Machine Learning for Retrieving Cloud Optical Thickness from Observed Reflectance: 3D Effects

CyberTraining 2020 Team 5

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Cloud optical thickness (COT)

- Vertical optical depth
- Determines how much solar radiation reaches the planet’s surface vs. how much is reflected or scattered
- Difficult to measure directly – radar, lidar, pyranometers
- Calculated (“retrieved”) from satellite observations of reflectance

Retrieval algorithm and assumptions

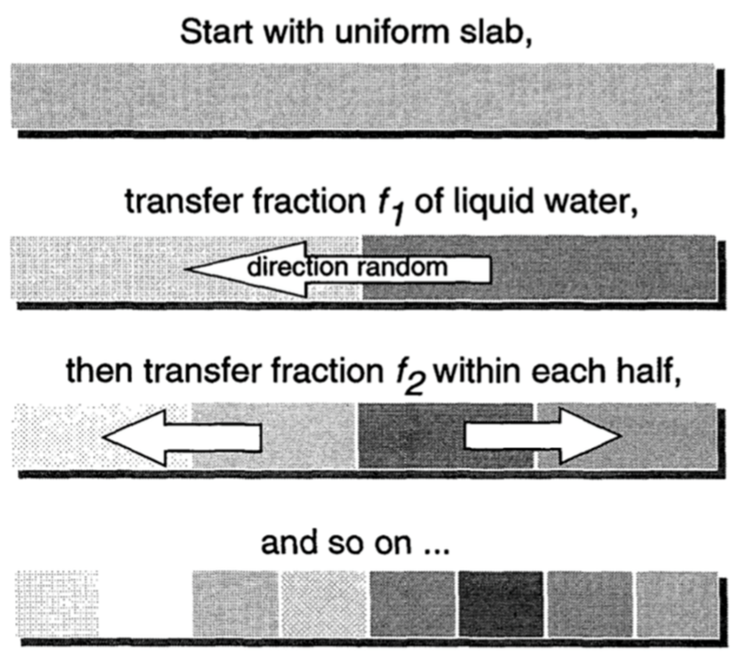
$$\tau_c' = (1-g)\tau_c = \frac{4K(\mu)K(\mu_0)}{3[R_\infty(\mu, \mu_0, \phi) - R(\tau_c; \mu, \mu_0, \phi)]} - 2q' - \frac{4A_g}{3(1-A_g)}$$

- Underlying assumptions: plane-parallel (2D) clouds, each pixel independent

- Actual clouds: 3D effects – horizontal transport of radiation

Synthetic data

- 1D fractal cloud profiles – “lines of cloud”



Synthetic data

- Three connected parameters:
  - Liquid water path (LWP), a measure of the weight of liquid water between two points in the atmosphere – fractal-like random variation
  - Cloud drop effective radius (CER), a measure of the size distribution of water drops within a cloud – fixed; randomly assigned to each profile
  - Cloud optical thickness (COT) – calculated from other two

3D Radiative Transfer Model (SHDOM)

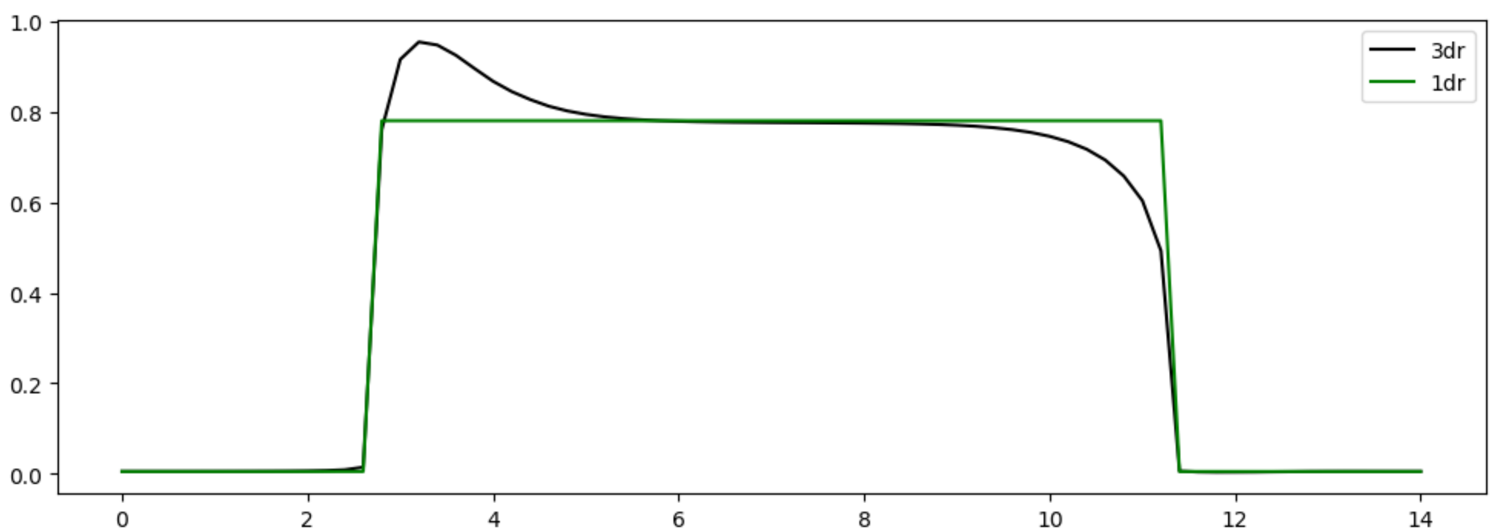
- Spherical Harmonic Discrete Ordinate Method (SHDOM)

- Inputs:
  - COT, CER, LWP
  - Solar zenith angle (SZA) – angle of the sunlight striking the cloud; 60°

- Outputs:
  - Reflectance

3D Radiative Transfer Model (SHDOM)

- “Step cloud” check



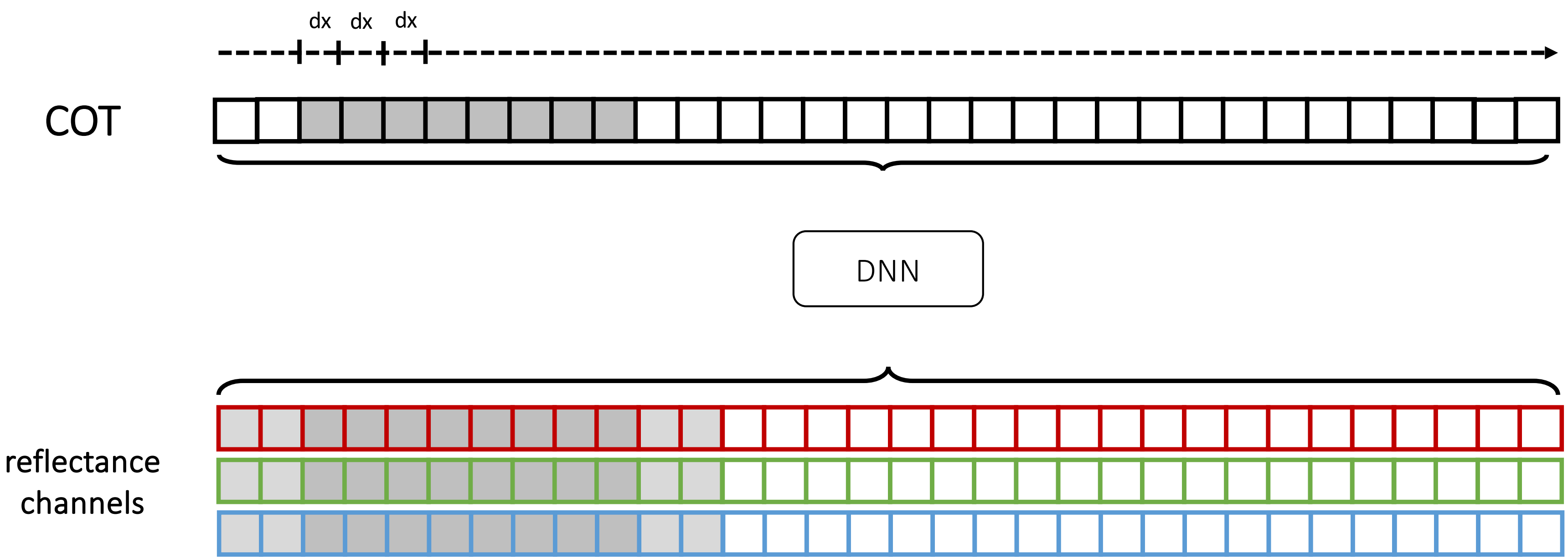
How to get from reflectance to COT?

- Historically an inverse problem

- Bispectral method – still used by MODIS, for example
    - One visible wavelength, one absorbing wavelength

- Simplification of machine learning: pattern recognition (statistical inference) rather than inversion

Deep neural network (DNN)



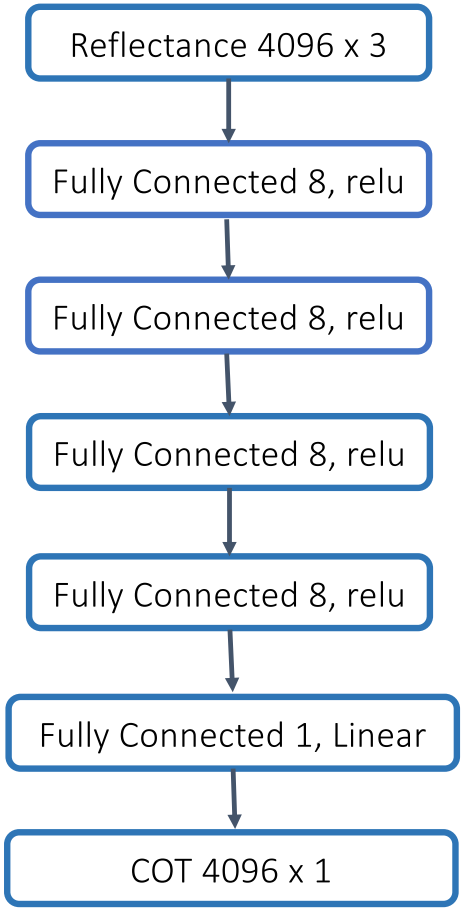
DNN structure

- Current DNN structure based on DNN-2r

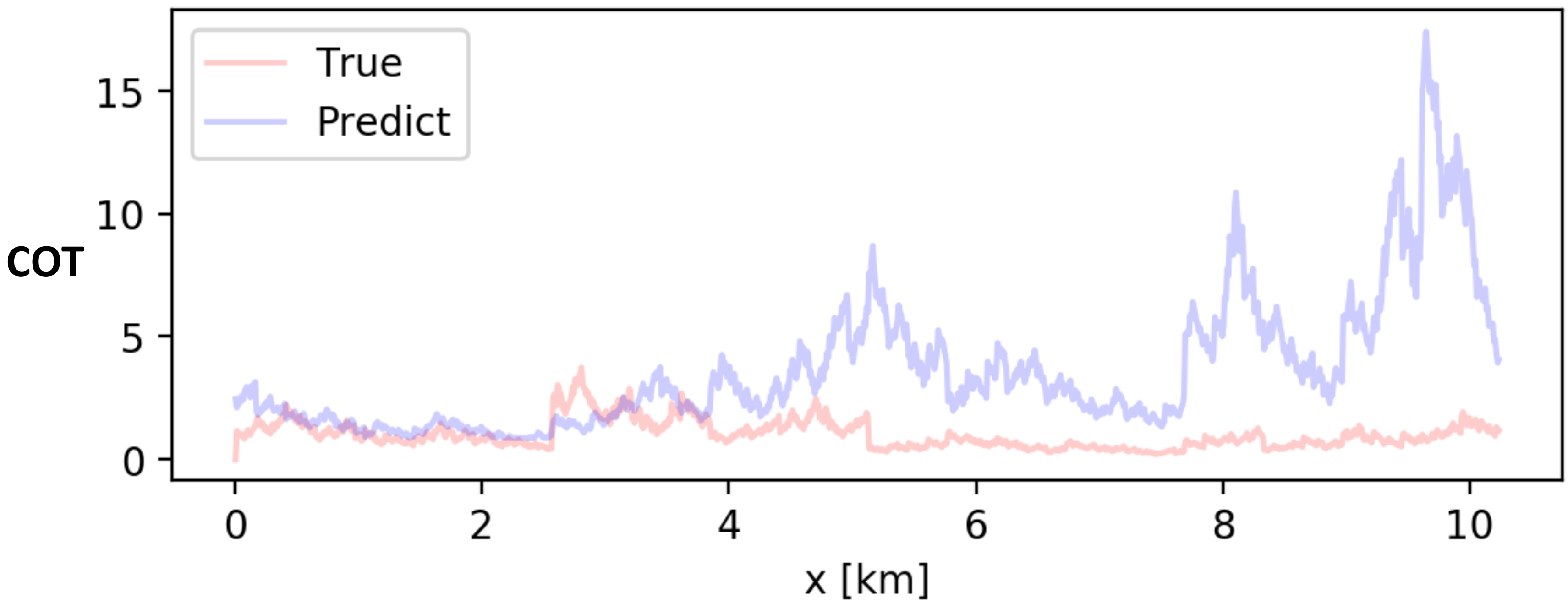
[Okamura et al 2017]

- Optimizer: Adam, Loss = mean_square_error

- Batch = 4, epochs =10



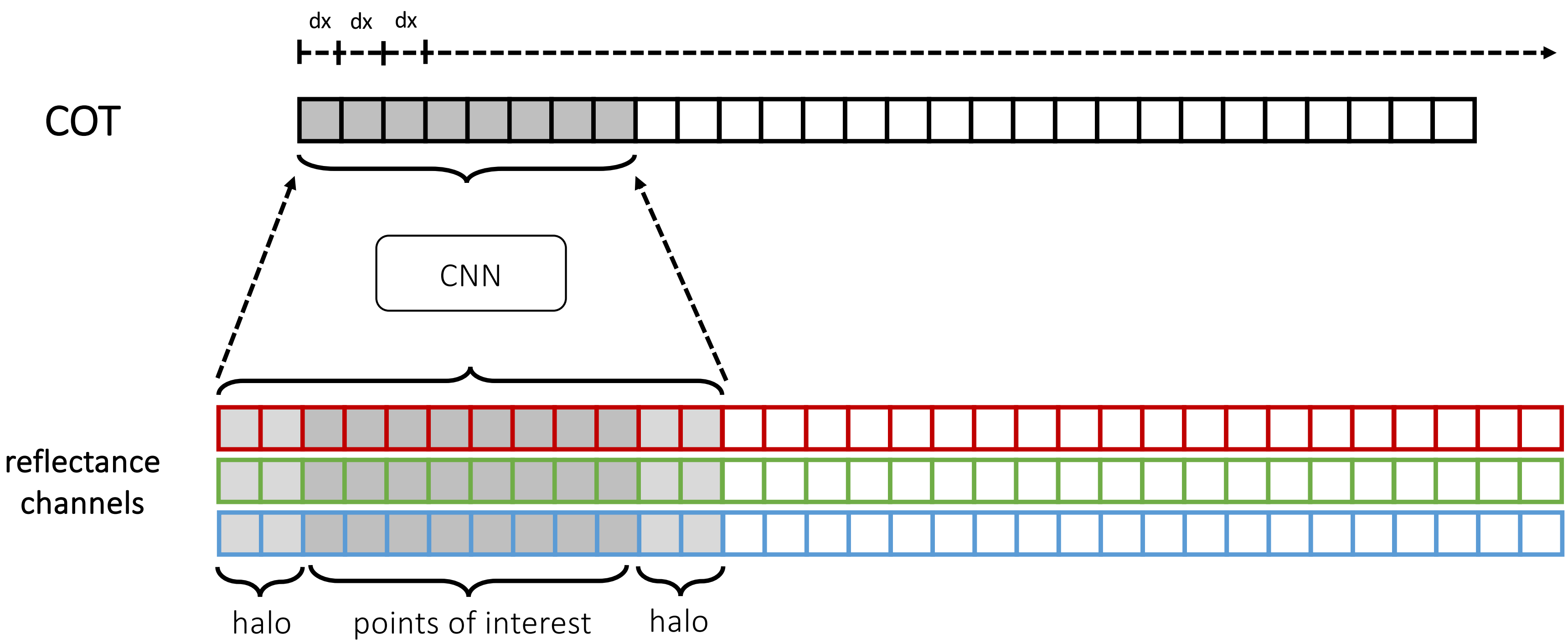
Results from deep neural network (DNN)



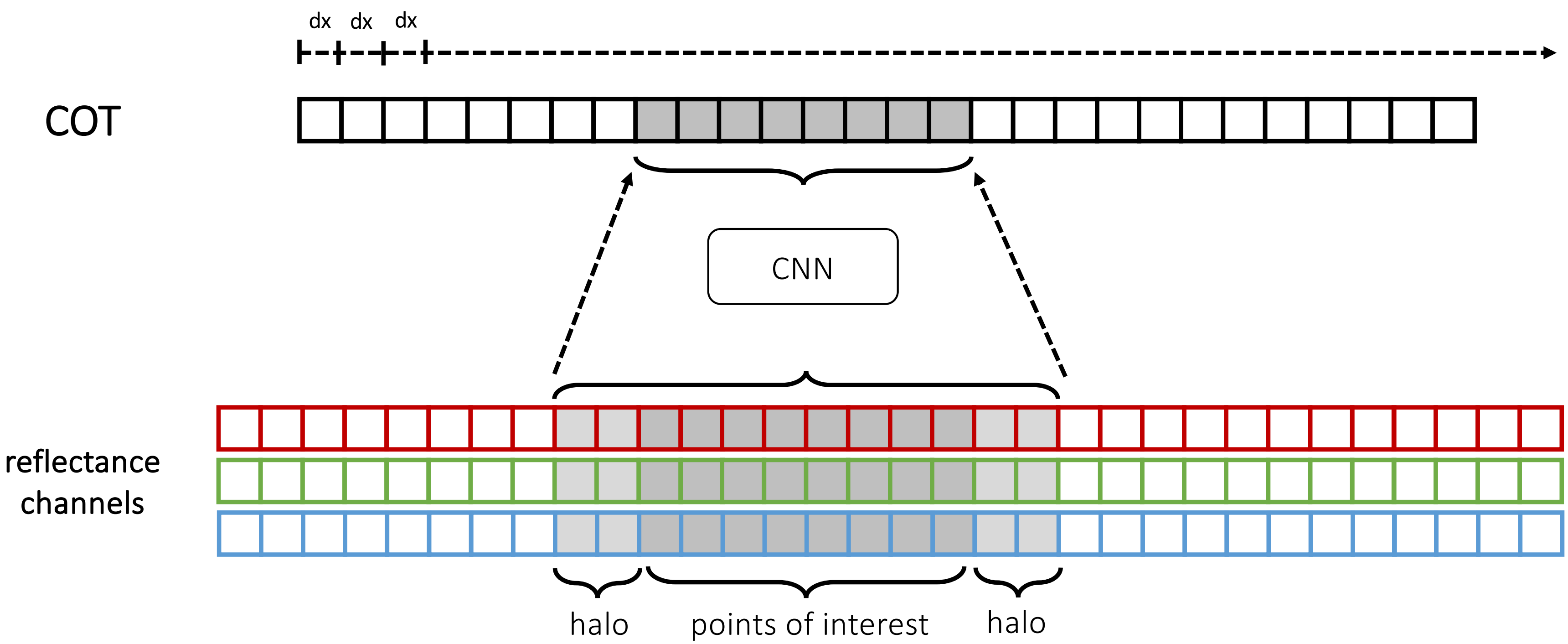
Results from deep neural network (DNN)

- Although MSE converged to a relatively low value, overall COT predictions were inaccurate (unphysical)
- Accuracy decreased with increasing spatial position
- Most likely explanation: overfitting

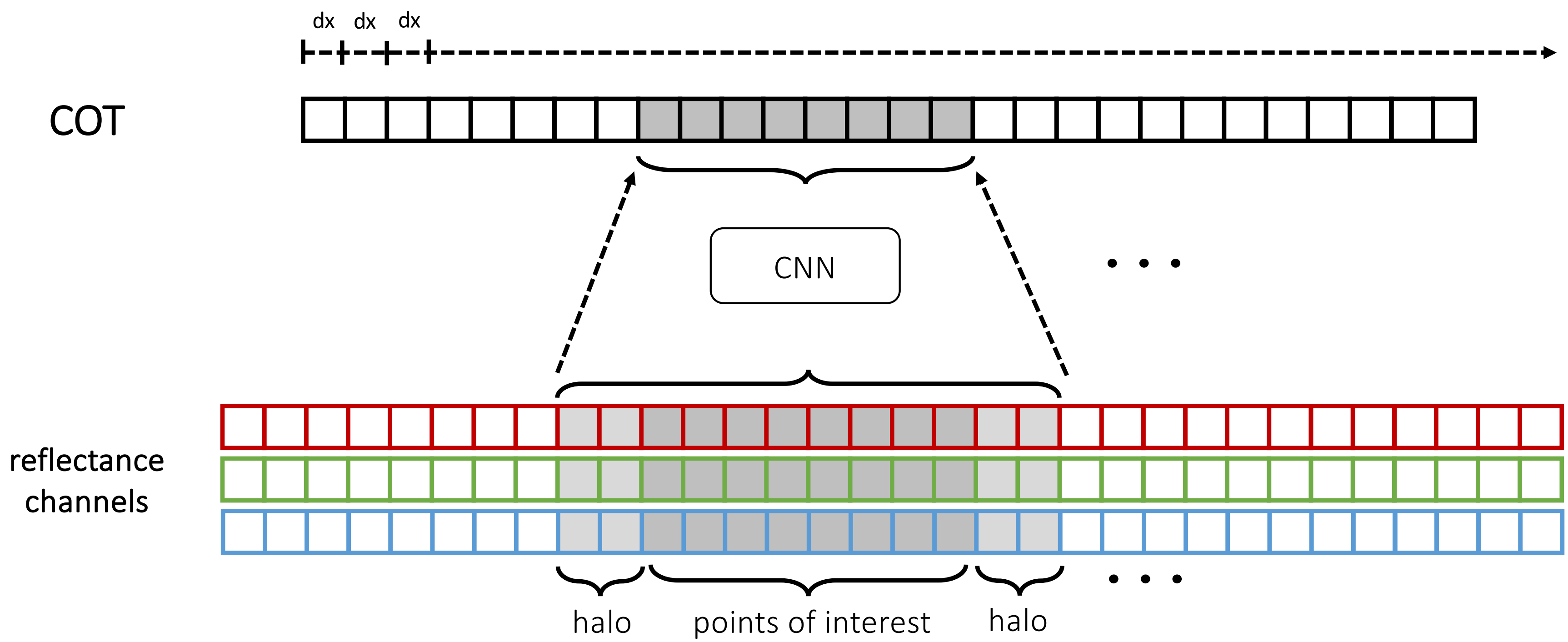
Convolutional neural network (CNN) spatial slicing



Convolutional neural network (CNN) spatial slicing

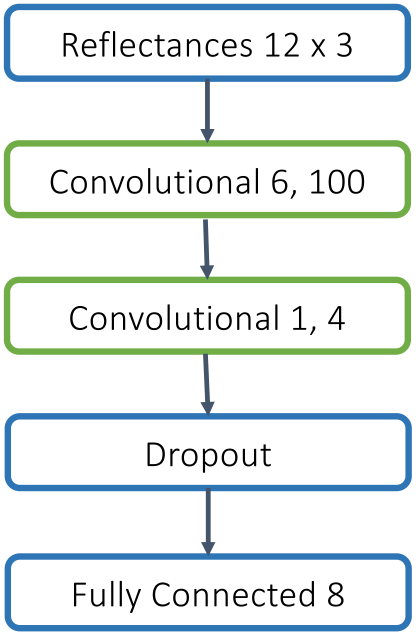


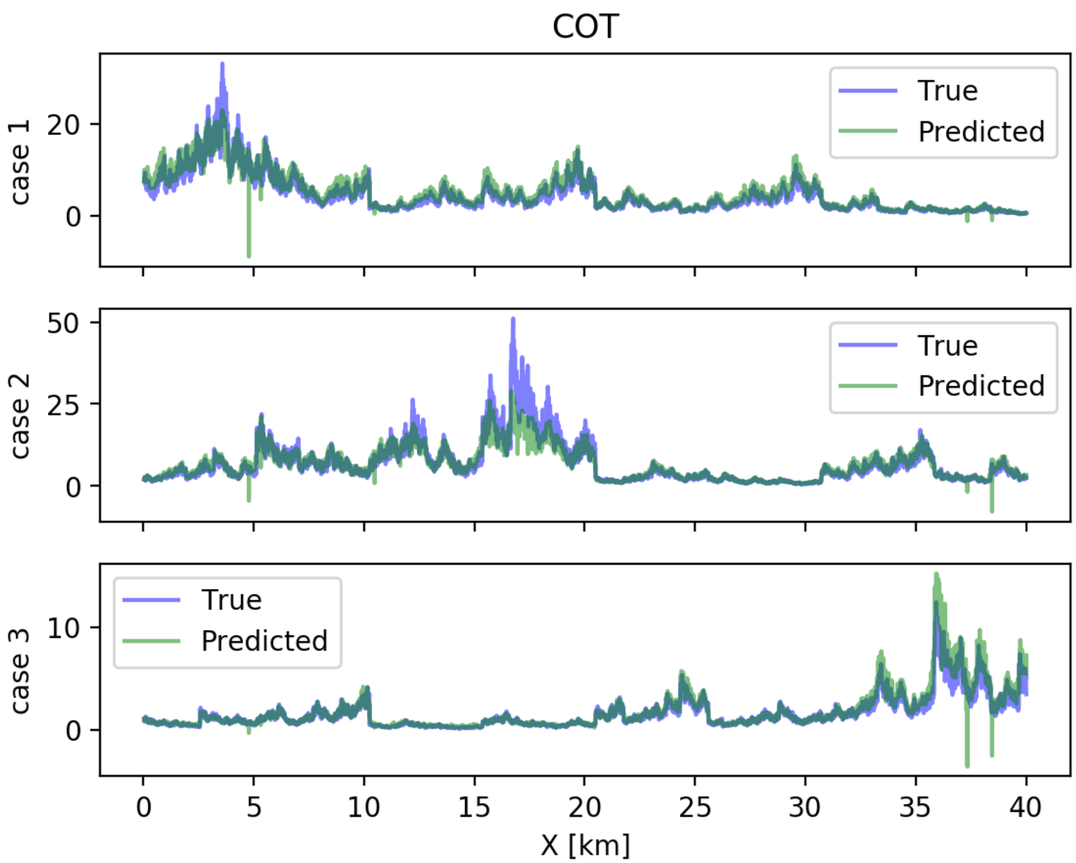
Convolutional neural network (CNN) spatial slicing



CNN structure

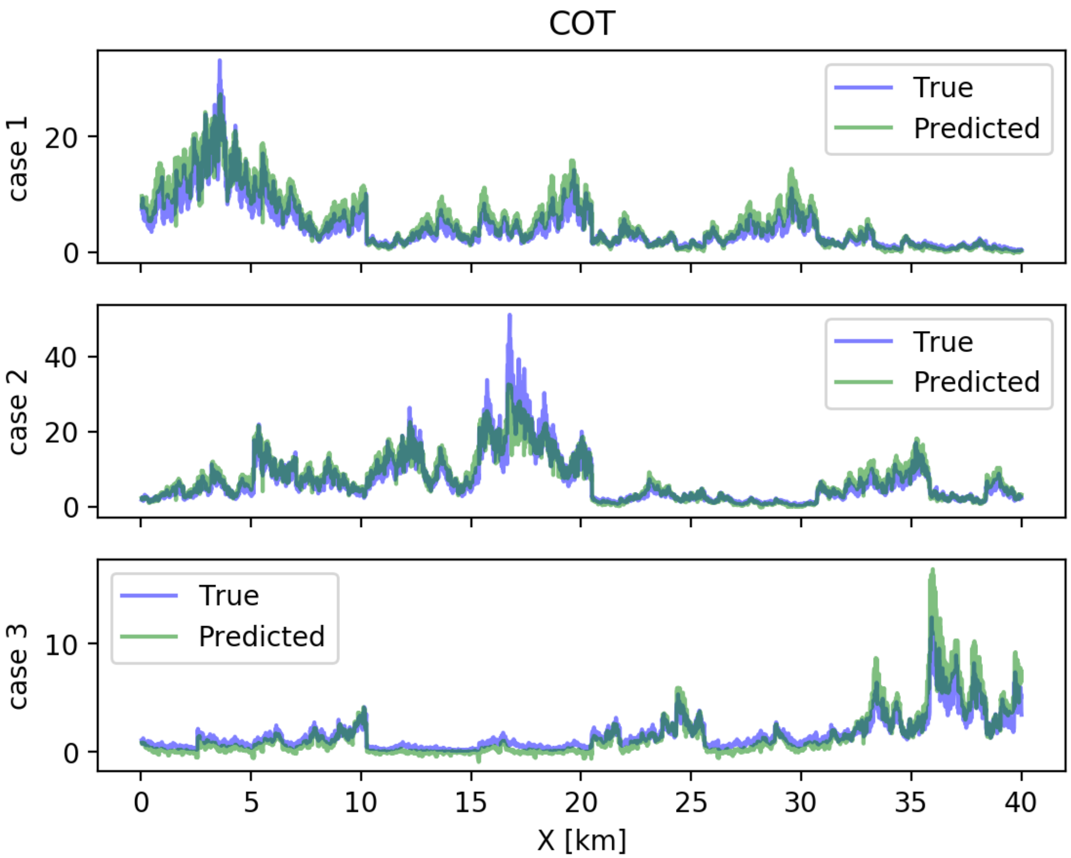
- Current CNN structure based on DNN-4w   [Okamura et al]
- Parallelization possible over spatial slices





Results from CNN

- Loss: mean squared logarithmic error
- Dropout rate: 0.5
- Batch size: 1024
- Epochs: 30



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Discussion of results

- The CNN was more successful than the DNN: why?
  - Not a one-to-one comparison – full data vs. spatial slicing
  - Nature of the data more closely resembles an image problem

- Edge (boundary) cases inherently more difficult

- More successful at predicting local rather than global COT
  - Some outliers and unphysical predictions – pre- or post-processing

Future directions

- Expanded dataset – tuning
  - More data to better cover parameter range
  - More parameter tuning and structural changes
- Emulating a multi-scale model
  - Using a DNN-based global method to inform the local CNN
- 2D data – testing on satellite data, e.g. MODIS
  - Structure of spatially sliced CNN lends itself to parallelization