CS 760: Machine Learning
Neural Networks III

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Logistics

- **Announcements**:
  - Homework 4 is out
  - Midterm: **next week**
    - Practice questions on canvas

Outline

- **Regularization**
  - Views, L1/L2 Effects
- **Other Forms of Regularization**
  - Data Augmentation, Noise, Early Stopping, Dropout
- **Convolutional Neural Networks** (next lecture)

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- **Regularization**
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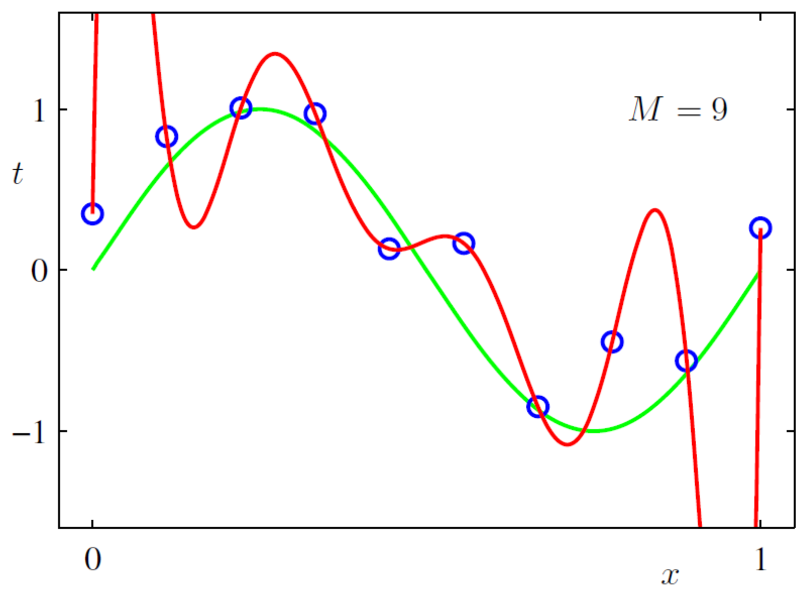
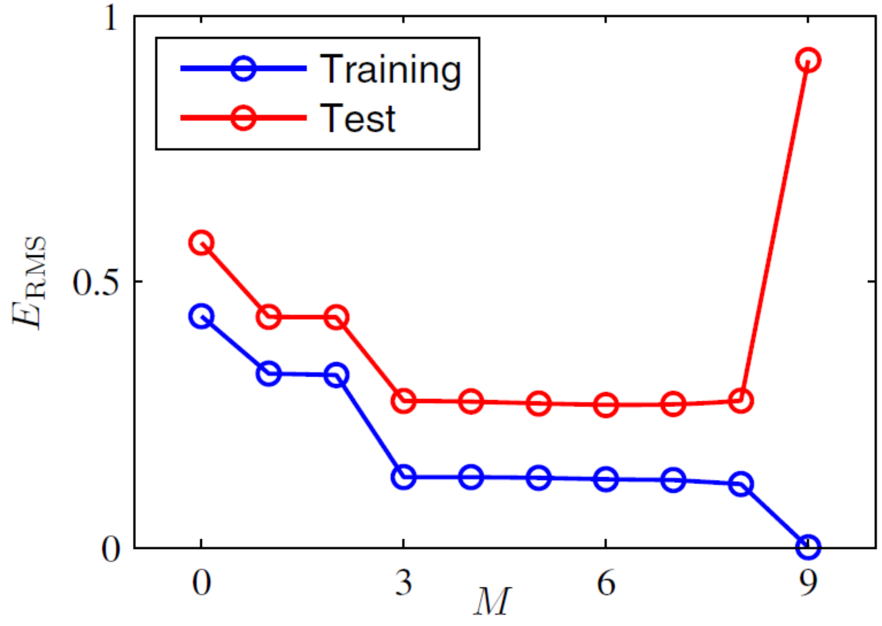
Review: Overfitting

- What is it? When empirical loss and expected loss are different
- Possible solutions:
  - Larger data set
  - Throwing away useless hypotheses also helps (**regularization**)





Review: Regularization

- In general: any method to **prevent overfitting**

- One approach: modify the optimization objective

- Different “views”
  - Hard constraint,
  - Soft constraint,
  - Bayesian view

Regularization: Hard Constraint View

- Training objective / parametrized version

$$\min_f \hat{L}(f) = \frac{1}{n}\sum_{i=1}^{n} l(f, x_i, y_i) \qquad \min_\theta \hat{L}(\theta) = \frac{1}{n}\sum_{i=1}^{n} l(\theta, x_i, y_i)$$

$$\text{subject to: } f \in \mathcal{H} \qquad \text{subject to: } \theta \in \Omega$$

- Constrain beyond it's natural choice

$$\min_\theta \hat{L}(\theta) = \frac{1}{n}\sum_{i=1}^{n} l(\theta, x_i, y_i) \qquad \min_\theta \hat{L}(\theta) = \frac{1}{n}\sum_{i=1}^{n} l(\theta, x_i, y_i)$$

$$\text{subject to: } R(\theta) \leq r \qquad \text{subject to: } ||\theta||_2^2 \leq r^2$$

L2 Regularization

Regularization: Soft Constraint View

- Equivalent to, for some parameter $\lambda\hat{}* > 0$

$$\min_{\theta} \hat{L}_R(\theta) = \frac{1}{n}\sum_{i=1}^{n} l(\theta, x_i, y_i) + \lambda^* R(\theta)$$

- For L2,

$$\min_{\theta} \hat{L}_R(\theta) = \frac{1}{n}\sum_{i=1}^{n} l(\theta, x_i, y_i) + \lambda^* ||\theta||_2^2$$

- Comes from **Lagrangian duality**

Regularization: Bayesian Prior View

- Recall our MAP version of training. Bayes law:

$$p(\theta|\{(x_i, y_i)\}_{i=1}^n) = \frac{p(\{(x_i, y_i)\}_{i=1}^n|\theta)p(\theta)}{p(\{(x_i, y_i)\}_{i=1}^n)}$$

- MAP (assuming iid data):

$$\hat{\theta}_{\text{MAP}} = \arg\max_\theta p(\theta|\{(x_i, y_i)\}_{i=1}^n)$$

$$= \arg\max_\theta \left(\underbrace{\log(p(\theta))}_{\text{Regularization}} + \underbrace{\sum_{i=1}^n \log p(x_i, y_i|\theta)}_{\text{MLE}} \right)$$

Choice of View?

- Typical choice for optimization: soft-constraint

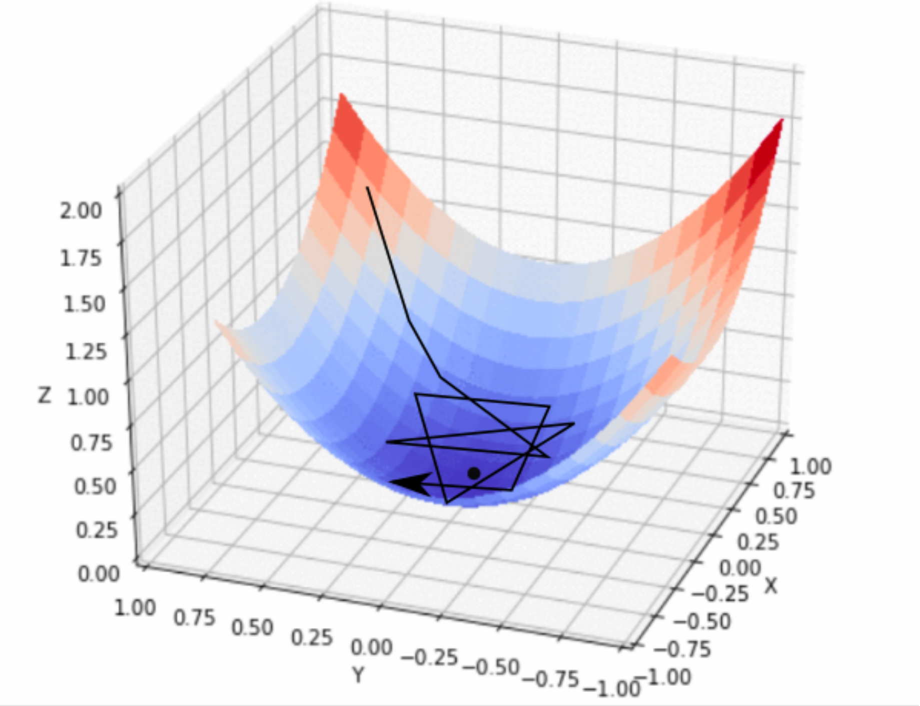
$$\min_{\theta} \hat{L}_R(\theta) = \hat{L}(\theta) + \lambda R(\theta)$$

- Hard constraint / Bayesian view: conceptual / for derivation
- Hard-constraint preferred if
  - Know the explicit bound
- Bayesian view preferred if
  - Domain knowledge easy to represent as a prior

Examples: L2 Regularization

$$\min_{\theta} \hat{L}_R(\theta) = \hat{L}(\theta) + \frac{\lambda}{2}||\theta||_2^2$$

- Questions: what are the
  - Effects on (stochastic) gradient descent?
  - Effects on the optimal solution?



L2 Regularization: **Effect on GD**

- Gradient of regularized objective

$$\nabla \hat{L}_R(\theta) = \nabla \hat{L}(\theta) + \lambda\theta$$

- Gradient descent update

$$\theta \leftarrow \theta - \eta \nabla \hat{L}_R(\theta) = \theta - \eta\, \nabla \hat{L}(\theta) - \eta\lambda\theta$$

$$= (1 - \eta\lambda)\theta - \eta\, \nabla \hat{L}(\theta)$$

- In words, **weight decay**

L2 Regularization: **Effect on Optimal Solution**

- Consider a quadratic approximation around θ^* the optimum for the unregularized loss.

$$\hat{L}(\theta) \approx \hat{L}(\theta^*) + (\theta - \theta^*)^T \nabla \hat{L}(\theta^*) + \frac{1}{2}(\theta - \theta^*)^T H(\theta - \theta^*)$$

Here, H is the hessian at θ^*

- Since θ^* is optimal,

$$\hat{L}(\theta) \approx \hat{L}(\theta^*) + \frac{1}{2}(\theta - \theta^*)^T H(\theta - \theta^*)$$

$$\nabla \hat{L}(\theta) \approx H(\theta - \theta^*)$$

L2 Regularization: **Effect on Optimal Solution**

- Gradient of regularized objective: $\nabla \hat{L}_R(\theta) \approx H(\theta - \theta^*) + \lambda\theta$

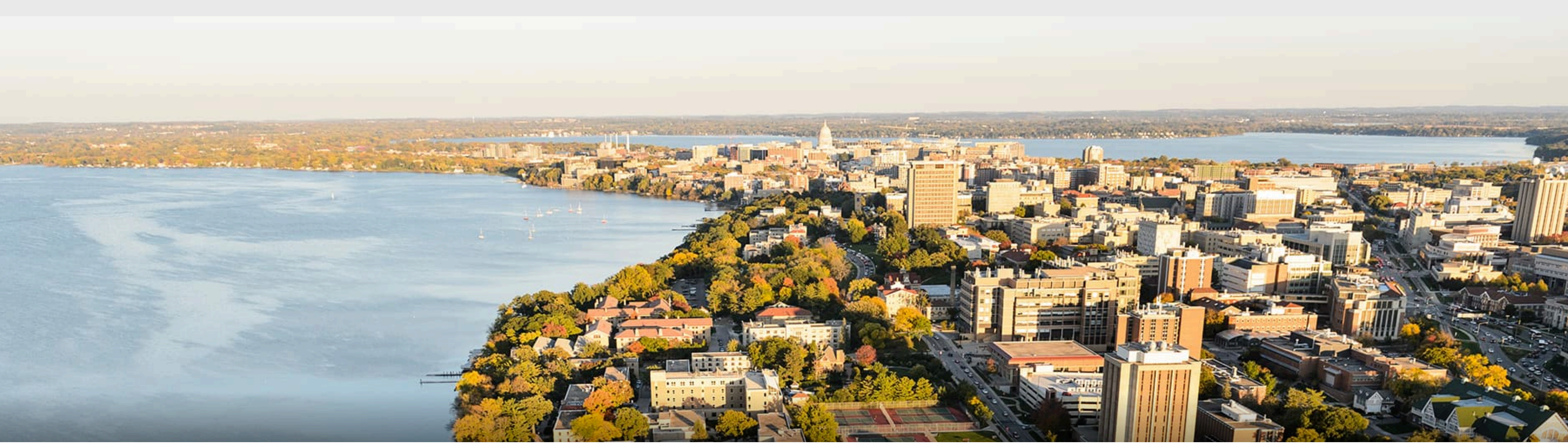
- On the optimal θ_R^*: $0 = \nabla \hat{L}_R(\theta_R^*) \approx H(\theta_R^* - \theta^*) + \lambda\theta_R^*$

$$\theta_R^* \approx (H + \lambda I)^{-1} H \theta^*$$

- H has eigendecomp. $H = Q\Lambda Q^T$, assume $(\Lambda + \lambda I)^{-1}$ exists:

$$\theta_R^* \approx (H + \lambda I)^{-1} H \theta^* = Q(\Lambda + \lambda I)^{-1} \Lambda Q^T \theta^*$$

Effect: **shrink along eigenvectors of** H



Break & Quiz

Q: Which of the following statement(s) is(are) TRUE about regularization parameter λ ?

A. λ is the tuning parameter that decides how much we want to penalize the flexibility of our model.

B. λ is usually set using cross validation.

1. True, True
2. True, False
3. False, True
4. False, False

Q: Which of the following statement(s) is(are) TRUE about regularization parameter λ ?

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1. True, True ←
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- The optimization problem can be viewed as following:

$$\text{minimize}(\text{Loss}(\text{Data}|\text{Model}) + \lambda\,\text{complexity}(\text{Model}))$$

- If the regularization parameter is large then it requires a small model complexity
- We have learned how to use cross validate to set hyperparameters including regularization parameters.

Q: Select the correct option about regression with L2 regularization (also called *Ridge Regression*).

A. *Ridge regression technique prevents coefficients from rising too high.*

B. *As $\lambda \rightarrow \infty$, the impact of the penalty grows, and the ridge regression coefficient estimates will approach infinity.*

1. Both statements are true.
2. Both statements are false.
3. Statement A is true, Statement B is false.
4. Statement B is true, Statement A is false.

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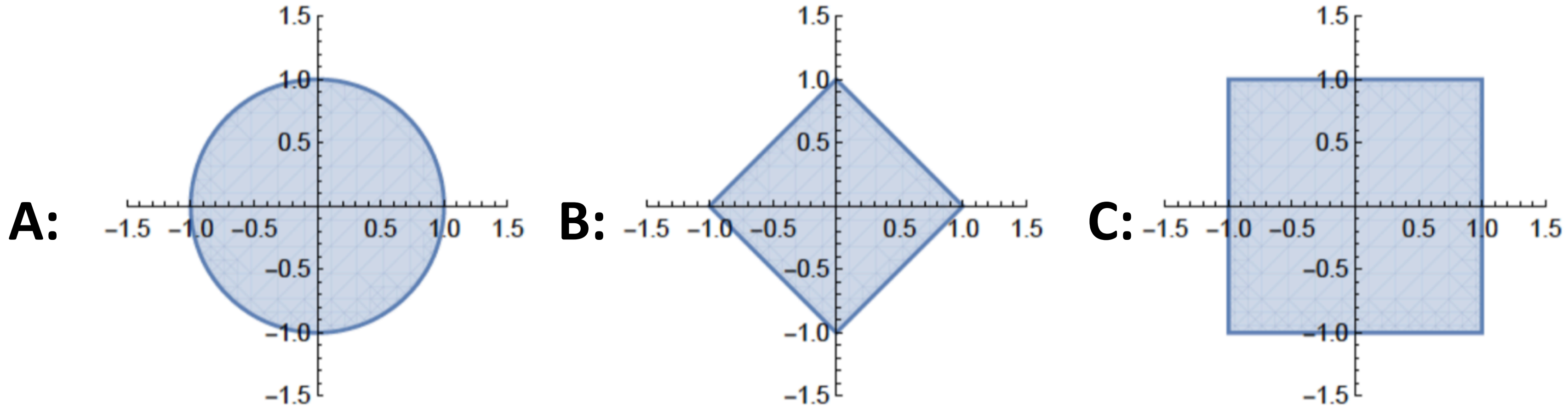
As $\lambda \to \infty$, the impact of the penalty grows, and the ridge regression coefficient estimates will approach zero.

Q: Following figure shows 3-norm sketches: $||x||_p<1$ for p = 1, 2, ∞.
Recall that $||x||_\infty = \max\{|x_i| \text{ for all } i\}$



1. A: 1, B: 2, C: ∞
2. A: 2, B: 1, C: ∞
3. A: 2, B: ∞, C: 1
4. A: ∞, B: 2, C: 1

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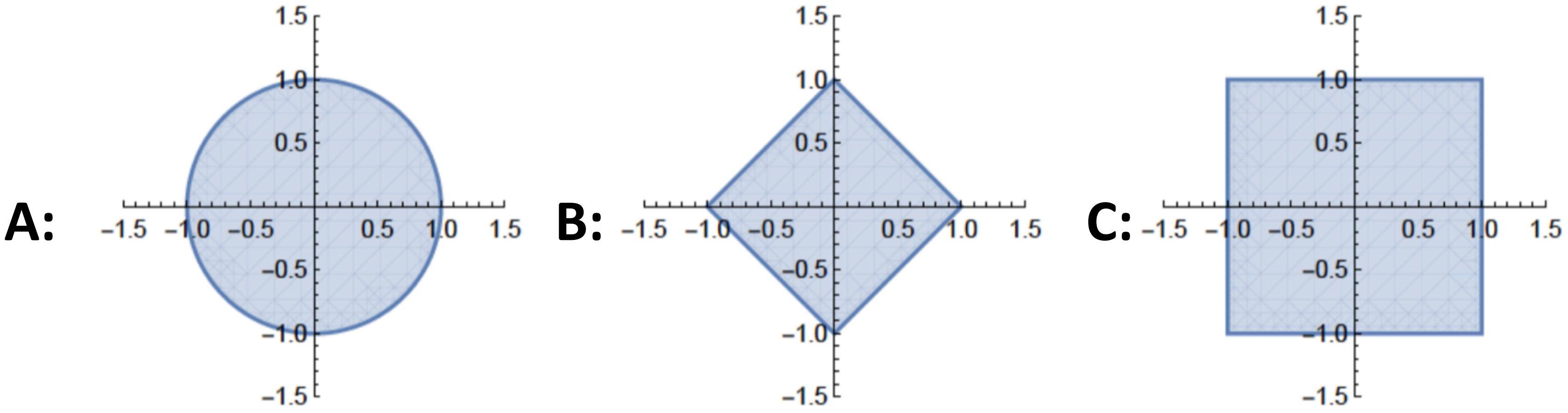

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Data Augmentation

Augmentation: transform + add new samples to dataset

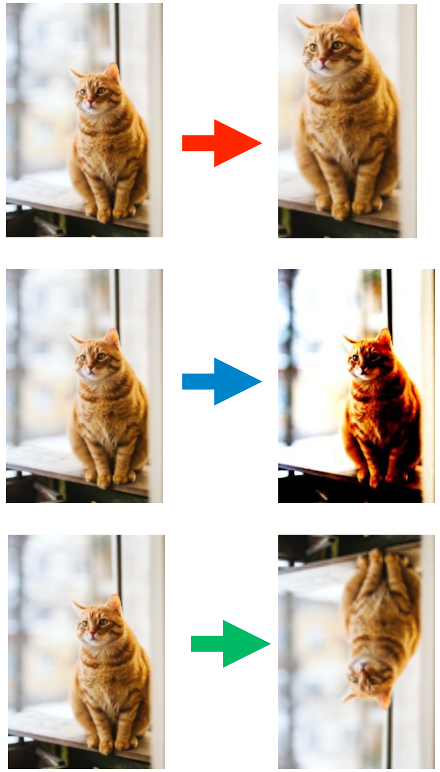
- Transformations: based on domain
- Idea: build **invariances** into the model
  - **Ex**: if all images have same alignment, model learns to use it
- Keep the label the same!

Data Augmentation: Examples

Examples of transformations for images

- **Crop** (and zoom)
- **Color** (change contrast/brightness)
- **Rotations+** (translate, stretch, shear, etc)

Many more possibilities. Combine as well!



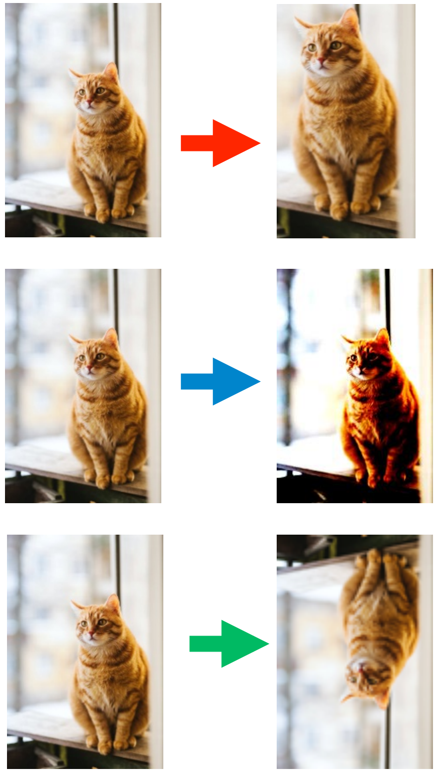
Q: how to deal with this at **test time**?

- A: transform, test, average

Combining & Automating Transformations

One way to automate the process:

- Apply every transformation and combinations
- **Downside:** most don't help…



Want a good policy, ie, → → → → →

- Active area of research: search for good policies

1. **Ratner et al**: "Learning to Compose Domain-Specific Transformations for Data Augmentation"
2. **Cubuk et al**: "AutoAugment: Learning Augmentation Strategies from Data"

Data Augmentation: Other Domains

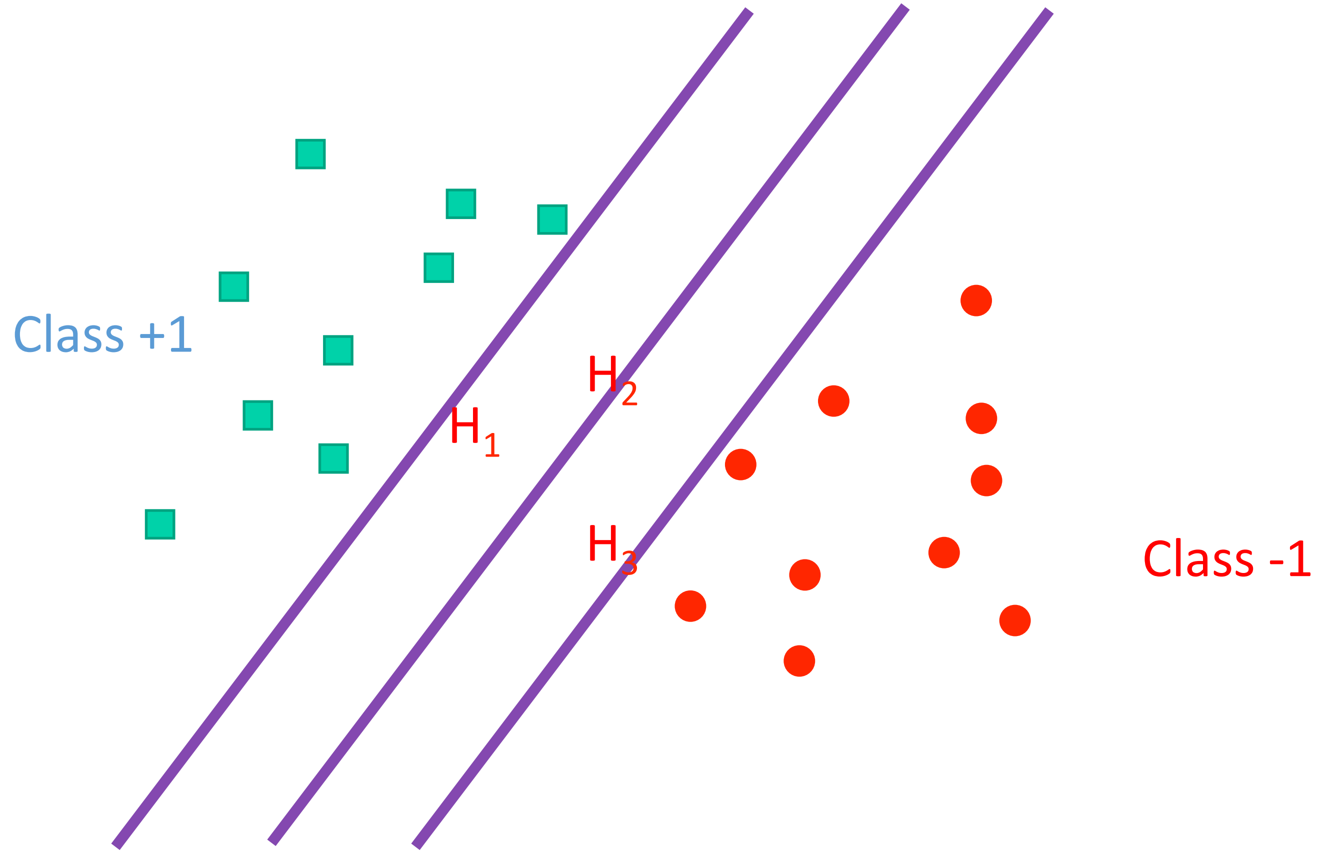
Not just for image data. For example, on text:

- Substitution
  - E.g., “It is a **great** day” → “It is a **wonderful** day”
  - Use a thesaurus for particular words
  - Or, use a model. Pre-trained word embeddings, language models
- Back-translation
  - “Given the low budget and production limitations, this movie is very good.” → “There are few budget items and production limitations to make this film a really good one”

Xie **et al**: “Unsupervised Data Augmentation for Consistency Training”

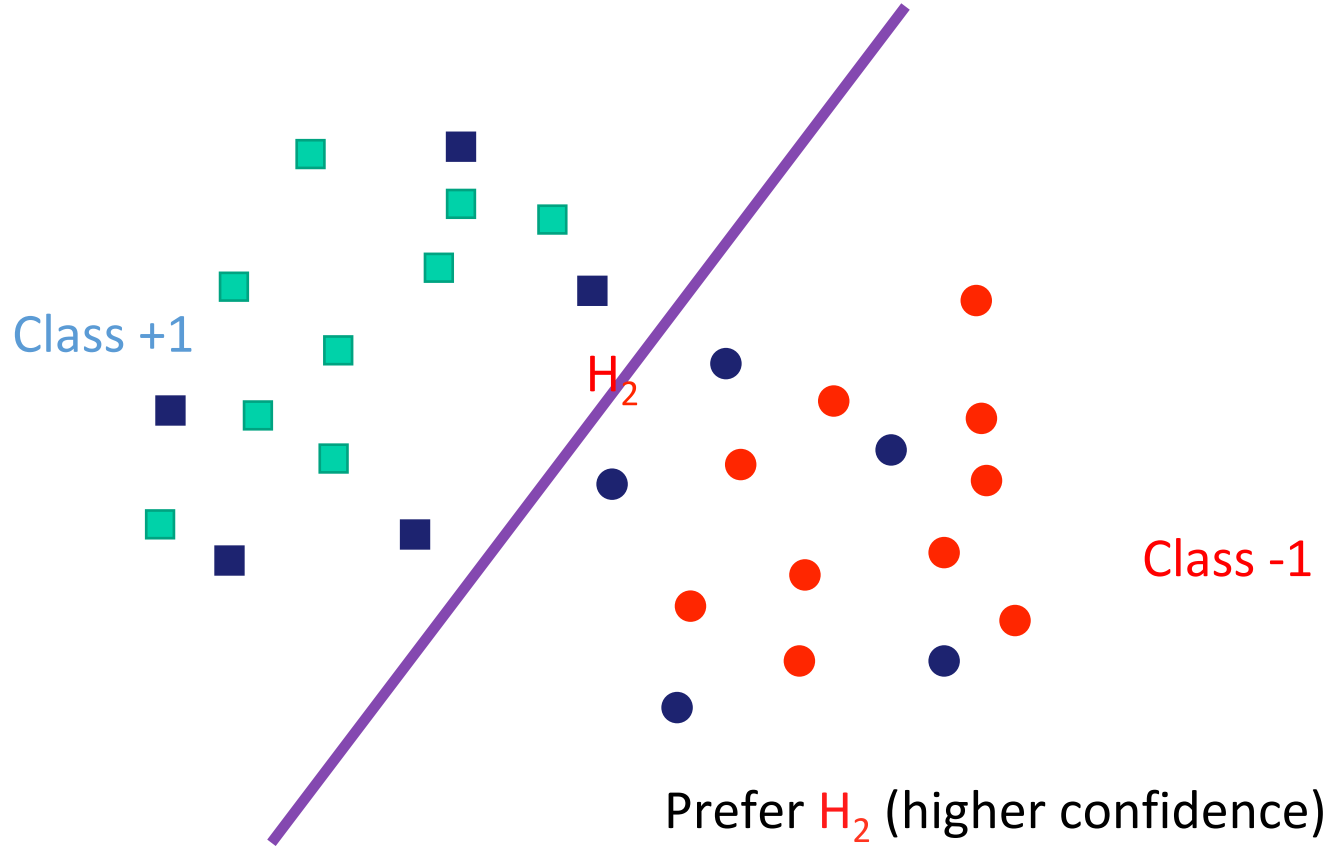
Adding Noise

- What if we have many solutions?



Adding Noise

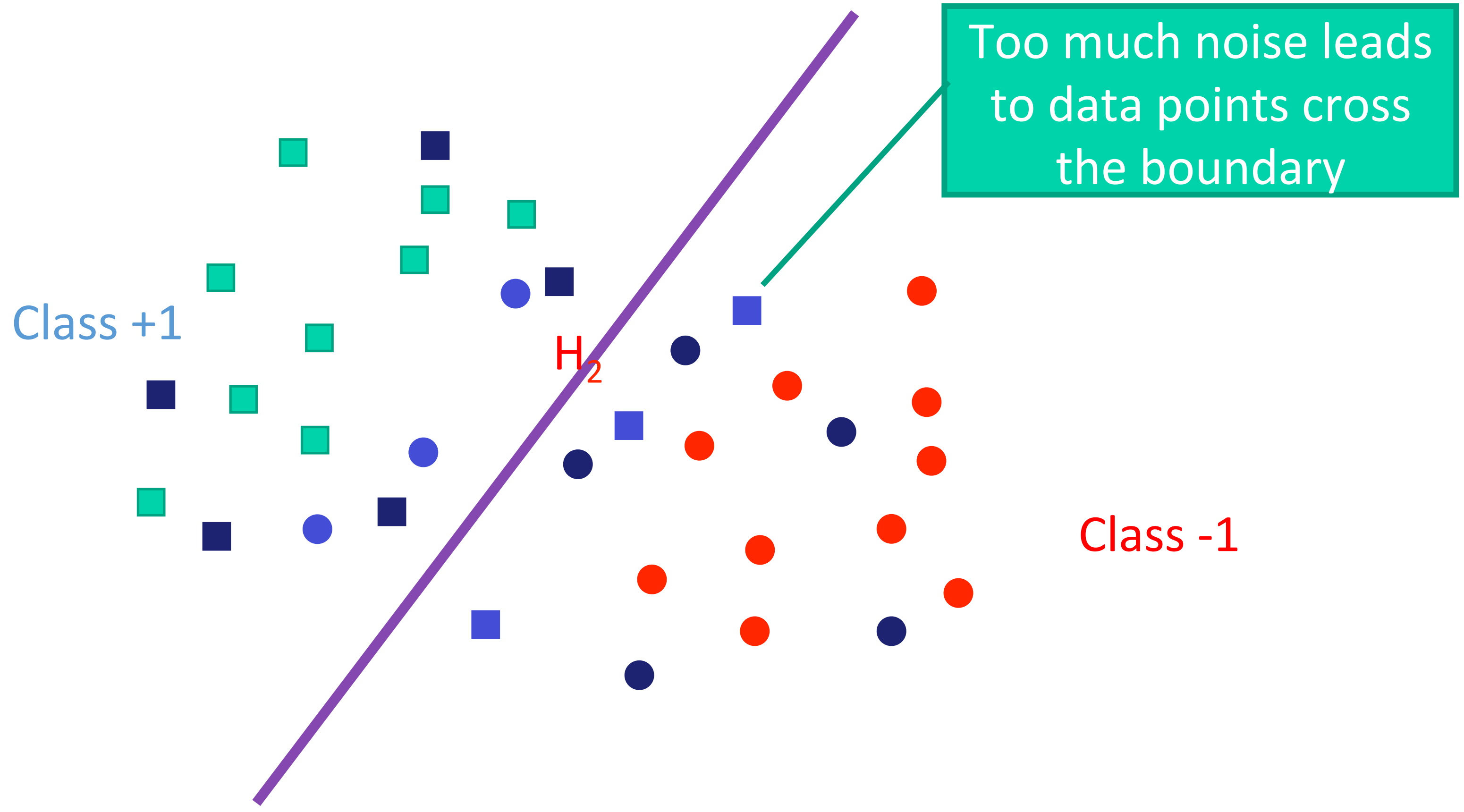
- Adding some amount of noise helps us pick solution:



Prefer H_2 (higher confidence)

Adding Noise

- Too much: hurts instead



Adding Noise: Equivalence to Weight Decay

- Suppose the hypothesis is $f(x) = w^T x,$ noise is $\epsilon \sim N(0, \lambda I)$
- After adding noise, the loss is

$$L(f) = \mathbb{E}_{x,y,\epsilon}[f(x+\epsilon) - y]^2 = \mathbb{E}_{x,y,\epsilon}[f(x) + w^T\epsilon - y]^2$$

$$L(f) = \mathbb{E}_{x,y,\epsilon}[f(x) - y]^2 + 2\mathbb{E}_{x,y,\epsilon}[w^T\epsilon(f(x) - y)] + \mathbb{E}_{x,y,\epsilon}[w^T\epsilon]^2$$

$$L(f) = \mathbb{E}_{x,y,\epsilon}[f(x) - y]^2 + \lambda\left||w|\right|^2$$

Early Stopping

- **Idea**: don't train the network to too small training error
  - Larger the hypothesis class, easier to find a hypothesis that fits the difference between the two
  - So: do not push the hypothesis too much; use validation error to decide when to stop

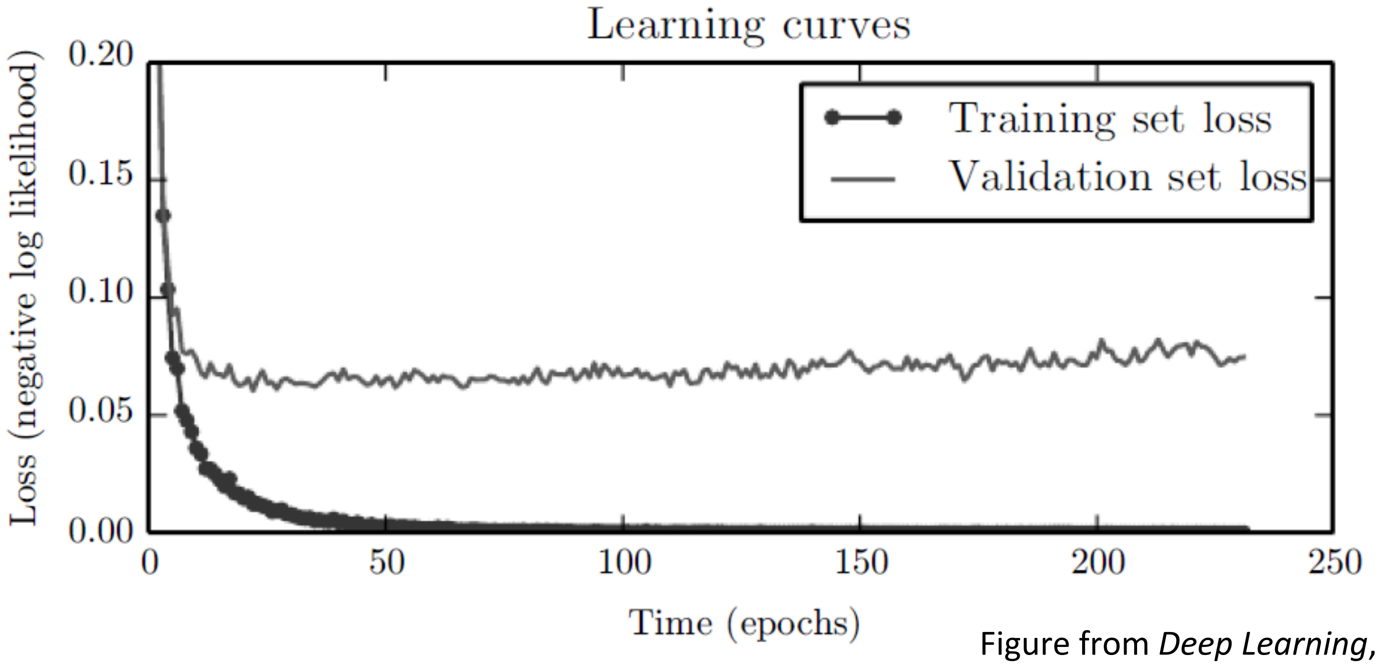


Figure from *Deep Learning*, Goodfellow, Bengio and Courville

Early Stopping

- Practically: when training, also output validation error
  - Every time validation error improved, store a copy of the weights
  - When validation error not improved for some time, stop
  - Return the copy of the weights stored

Dropout

- **Basic idea**: randomly select weights to update

- In each update step
  - Randomly apply a binary mask to all the input and hidden units
  - Multiply the mask bits with the units and do the update as usual

- Typical dropout prob: 0.2 for input and 0.5 for hidden units

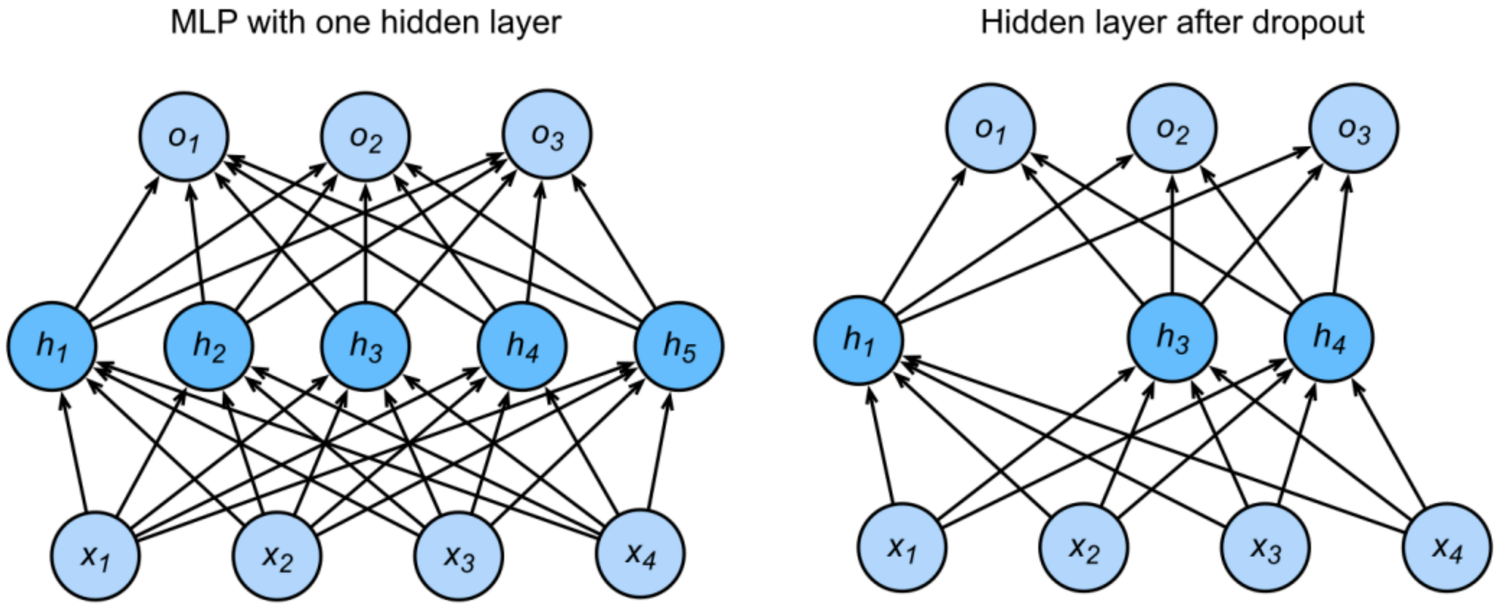
Applying Dropout

$$\mathbf{h} = \sigma(\mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)})$$

$$\mathbf{h}' = \text{dropout}(\mathbf{h})$$

$$\mathbf{o} = \mathbf{W}^{(2)}\mathbf{h}' + \mathbf{b}^{(2)}$$

$$\mathbf{p} = \text{softmax}(\mathbf{o})$$



Applying Dropout

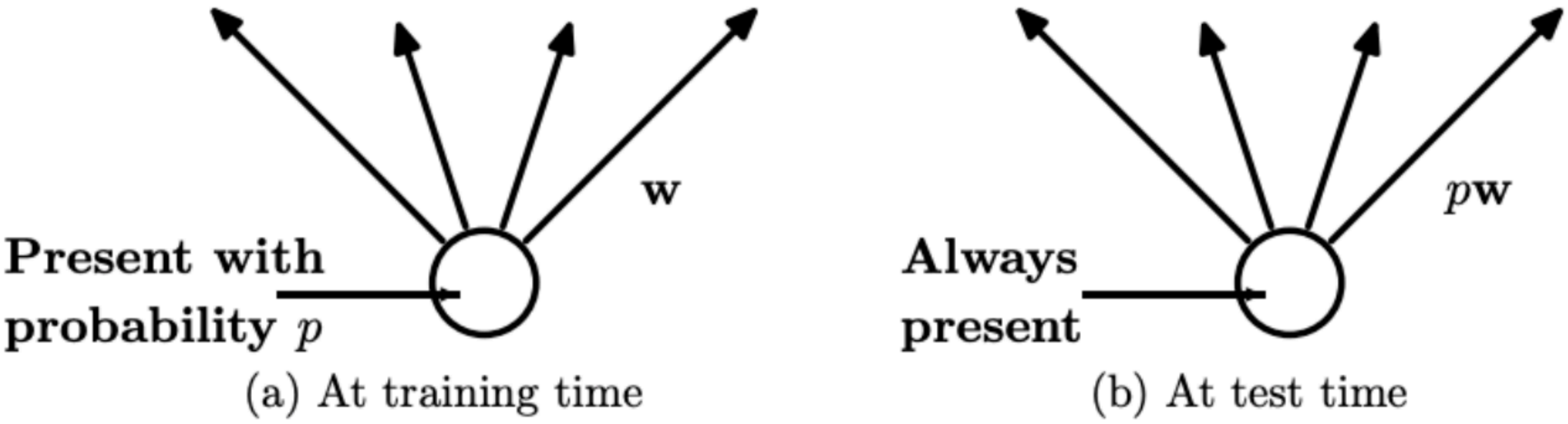


Figure 2: **Left**: A unit at training time that is present with probability p and is connected to units in the next layer with weights $\mathbf{w}$. **Right**: At test time, the unit is always present and the weights are multiplied by p. The output at test time is same as the expected output at training time.

Break & Quiz

Q2-2: Are these statements true or false?
(A) We can use validation data to decide when to stop early.
(B) We can think early stopping as a regularization to limit the volume of parameter space reachable from the initial parameter.

1. True, True
2. True, False
3. False, True
4. False, False

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1. True, True ←
2. True, False
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(A) As is shown in the lecture.
(B) That’s true. Early stopping will limit the training time and thus potentially limit the space the training can search.

Thanks Everyone!

Some of the slides in these lectures have been adapted/borrowed from materials developed by Mark Craven, David Page, Jude Shavlik, Tom Mitchell, Nina Balcan, Elad Hazan, Tom Dietterich, Pedro Domingos, Jerry Zhu, Yingyu Liang, Volodymyr Kuleshov, Sharon Li, and Fred Sala