PyTorch Supplement

CSE354 - Spring 2021
Natural Language Processing

General Ingredients for Pytorch

1. The model (defined in an *nn.module* object)

2. The loss function

3. The training loop

General Ingredients for Pytorch

1. The model (defined in an *nn.module* object)

   maps X to y_pred

2. The loss function

   evaluates ypred versus y

3. The training loop

   runs the model and loss in loop with gradient descent.

1. The model

maps X *(features) to* ypred *(prediction of* y*)*

```
class LogReg(nn.Module):

    def __init__(self, num_feats, learn_rate = 0.01, device = torch.device("cpu") ):
        #the constructor; define any layer objects (e.g. Linear)
        super(LogReg, self).__init__()
        self.linear = nn.Linear(num_feats+1, 1) #add 1 to features for intercept

    def forward(self, X):
        #This is where the model itself is defined.
        #For binary logistic regression the model takes in X and returns
        #a probability (a value between 0 and 1)

        newX = torch.cat((X, torch.ones(X.shape[0], 1)), 1) #add intercept

        return 1/(1 + torch.exp(-self.linear(newX))) #log func on the linear output
```

1. The model

maps X *(features) to* ypred *(prediction of* y*)*

```
import torch
import torch.nn as nn
```

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"log loss" or *"normalized log loss":*

$$\boxed{J(\beta) = -\frac{1}{N}\sum_{i=1}^{N} y_i log\ p(x_i) + (1 - y_i) log\ (1 - p)(x_i)}$$

2. The loss function

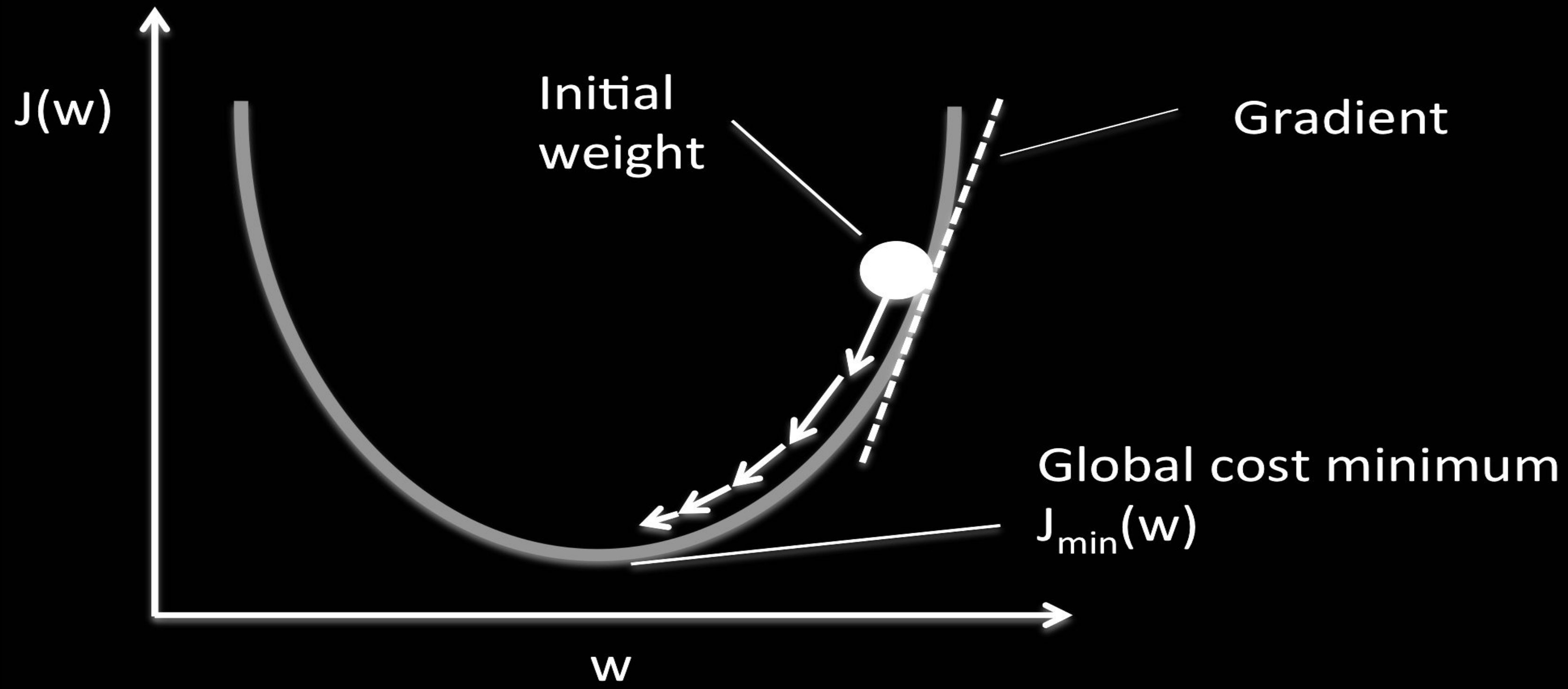
evaluates ypred *versus* y

```
#e.g.
def normalizedLogLoss(ypred, ytrue):
    ##Given:
    #  ypred - a vector (torch 1-d tensor) of predictions from the model.
    #          these are probabilities (values between 0 and 1)
    #  ytrue - a vector (torch 1-d tensor) of the true labels
    #Output:
    #  the logloss

    logloss = -1*torch.sum(ytrue*torch.log(ypred) + (1 - ytrue)*torch.log(1-ypred))
    N = ytrue.shape[0]
    normlogloss = (1/N)*logloss

    return normlogloss

    #alternative: return torch.nn.BCELoss(size_average=True)(ypred, ytrue)
```



(http://rasbt.github.io/mlxtend/user_guide/general_concepts/gradient-optimization/)

"log loss" or *"normalized log loss"*:

$$\boxed{J(\beta) = -\frac{1}{N}\sum_{i=1}^{N} y_i log\ p(x_i) + (1 - y_i) log\ (1 - p)(x_i)}$$

3. The training loop

runs the model and loss in loop with gradient descent.

```
#runs the training loop of pytorch model:
sgd = torch.optim.SGD(model.parameters(), lr=learning_rate) #gradient descent
loss_func = nn.CrossEntropyLoss() #includes log

#training loop:
for i in range(epochs):
    model.train() #tells pytorch we are training
    sgd.zero_grad() #sets the gradients to 0

    #forward pass:
    ypred = model(Xtrain)
    loss = loss_func(ypred, ytrain)

    #backward pass: runs gradient descent (or variant)
    loss.backward() #computes gradients
    sgd.step()      #updates parameters

    if i % 20 == 0:
        print("  epoch: %d, loss: %.5f" %(i, loss.item()))
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Easy!

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Easy!

```
ypred = model(X)
```

From binary logistic regression to multiclass softmax

Two updates

- Model (forward method)
- Loss function

Pytorch Specifics: Model

```
class LogReg(nn.Module):
    ...

    def forward(self, X):
        #This is where the model itself is defined.
        #For logistic regression the model takes in X and returns
        #the results of a decision function

        newX = torch.cat((X, torch.ones(X.shape[0], 1)), 1) #add intercept

        return 1/(1 + torch.exp(-self.linear(newX)))
                                  #logistic function on the linear output
```

Pytorch Specifics: Model

```
class MultiClassLogReg(nn.Module):
    def __init__(self, num_feats, num_classes,
                 learn_rate = 0.01, device = torch.device("cpu") ):
        #the constructor; define any layer objects (e.g. Linear)
        super(LogReg, self).__init__()
        self.linear = nn.Linear(num_feats+1, num_classes)

    def forward(self, X):
        #This is where the model itself is defined.
        #For logistic regression the model takes in X and returns
        #the results of a decision function

        newX = torch.cat((X, torch.ones(X.shape[0], 1)), 1) #add intercept

        #return 1/(1 + torch.exp(-self.linear(newX)))
                                          #logistic function on the linear output

        return self.linear(newX) #only use linear if using cross-entropy loss
```

Pytorch Specifics: loss

```
#runs the training loop of pytorch model:
sgd = torch.optim.SGD(model.parameters(), lr=learning_rate)
loss_func = nn.CrossEntropyLoss() #includes log


#training loop:
for i in range(epochs):
    model.train()
    sgd.zero_grad()
    #forward pass:
    ypred = model(X)
    loss = loss_func(ypred, y)
    #backward: /(applies gradient descent)
    loss.backward()
    sgd.step()

    if i % 20 == 0:
        print("  epoch: %d, loss: %.5f" %(i, loss.item()))
```

Two equivalent options for multi-class:

option 1 (what the previous slides covered)

```
#in model/forward:
        return self.linear(newX) #only use linear if using cross-entropy loss

#in loss/train:
        loss_func = nn.CrossEntropyLoss() #includes log softmax
                #alternative: nn.NLLLoss() #negative log likelikelihood loss
```

option 2

```
#in model/forward:
        return nn.log_softmax(self.linear(newX)) #log softmax is multiclass

#in loss/train:
        loss_func = nn.NLLLoss() #negative log likelikelihood loss
```