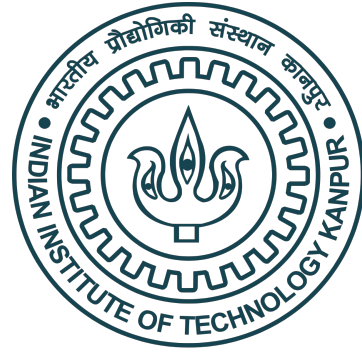


# PHY654

## Machine learning (ML) in particle physics



Swagata Mukherjee • IIT Kanpur  
5th and 7th September 2024

← → ↻ <https://www.google.com/search?q=neural+network+for+solving+differential+equation+physics+arxiv>

neural network for solving differential equation physics arxiv

arXiv  
<https://arxiv.org> > hep-ph

**Solving differential equations with neural networks ...**  
by ML Piscopo · 2019 · Cited by 121 — We introduce a novel way of finding a numerical solution to wide classes of **differential equations**. We find our approach to be very flexible a...

arXiv  
<https://arxiv.org> > math-ph

**Invariant Physics-Informed Neural Networks for Ordinary ...**  
by S Arora · 2023 · Cited by 3 — In this paper we introduce invariant **physics-informed neural networks for ordinary differential equations** that admit a finite-dimensional group of Lie...

arXiv  
<https://arxiv.org> > physics

**[2403.00599] A hands-on introduction to Physics-Informed ...**  
by H Baty · 2024 — I provide an introduction to the application of **deep learning and neural networks for solving partial differential equations (PDEs)**.

arXiv  
<https://arxiv.org> > cs

**[2006.14372] Solving Differential Equations Using Neural ...**  
by C Flamant · 2020 · Cited by 37 — We propose that a **neural network** be used as a **solution bundle**, a collection of **solutions** to an **ODE** for various initial states and system parameters.

arXiv  
<https://arxiv.org> > cs

**Discovering Physics-Informed Neural Networks Model for ...**  
by B Zhang · 2024 — This article proposes an evolutionary computation method aimed at discovering the PINNs model with higher approximation accuracy and faster convergence rate.

# Solving DE using NN: an active research area

PINN: Physics-Informed  
Neural Networks

Applications to the calculation of  
cosmological phase transitions.  
*Phys. Rev. D 100, 016002 (2019)*

Laplace equation,  
Poisson equations,  
Helmholtz equations,  
Grad-Shafranov equations,  
etc

# Mini-batch gradient descent

What if  $m$  is VERY large? Eg: 5 or 10 Million.  
 $m$ =number of training example.

In that case, it's difficult to process all  $m$  examples together, instead do mini-batch gradient descent.

Split your large training set into several mini training sets (mini-batches).

Mini-batch size: what to choose?

Two extremes

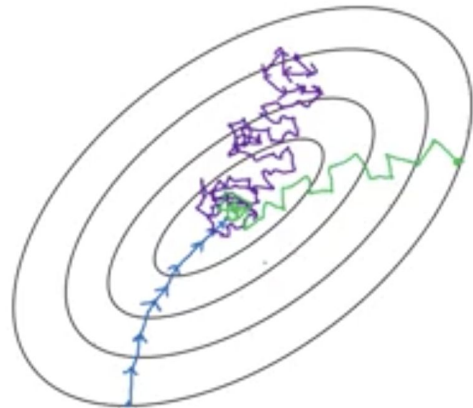
Mini-batch size:  $m \rightarrow$  Batch Gradient Descent

Mini-batch size: 1  $\rightarrow$  Stochastic Gradient Descent (very noisy)

In practise we use something in between.

Generally one can try mini-batch sizes of 64 or 128 or ..... 1024

The way computer memory is laid out and accessed, code may run faster if mini-batch size is  $2^x$



# Multi-class classification

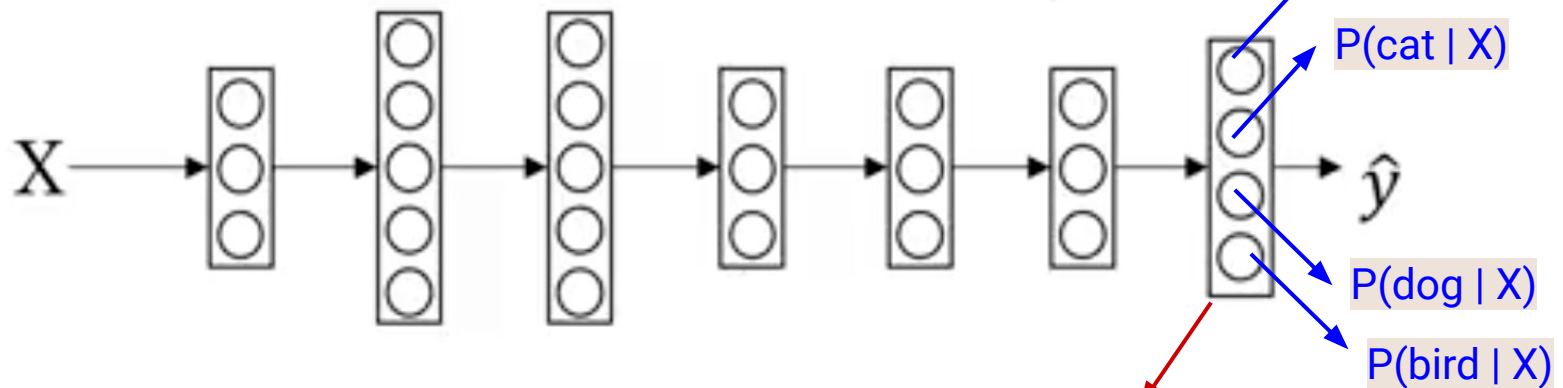
So far we discussed **binary** classification → cat (1) vs non-cat (0)

loss='binary\_crossentropy'

C = number of classes = 4

But we can have **multiple** classes → cat (1), dog (2), bird (3), other (0)

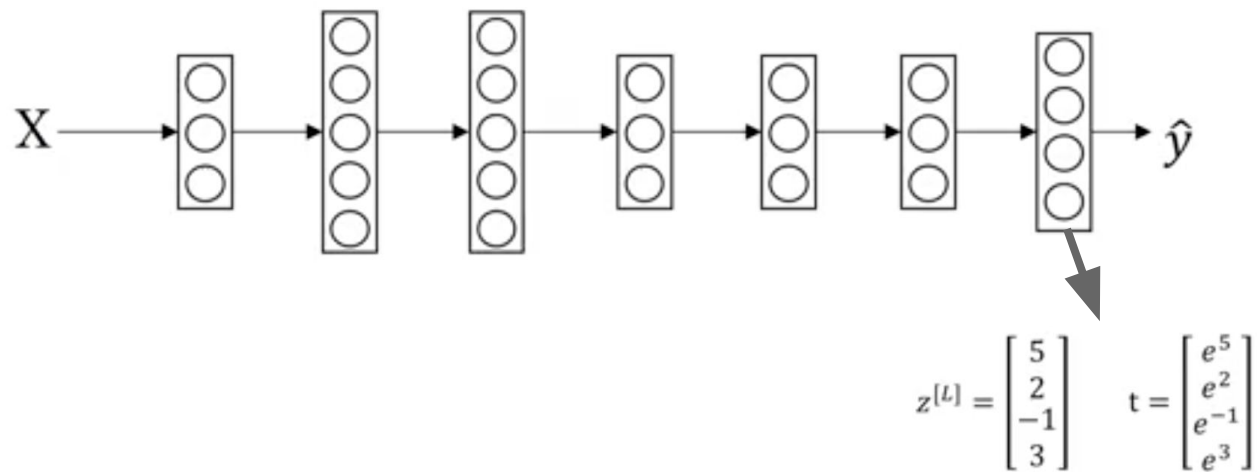
loss='categorical\_crossentropy'



Number of units in output layer = C = 4

$\hat{y}$  is (4,1) dimensional vector

# Softmax activation function



$$\mathbf{a}^{[l]} = g^{[l]}(z^{[l]}) = \begin{bmatrix} e^5 / (e^5 + e^2 + e^{-1} + e^3) \\ e^2 / (e^5 + e^2 + e^{-1} + e^3) \\ e^{-1} / (e^5 + e^2 + e^{-1} + e^3) \\ e^3 / (e^5 + e^2 + e^{-1} + e^3) \end{bmatrix} = \begin{bmatrix} 0.842 \\ 0.042 \\ 0.002 \\ 0.114 \end{bmatrix}$$

# Non-numerical data

```
[1] from sklearn.preprocessing import LabelEncoder
```

```
▶ colors = ['red', 'blue', 'green', 'red', 'green']  
  encoder = LabelEncoder()
```

```
  encoded_colors = encoder.fit_transform(colors)  
  print(encoded_colors)
```

```
⇒ [2 0 1 2 1]
```

Use label encoding to convert non-numerical data into numerical form.

# One-hot encoding

```
[10] import numpy as np
      y_real = np.array([0, 0, 1, 2, 2, 1, 1, 0, 1, 2])
      type(y_real)
```

```
↳ numpy.ndarray
```

```
[17] print (y_real)
```

```
↳ [0 0 1 2 2 1 1 0 1 2]
```

```
▶ encoder_y = OneHotEncoder(sparse_output=False)
  y_real_oh = encoder_y.fit_transform(y_real.reshape(-1,1))
```

```
▶ print (y_real_oh)
```


```
↳ [[1. 0. 0.]
     [1. 0. 0.]
     [0. 1. 0.]
     [0. 0. 1.]
     [0. 0. 1.]
     [0. 1. 0.]
     [0. 1. 0.]
     [1. 0. 0.]
     [0. 1. 0.]
     [0. 0. 1.]]
```

Use one hot encoding to convert categorical or numerical variables into binary vectors.

# Feature normalization

```
[35] X =      ([200.9, 0.04],  
                [205.1, 0.01],  
                [223.2, 0.09],  
                [254.0, 0.10]  
                )  
  
from sklearn.preprocessing import StandardScaler  
sc = StandardScaler()  
X_normalized = sc.fit_transform(X)
```

```
 print (X_normalized)
```

```
 [[-0.95126609 -0.54433105]  
  [-0.75049636 -1.36082763]  
  [ 0.11472556  0.81649658]  
  [ 1.58703689  1.08866211]]
```

Use standard scaler to  
normalize features (X).



# Tensorflow and Keras

- TensorFlow is an open-source library for ML.
  - Offers high level of flexibility
  - You can define every aspect of your NN architecture and training process.
  - But flexibility comes at a cost. Sometimes, it can be challenging for beginners to grasp
- Keras is an open-source library for ML that runs on top of Tensorflow.
  - Keras is designed to be user-friendly
  - Excellent choice for newcomers to deep learning.

# Keras: example code

XOR Gate

[https://github.com/swagata87/IITKanpurPhy654/blob/main/XOR\\_NN\\_keras.ipynb](https://github.com/swagata87/IITKanpurPhy654/blob/main/XOR_NN_keras.ipynb)

Ising model

[https://github.com/swagata87/IITKanpurPhy654/blob/main/Ising\\_model.ipynb](https://github.com/swagata87/IITKanpurPhy654/blob/main/Ising_model.ipynb)

[About Keras](#)[Getting started](#)[Developer guides](#)[Keras 3 API documentation](#)[Models API](#)[Layers API](#)[Callbacks API](#)[Ops API](#)[Optimizers](#)[Metrics](#)[Losses](#)[Data loading](#)[Built-in small datasets](#)[MNIST digits classification dataset](#)[CIFAR10 small images classification dataset](#)[CIFAR100 small images classification dataset](#)[IMDB movie review sentiment classification dataset](#)[Reuters newswire classification dataset](#)[Fashion MNIST dataset, an alternative to MNIST](#)[California Housing price regression dataset](#)[Keras 3 API documentation / Datasets](#)

## Datasets

The `keras.datasets` module provide a few toy datasets (already-vectorized, in Numpy format) that can be used for debugging a model or creating simple code examples.

If you are looking for larger & more useful ready-to-use datasets, take a look at [TensorFlow Datasets](#).

### Available datasets

#### MNIST digits classification dataset

- `load_data` function

#### CIFAR10 small images classification dataset

- `load_data` function

#### CIFAR100 small images classification dataset

- `load_data` function

#### IMDB movie review sentiment classification dataset

- `load_data` function
- `get_word_index` function

#### Reuters newswire classification dataset

- `load_data` function
- `get_word_index` function

#### Fashion MNIST dataset, an alternative to MNIST

- `load_data` function

#### California Housing price regression dataset

- `load_data` function

### Datasets

#### ◆ Available datasets

[MNIST digits classification dataset](#)[CIFAR10 small images classification dataset](#)[CIFAR100 small images classification dataset](#)[IMDB movie review sentiment classification dataset](#)[Reuters newswire classification dataset](#)[Fashion MNIST dataset, an alternative to MNIST](#)[California Housing price regression dataset](#)

It is possible to use these dataset to practice your ML skills

# Multi-layer perceptron (MLP)

- Another name of Neural Net.
- Fully connected neurons with a nonlinear activation function.

# CNN

Convolutional Neural Network (ConvNet)

CNN takes (mainly) images as input

We can train a usual DNN on images as well.

But, number of features become huge. As a result, number of weights is also huge.

Difficult to train even for a small image size.

Need to exploit spatial proximity of features.

# Convolution (example of 2D image, aka grayscale image)

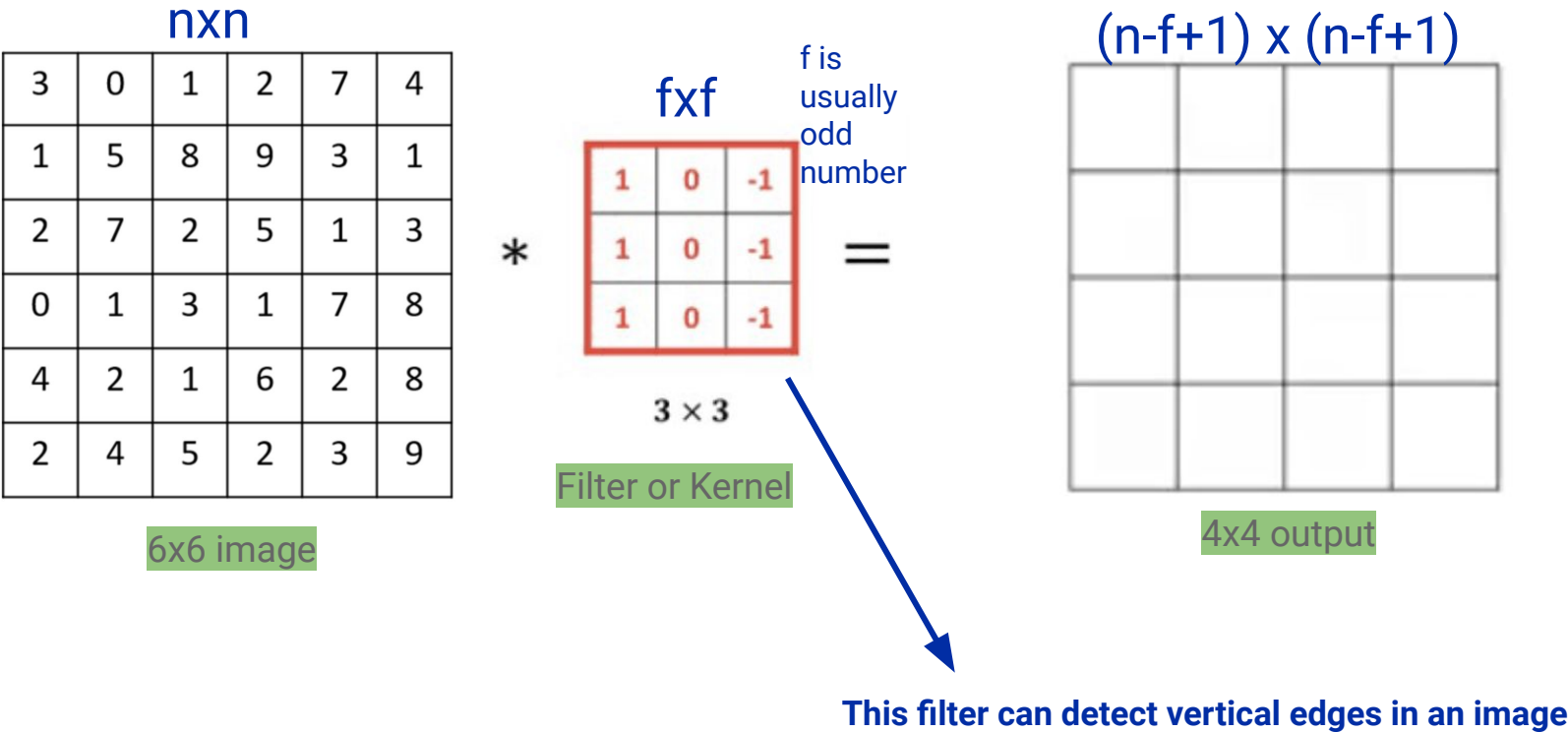
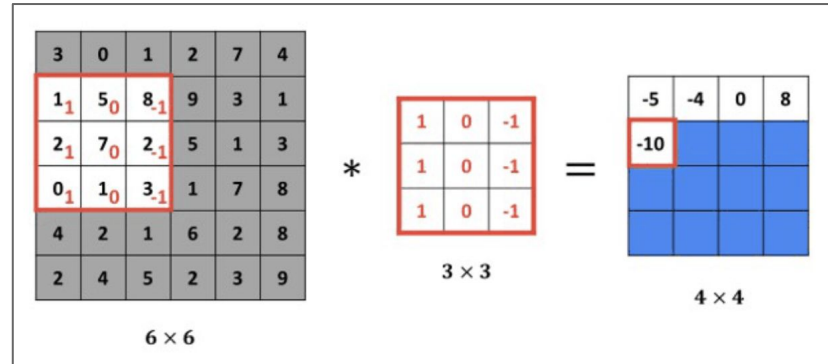
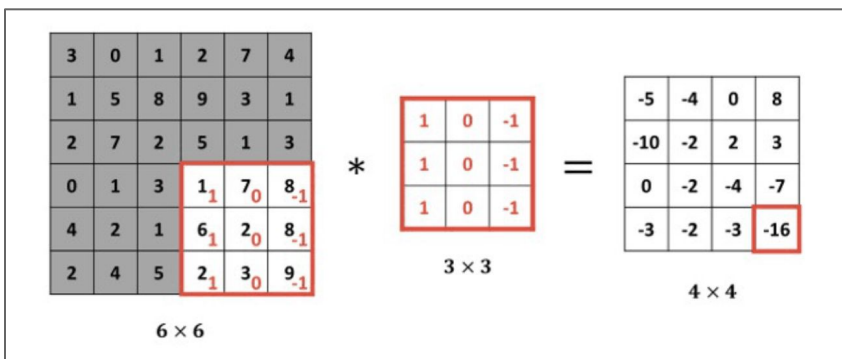
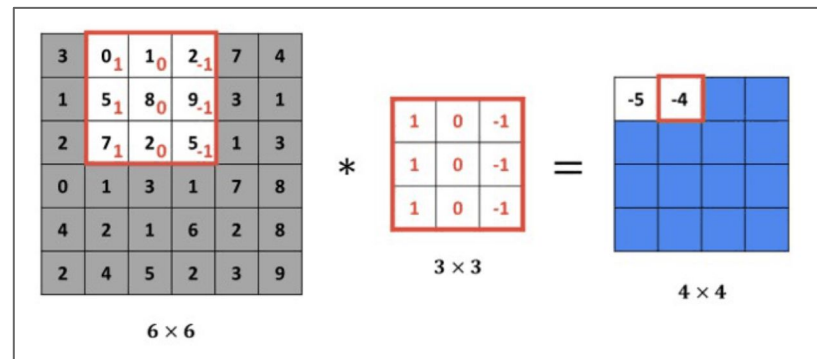
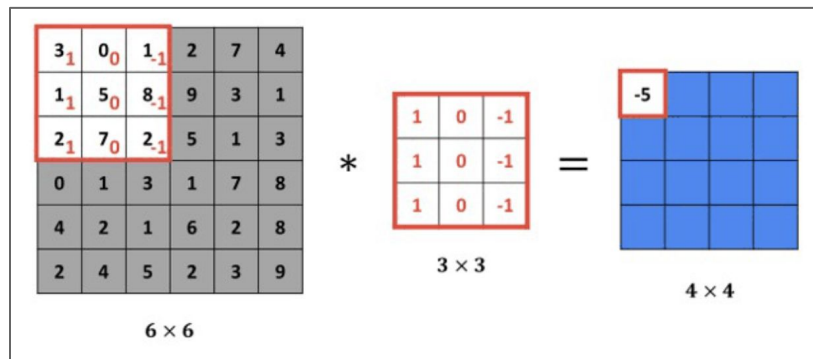


Image shrinks →

# Convolution



A convolution operation converts all the pixels in its receptive field into a single value.

If you apply a convolution to an image, generally you will be decreasing the image size and bringing all the information in the receptive field together into a single pixel.



# Vertical edge detector

2D image / grayscale

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

6 x 6

1	0	-1
1	0	-1
1	0	-1




3 x 3

\*

-0	30	30	0
0	30	30	0
0	30	30	0
0	30	30	0

4 x 4

=

0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10

6 x 6

1	0	-1
1	0	-1
1	0	-1

3 x 3

\*

0	-30	-30	0
0	-30	-30	0
0	-30	-30	0
0	-30	-30	0

4 x 4

=

