CS378: Natural Language Processing
Lecture 6: NN Implementation

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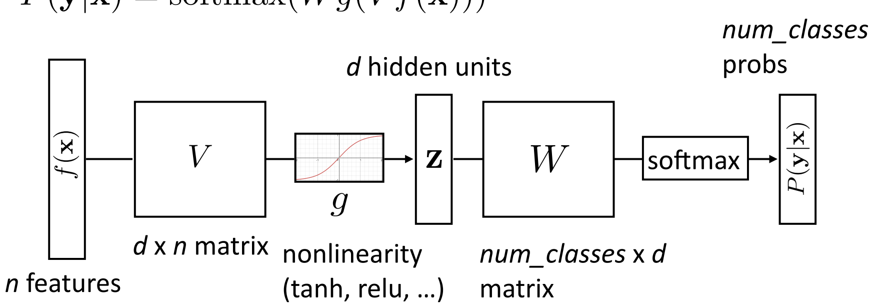
Announcements

- A1 due today at 5pm
- A2 out late tonight
- Goldberg reading link fixed

Recall: Feedforward NNs

$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(W g(V f(\mathbf{x})))$$



Recall: Training Feedforward NNs

$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(W g(V f(\mathbf{x})))$$

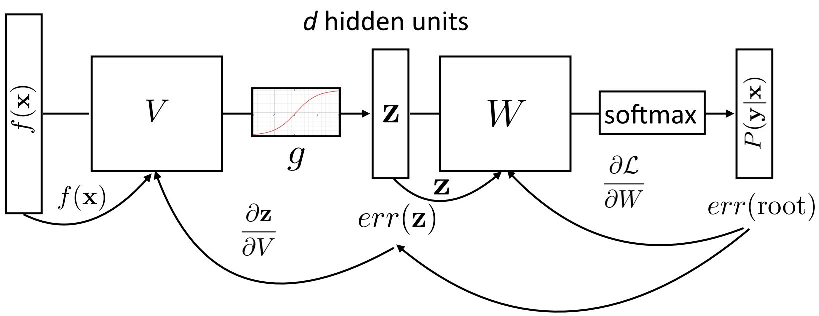
- Maximize log likelihood of training data. For one point:

$$\mathcal{L}(\mathbf{x}, i^*) = \log P(y = i^*|\mathbf{x}) = \log\left(\text{softmax}(W\mathbf{z}) \cdot e_{i^*}\right)$$

- How to compute the gradient with respect to *W* and *V*?

Recall: Backpropagation

$$P(\mathbf{y}|\mathbf{x}) = \mathrm{softmax}(Wg(Vf(\mathbf{x})))$$



This Lecture

- Neural net implementation / PyTorch 101
- Neural net training
- Word representations

Implementing Neural Networks: PyTorch 101

Computation Graphs

- Computing gradients is hard!
- Automatic differentiation: instrument code to keep track of derivatives

```
y = x * x    --codegen-->    (y,dy) = (x * x, 2 * x * dx)
```

- Computation is now something we need to reason about symbolically
- Use a library like Pytorch or Tensorflow. This class: Pytorch
- **Ensuing code examples are on the course website: ffnn_example.py under “Readings”**

PyTorch

- Framework for defining computations that provides easy access to derivatives
- Module: defines a neural network (can use wrap other modules which implement predefined layers)
- If forward() uses crazy stuff, you have to write backward yourself

torch.nn.Module

```
# Takes an example x and computes result
forward(x):
  ...
# Computes gradient after forward() is called
backward(): # produced automatically
  ...
```

Computation Graphs in Pytorch

- Define forward pass for $P(\mathbf{y}|\mathbf{x}) = \text{softmax}(W g(V f(\mathbf{x})))$

```
class FFNN(nn.Module):
    def __init__(self, input_size, hidden_size, out_size):
        super(FFNN, self).__init__()
        self.V = nn.Linear(input_size, hidden_size)
        self.g = nn.Tanh() # or nn.ReLU(), sigmoid()...
        self.W = nn.Linear(hidden_size, out_size)
        self.softmax = nn.Softmax(dim=0)

    def forward(self, x):
        return self.softmax(self.W(self.g(self.V(x))))
```

apply is syntactic sugar for forward

Input to Network

- Whatever you define with torch.nn needs its input as some sort of tensor, whether it's integer word indices or real-valued vectors

```
def form_input(x) -> torch.Tensor:
  # Index words/embed words/etc.
  return torch.from_numpy(x).float()
```

- More on this later

Training and Optimization

$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(W g(V f(\mathbf{x})))$

one-hot vector of the label (e.g., [0, 1, 0])

```
ffnn = FFNN(inp, hid, out)
optimizer = optim.Adam(ffnn.parameters(), lr=lr)
for epoch in range(0, num_epochs):
    for (input, gold_label) in training_data:
        ffnn.zero_grad() # clear gradient variables
        probs = ffnn.forward(input)
        loss = torch.neg(torch.log(probs)).dot(gold_label)
        loss.backward()
        optimizer.step()
```

negative log-likelihood of correct answer

Optimization in Pytorch

```
optimizer = optim.SGD(network.parameters(), lr=0.01)

optimizer = optim.Adam(network.parameters(), lr=0.001)
```

- Learning rates for deep learning are often tiny! (0.01 or lower)
- Adam: adaptive method, incorporates momentum (gradient is smoothed with running average of past gradients). We will discuss a bit more but it's outside the scope of this class.

Initialization in Pytorch

```
class FFNN(nn.Module):
    def __init__(self, inp, hid, out):
        super(FFNN, self).__init__()
        self.V = nn.Linear(inp, hid)
        self.g = nn.Tanh()
        self.W = nn.Linear(hid, out)
        self.softmax = nn.Softmax(dim=0)
        nn.init.uniform(self.V.weight)
```

- Initializing to a nonzero value is critical, more in a bit

Training a Model

Define a computation graph

Initialize weights and optimizer

For each epoch:

- For each batch of data:
  - Zero out gradient
  - Compute loss on batch
  - Autograd to compute gradients and take step

Decode test set

Batching in Neural Networks

Batching

- Batching data gives speedups due to more efficient matrix operations
- Need to make the computation graph process a batch at the same time

```
# input is [batch_size, num_feats]
# gold_label is [batch_size, num_classes]
def make_update(input, gold_label)
    ...
    probs = ffnn.forward(input) # [batch_size, num_classes]
    loss = torch.sum(torch.neg(torch.log(probs)).dot(gold_label))
    ...
```

- Batch sizes from 1-100 often work well

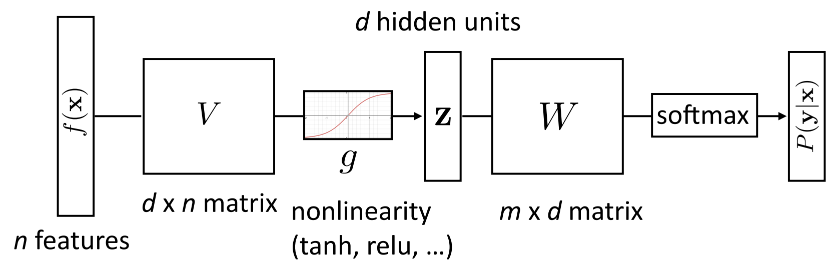
Optimization Redux

Nonconvex Optimization

- For logistic regression, there is a global optimum: sum of log probabilities is a convex function in the weights
- Neural networks are much harder to optimize!

How does initialization affect learning?

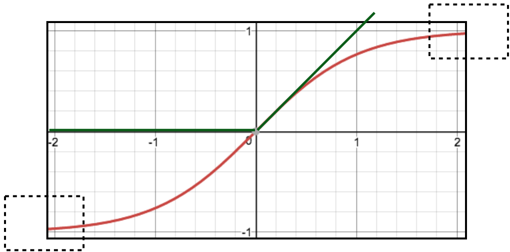
$$P(\mathbf{y}|\mathbf{x}) = \mathrm{softmax}(Wg(Vf(\mathbf{x})))$$



- How do we initialize V and W? What consequences does this have?
- *Nonconvex* problem, so initialization matters!

How does initialization affect learning?

- Nonlinear model…how does this affect things?



- If cell activations are too large in absolute value, gradients are small
- ReLU: larger dynamic range (all positive numbers), but can produce big values, can break down if everything is too negative

Initialization

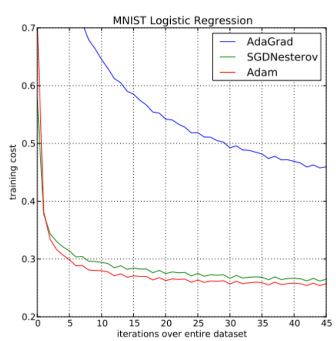
1) Can't use zeroes for parameters to produce hidden layers: all values in that hidden layer are always 0 and have gradients of 0, never change

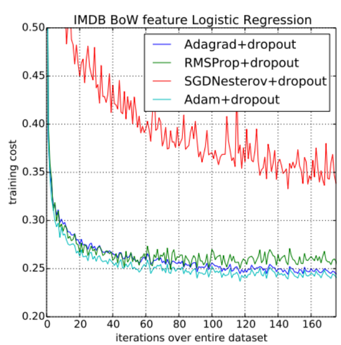
2) Initialize too large and cells are saturated

- Can do random uniform / normal initialization with appropriate scale
- Fancier initializers (Xavier Glorot initializer, Kaiming He) to match variances across layers

Optimizer

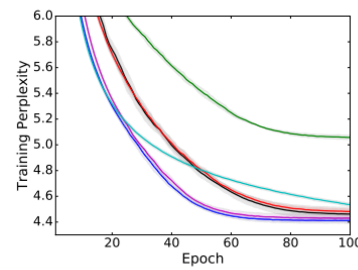
- Adam (Kingma and Ba, ICLR 2015) is very widely used
- Adaptive step size, incorporates momentum



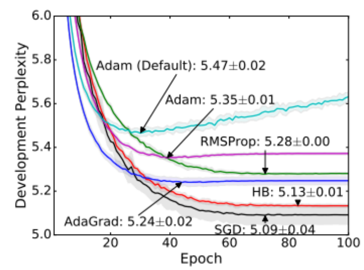


Optimizer

- Wilson et al. NIPS 2017: adaptive methods can actually perform badly at test time (Adam is in pink, SGD in black)
- Check dev set periodically, decrease learning rate if not making progress



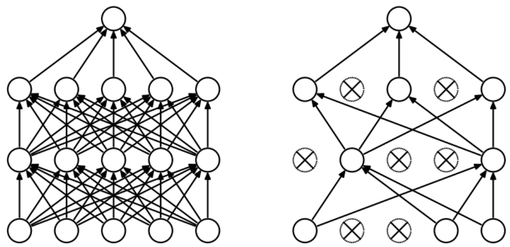
(e) Generative Parsing (Training Set)



(f) Generative Parsing (Development Set)

Dropout

- Probabilistically zero out parts of the network during training to prevent overfitting, use whole network at test time
- Form of stochastic regularization
- Similar to benefits of ensembling: network needs to be robust to missing signals, so it has redundancy



(a) Standard Neural Net (b) After applying dropout.

- Dropout layers exist in PyTorch

Srivastava et al. (2014)

Nonconvex Optimization

- For logistic regression, there is a global optimum: sum of log probabilities is a convex function in the weights
- Neural networks are hard to optimize

Big Points

- Basic recipe (take gradients + apply update) is still the same
- Neural networks need to be **initialized to nonzero values**
- **Optimizer choice is very important; use Adam unless you know what you're doing**