Advanced techniques

Lecture 4

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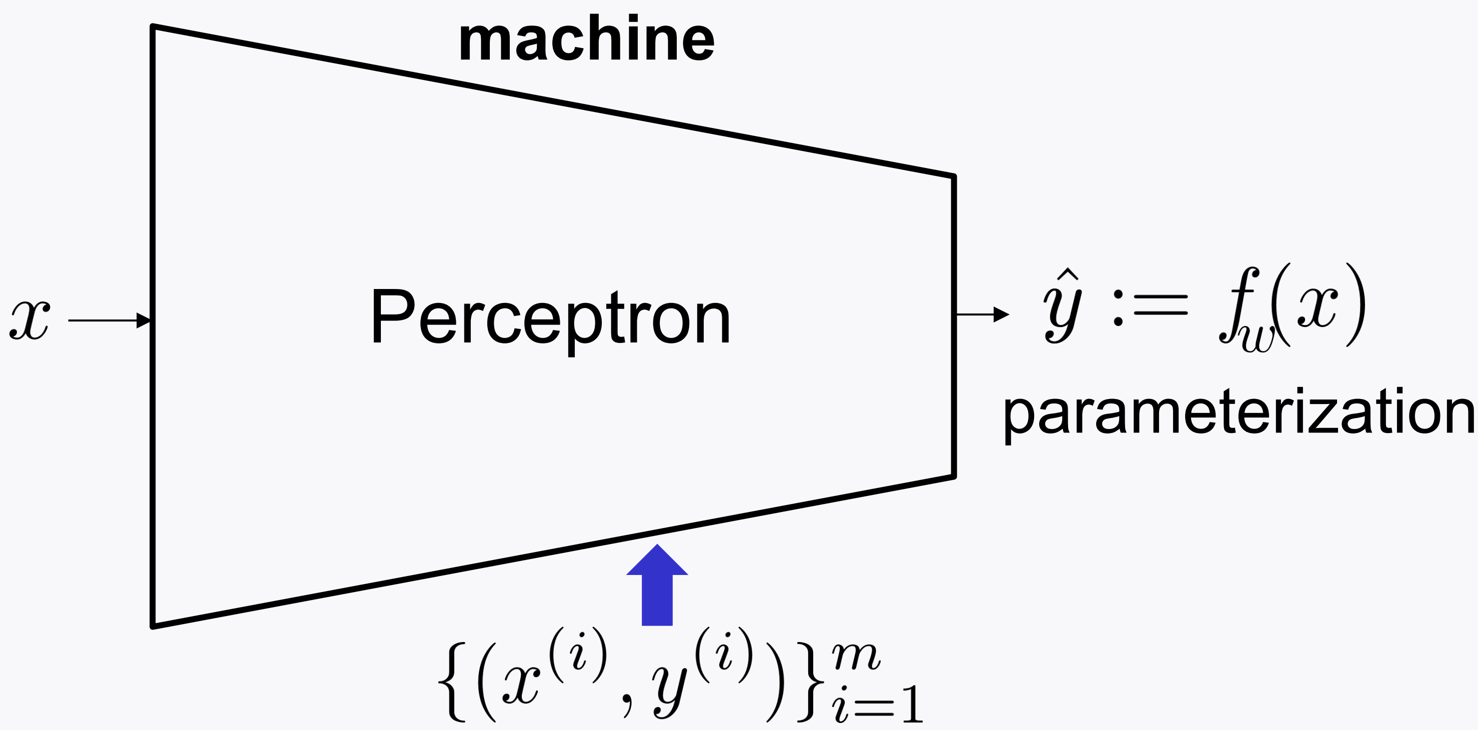
Data organization & generalization techniques

Recap: Machine learning

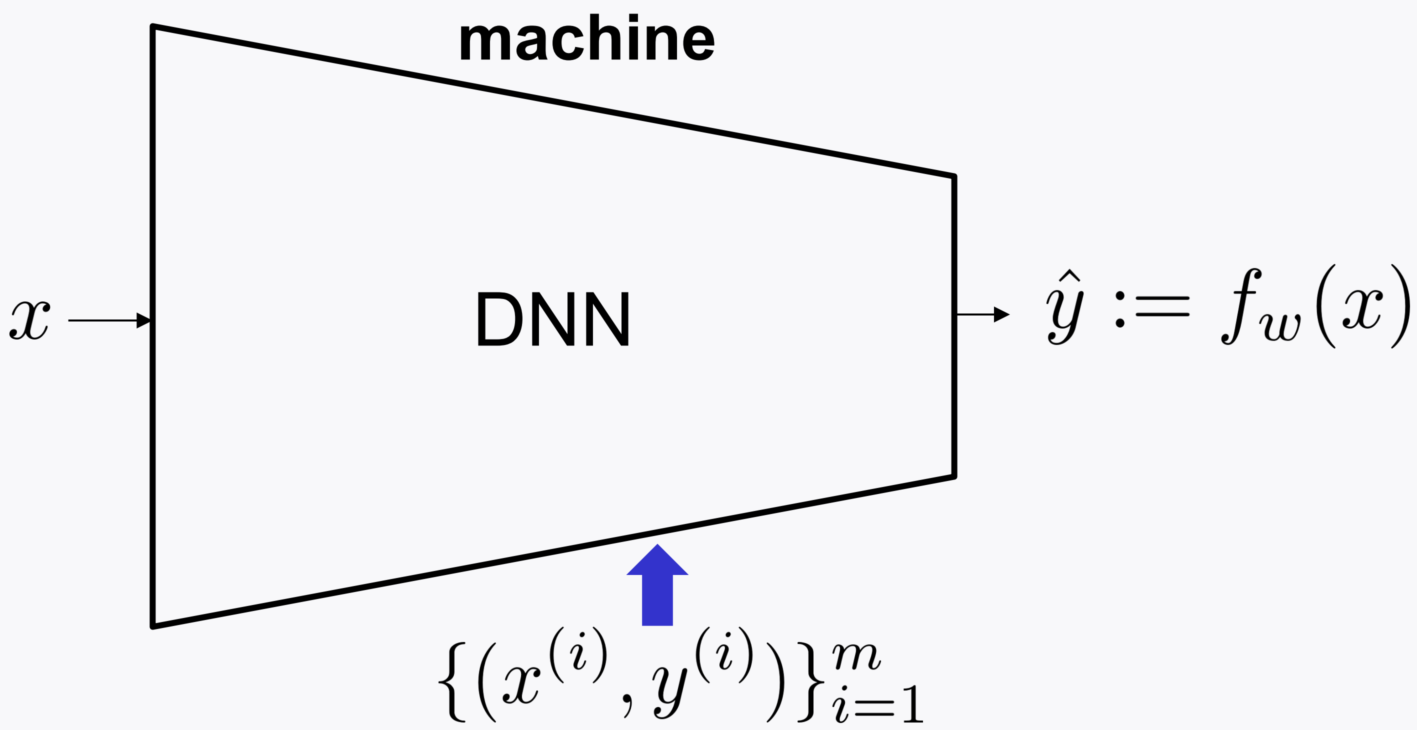


No activation + squared-error loss: **Least Squares**

Logistic act. + cross entropy loss: **Logistic regression**

Algorithm: Gradient descent

Recap: Deep neural networks



Rule of thumb: ReLU (@hidden); Logistic (@output)

Cross entropy loss

Algorithm: Gradient descent via backprop

Recap: Scikit-learn coding for LS

```
from   sklearn.datasets           import load_iris
from   sklearn.model_selection    import train_test_split

X,y=load_iris(return_X_y=True)
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2)


from   sklearn.linear_model       import RidgeClassifier

Model_LS = RidgeClassifier()

Model_LS.fit(X_train,y_train)

Model_LS.predict(X_test)

Model_LS.score(X_test,y_test)
```

Recap: Scikit-learn coding for LR

```
from    sklearn.datasets            import load_iris
from    sklearn.model_selection     import train_test_split

X,y=load_iris(return_X_y=True)
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2)
```

```
from    sklearn.linear_model        import LogisticRegression

Model_LR = LogisticRegression()
Model_LR.fit(X_train,y_train)
Model_LR.predict(X_test)
Model_LR.score(X_test,y_test)
```

Recap: TensorFlow coding for DNN

```
from tensorflow.keras.datasets import mnist
from tensorflow.keras.layers import Flatten, Dense
from tensorflow.keras.models import Sequential

(X_train, y_train),(X_test, y_test) = mnist.load_data()
X_train, X_test = X_train/255.0, X_test/255.0

Model_NN = Sequential()
Model_NN.add(Flatten(input_shape=(28,28)))
Model_NN.add(Dense(128,activation='relu'))
Model_NN.add(Dense(10,activation='softmax'))

Model_NN.compile(optimizer='adam', \
loss='sparse_categorical_crossentropy', metrics=['acc'])
Model_NN.fit(X_train, y_train, epochs=10)
Model_NN.predict(X_test)
Model_NN.evaluate(X_test, y_test)
```

*See Appendix for details on **softmax** activation.

Question

How to improve model performance?

Outline of today's lectures

Will explore several techniques for **improvement.**

1. Data organization (train/validation/test sets)
2. Generalization techniques
3. Weight initialization
4. Techniques for training stability
5. Hyperparameter search
6. Cross validation

Focus of Lecture 4

Will explore several techniques for **improvement.**

1. Data organization (train/validation/test sets)
2. Generalization techniques
3. Weight initialization
4. Techniques for training stability
5. Hyperparameter search
6. Cross validation

Train vs. validation vs. test sets

Data seen during training:

train set

Role: *training* model parameters

validation set

Role: *Hyperparameter* search

Data unseen during training: test set

How to split train/val/test sets?

Two important factors to consider:

1. How big "m" is

2. Data distribution

How big "*m*" is

A deciding factor for the **split ratio**.

Small scale:	$m \leq 1,000$	train:val:test = 60:20:20
Middle:	$1,000 \leq m \leq 10,000$	80:10:10
Large:	$10,000 \leq m \leq 1,000,000$	98:1:1
Ultra-large:	$m \geq 1,000,000$	99.9:0.05:0.05

Data distribution

val set dist. ~ test set dist. ~ target dist.

Easy to implement in Tensorflow.

Generalization techniuqes

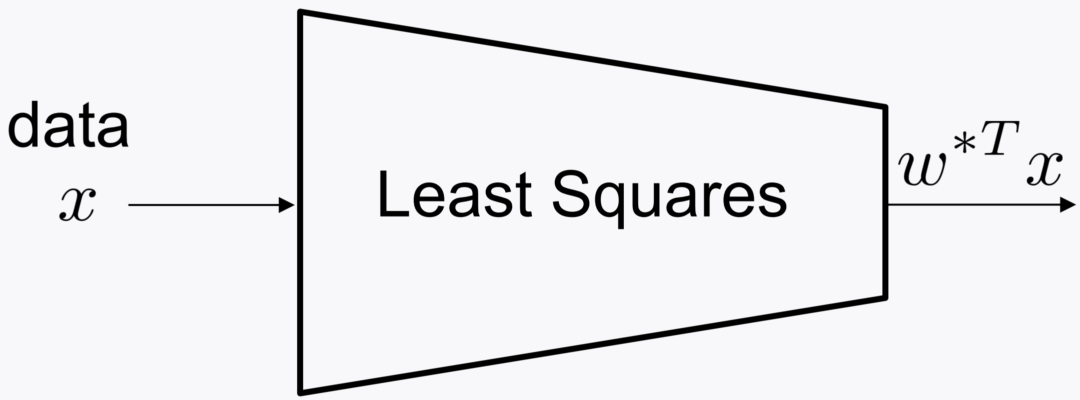
1. Regularization

2. Data augmentation

3. Early stopping

4. Dropout

Regularization: Motivation



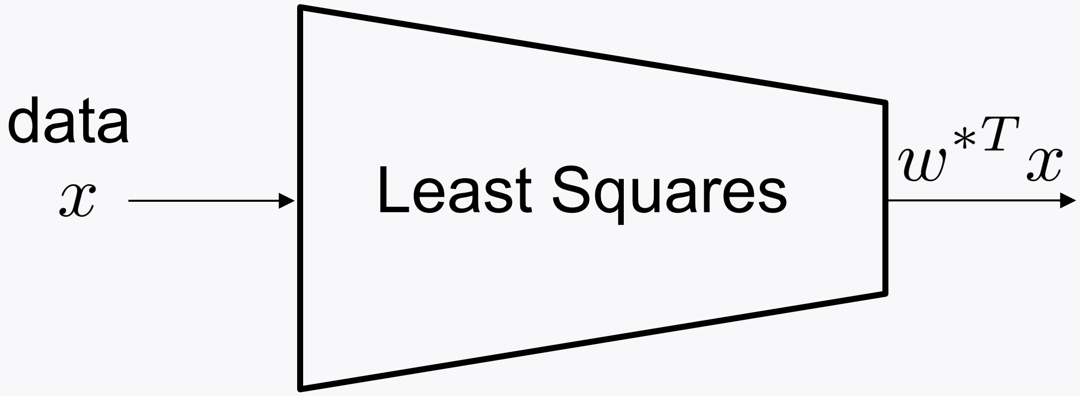
In reality: x contains some noise.

Want: Classifier being robust to such noise.

Challenge:

Large values of w^* can boost up such noise.

Regularization: Motivation



For robustness, we want: $\|w^*\|^2 \downarrow$

Note: At the same time, we also want:

$$\text{Loss Function} \downarrow$$

Regularization: Idea

Regulate two objectives at the same time.

$$\min_{w} \text{Loss Function} + \lambda \|w\|^2$$

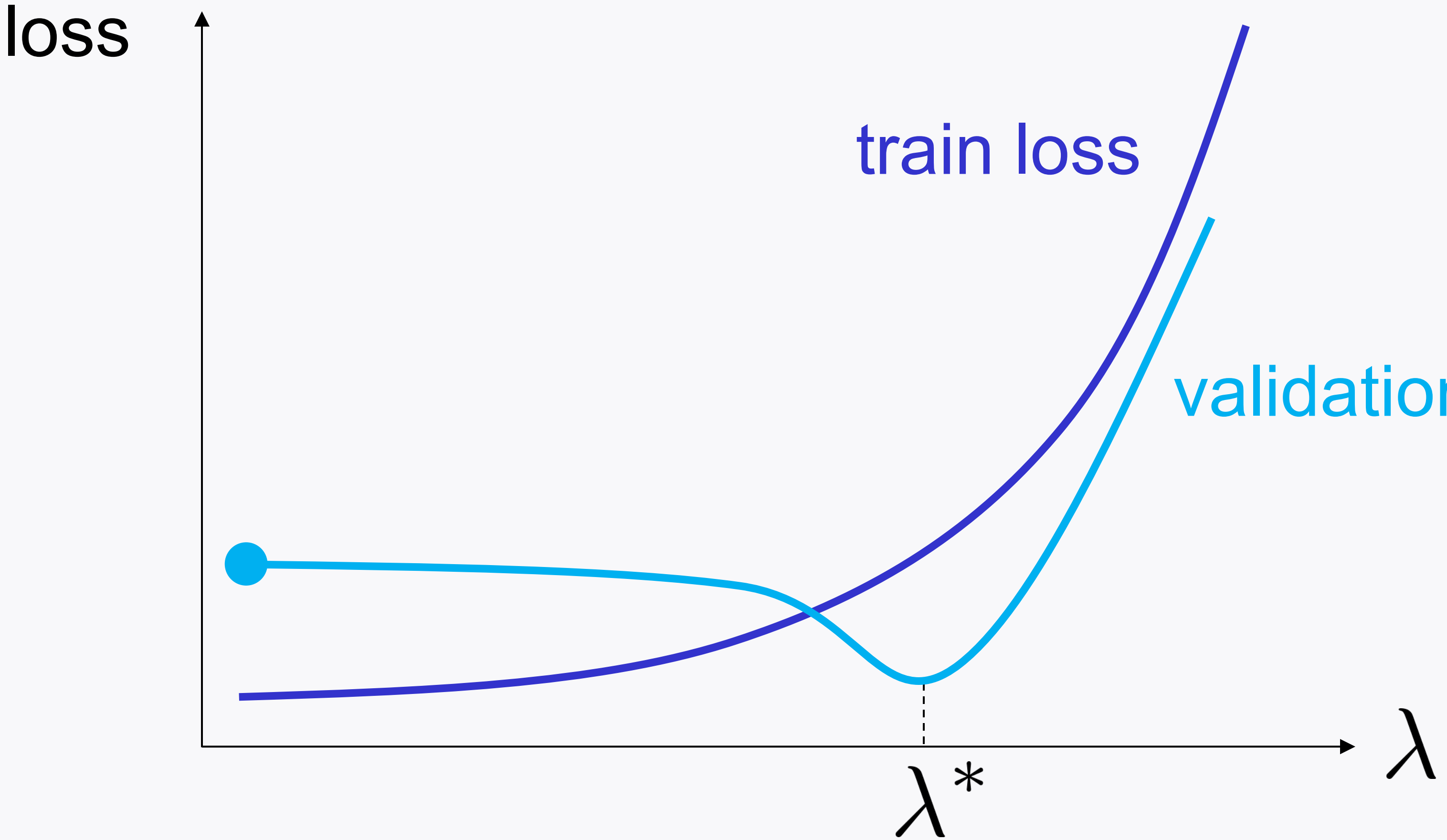
λ : regularization factor

It is a **hyperparameter**!

How to choose?

Regularization: How λ affects?

Regularization: How to choose λ ?



Find the **sweet spot** that minimizes validation loss.

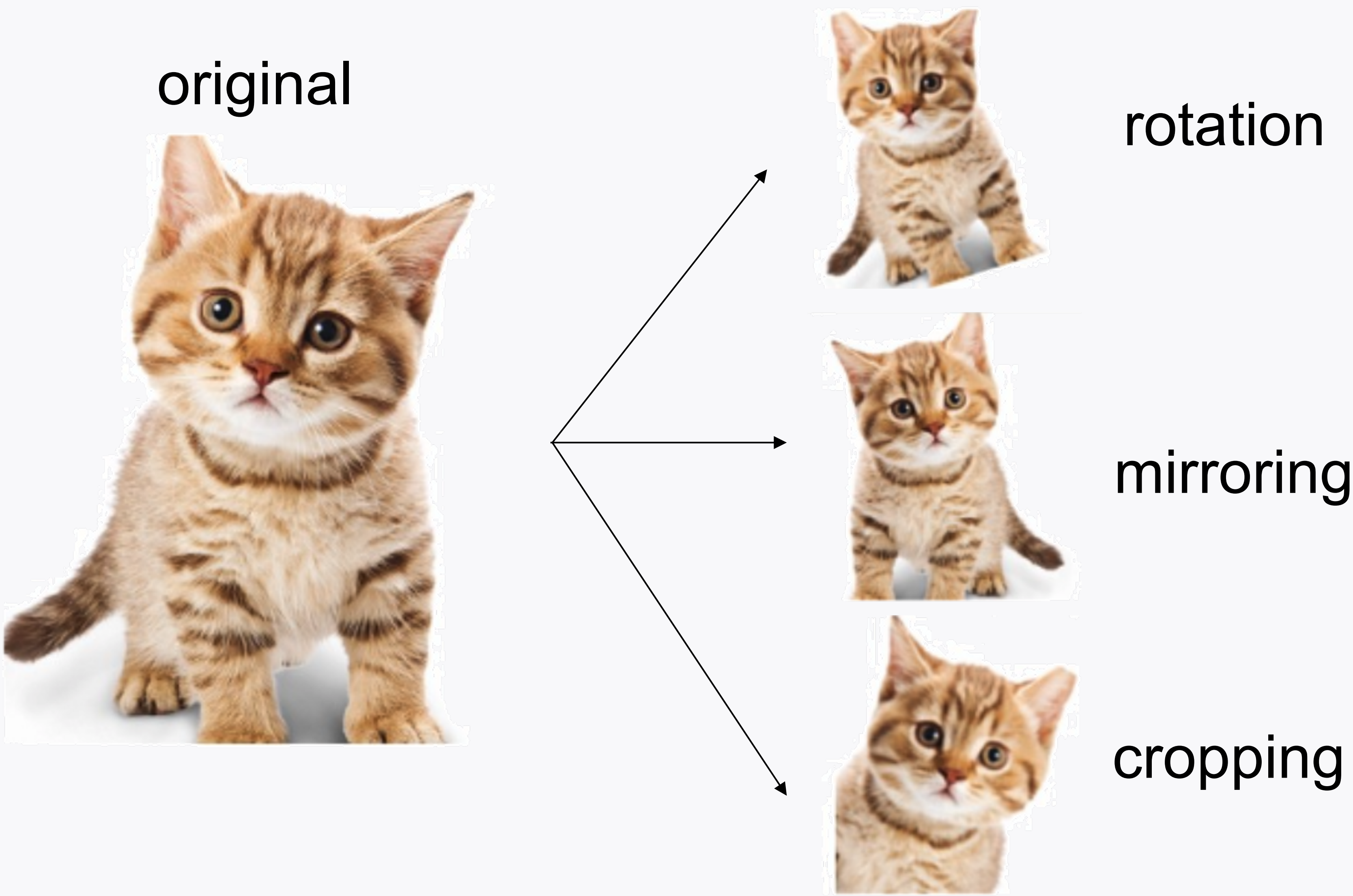
Data augmentation

Idea: Artificially generate diverse data by perturbing original data.

This way: Can make model resilient to unseen data.

Hence: Can improve generalization capability.

Data augmentation for image data



Data augmentation for generic data

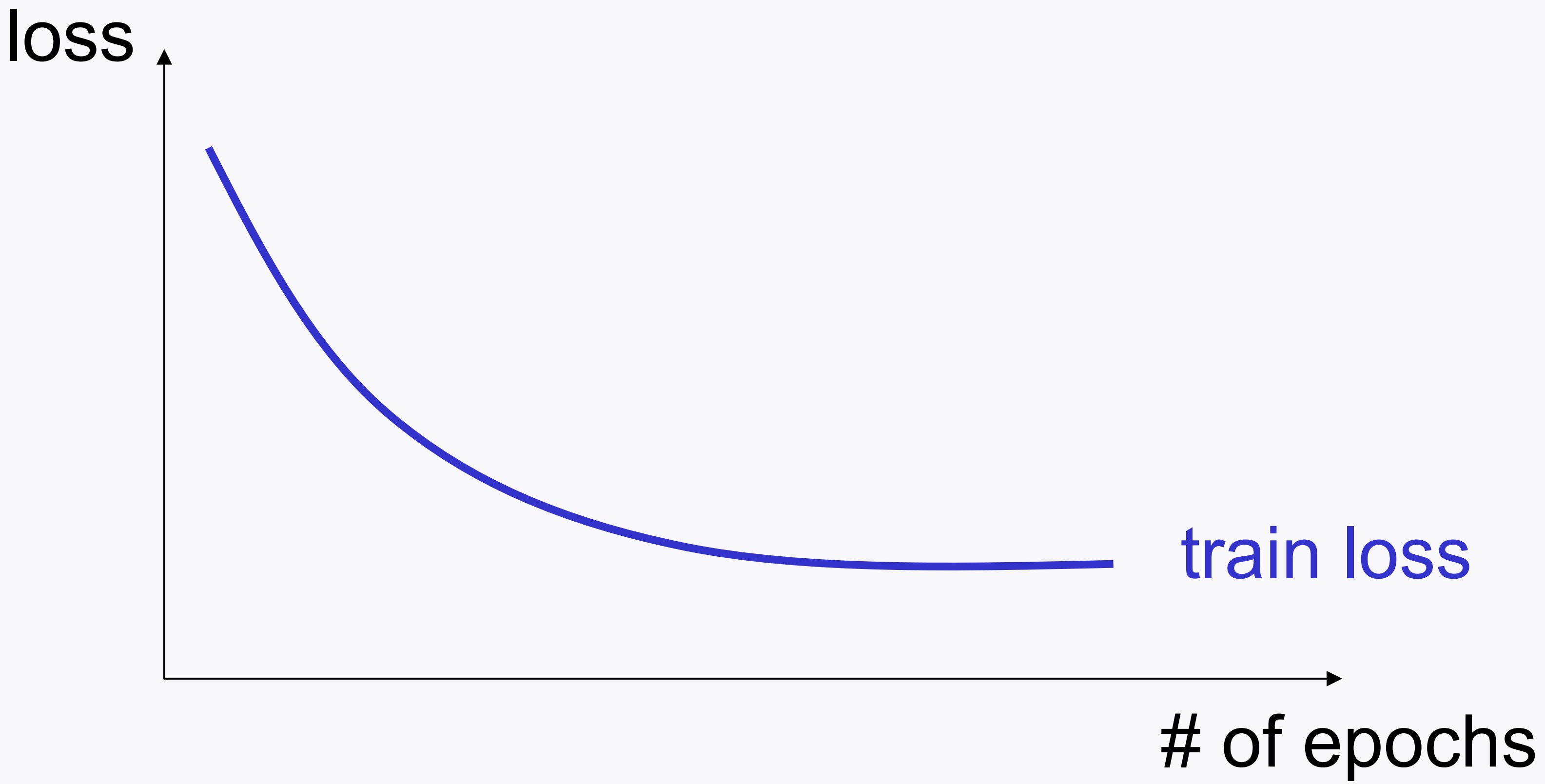
Original data: $\{(x^{(i)}, y^{(i)})\}_{i=1}^{m}$

One prominent way is to add random noise:

$$x^{(i)} + n$$

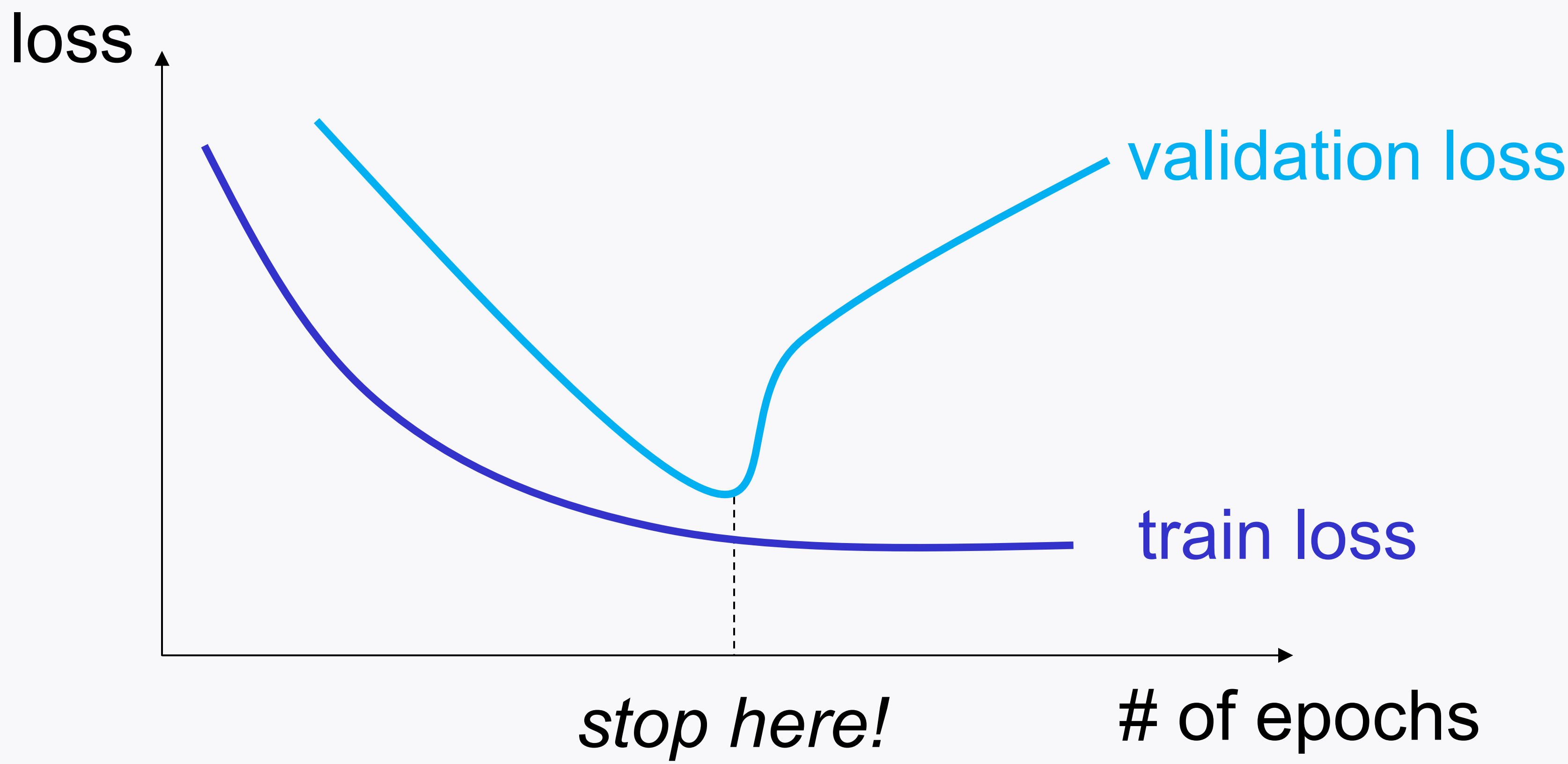
random noise

Early stopping: Motivation



Large # of epochs: More **overfitting** to train sets.

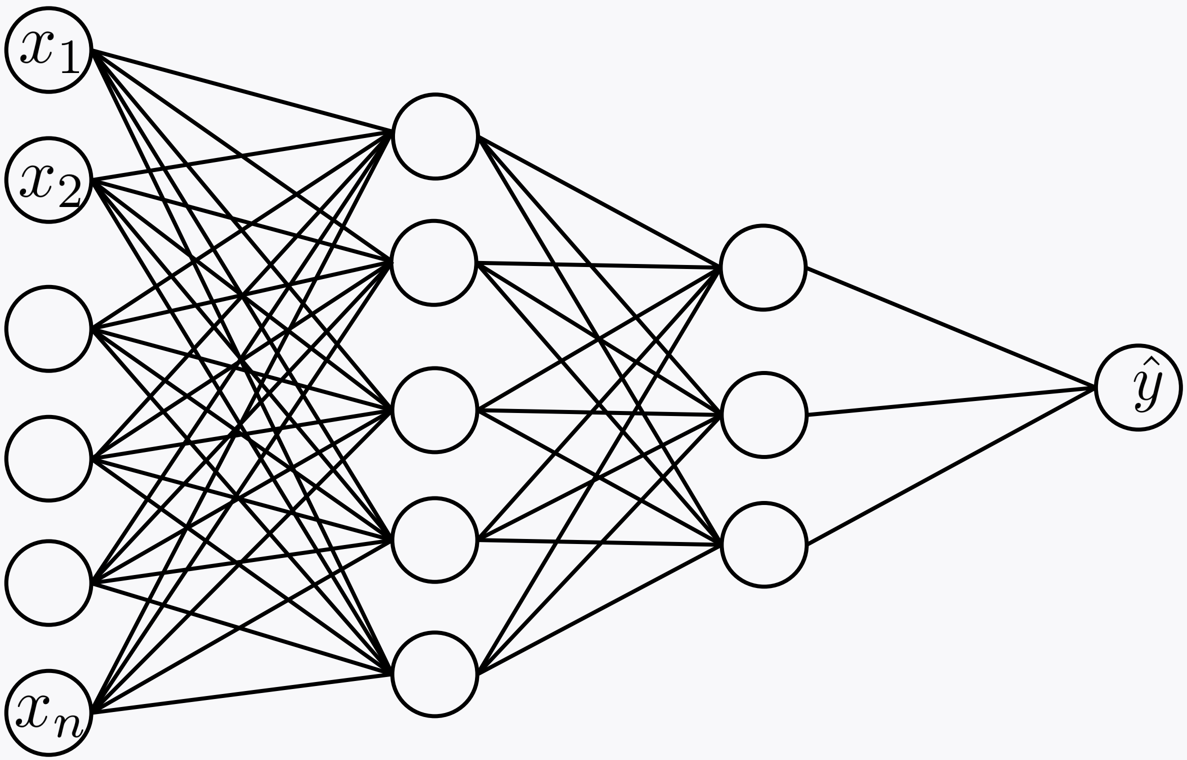
Early stopping: Idea



To avoid overfitting: Rely on validation loss.

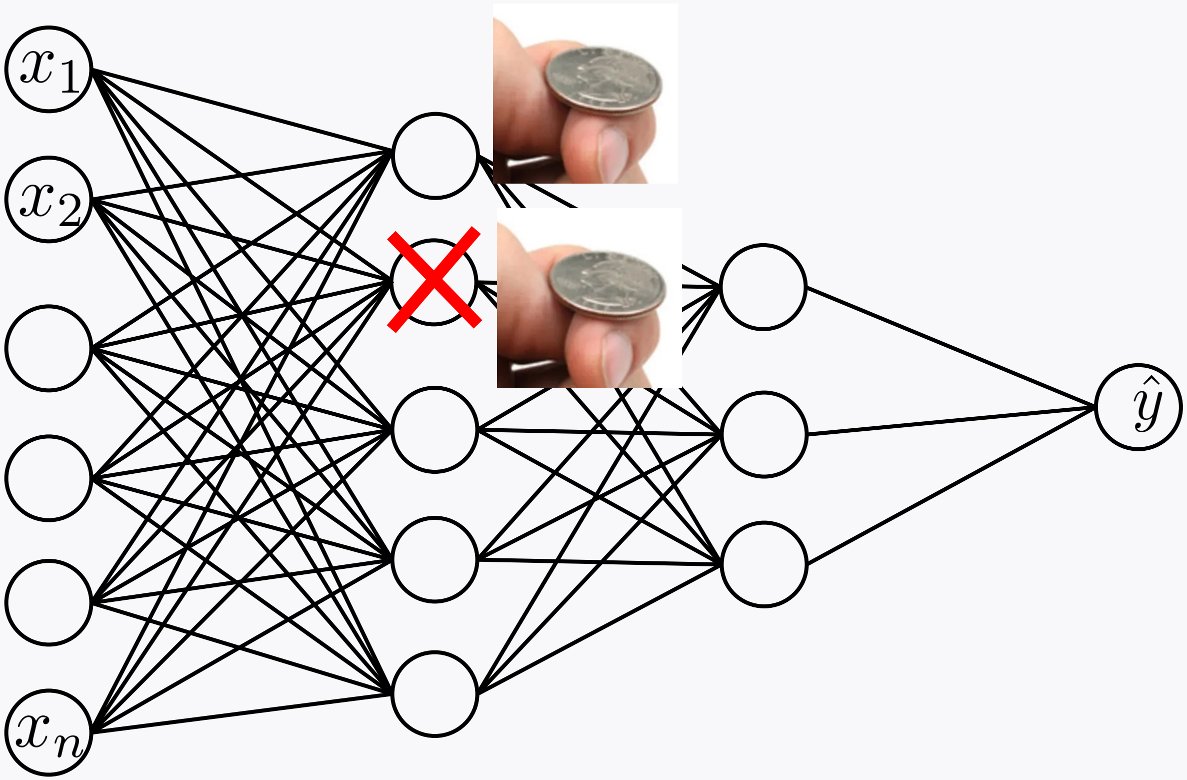
Dropout

During training: **Per example**, randomly remove neurons independently across them.



Dropout

Dropout rate: *p* (e.g., 0.5)



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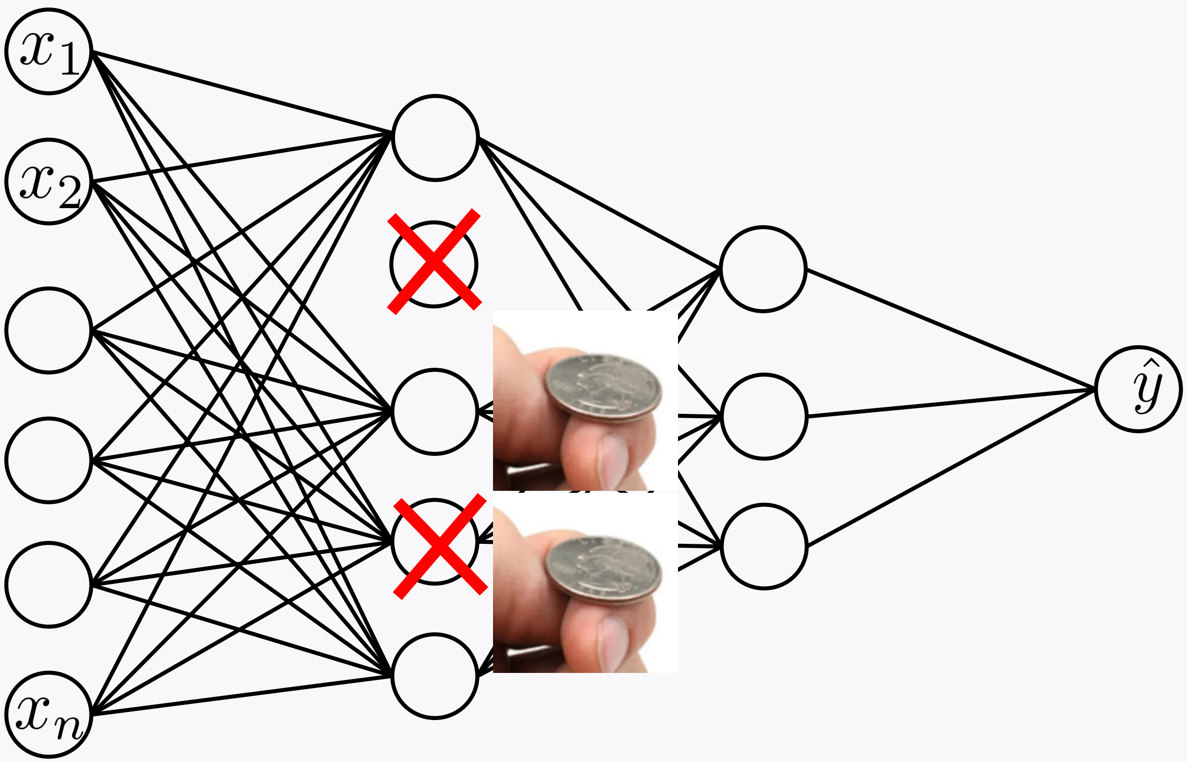

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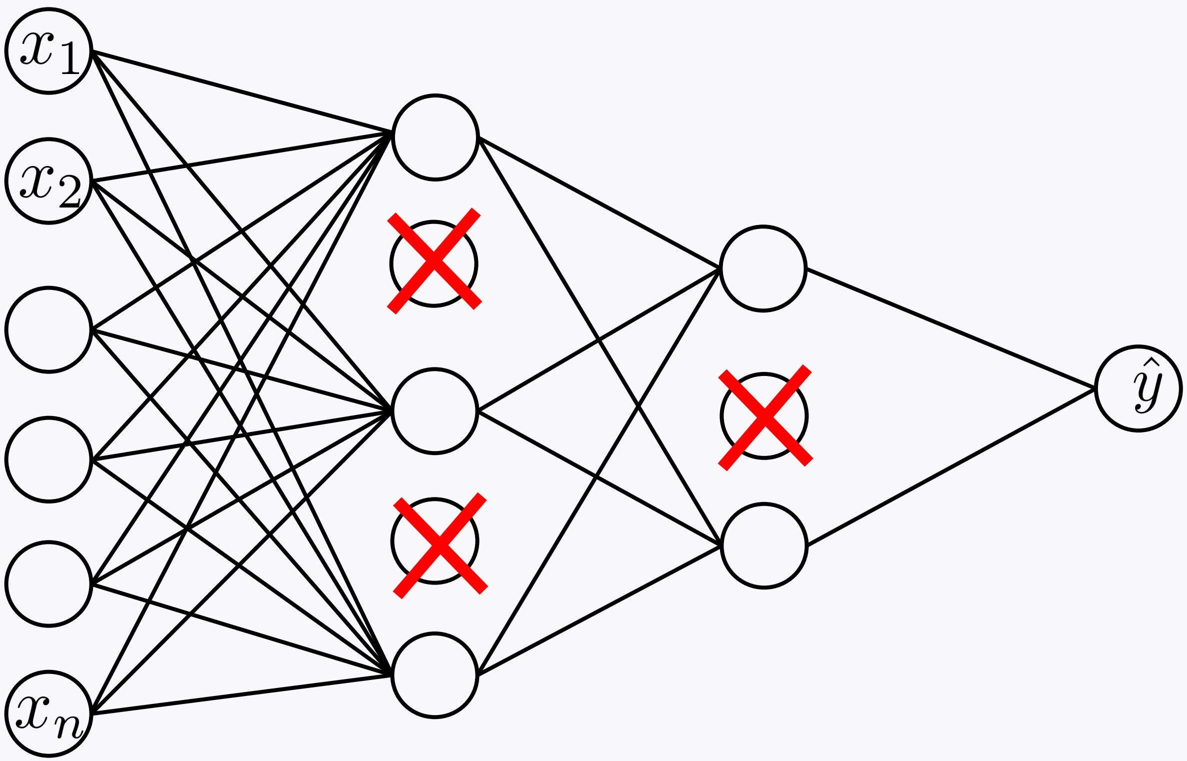


Generate this partial NN per example.

Why dropout works?

Experience many smaller NNs.

Can interpret the resulting NN as an **averaging ensemble** of all these smaller NNs.

Not overfit to a particular NN; hence generalize better.

Look ahead

Will study:

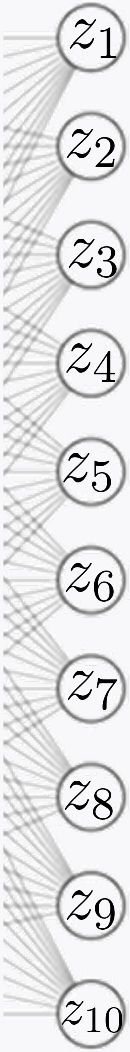
weight initialization

techniques for training stability

Appendix:
Softmax activation

Softmax activation for output layer

output layer



softmax

10 classes

$$\hat{y}_j = \frac{e^{z_j}}{\sum_{k=1}^{10} e^{z_k}}$$

Loss function for maximizing likelihood

Turns out: The loss function is again cross entropy loss.

$$\ell_{\mathsf{CE}}(y, \hat{y}) = \sum_{j=1}^{10} -y_j \log \hat{y}_j$$

y

one-hot vector (label=2)

$$\begin{array}{c} \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \end{array} \begin{array}{c} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \\ 8 \\ 9 \end{array}$$