Machine Learning

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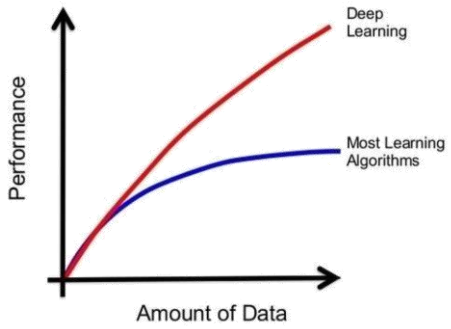
Agenda

- A quick recap of the last lecture
- PyTorch Components
  - Tensors
  - Autograd
  - Optimizers & Loss functions
  - Model
- PyTorch model training
- Saving model and Deployment
- Hands-on example
- Q & A

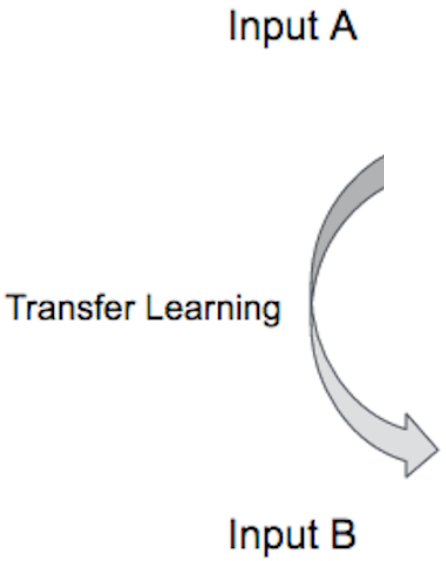
Recap

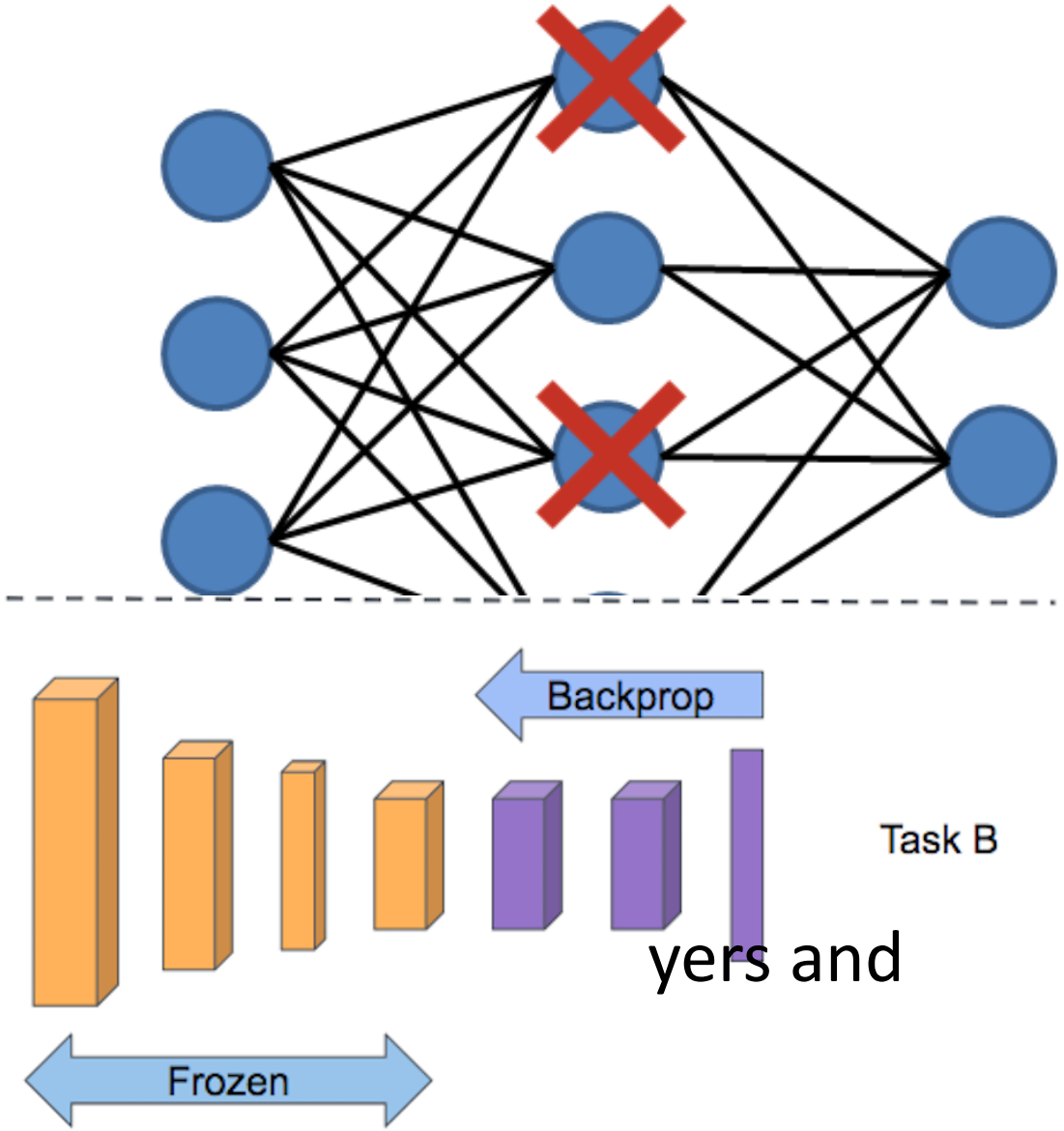
Data Augmentation



Why Deep Learning? Slide by Andrew Ng

- How machine lea
  scale with amoun
- So let's try to incr
  our DNN
- **NB**: Creating dupl
  overfitting
- Data augmentatic
  simple way that n
  of overfitting





yers and

rarely used after convolutional layers

Recap (2)

Early Stopping

- While training large capacity n
  loss will be steadily decreasing
  kind of U-shape curve decreas
- Stop the training at
  the lowest validation
  loss point

Batch normalization (2)

Must read Resource

- Standardizes the input mini-batch before being fed to the next layer
- For inferencing Exponential Moving Average of the mean and variance are calculated
- ! and " are learned parameters

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β
Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

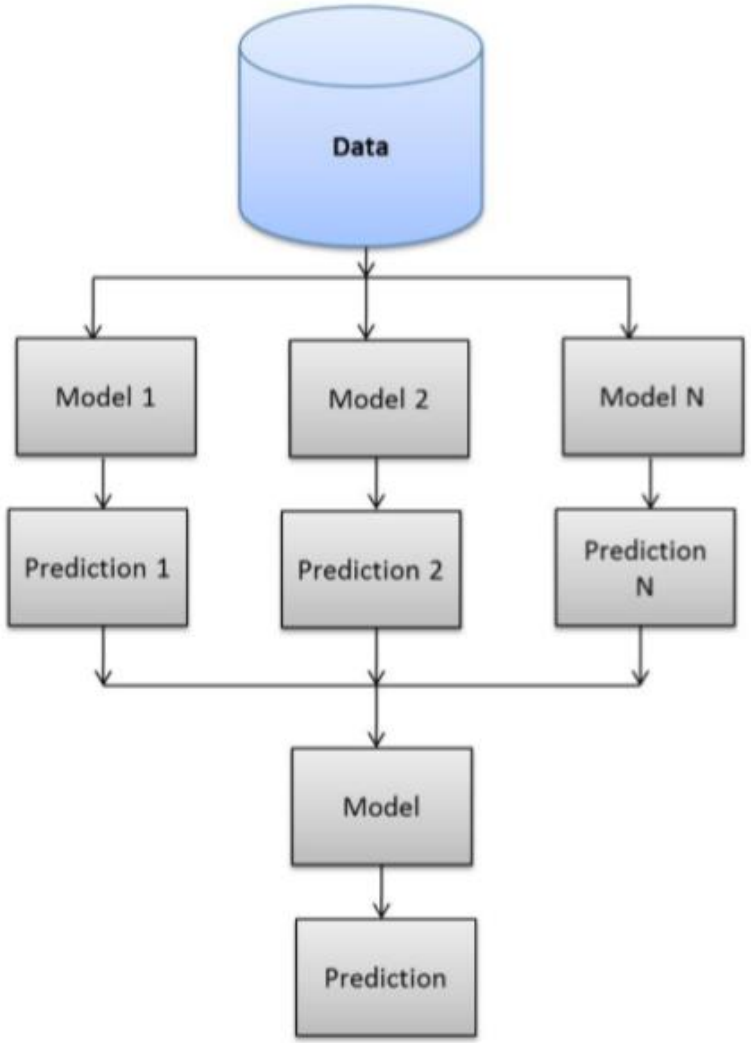
$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma^2_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m}(x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma^2_{\mathcal{B}} + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Algorithm 1: Batch Normalizing Transform, applied to activation x over a mini-batch.



Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift

Tensors

- Tensors are similar to NumPy’s ndarrays
- Can run on GPUs or other hardware accelerators
- Optimized for automatic differentiation

Autograd

- Automatic differentiation package : No need to worry about back propagation partial derivatives and chain rule
- Tensors track their computational history and support gradient computation
- **`requires_grad=True`** : Tells PyTorch that we want to compute gradients for the specific tensor

Autograd : `backward()`

- The **`backward()`** function is responsible for calculation of gradients and **accumulate** (not apply) them in respective tensors

- The tensor with **`requires_grad=True`**: has attribute to check the gradients values : ‘**`grad`**’

- Because of the **accumulate** it is important to zero the accumulated values before any calculations ‘`zero_()`’

Optimizers

- Optimizers facilitate the update of tensors values with the gradients

- In PyTorch the reset of accumulated gradients is facilitated by the optimizer **‘zero_grad()’**

- To facilitate the updates of tensors values with the gradient values and learning rate **‘step()’** method should be evoked

Loss Functions

Recap on Linear Regression Loss function

Mean Squared Error (MSE)

$$f(x_i) = w_0 + w_1 x_i$$

$$e_i = y_i - f(x_i)$$

$$\mathcal{L}(w_0, w_1) = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - (w_0 + w_1 x_i)\right)^2$$

We need to find the value of parameters that minimize this cost or loss function.

`torch.nn.MSELoss`

Recap on Logistic Regression Loss Function

Loss Function of Logistic Regression (4)

$$\mathcal{L}(\boldsymbol{w}) = -\frac{1}{n}\sum_{i=1}^{n} y^i \log\left(p\left(x^i\right)\right) + \left(1 - y^i\right)\log\left(1 - p\left(x^i\right)\right)$$

- Given this loss function, what do you think we are gonna do next?

- We will define our objective function

$$\underset{w_o, w_1}{\operatorname{argmin}}\ \mathcal{L}(\boldsymbol{w})$$

`torch.nn.BCELoss`

Other Loss functions

- Kullback-Leibler divergence : **`torch.nn.KLDivLoss`**
- Cosine Embedding : **`torch.nn.CosineEmbeddingLoss`**
- Negative log likelihood loss : **`torch.nn.NLLLoss`**
- Cross entropy loss : **`nn.CrossEntropyLoss`**

In PyTorch a loss function is called ***criterion***

More Loss functions and description

Creating a simple ANN & DNN

Model

- A **model** is represented by a regular **Python class** that inherits from the **Module** class
- **`__init__(self)`:** it defines the parts that make up the model
- **`forward(self,x)`:** performs a forward pass

```
import torch

class myModel(torch.nn.Module):
   def __init__(self) :
     super(...).__init__()
       ...
   def forward(self,x):
     ...
     return x
```

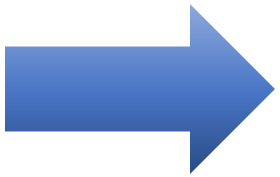
Model important attributes

- **`model.train()`** : sets the model to training mode. Keep track of the gradients and computations in the gragh
- **`model.eval()`** : sets the model to evaluation mode (no need to accumulate gradients and ignore dropout)
- **`model.parameters()`** : retrieves an iterator over all model's parameters
- **`model.state_dict()`** : retrieves model current values for all parameters

Sequential Models

```
import torch

class myModel(torch.nn.Module):
   def __init__(self) :
     super(...).__init__()
       ...
   def forward(self,x):
     ...
```



```
import torch

model = torch.nn.Sequential(...)
model.train()
...
model.eval()
```

Training the model

Typical procedure in training a neural network using PyTorch:

1. Define the model
2. Define loss function
3. Define optimizer
4. Define training loop

```
import torch
import torch.optim as optim

# 1. define model
model = torch.nn.Sequential(...)

# 2. define loss function (i.e regression)
loss_function = torch.nn.MSELoss()

# 3. Define Optimizer
optimizer = optim.SGD(model.parameters(),
                      lr=0.1)

# define training loop

Next slide ...
```

Training the model

Typical procedure in training a neural network using PyTorch:

1. Define the model
2. Define loss function
3. Define optimizer
4. **Define training loop**

```
import torch

# 4. Define training loop
for epoch in range(n_epochs):
 for batch in batches:
   inputs = batch[0].to(device)
   labels = batch[1].to(device)

   # zero the parameter gradients
   optimizer.zero_grad()

   # forward + backward + optimize
   outputs = net(inputs)
   loss = loss_function(outputs, labels)

   # accumulate gradients and update params
   loss.backward()
   optimizer.step()
```

Saving and loading Model

- PyTorch models store the learned parameters in an internal state dictionary `model.state_dict()`
- Can be persisted via the PyTorch save method `torch.save(...)`

```
import torch
model = torch.nn.Sequential(...)
torch.save(model.state_dict(), 'model_weights.pt')
.....
model.load_state_dict(torch.load('model_weights.pt'))
```

Simple Regression problem

$$f(x) = w_0 + w_1 x_i$$

Task : Estimate w_0 and w_1

What is the Loss function ???

Which simple optimizer can be used ??

Hands-on tasks

- Task 1 : Implement Linear regression using Numpy
- Task 2 : Modify task 1 implementation using PyTorch tensors
- Task 3 : Implement linear regression using torch Model
- Task 4 : Add TensorBoard to the implementation
- Task 5 : Use Pretrained models

Resources

https://pytorch.org

Thank You