NN_Jax_PDE7

June 21, 2022

1 Solving PDEs with Jax - Problem 7

1.1 Description

1.1.1 Average time of execution

Between 2 and 3 minutes on GPU

1.1.2 PDE

We will try to solve the problem 7 of the article https://ieeexplore.ieee.org/document/712178
$\Delta\psi(x, y) = f(x, y)$ on $\Omega = [0, 1]^2$
where $f(x, y) = (2 - \pi^2 y^2)\sin(\pi x)$

1.1.3 Boundary conditions

$\psi(0, y) = \psi(1, y) = \psi(x, 0) = 0$ and $\frac{\partial\psi}{\partial y}(x, 1) = 2\sin(\pi x)$

1.1.4 Loss function

The loss to minimize here is $\mathcal{L} = ||\Delta\psi(x, y) - f(x, y)||_2$

1.1.5 Analytical solution

The true function ψ should be $\psi(x, y) = y^2 sin(\pi x)$

1.1.6 Approximated solution

We want find a solution $\psi(x, y) = A(x, y) + F(x, y)N(x, y)$ s.t:
$F(x, y) = \sin(x - 1)\sin(y - 1)\sin(x)\sin(y)$
$A(x, y) = y\sin(\pi x)$

2 Importing libraries

[1]:
```
# Jax libraries
from jax import value_and_grad,vmap,jit,jacfwd
from functools import partial
from jax import random as jran
from jax.example_libraries import optimizers as jax_opt
from jax.nn import tanh
```

```
from jax.lib import xla_bridge
import jax.numpy as jnp

# Others libraries
from time import time
import matplotlib.pyplot as plt
import numpy as np
import os
import pickle
print(xla_bridge.get_backend().platform)
```

gpu

3 Multilayer Perceptron

[2]:
```
class MLP:
    """
        Create a multilayer perceptron and initialize the neural network
    Inputs :
        A SEED number and the layers structure
    """

    # Class initialization
    def __init__(self,SEED,layers):
        self.key=jran.PRNGKey(SEED)
        self.keys = jran.split(self.key,len(layers))
        self.layers=layers
        self.params = []

    # Initialize the MLP weigths and bias
    def MLP_create(self):
        for layer in range(0, len(self.layers)-1):
            in_size,out_size=self.layers[layer], self.layers[layer+1]
            std_dev = jnp.sqrt(2/(in_size + out_size ))
            weights=jran.truncated_normal(self.keys[layer], -2, 2,␣
↪shape=(out_size, in_size), dtype=np.float32)*std_dev
            bias=jran.truncated_normal(self.keys[layer], -1, 1, shape=(out_size,␣
↪1), dtype=np.float32).reshape((out_size,))
            self.params.append((weights,bias))
        return self.params

    # Evaluate a position XY using the neural network
    @partial(jit, static_argnums=(0,))
    def NN_evaluation(self,new_params, inputs):
        for layer in range(0, len(new_params)-1):
            weights, bias = new_params[layer]
```

```
            inputs = tanh(jnp.add(jnp.dot(inputs, weights.T), bias))
        weights, bias = new_params[-1]
        output = jnp.dot(inputs, weights.T)+bias
        return output

    # Get the key associated with the neural network
    def get_key(self):
        return self.key
```

4 Two dimensional PDE operators

[3]:
```
class PDE_operators2d:
    """
        Class with the most common operators used to solve PDEs
    Input:
        A function that we want to compute the respective operator
    """

    # Class initialization
    def __init__(self,function):
        self.function=function

    # Compute the two dimensional laplacian
    def laplacian_2d(self,params,inputs):
        fun = lambda params,x,y: self.function(params, x,y)
        @partial(jit)
        def action(params,x,y):
            u_xx = jacfwd(jacfwd(fun, 1), 1)(params,x,y)
            u_yy = jacfwd(jacfwd(fun, 2), 2)(params,x,y)
            return u_xx + u_yy
        vec_fun = vmap(action, in_axes = (None, 0, 0))
        laplacian = vec_fun(params, inputs[:,0], inputs[:,1])
        return laplacian

    # Compute the partial derivative in x
    @partial(jit, static_argnums=(0,))
    def du_dx(self,params,inputs):
        fun = lambda params,x,y: self.function(params, x,y)
        @partial(jit)
        def action(params,x,y):
            u_x = jacfwd(fun, 1)(params,x,y)
            return u_x
        vec_fun = vmap(action, in_axes = (None, 0, 0))
        return vec_fun(params, inputs[:,0], inputs[:,1])

    # Compute the partial derivative in y
```

```python
    @partial(jit, static_argnums=(0,))
    def du_dy(self,params,inputs):
        fun = lambda params,x,y: self.function(params, x,y)
        @partial(jit)
        def action(params,x,y):
            u_y = jacfwd(fun, 2)(params,x,y)
            return u_y
        vec_fun = vmap(action, in_axes = (None, 0, 0))
        return vec_fun(params, inputs[:,0], inputs[:,1])
```

5 Physics Informed Neural Networks

[4]:
```python
class PINN:
    """
    Solve a PDE using Physics Informed Neural Networks
    Input:
        The evaluation function of the neural network
    """

    # Class initialization
    def __init__(self,NN_evaluation):
        self.operators=PDE_operators2d(self.solution)
        self.laplacian=self.operators.laplacian_2d
        self.NN_evaluation=NN_evaluation

    # Definition of the function A(x,y) mentioned above
    @partial(jit, static_argnums=(0,))
    def A_function(self,inputX,inputY):
        return jnp.multiply(inputY,jnp.sin(jnp.pi*inputX)).reshape(-1,1)

    # Definition of the function F(x,y) mentioned above
    @partial(jit, static_argnums=(0,))
    def F_function(self,inputX,inputY):
        F1=jnp.multiply(jnp.sin(inputX),jnp.sin(inputX-jnp.ones_like(inputX)))
        F2=jnp.multiply(jnp.sin(inputY),jnp.sin(inputY-jnp.ones_like(inputY)))
        return jnp.multiply(F1,F2).reshape((-1,1))

    # Definition of the function f(x,y) mentioned above
    @partial(jit, static_argnums=(0,))
    def target_function(self,inputs):
        return jnp.multiply(2-jnp.pi**2*inputs[:,1]**2,jnp.sin(jnp.pi*inputs[:
↪,0])).reshape(-1,1)

    # Compute the solution of the PDE on the points (x,y)
    @partial(jit, static_argnums=(0,))
    def solution(self,params,inputX,inputY):
```

```python
        inputs=jnp.column_stack((inputX,inputY))
        NN = vmap(partial(jit(self.NN_evaluation), params))(inputs)
        F=self.F_function(inputX,inputY)
        A=self.A_function(inputX,inputY)
        return jnp.add(jnp.multiply(F,NN),A).reshape(-1,1)

    # Compute the loss function
    @partial(jit, static_argnums=(0,))
    def loss_function(self,params,batch):
        targets=self.target_function(batch)
        preds=self.laplacian(params,batch).reshape(-1,1)
        return jnp.linalg.norm(preds-targets)

    # Train step
    @partial(jit, static_argnums=(0,))
    def train_step(self,i, opt_state, inputs):
        params = get_params(opt_state)
        loss, gradient = value_and_grad(self.loss_function)(params,inputs)
        return loss, opt_update(i, gradient, opt_state)
```

6 Initialize neural network

[5]:
```python
# Neural network parameters
SEED = 351
n_features, n_targets = 2, 1            # Input and output dimension
layers = [n_features,30,30,n_targets]   # Layers structure

# Initialization
NN_MLP=MLP(SEED,layers)
params = NN_MLP.MLP_create()            # Create the MLP
NN_eval=NN_MLP.NN_evaluation            # Evaluate function
solver=PINN(NN_eval)
key=NN_MLP.get_key()
```

7 Train parameters

[6]:
```python
batch_size = 10000
num_batches = 5000
report_steps=100
loss_history = []
```

8 Adam optimizer

It's possible to continue the last training if we use options=1

[7]:
```
opt_init, opt_update, get_params = jax_opt.adam(0.001)

options=0
if options==0:  # Start a new training
    opt_state=opt_init(params)

else:           # Continue the last training
    # Load trained parameters for a NN with the layers [2,30,30,1]
    best_params = pickle.load(open("./NN_saves/NN_jax_params.pkl", "rb"))
    opt_state = jax_opt.pack_optimizer_state(best_params)
    params=get_params(opt_state)
```

9 Solving PDE

[8]:
```
# Main loop to solve the PDE
for ibatch in range(0,num_batches):
    ran_key, batch_key = jran.split(key)
    XY_train = jran.uniform(batch_key, shape=(batch_size, n_features), minval=0,␣
 ↪maxval=1)

    loss, opt_state = solver.train_step(ibatch,opt_state, XY_train)
    loss_history.append(float(loss))

    if ibatch%report_steps==report_steps-1:
        print("Epoch n°{}: ".format(ibatch+1), loss.item())
    if ibatch%5000==0:
        trained_params = jax_opt.unpack_optimizer_state(opt_state)
        pickle.dump(trained_params, open("./NN_saves/NN_jax_checkpoint.pkl",␣
 ↪"wb"))
```

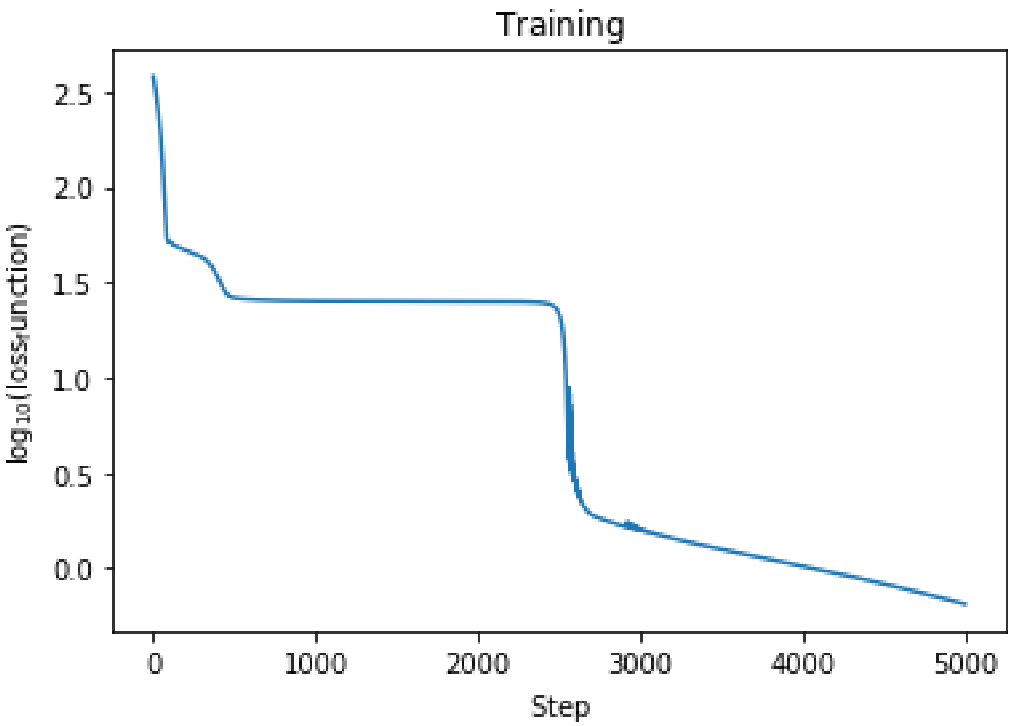
```
Epoch n°100:  51.512939453125
Epoch n°200:  46.51912307739258
Epoch n°300:  42.64119338989258
Epoch n°400:  33.17741394042969
Epoch n°500:  26.215749740600586
Epoch n°600:  25.726898193359375
Epoch n°700:  25.509136199951172
Epoch n°800:  25.38051414489746
Epoch n°900:  25.301254272460938
Epoch n°1000:  25.25128746032715
Epoch n°1100:  25.219179153442383
Epoch n°1200:  25.198118209838867
Epoch n°1300:  25.18391227722168
Epoch n°1400:  25.173906326293945
Epoch n°1500:  25.166357040405273
Epoch n°1600:  25.160057067871094
```

```
Epoch n°1700:  25.15407371520996
Epoch n°1800:  25.147520065307617
Epoch n°1900:  25.139297485351562
Epoch n°2000:  25.12759780883789
Epoch n°2100:  25.108728408813477
Epoch n°2200:  25.073389053344727
Epoch n°2300:  24.990821838378906
Epoch n°2400:  24.697917938232422
Epoch n°2500:  21.53030776977539
Epoch n°2600:  2.905454635620117
Epoch n°2700:  1.9075847864151
Epoch n°2800:  1.764595627784729
Epoch n°2900:  1.6564691066741943
Epoch n°3000:  1.5811333656311035
Epoch n°3100:  1.5079995393753052
Epoch n°3200:  1.4330010414123535
Epoch n°3300:  1.367269515991211
Epoch n°3400:  1.3085545301437378
Epoch n°3500:  1.2546205520629883
Epoch n°3600:  1.2040598392486572
Epoch n°3700:  1.1561177968978882
Epoch n°3800:  1.1100894212722778
Epoch n°3900:  1.0660297870635986
Epoch n°4000:  1.0234265327453613
Epoch n°4100:  0.9823218584060669
Epoch n°4200:  0.942297101020813
Epoch n°4300:  0.9031723737716675
Epoch n°4400:  0.8647996187210083
Epoch n°4500:  0.827095627784729
Epoch n°4600:  0.7899556159973145
Epoch n°4700:  0.753333330154419
Epoch n°4800:  0.7173778414726257
Epoch n°4900:  0.6819291710853577
Epoch n°5000:  0.6473612785339355
```

10 Plot loss function

[9]:
```
fig, ax = plt.subplots(1, 1)
__=ax.plot(np.log10(loss_history))
xlabel = ax.set_xlabel(r'${\rm Step}$')
ylabel = ax.set_ylabel(r'$\log_{10}{\rm (loss_function)}$')
title = ax.set_title(r'${\rm Training}$')
plt.show
```

[9]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```

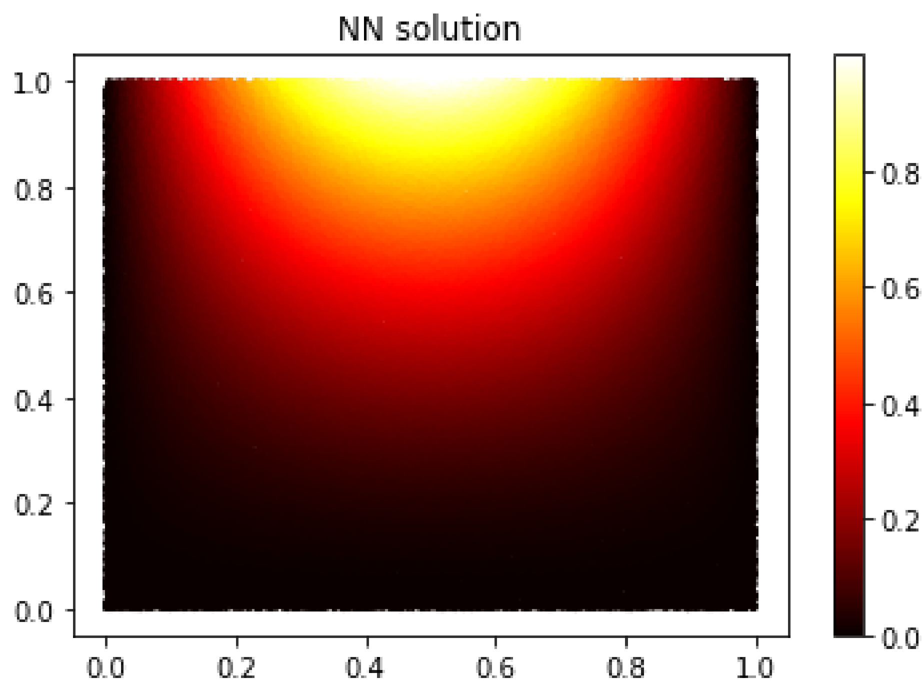


11 Approximated solution

We plot the solution obtained with our NN

[10]:
```
plt.figure()
params=get_params(opt_state)
n_points=100000
ran_key, batch_key = jran.split(key)
XY_test = jran.uniform(batch_key, shape=(n_points, n_features), minval=0,␣
 ↪maxval=1)

predictions = solver.solution(params,XY_test[:,0],XY_test[:,1])
plt.scatter(XY_test[:,0],XY_test[:,1], c=predictions, cmap="hot",s=2)
plt.clim(vmin=jnp.min(predictions),vmax=jnp.max(predictions))
plt.colorbar()
plt.title("NN solution")
plt.show()
```



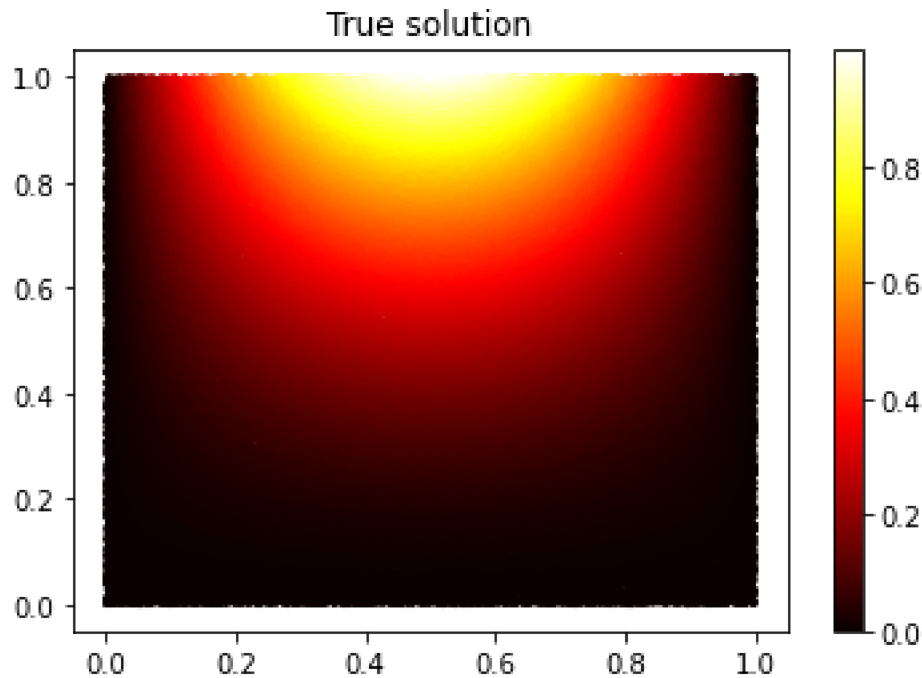
12 True solution

We plot the true solution, its form was mentioned above

[11]:
```
def true_solution(inputs):
    return jnp.multiply(inputs[:,1]**2,jnp.sin(jnp.pi*inputs[:,0]))

plt.figure()
n_points=100000
ran_key, batch_key = jran.split(key)
XY_train = jran.uniform(batch_key, shape=(n_points, n_features), minval=0,␣
 ↪maxval=1)

true_sol = true_solution(XY_test)
plt.scatter(XY_test[:,0],XY_test[:,1], c=true_sol, cmap="hot",s=2)
plt.clim(vmin=jnp.min(true_sol),vmax=jnp.max(true_sol))
plt.colorbar()
plt.title("True solution")
plt.show()
```



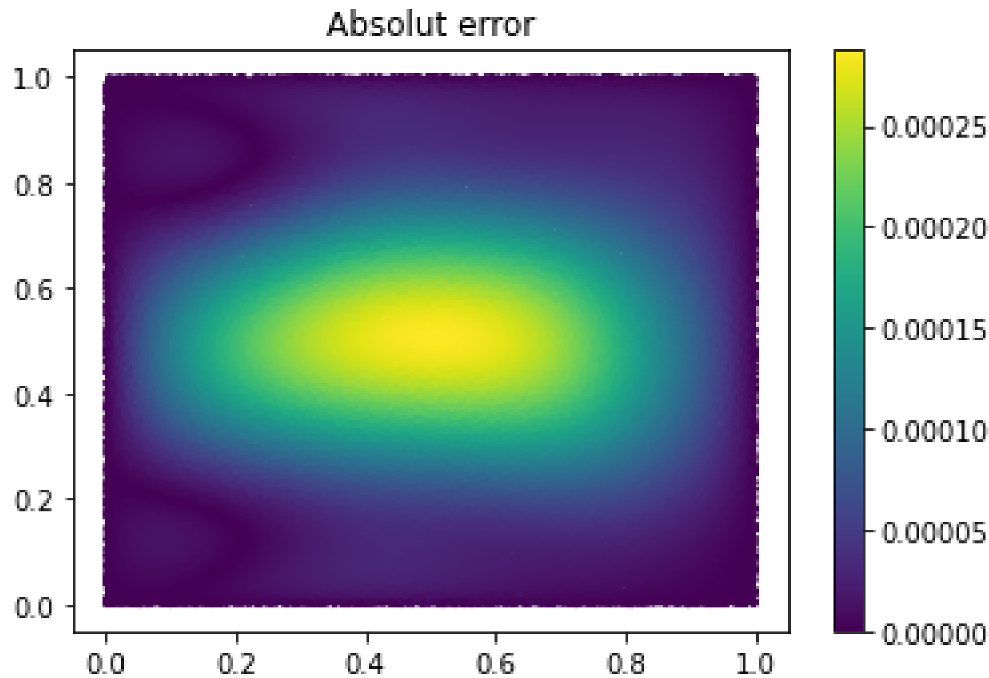
13 Absolut error

We plot the absolut error, it's |true solution - neural network output|

[12]:
```
plt.figure()
params=get_params(opt_state)
n_points=100000
ran_key, batch_key = jran.split(key)
XY_test = jran.uniform(batch_key, shape=(n_points, n_features), minval=0,␣
 ↪maxval=1)

predictions = solver.solution(params,XY_test[:,0],XY_test[:,1])[:,0]
true_sol = true_solution(XY_test)
error=abs(predictions-true_sol)

plt.scatter(XY_test[:,0],XY_test[:,1], c=error, cmap="viridis",s=2)
plt.clim(vmin=0,vmax=jnp.max(error))
plt.colorbar()
plt.title("Absolut error")
plt.show()
```



14 Save NN parameters

[13]:
```
trained_params = jax_opt.unpack_optimizer_state(opt_state)
pickle.dump(trained_params, open("./NN_saves/NN_jax_params.pkl", "wb"))
```