Geospatial Artificial Intelligence (GeoAI) for Sustainable Biodiversity Conservation

Getachew Workineh Gella[Getch], Stefan Lang

Christian Doppler Laboratory for Geospatial and EO-Based Humanitarian Technologies (GEOHUM), Department of Geoinformatics—Z_GIS, Paris Lodron University of Salzburg

Contents

- Biodiversity and its threats
- Can we leverage GeoAI in biodiversity conservation
- GeoAI: introducing the realm
- Basic concepts in GeoAI focused on deep learning
- Python demo [on semantic segmentation][Pytorch][*gmil account needed*]
- Python demo [on Sequence prediction][Tensorflow][*gmil account needed*]

Biodiversity

the term biodiversity (from "biological diversity") refers to the variety of life on Earth at all its levels, from genes to ecosystems, and can encompass the evolutionary, ecological, and cultural processes that sustain life.
American Museum of Natural History

Exploration
survey and monitor ***species, habitats, and their interactions***, measure, and collect data on various dimensions, such as population sizes and trends, distribution and habitat use, and impacts of management or other human activities

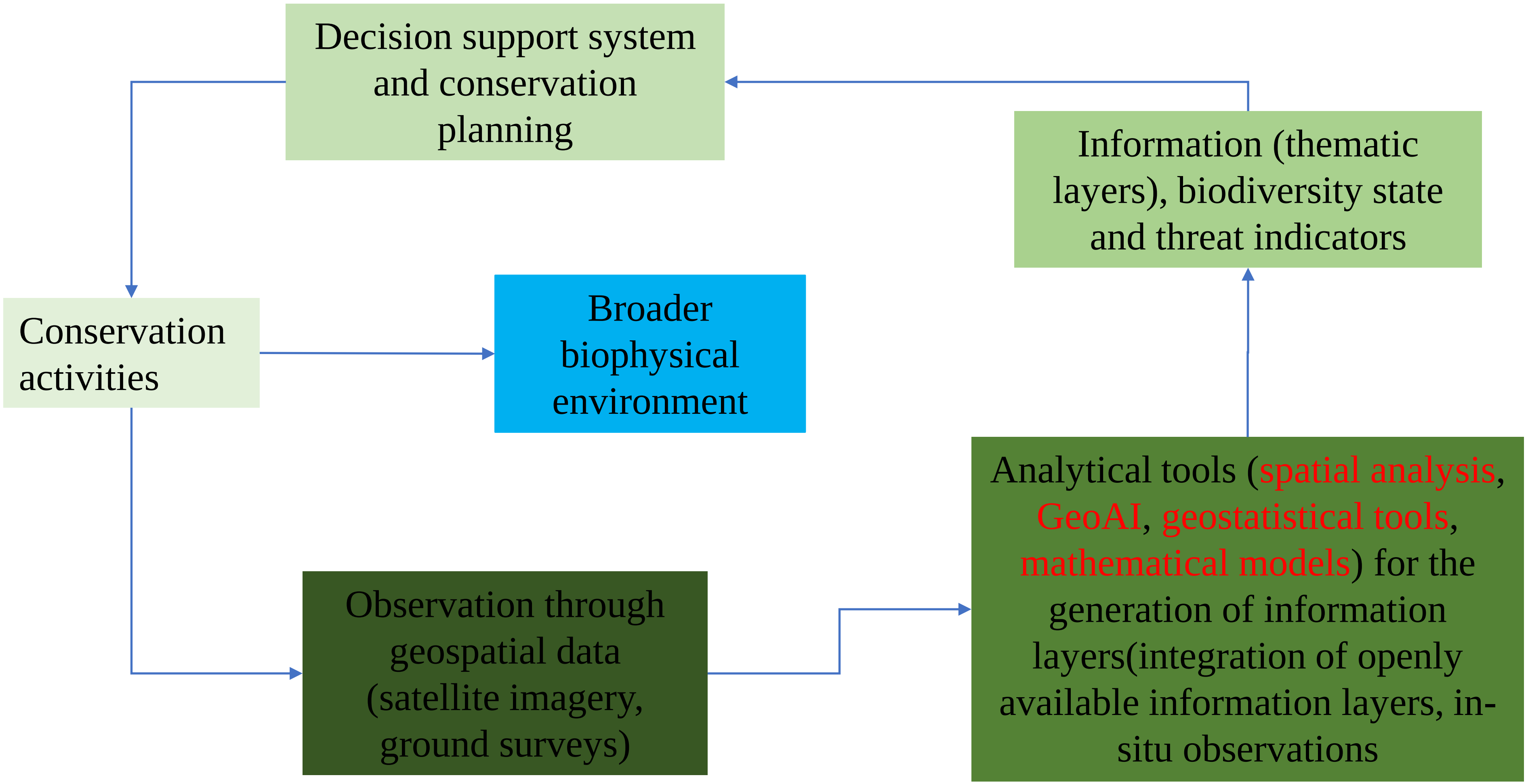
Tools
imaging systems such as **remote sensing** and drones to capture images across an area. **Machine learning and mathematical modeling** can be used to identify and count species or classify landscape types captured in these images or in video or audio clips.

Synthesizing evidence
evidence that decision-makers need to enact effective and sustainable conservation approaches

Threats to biodiversity

Threats to biodiversity	GeoAI application
Settlement encroachment	Large scale monitoring settlement expansion
Land use change (agriculture, timber production, mining)	Monitoring agricultural expansion, automatic detection of logging sites, detection of illegal mining areas/sites in natural reserves
Habitat fragmentation	Generation of habitat and landscape level land cover information and quantifying habitat fragmentation, anticipated corrosion effect, ...
Overfishing and illegal hunting	Detection fishing vessel density, automatic detection and counting of wild animals
Wildlife migration	Predicting migratory patterns and habitat preferences of wild animals
Forest fire	Predicting forest fire susceptibility

Biodiversity monitoring and conservation



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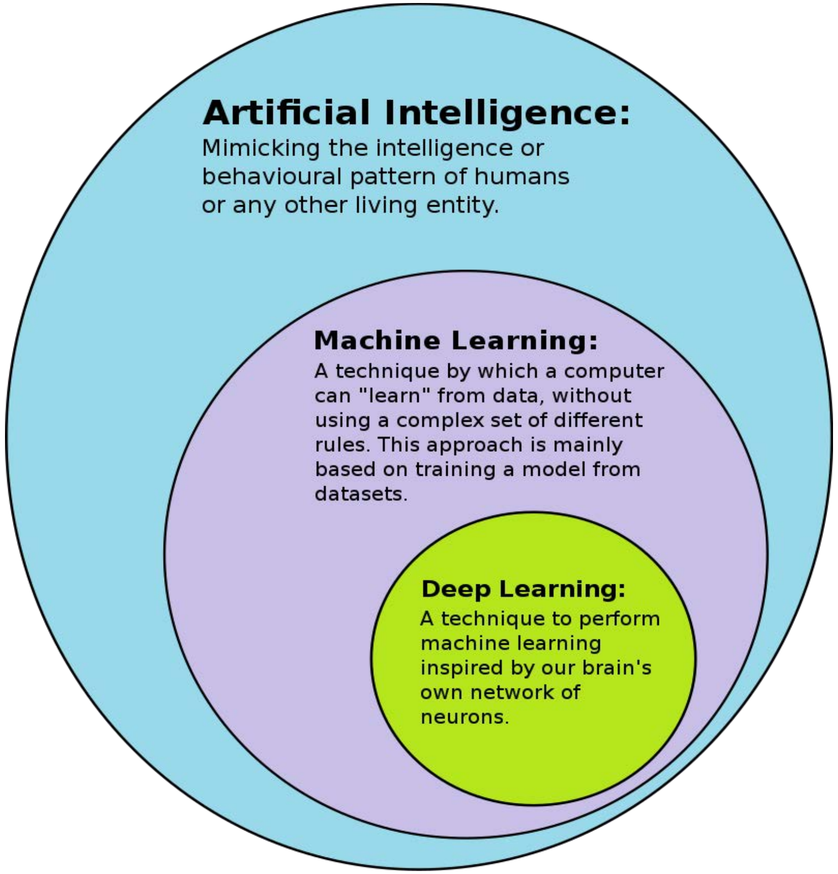
GeoAI

Geospatial artificial intelligence (GeoAI) is the application of artificial intelligence (AI) fused with geospatial data, science, and technology to accelerate understanding of real-world objects and phenomena … ESRI



Any data with spatially explicit information(earth observation imagery, ground surveys, geotagged and crowd sourced data, geolocated in-situ data) and the science and technology to deal with

Forest stand, buildings, urban sprawl, tree and animal species distribution and its change, flows of good and services, flow of nutrients, traffic, population density, natural hazards, biomass changes, carbon emission…

Regression

Elevation(x_1)	Soil PH(x_2)	Tree biomass(y)
176	6.5	0.6
150	6.3	1.1
170	6.0	0.3
100	7.0	0.4
120	8.0	1.6
135	1.0	1.1
125	7.0	0.1

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2$$

$$\beta_1 = \frac{Cov(y, x_1)}{Var(x_1)}$$

Objective is finding a regression line that gives minimum error deviations between predicted and reference

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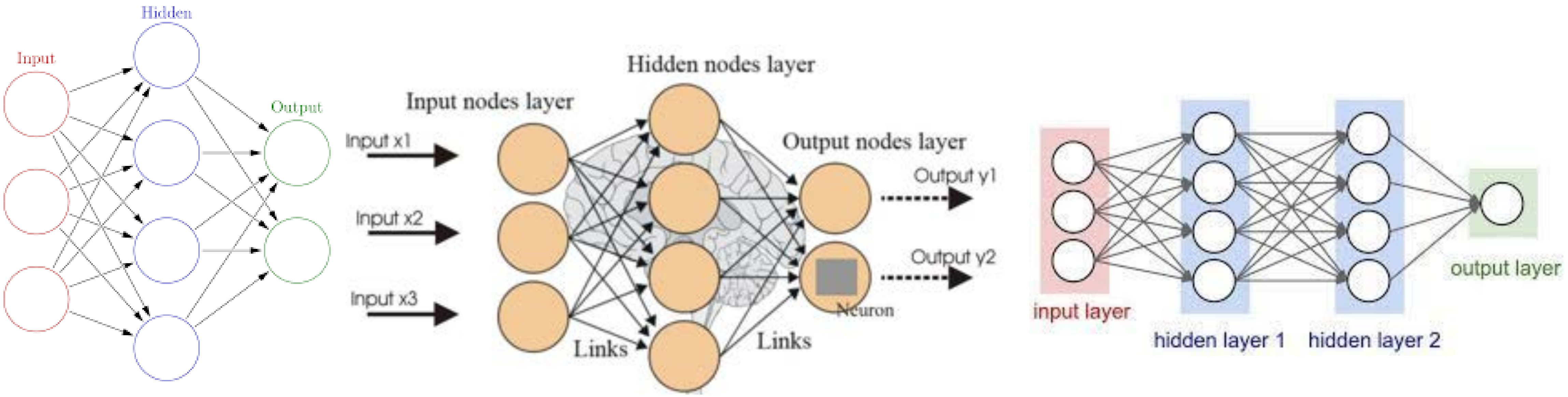
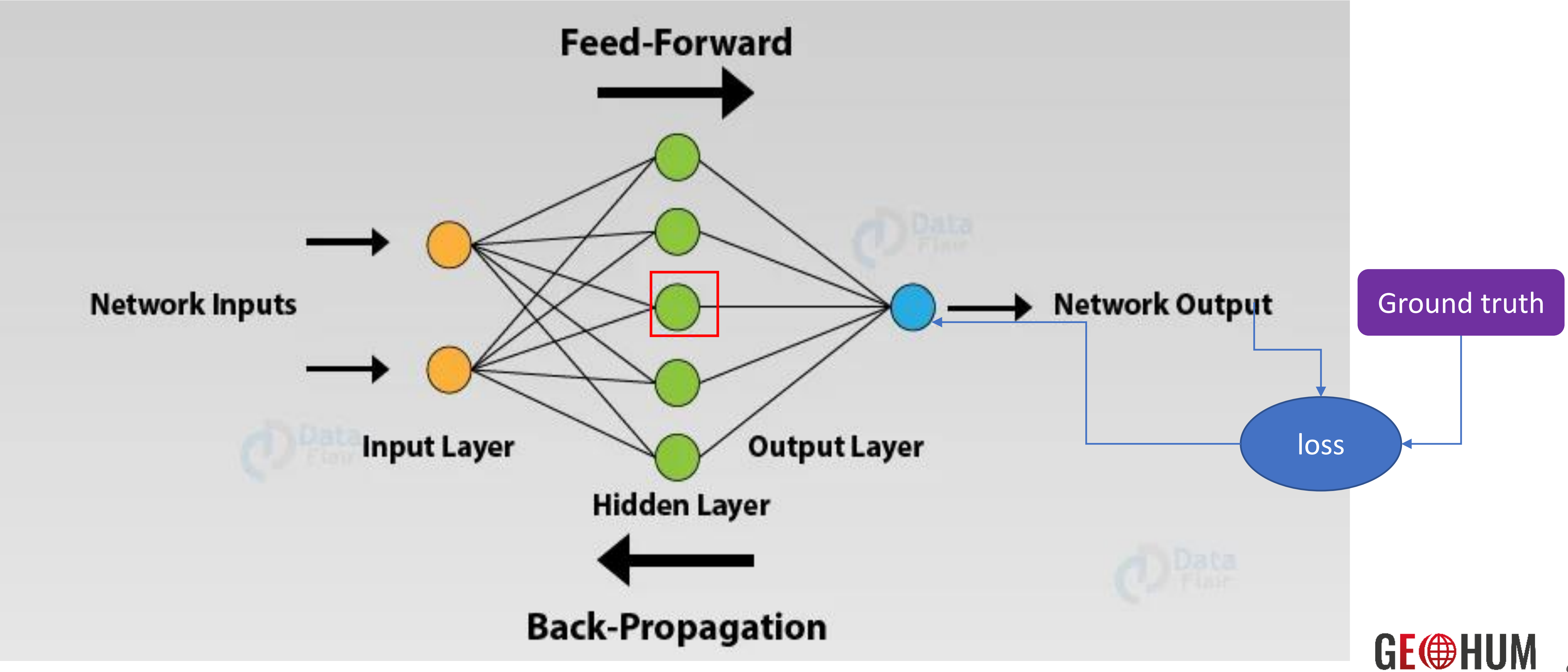
Artificial Neural Networks

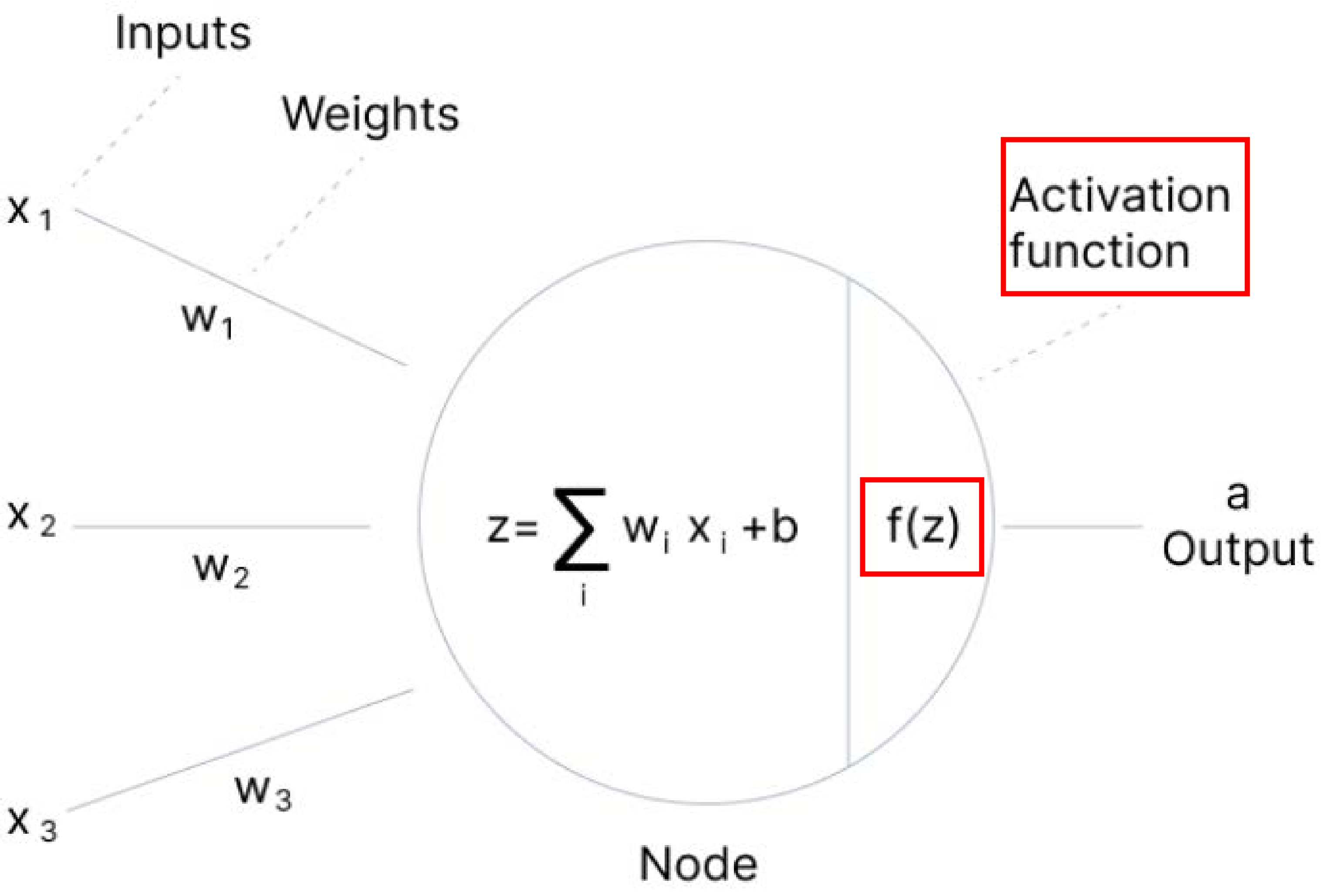


… ***Artificial Neural Network*** can be visualized as ***layers of interconnected*** "***neurons***," where the connections are "***weighted***". Neurons receive inputs from the previous layer where a calculation is performed before passing the output to the next layer

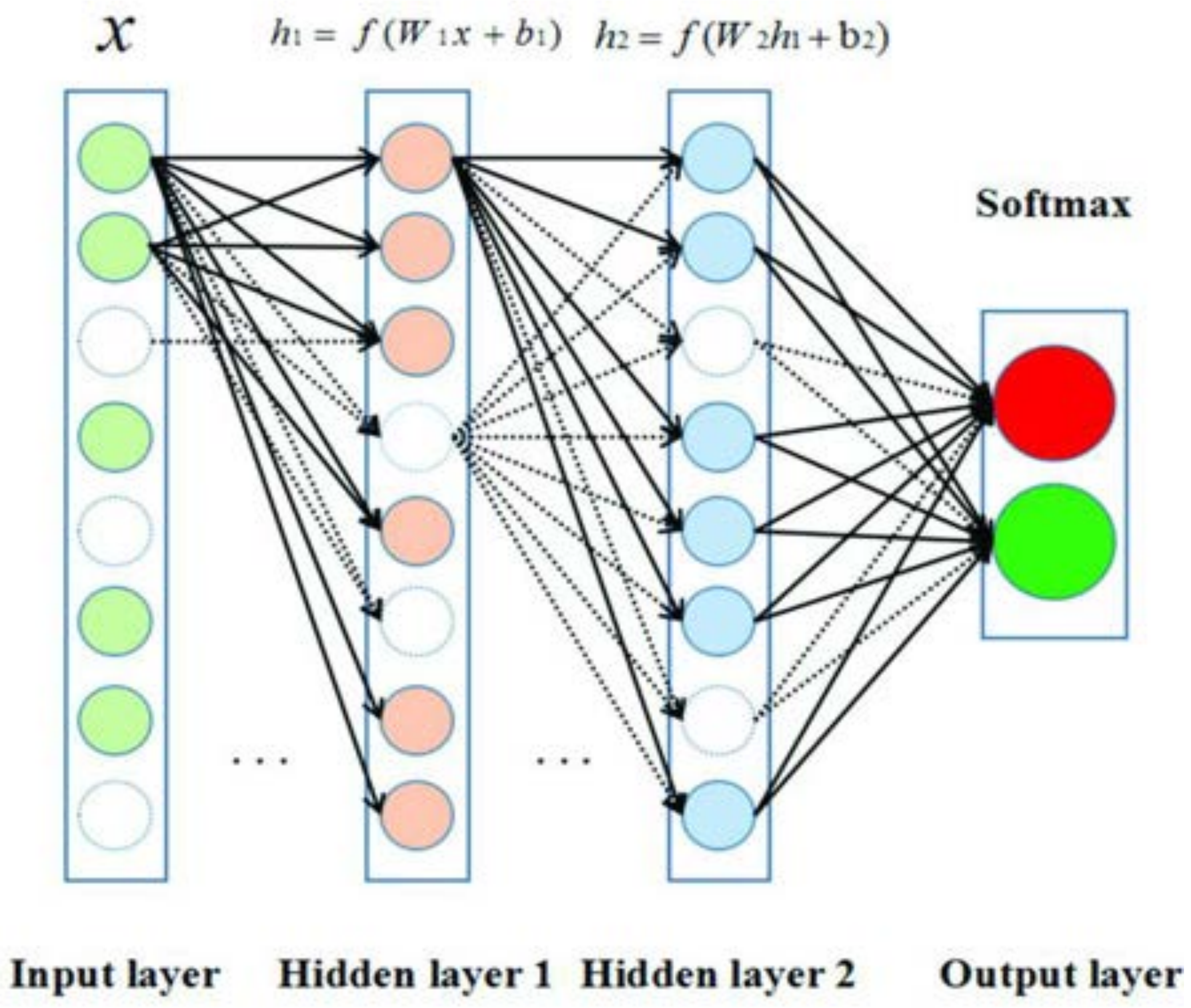
connected computational units..

How Artificial Neural Networks learn?




Inputs
Weights
x_1
w_1
x_2
w_2
x_3
w_3
Activation function
$z = \sum_i w_i x_i + b$
$f(z)$
a
Output
Node

Deep Neural Networks



Simple regression equation
for on input and one output

$$Y = ax + b$$

$$Y = f(ax + b)$$

where $f(.)$ is any none-linear activation function

Elevation	Soil PH	Tree biomass
176	6.5	0.6
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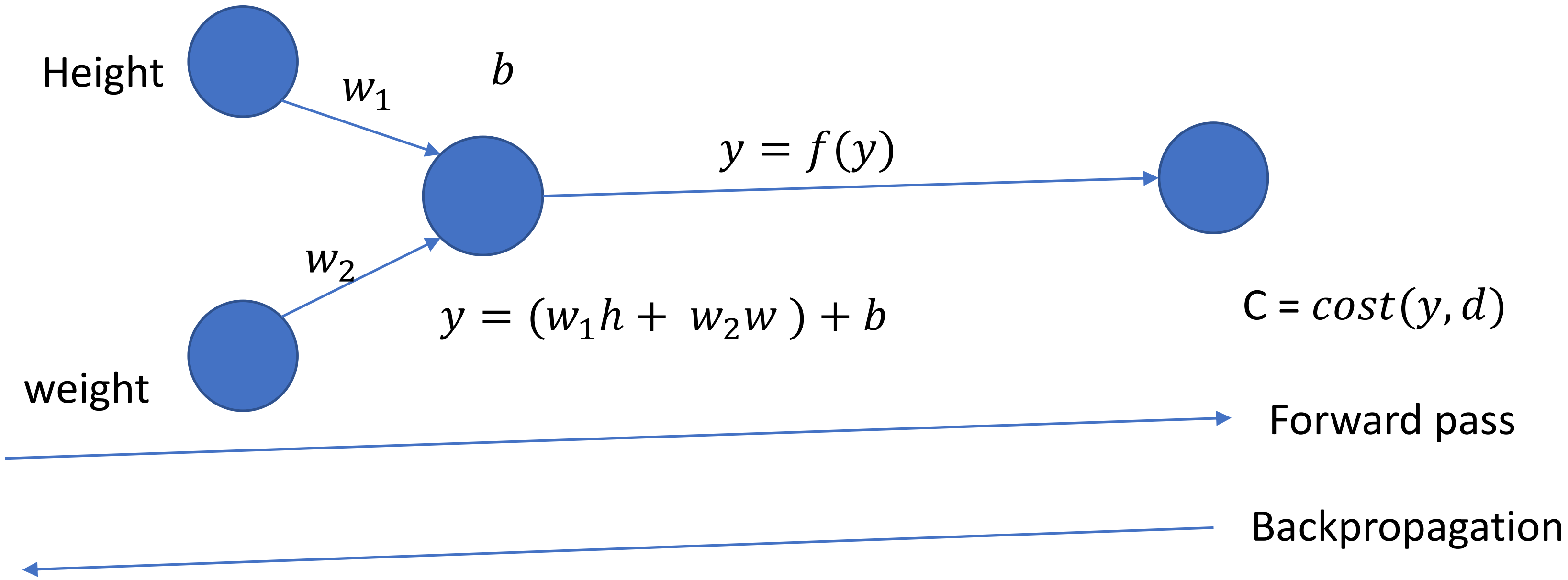


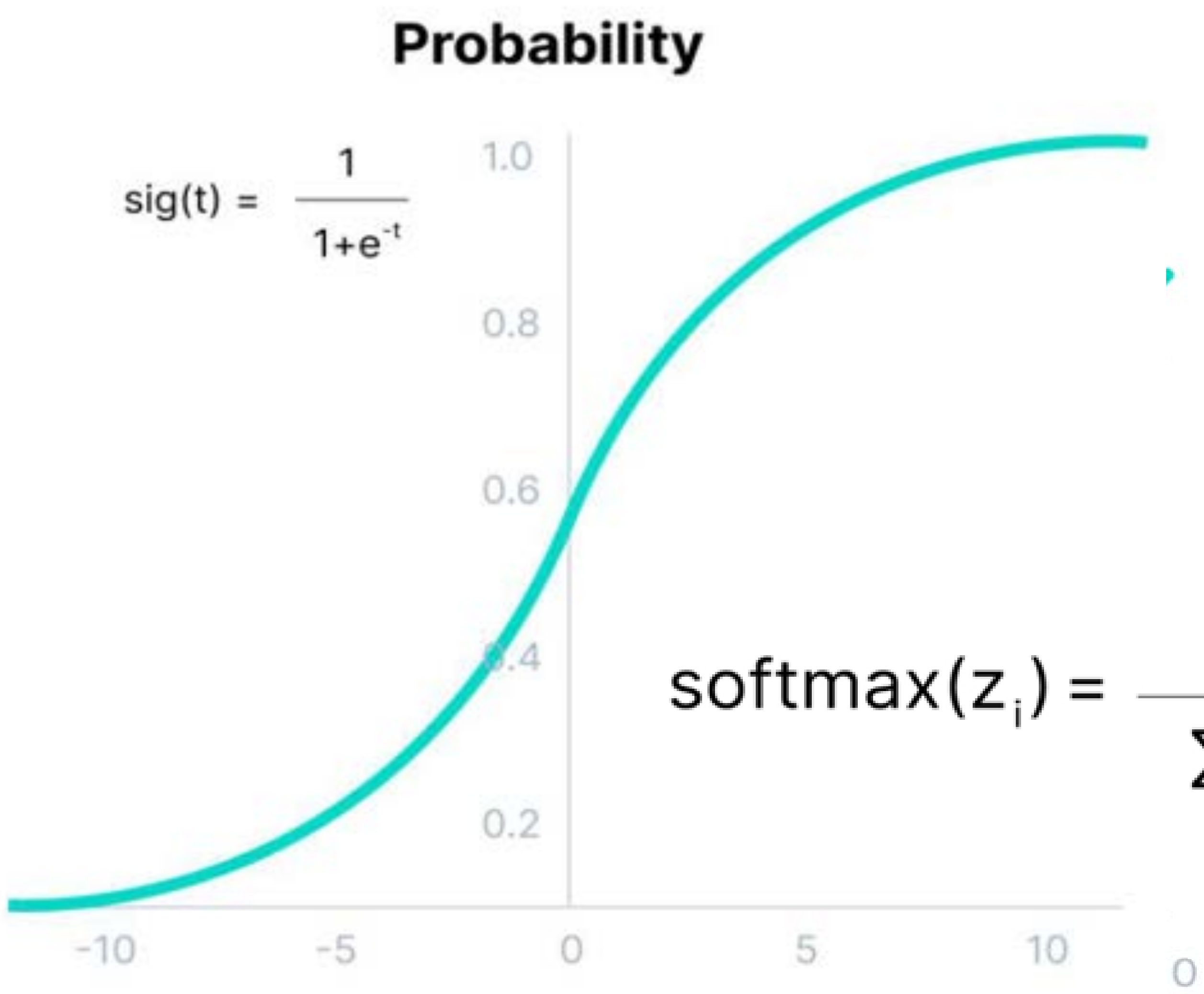
$$w_1 := w - \varepsilon \frac{\partial c}{w_1}$$

$$w_2 := w_2 - \varepsilon \frac{\partial c}{w_2}$$

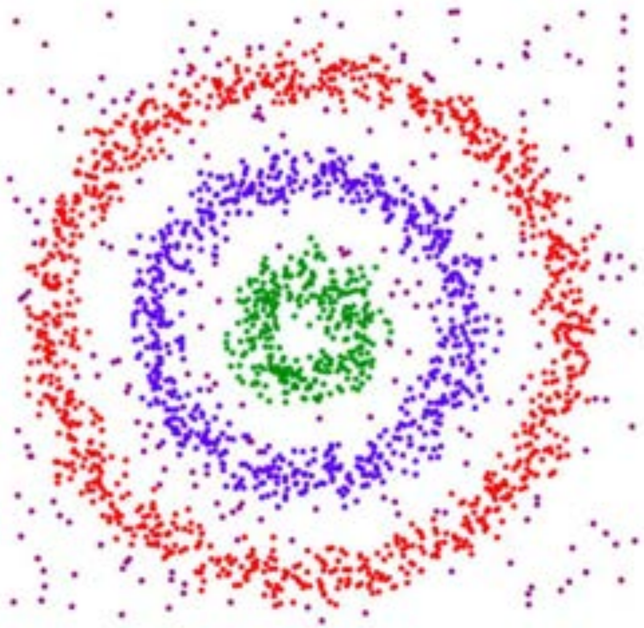
$$b := b - \varepsilon \frac{\partial c}{b}$$

$$\frac{\partial C}{w} = \left[\frac{\partial c}{w_1}, \frac{\partial c}{w_2}\right]$$

Activation functions

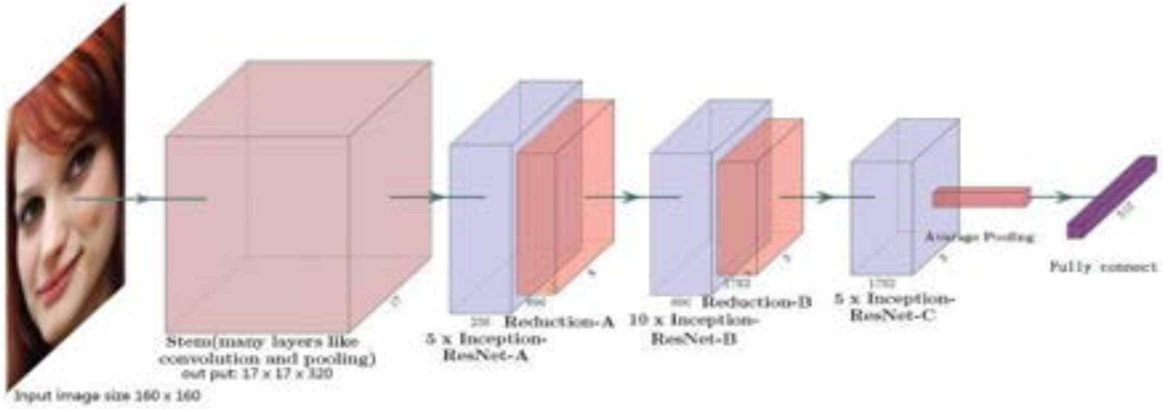


$$\text{softmax}(z_i) = \frac{\exp(z_i)}{\Sigma_j \exp(z_j)}$$



Loss as a key component for learning

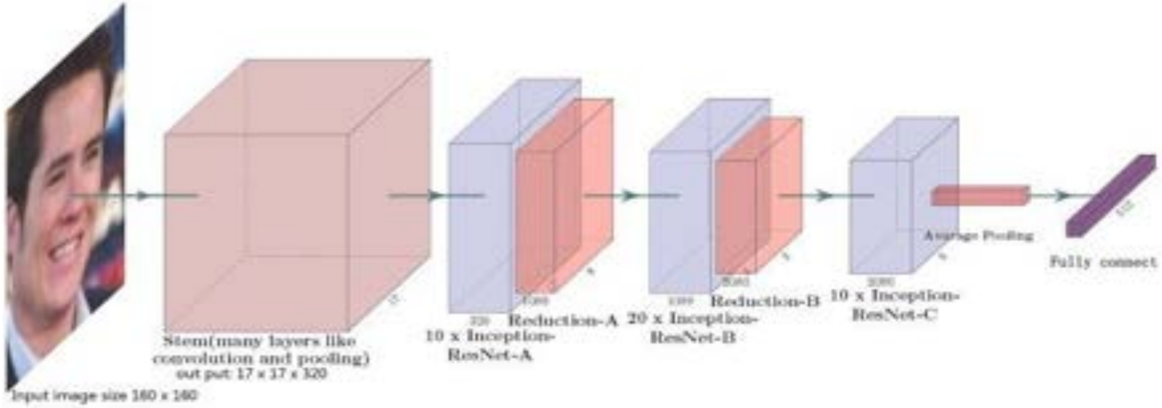
Loss is a metric to measure the *deviation* of the network predictions either *with ground truth* or other *outputs from other network*



(a) architecture of Inception-ResNet v1

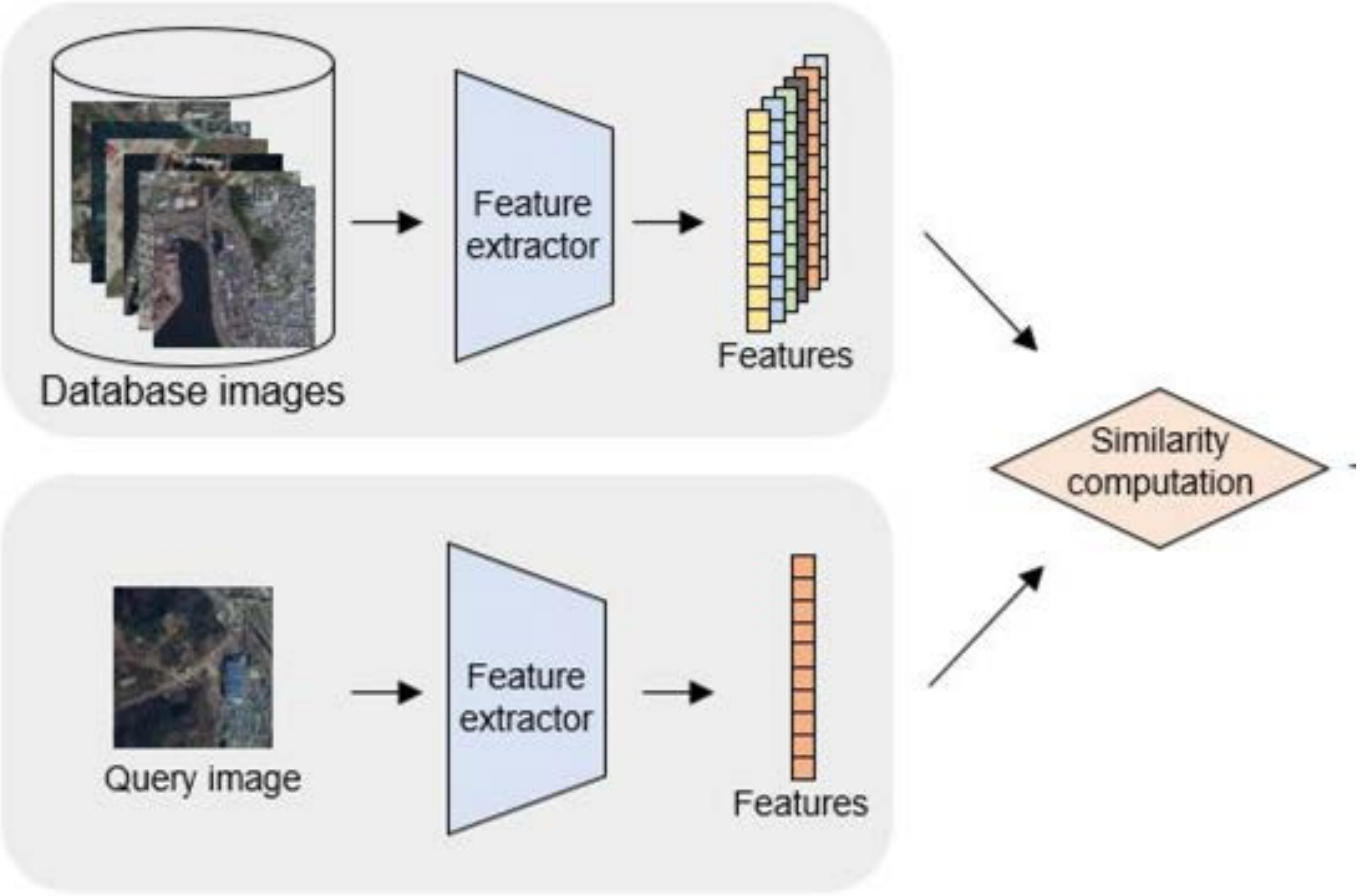
0

Male: 0
Female: 1



(b) architecture of Inception-ResNet v2

1


Database images
Feature extractor
Features
Similarity computation
Query image
Feature extractor
Features

How to chose specific loss function

- Activation function in the last layer
- Type of a task
  - Regression
  - Classification
  - Segmentation
  - Detection
  - Feature extraction or feature matching
- Expected output from the model

Backpropagation: optimizers as engine for learning

- Backward propagation of loss in the form of gradients
- Is a method where the neural network updates (adjusts) weights and biases for trainable parameters based on loss obtained on previous steps (iterations)
- Using chain rule, computes derivatives and adjusts the weights accordingly
- This is automatically done by the ***optimization algorithms***

$$\left\{ \begin{array}{c} w_1 := w - \varepsilon \frac{\partial c}{w_1} \\ w_2 := w_2 \text{-} \ \varepsilon \frac{\partial c}{w_2} \\ b := b \text{ - } \varepsilon \frac{\partial c}{b} \end{array} \right\} \left\{ \frac{\partial C}{w} = \left[\frac{\partial c}{w_1}, \frac{\partial c}{w_2} \right] \right\}$$

- SGD
- RMSprop
- Adam
- AdamW
- Adadelta
- Adagrad
- Adamax
- Adafactor
- Nadam
- Ftrl

With same basic principle, *few variations*

On using additional hyper parameters like

- ***Considering previous gradients and use of momentum***
- ***Adaptive learning rate***
- ***Gradient accumulation***
- ***Data sampling during the forward pass***

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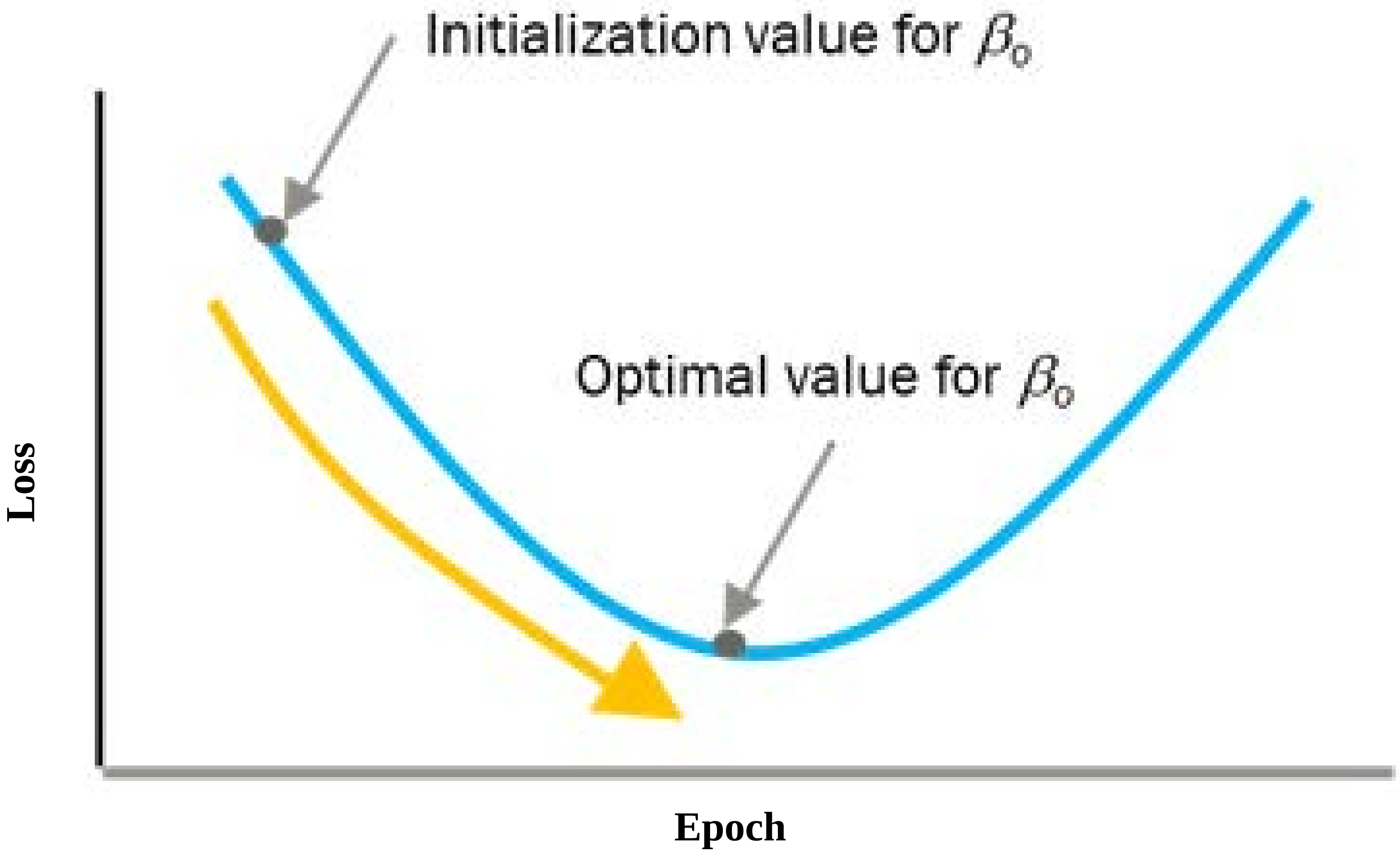
Trainable parameters and hyperparameters

parameters

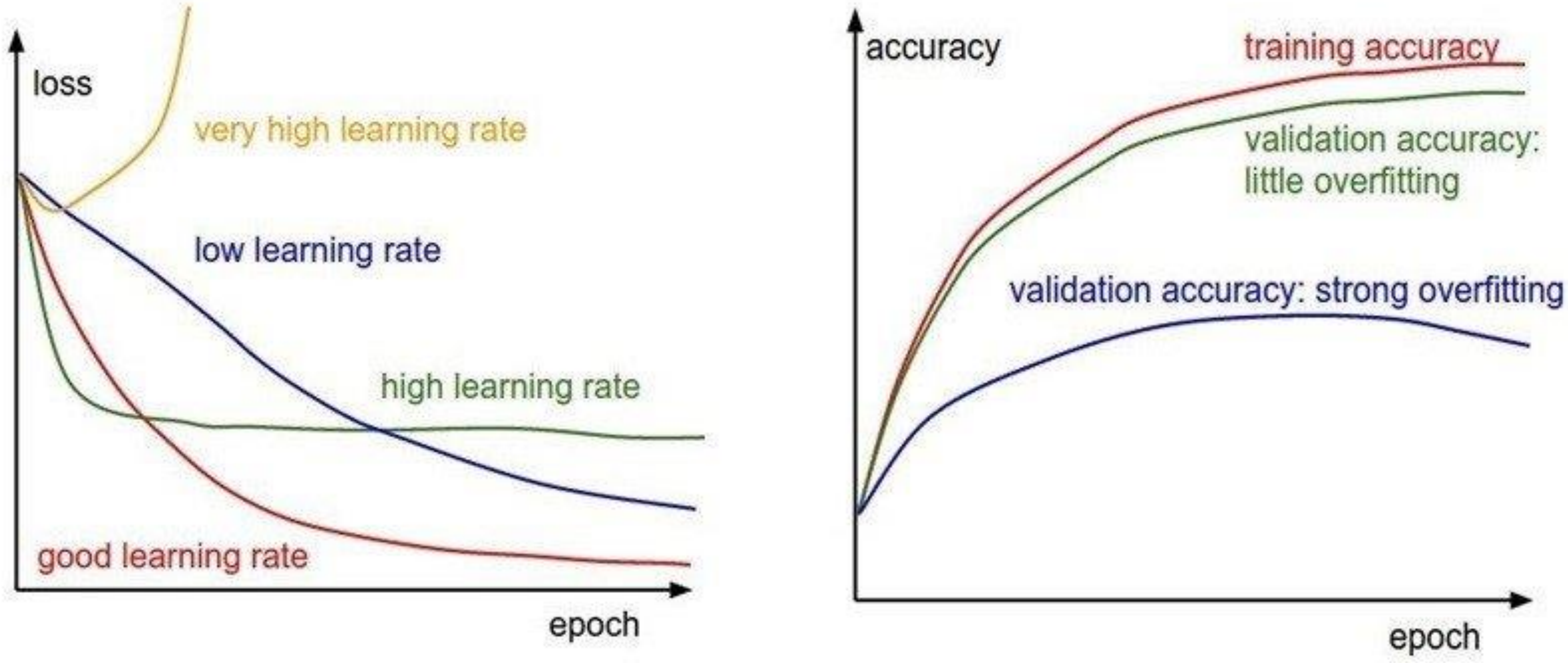
Hyperparameters(design or task specific parameters)
Learning rate
Momentum
Number of training steps
Choice of activation functions
Choice of alternative losses
Weight update strategies
.
.
.

Trainable parameters
Model weights
Model biases

Tunning learning rate and minimizing loss



Interpreting loss curves



Number of iterations

Deep neural networks and image handling

- Deep neural networks can efficiently handle tabular data
  - Columns(attributes)
  - Rows(observations)
- Need to include geometry and location information from 2-D or 3-D images into deep neural networks
- Learning from images for example detection, segmentation and localization tasks need to learn abstract features like contours, orientations, size and spatial neighbourhood from images
- Then ***Convolutional Neural Networks (CNN),*** are specialized neural architectures to handle learning from 2-D and 3-D image space

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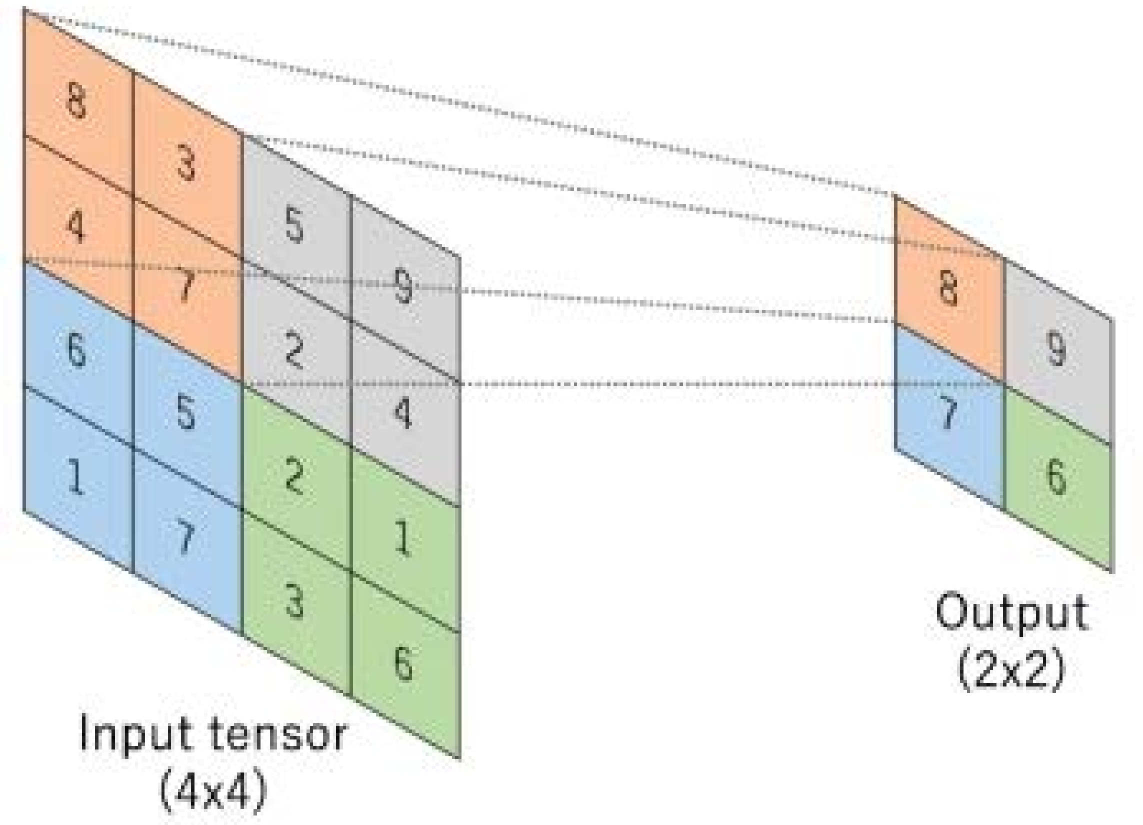
Neural networks with image inputs (CNN)

Convolution **Kernel** **Pooling** **Feature maps** **Non-linear activations**



Size of output layer maps

$$\frac{W - K + 2P}{S} + 1.$$

- W = Input feature map/image size
- K = Kernel size (the width/length of the kernel)
- P = Padding (Number of pixels padded after/before the convolution)
- S = Stride (the amount of pixel space the kernel move)

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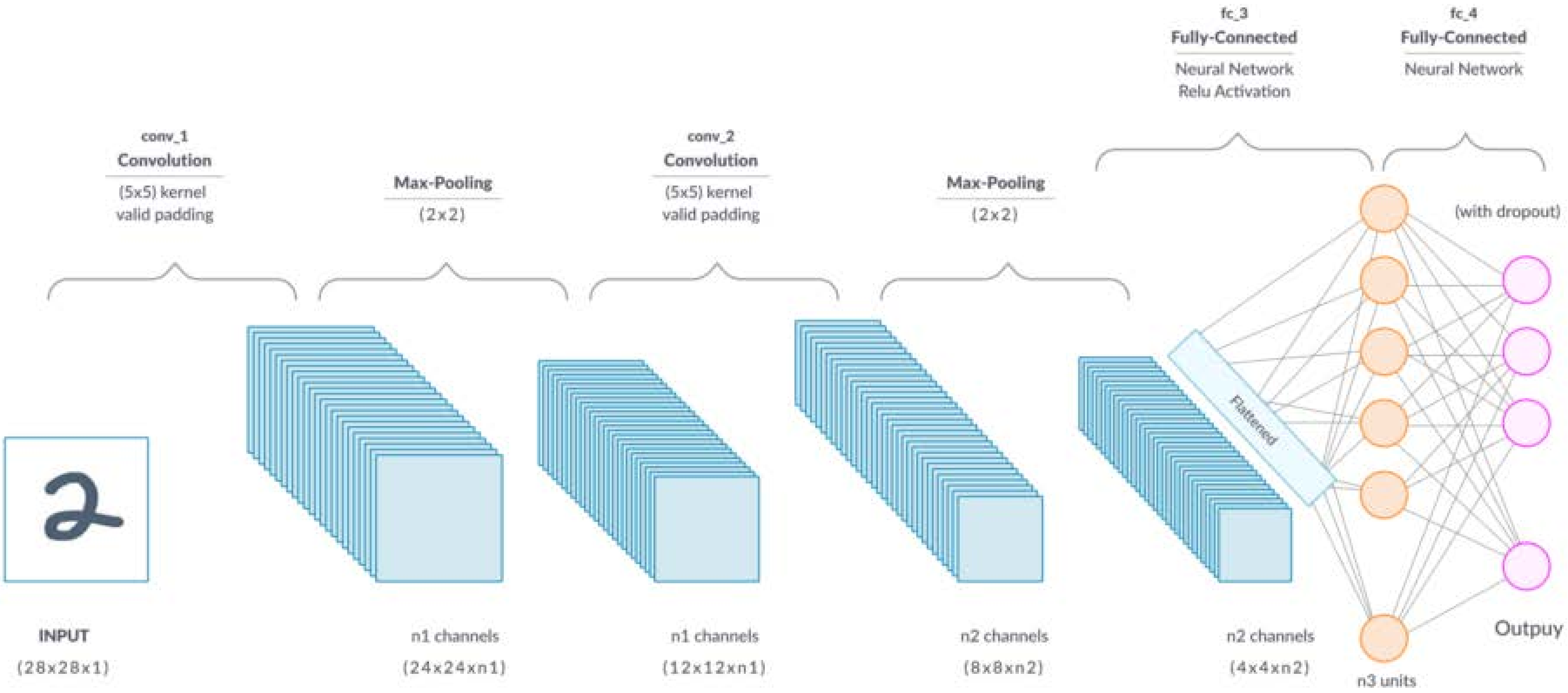
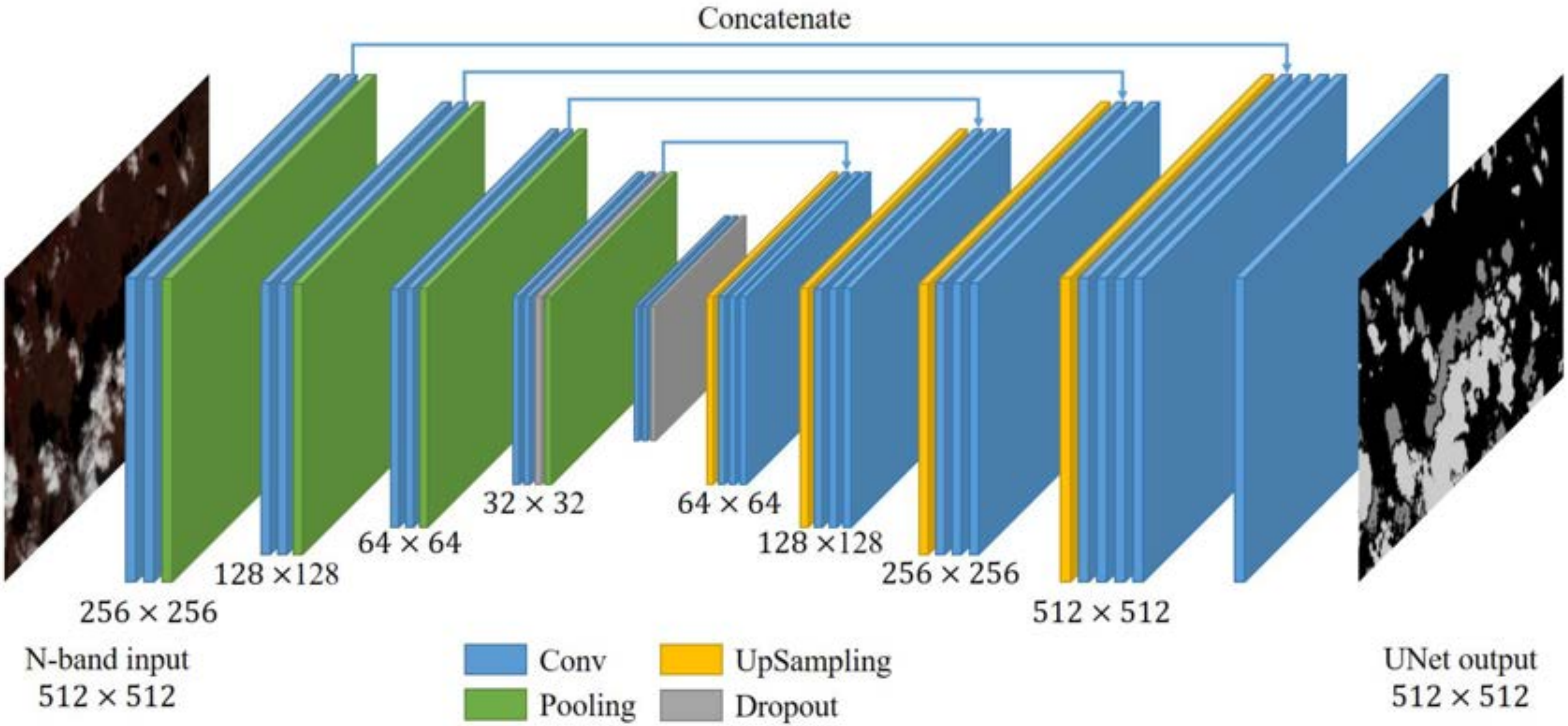
Fully connected vs Fully Convolutional



Encoder decoder architectures



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Incorporating time into deep learning frameworks

- Provided that deep neural networks and convolutional neural networks were not explicitly design to handle temporal information in time series data
  - Text processing in natural language processing where sequences of words and tokens matter
  - Phenological information to model evolution of events from time series satellite image
    - Tree development
    - Invasive species and tree species mapping
    - Predicting patterns of migratory birds, paste infestation using movement data
    - Forecasting hydrological events like drought and flooding

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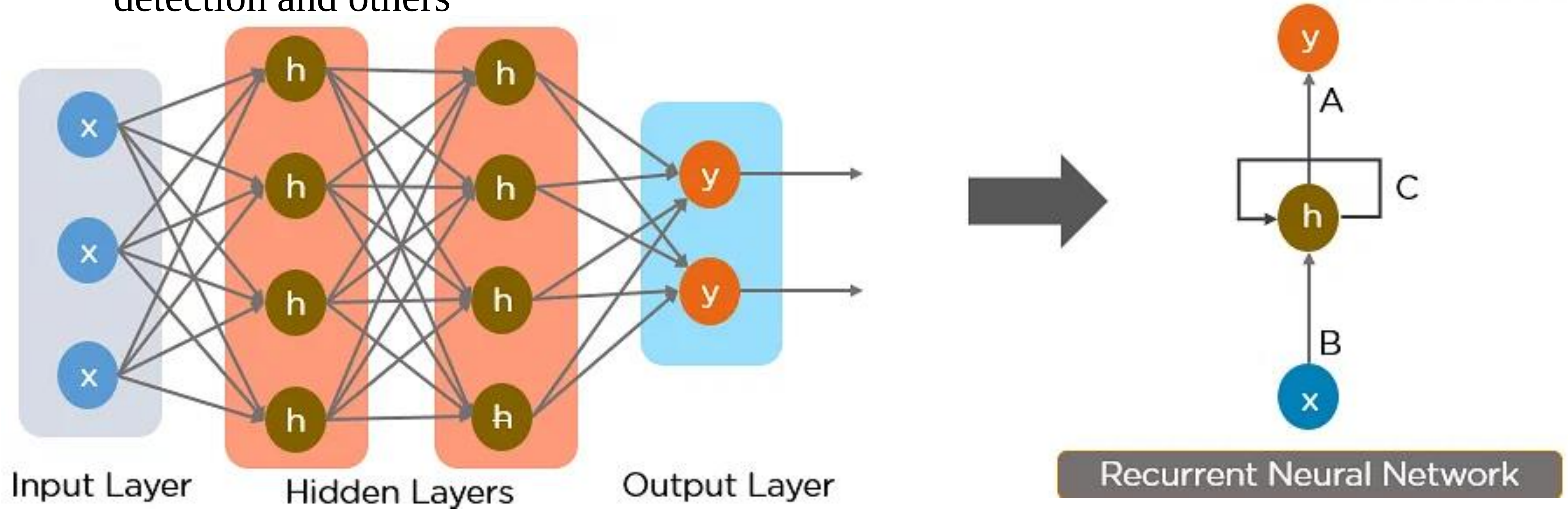
Recurrent Neural Networks

- ANNs with recurrent connections are called *recurrent neural networks* (RNNs), which are capable of modelling ***sequential data*** for sequence recognition and prediction
  - Time series remotely sensed images for regression, forecasting, classification, outlier detection and others



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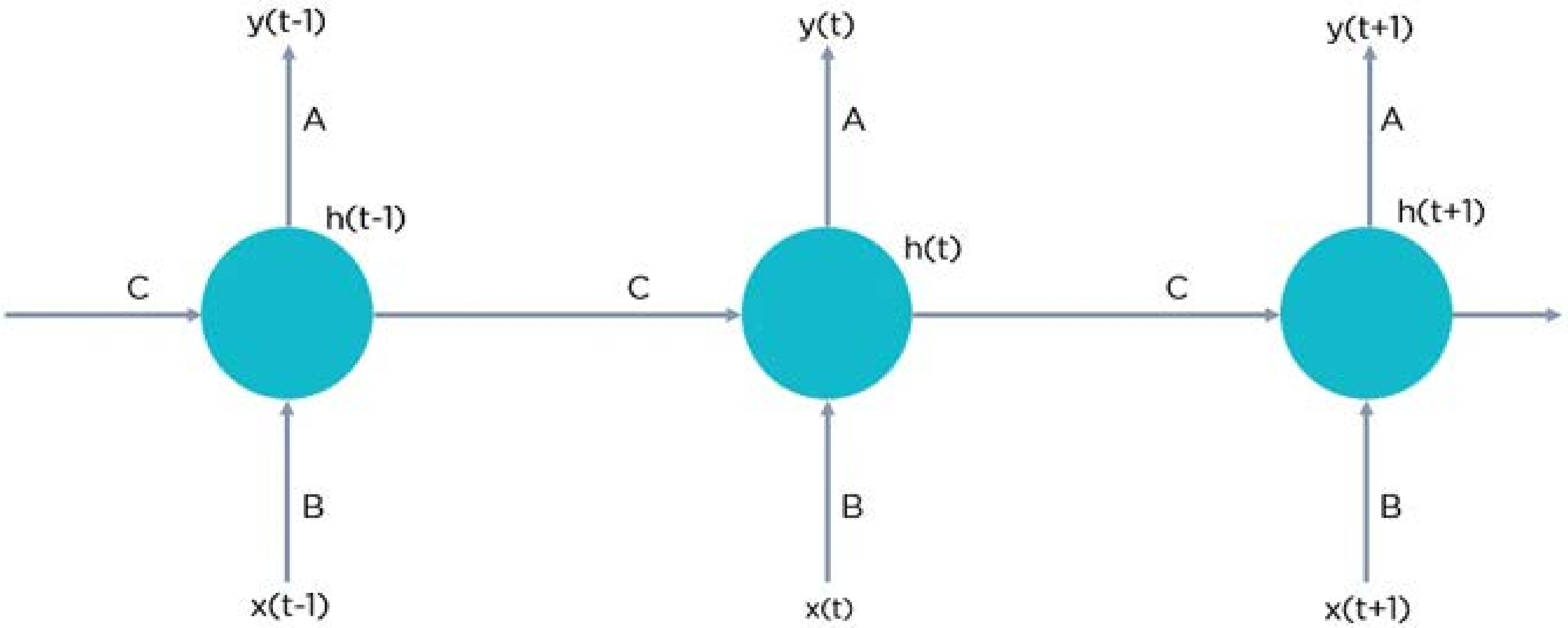
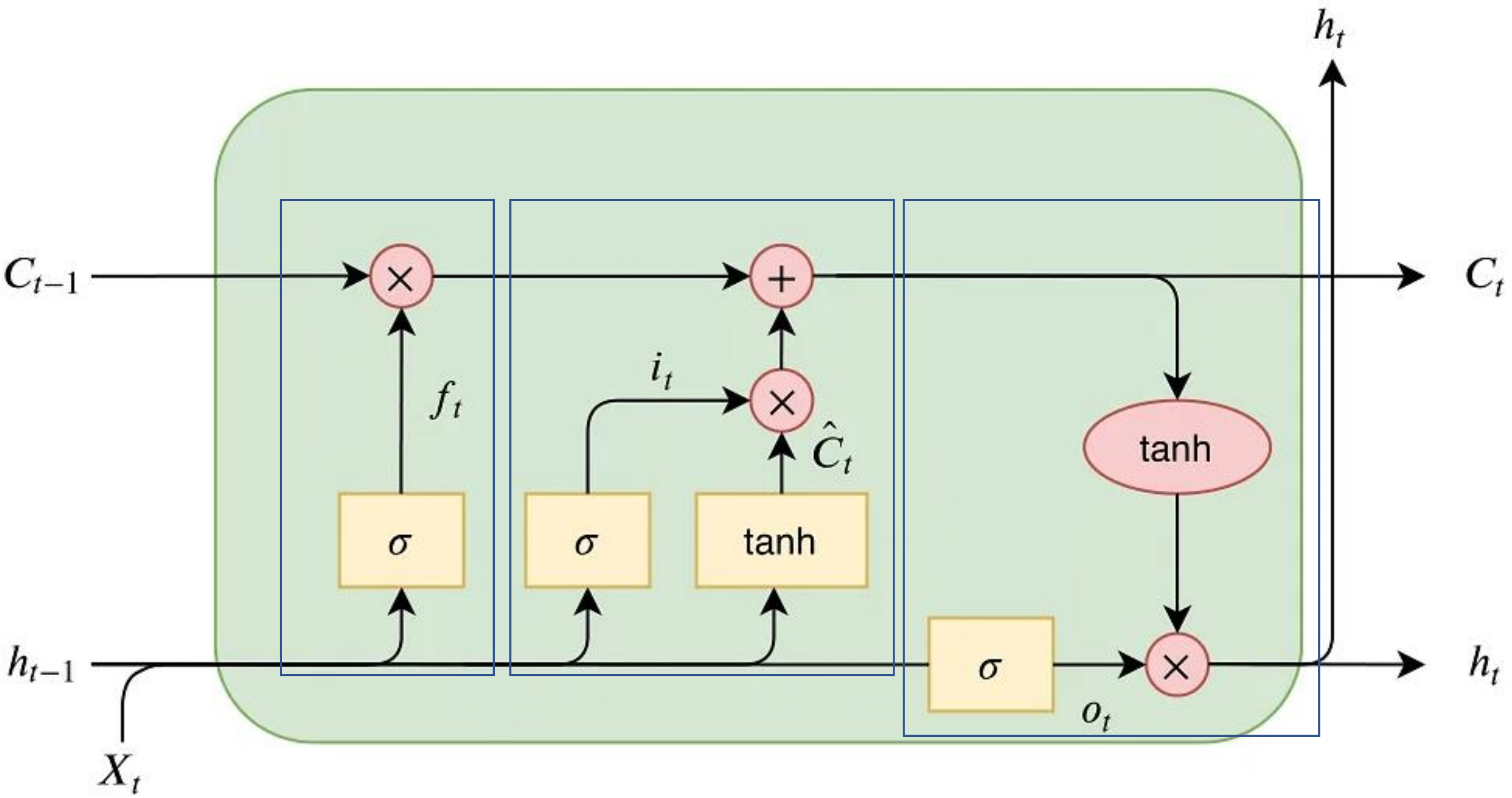


$$h(t) = f_c\,(h(t-1), x(t))$$

$h(t)$ = new state
f_c = function with parameter c
$h(t-1)$ = old state
$x(t)$ = input vector at time step t

LSTM



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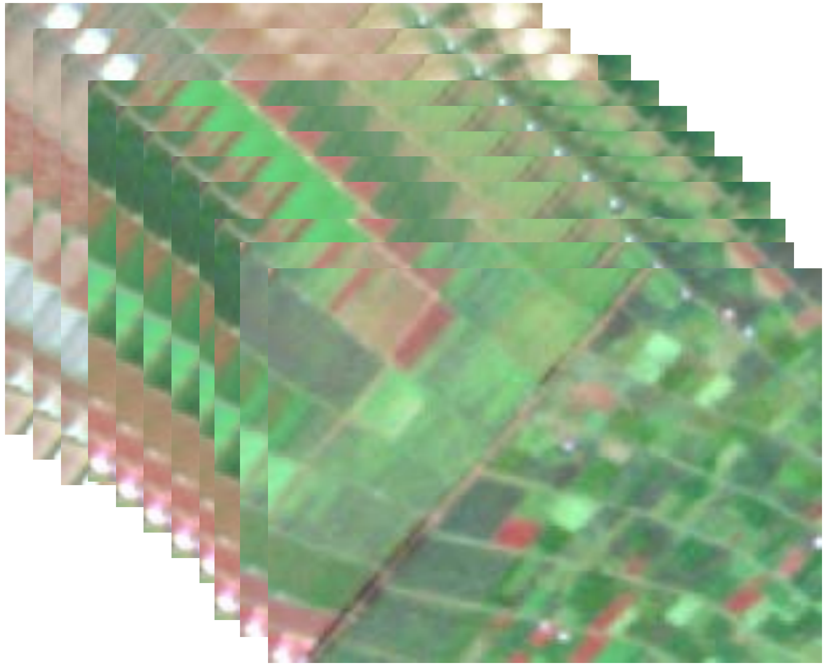
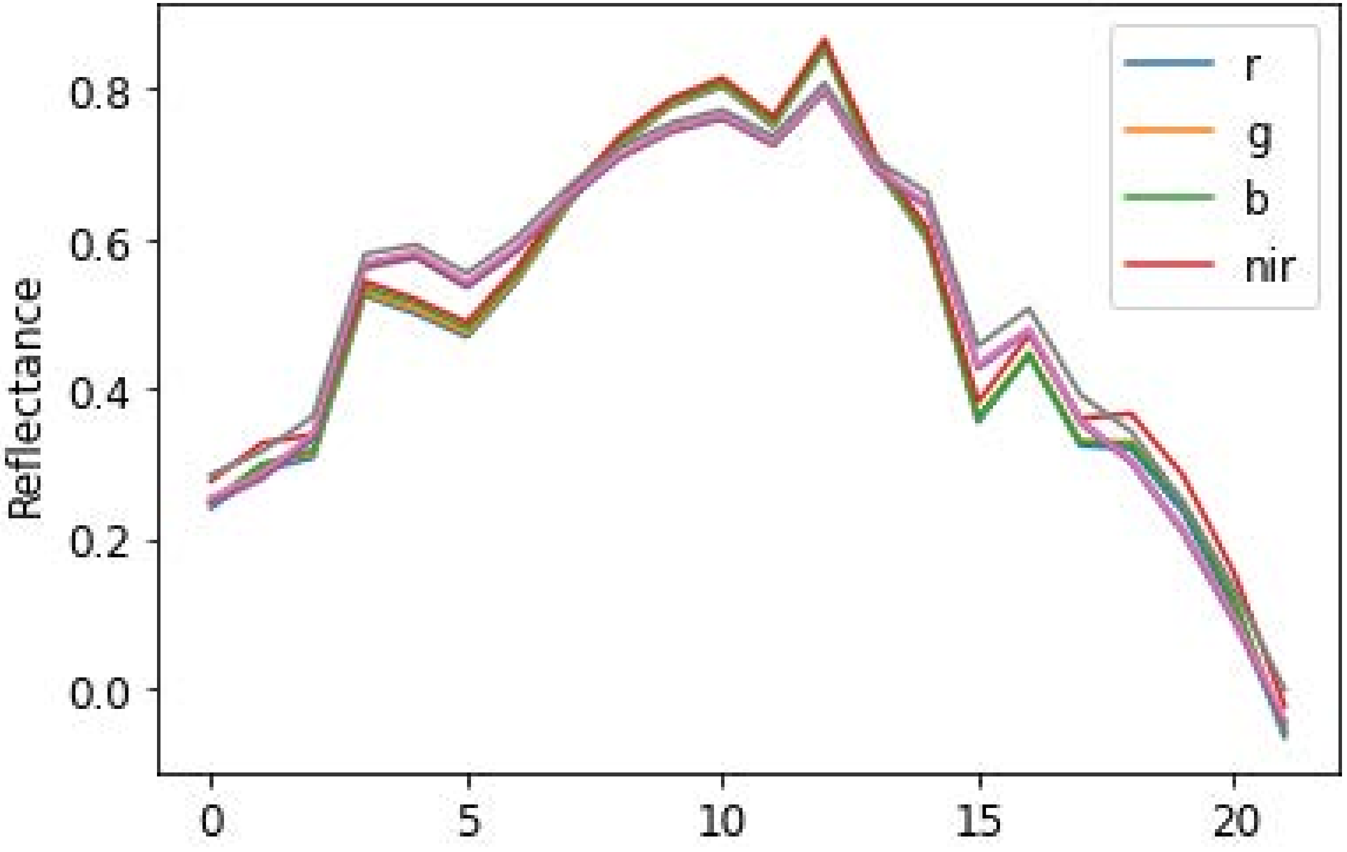
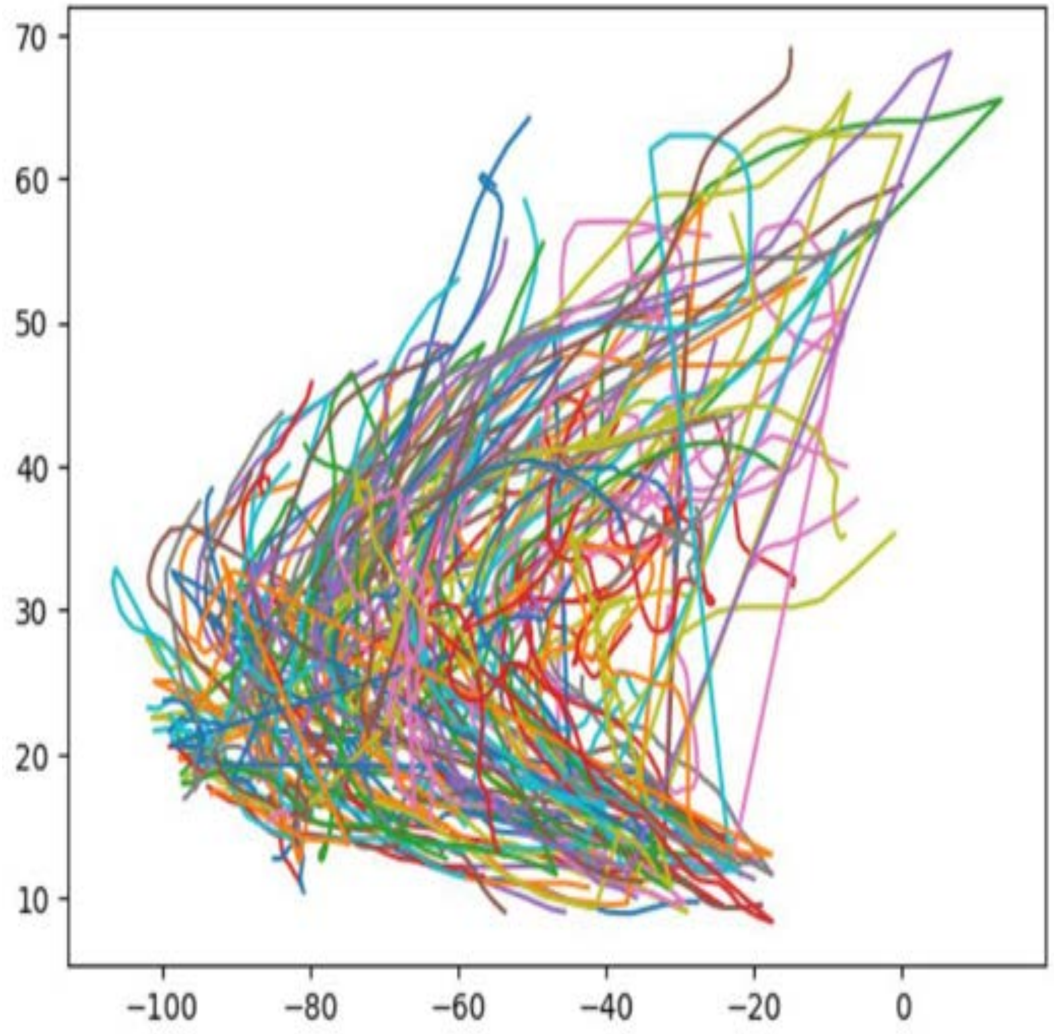
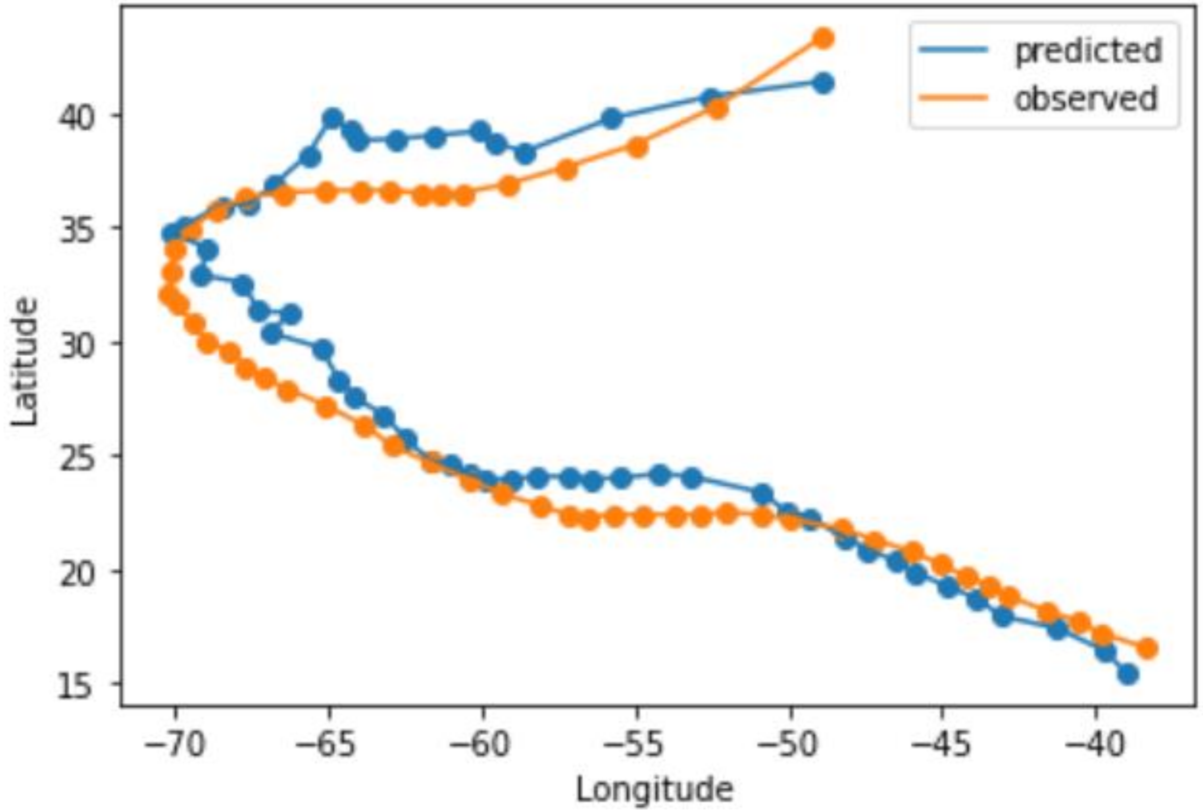
Examples of LSTM inputs for time series classification





LSTM examples for sequence-to-sequence or point prediction





Code and data: https://github.com/getch-geohum/plus-deepdata-social-good

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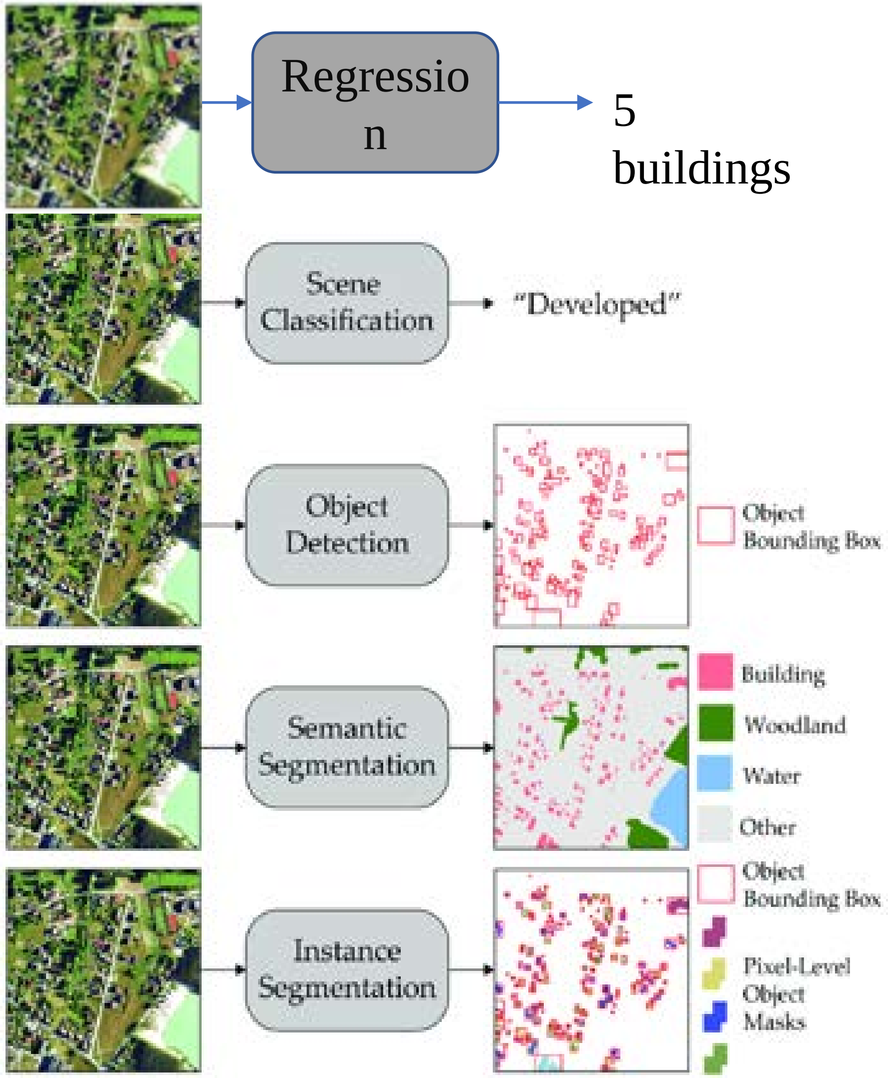
Task related terminologies

- Regression
- Classification (pixel and scene)
- Semantic segmentation
- Instance segmentation
- Detection



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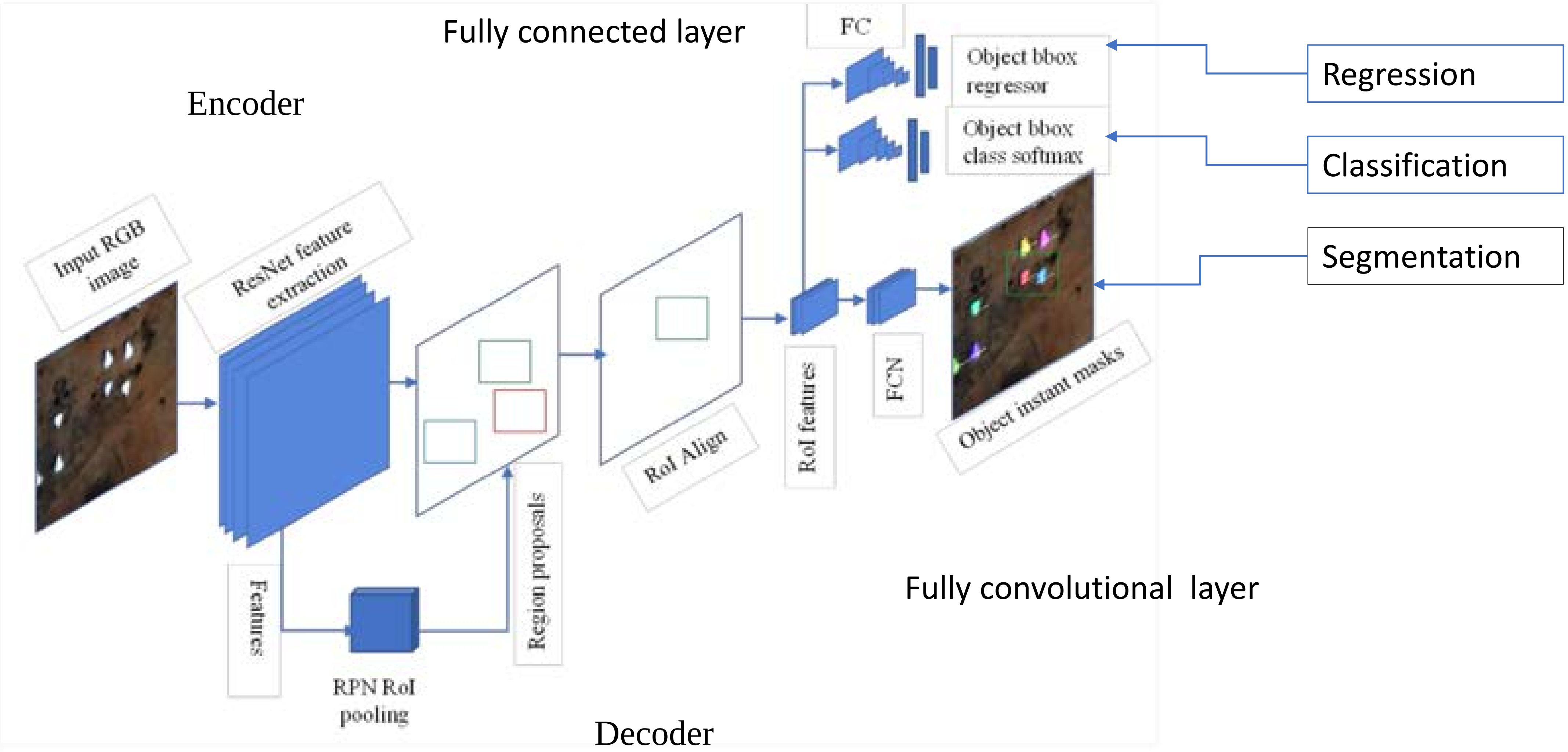
Question: determine the tas either as regression or classification task

Elevation(x_1)	Soil PH(x_2)	Tree biomass(y)
176	6.5	0.6
150	6.3	1.1
170	6.0	0.3
100	7.0	0.4
120	8.0	1.6
135	1.0	1.1
125	7.0	0.1

Elevation(x_1)	Soil PH(x_2)	Tree biomass(y)
176	6.5	0
150	6.3	1
170	6.0	1
100	7.0	0
120	8.0	1
135	1.0	0
125	7.0	0

Complex models: bringing multiple tasks together (Mask RCNN)



Evaluation metrics

Task	Metrics	Comparison unit
Regression	MAE, RMSE, Absolute deviation	Element wise prediction values(continues values)
Classification	Precision, recall, overall accuracy, True Positives, False Positives, F-1 score	Pixels or categories
Semantic segmentation	F-1 score, Intersection over Union (IOU)	Pixels
Instance segmentation	Mean average precision (mAP), Intersection Over Union	Either object boundaries or masks or bounding boxes
Detection	Intersection over Union, Mean average precision (mAP),	Object bounding boxes

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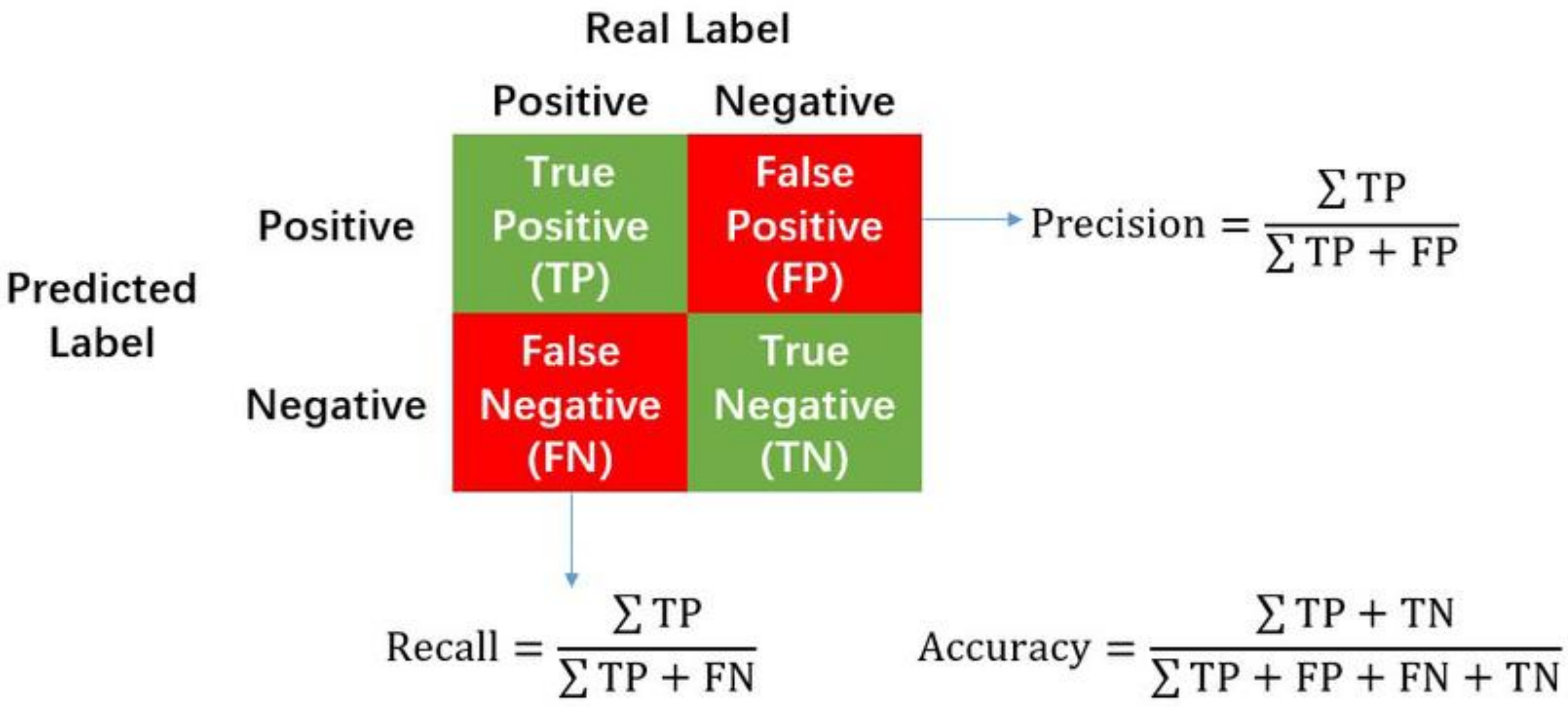
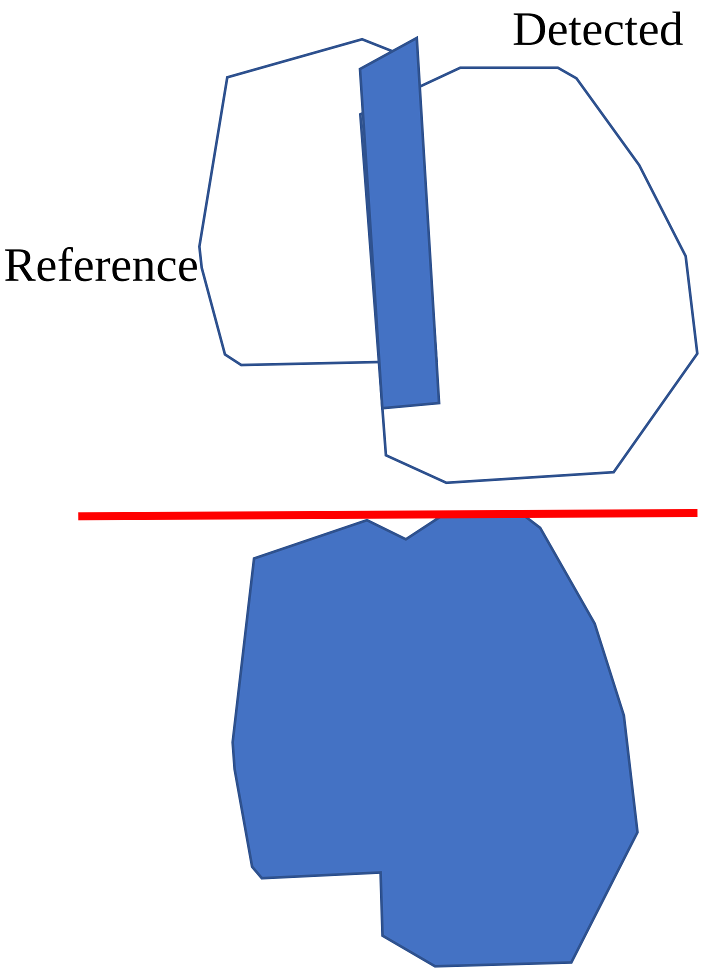


$$F - 1\, score = 2 * \frac{Precision * Recall}{Precisio + Recall}$$

Evaluation metrics object based

Metric	Notation	Formulation
Mean Intersection over Union	MIoU	$\frac{1}{N}\sum_{i=1}^{N} IoU$
Correctness	C_r	$\frac{T_{po}}{T_{po}+F_{po}}$
Completeness	C_m	$\frac{T_{po}}{T_{po}+F_{no}}$
Quality	Q_l	$\frac{T_{po}}{T_{po}+F_{po}+F_{no}}$
Object based F1 score	$F1_o$	$2*\frac{C_r*C_m}{C_r+C_m}$

MIoU: Mean Intersection over Union, T_{po}, F_{po} and F_{no} is number of true positive, false positive and false negative objects



Challenges in deep learning for information extraction

Computational resource

Data

- Availability
- Quality
  - Attribute
  - Geometric

Complexity

- Inherent characteristics of objects (tree species resembling spectral

transferability of models

- Changing season and geography
- Changing time and sensor
- Bring shifts in data distributions

Learning strategies as wider solution spaces

- Supervised (***transfer learning***)
- Domain adaptation
- Semi-supervised
- Weakly supervised
- Unsupervised (representation learning)

Deep learning frameworks and tools

Code repositoris

- https://github.com/getch-geohum/GORILLA
- https://github.com/getch-geohum/plus-deepdata-social-good