Insurance cost prediction using PyTorch

August 11, 2021

[1]:
```python
import torch
import torchvision
import torch.nn as nn
import pandas as pd
import matplotlib.pyplot as plt
import torch.nn.functional as F
from torchvision.datasets.utils import download_url
from torch.utils.data import DataLoader, TensorDataset, random_split

#!conda install numpy pytorch torchvision cpuonly -c pytorch -y
```

[2]:
```python
#Step 1: Download and explore the data

DATA_FILENAME = "insurance.csv"
dataframe_raw = pd.read_csv(DATA_FILENAME)
dataframe_raw.head()

#We're going to do a slight customization of the data, so that you every␣
↪participant receives a slightly different version of the dataset. Fill in␣
↪your name below as a string (enter at least 5 characters)
```

[2]:

	age	sex	bmi	children	smoker	region	charges
0	19	female	27.900	0	yes	southwest	16884.92400
1	18	male	33.770	1	no	southeast	1725.55230
2	28	male	33.000	3	no	southeast	4449.46200
3	33	male	22.705	0	no	northwest	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520

[3]:
```python
your_name = "Todor" # at least 5 characters

#The customize_dataset function will customize the dataset slightly using your␣
↪name as a source of random numbers.
```

[4]:
```python
def customize_dataset(dataframe_raw, rand_str):
    dataframe = dataframe_raw.copy(deep=True)
    # drop some rows
```

```python
    dataframe = dataframe.sample(int(0.95*len(dataframe)),␣
↪random_state=int(ord(rand_str[0])))
    # scale input
    dataframe.bmi = dataframe.bmi * ord(rand_str[1])/100.
    # scale target
    dataframe.charges = dataframe.charges * ord(rand_str[2])/100.
    # drop column
    if ord(rand_str[3]) % 2 == 1:
        dataframe = dataframe.drop(['region'], axis=1)
    return dataframe
```

[5]:
```python
dataframe = customize_dataset(dataframe_raw, your_name)
dataframe.head()
```

[5]:

	age	sex	bmi	children	smoker	charges
647	40	female	25.9407	3	no	8252.28430
1272	43	male	28.3272	5	no	14478.33015
880	22	male	38.6280	3	no	3443.06400
957	24	male	29.7369	1	no	12609.88702
1209	59	male	41.1810	1	no	12347.17200

[6]:
```python
#Let us answer some basic questions about the dataset.
```

[7]:
```python
#Q: How many rows does the dataset have?

num_rows = dataframe.shape[0]
print(num_rows)
```

1271

[8]:
```python
#Q: How many columns doe the dataset have

num_cols = dataframe.shape[1]
print(num_cols)
```

6

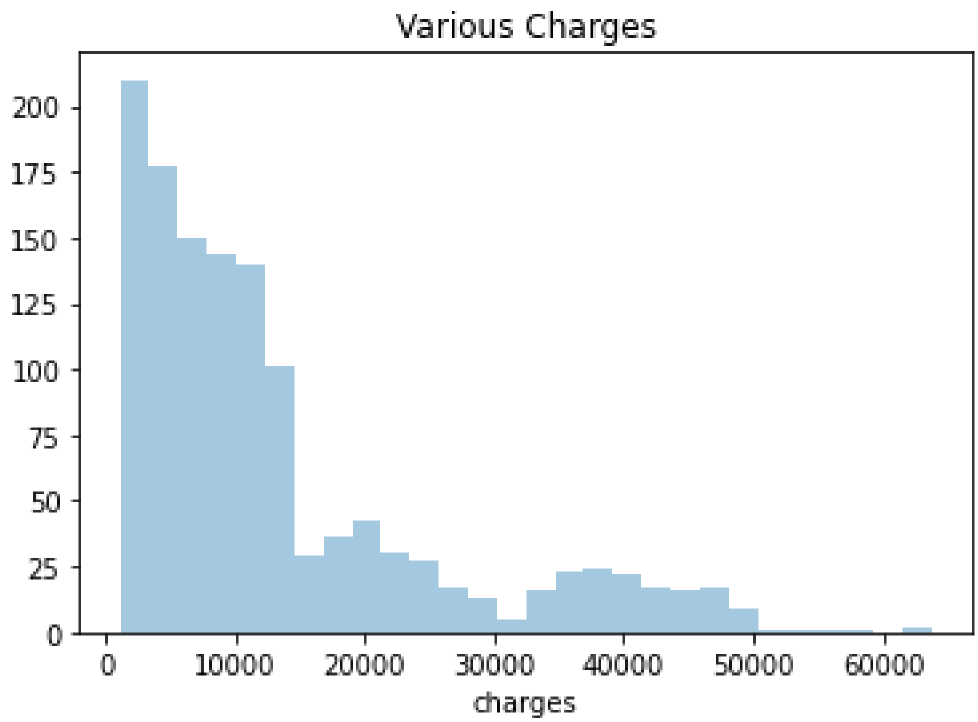
[9]:
```python
#Q: What are the column titles of the input variables? Hint: sex is one of them.
↪ List the columns that are not numbers.

input_cols = ['age', 'sex', 'bmi', 'children', 'smoker']

# a little fix of the code

input_cols = dataframe.columns[:5].tolist()
categorical_cols = dataframe.select_dtypes(exclude='number').columns.tolist()
```

[10]:
```python
#Q: What are the column titles of output/target variable(s)?

output_cols = ['charges']
```

[11]:
```python
print(dataframe['charges'].min())
print(dataframe['charges'].max())



import seaborn as sns

plt.title("Various Charges")
sns.distplot(dataframe.charges, kde=False);
```

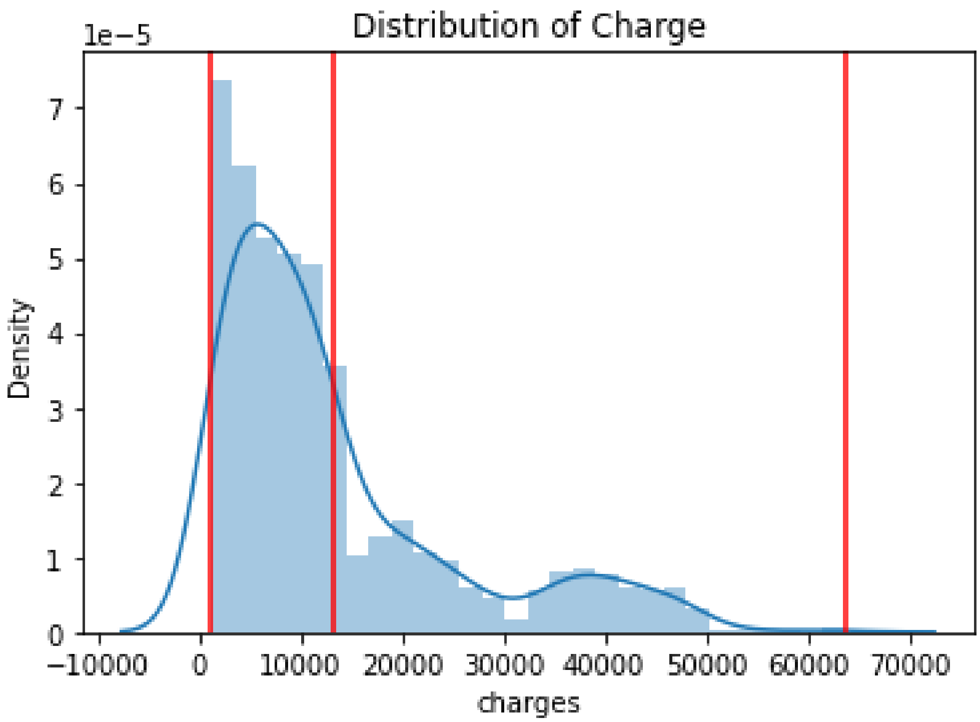
```
1121.8739
63770.42801
```

```
C:\ProgramData\Miniconda3\lib\site-packages\seaborn\distributions.py:2557:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```



[12]:
```
#Q: (Optional) What is the minimum, maximum and average value of the charges␣
↪column? Can you show the distribution of values in a graph? Use this data␣
↪visualization cheatsheet

plt.title("Distribution of Charge")

sns.distplot(dataframe.charges)
plt.axvline(x=dataframe['charges'].min(),color="red")
plt.axvline(x=dataframe['charges'].max(),color="red")
plt.axvline(x=dataframe['charges'].mean(),color="red")
```

[12]: <matplotlib.lines.Line2D at 0x2868c5720a0>



[13]:
```
#Step 2: Prepare the dataset for training
```

[14]:
```
#We need to convert the data from the Pandas dataframe into a PyTorch tensors␣
↪for training. To do this, the first step is to convert it numpy arrays. If␣
↪you've filled out input_cols, categorial_cols and output_cols correctly,␣
↪this following function will perform the conversion to numpy arrays.
```

[15]:
```
def dataframe_to_arrays(dataframe):
    # Make a copy of the original dataframe
    dataframe1 = dataframe.copy(deep=True)
```

```python
    # Convert non-numeric categorical columns to numbers
    for col in categorical_cols:
        dataframe1[col] = dataframe1[col].astype('category').cat.codes
    # Extract input & outupts as numpy arrays
    inputs_array = dataframe1[input_cols].to_numpy()
    targets_array = dataframe1[output_cols].to_numpy()
    return inputs_array, targets_array
```

[16]:
```python
#Read through the Pandas documentation to understand how we're converting␣
↪categorical variables into numbers.
```

[17]:
```python
inputs_array, targets_array = dataframe_to_arrays(dataframe)
inputs_array, targets_array
```

[17]:
```
(array([[40.    , 0.    , 25.9407, 3.    , 0.    ],
        [43.    , 1.    , 28.3272, 5.    , 0.    ],
        [22.    , 1.    , 38.628 , 3.    , 0.    ],
        …,
        [24.    , 1.    , 25.974 , 0.    , 0.    ],
        [39.    , 0.    , 46.398 , 0.    , 0.    ],
        [58.    , 1.    , 42.18  , 0.    , 0.    ]]),
 array([[ 8252.2843 ],
        [14478.33015],
        [ 3443.064  ],
        …,
        [ 1969.614  ],
        [ 5662.225  ],
        [11365.952  ]]))
```

[18]:
```python
#Q: Convert the numpy arrays inputs_array and targets_array into PyTorch␣
↪tensors. Make sure that the data type is torch.float32.

inputs = torch.from_numpy(inputs_array).type(torch.float32)
targets = torch.from_numpy(targets_array).type(torch.float32)
inputs, targets
```

[18]:
```
(tensor([[40.0000,  0.0000, 25.9407,  3.0000,  0.0000],
         [43.0000,  1.0000, 28.3272,  5.0000,  0.0000],
         [22.0000,  1.0000, 38.6280,  3.0000,  0.0000],
         …,
         [24.0000,  1.0000, 25.9740,  0.0000,  0.0000],
         [39.0000,  0.0000, 46.3980,  0.0000,  0.0000],
         [58.0000,  1.0000, 42.1800,  0.0000,  0.0000]]),
 tensor([[ 8252.2842],
         [14478.3301],
         [ 3443.0640],
         …,
```

```
          [ 1969.6140],
          [ 5662.2251],
          [11365.9521]]))
```

[19]:
```
inputs.dtype, targets.dtype
```

[19]:
```
(torch.float32, torch.float32)
```

[20]:
```
#Next, we need to create PyTorch datasets & data loaders for training &␣
↪validation. We'll start by creating a TensorDataset.
```

[21]:
```
dataset = TensorDataset(inputs, targets)
```

[22]:
```
#**Q: Pick a number between 0.1 and 0.2 to determine the fraction of data that␣
↪will be used for creating the validation set. Then use random_split to␣
↪create training & validation datasets. **
```

[23]:
```
val_percent = 0.18 # between 0.1 and 0.2
val_size = int(num_rows * val_percent)
train_size = num_rows - val_size


train_ds, val_ds = random_split(dataset, [train_size, val_size])
# Use the random_split function to split dataset into 2 parts of the desired␣
↪length

#Finally, we can create data loaders for training & validation.
```

[24]:
```
#Q: Pick a batch size for the data loader.
```

[25]:
```
batch_size = 25
```

[26]:
```
train_loader = DataLoader(train_ds, batch_size, shuffle=True)
val_loader = DataLoader(val_ds, batch_size)
```

[27]:
```
#Let's look at a batch of data to verify everything is working fine so far.
```

[28]:
```
for xb, yb in train_loader:
    print("inputs:", xb)
    print("targets:", yb)
    break
```

```
inputs: tensor([[46.0000,  1.0000, 44.8162,  2.0000,  0.0000],
        [27.0000,  1.0000, 36.1693,  3.0000,  0.0000],
        [21.0000,  1.0000, 32.1623,  0.0000,  0.0000],
        [24.0000,  0.0000, 26.8897,  0.0000,  0.0000],
        [31.0000,  1.0000, 29.8424,  1.0000,  0.0000],
```

```
        [19.0000,  1.0000, 33.9549,  0.0000,  0.0000],
        [27.0000,  1.0000, 33.8550,  0.0000,  0.0000],
        [35.0000,  1.0000, 27.1062,  3.0000,  1.0000],
        [21.0000,  1.0000, 30.3696,  0.0000,  0.0000],
        [19.0000,  0.0000, 30.9690,  0.0000,  1.0000],
        [22.0000,  0.0000, 25.7298,  0.0000,  0.0000],
        [48.0000,  0.0000, 35.8530,  2.0000,  0.0000],
        [52.0000,  0.0000, 34.1658,  1.0000,  0.0000],
        [18.0000,  0.0000, 32.3731,  0.0000,  0.0000],
        [44.0000,  0.0000, 40.4928,  0.0000,  0.0000],
        [40.0000,  0.0000, 33.0891,  1.0000,  0.0000],
        [45.0000,  1.0000, 26.9841,  5.0000,  0.0000],
        [45.0000,  1.0000, 44.1836,  0.0000,  0.0000],
        [31.0000,  0.0000, 36.2748,  1.0000,  0.0000],
        [26.0000,  0.0000, 25.0971,  0.0000,  0.0000],
        [62.0000,  0.0000, 43.5120,  0.0000,  0.0000],
        [50.0000,  1.0000, 29.3151,  0.0000,  0.0000],
        [18.0000,  0.0000, 33.6385,  0.0000,  0.0000],
        [56.0000,  1.0000, 35.2869,  2.0000,  1.0000],
        [51.0000,  0.0000, 40.3873,  3.0000,  0.0000]])
targets: tensor([[ 8733.2295],
        [ 4846.9199],
        [ 1906.3583],
        [ 2842.7607],
        [ 4441.2134],
        [ 1639.5631],
        [ 2494.0220],
        [19361.9980],
        [ 2104.1133],
        [16884.9238],
        [ 2731.9121],
        [10043.2490],
        [10797.3359],
        [ 7323.7349],
        [12797.2100],
        [ 6500.2358],
        [ 9788.8662],
        [ 7448.4038],
        [ 4738.2681],
        [ 3176.8159],
        [13470.8604],
        [ 8827.2100],
        [ 2203.7358],
        [43813.8672],
        [11436.7383]])
```

[29]:
```
#Step 3: Create a Linear Regression Model
```

[30]:
```
#Our model itself is a fairly straightforward linear regression (we'll build␣
↪more complex models in the next assignment).
```

[31]:
```
input_size = len(input_cols)
output_size = len(output_cols)
input_size, output_size
```

[31]:
```
(5, 1)
```

[32]:
```
#Q: Complete the class definition below by filling out the constructor␣
↪(__init__), forward, training_step and validation_step methods.

#Hint: Think carefully about picking a good loss fuction (it's not cross␣
↪entropy). Maybe try 2-3 of them and see which one works best. See https://
↪pytorch.org/docs/stable/nn.functional.html#loss-functions
```

[33]:
```
class InsuranceModel(nn.Module):
    def __init__(self):
        super().__init__()
        self.linear = nn.Linear(input_size, output_size) # fill this (hint: use␣
↪input_size & output_size defined above)

    def forward(self, xb):
        out = self.linear(xb)                          # fill this
        return out

    def training_step(self, batch):
        inputs, targets = batch
        # Generate predictions
        out = self(inputs)
        # Calcuate loss
        loss = F.l1_loss (out, targets)                          # fill this
        # mse_loss works best when the data is normalized. since this is␣
↪skewed, use l1_loss
        return loss

    def validation_step(self, batch):
        inputs, targets = batch
        # Generate predictions
        out = self(inputs)
        # Calculate loss
        loss = F.l1_loss (out, targets)                          # fill this  ␣
↪
        return {'val_loss': loss.detach()}

    def validation_epoch_end(self, outputs):
        batch_losses = [x['val_loss'] for x in outputs]
```

```
        epoch_loss = torch.stack(batch_losses).mean()   # Combine losses
        return {'val_loss': epoch_loss.item()}

    def epoch_end(self, epoch, result, num_epochs):
        # Print result every 20th epoch
        if (epoch+1) % 20 == 0 or epoch == num_epochs-1:
            print("Epoch [{}], val_loss: {:.4f}".format(epoch+1,␣
↪result['val_loss']))
```

[34]:
```
#Let us create a model using the InsuranceModel class. You may need to come␣
↪back later and re-run the next cell to reinitialize the model, in case the␣
↪loss becomes nan or infinity.
```

[35]:
```
model = InsuranceModel()
```

[36]:
```
#Let's check out the weights and biases of the model using model.parameters.
```

[37]:
```
list(model.parameters())
```

[37]:
```
[Parameter containing:
 tensor([[ 0.4234,  0.1851,  0.1789, -0.1294,  0.3414]], requires_grad=True),
 Parameter containing:
 tensor([-0.0034], requires_grad=True)]
```

[38]:
```
#Step 4: Train the model to fit the data
```

[39]:
```
#To train our model, we'll use the same fit function explained in the lecture.␣
↪That's the benefit of defining a generic training loop - you can use it for␣
↪any problem.
```

[40]:
```
def evaluate(model, val_loader):
    outputs = [model.validation_step(batch) for batch in val_loader]
    return model.validation_epoch_end(outputs)

def fit(epochs, lr, model, train_loader, val_loader, opt_func=torch.optim.SGD):
    history = []
    optimizer = opt_func(model.parameters(), lr)
    for epoch in range(epochs):
        # Training Phase
        for batch in train_loader:
            loss = model.training_step(batch)
            loss.backward()
            optimizer.step()
            optimizer.zero_grad()
        # Validation phase
        result = evaluate(model, val_loader)
        model.epoch_end(epoch, result, epochs)
```

```
        history.append(result)
    return history
```

[41]:
```
#Q: Use the evaluate function to calculate the loss on the validation set␣
↪before training.
```

[42]:
```
result = evaluate(model, val_loader) # Use the the evaluate function
print(result)
```

```
{'val_loss': 13696.3515625}
```

[43]:
```
#We are now ready to train the model. You may need to run the training loop␣
↪many times, for different number of epochs and with different learning␣
↪rates, to get a good result. Also, if your loss becomes too large (or nan),␣
↪you may have to re-initialize the model by running the cell model =␣
↪InsuranceModel(). Experiment with this for a while, and try to get to as low␣
↪a loss as possible.
```

[44]:
```
#Q: Train the model 4-5 times with different learning rates & for different␣
↪number of epochs.

#Hint: Vary learning rates by orders of 10 (e.g. 1e-2, 1e-3, 1e-4, 1e-5, 1e-6)␣
↪to figure out what works.
```

[45]:
```
epochs = 100
lr = 1e-1
history1 = fit(epochs, lr, model, train_loader, val_loader)
```

```
Epoch [20], val_loss: 7099.5327
Epoch [40], val_loss: 7091.5654
Epoch [60], val_loss: 7086.2061
Epoch [80], val_loss: 7074.0610
Epoch [100], val_loss: 7069.6069
```

[46]:
```
epochs = 40
lr = 1e-2
history2 = fit(epochs, lr, model, train_loader, val_loader)
```

```
Epoch [20], val_loss: 7063.9424
Epoch [40], val_loss: 7063.0249
```

[47]:
```
epochs = 50
lr = 1e-1
history3 = fit(epochs, lr, model, train_loader, val_loader)
```

```
Epoch [20], val_loss: 7054.9111
Epoch [40], val_loss: 7048.6455
Epoch [50], val_loss: 7047.9463
```

[48]:
```
epochs = 50
lr = 1e-2
history4 = fit(epochs, lr, model, train_loader, val_loader)
```

```
Epoch [20], val_loss: 7042.9736
Epoch [40], val_loss: 7042.3213
Epoch [50], val_loss: 7041.7905
```

[49]:
```
epochs = 50
lr = 1e-3
history5 = fit(epochs, lr, model, train_loader, val_loader)
```

```
Epoch [20], val_loss: 7041.7705
Epoch [40], val_loss: 7041.7827
Epoch [50], val_loss: 7041.7588
```

[50]:
```
#Q: What is the final validation loss of your model?
```

[51]:
```
val_loss = history5[-1]['val_loss']
val_loss
```

[51]: 7041.7587890625

[52]:
```
#Step 5: Make predictions using the trained model
```

[53]:
```
#Q: Complete the following function definition to make predictions on a single␣
↪input
```

[54]:
```
def predict_single(input, target, model):
    inputs = input.unsqueeze(0)
    predictions = model(inputs)                # fill this
    prediction = predictions[0].detach()
    print("Input:", input)
    print("Target:", target)
    print("Prediction:", prediction)
```

[55]:
```
input, target = val_ds[0]
predict_single(input, target, model)
```

```
Input: tensor([50.0000,  1.0000, 28.0830,  0.0000,  0.0000])
Target: tensor([8442.6670])
Prediction: tensor([10508.6836])
```

[56]:
```
input, target = val_ds[10]
predict_single(input, target, model)
```

```
Input: tensor([61.0000,  0.0000, 34.5876,  0.0000,  0.0000])
Target: tensor([13429.0352])
```

```
Prediction: tensor([12854.3486])
```

[57]:
```
input, target = val_ds[23]
predict_single(input, target, model)
```

```
Input: tensor([40.0000,  0.0000, 32.8560,  0.0000,  0.0000])
Target: tensor([5910.9438])
Prediction: tensor([7661.6782])
```