Zagatti_HW06

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1 Homework 06 - Sebastiano Zagatti

[1]:
```
!pip install torch
!pip install pyro-ppl

import pyro
import torch
import pyro.distributions as dist
import pyro.optim as optim
from pyro.infer import SVI, Trace_ELBO
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
from pyro.infer import Predictive
import torch.distributions.constraints as constraints
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: torch in /usr/local/lib/python3.7/dist-packages
(1.11.0+cu113)
Requirement already satisfied: typing-extensions in
/usr/local/lib/python3.7/dist-packages (from torch) (4.2.0)
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: pyro-ppl in /usr/local/lib/python3.7/dist-
packages (1.8.1)
Requirement already satisfied: opt-einsum>=2.3.2 in
/usr/local/lib/python3.7/dist-packages (from pyro-ppl) (3.3.0)
Requirement already satisfied: torch>=1.11.0 in /usr/local/lib/python3.7/dist-
packages (from pyro-ppl) (1.11.0+cu113)
Requirement already satisfied: tqdm>=4.36 in /usr/local/lib/python3.7/dist-
packages (from pyro-ppl) (4.64.0)
Requirement already satisfied: pyro-api>=0.1.1 in /usr/local/lib/python3.7/dist-
packages (from pyro-ppl) (0.1.2)
Requirement already satisfied: numpy>=1.7 in /usr/local/lib/python3.7/dist-
packages (from pyro-ppl) (1.21.6)
Requirement already satisfied: typing-extensions in
```

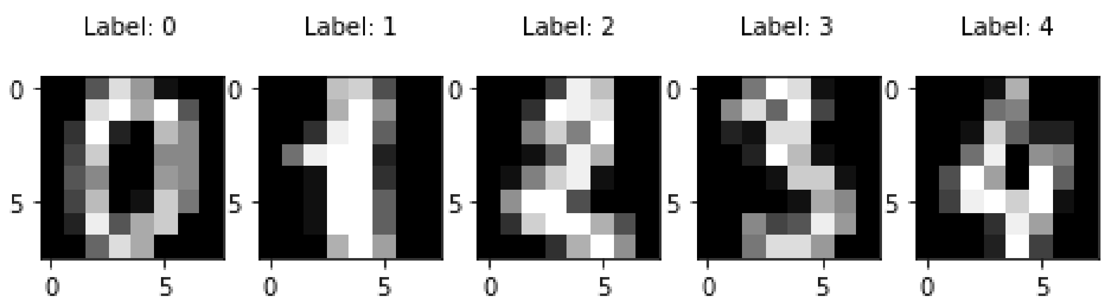
```
/usr/local/lib/python3.7/dist-packages (from torch>=1.11.0->pyro-ppl) (4.2.0)
```

[2]:
```python
import sklearn
from sklearn.datasets import load_digits
from sklearn.model_selection import train_test_split

dataset = load_digits()
x, y = dataset.data, dataset.target
print("predictors shape =", x.shape)
print("labels shape =", y.shape)
print("n. unique labels =", len(np.unique(y)))
```

```
predictors shape = (1797, 64)
labels shape = (1797,)
n. unique labels = 10
```

[3]:
```python
plt.figure(figsize=(8,3))
for index, (image, label) in enumerate(zip(x[0:5], y[0:5])):
 plt.subplot(1, 5, index + 1)
 plt.imshow(np.reshape(image, (8,8)), cmap=plt.cm.gray)
 plt.title('Label: %i\n' % label, fontsize = 10)
```



1. Normalize the matrix of predictors and perform a train/test split using `train_test_split` from `sklearn` library

[4]:
```python
df = pd.DataFrame(data = dataset['data'], columns = dataset['feature_names'])
df = (df-df.min())/(df.max()-df.min())
df = df.fillna(0)
df.head()
```

[4]:

	pixel_0_0	pixel_0_1	pixel_0_2	pixel_0_3	pixel_0_4	pixel_0_5	\
0	0.0	0.0	0.3125	0.8125	0.5625	0.0625	
1	0.0	0.0	0.0000	0.7500	0.8125	0.3125	
2	0.0	0.0	0.0000	0.2500	0.9375	0.7500	
3	0.0	0.0	0.4375	0.9375	0.8125	0.0625	
4	0.0	0.0	0.0000	0.0625	0.6875	0.0000	

```
   pixel_0_6  pixel_0_7  pixel_1_0  pixel_1_1  …  pixel_6_6  pixel_6_7  \
0        0.0        0.0        0.0        0.0  …     0.0000        0.0
1        0.0        0.0        0.0        0.0  …     0.0000        0.0
2        0.0        0.0        0.0        0.0  …     0.3125        0.0
3        0.0        0.0        0.0        0.5  …     0.5625        0.0
4        0.0        0.0        0.0        0.0  …     0.0000        0.0

   pixel_7_0  pixel_7_1  pixel_7_2  pixel_7_3  pixel_7_4  pixel_7_5  \
0        0.0        0.0     0.3750     0.8125     0.6250     0.0000
1        0.0        0.0     0.0000     0.6875     1.0000     0.6250
2        0.0        0.0     0.0000     0.1875     0.6875     1.0000
3        0.0        0.0     0.4375     0.8125     0.8125     0.5625
4        0.0        0.0     0.0000     0.1250     1.0000     0.2500

   pixel_7_6  pixel_7_7
0     0.0000        0.0
1     0.0000        0.0
2     0.5625        0.0
3     0.0000        0.0
4     0.0000        0.0

[5 rows x 64 columns]
```

[5]:
```python
features = torch.stack([torch.tensor(df[colname].values) for colname in df],␣
 ↪dim=1)

x_train, x_test, y_train, y_test = train_test_split(features, dataset.target,␣
 ↪test_size=0.2, random_state=1)

x_train = torch.tensor(x_train, dtype=torch.float)
x_test = torch.tensor(x_test.double(), dtype=torch.float)
y_train = torch.tensor(y_train, dtype=torch.float)
y_test = torch.tensor(y_test, dtype=torch.float)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:5: UserWarning: To
copy construct from a tensor, it is recommended to use
sourceTensor.clone().detach() or
sourceTensor.clone().detach().requires_grad_(True), rather than
torch.tensor(sourceTensor).
  """
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:6: UserWarning: To
copy construct from a tensor, it is recommended to use
sourceTensor.clone().detach() or
sourceTensor.clone().detach().requires_grad_(True), rather than
torch.tensor(sourceTensor).
```

[6]:
```
x_train.shape, x_test.shape, y_train.shape, y_test.shape
```

[6]:
```
(torch.Size([1437, 64]),
 torch.Size([360, 64]),
 torch.Size([1437]),
 torch.Size([360]))
```

2. Use pyro to write a multinomial bayesian logistic regression model. You should define both a `guide()` function and a `model()` function. Use a Categorical distribution on the outcomes to solve this multiclass classification problem.

[7]:
```
def model(x, y):
    n_observations, n_predictors = x.shape

    w = pyro.sample("w", dist.Normal(torch.zeros(n_predictors,10), torch.
 ↪ones(n_predictors,10)).to_event(2))
    b = pyro.sample("b", dist.Normal(torch.zeros(10), torch.ones(10)).
 ↪to_event(1))

    y_hat = torch.mm(x,w) + b

    sm = torch.softmax(y_hat, dim=-1)

    with pyro.plate("data", n_observations):
        y_final = pyro.sample("y_final", dist.Categorical(probs=sm), obs=y)

def guide(x, y):

    n_observations, n_predictors = x.shape

    w_loc = pyro.param("w_loc", torch.rand(n_predictors, 10))
    w_scale = pyro.param("w_scale", torch.rand(n_predictors,10),␣
 ↪constraint=constraints.positive)

    w = pyro.sample("w", dist.Normal(w_loc, w_scale).to_event(2))

    b_loc = pyro.param("b_loc", torch.rand(10))
    b_scale = pyro.param("b_scale", torch.rand(10), constraint=constraints.
 ↪positive)

    b = pyro.sample("b", dist.Normal(b_loc, b_scale).to_event(1))
```

3. Run SVI inference using pyro `Adam` optimizer and plot the ELBO loss using `matplotlib.plot` function

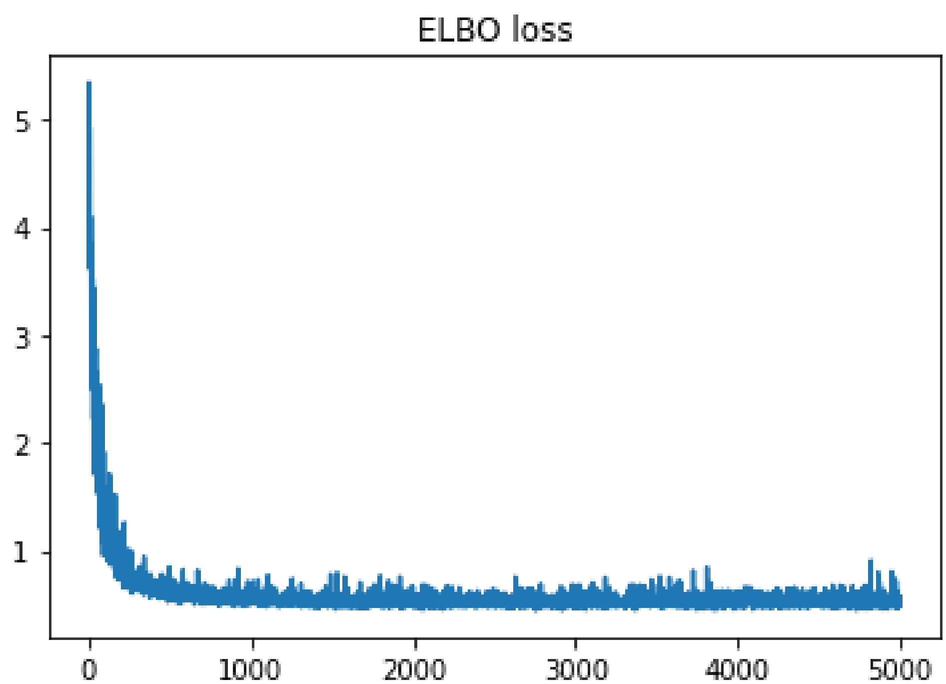
[8]:
```
svi = SVI(model = model, guide = guide, optim = pyro.optim.Adam({'lr': 0.02}),␣
 ↪loss = Trace_ELBO())
```

[9]:
```
losses = []
for step in range(5000):
  loss = svi.step(x_train, y_train)/len(x_train)
  losses.append(loss)
  if step % 1000 == 0:
    print(f"Step {step} : loss = {loss}")

plt.title("ELBO loss")
plt.plot(losses)
```

```
Step 0 : loss = 4.7879189708287635
Step 1000 : loss = 0.535164639612993
Step 2000 : loss = 0.5043414938176102
Step 3000 : loss = 0.4617081206958163
Step 4000 : loss = 0.4927929531142541
```

[9]:
```
[<matplotlib.lines.Line2D at 0x7f60e8439e10>]
```



4. Evaluate your model on the test data: compute the overall test accuracy and the class-wise accuracy for the 10 categories.

[10]:
```
inferred_w = pyro.get_param_store()["w_loc"]
inferred_b = pyro.get_param_store()["b_loc"]

reshaped_w = inferred_w.reshape(inferred_w.shape[0]*inferred_w.shape[1],1)
```

[11]:
```
def predict_class(x,w,b):
    n_observations, n_predictors = x.shape
    scores = torch.mm(x,w) + b.repeat(n_observations,1)
    probs = torch.softmax(scores, dim=-1)
    return torch.argmax(probs, dim=-1)
```

[12]:
```
import pandas as pd

correct_predictions = (predict_class(x_test,inferred_w,inferred_b) == y_test).
 ↪sum().item()
print(f"test accuracy = {correct_predictions/len(x_test)*100:.2f}%")

y_test_df = pd.DataFrame(y_test, columns=["Target"])

for i in range(10):
    y_test_i = y_test_df.loc[y_test_df.Target == i]
    indices_class_i = y_test_i.index
    correct_predictions_i = (predict_class(x_test[indices_class_i,:
 ↪],inferred_w,inferred_b) == y_test[indices_class_i]).sum().item()
    print(f"test accuracy over class {i} = {correct_predictions_i/
 ↪len(x_test[indices_class_i])*100:.2f}%")
```

```
test accuracy = 98.61%
test accuracy over class 0 = 97.67%
test accuracy over class 1 = 100.00%
test accuracy over class 2 = 100.00%
test accuracy over class 3 = 100.00%
test accuracy over class 4 = 100.00%
test accuracy over class 5 = 96.67%
test accuracy over class 6 = 100.00%
test accuracy over class 7 = 97.30%
test accuracy over class 8 = 96.55%
test accuracy over class 9 = 97.06%
```