

Neural Networks and Deep Learning for Space Physics



Source: xkcd

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CEDAR 2019 Tutorial

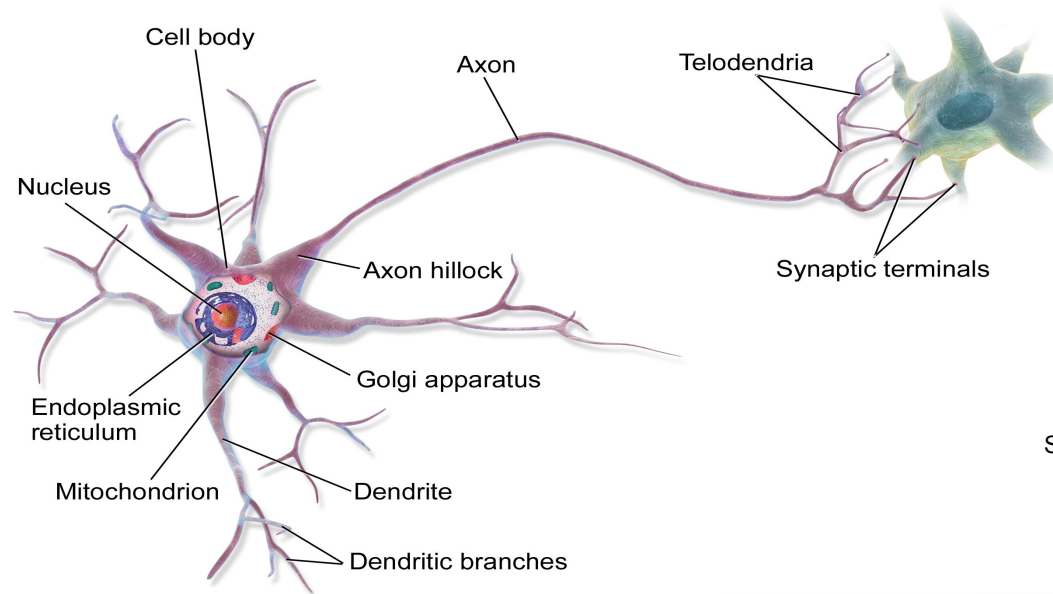
Neural Networks

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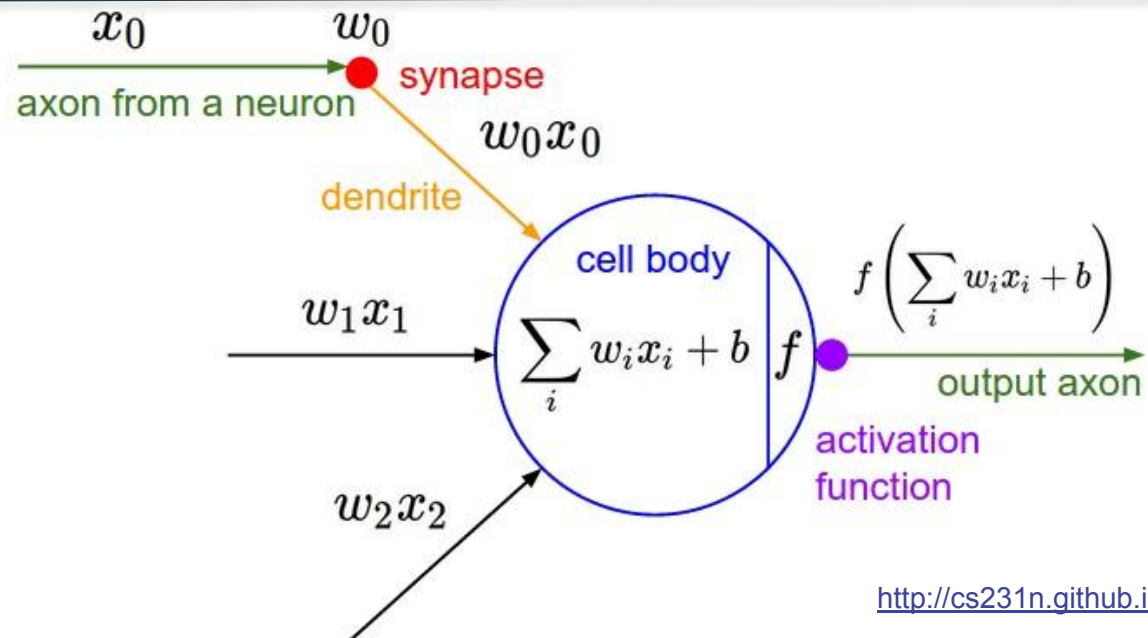
How does a neuron operate?

Biological



Source:Wikipedia

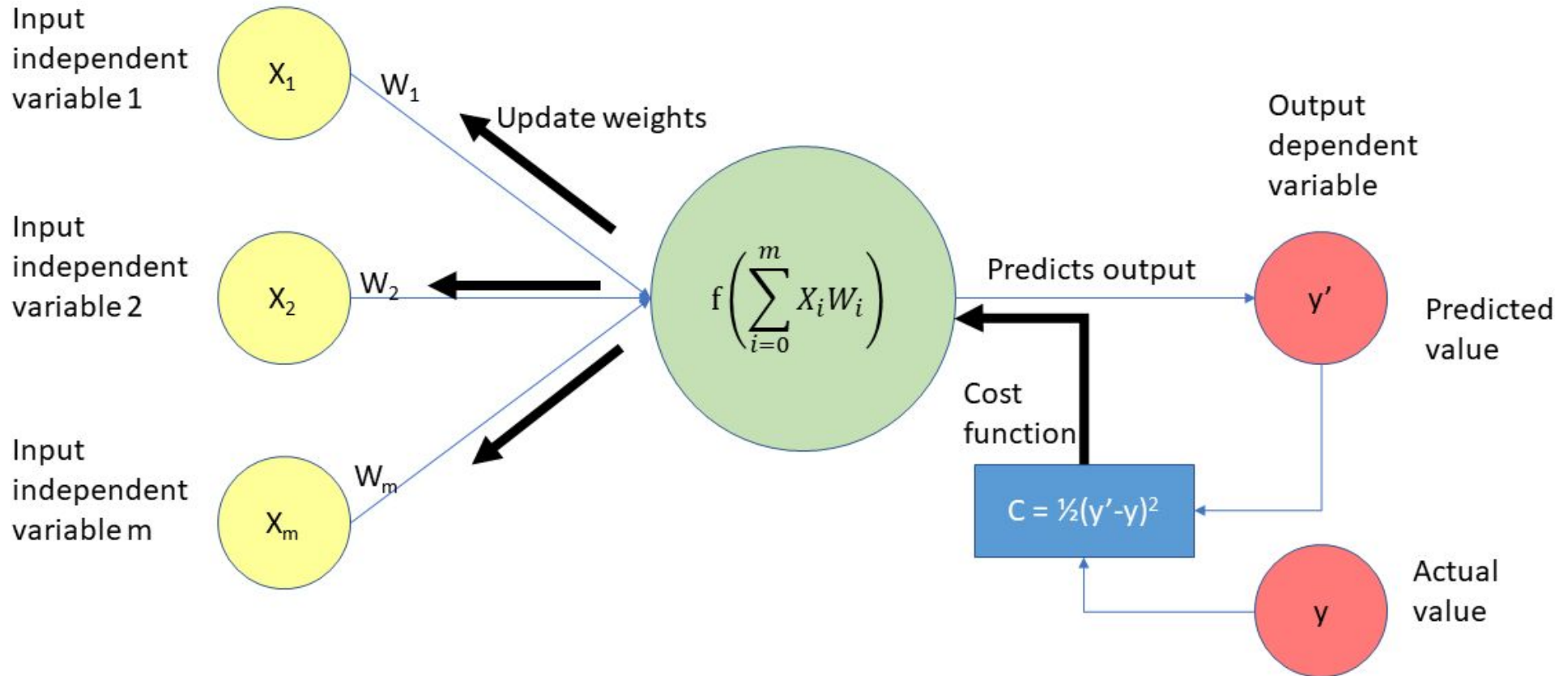
Artificial



A brief history of neural networks

- In 1943, neurophysicist Warren McCulloch and the mathematician Walter Pitts proposed a simplified computational model of how biological neurons might work, but their model lacked a mechanism for learning
- In 1949, Donald Hebb published 'Cells that fire together, wire together'
- In 1960, Frank Rosenblatt developed a 'Perceptron' - a simple neural network with a linear activation function - capable of classifying shapes
- Between 1960's to 1980's there were ups and downs in usage
- In recent times, the increase in computational power and data infrastructure has made it possible to use neural networks to their potential

How does a neural network learn?



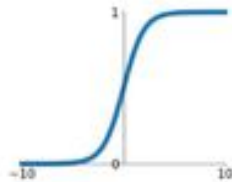
The goal is to minimize the cost function

Activation functions

- Also known as ‘transfer function’ - calculates the weighted sum, and decides whether to ‘fire’ a neuron or not.
- Most common example - a step function.
- Non-linear activation functions help solve complex problems

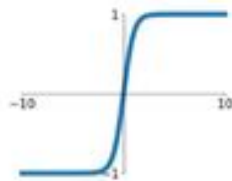
Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



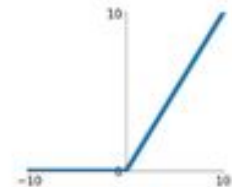
tanh

$$\tanh(x)$$



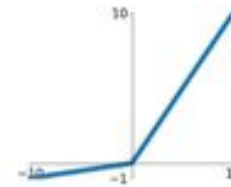
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

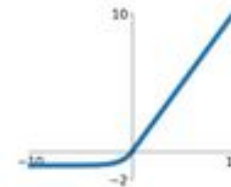


Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

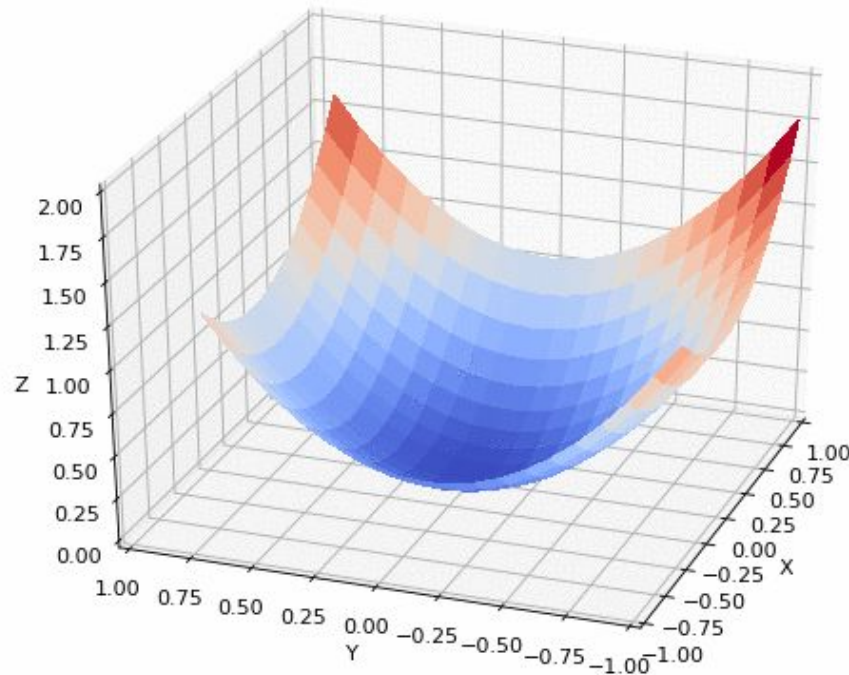
ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



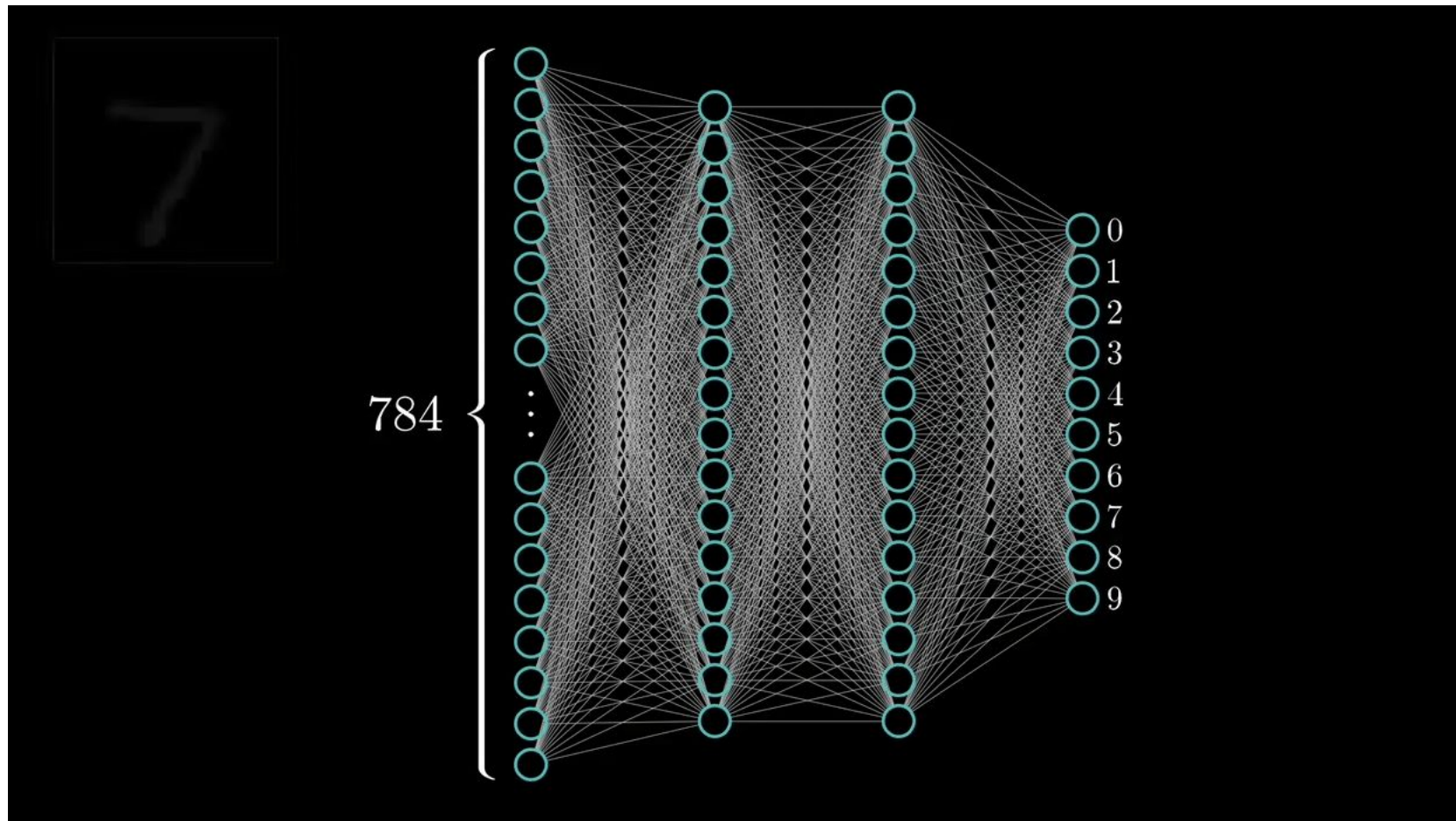
Cost function minimization

Most commonly used technique - **Gradient descent** is an optimization algorithm used to minimize some function by iteratively moving in the direction of steepest **descent** as defined by the negative of the **gradient**.

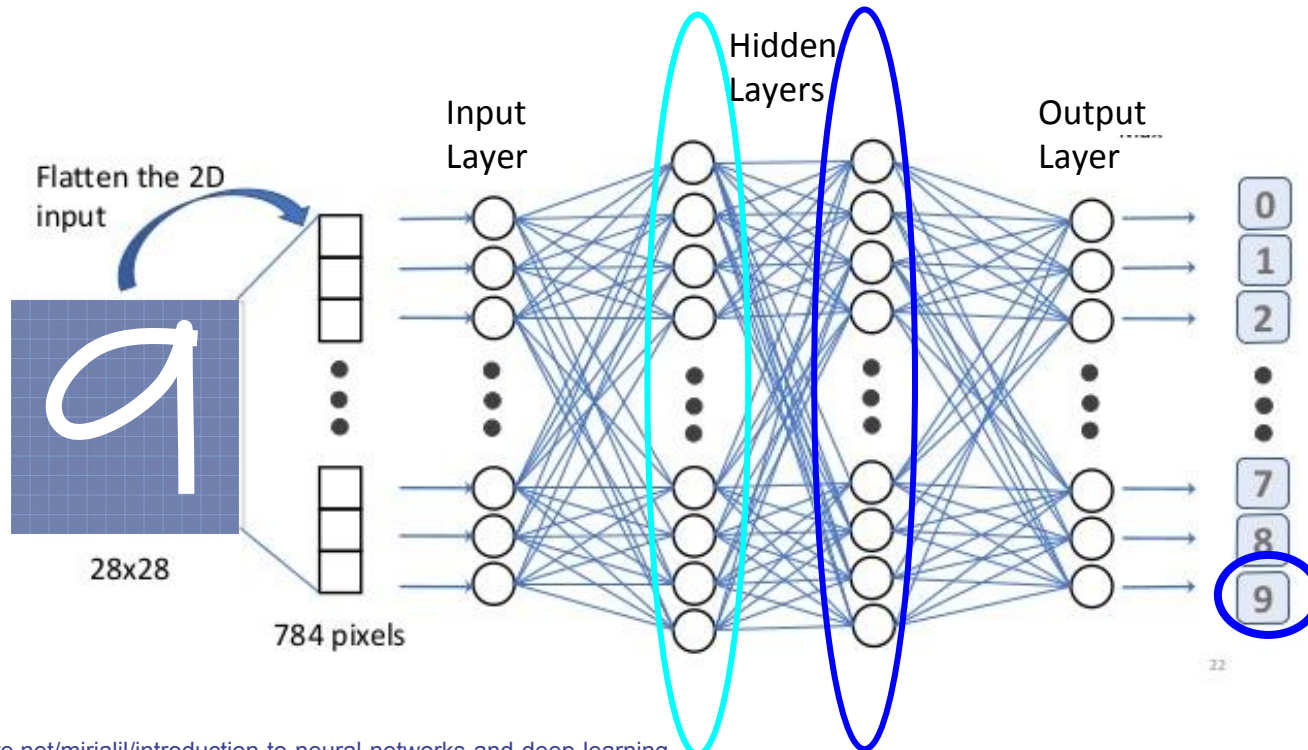
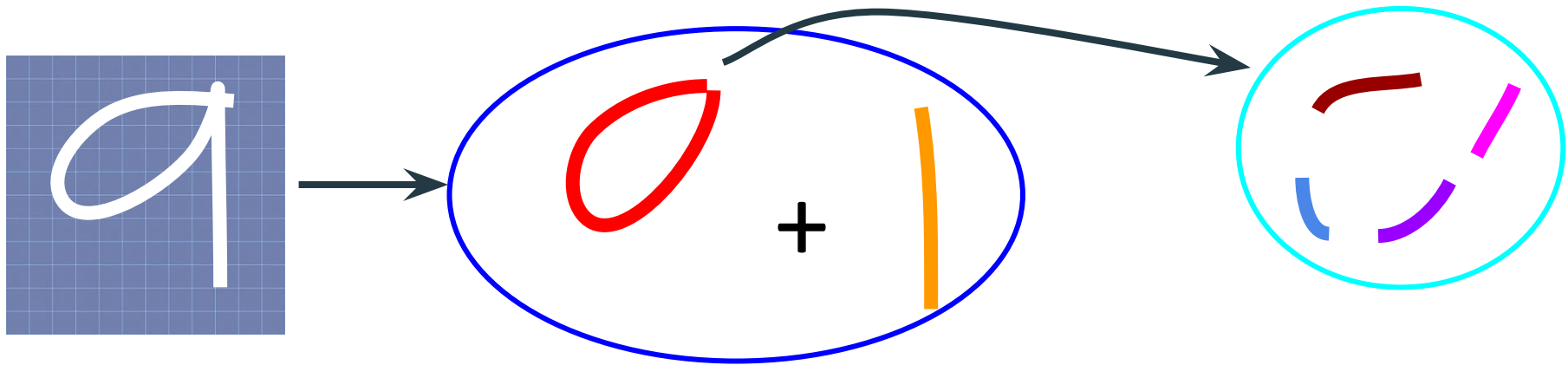


<https://blog.paperspace.com/intro-to-optimization-in-deep-learning-gradient-descent/>

Supervised learning



How does a neural network 'recognize' a pattern?

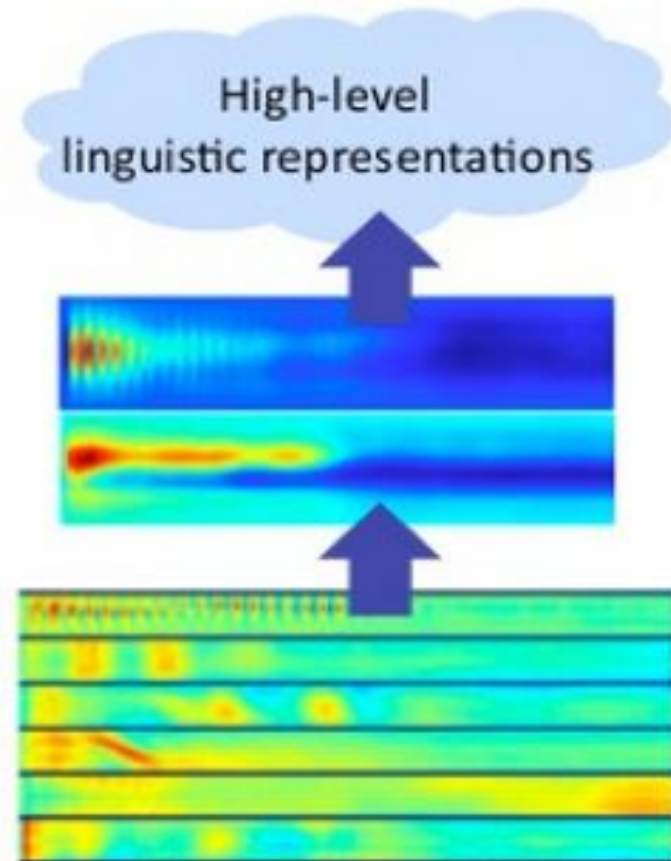
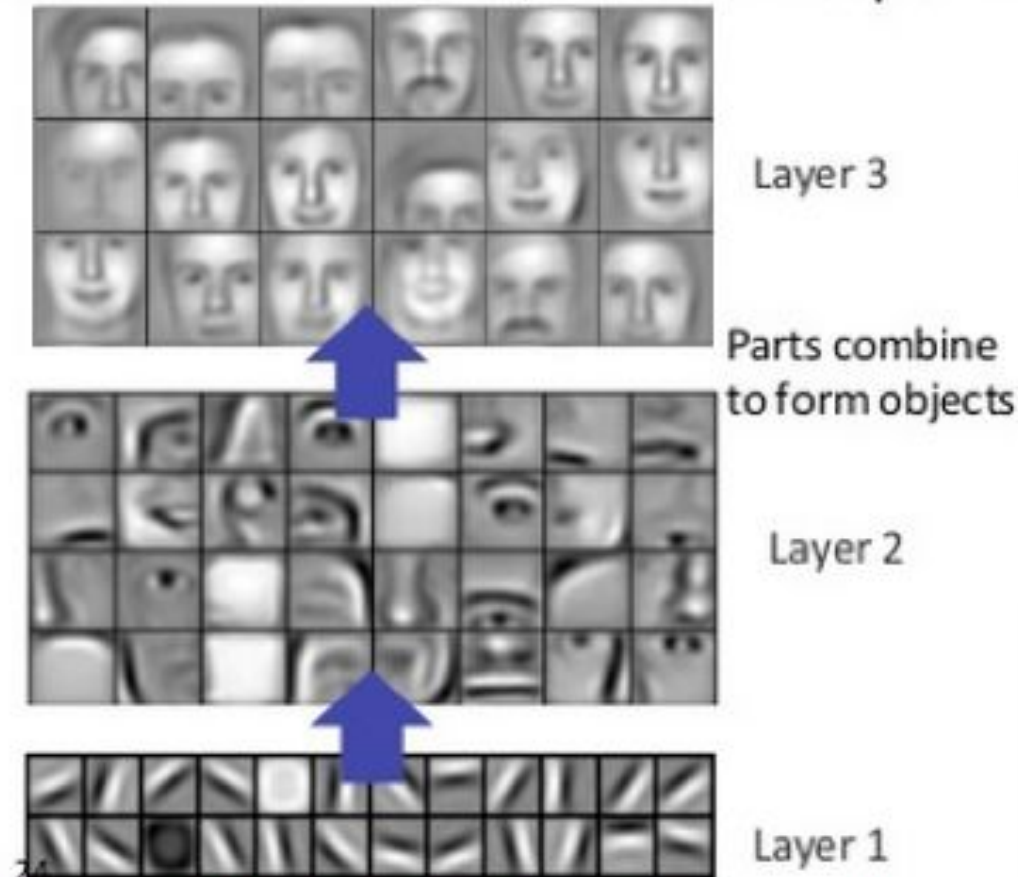


Deep Learning

- The higher the number of 'hidden' layers, the 'deeper' the network goes.
- A neural net with two or more hidden layers is qualified as 'deep'
- Each layer in a 'deep' network trains on a distinct set of features based on the output from previous layer
- Deeper the net, more complex are the features it can recognize

Deep Learning Examples

Successive model layers learn deeper intermediate representations



Training, Validation, Testing Neural Nets

Training Dataset: The sample of data used to fit the model. (*Largest*)

Validation Dataset: The sample of data used to provide an unbiased evaluation of a model fit on the training dataset while tuning model hyperparameters. The evaluation becomes more biased as skill on the validation dataset is incorporated into the model configuration.

Test Dataset: The sample of data used to provide an unbiased evaluation of a final model fit on the training dataset. (*Something that the model has never seen*)



Commonly used Neural Networks

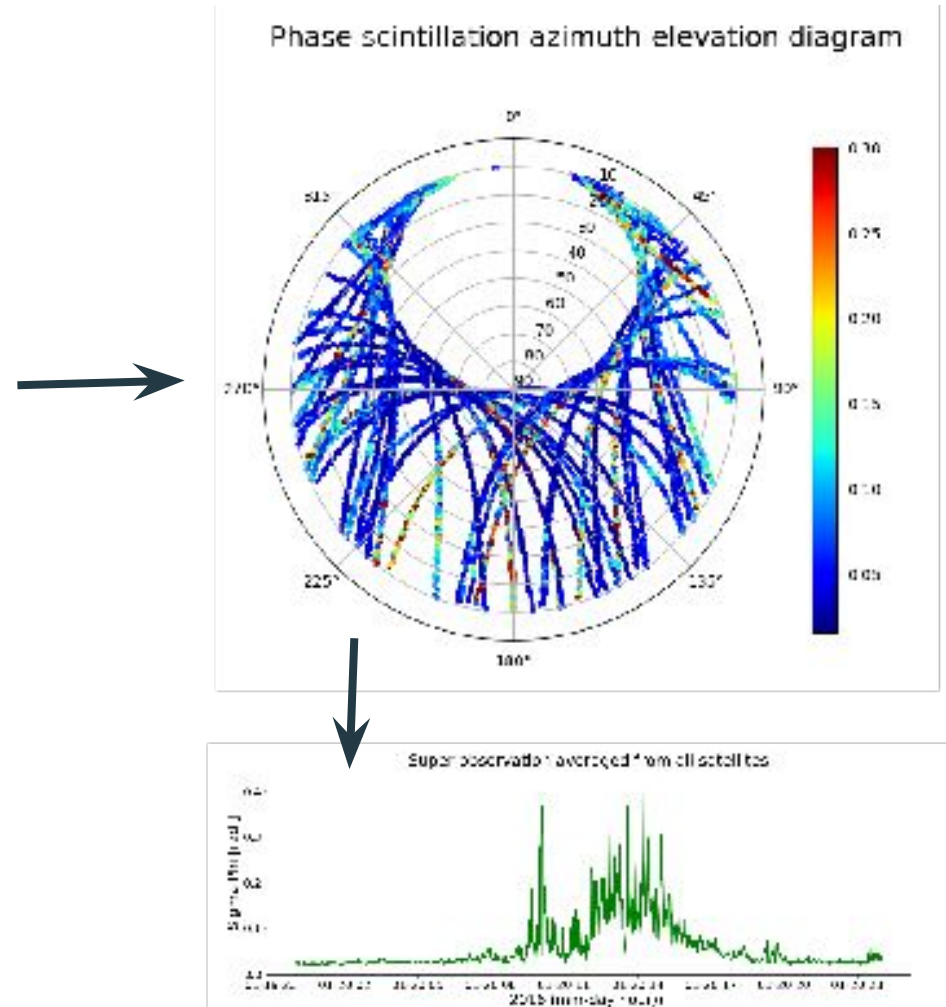
- Feed forward - Multilayer Perceptron (MLP)
- Convolutional Neural Networks (CNN):
Commonly used for image analysis
- Recurrent Neural Networks (RNN): Commonly used for temporal sequence analysis

Applications in space science: GPS Scintillation Prediction

DATA

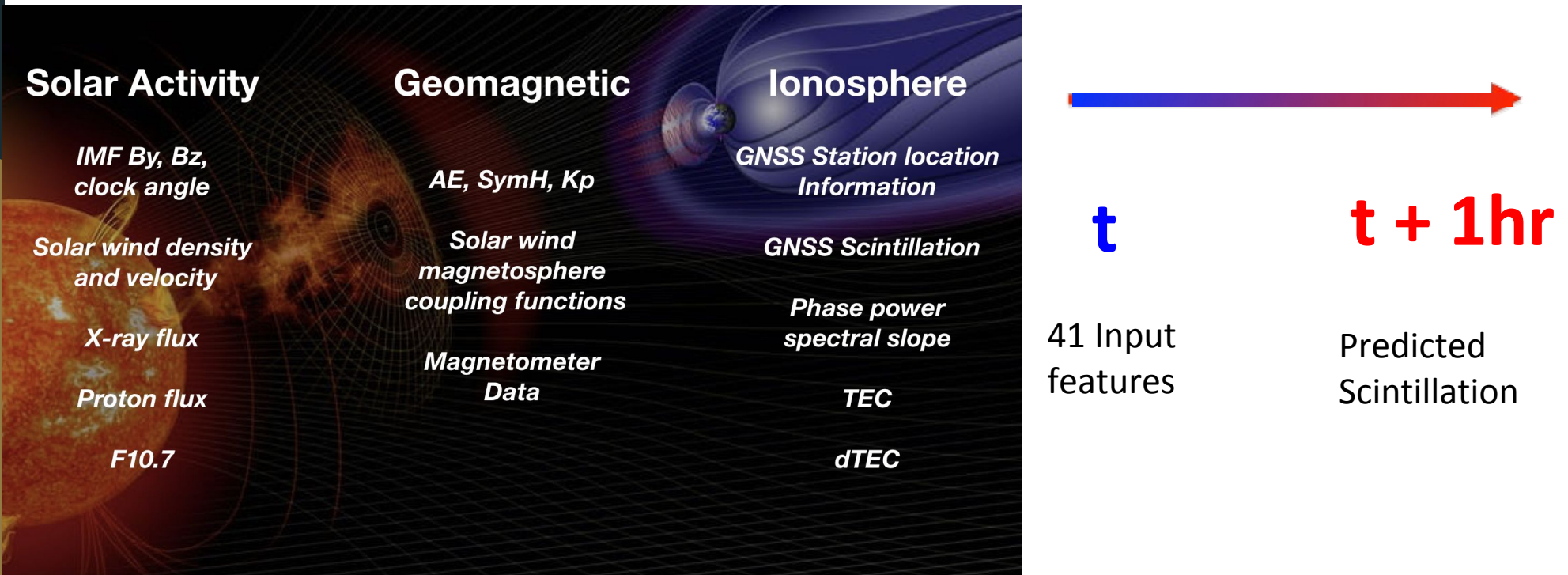


Canadian High Arctic Ionospheric Network (CHAIN)



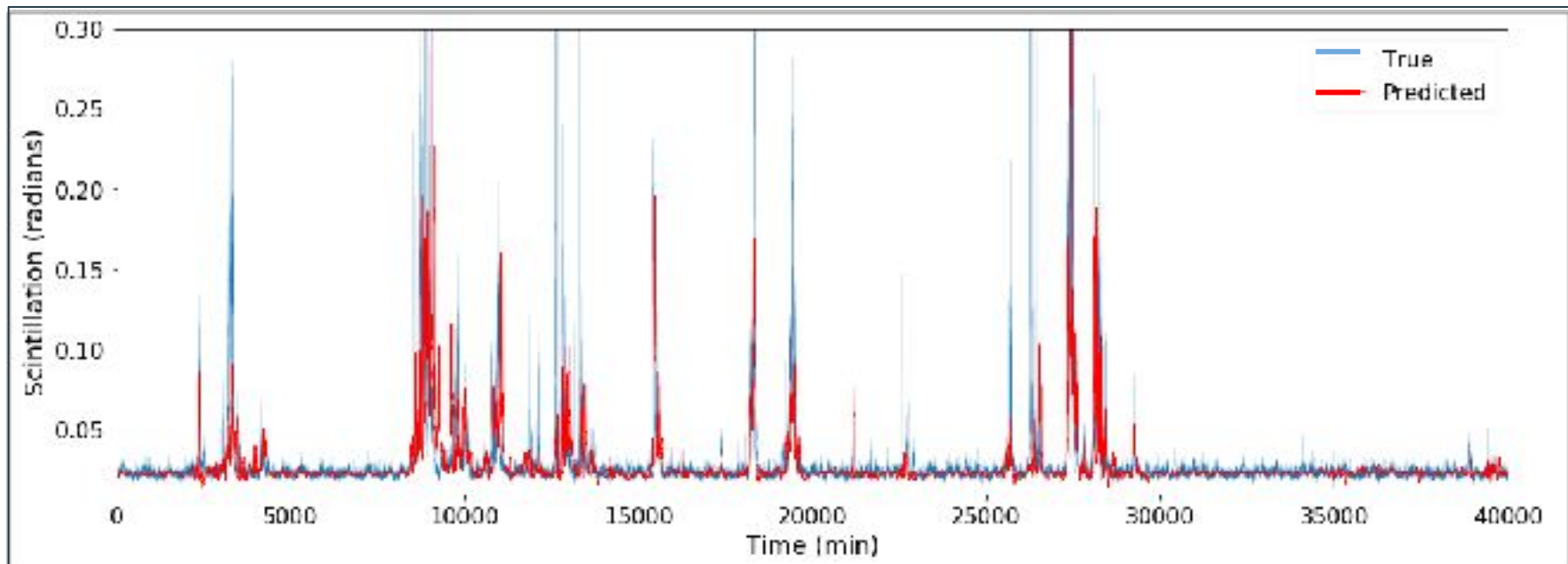
Applications in space science: GPS Scintillation Prediction

Building a predictive model GNSS scintillations using inputs from solar activity, magnetospheric coupling and ionosphere



Applications in space science: GPS Scintillation Prediction

- **Training data:** 2015-2016 | Test on: 2017
- **Model:** Multilayer perceptron - 4 hidden layers and 128 nodes in each layer
- **Activation function:** Exponential Linear Unit (ELU)
- **Optimizer:** Adam (extension of gradient descent)



Applications in space science: GPS Scintillation Prediction

- 96% True results over all predicted results ('Recall')
- Localized model performed much better than a model developed for all sites together - Why?
- Adding co-located magnetometer data improved the prediction accuracy - Why?

So, should you use Deep Learning?

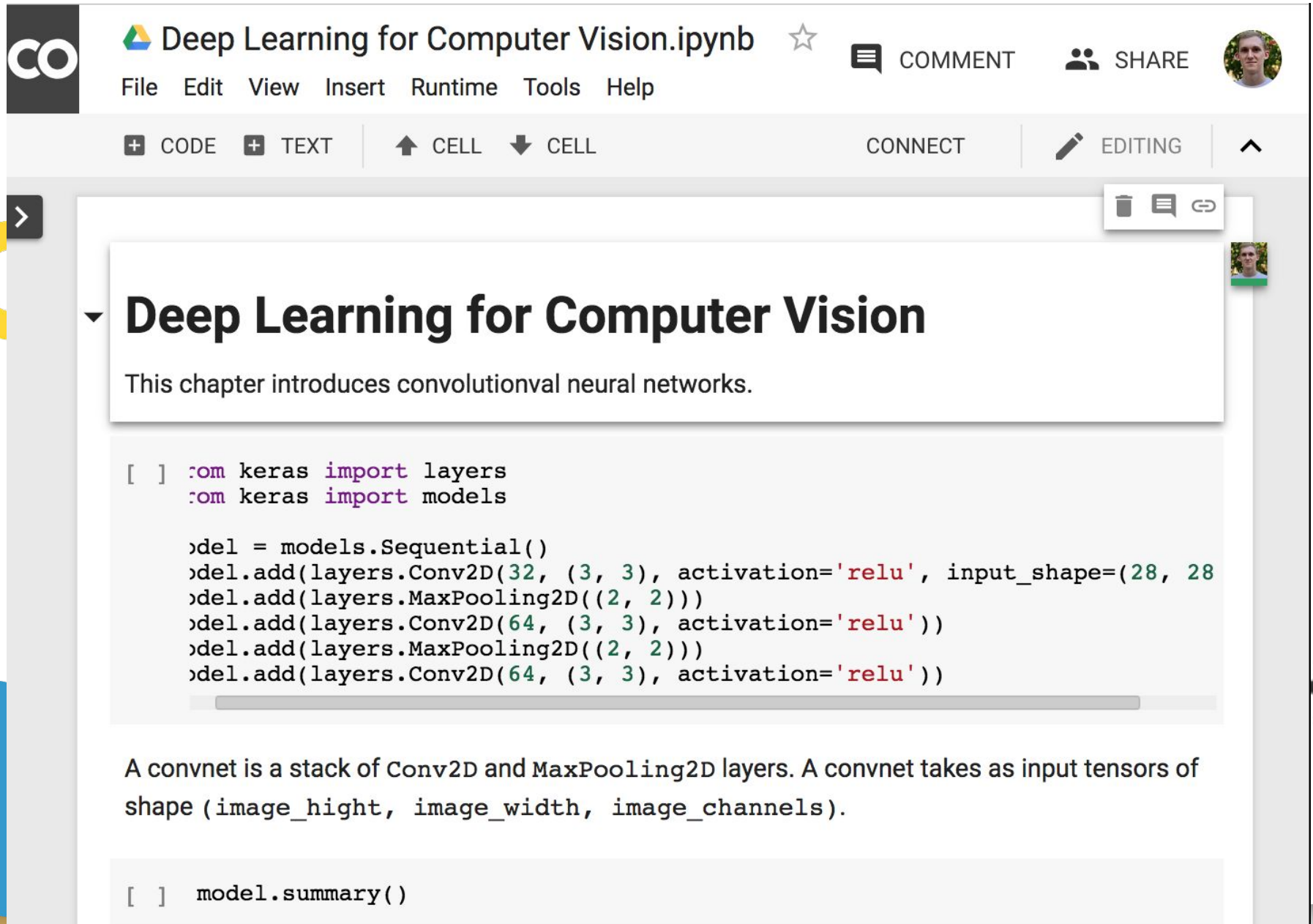
Advantages

- Massive amounts of data available
- Computational power to match the available massive amounts of data
- Advances in algorithms that make them much faster to run and access more data than before
- Ability to outperform nearly every other ML algorithms

Disadvantages

- Black Box - what are underlying rules that gave you the output you did
- While libraries with simplified functions exist, more complex challenges require longer development and resources
- Your neural network is only as good as your training data - requires massive amount to train properly
- More computationally expensive

Tools to explore deep learning



The image shows a Jupyter Notebook interface with a dark theme. At the top, there's a header with the 'CO' logo, the title 'Deep Learning for Computer Vision.ipynb', and icons for star, comment, and share. Below the header is a menu bar with 'File', 'Edit', 'View', 'Insert', 'Runtime', 'Tools', and 'Help'. A secondary toolbar contains '+ CODE', '+ TEXT', '↑ CELL', '↓ CELL', 'CONNECT', 'EDITING', and an expand/collapse icon. The main content area has a title 'Deep Learning for Computer Vision' and a subtitle 'This chapter introduces convolutional neural networks.' Below this is a code cell with Python code for building a convolutional neural network using Keras. The code defines a sequential model with three layers: two convolutional layers and two max pooling layers. The final cell shows the command to print the model summary.

CO Deep Learning for Computer Vision.ipynb ☆ COMMENT SHARE

File Edit View Insert Runtime Tools Help

+ CODE + TEXT ↑ CELL ↓ CELL CONNECT EDITING ^

Deep Learning for Computer Vision

This chapter introduces convolutional neural networks.

```
[ ] :om keras import layers
:om keras import models

model = models.Sequential()
model.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(64, (3, 3), activation='relu'))
```

A convnet is a stack of Conv2D and MaxPooling2D layers. A convnet takes as input tensors of shape (image_height, image_width, image_channels).

```
[ ] model.summary()
```

Opportunities that combine Space Physics and Machine Learning

8-week AI accelerator program
hosted by SETI Institute



SETI INSTITUTE

LIVING WITH OUR STAR
FDL 2019

THE MOON FOR GOOD
FDL 2019

ASTRONAUT HEALTH
FDL 2019

MISSION CONTROL FOR EARTH
FDL 2019

PLANETARY DEFENSE
FDL 2019

Google Cloud

intel AI

IBM

Hewlett Packard Enterprise

nVIDIA

ESA LUXEMBOURG SPACE AGENCY

XPRIZE

CSA ASI

LOCKHEED MARTIN

kx

miso

What to do next?

- Go through CEDAR and identify long standing questions with enough relevant data, where ML approaches can be used
- Take a statistics course at your university
- Look up simple web-based ML tutorials
- Learn Python - play with canned tutorials on tools like Google Colab - or install Scikit-Learn on your machine
- Familiarize yourselves with geospace Python tools that help you access data - attend sessions and hackathons planned during CEDAR -
 - Python session and Hackathon on Monday
 - Integrated Geoscience Observatory workshop on Wednesday
 - Geospace Data Science on Thursday

Additional Resources

- Hands-On Machine Learning with Scikit-Learn & TensorFlow - O'reilly book by Aurelien Geron
- <http://www.scs.ryerson.ca/~aharley/neural-networks/>
- Coursera Course on Machine Learning by Andrew Ng