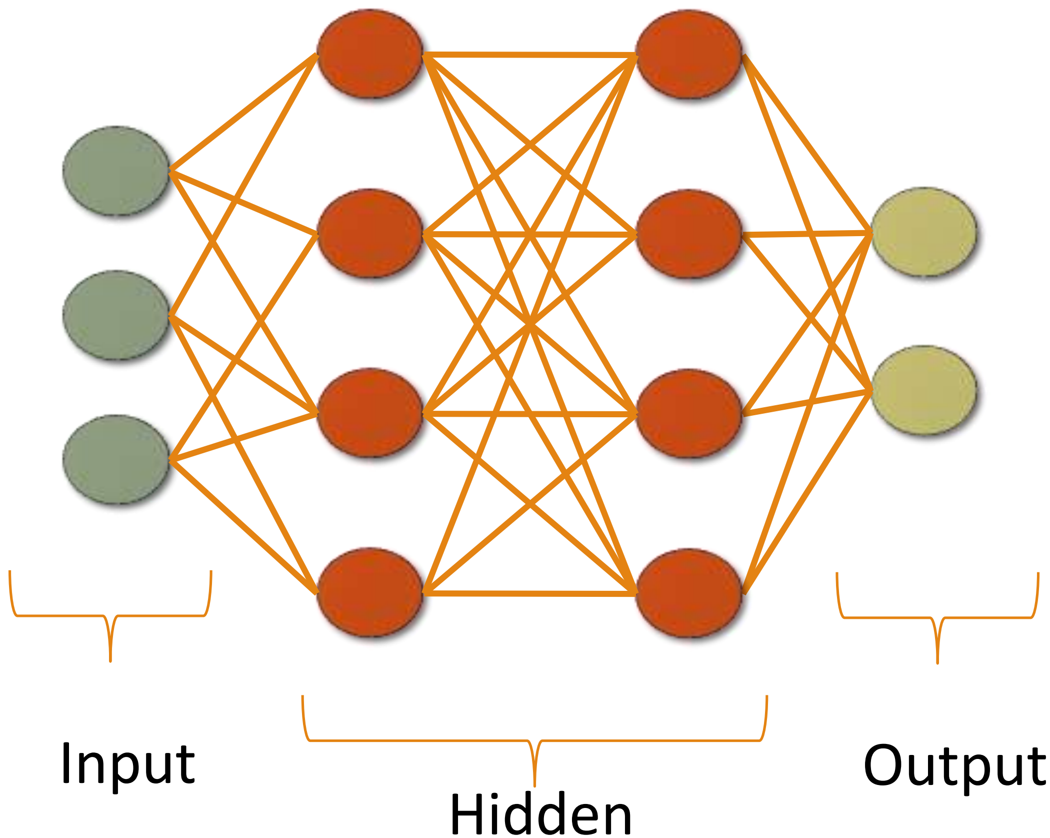






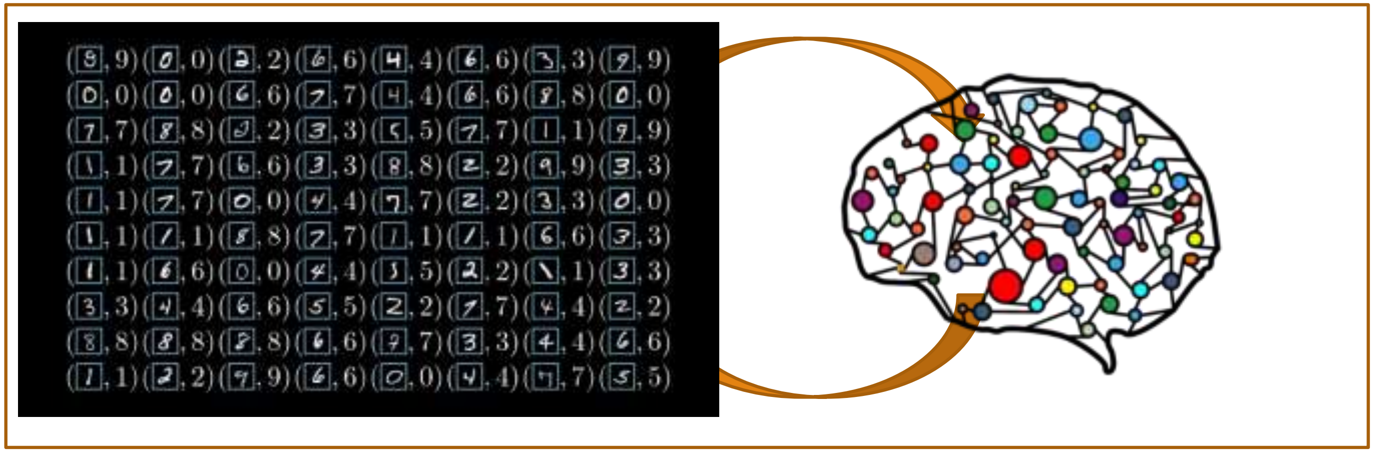
Key components of ANN

- Architecture (input/hidden/output layers)



Key processing in ANN

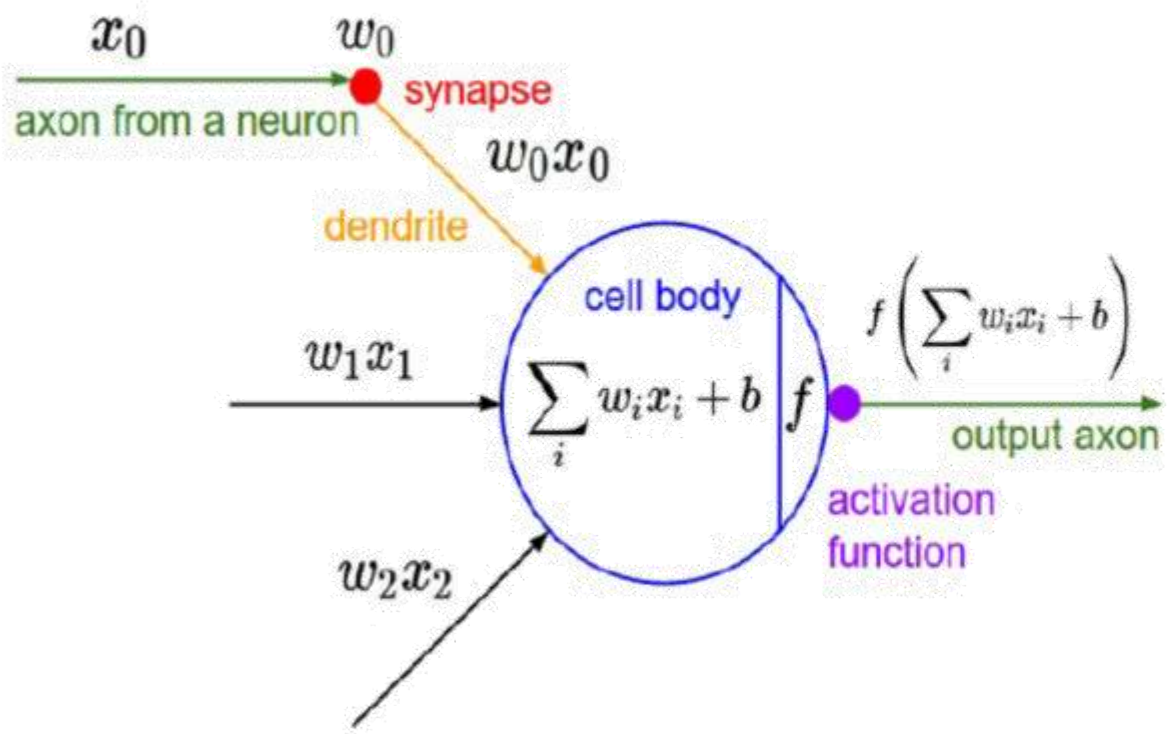
Training



Inference (Test)

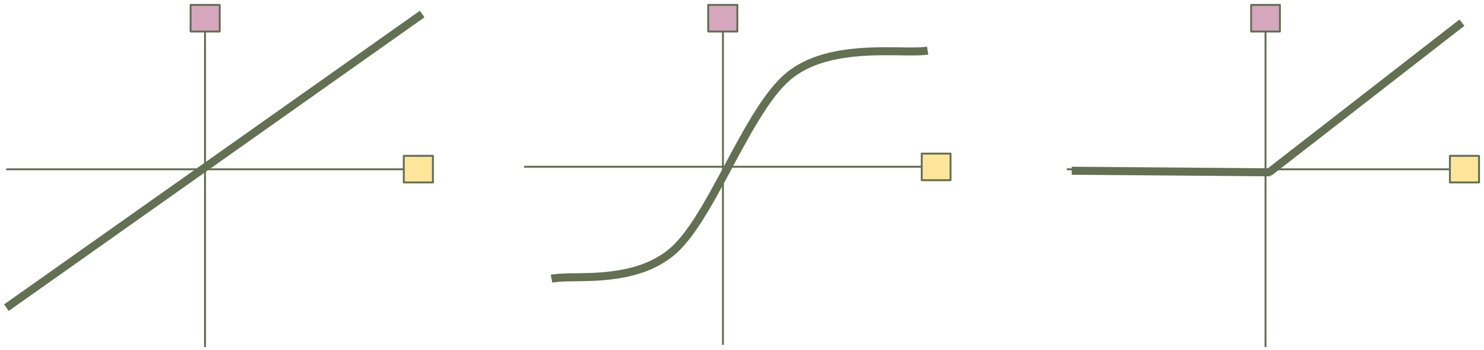
Key components of ANN

- Architecture (input/hidden/output layers)
- Weights



Key components of ANN

- Architecture (input/hidden/output layers)
- Weights
- Activations



LINEAR

LOGISTIC / SIGMOIDAL / TANH

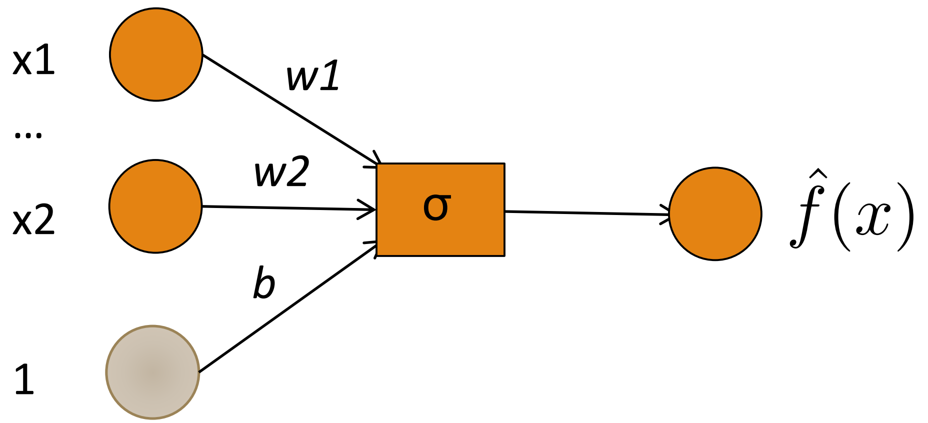
RECTIFIED LINEAR (ReLU)

Perceptron: an early attempt

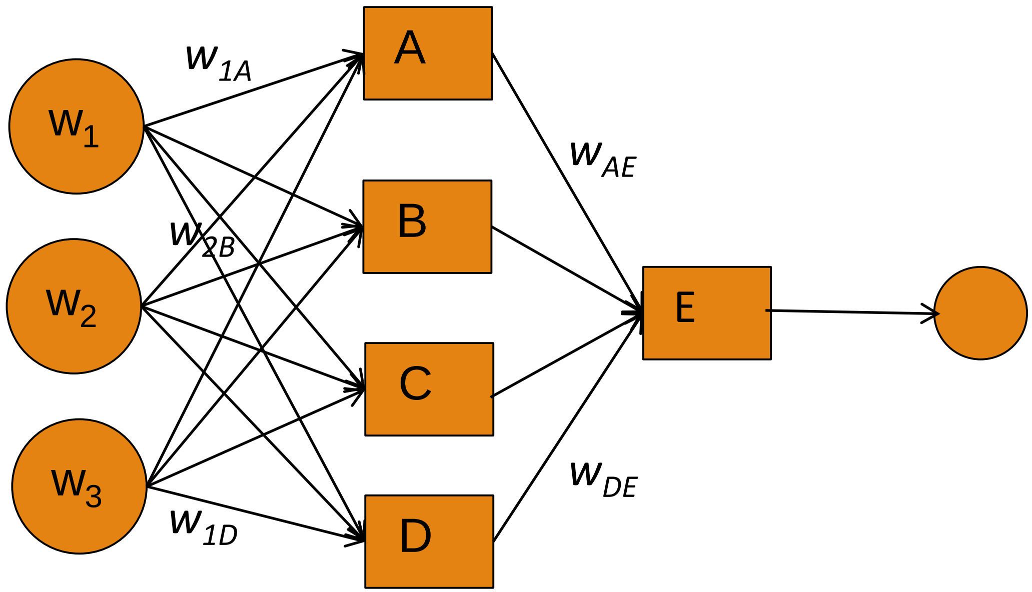
Activation function

$$\hat{f}(x) = \sigma(w \cdot x + b) \qquad \sigma(y) = \begin{cases} 1, & y > 0 \\ 0, & o/w \end{cases}$$

Need to tune w and b



Multilayer perceptron

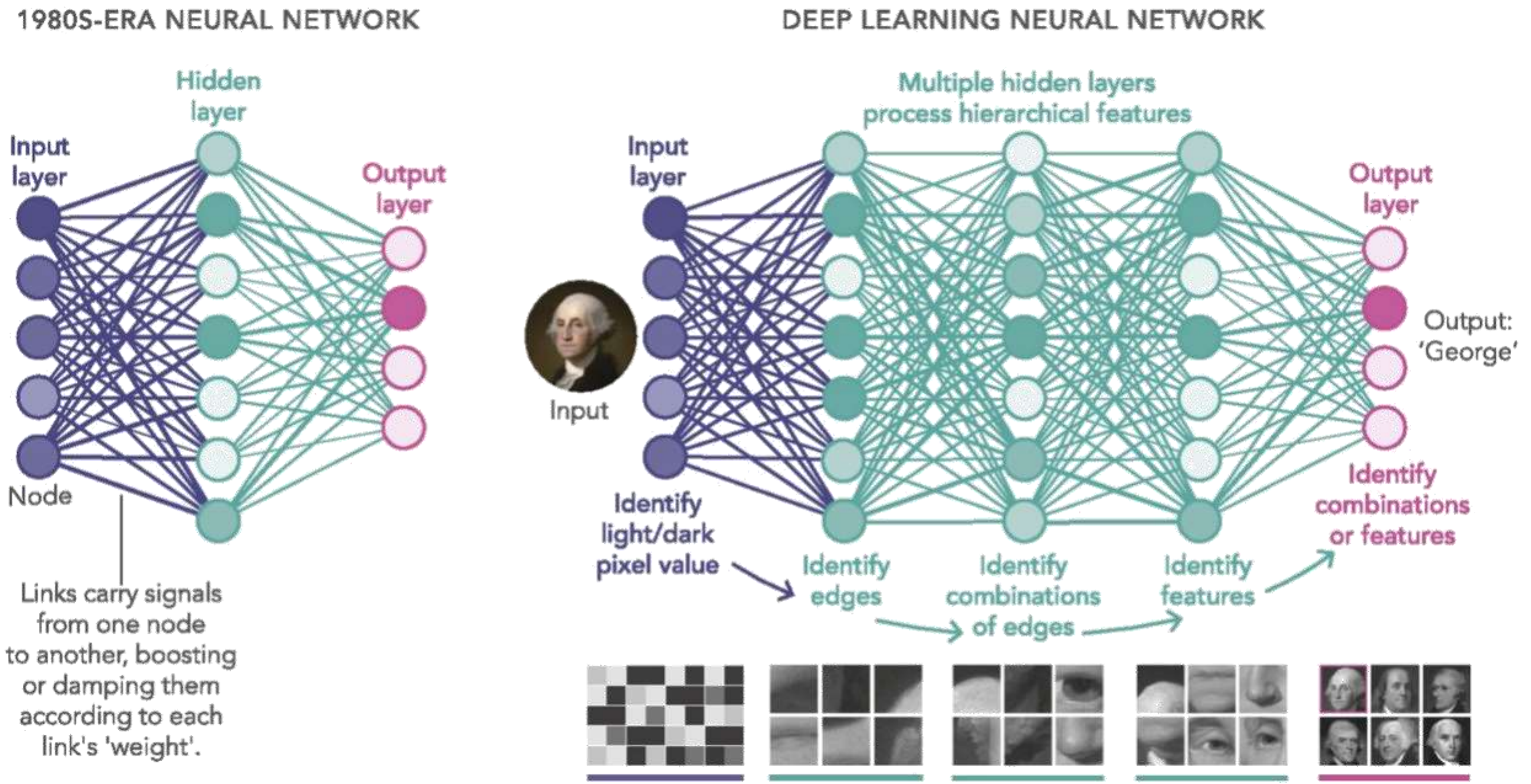


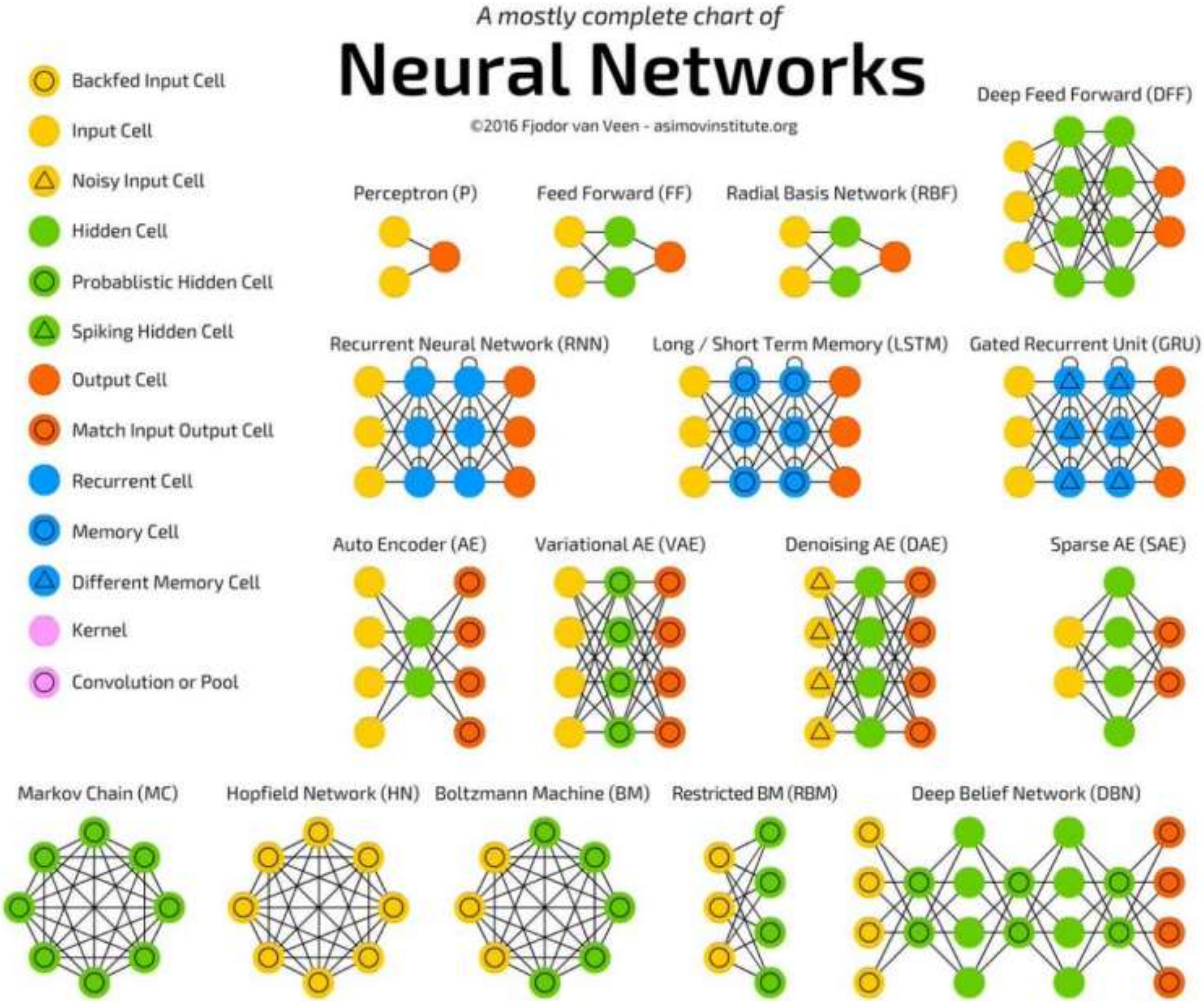
We just added a neuron layer!

We just introduced non-linearity!

A neuron is of the form **σ(w.x + b)** where **σ** is an *activation* function

Deep Neural Networks





Sasen Cain (@spectralradius)

Training & Testing

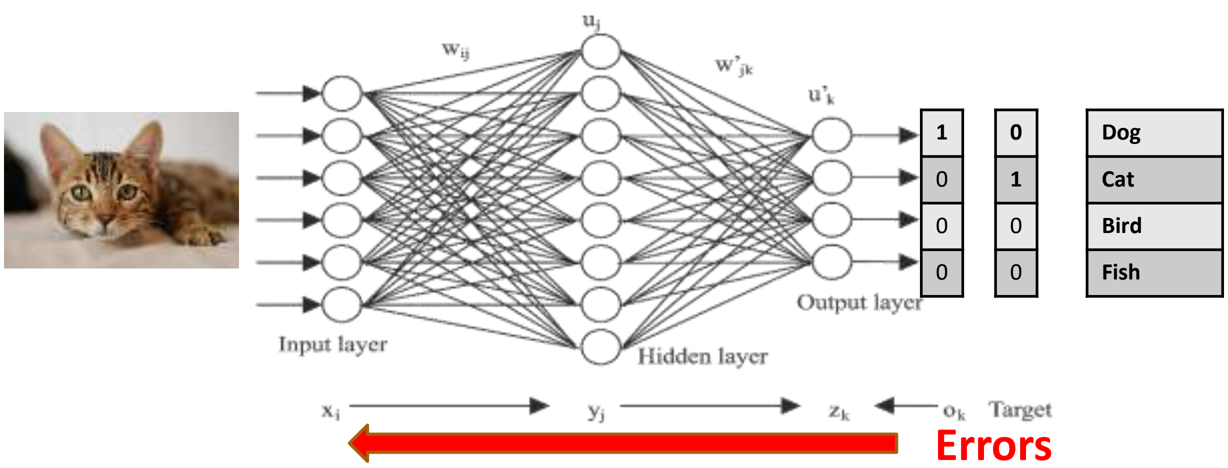
Training: determine weights

- Supervised: labeled training examples
- Unsupervised: no labels available
- Reinforcement: examples associated with rewards

Testing (Inference): apply weights to new examples

Training DNN

1. Get batch of data
2. Forward through the network -> compute loss
3. Backpropagate error
4. Update weights based on gradient



Training DNN

Input: x_i Target: y_i DNN: $f(\cdot;\theta)$

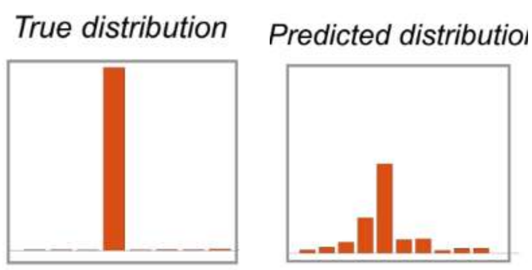
Forward pass $\hat{y}_i = f(x_i;\theta)$

Compute loss

- Regression: Root Mean Squared Error (RMSE)

$$\mathcal{L}(\hat{y}, y) = \frac{1}{2N}\sum_i (y_i - f(x_i;\theta))^2$$

- Classification: Categorical Cross Entropy (CCE)



$$\mathcal{L}(\hat{y}, y) = -\frac{1}{N}\sum_i \sum_j y_{ij}\log \hat{y}_{ij}$$

Gradient Descent

➤ Minimize function J w.r.t. parameters θ

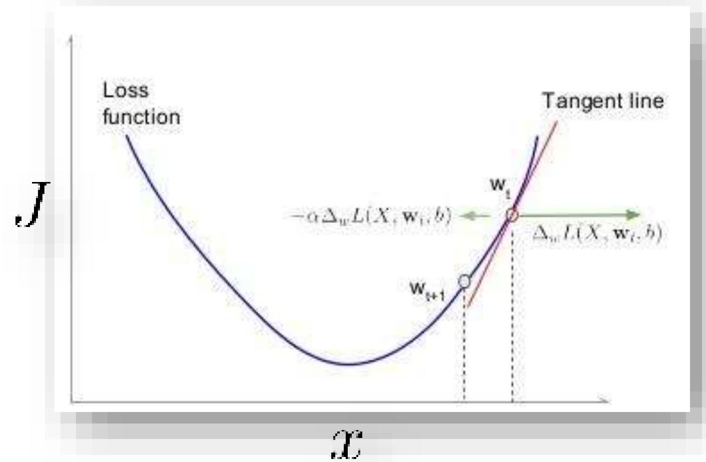
New weights

$$\theta^* = \theta - n * \nabla\mathcal{L}(y, x; \theta)$$

Gradient

Old weights

Learning rate



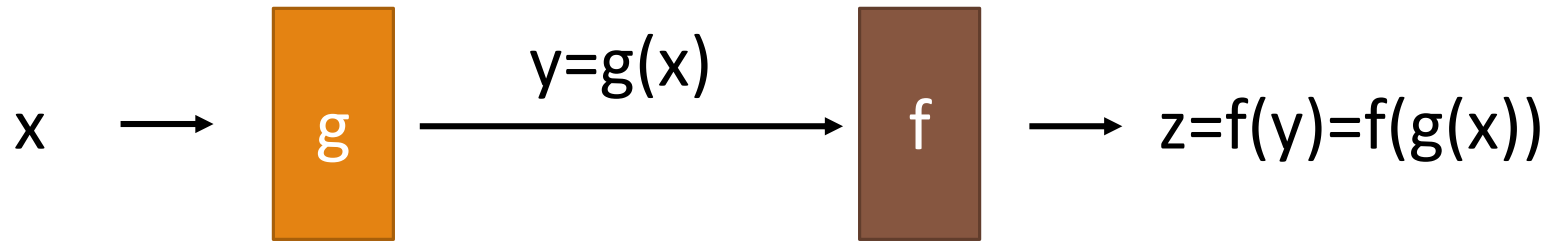
- Gradient

$$\nabla\mathcal{L}(x) = \left(\frac{\partial\mathcal{L}(x)}{\partial x_1}, \frac{\partial\mathcal{L}(x)}{\partial x_2}, \ldots, \frac{\partial\mathcal{L}(x)}{\partial x_n}\right)$$

- Stochastic Gradient Descend

$$\theta^* := \theta - n \sum_{i=1}^{N} \nabla\mathcal{L}(y_i, x_i; \theta)$$

Backpropagation



Chain rule:

- **Single variable**

$$\frac{dz}{dx} = \frac{dz}{dy}\frac{dy}{dx}.$$

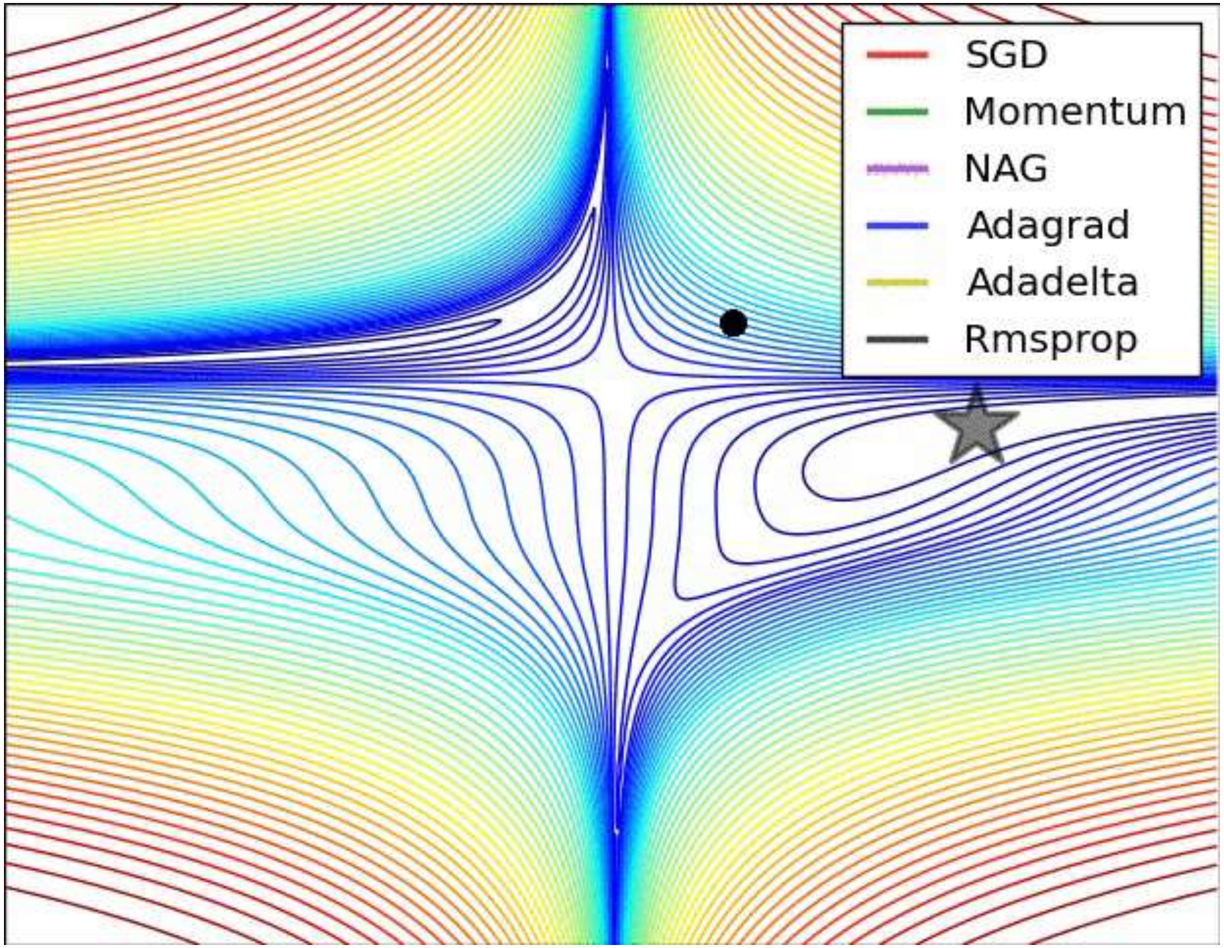
- **Multiple variables**

$$\frac{\partial z}{\partial x_i} = \sum_j \frac{\partial z}{\partial y_j}\frac{\partial y_j}{\partial x_i}.$$

Optimization algorithms

Optimization algorithm	Core idea	Pros	Cons
SGD [140]	Computes the gradient of mini-batches iteratively and updates the parameters	• Easy to implement	• Setting a global learning rate required • Algorithm may get stuck on saddle points or local minima • Slow in terms of convergence • Unstable
Nesterov's momentum [125]	Introduces momentum to maintain the last gradient direction for the next update	• Stable • Faster learning • Can escape local minima	• Setting a learning rate needed
Adagrad [126]	Applies different learning rates to different parameters	• Learning rate tailored to each parameter • Handle sparse gradients well	• Still requires setting a global learning rate • Gradients sensitive to the regularizer • Learning rate becomes very slow in the late stages
Adadelta [141]	Improves Adagrad, by applying a self-adaptive learning rate	• Does not rely on a global learning rate • Faster speed of convergence • Fewer hyper-parameters to adjust	• May get stuck in a local minima at late training
RMSprop [140]	Employs root mean square as a constraint of the learning rate	• Learning rate tailored to each parameter • Learning rate do not decrease dramatically at late training • Works well in RNN training	• Still requires a global learning rate • Not good at handling sparse gradients
Adam [127]	Employs a momentum mechanism to store an exponentially decaying average of past gradients	• Learning rate stailored to each parameter • Good at handling sparse gradients and non-stationary problems • Memory-efficient • Fast convergence	• It may turn unstable during training

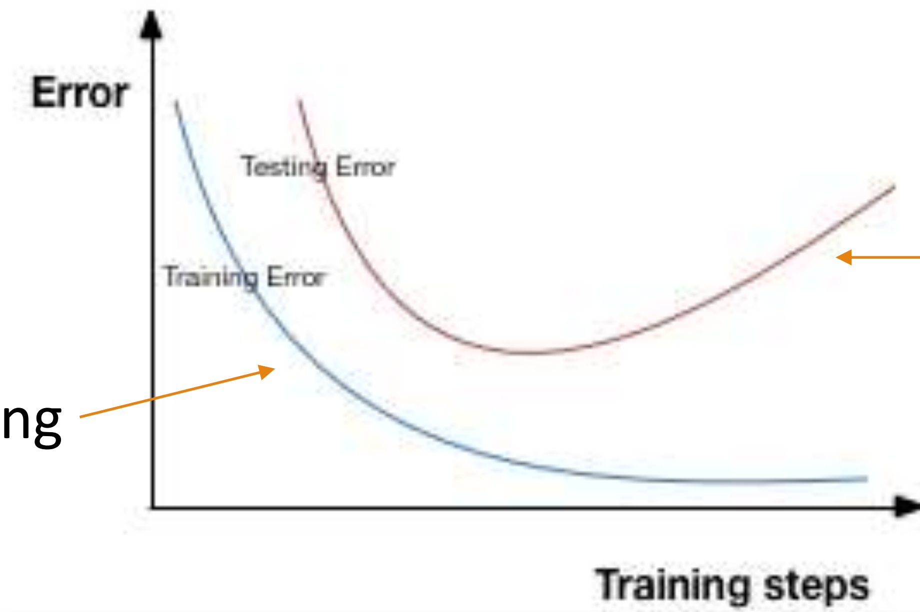
Visualization

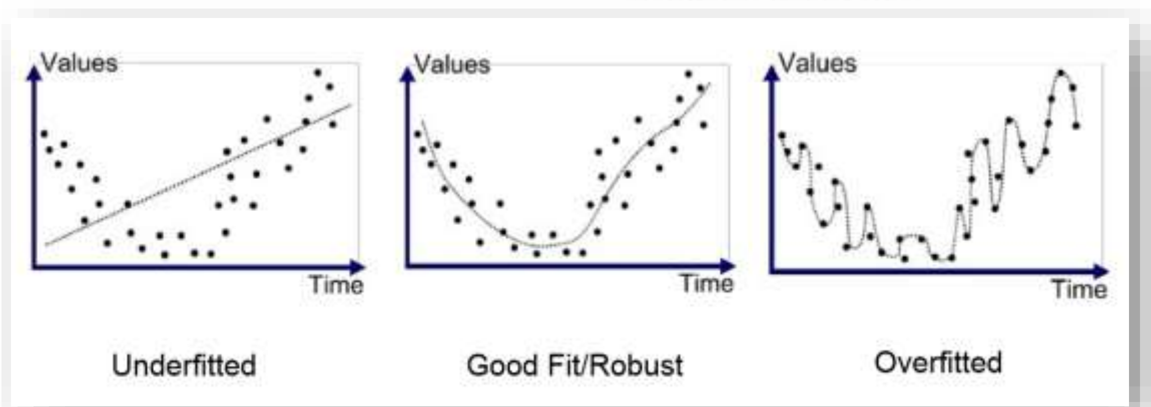


Training Characteristics

Over-fitting

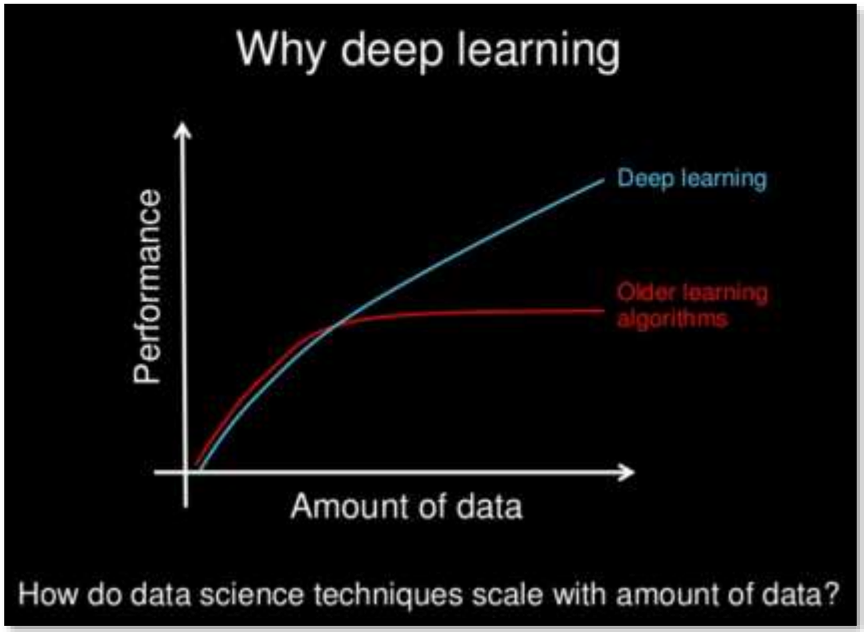
Under-fitting

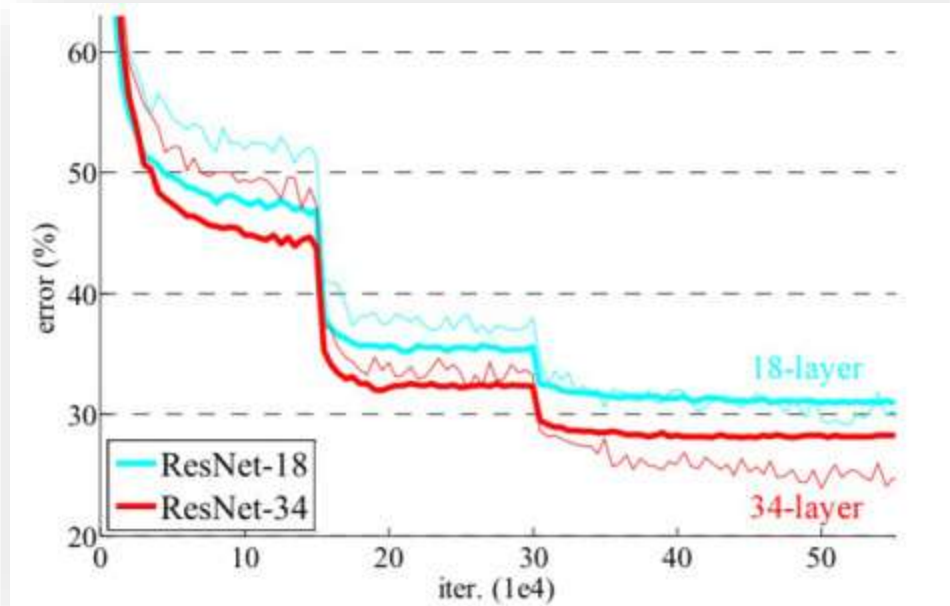




Why Today?

Lots of Data

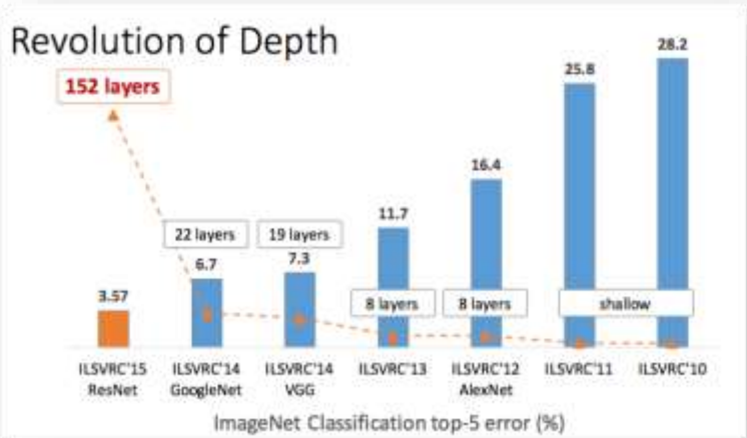


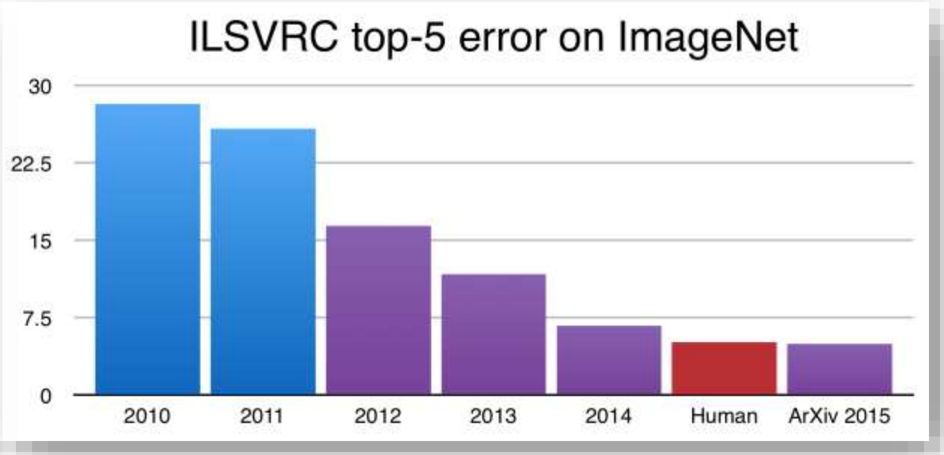


Why Today?

Lots of Data

Deeper Learning



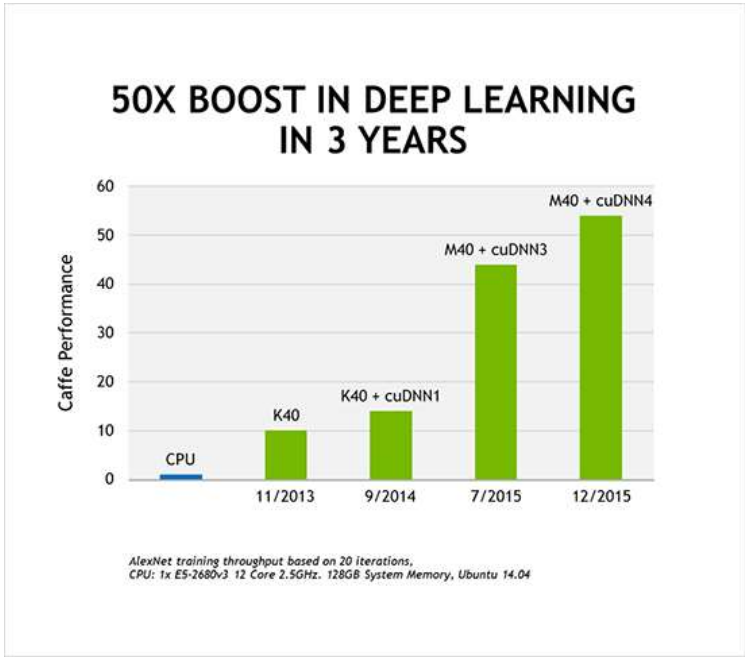


Why Today?

Lots of Data

Deep Learning

More Power



https://blogs.nvidia.com/blog/2016/01/12/accelerating-ai-artificial-intelligence-gpus/
https://www.slothparadise.com/what-is-cloud-computing/