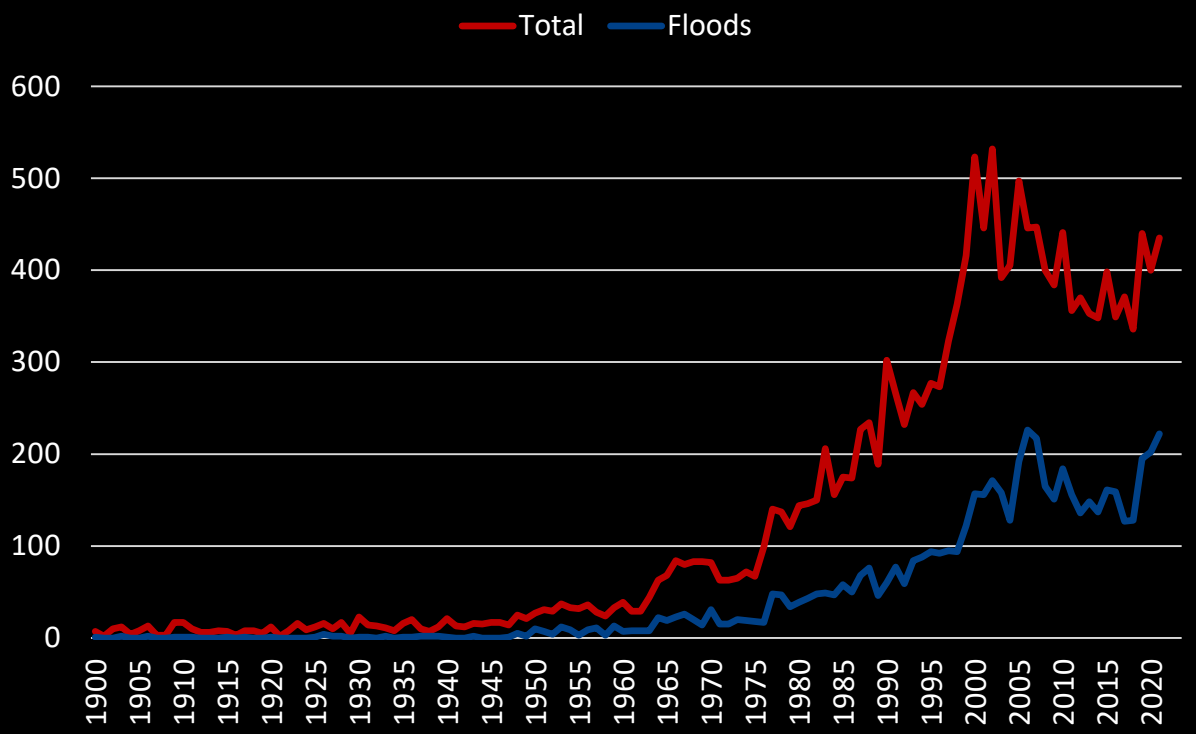
Post-event building damage assessment

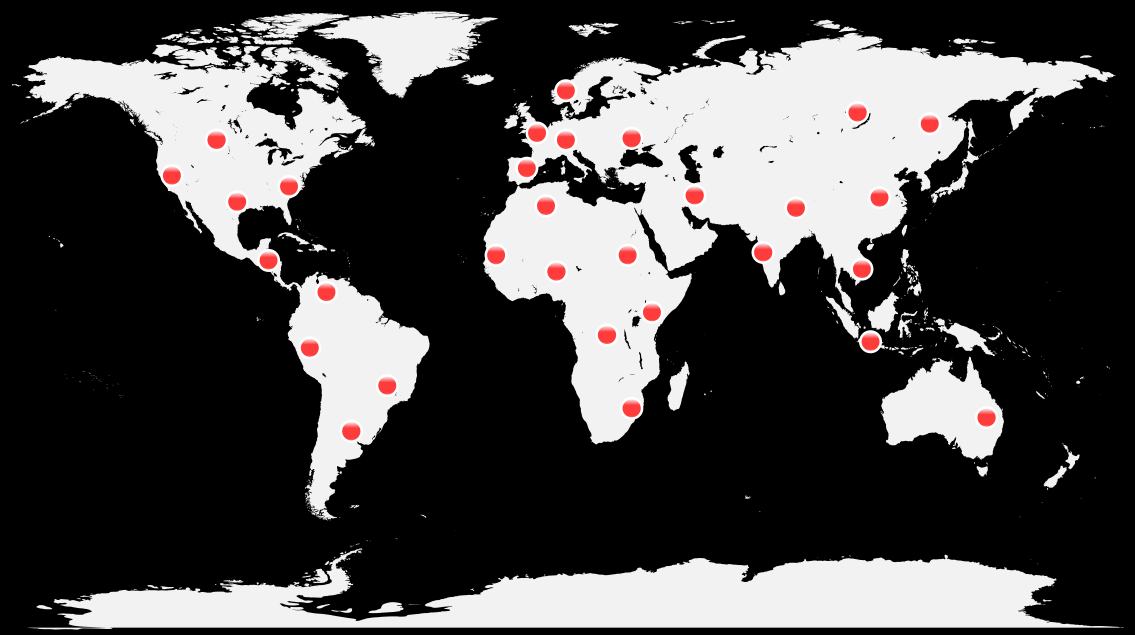
Machine learning techniques for remote sensing data interpretation with application to disaster impact assessment.

Presenter: Victor Hertel
Prof. Dr. Christian Geiß

DLR

Increase of documented natural disasters since 1900





Data: EM-DAT - the International Disaster Database

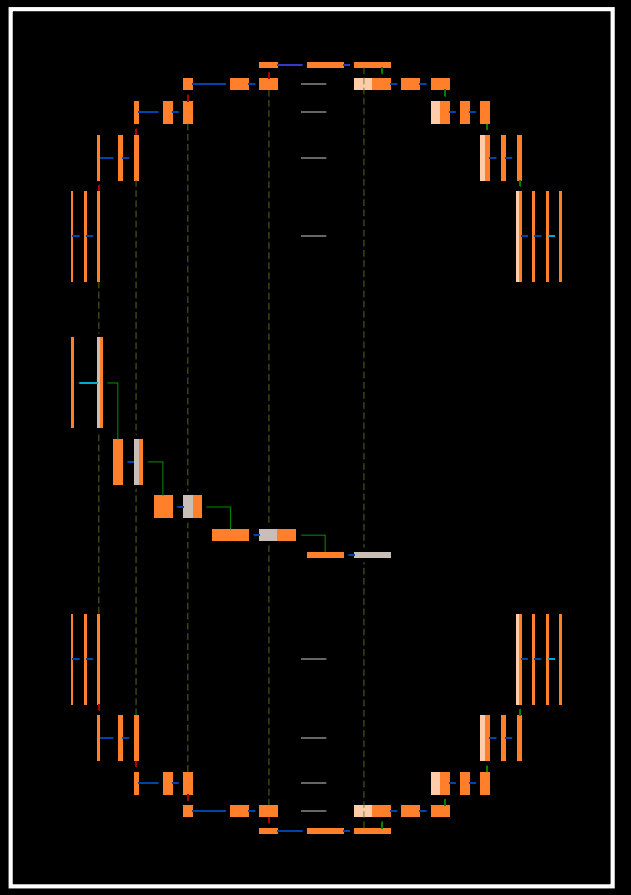

Esri Community Maps Contributors, Land NRW, LVermGeo RP, Esri, HERE, Garmin, Foursquare, GeoTechnologies, Inc, METI/NASA, USGS, Sources: Esri, Airbus DS, USGS, NGA, NASA, CGIAR, N Robinson, N
Geodatastyrelsen, Rijkswaterstaat, GSA, Geoland, FEMA, Intermap and the
Date: 16/07/2021
Source: DLR

How can remote sensing data be used for rapid ***building damage assessment***?

Image analysis through artificial intelligence

- 20 068 satellite images
- 850 736 buildings
- 45 361 km^2
- 19 natural disasters

Database: *xBD*



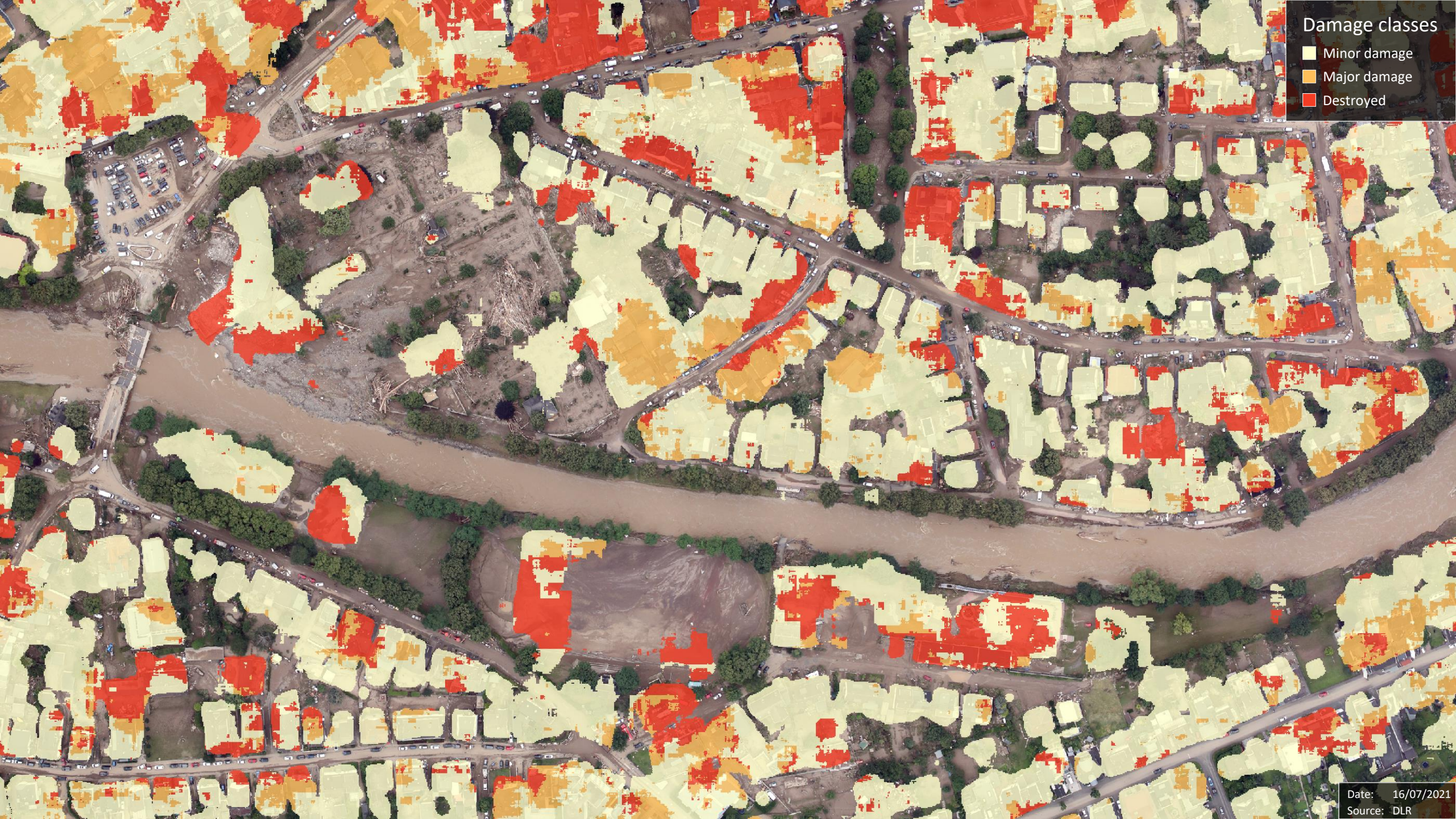
AI model

Image analysis through artificial intelligence

- 20 068 satellite images
- 850 736 buildings
- 45 361 km^2
- 19 natural disasters

Database: *xBD*

Change detection


Damage classes
Minor damage
Major damage
Destroyed
Date: 16/07/2021
Source: DLR

Session objectives

Application relevance

Machine learning workflow

Code implementation

→ *optimize pre-trained model for volcanic building damage assessment*

GitHub Repository: https://github.com/vhertel/bda-session-bonn

Terminology

Loss function	Measures the error between model predictions and actual values. The objective is to minimize this error during training.
Optimizer	Adjusts model parameters during training to minimize the loss function. It helps find the best values for the parameters by updating them iteratively based on gradients (backpropagation).
Learning rate	Controls how fast a model learns by determining the step size during parameter updates. Influences the speed of convergence and model accuracy.
Epoch	Complete pass through the training dataset during model training.
Batch	Subset of training dataset processed together during training before model parameter updates.
Data splitting	Dividing a dataset into three subsets: training, validation, and test sets.

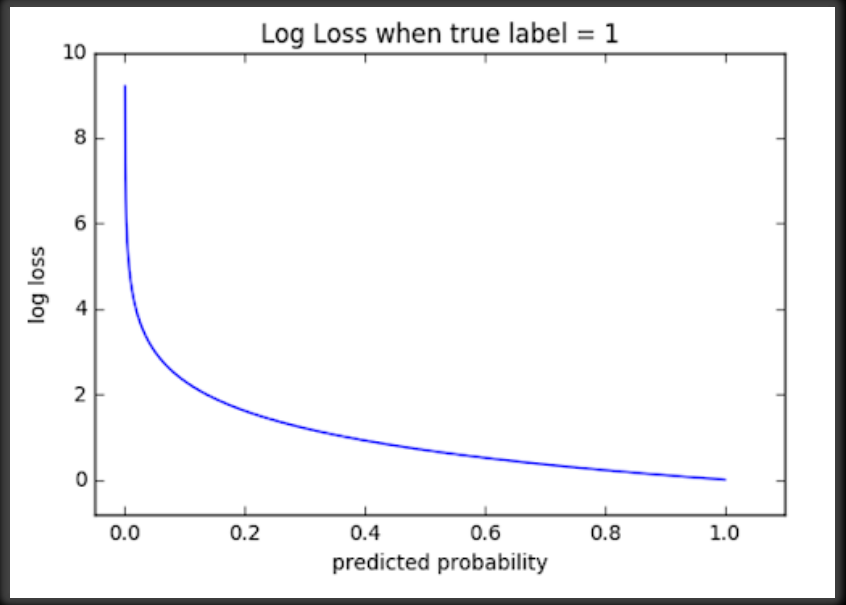
Basics: *loss function*

$f(Y, \hat{Y})$ = Error between model predictions and actual values

Y Actual value $\hat{Y}$ Model prediction n Number of samples i i^{th} sample in dataset

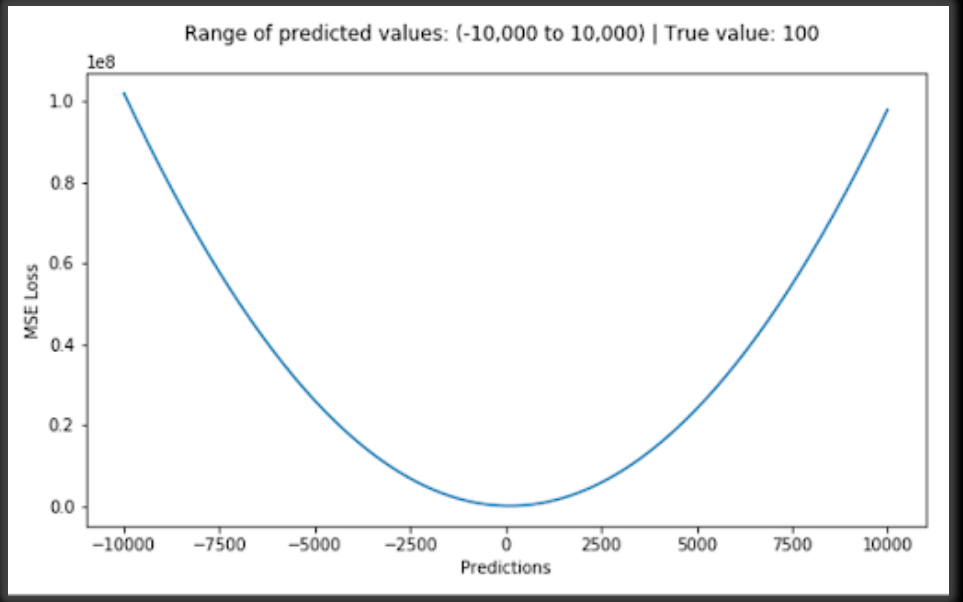
Classification: $Y \in \mathbb{Z}$ → discrete values

Cross-entropy loss: $L = -\frac{1}{n}\sum_{i=1}^{n} y_i \cdot \log(\hat{y}_i)$

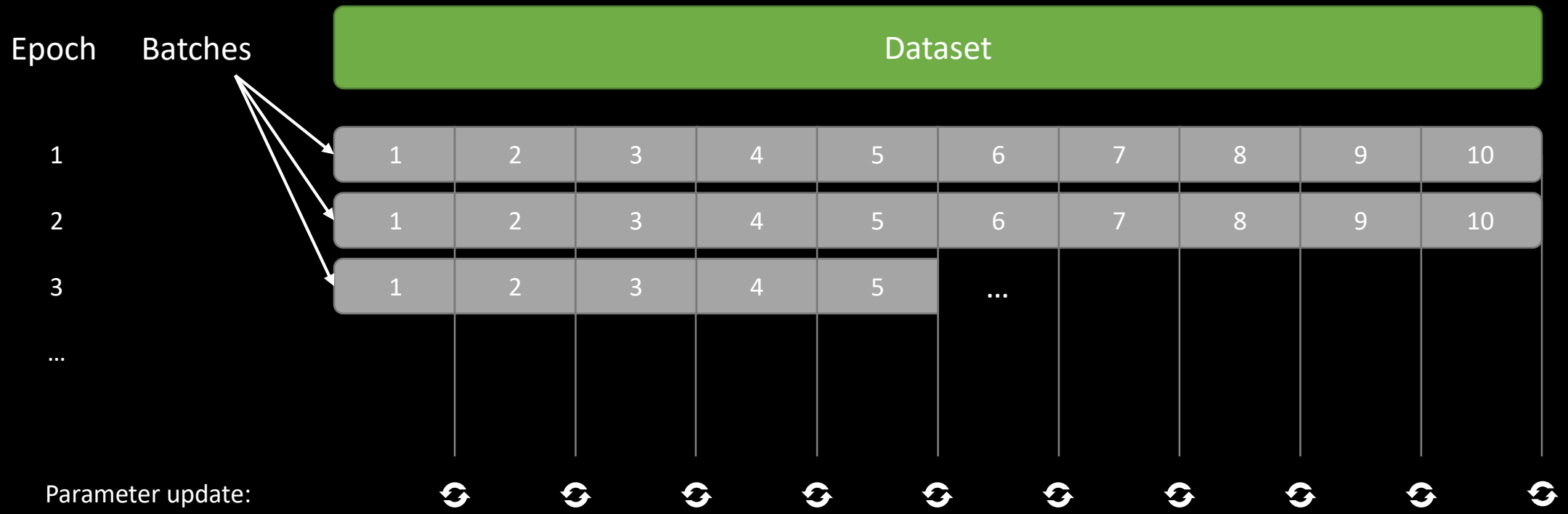


Regression: $Y \in \mathbb{R}$ → continuous values

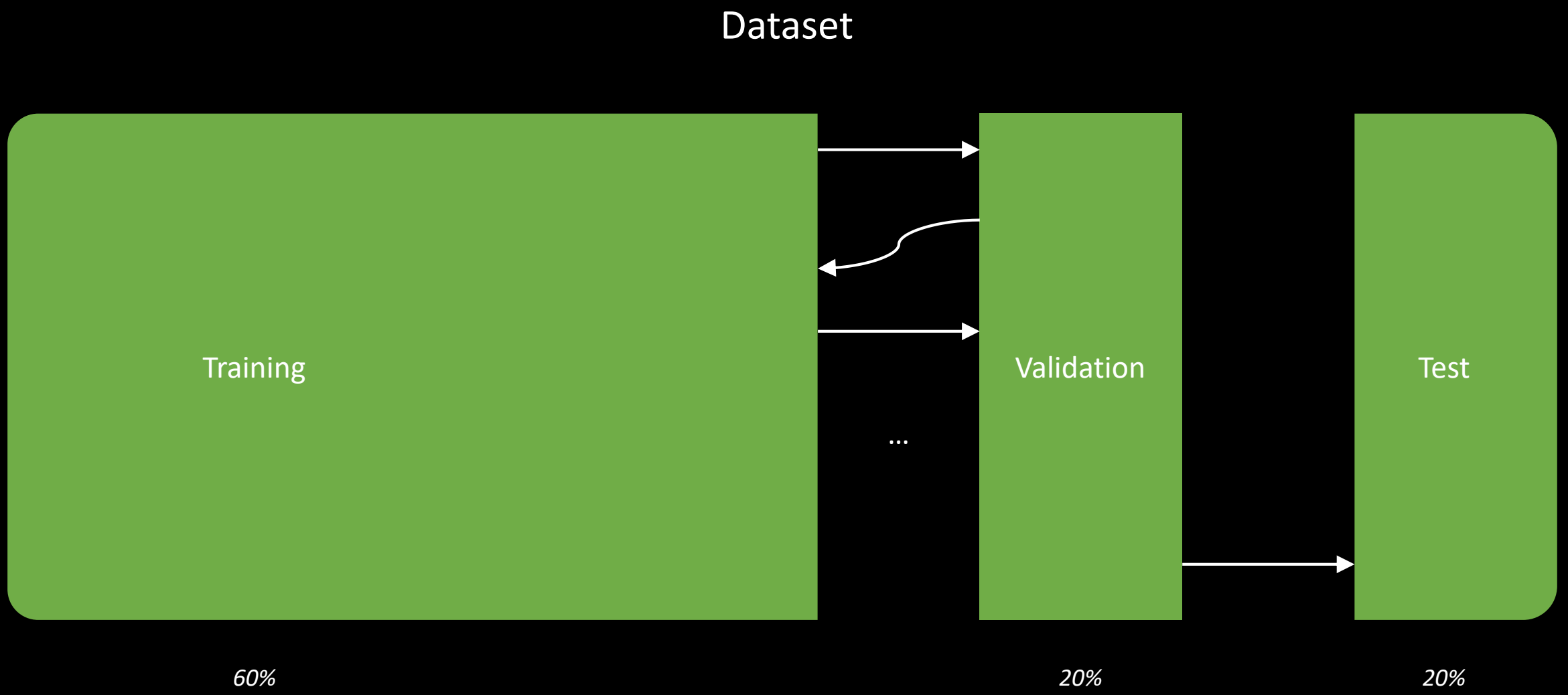
Mean squared error: $\text{MSE} = \frac{1}{n}\sum_{i=1}^{n} (\hat{y}_i - y_i)^2$



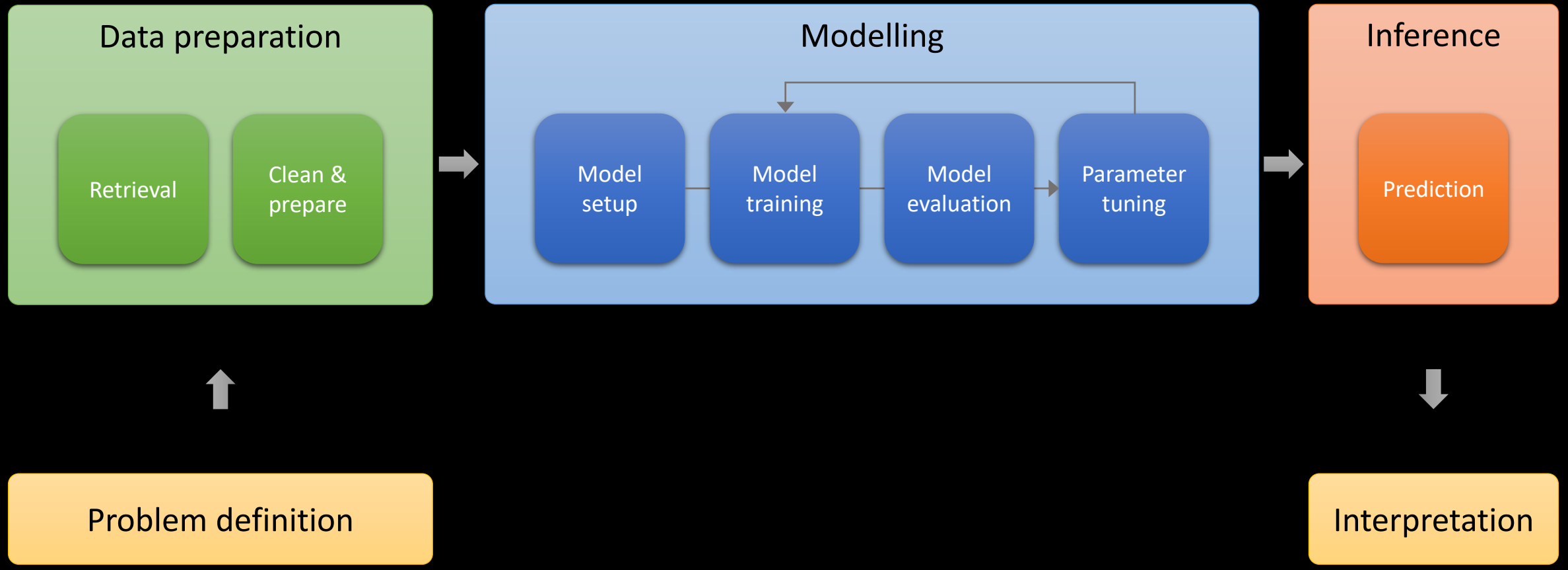
Basics: *epoch & batch*



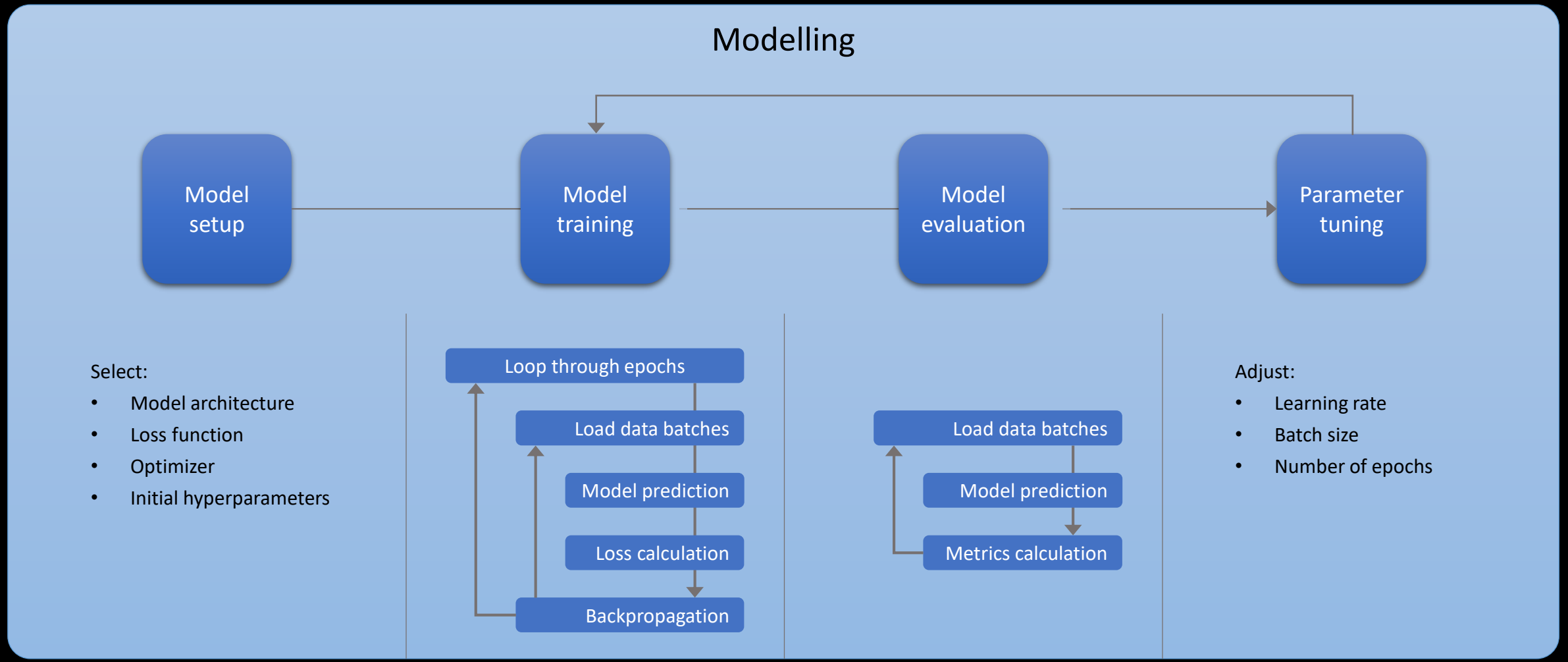
Basics: *data splitting*



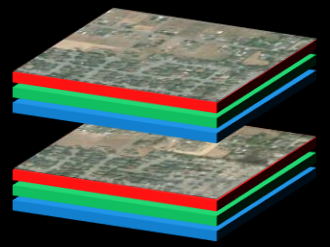
Basics: *machine learning workflow*



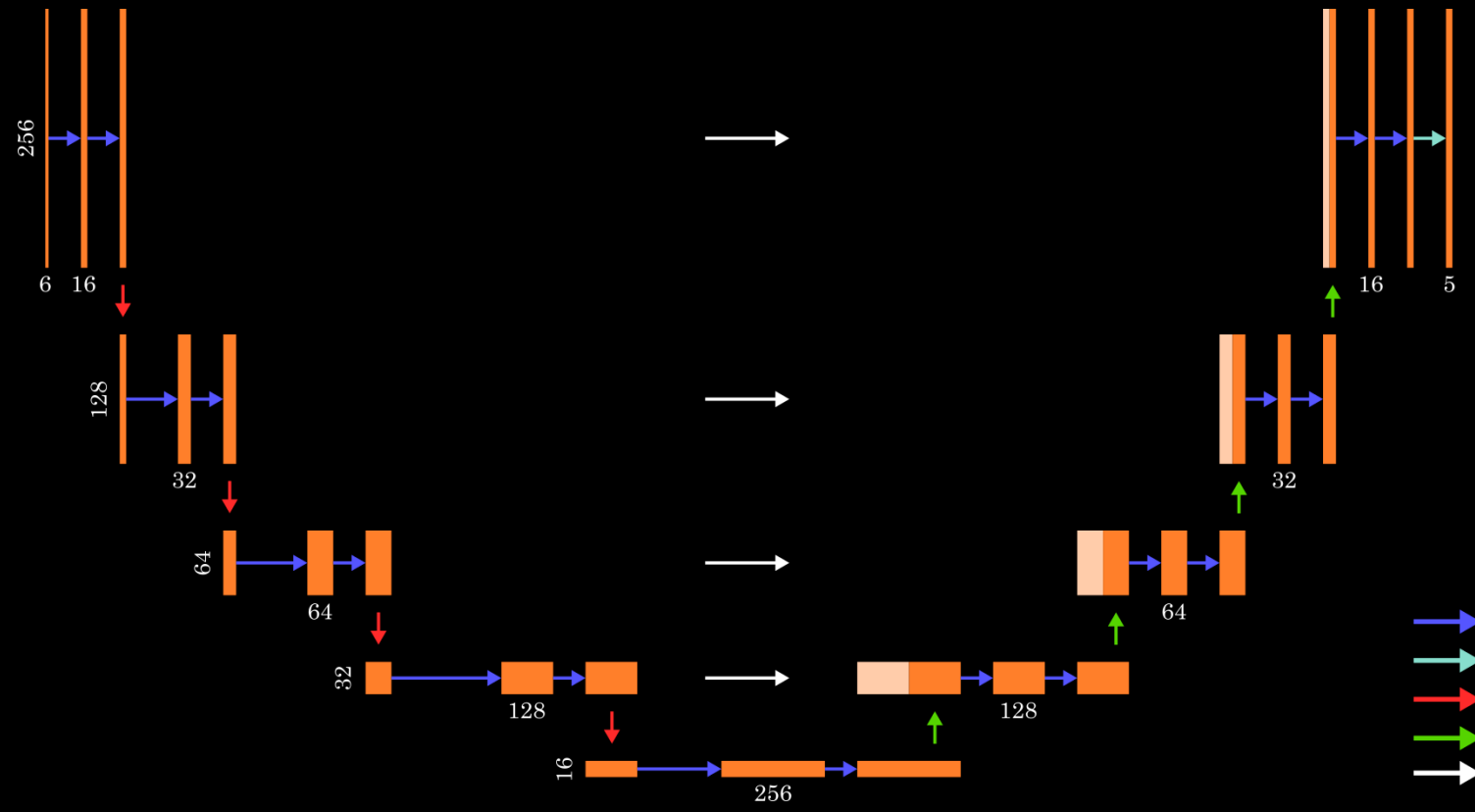
Basics: *machine learning workflow*

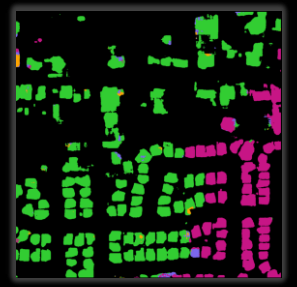


Basics: *u-net model architecture*



Stacked pre and post disaster imagery (6 bands)





Basics: *model architecture*