

# poisson\_1d

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## 1 Modelling poisson using PINN

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Written as part of FlowNet package, a TensorFlow based neural network package to solve fluid flow PDEs.

Solving the poisson equation  $-\Delta u = f$  using a physics informed neural network

### 1.1 1D problem poisson problem

#### 1.1.1 Manufactured solution

We use  $u = 3\sin(4x)$  for  $x \in [-1, 1]$

#### 1.1.2 Importing packages

```
[665]: import numpy as np
import tensorflow as tf
from tensorflow import keras
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
```

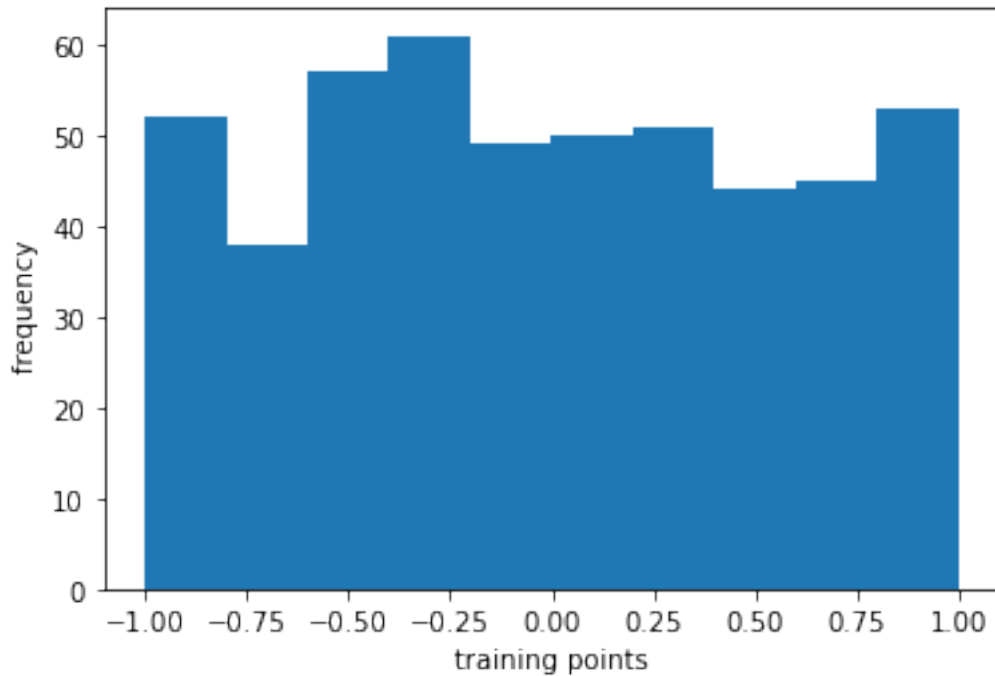
### 1.2 Manufacturing data for trainig

```
[666]: np.random.seed(123)
X_tr_pde = np.random.uniform(-1,1,500).reshape(500,1)
```

Plotting histogram of randomly selected points to make sure they are uniformly distributed

```
[609]: plt.hist(X_tr_pde)
plt.xlabel("training points")
plt.ylabel("frequency ")
```

```
[609]: Text(0, 0.5, 'frequency ')
```



```
[610]: Y_tr_pde = np.zeros((X_tr_pde.shape[0],1))
```

```
[611]: Y_tr_pde = np.concatenate([Y_tr_pde,np.zeros((Y_tr_pde.shape[0],1))],axis=1)
Y_tr_pde.shape
```

```
[611]: (500, 2)
```

```
[572]: X_tr_Dr_bc_left = -1*np.ones(200).reshape(200,1)
X_tr_Dr_bc_right = 1*np.ones(200).reshape(200,1)
X_bc = np.concatenate([X_tr_Dr_bc_left,X_tr_Dr_bc_right],axis=0)

Y_tr_bc = 3*np.sin(4*X_bc)
Y_tr_bc = np.concatenate([Y_tr_bc,np.ones((Y_tr_bc.shape[0],1))],axis=1)
```

### 1.2.1 Scaling the inputs(optional)

```
[612]: # from sklearn.preprocessing import StandardScaler

# scaler = StandardScaler()
# X_tr_pde = scaler.fit_transform(X_tr_pde)
```

```
[613]: X_tr = np.concatenate((X_tr_pde, X_bc), axis=0)
Y_tr = np.concatenate((Y_tr_pde, Y_tr_bc), axis=0)
```

```
[614]: # from sklearn.preprocessing import StandardScaler
```

```
# scaler = StandardScaler()
# X_tr = scaler.fit_transform(X_tr)
# X_tr.std()
```

```
[615]: (X_tr[0:3] +0.0056276)/4.520744138916567
```

```
[615]: array([[ 0.0881638 ],
          [-0.0933682 ],
          [-0.11959745]])
```

### 1.3 Defining the NN model (custom Keras model)

- **Model specifications:** 7 layers: 1 input layer, 3 hidden layers with 20 neurons each, 1 dense intermediate layer, 1 gradient layer, 1 laplacian layer, 1 pde layer.
- Output is a list of two elements: value of function and value of the pde operator.
- mean squared error is used for finding the cost function.
- Specialized, sgd( stochastic gradient descent) type optimizer is used: either nadam or adam.
- tanh activation functions are used.

```
[623]: from tensorflow.keras import backend as K
class Poisson1d(tf.keras.Model):

    def __init__(self):
        super(Poisson1d, self).__init__()
#         self.batch_norm = keras.layers.BatchNormalization()
        self.flatten_input = keras.layers.Flatten()

        he_kernel_init = keras.initializers.he_uniform()

        self.dense_1 = keras.layers.Dense(20, activation="tanh",
                                           kernel_initializer=he_kernel_init,
                                           name="dense_1")
        self.dense_2 = keras.layers.Dense(20, activation="tanh",
                                           kernel_initializer=he_kernel_init,
                                           name="dense_2")
        self.dense_3 = keras.layers.Dense(20, activation="tanh",
                                           kernel_initializer=he_kernel_init,
                                           name="dense_3")
        self.dense_4 = keras.layers.Dense(1,
                                           name="dense_4")

    def findGrad(self,func,argm):
        return keras.layers.Lambda(lambda x: K.gradients(x[0],x[1])[0])_
→([func,argm])
```

```

def findPdeLayer(self, pde_lhs, input_arg):
    return keras.layers.Lambda(lambda z: z[0] + 48*tf.sin(4*z[1]))
→([pde_lhs, input_arg])

def call(self, inputs):
#     layer_0 = self.batch_norm_input(inputs)
    layer_0 = self.flatten_input(inputs)
#     layer_0_1 = self.batch_norm_input(layer_0)
    layer_1 = self.dense_1(layer_0)
#     layer_2_0 = self.batch_norm_input(layer_1)
    layer_2 = self.dense_2(layer_1)
#     layer_3_0 = self.batch_norm(layer_2)
    layer_3 = self.dense_3(layer_2)
    layer_4 = self.dense_4(layer_3)

    grad_layer = self.findGrad(layer_4, inputs)
    laplace_layer = self.findGrad(grad_layer, inputs)
    pde_layer = self.findPdeLayer(laplace_layer, inputs)

    return layer_4, pde_layer

```

### 1.3.1 Defining the loss functions

```

[628]: #Loss coming from the boundary terms
def u_loss(y_true, y_pred):
    y_true_act = y_true[:, :-1]
    at_boundary = tf.cast(y_true[:, -1:, :], bool)
    u_sq_error = (1/2)*tf.square(y_true_act-y_pred)
    return tf.where(at_boundary, u_sq_error, 0.)

#Loss coming from the PDE constrain
def pde_loss(y_true, y_pred):
    y_true_act = y_true[:, :-1]
    at_boundary = tf.cast(y_true[:, -1:, :], bool)
    #need to change this to just tf.square(y_pred) after pde constrain is added
→to grad_layer
#     pde_sq_error = (1/2)*tf.square(y_true_act-y_pred)
    pde_sq_error = (1/2)*tf.square(y_pred)
    return tf.where(at_boundary, 0., pde_sq_error)

```

### 1.3.2 Instantiating and compiling the poisson\_model

```

[633]: poisson_NN = Poisson1d()

```

```

[634]: poisson_NN.compile(loss=[u_loss, pde_loss], optimizer="adam")

```

```
[635]: poisson_NN.fit(x=X_tr, y=Y_tr, epochs=100)
```

```
Epoch 1/100
29/29 [=====] - 0s 8ms/step - loss: 259.7652 -
output_1_loss: 1.6987 - output_2_loss: 258.0666
Epoch 2/100
29/29 [=====] - 0s 8ms/step - loss: 199.6366 -
output_1_loss: 3.7078 - output_2_loss: 195.9288
Epoch 3/100
29/29 [=====] - 0s 4ms/step - loss: 167.5798 -
output_1_loss: 5.7012 - output_2_loss: 161.8786
Epoch 4/100
29/29 [=====] - 0s 6ms/step - loss: 147.2352 -
output_1_loss: 6.9477 - output_2_loss: 140.2874
Epoch 5/100
29/29 [=====] - 0s 6ms/step - loss: 127.5192 -
output_1_loss: 8.2436 - output_2_loss: 119.2756
Epoch 6/100
29/29 [=====] - 0s 7ms/step - loss: 107.6846 -
output_1_loss: 9.3374 - output_2_loss: 98.3473
Epoch 7/100
29/29 [=====] - 0s 7ms/step - loss: 94.4738 -
output_1_loss: 10.1162 - output_2_loss: 84.3576
Epoch 8/100
29/29 [=====] - 0s 6ms/step - loss: 82.4624 -
output_1_loss: 10.6387 - output_2_loss: 71.8237
Epoch 9/100
29/29 [=====] - 0s 3ms/step - loss: 69.6333 -
output_1_loss: 10.6447 - output_2_loss: 58.9887
Epoch 10/100
29/29 [=====] - 0s 4ms/step - loss: 55.9477 -
output_1_loss: 10.3795 - output_2_loss: 45.5682
Epoch 11/100
29/29 [=====] - 0s 9ms/step - loss: 42.3476 -
output_1_loss: 9.9878 - output_2_loss: 32.3598
Epoch 12/100
29/29 [=====] - 0s 8ms/step - loss: 29.1121 -
output_1_loss: 9.2851 - output_2_loss: 19.8270
Epoch 13/100
29/29 [=====] - 0s 8ms/step - loss: 19.3638 -
output_1_loss: 8.3920 - output_2_loss: 10.9718
Epoch 14/100
29/29 [=====] - 1s 19ms/step - loss: 14.4945 -
output_1_loss: 7.5555 - output_2_loss: 6.9389
Epoch 15/100
29/29 [=====] - 0s 8ms/step - loss: 12.6046 -
output_1_loss: 6.7571 - output_2_loss: 5.8475
```

Epoch 16/100  
29/29 [=====] - 0s 14ms/step - loss: 10.5798 -  
output\_1\_loss: 5.9927 - output\_2\_loss: 4.5870  
Epoch 17/100  
29/29 [=====] - 0s 6ms/step - loss: 9.1434 -  
output\_1\_loss: 5.2864 - output\_2\_loss: 3.8570  
Epoch 18/100  
29/29 [=====] - 0s 10ms/step - loss: 7.8388 -  
output\_1\_loss: 4.6431 - output\_2\_loss: 3.1957  
Epoch 19/100  
29/29 [=====] - 0s 7ms/step - loss: 6.9969 -  
output\_1\_loss: 4.1099 - output\_2\_loss: 2.8870  
Epoch 20/100  
29/29 [=====] - 0s 14ms/step - loss: 6.1960 -  
output\_1\_loss: 3.6754 - output\_2\_loss: 2.5206  
Epoch 21/100  
29/29 [=====] - 0s 9ms/step - loss: 5.5211 -  
output\_1\_loss: 3.2757 - output\_2\_loss: 2.2454  
Epoch 22/100  
29/29 [=====] - 0s 8ms/step - loss: 4.7912 -  
output\_1\_loss: 2.8491 - output\_2\_loss: 1.9420  
Epoch 23/100  
29/29 [=====] - 0s 8ms/step - loss: 4.2952 -  
output\_1\_loss: 2.4328 - output\_2\_loss: 1.8624  
Epoch 24/100  
29/29 [=====] - 0s 10ms/step - loss: 3.6080 -  
output\_1\_loss: 2.0475 - output\_2\_loss: 1.5605  
Epoch 25/100  
29/29 [=====] - 0s 12ms/step - loss: 2.9790 -  
output\_1\_loss: 1.7081 - output\_2\_loss: 1.2709  
Epoch 26/100  
29/29 [=====] - 1s 19ms/step - loss: 2.4628 -  
output\_1\_loss: 1.4023 - output\_2\_loss: 1.0605  
Epoch 27/100  
29/29 [=====] - 0s 11ms/step - loss: 2.0742 -  
output\_1\_loss: 1.1864 - output\_2\_loss: 0.8878  
Epoch 28/100  
29/29 [=====] - 0s 9ms/step - loss: 1.7676 -  
output\_1\_loss: 1.0167 - output\_2\_loss: 0.7509  
Epoch 29/100  
29/29 [=====] - 0s 9ms/step - loss: 1.5395 -  
output\_1\_loss: 0.8897 - output\_2\_loss: 0.6498  
Epoch 30/100  
29/29 [=====] - 0s 10ms/step - loss: 1.3731 -  
output\_1\_loss: 0.7909 - output\_2\_loss: 0.5822  
Epoch 31/100  
29/29 [=====] - 0s 8ms/step - loss: 1.2571 -  
output\_1\_loss: 0.7032 - output\_2\_loss: 0.5539

Epoch 32/100  
29/29 [=====] - 0s 8ms/step - loss: 1.0477 -  
output\_1\_loss: 0.6191 - output\_2\_loss: 0.4286  
Epoch 33/100  
29/29 [=====] - 0s 10ms/step - loss: 0.9775 -  
output\_1\_loss: 0.5610 - output\_2\_loss: 0.4165  
Epoch 34/100  
29/29 [=====] - 0s 6ms/step - loss: 0.8646 -  
output\_1\_loss: 0.5001 - output\_2\_loss: 0.3645  
Epoch 35/100  
29/29 [=====] - 0s 7ms/step - loss: 0.8120 -  
output\_1\_loss: 0.4500 - output\_2\_loss: 0.3620  
Epoch 36/100  
29/29 [=====] - 0s 9ms/step - loss: 0.7423 -  
output\_1\_loss: 0.4108 - output\_2\_loss: 0.3315  
Epoch 37/100  
29/29 [=====] - 0s 13ms/step - loss: 0.6386 -  
output\_1\_loss: 0.3692 - output\_2\_loss: 0.2693  
Epoch 38/100  
29/29 [=====] - 0s 17ms/step - loss: 0.5728 -  
output\_1\_loss: 0.3305 - output\_2\_loss: 0.2423  
Epoch 39/100  
29/29 [=====] - 0s 12ms/step - loss: 0.5022 -  
output\_1\_loss: 0.2914 - output\_2\_loss: 0.2108  
Epoch 40/100  
29/29 [=====] - 0s 8ms/step - loss: 0.4589 -  
output\_1\_loss: 0.2579 - output\_2\_loss: 0.2010  
Epoch 41/100  
29/29 [=====] - 0s 12ms/step - loss: 0.4043 -  
output\_1\_loss: 0.2306 - output\_2\_loss: 0.1737  
Epoch 42/100  
29/29 [=====] - 0s 8ms/step - loss: 0.3789 -  
output\_1\_loss: 0.2028 - output\_2\_loss: 0.1761  
Epoch 43/100  
29/29 [=====] - 0s 8ms/step - loss: 0.3445 -  
output\_1\_loss: 0.1821 - output\_2\_loss: 0.1624  
Epoch 44/100  
29/29 [=====] - 1s 20ms/step - loss: 0.3695 -  
output\_1\_loss: 0.1614 - output\_2\_loss: 0.2081  
Epoch 45/100  
29/29 [=====] - 0s 8ms/step - loss: 0.2772 -  
output\_1\_loss: 0.1431 - output\_2\_loss: 0.1341  
Epoch 46/100  
29/29 [=====] - 0s 8ms/step - loss: 0.2570 -  
output\_1\_loss: 0.1235 - output\_2\_loss: 0.1336  
Epoch 47/100  
29/29 [=====] - 0s 9ms/step - loss: 0.2372 -  
output\_1\_loss: 0.1082 - output\_2\_loss: 0.1290

Epoch 48/100  
29/29 [=====] - 0s 11ms/step - loss: 0.2071 -  
output\_1\_loss: 0.0952 - output\_2\_loss: 0.1119  
Epoch 49/100  
29/29 [=====] - 0s 16ms/step - loss: 0.1887 -  
output\_1\_loss: 0.0816 - output\_2\_loss: 0.1071  
Epoch 50/100  
29/29 [=====] - 0s 9ms/step - loss: 0.1826 -  
output\_1\_loss: 0.0705 - output\_2\_loss: 0.1121  
Epoch 51/100  
29/29 [=====] - 0s 8ms/step - loss: 0.1690 -  
output\_1\_loss: 0.0628 - output\_2\_loss: 0.1063  
Epoch 52/100  
29/29 [=====] - 0s 8ms/step - loss: 0.1603 -  
output\_1\_loss: 0.0537 - output\_2\_loss: 0.1066  
Epoch 53/100  
29/29 [=====] - 0s 13ms/step - loss: 0.1697 -  
output\_1\_loss: 0.0455 - output\_2\_loss: 0.1243  
Epoch 54/100  
29/29 [=====] - 0s 12ms/step - loss: 0.1362 -  
output\_1\_loss: 0.0394 - output\_2\_loss: 0.0968  
Epoch 55/100  
29/29 [=====] - 0s 14ms/step - loss: 0.1200 -  
output\_1\_loss: 0.0342 - output\_2\_loss: 0.0857  
Epoch 56/100  
29/29 [=====] - 0s 9ms/step - loss: 0.1060 -  
output\_1\_loss: 0.0292 - output\_2\_loss: 0.0768  
Epoch 57/100  
29/29 [=====] - 0s 11ms/step - loss: 0.1285 -  
output\_1\_loss: 0.0248 - output\_2\_loss: 0.1037  
Epoch 58/100  
29/29 [=====] - 0s 10ms/step - loss: 0.0924 -  
output\_1\_loss: 0.0206 - output\_2\_loss: 0.0718  
Epoch 59/100  
29/29 [=====] - 0s 13ms/step - loss: 0.0891 -  
output\_1\_loss: 0.0174 - output\_2\_loss: 0.0717  
Epoch 60/100  
29/29 [=====] - 0s 5ms/step - loss: 0.0812 -  
output\_1\_loss: 0.0147 - output\_2\_loss: 0.0664  
Epoch 61/100  
29/29 [=====] - 0s 9ms/step - loss: 0.0689 -  
output\_1\_loss: 0.0127 - output\_2\_loss: 0.0562  
Epoch 62/100  
29/29 [=====] - 0s 5ms/step - loss: 0.0796 -  
output\_1\_loss: 0.0104 - output\_2\_loss: 0.0691  
Epoch 63/100  
29/29 [=====] - 0s 10ms/step - loss: 0.0631 -  
output\_1\_loss: 0.0085 - output\_2\_loss: 0.0546



Epoch 64/100  
29/29 [=====] - 0s 6ms/step - loss: 0.0613 -  
output\_1\_loss: 0.0069 - output\_2\_loss: 0.0544  
Epoch 65/100  
29/29 [=====] - 0s 8ms/step - loss: 0.0605 -  
output\_1\_loss: 0.0054 - output\_2\_loss: 0.0551  
Epoch 66/100  
29/29 [=====] - 0s 5ms/step - loss: 0.0541 -  
output\_1\_loss: 0.0045 - output\_2\_loss: 0.0496  
Epoch 67/100  
29/29 [=====] - 0s 14ms/step - loss: 0.0599 -  
output\_1\_loss: 0.0035 - output\_2\_loss: 0.0564  
Epoch 68/100  
29/29 [=====] - 0s 6ms/step - loss: 0.0621 -  
output\_1\_loss: 0.0029 - output\_2\_loss: 0.0592  
Epoch 69/100  
29/29 [=====] - 0s 12ms/step - loss: 0.0662 -  
output\_1\_loss: 0.0025 - output\_2\_loss: 0.0637  
Epoch 70/100  
29/29 [=====] - 0s 9ms/step - loss: 0.0576 -  
output\_1\_loss: 0.0017 - output\_2\_loss: 0.0559  
Epoch 71/100  
29/29 [=====] - 0s 6ms/step - loss: 0.0537 -  
output\_1\_loss: 0.0015 - output\_2\_loss: 0.0522  
Epoch 72/100  
29/29 [=====] - 0s 9ms/step - loss: 0.0597 -  
output\_1\_loss: 0.0011 - output\_2\_loss: 0.0586  
Epoch 73/100  
29/29 [=====] - 0s 10ms/step - loss: 0.0433 -  
output\_1\_loss: 8.0166e-04 - output\_2\_loss: 0.0425  
Epoch 74/100  
29/29 [=====] - 0s 13ms/step - loss: 0.0458 -  
output\_1\_loss: 5.7144e-04 - output\_2\_loss: 0.0452  
Epoch 75/100  
29/29 [=====] - 0s 9ms/step - loss: 0.0509 -  
output\_1\_loss: 3.3017e-04 - output\_2\_loss: 0.0506  
Epoch 76/100  
29/29 [=====] - 0s 16ms/step - loss: 0.0572 -  
output\_1\_loss: 4.1536e-04 - output\_2\_loss: 0.0568  
Epoch 77/100  
29/29 [=====] - 0s 11ms/step - loss: 0.0598 -  
output\_1\_loss: 2.8450e-04 - output\_2\_loss: 0.0595  
Epoch 78/100  
29/29 [=====] - 0s 5ms/step - loss: 0.0454 -  
output\_1\_loss: 1.8232e-04 - output\_2\_loss: 0.0453  
Epoch 79/100  
29/29 [=====] - 0s 6ms/step - loss: 0.0440 -  
output\_1\_loss: 1.1054e-04 - output\_2\_loss: 0.0439

Epoch 80/100  
29/29 [=====] - 0s 9ms/step - loss: 0.0441 -  
output\_1\_loss: 1.1150e-04 - output\_2\_loss: 0.0440  
Epoch 81/100  
29/29 [=====] - 0s 11ms/step - loss: 0.0662 -  
output\_1\_loss: 2.7556e-04 - output\_2\_loss: 0.0659  
Epoch 82/100  
29/29 [=====] - 0s 8ms/step - loss: 0.0587 -  
output\_1\_loss: 1.0060e-04 - output\_2\_loss: 0.0586  
Epoch 83/100  
29/29 [=====] - 0s 9ms/step - loss: 0.0475 -  
output\_1\_loss: 1.2469e-04 - output\_2\_loss: 0.0474  
Epoch 84/100  
29/29 [=====] - 0s 12ms/step - loss: 0.0620 -  
output\_1\_loss: 1.9952e-04 - output\_2\_loss: 0.0618  
Epoch 85/100  
29/29 [=====] - 0s 7ms/step - loss: 0.0734 -  
output\_1\_loss: 2.8111e-04 - output\_2\_loss: 0.0731  
Epoch 86/100  
29/29 [=====] - 0s 9ms/step - loss: 0.0401 -  
output\_1\_loss: 9.4932e-05 - output\_2\_loss: 0.0400  
Epoch 87/100  
29/29 [=====] - 0s 10ms/step - loss: 0.0352 -  
output\_1\_loss: 1.5613e-04 - output\_2\_loss: 0.0350  
Epoch 88/100  
29/29 [=====] - 0s 7ms/step - loss: 0.0378 -  
output\_1\_loss: 2.0924e-04 - output\_2\_loss: 0.0376  
Epoch 89/100  
29/29 [=====] - 0s 7ms/step - loss: 0.0394 -  
output\_1\_loss: 2.8825e-04 - output\_2\_loss: 0.0391  
Epoch 90/100  
29/29 [=====] - 0s 8ms/step - loss: 0.0496 -  
output\_1\_loss: 3.8716e-04 - output\_2\_loss: 0.0492  
Epoch 91/100  
29/29 [=====] - 0s 7ms/step - loss: 0.0464 -  
output\_1\_loss: 3.6435e-04 - output\_2\_loss: 0.0460  
Epoch 92/100  
29/29 [=====] - 0s 7ms/step - loss: 0.0418 -  
output\_1\_loss: 3.4827e-04 - output\_2\_loss: 0.0415  
Epoch 93/100  
29/29 [=====] - 0s 7ms/step - loss: 0.0472 -  
output\_1\_loss: 4.5195e-04 - output\_2\_loss: 0.0467  
Epoch 94/100  
29/29 [=====] - 0s 10ms/step - loss: 0.0305 -  
output\_1\_loss: 4.2057e-04 - output\_2\_loss: 0.0301  
Epoch 95/100  
29/29 [=====] - 0s 7ms/step - loss: 0.0282 -  
output\_1\_loss: 4.6182e-04 - output\_2\_loss: 0.0278

```

Epoch 96/100
29/29 [=====] - 0s 10ms/step - loss: 0.0415 -
output_1_loss: 3.9756e-04 - output_2_loss: 0.0411
Epoch 97/100
29/29 [=====] - 0s 8ms/step - loss: 0.0256 -
output_1_loss: 4.7936e-04 - output_2_loss: 0.0251
Epoch 98/100
29/29 [=====] - 0s 15ms/step - loss: 0.0375 -
output_1_loss: 5.0414e-04 - output_2_loss: 0.0370
Epoch 99/100
29/29 [=====] - 0s 10ms/step - loss: 0.0350 -
output_1_loss: 4.9992e-04 - output_2_loss: 0.0345
Epoch 100/100
29/29 [=====] - 0s 11ms/step - loss: 0.0268 -
output_1_loss: 5.2197e-04 - output_2_loss: 0.0262

```

[635]: <tensorflow.python.keras.callbacks.History at 0x7f64b425cfa0>

## 1.4 Testing the trained network

[636]: `X_test_st = np.random.uniform(-1,1,100).reshape(100,1)`

### 1.4.1 Scaling the test set (only if the training data was scaled)

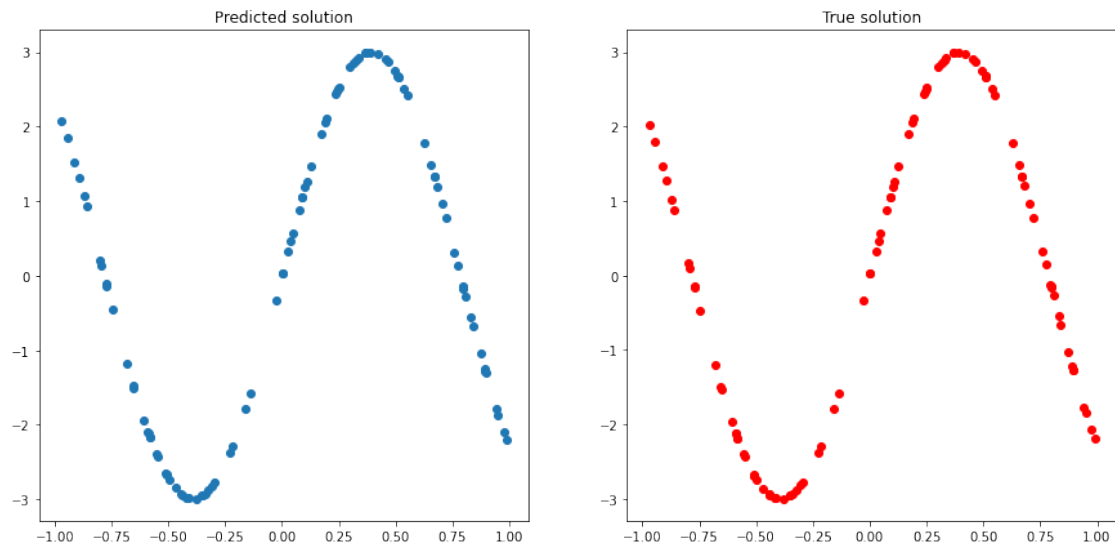
[637]: `# #Scaling test set`  
`# X_test_st_2 = scaler.transform(X_test_st)`  
`#xtrain: mean, std: -0.005627660222786496 4.520744138916567`

[638]: `Y_test = poisson_NN.predict(X_test_st)`

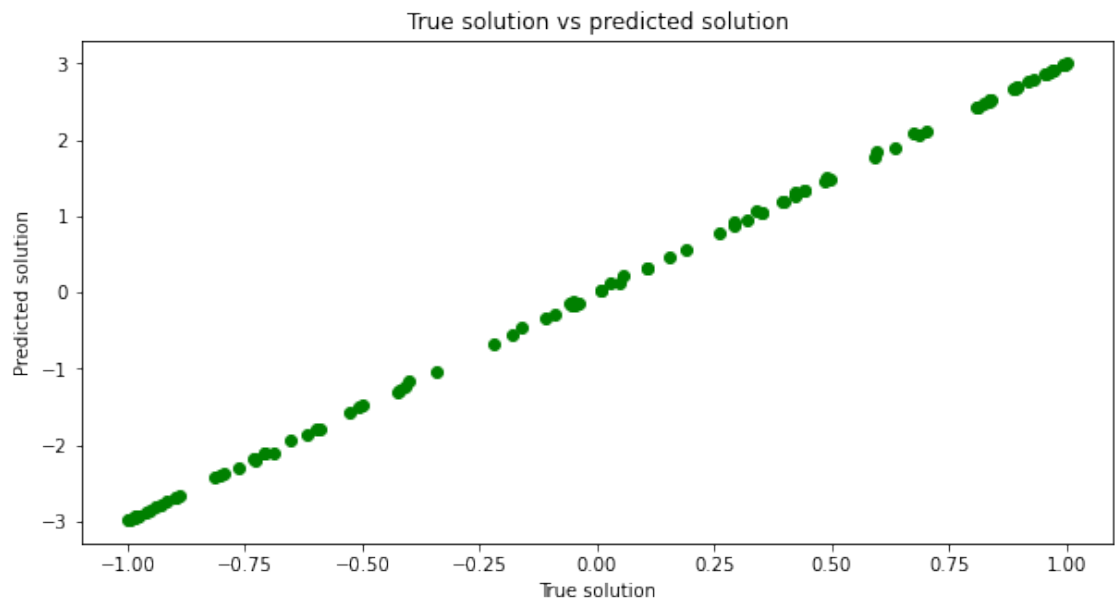
### 1.4.2 Plotting the true and predicted solutions

[662]: `# fig, ax = plt.subplots(nrows=2,ncols=2, figsize=(10,10))`  
`#plotting predicted solution`  
`plt.figure(figsize=(15,7))`  
`plt.subplot(1,2,1)`  
`plt.scatter(X_test_st, Y_test[0][:,0])`  
`plt.title("Predicted solution")`  
  
`plt.subplot(1,2,2)`  
`plt.scatter(X_test_st, 3*np.sin(4*X_test_st), c="r")`  
`plt.title("True solution")`

[662]: `Text(0.5, 1.0, 'True solution')`



```
[664]: #True vs predicted solution
plt.figure(figsize=(10,5))
plt.scatter(np.sin(4*X_test_st), Y_test[0][:,0], c="g")
plt.title("True solution vs predicted solution")
plt.xlabel("True solution")
plt.ylabel("Predicted solution")
plt.show()
```



### 1.4.3 Notes to be made

- For second order pde, some form of normalization is needed for convergence.
- If the the input data already comes normalized, there is no problem.
- If the data is not normalized, then we would want to some kind of normalization technique like batch normalization or normalization of incoming data.