Day 1 Lecture 5

Training

Goal

Given some paired training examples $\{(\mathbf{x}_i, y_i): \mathbf{x}_i \in \mathbf{X}, y_i \in \mathbf{Y}\}$ produce a function $y = f(\mathbf{x})$ such that $f(\mathbf{x})$ **generalizes well** to previously unseen data.

Examples

- **X** are times of day, **Y** are light levels
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- **X** are measurements from sensors (temp, humidity, brightness, etc.), **Y** is {rain, no rain}
- **X** are words occurring in an email, **Y** is {spam, not spam}
- **X** are vectors of image pixels, **Y** is {cat, dog, car, person, …}
- **X** are recorded audio fragments, **Y** are words

Loss function

Classification Metrics:

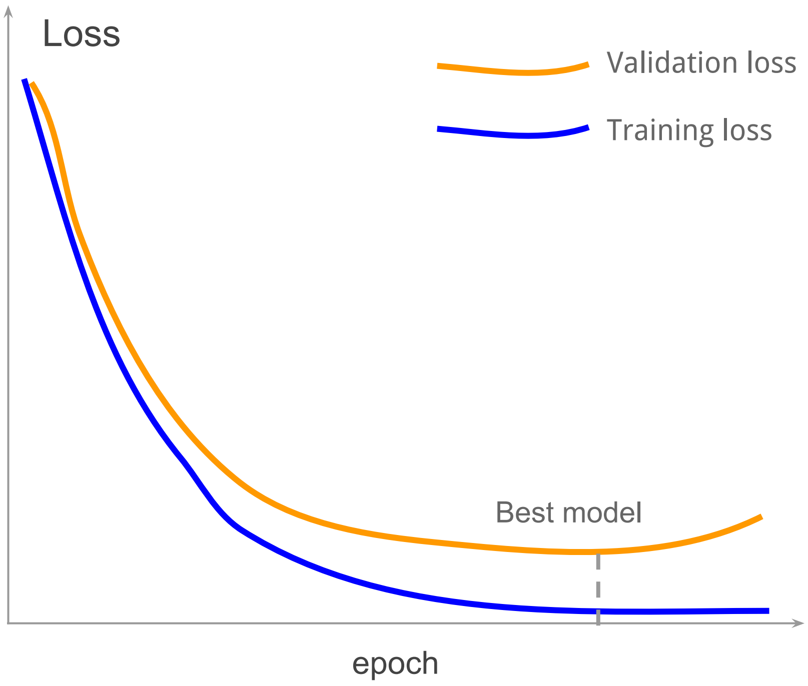
$$Accuracy = \frac{\boxed{TP+TN}}{\boxed{TP+TN+FP+FN}} \longrightarrow \text{Not differenciable!}$$

Example: Binary cross entropy:

$$L = -\frac{1}{N}\sum_{i=1}^{N} y_i \log f(\mathbf{x}_i) + (1-y_i)\log(1-f(\mathbf{x}_i))$$

Training and monitoring progress

1. Split data into train, validation, and test sets
   - Keep 10-30% of data for validation
2. Fit model parameters on train set using SGD
3. After each epoch:
   - **Test model on validation set** and compute loss
     - Also compute whatever other metrics you are interested in, e.g. top-5 accuracy
   - Save a snapshot of the model
4. Plot **learning curves** as training progresses
5. Stop when validation loss starts to increase
6. Use model with minimum validation loss



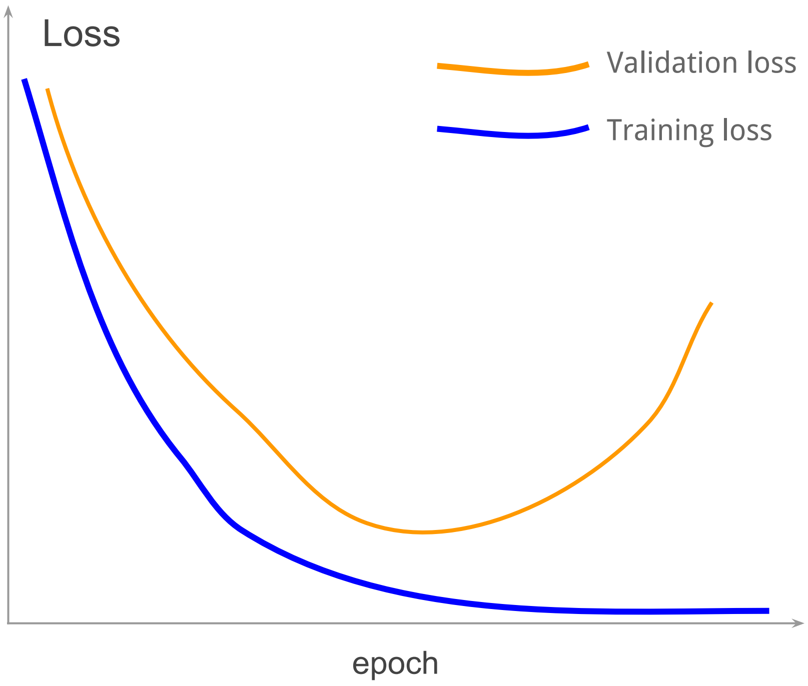
Overfitting

Symptoms:

- Validation loss decreases at first, then starts increasing
- Training loss continues to go down

Try:

- Find more training data
- Add stronger regularization
  - dropout, drop-connect, L2
- Data augmentation (flips, rotations, noise)
- Reduce complexity of your model



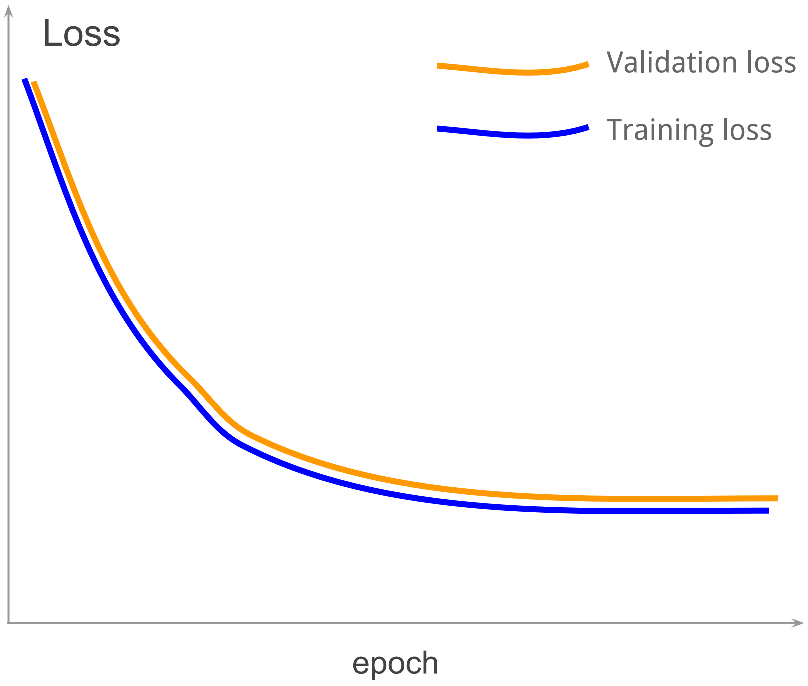
Underfitting

Symptoms:

- Training loss decreases at first but then stops
- Training loss still high
- Training loss tracks validation loss

Try:

- Increase model capacity
  - Add more layers, increase layer size
- Use more suitable network architecture
  - E.g. multi-scale architecture
- Decrease regularization strength



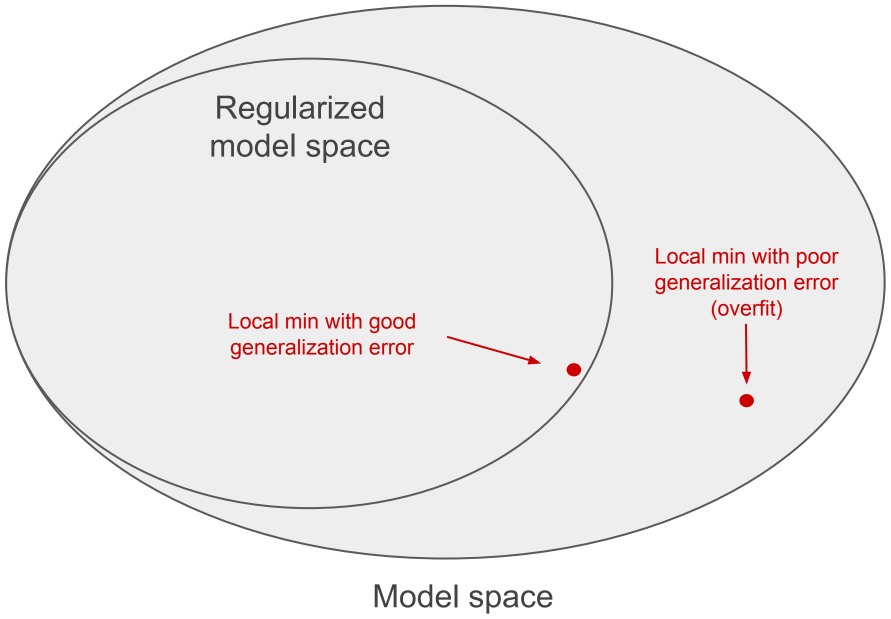
Structural risk minimization

Early stopping is a form of structural risk minimization

- Limits the space of models we explore to only those we expect to have good generalization error
- Helps prevent **overfitting**
- A type of **regularization**

Other regularization techniques:

- Weight constraints: e.g. **L2 regularization**
  - Aka. weight decay
- Dropout
- Transfer learning, pretraining



Weight decay

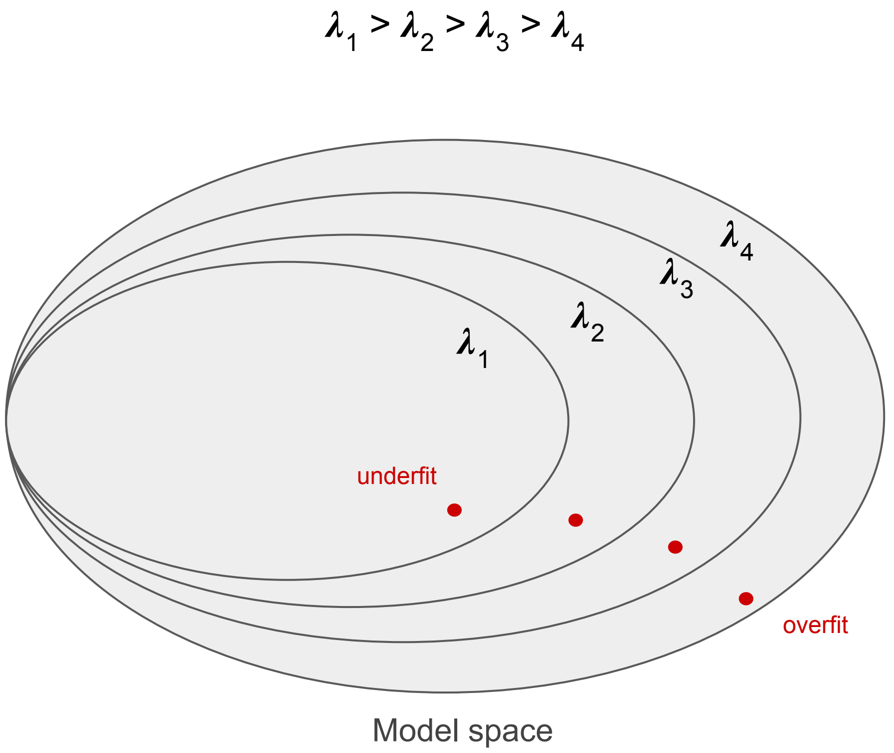
Add a penalty to the loss function for large weights

L2 regularization on weights

$$L = L_{\text{data}} + \frac{\lambda}{2}||W||_2^2$$

Differentiating, this translates to decaying the weights with each gradient descent step

$$w_{t+1} = w_t - \alpha\Delta_w L_{\text{data}} - \lambda w$$



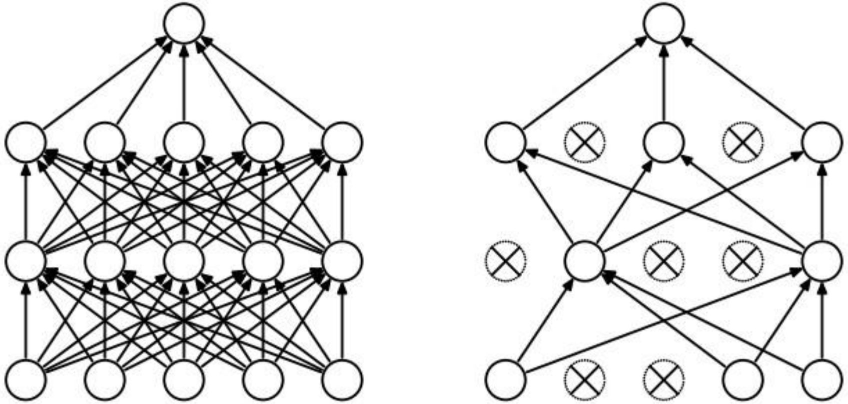
Dropout

Modern regularization technique for deep nets

Used by most modern convnets

Method:

- During training, outputs of a layer to zero randomly with probability p
  - Prevents units from co-adapting too much
  - Forces network to learn more robust features
- At test time, dropout is disabled and unit output is multiplied by p



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

Srivastava et al. **Dropout: A simple way to prevent neural networks from overfitting.** JRML 15(1), 2014, pp 1929-1958.

Hyperparameters

Can already see we have lots of **hyperparameters** to choose:

1. Learning rate
2. Regularization constant
3. Number of epochs
4. Number of hidden layers
5. Nodes in each hidden layer
6. Weight initialization strategy
7. Loss function
8. Activation functions
9. …

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Choosing these is difficult, and a bit of an art.

There are some reasonable **heuristics**:

1. Try 0.1 for the learning rate. If this doesn't work, divide by 3. Repeat.
2. Multiply LR by 0.1 every 1-10 epochs.
3. Try ~ 0.00001 as regularization constant
4. Try an existing network architecture and adapt it for your problem
5. Start smallish, keep adding layers and nodes until you overfit too much

You can also do a **hyperparameter search** if you have enough compute:

- Randomized search tends to work well