Advanced techniques

Lecture 4

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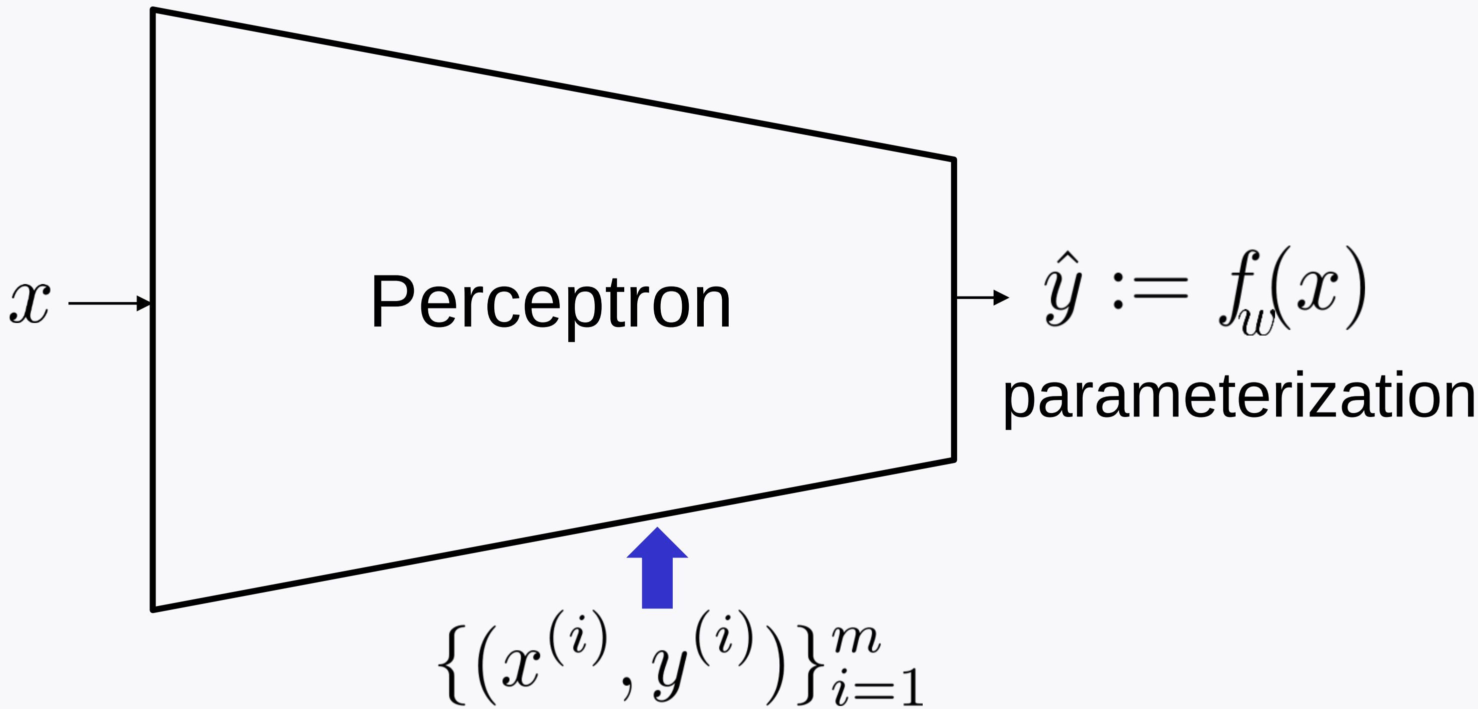
Data organization & generalization techniques

Recap: Machine learning

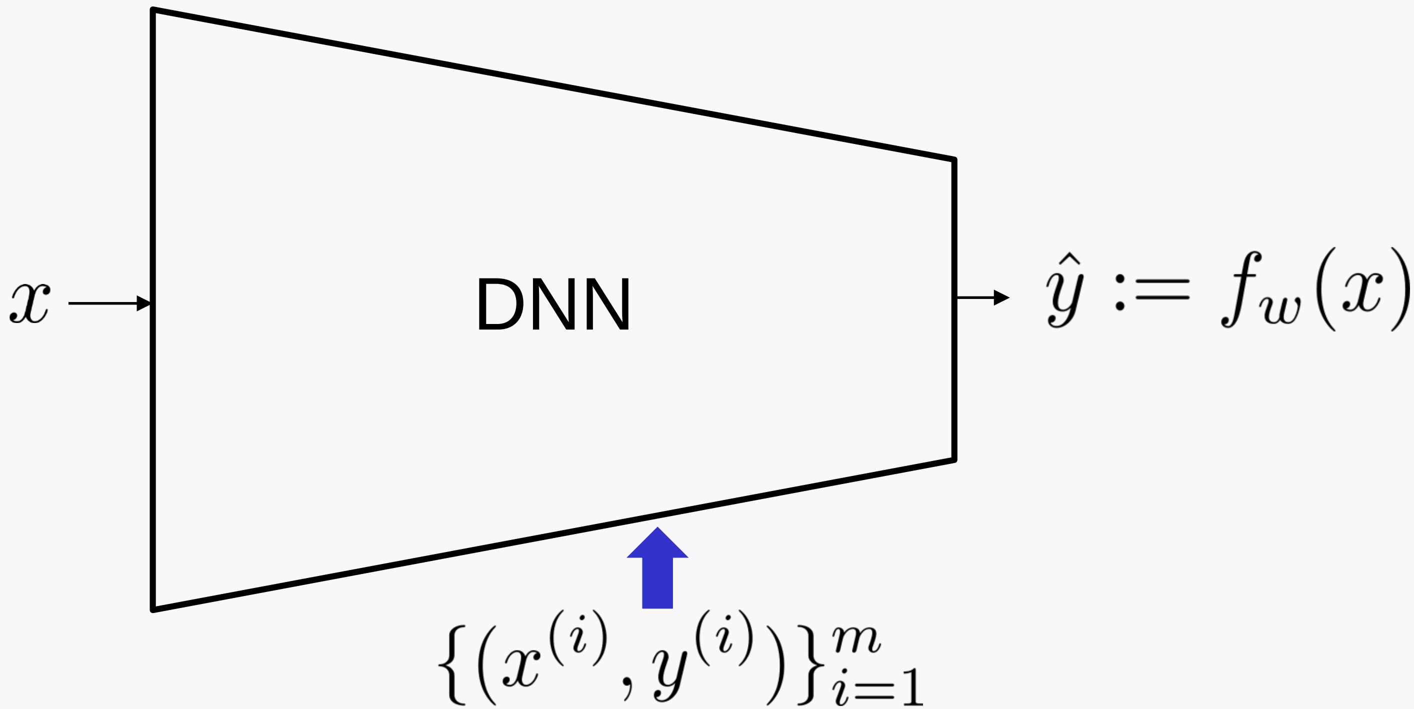


No activation + squared error loss: **Least Squares**

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

Algorithm: Gradient descent

Recap: Deep neural networks



ReLU (@hidden); Logistic (@output); Cross entropy loss

Algorithm: Gradient descent

Efficient method: backprop

Practical variant: Adam optimizer

Recap: Scikit-learn coding for LS

```
from    sklearn.datasets            import load_iris
from    sklearn.model_selection     import train_test_split
iris=load_iris()
X=iris.data
y=iris.target
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

iris=load_iris()
X=iris.data
y=iris.target
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.models import Sequential
from tensorflow.keras.layers import Flatten
from tensorflow.keras.layers import Dense

(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)
```

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:	$m \leq 1,000$	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

Set the split ratio such that $m_{\text{test}} \approx 100 \sim 1000$

Data distribution

val data dist. ~ test data dist. ~ target dist.

Take the rest as training data.

Coding implementation is easy.

Generalization techniuqes

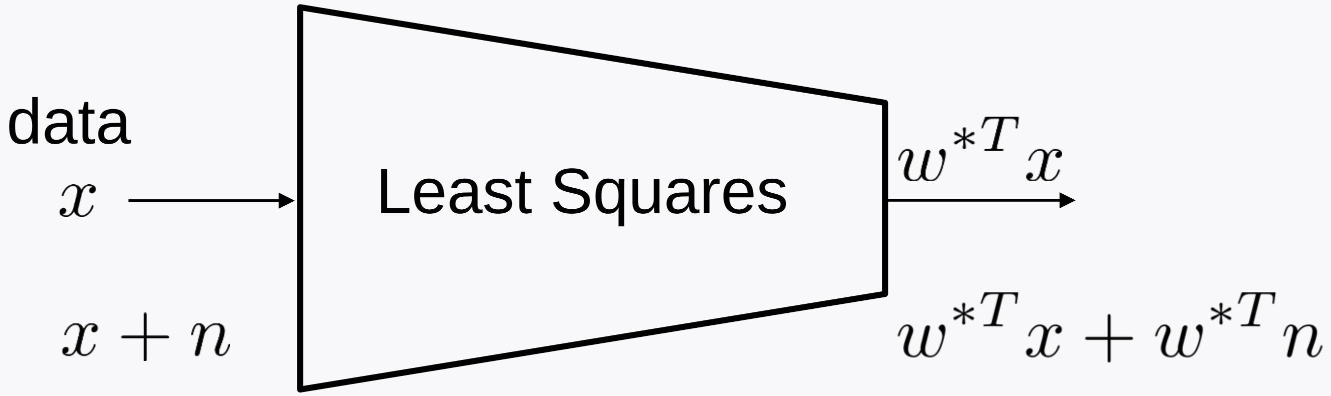
1. Regularization

2. Data augmentation

3. Early stopping

4. Dropout

Regularization: Motivation



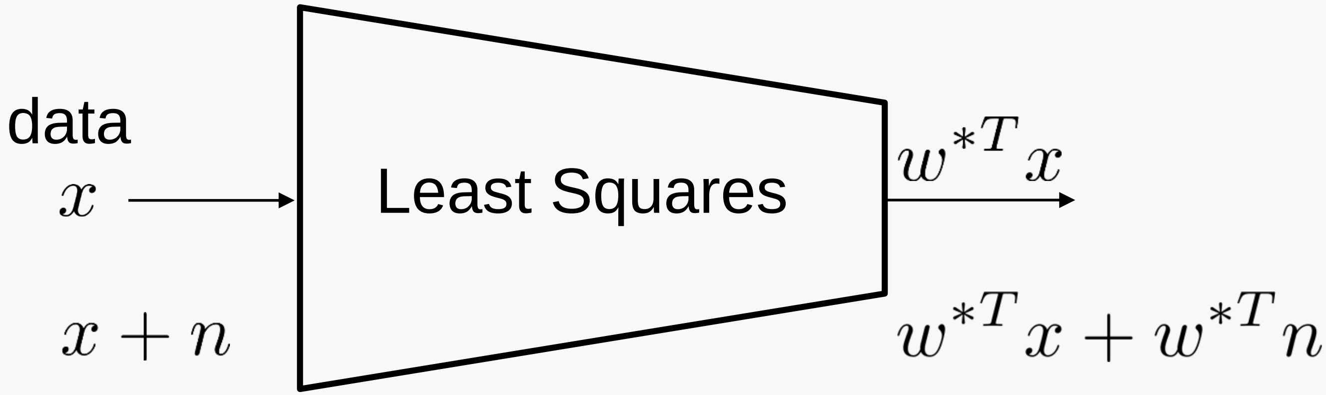
In reality: x contains some noise.

Want: model 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.

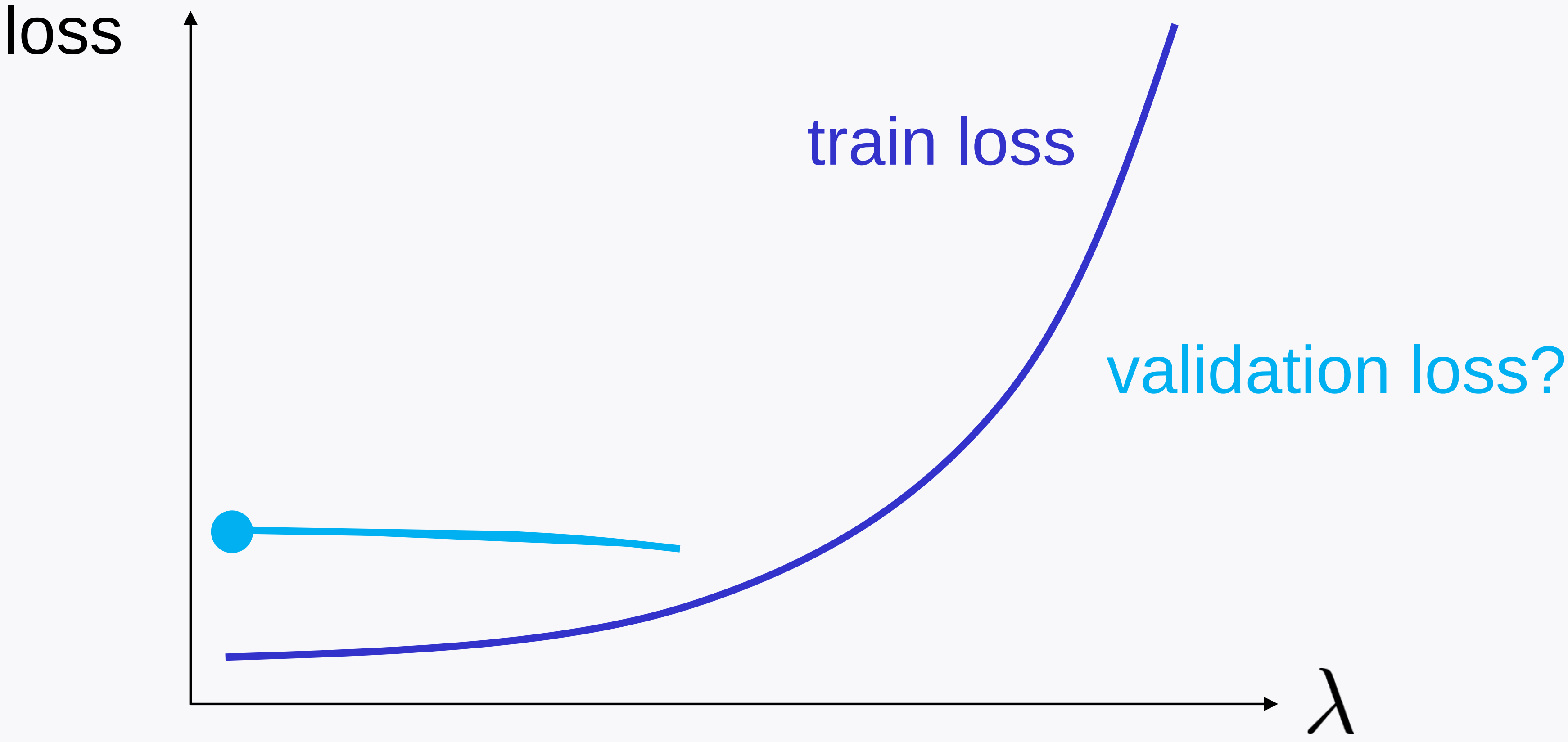
$$\min_{w} \text{Loss Function} + \lambda \|w\|^2$$

λ : regularization factor

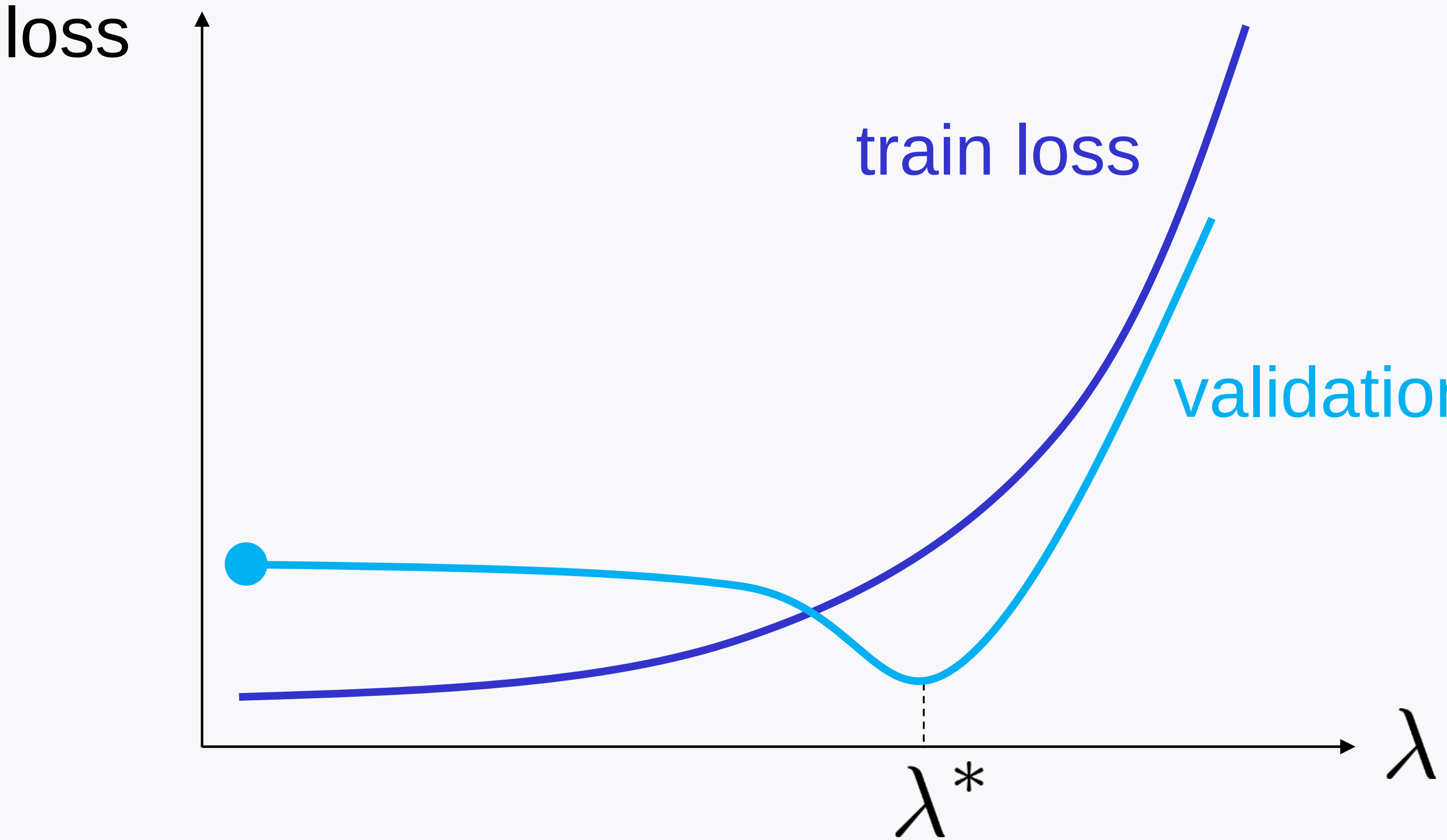
It is a **hyperparameter**!

How to choose?

Regularization: How λ affects?



Regularization: How to choose λ ?



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

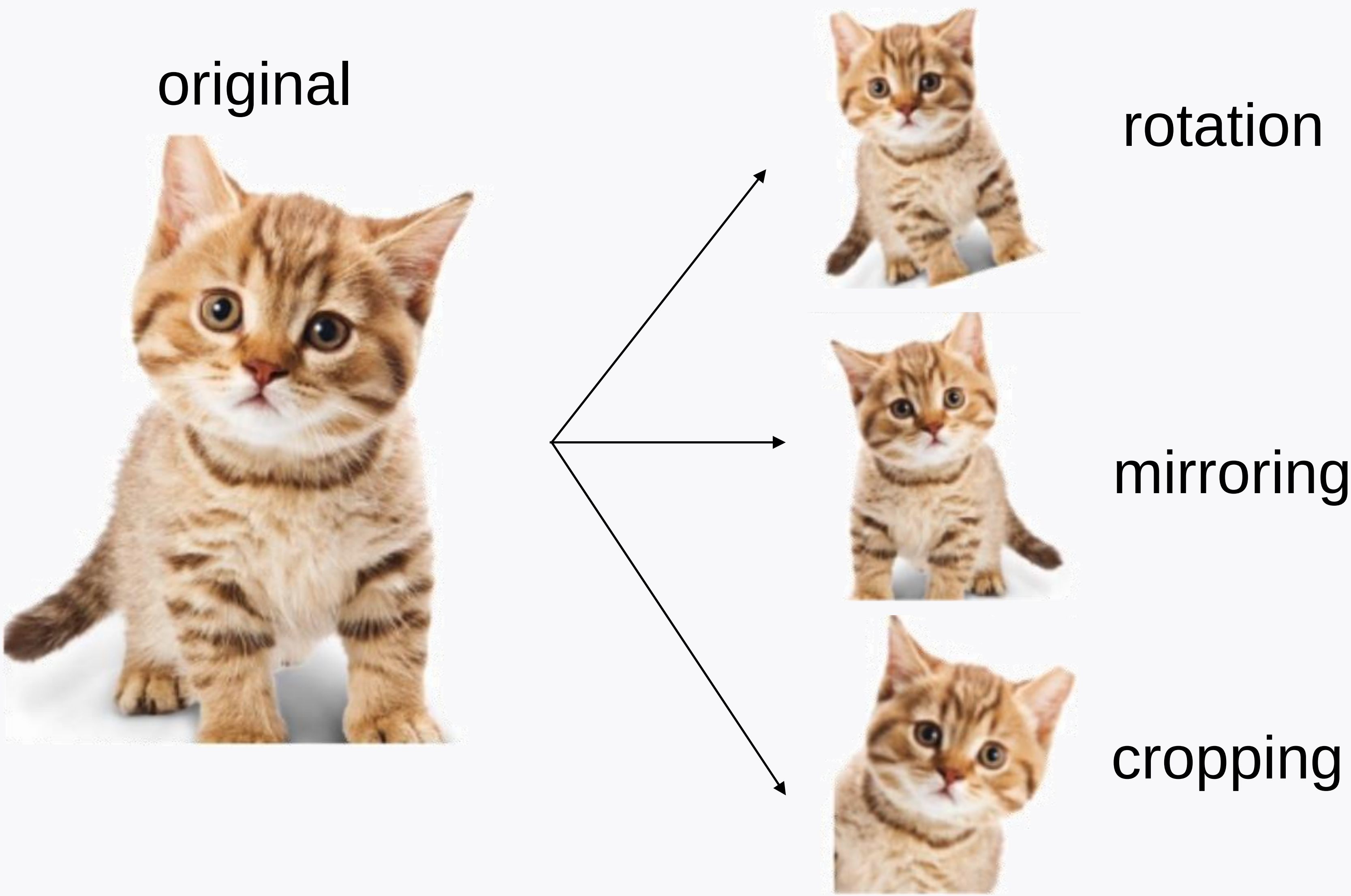
Data augmentation

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 numerical data

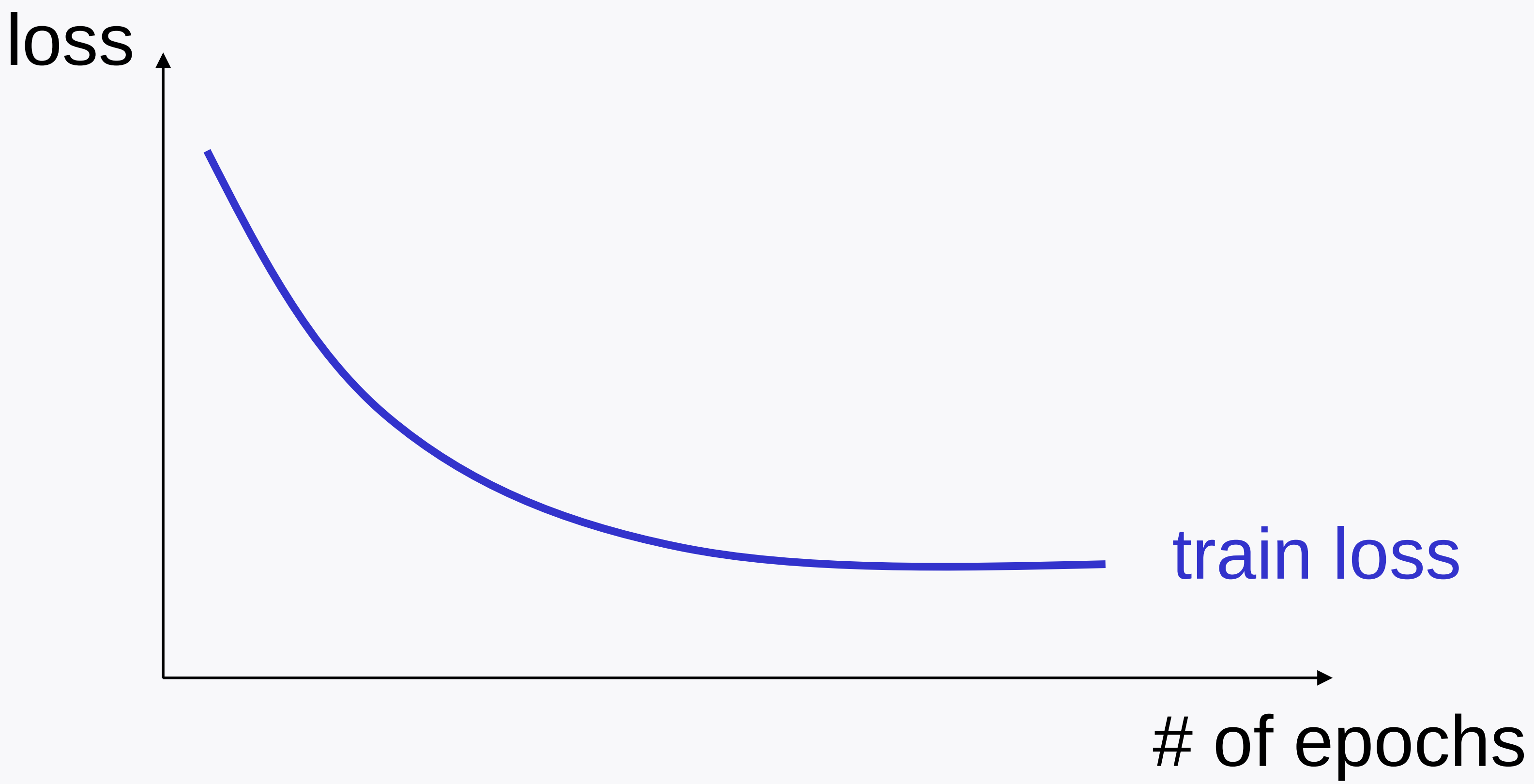
Original data: $\{(x^{(i)}, y^{(i)})\}_{i=1}^{m}$

One prominent way is to add random noise:

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

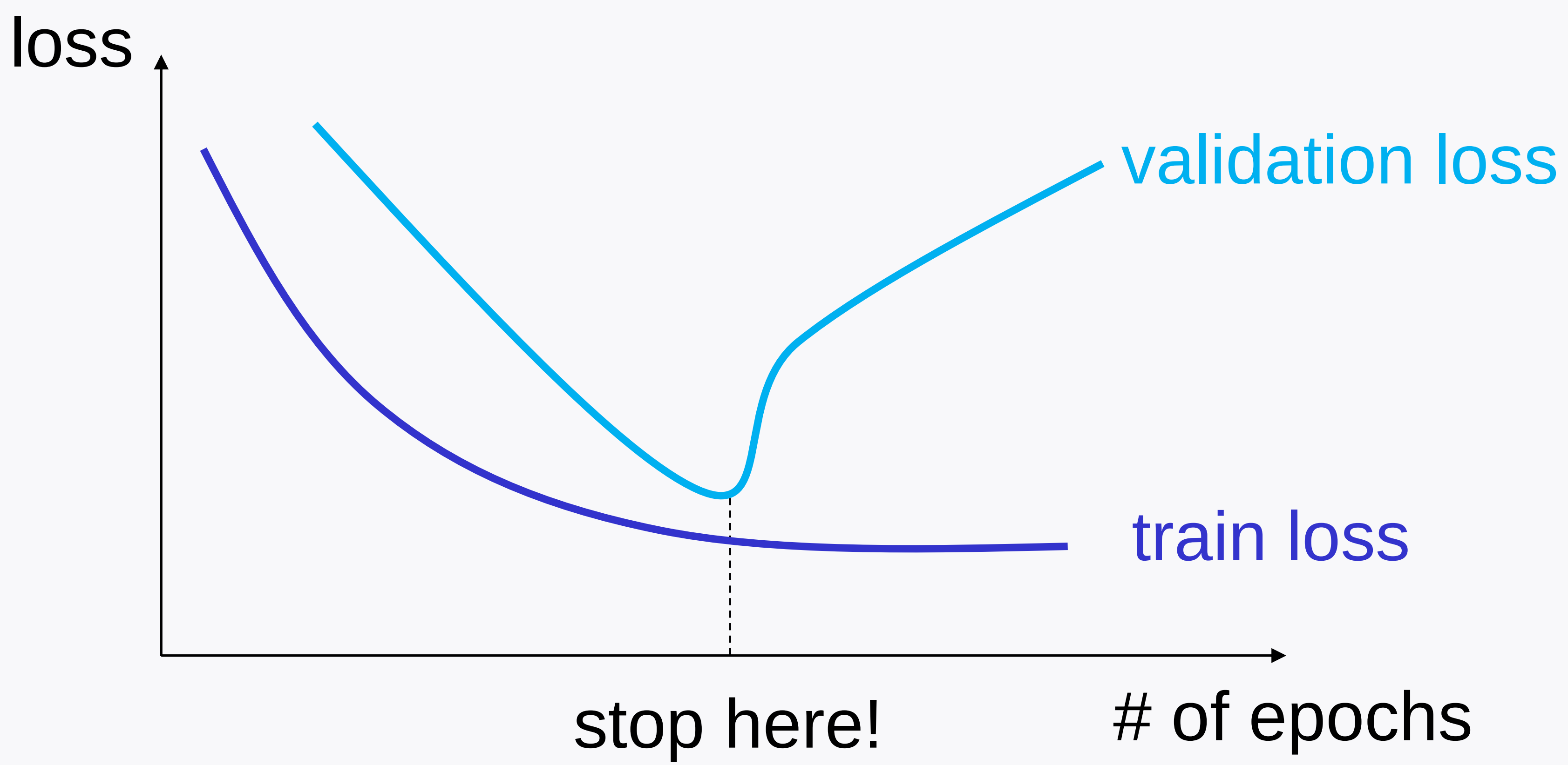
random noise

Early stopping: Motivation



Large # of epochs: **Overfitting** to train data.

Early stopping: Idea



To avoid overfitting: Rely on validation loss.

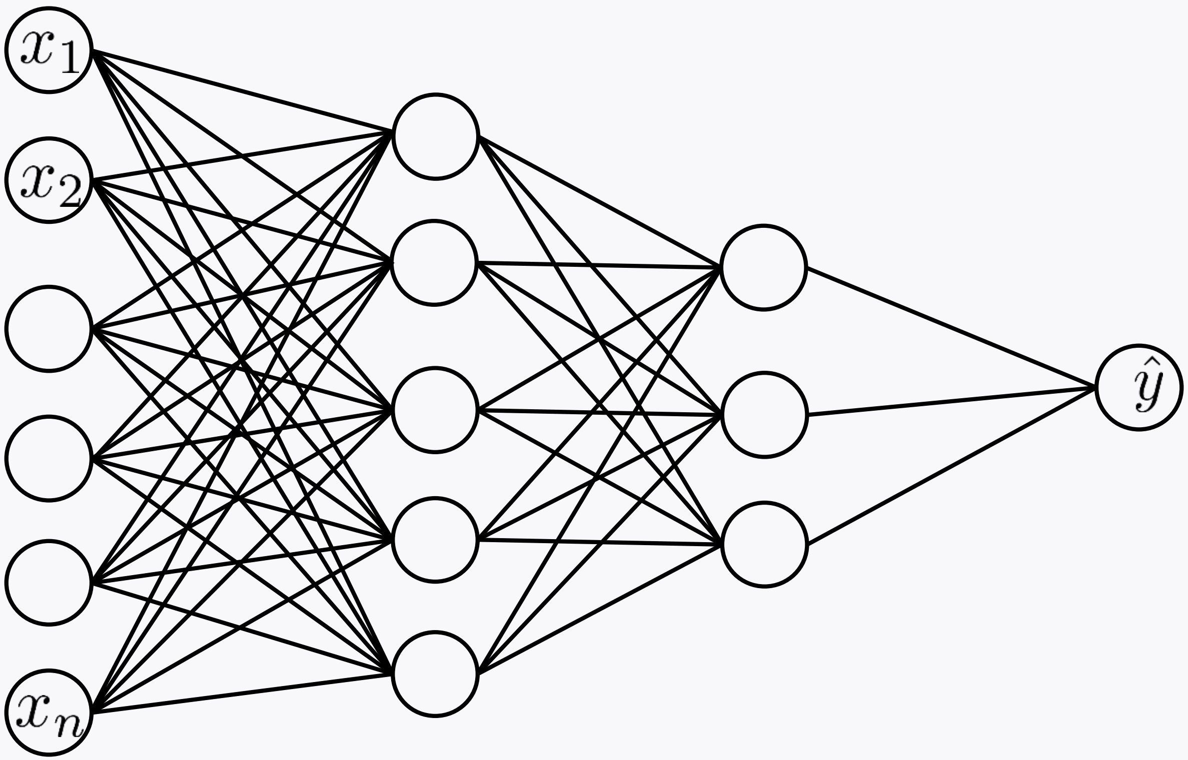
Dropout

$$J(w) = \frac{1}{m_{\mathcal{B}}} \sum_{i=1}^{m_{\mathcal{B}}} \ell(y^{(i)}, \hat{y}^{(i)})$$

In computing a prediction $\hat{y}^{(i)}$ **per example**, construct a random neural network.

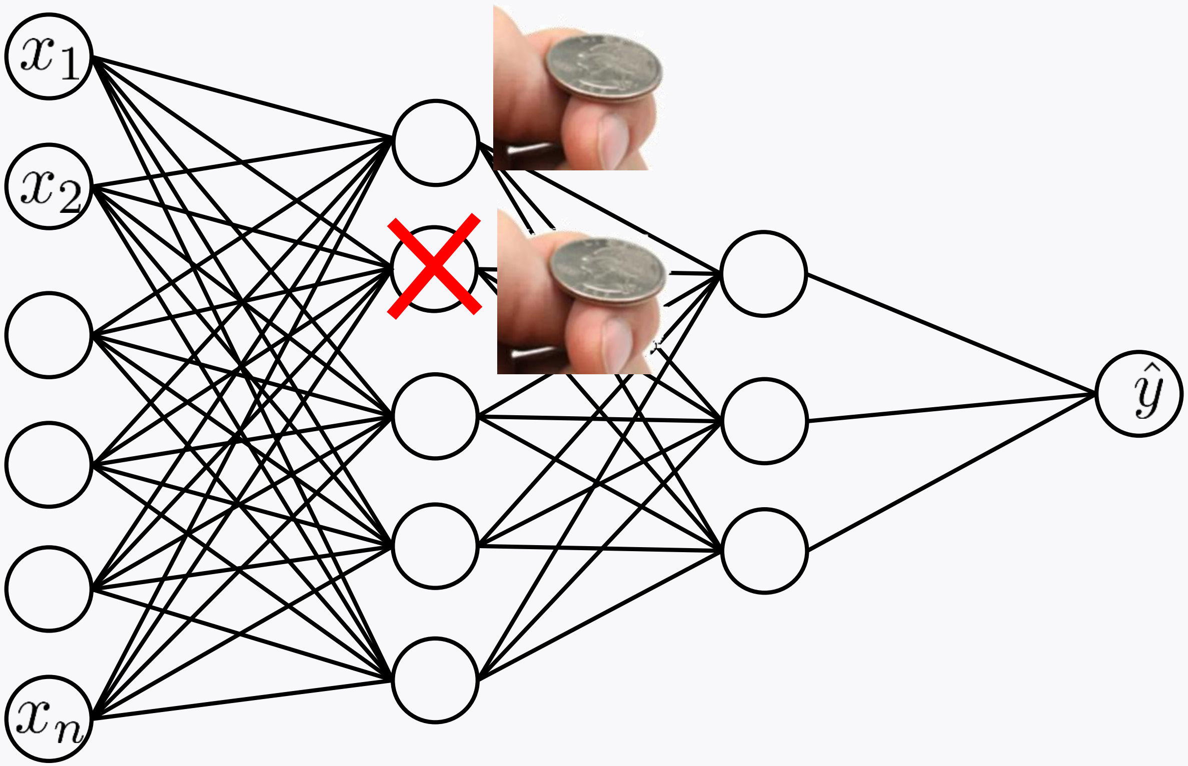
How to construct a random neural network?

Construction of a random neural network



Construction of a random neural network

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



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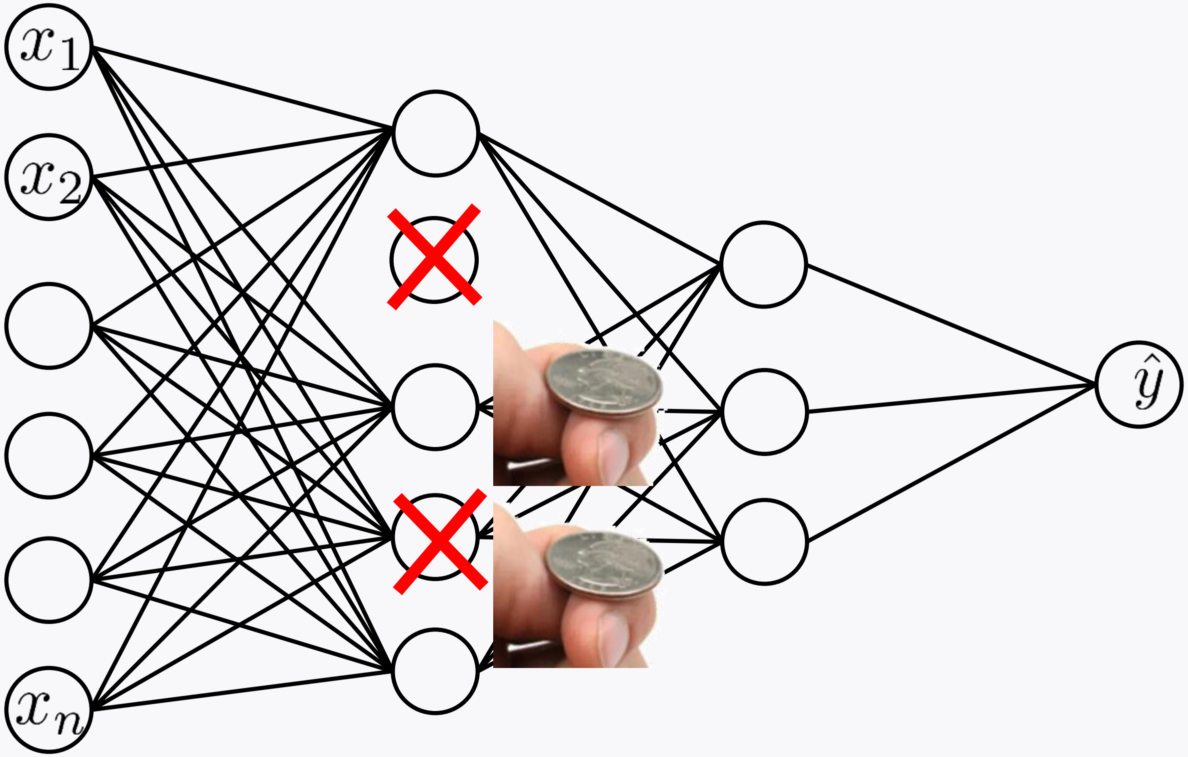

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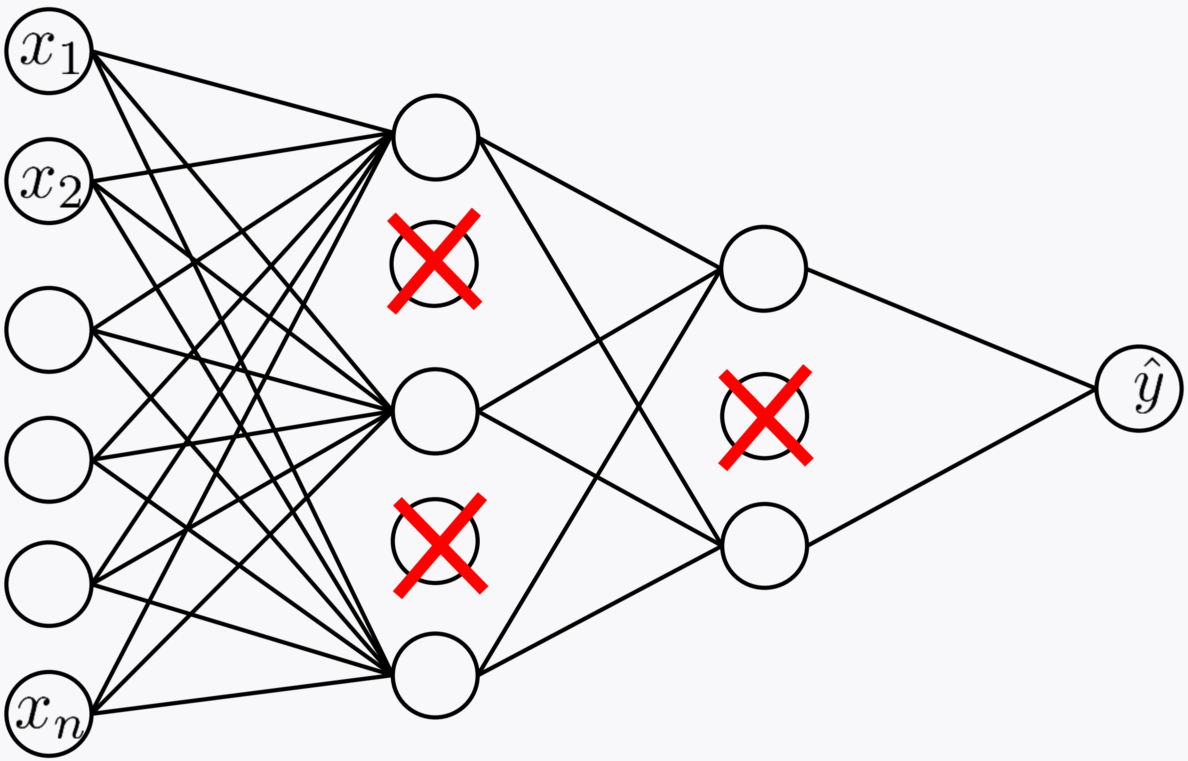

Generate this partial NN per example.

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