Understanding model optimization

INTRODUCTION TO DEEP LEARNING IN PYTHON

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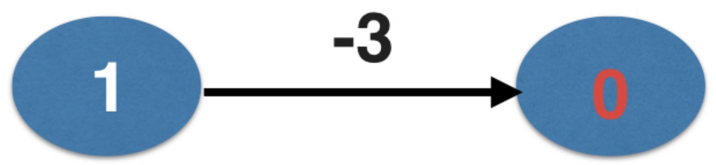
Why optimization is hard

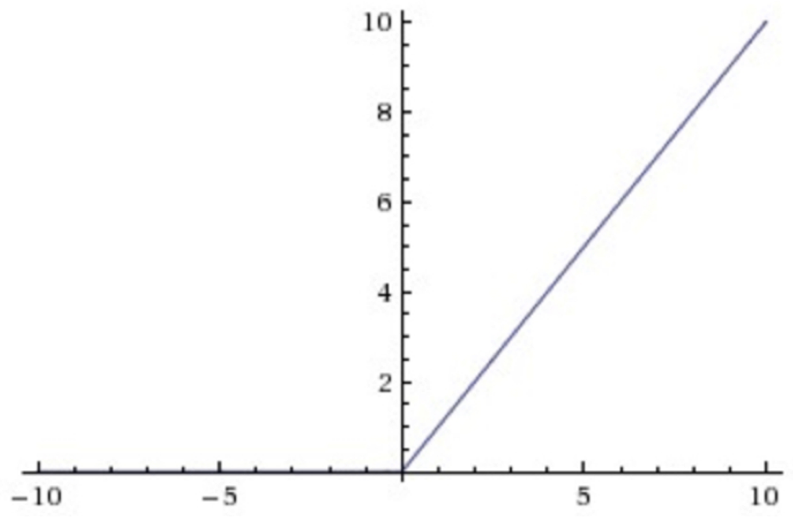
- Simultaneously optimizing 1000s of parameters with complex relationships
- Updates may not improve model meaningfully
- Updates too small (if learning rate is low) or too large (if learning rate is high)

Stochastic gradient descent

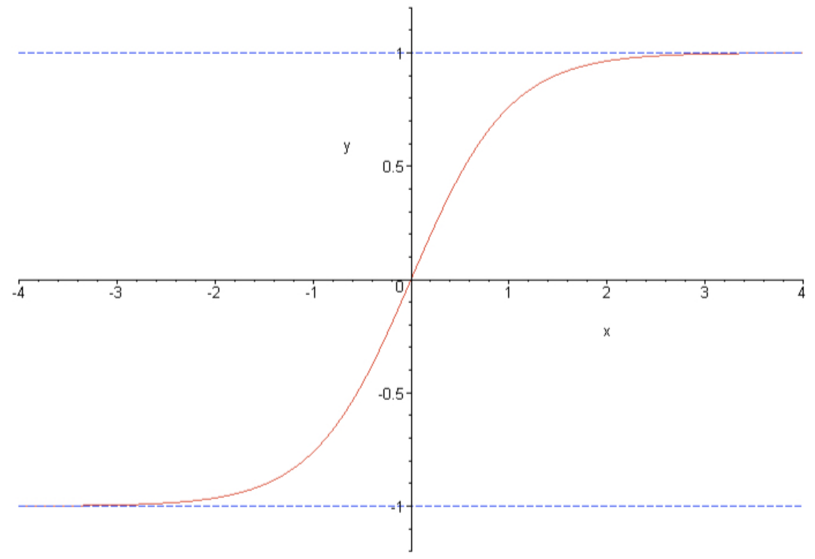
```
def get_new_model(input_shape = input_shape):
    model = Sequential()
    model.add(Dense(100, activation='relu', input_shape = input_shape))
    model.add(Dense(100, activation='relu'))
    model.add(Dense(2, activation='softmax'))
    return(model)

lr_to_test = [.000001, 0.01, 1]

# loop over learning rates
for lr in lr_to_test:
   model = get_new_model()
   my_optimizer = SGD(lr=lr)
   model.compile(optimizer = my_optimizer, loss = 'categorical_crossentropy')
   model.fit(predictors, target)
```

The dying neuron problem





Vanishing gradients



tanh function

Vanishing gradients

- Occurs when many layers have very small slopes (e.g. due to being on flat part of tanh curve)
- In deep networks, updates to backprop were close to 0

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Model validation

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Validation in deep learning

- Commonly use validation split rather than cross-validation
- Deep learning widely used on large datasets
- Single validation score is based on large amount of data, and is reliable
- Repeated training from cross-validation would take long time

Model validation

```python
model.compile(optimizer = 'adam', loss = 'categorical_crossentropy', metrics=['accuracy'])
model.fit(predictors, target, validation_split=0.3)
```

```
Epoch 1/10
89648/89648 [=====] - 3s - loss: 0.7552 - acc: 0.5775 - val_loss: 0.6969 - val_acc: 0.5561
Epoch 2/10
89648/89648 [=====] - 4s - loss: 0.6670 - acc: 0.6004 - val_loss: 0.6580 - val_acc: 0.6102
...
Epoch 8/10
89648/89648 [=====] - 5s - loss: 0.6578 - acc: 0.6125 - val_loss: 0.6594 - val_acc: 0.6037
Epoch 9/10
89648/89648 [=====] - 5s - loss: 0.6564 - acc: 0.6147 - val_loss: 0.6568 - val_acc: 0.6110
Epoch 10/10
89648/89648 [=====] - 5s - loss: 0.6555 - acc: 0.6158 - val_loss: 0.6557 - val_acc: 0.6126
```

Early Stopping

```
from keras.callbacks import EarlyStopping

early_stopping_monitor = EarlyStopping(patience=2)

model.fit(predictors, target, validation_split=0.3, nb_epoch=20,
          callbacks = [early_stopping_monitor])
```

Output from early stopping

```
Train on 89648 samples, validate on 38421 samples
Epoch 1/20
89648/89648 [====] - 5s - loss: 0.6550 - acc: 0.6151 - val_loss: 0.6548 - val_acc: 0.6151
Epoch 2/20
89648/89648 [====] - 6s - loss: 0.6541 - acc: 0.6165 - val_loss: 0.6537 - val_acc: 0.6154
...
Epoch 8/20
89648/89648 [====] - 6s - loss: 0.6527 - acc: 0.6181 - val_loss: 0.6531 - val_acc: 0.6160
Epoch 9/20
89648/89648 [====] - 7s - loss: 0.6524 - acc: 0.6176 - val_loss: 0.6513 - val_acc: 0.6172
Epoch 10/20
89648/89648 [====] - 6s - loss: 0.6527 - acc: 0.6176 - val_loss: 0.6549 - val_acc: 0.6134
Epoch 11/20
89648/89648 [====] - 6s - loss: 0.6522 - acc: 0.6178 - val_loss: 0.6517 - val_acc: 0.6169
```

Experimentation

- Experiment with different architectures
- More layers
- Fewer layers
- Layers with more nodes
- Layers with fewer nodes
- Creating a great model requires experimentation

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Thinking about model capacity

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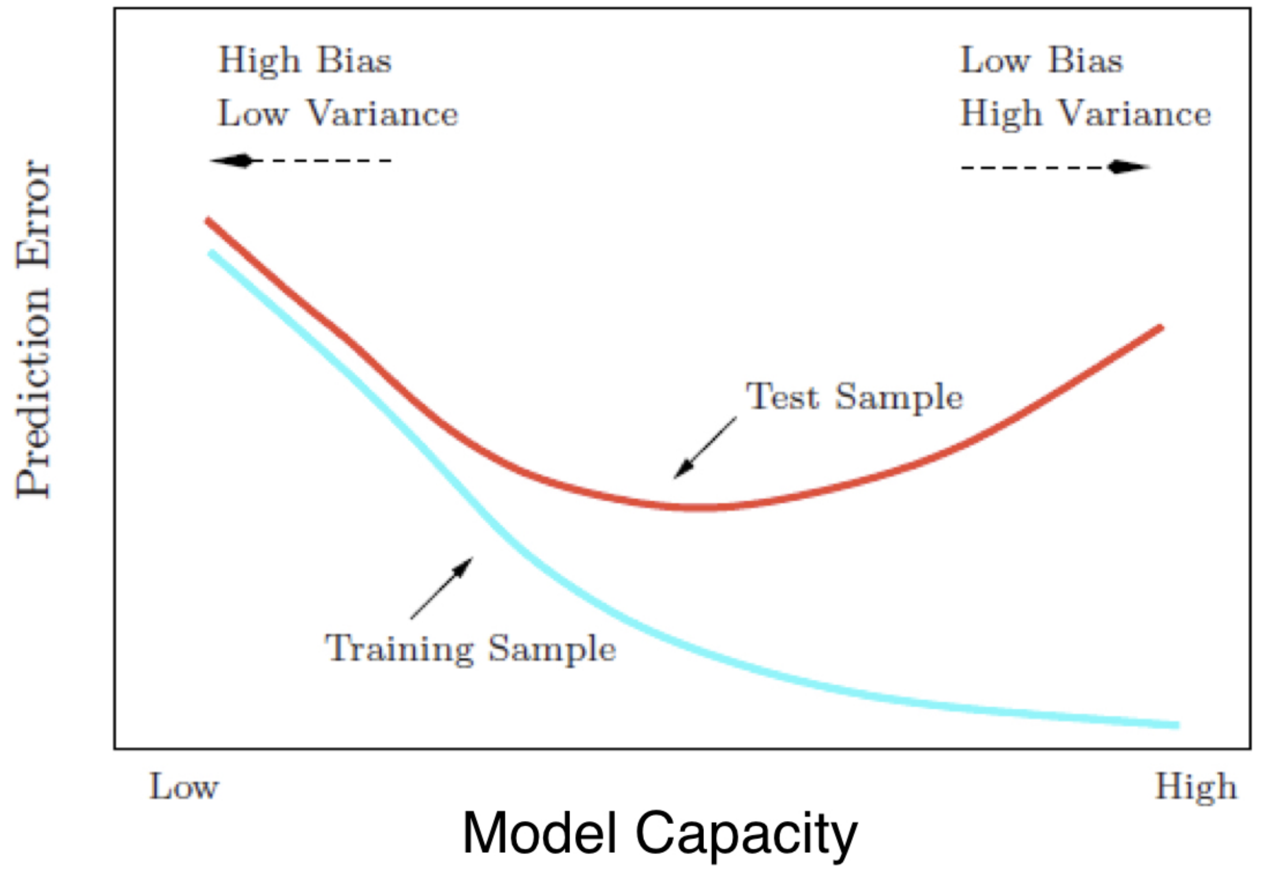
Overfitting



Workflow for optimizing model capacity

- Start with a small network
- Gradually increase capacity
- Keep increasing capacity until validation score is no longer
improving

Sequential experiments

Hidden Layers	Nodes Per Layer	Mean Squared Error	Next Step
1	100	5.4	Increase Capacity
1	250	4.8	Increase Capacity
2	250	4.4	Increase Capacity
3	250	4.5	Decrease Capacity
3	200	4.3	Done

Sequential experiments

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Stepping up to images

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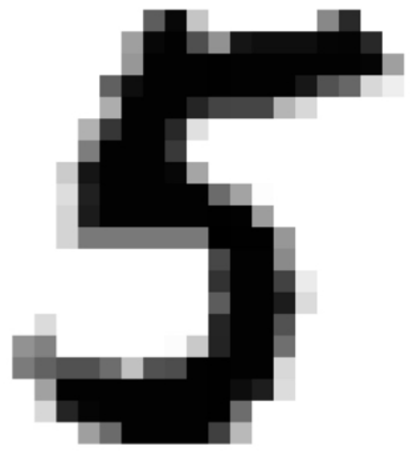
Recognizing handwritten digits

- MNIST dataset
- 28 x 28 grid flattened to 784 values for each image
- Value in each part of array denotes darkness of that pixel



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Final thoughts

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Next steps

- Start with standard prediction problems on tables of numbers
- Images (with convolutional neural networks) are common next steps
- keras.io for excellent documentation
- Graphical processing unit (GPU) provides dramatic speedups in model training times
- Need a CUDA compatible GPU
- For training on using GPUs in the cloud look here:
    - **http://bit.ly/2mYQXQb**

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