

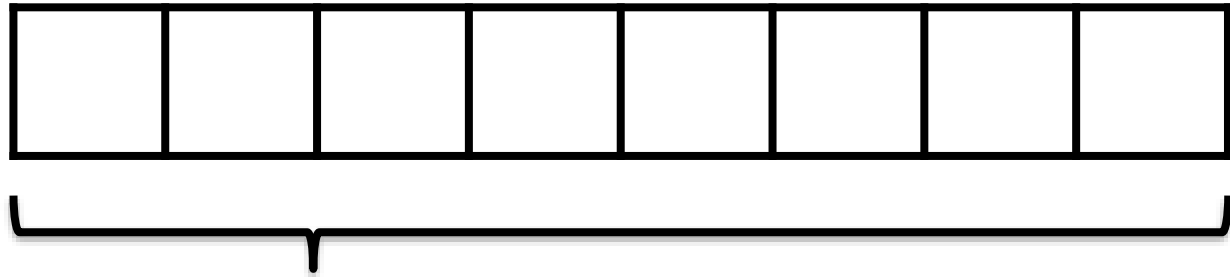
Beyond Supervised Learning

August 3, 2019

MMCi Applied Data Science
Block 5, Lecture 3

Matthew Engelhard

Supervised Learning



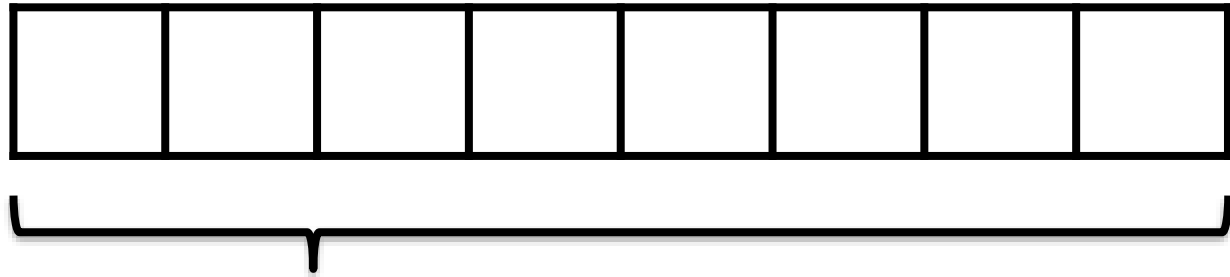
x , data/features for
a subject or patient



y , associated
value or label

The learning process: find the equation that best predicts y based on x

Supervised Learning: Classification



x , data/features for
a subject or patient



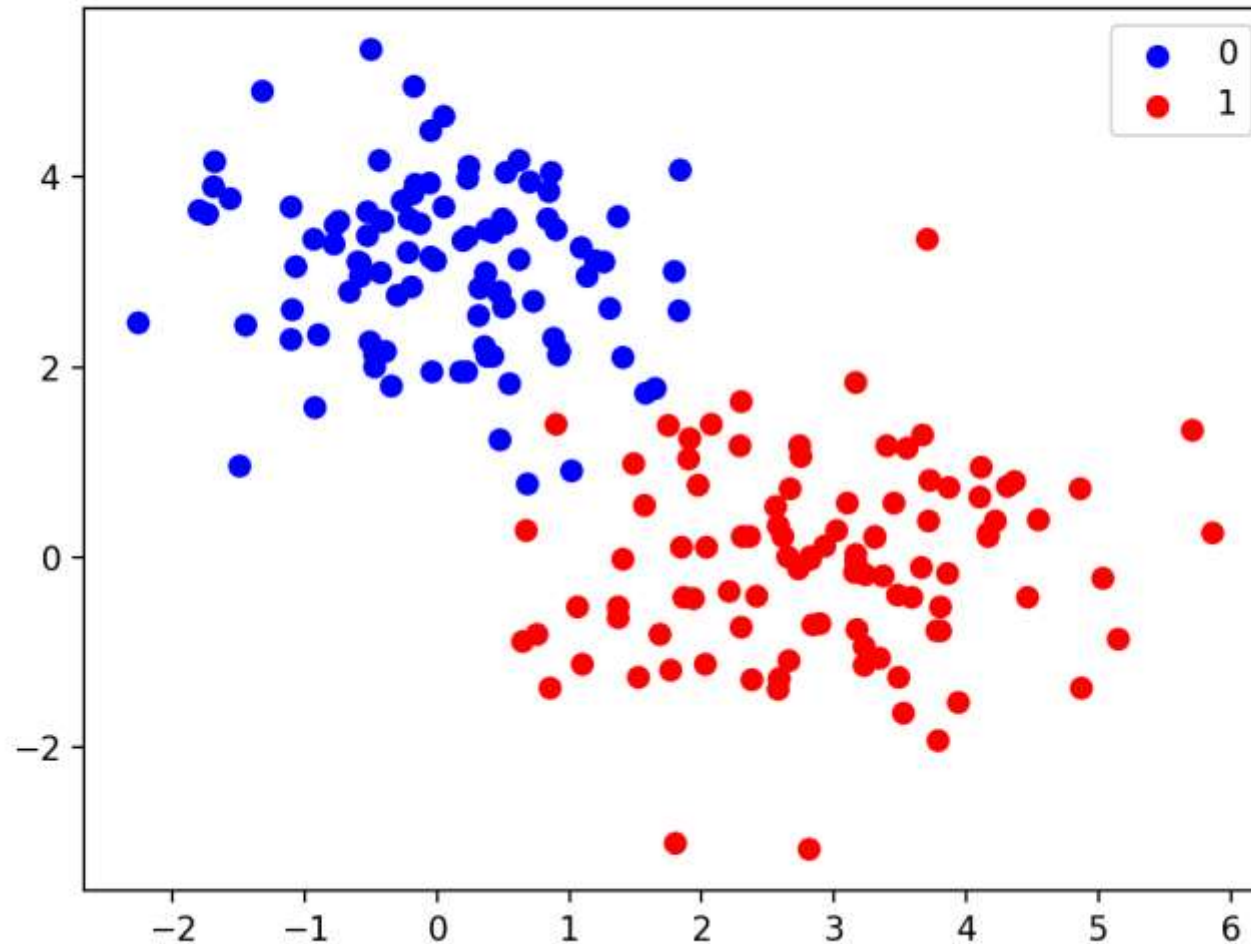
y , categorical
label

The learning process: find the equation that best predicts y based on x

Supervised Learning: Classification

Goal:

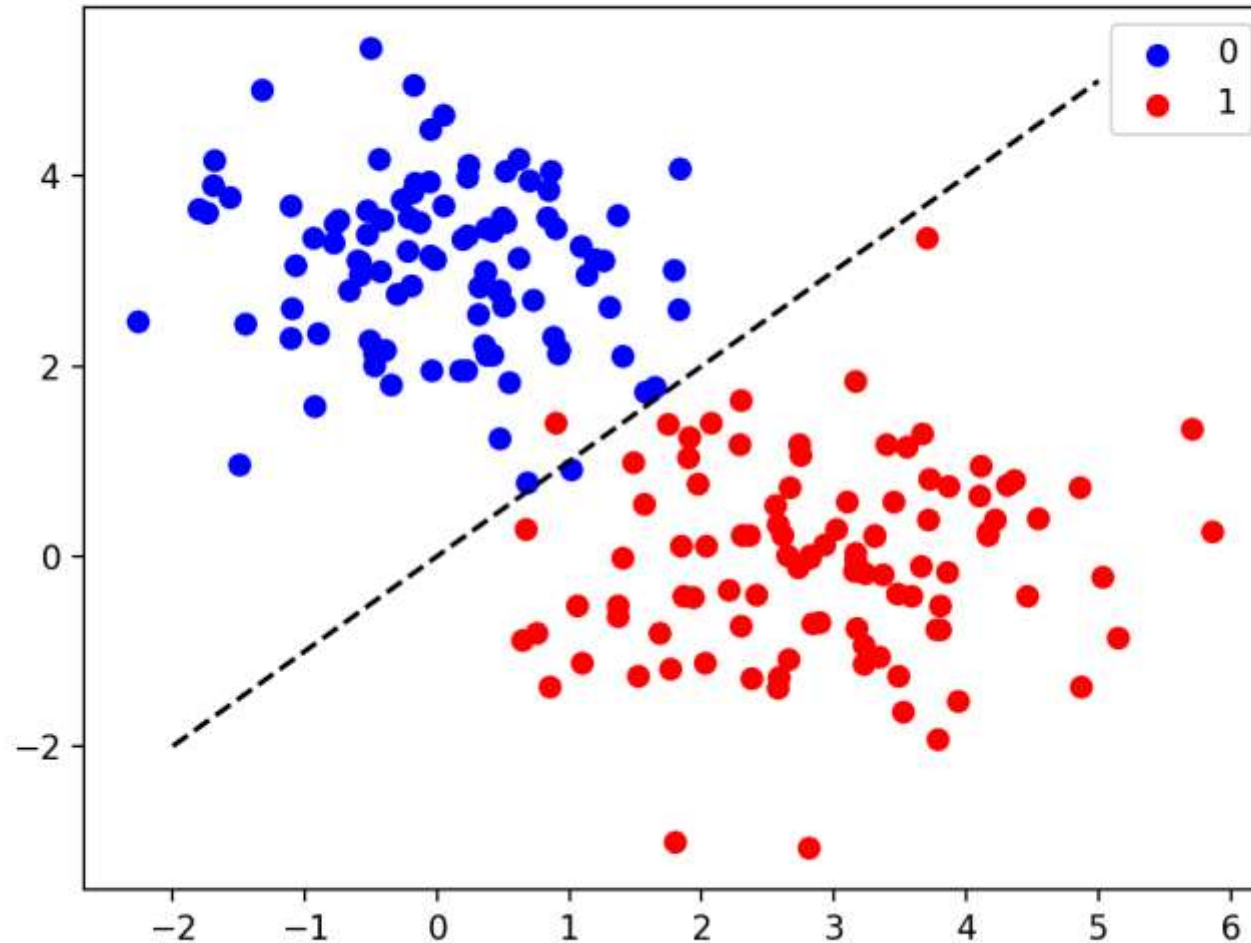
Learn a **decision boundary** that separates 0s from 1s



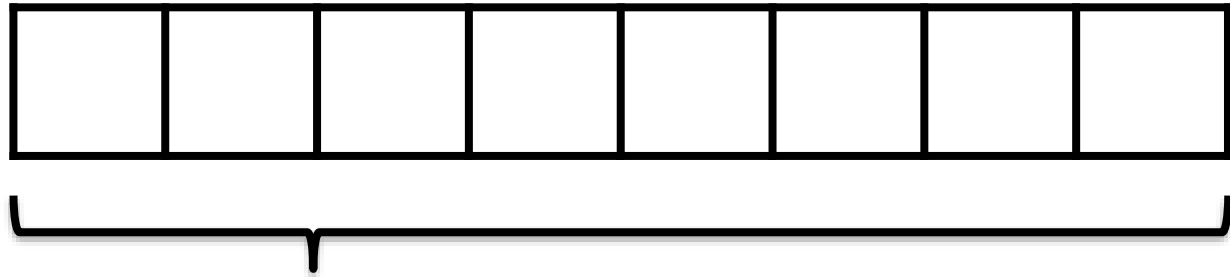
Supervised Learning: Classification

Goal:

Learn a **decision boundary** that separates 0s from 1s



Supervised Learning: Regression



x , data/features for
a subject or patient



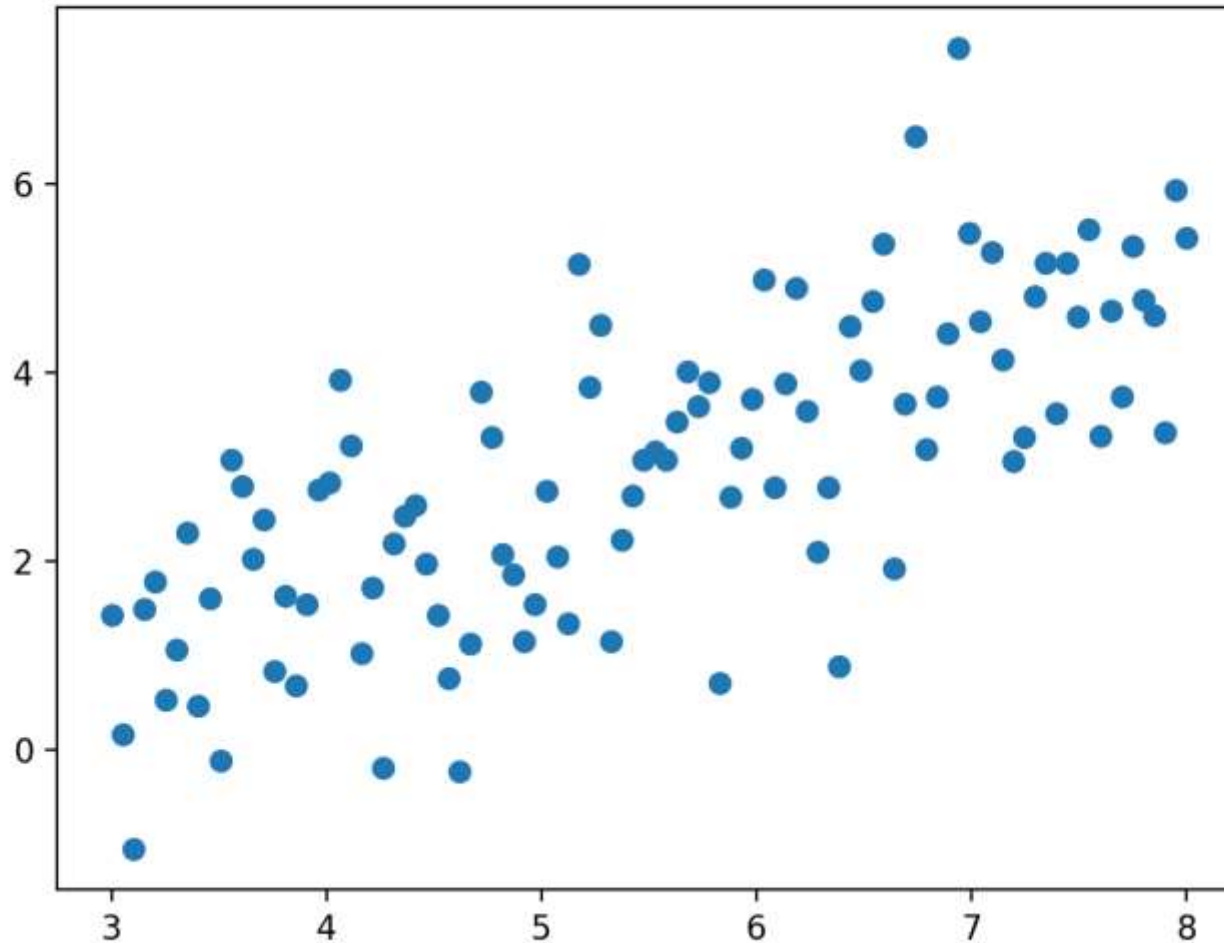
y , numeric
value

The learning process: find the equation that best predicts y based on x

Supervised Learning: Regression

Goal:

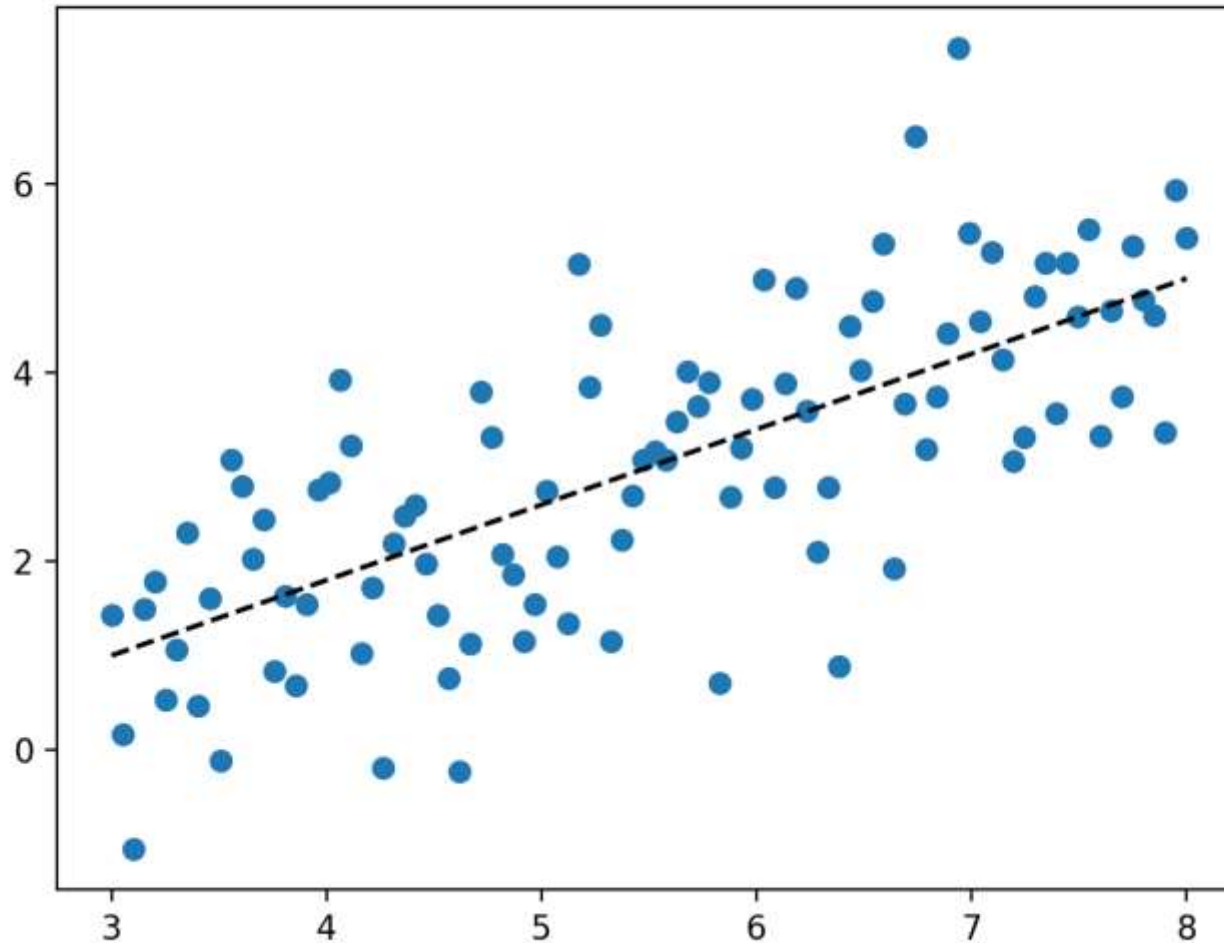
Learn a function
that predicts y
based on x



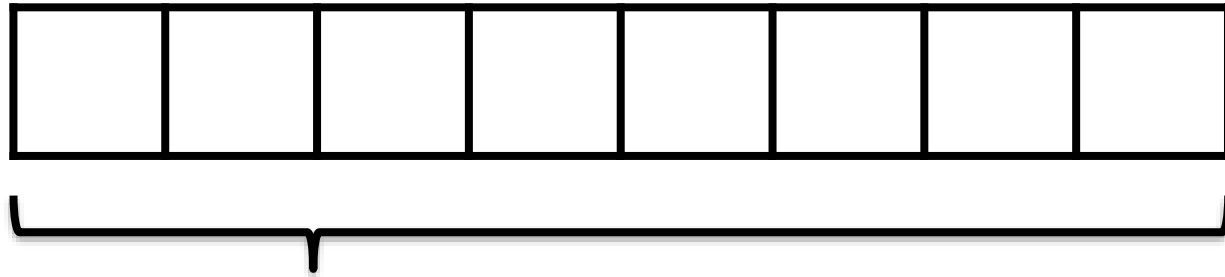
Supervised Learning: Regression

Goal:

Learn a function that predicts y based on x



Unsupervised Learning

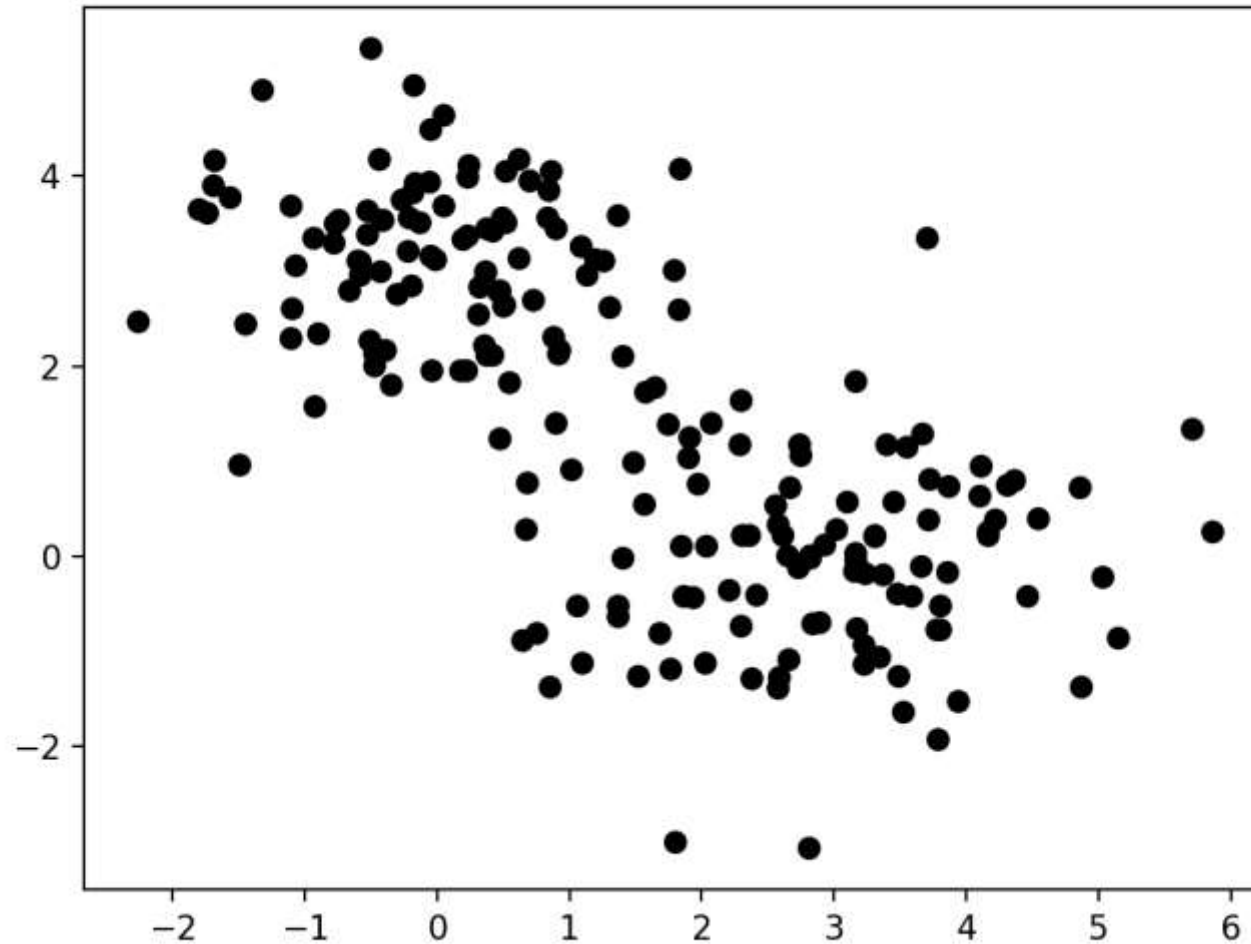


x , data/features for
a subject or patient

The learning process:

- find structure or patterns in the data
- describe the data or create new, similar data

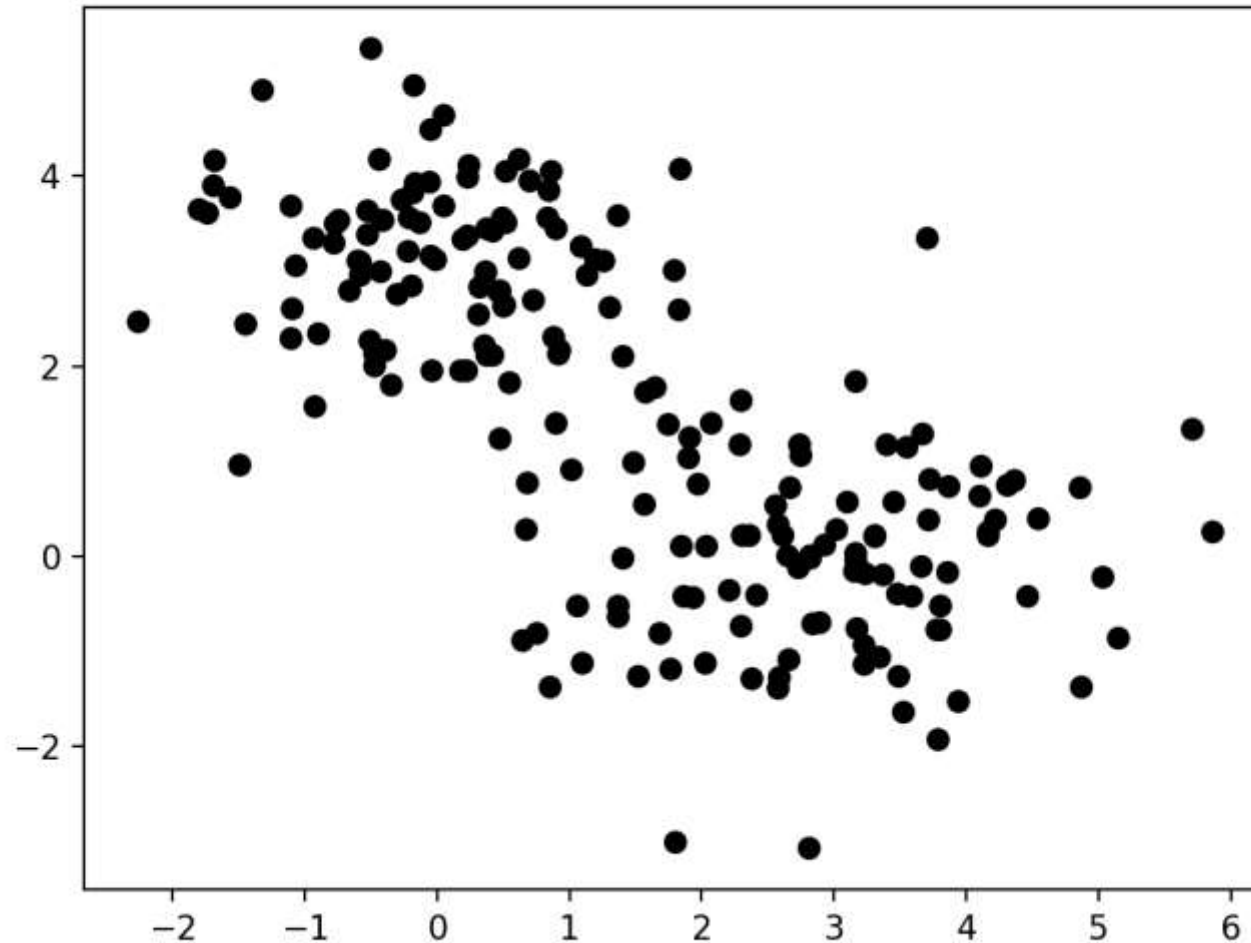
Unsupervised Learning



Unsupervised Learning: Clustering

Goal:

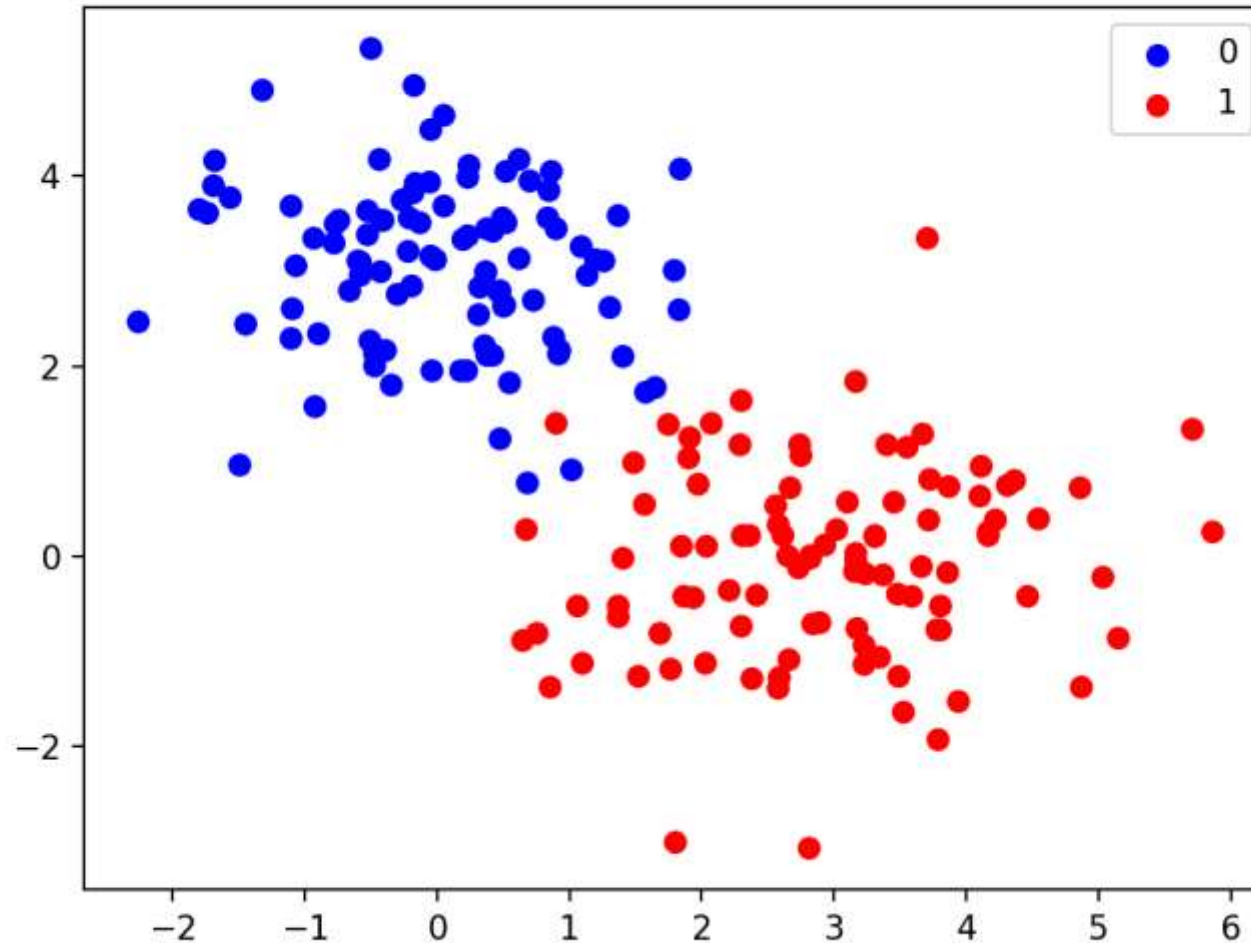
**Assign points to
distinct groups
with shared
characteristics**



Unsupervised Learning: Clustering

Goal:

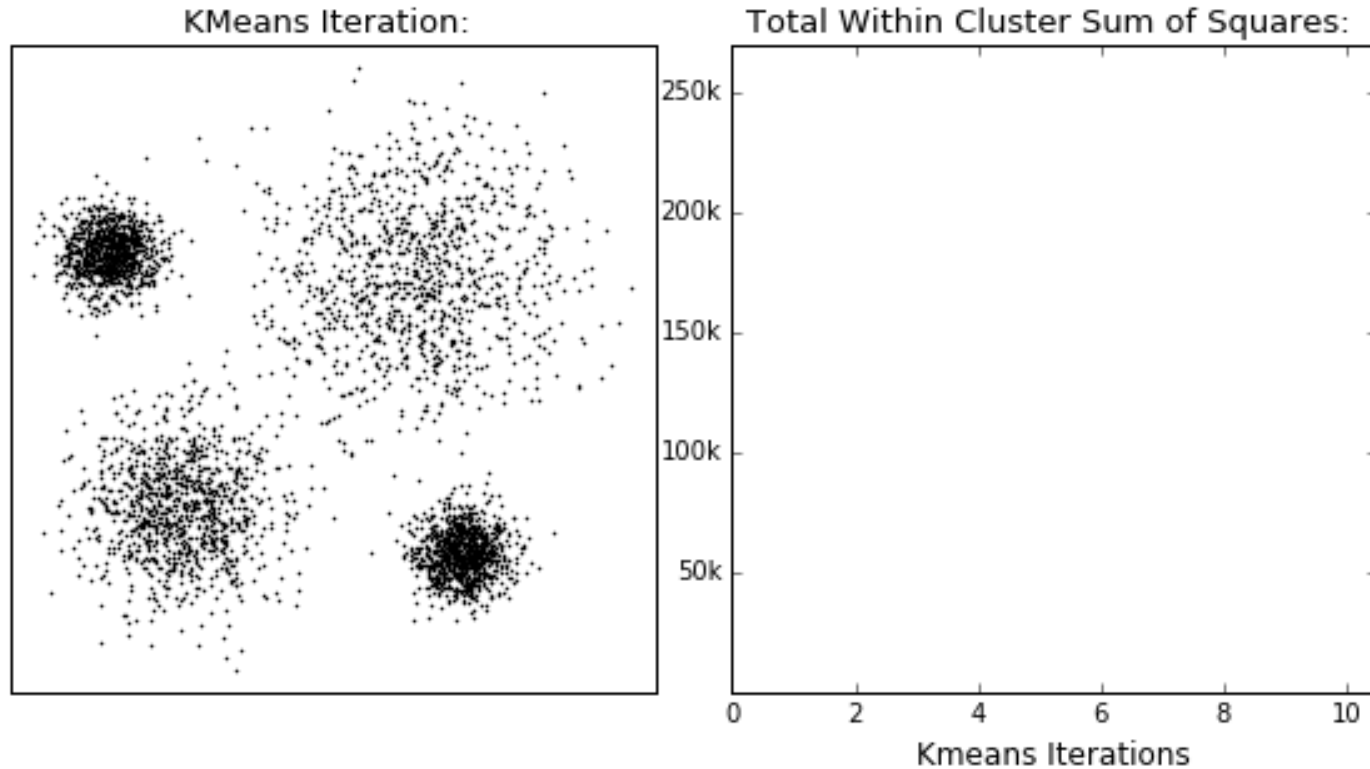
**Assign points to
distinct groups
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characteristics**



Example of K-Means Clustering

Goal:

Assign points to distinct groups with shared characteristics

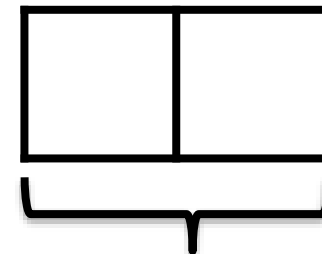
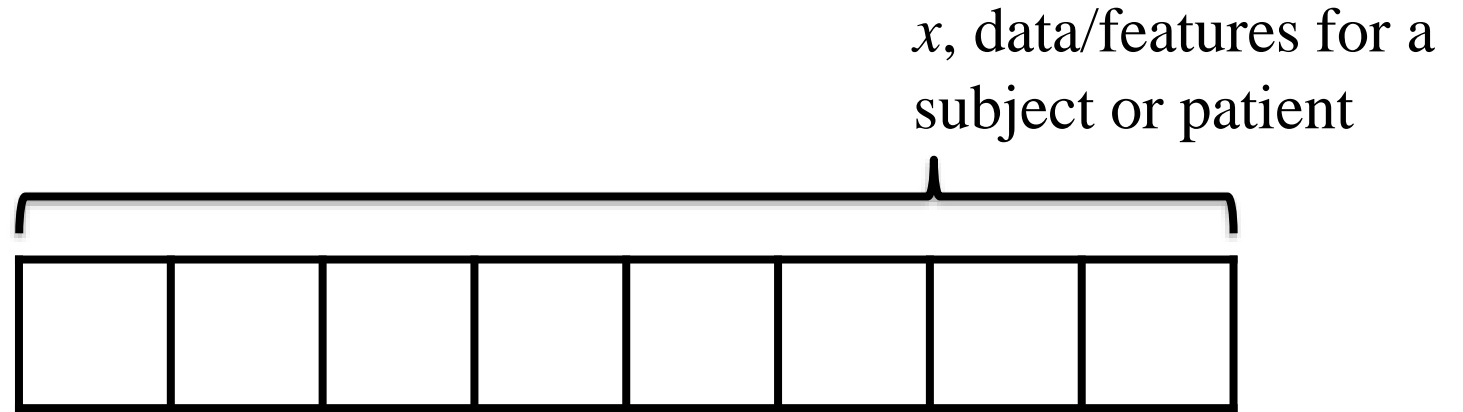


- sensitive to initialization
- minimize $\sum \text{distance}^2$ from points to centers

Unsupervised Learning: Dimensionality Reduction

Goal:

Describe a large number of features in terms of a smaller number of features

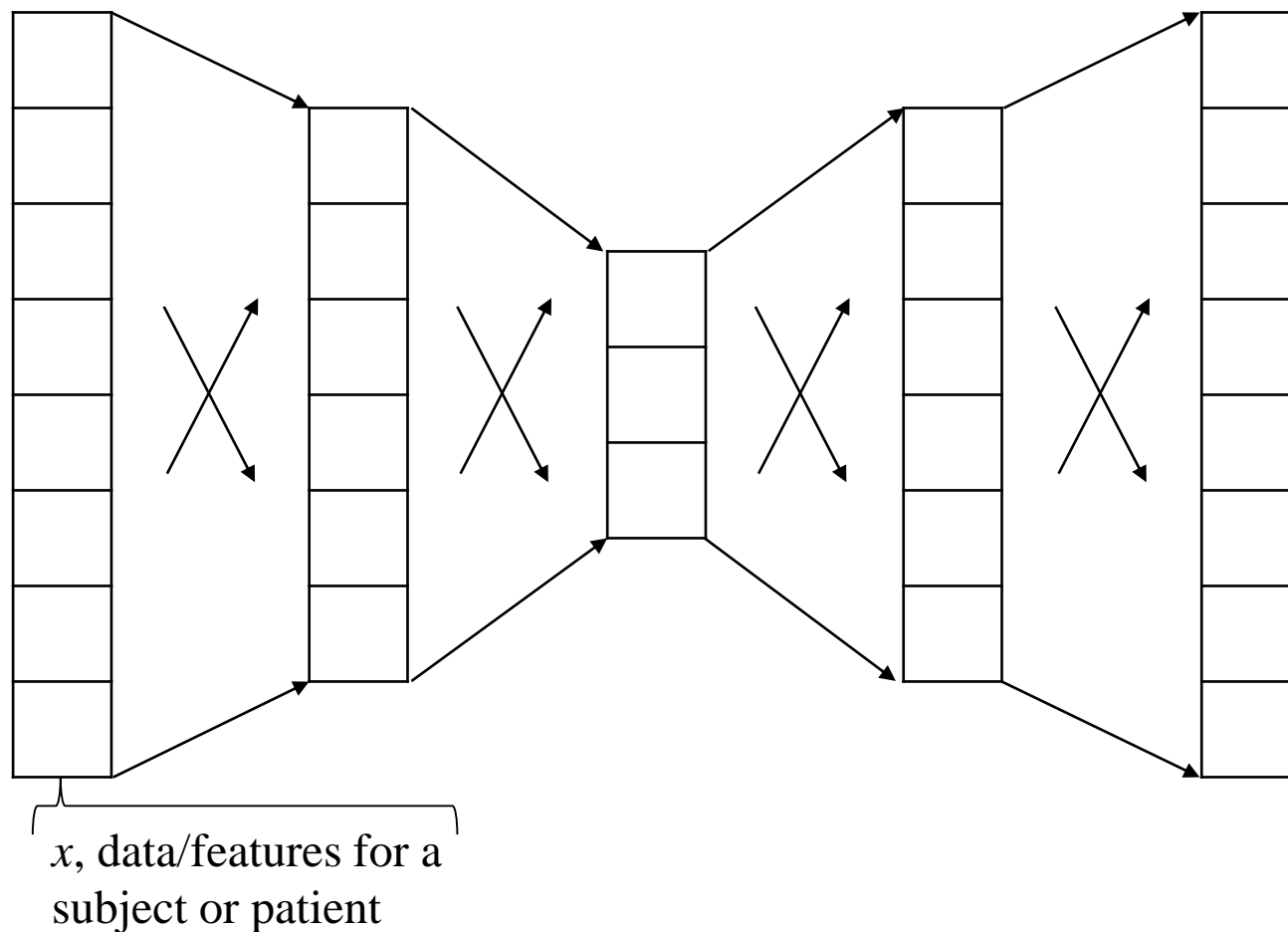


z , lower-dimensional representation (or embedding) of x

Dimensionality Reduction Example: Autoencoder

Goal:

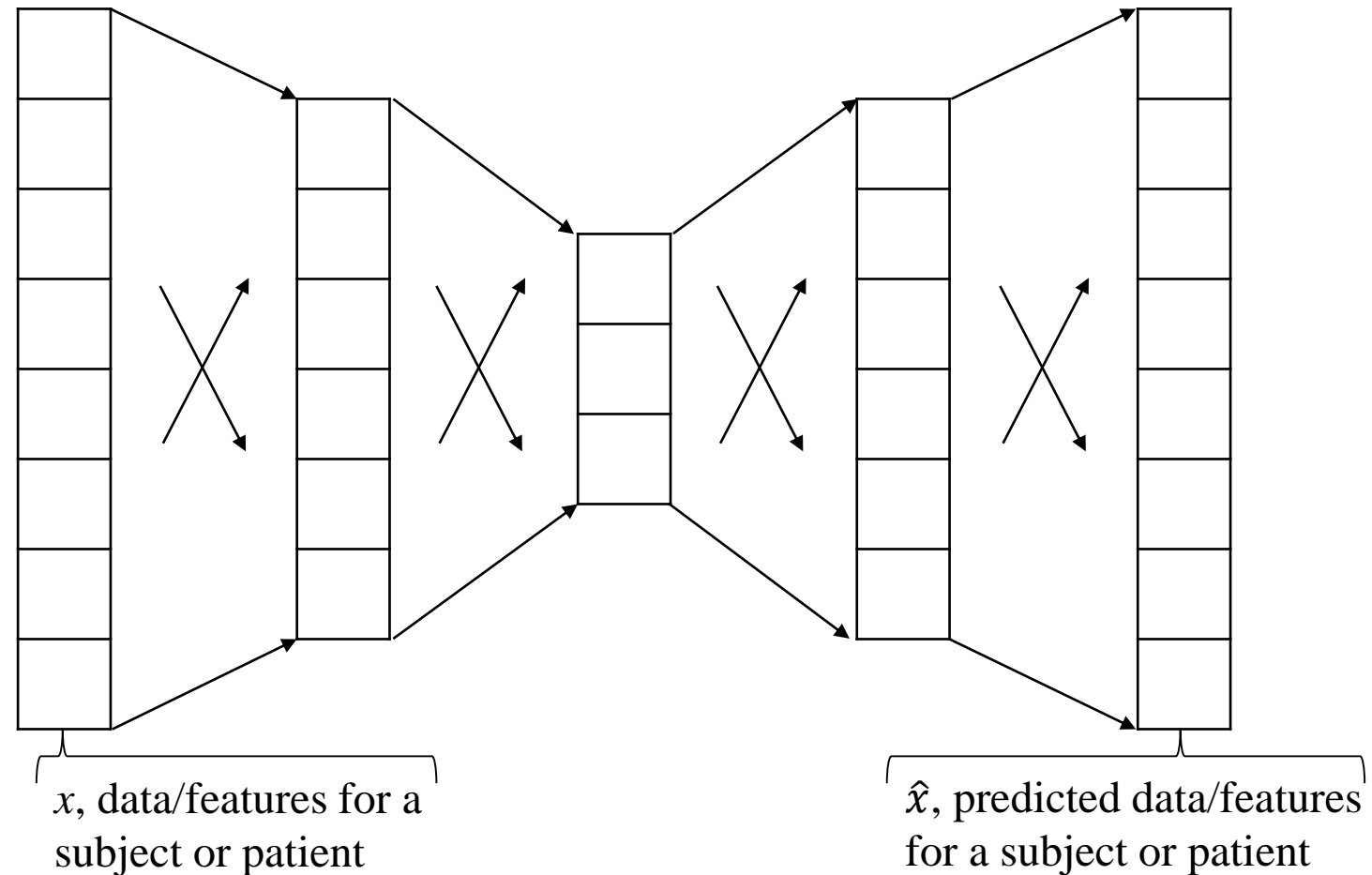
- Describe a large number of features in terms of a smaller number of features
- Train to minimize **reconstruction loss**



Dimensionality Reduction Example: Autoencoder

Goal:

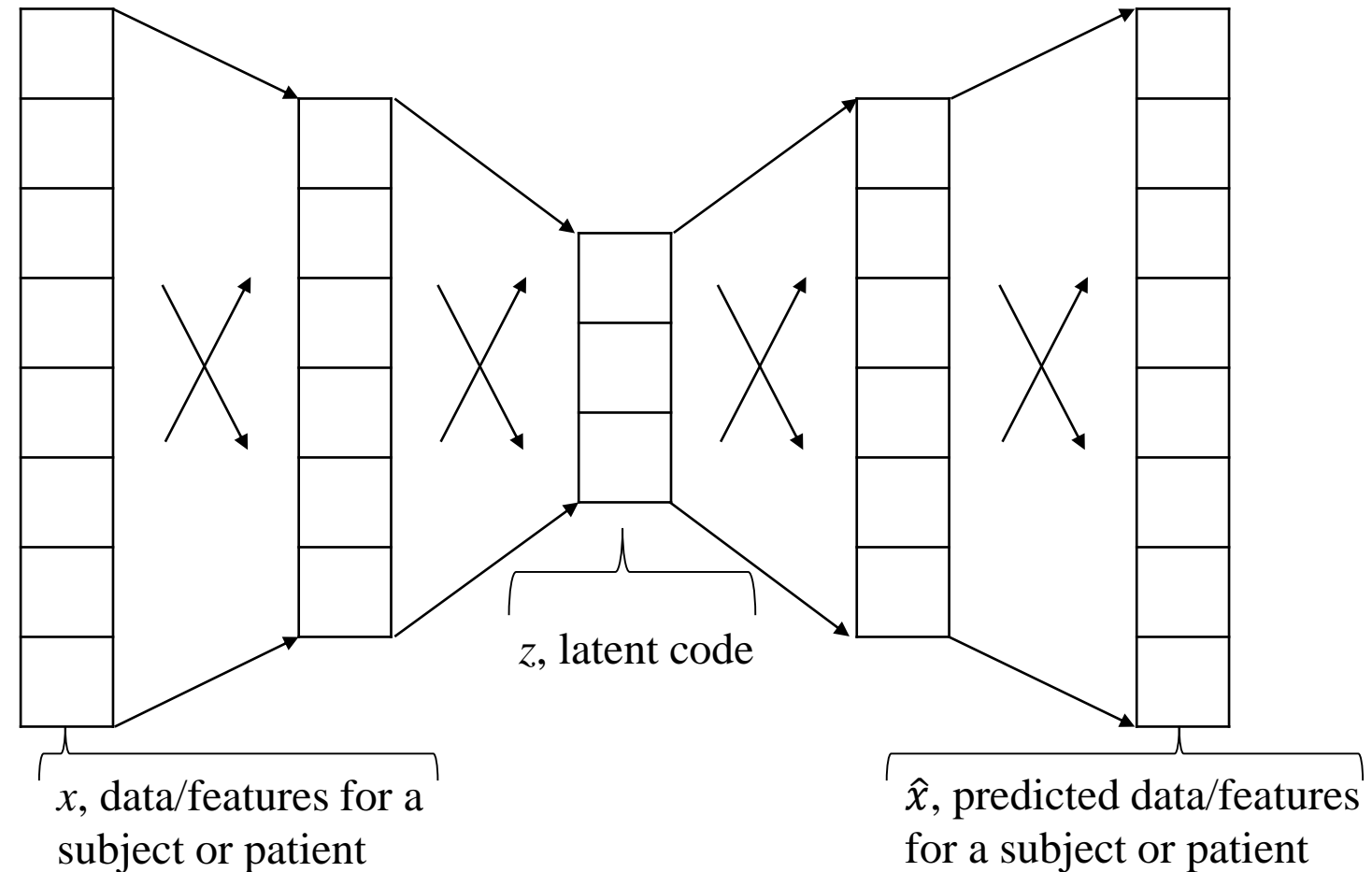
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Dimensionality Reduction Example: Autoencoder

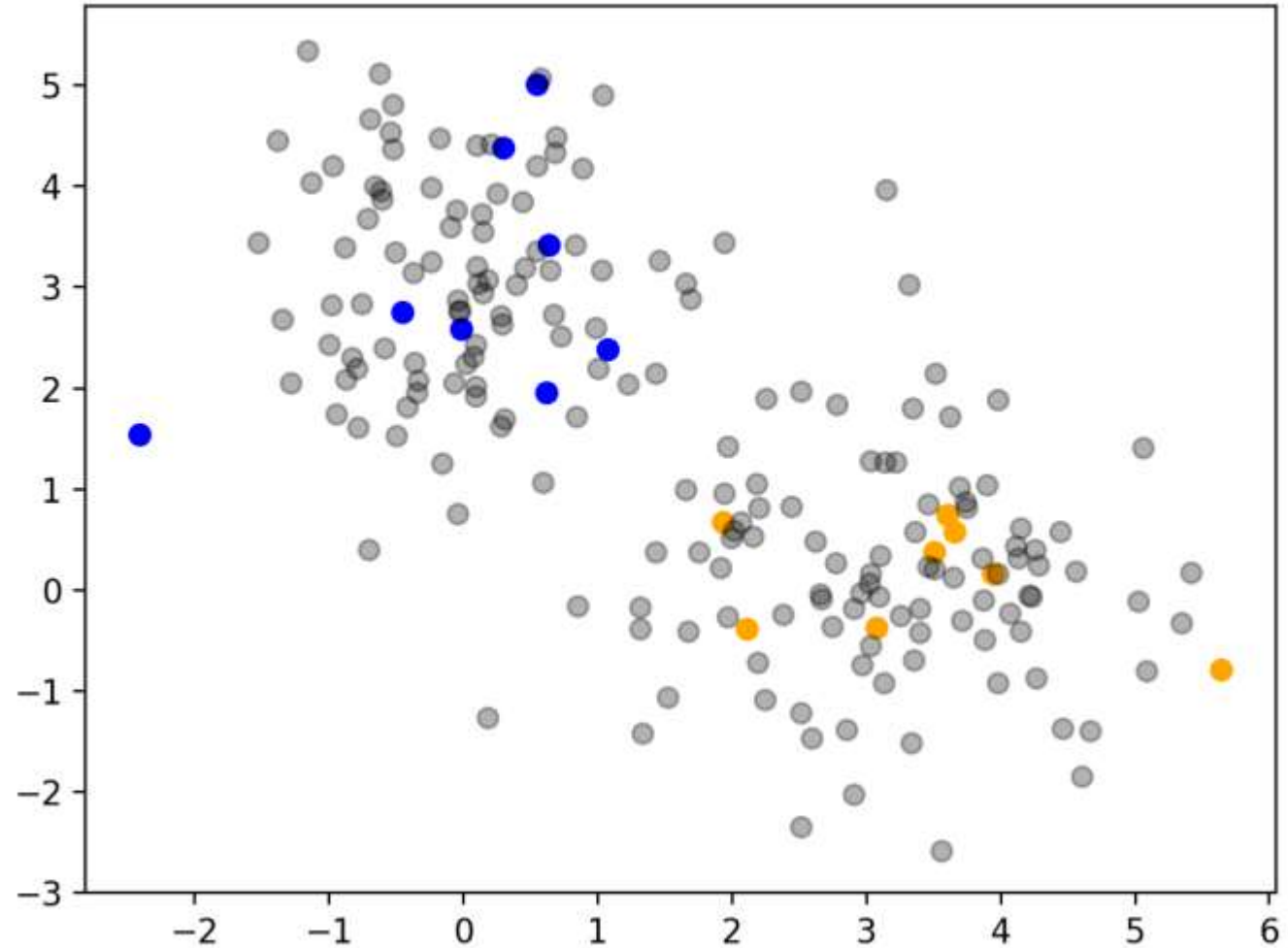
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- Describe a large number of features in terms of a smaller number of features
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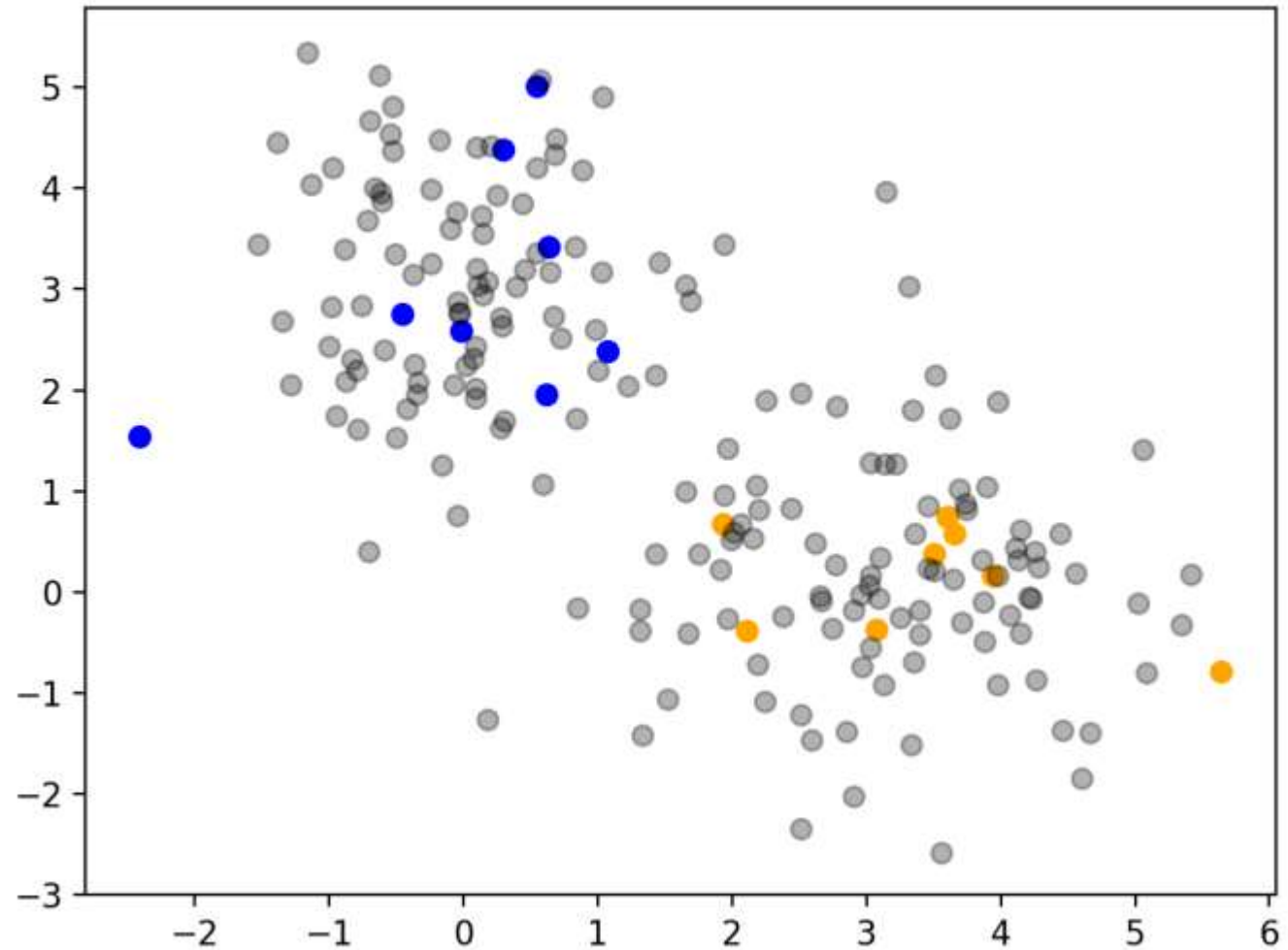
Semi-Supervised Learning

- Some points are labeled, some are not
- Try to use the unlabeled data to help us reason about the labeled data



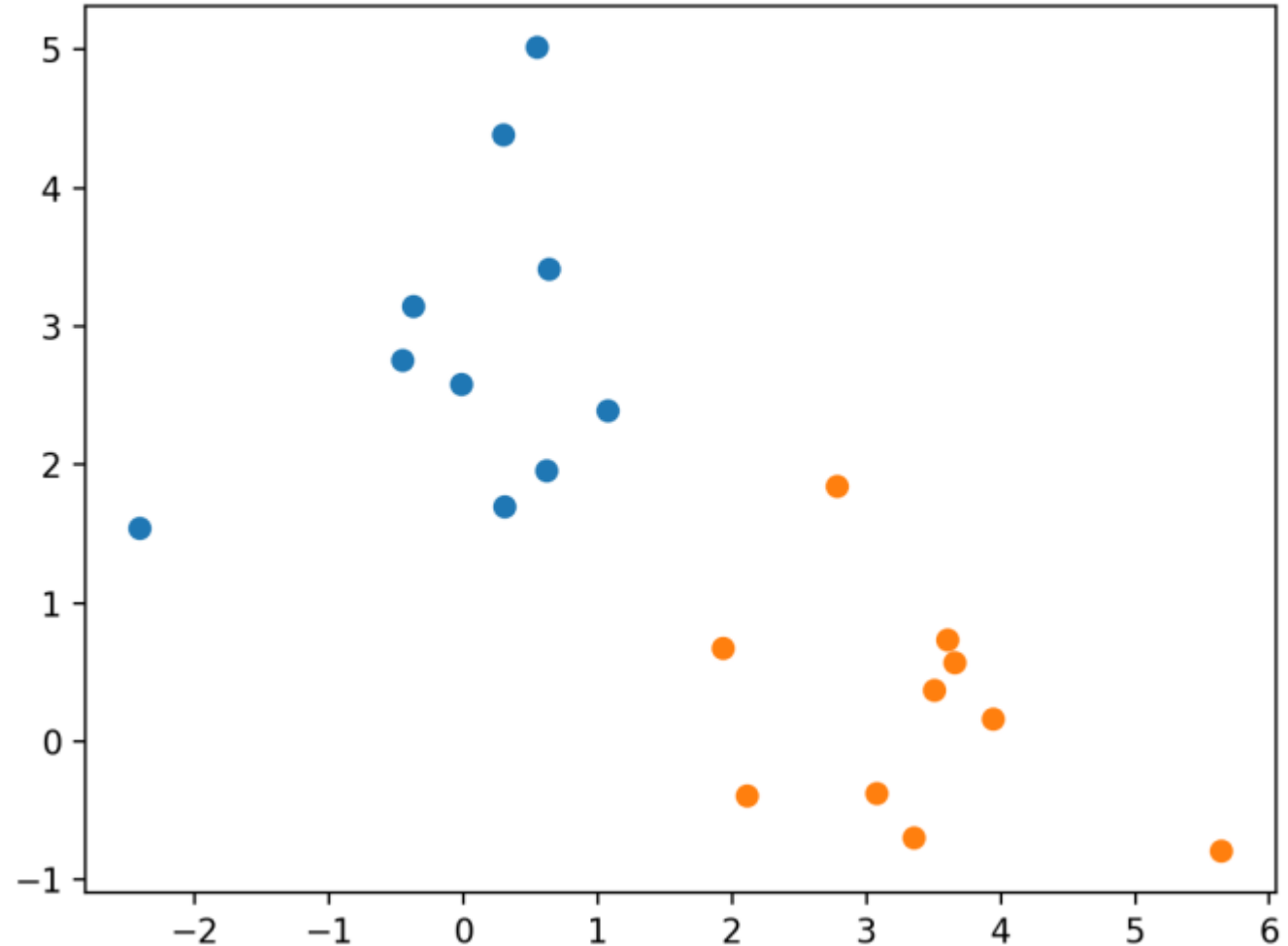
Active Learning

- Some points are labeled, some are not
- We can get additional labels, but at a cost
- Request labels we believe will improve our classifier the most



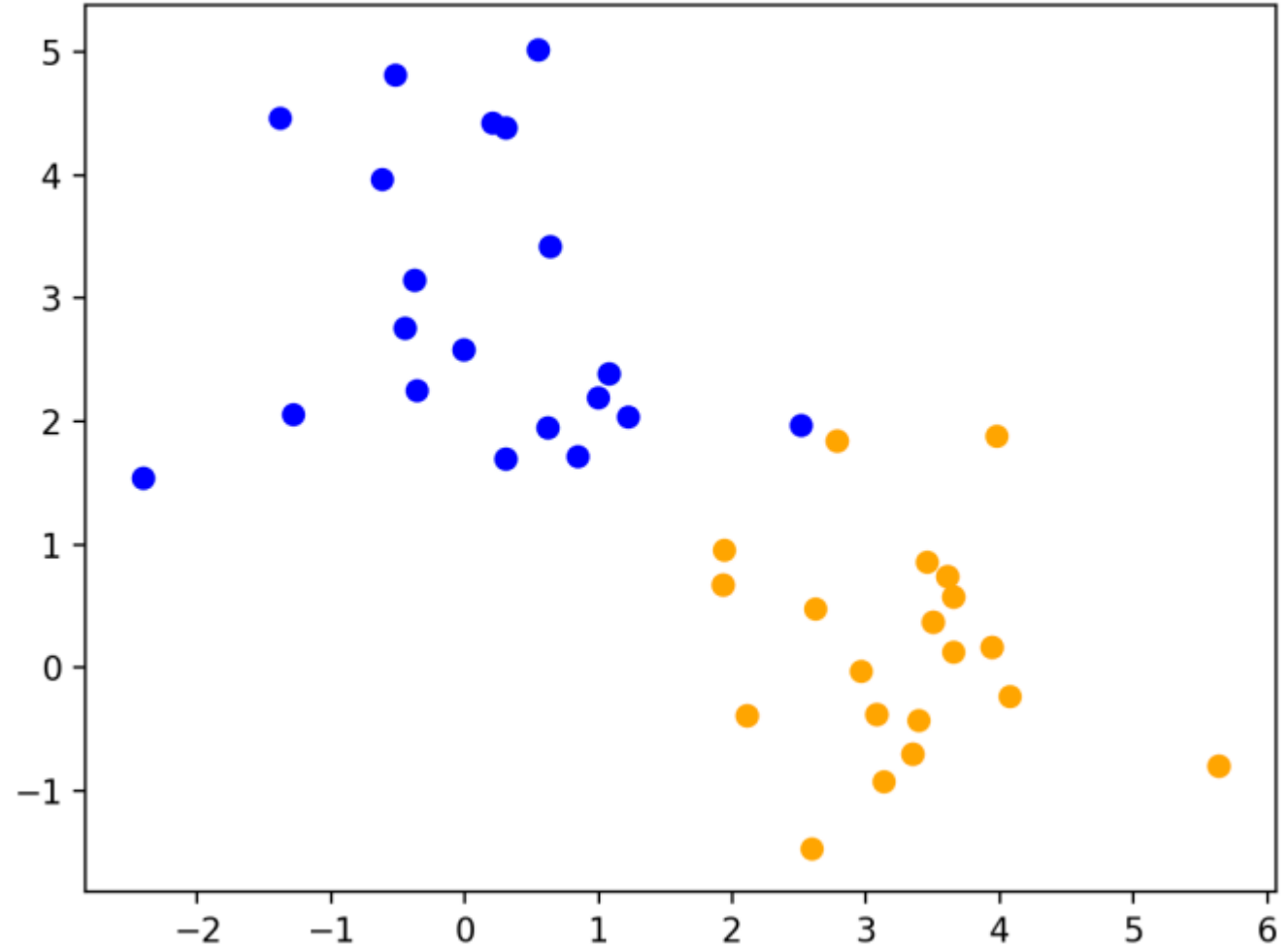
Online Learning

- Data arrives one point at a time, or in batches
- Continually improve our classifier without having to retrain from scratch with each arrival
- Uses a learning rate, much like RL



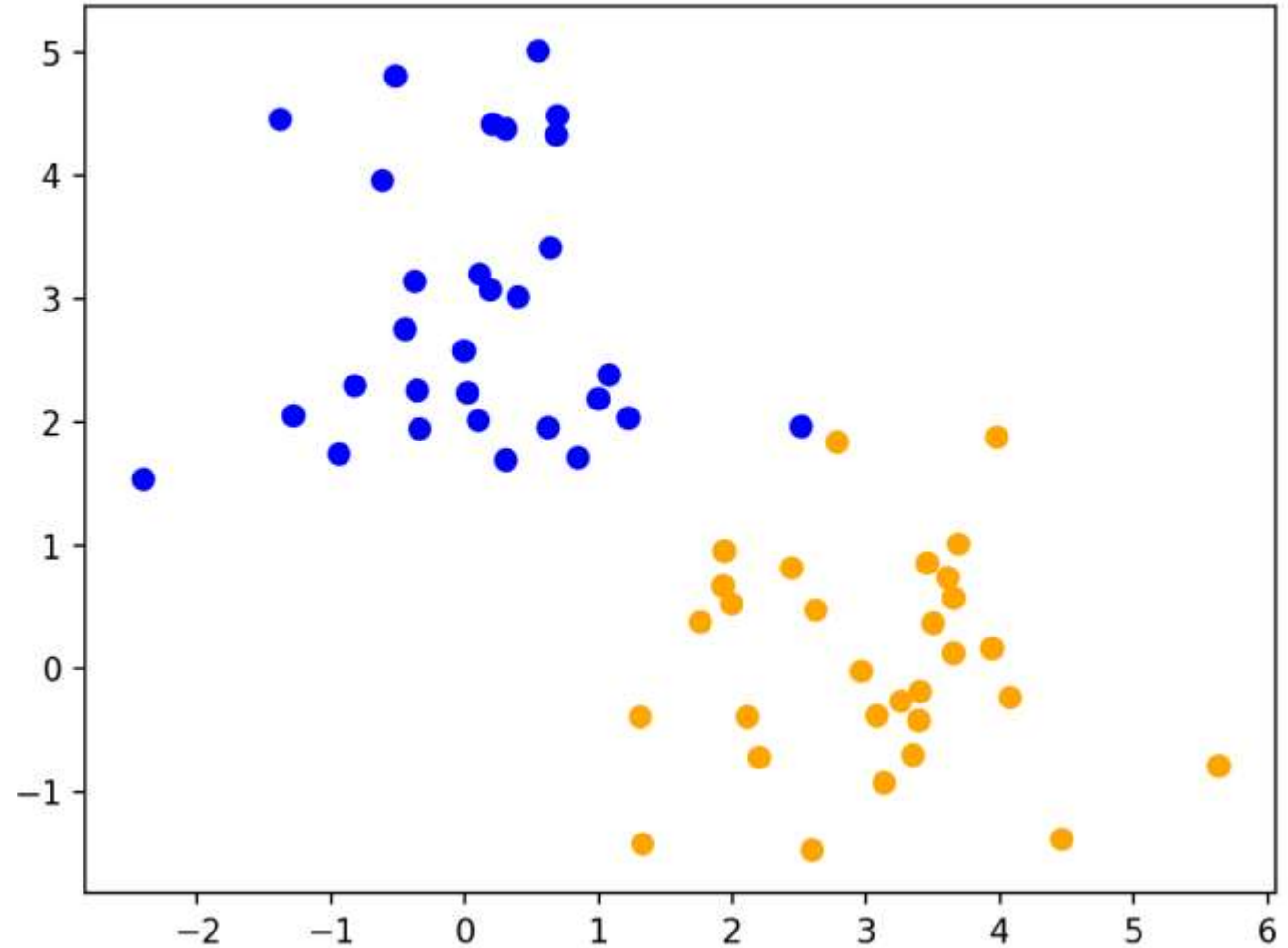
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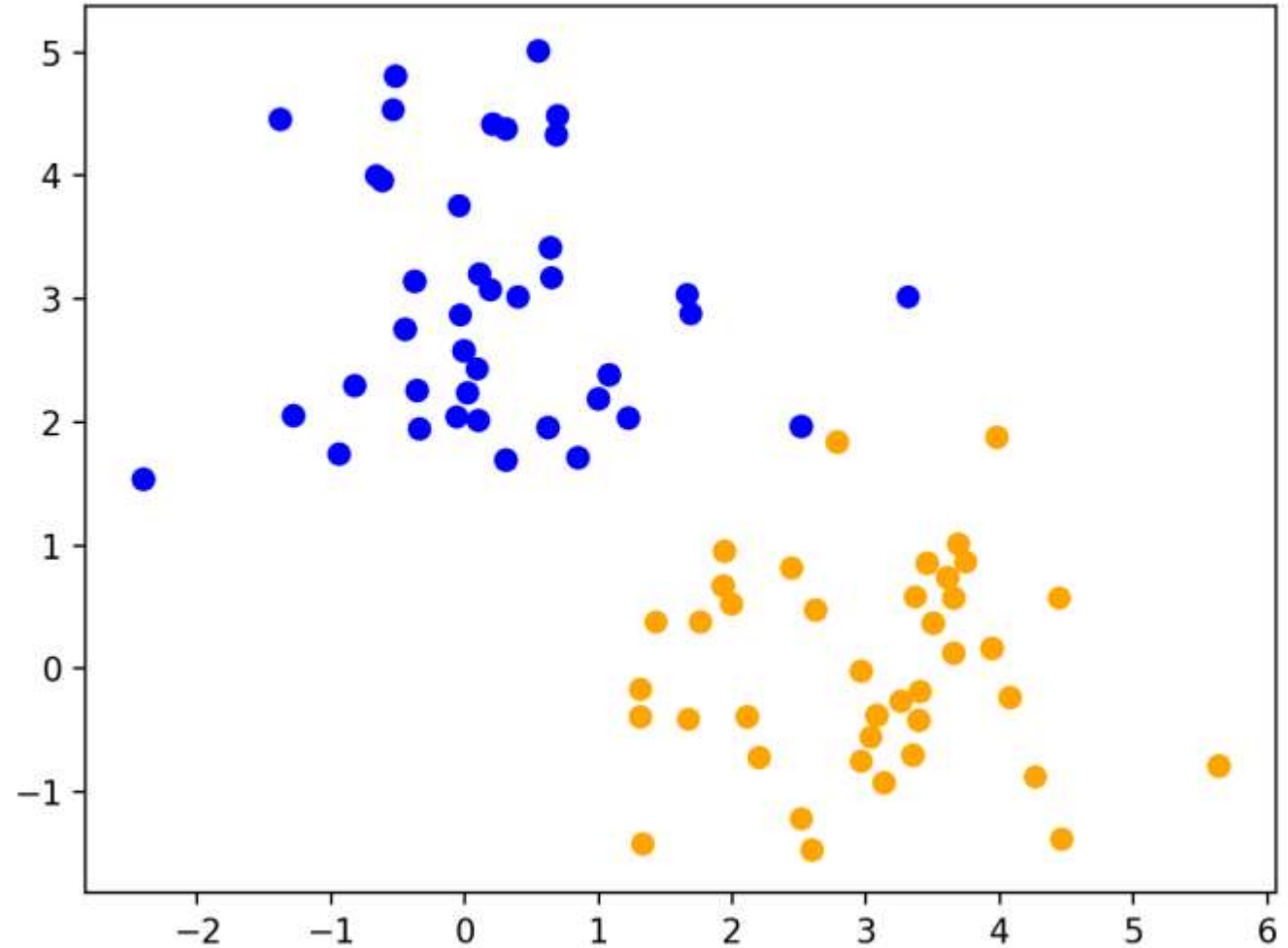
Online Learning

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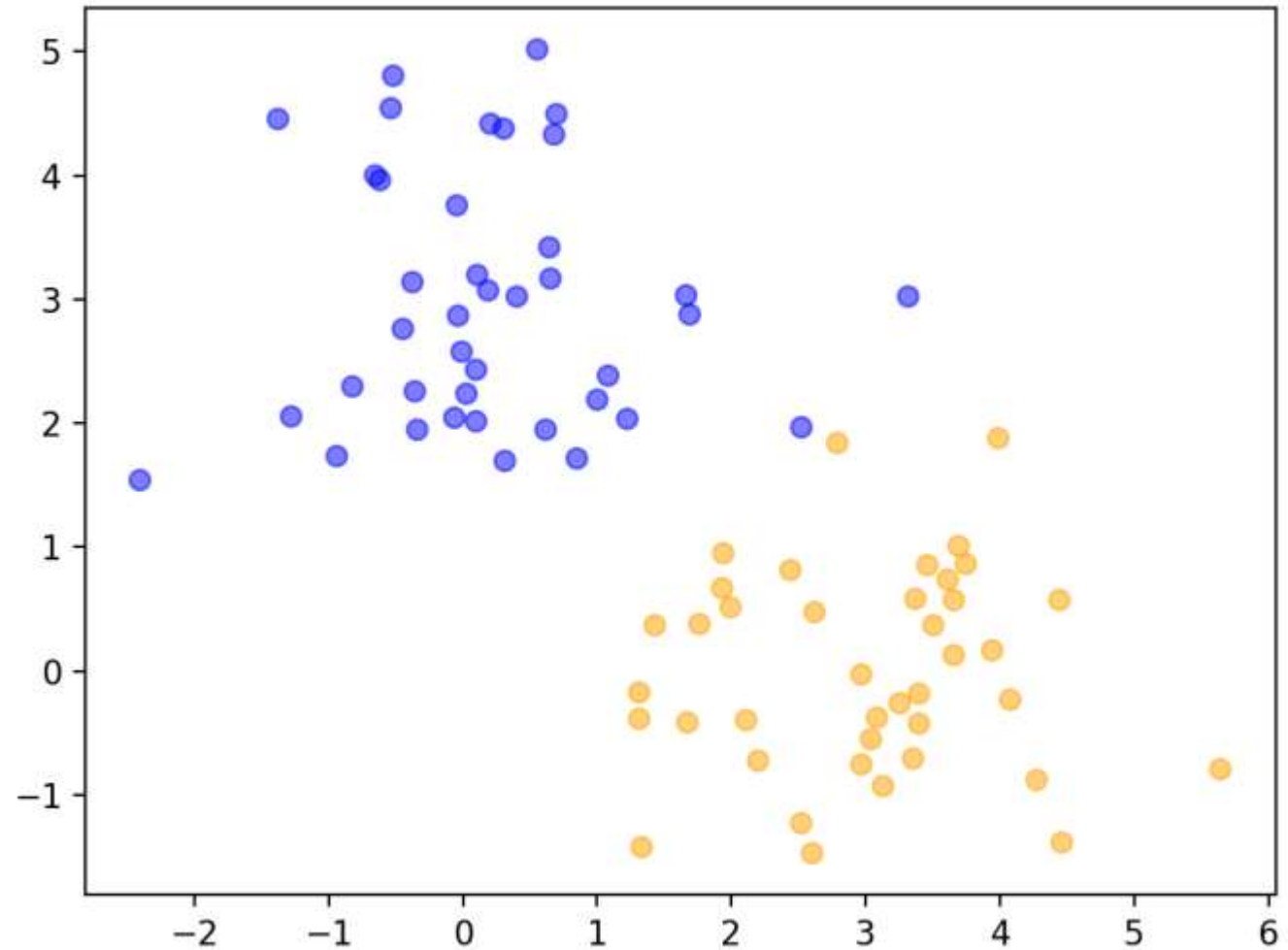
Online Learning

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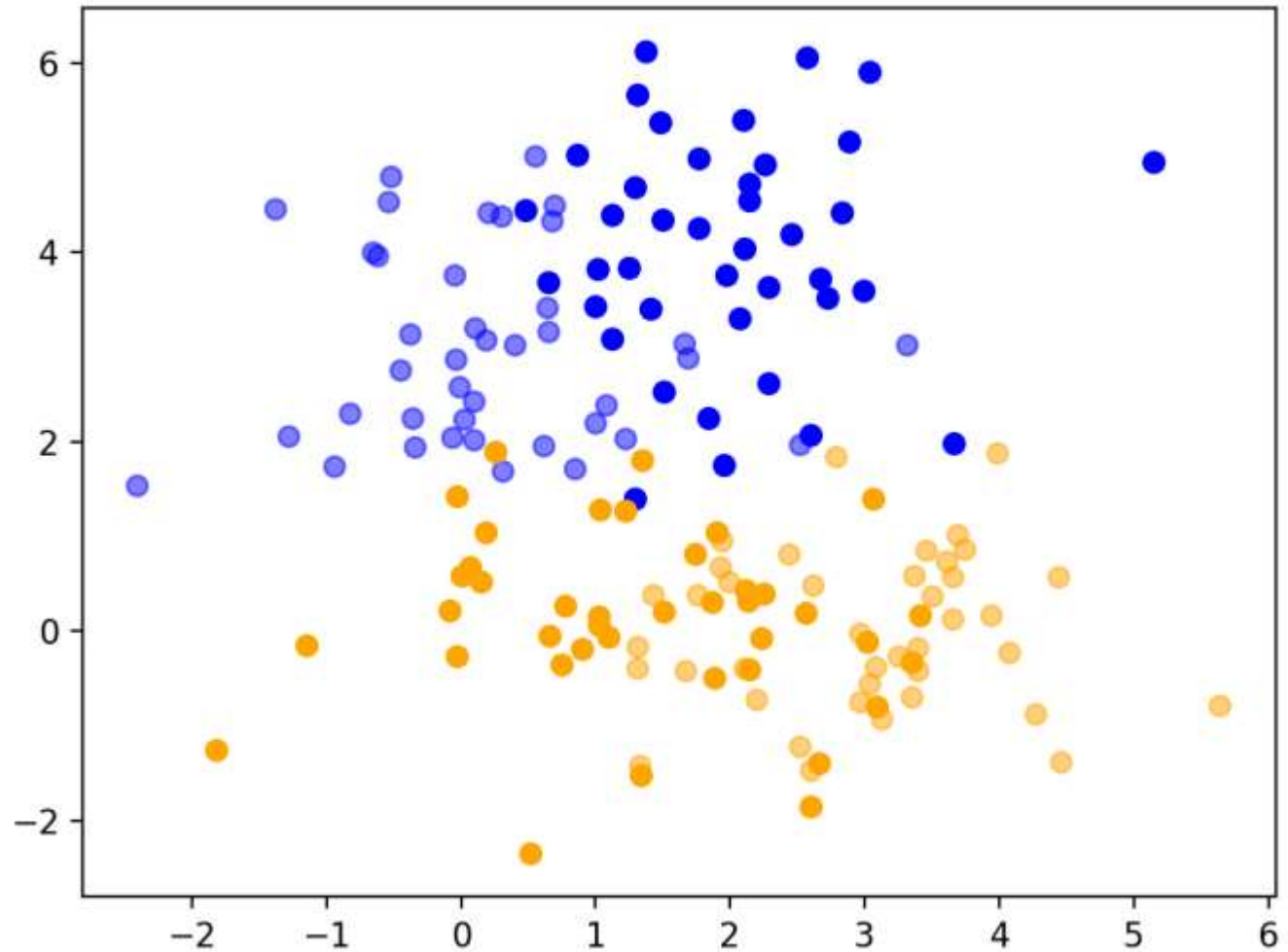
Lifelong Learning

- Similar to lifelong learning; also uses a learning rate
- Data characteristics change over time
- Continually refine our classifier to adjust to these changing characteristics



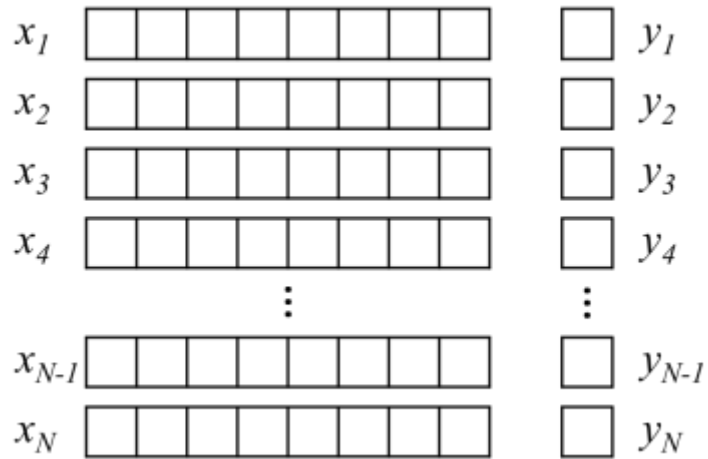
Lifelong Learning

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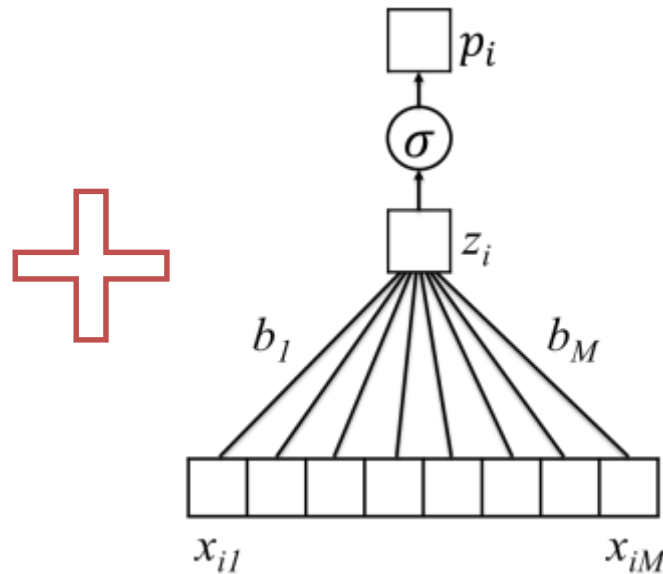


WE HAVE COVERED A LOT!

Learning Model Parameters

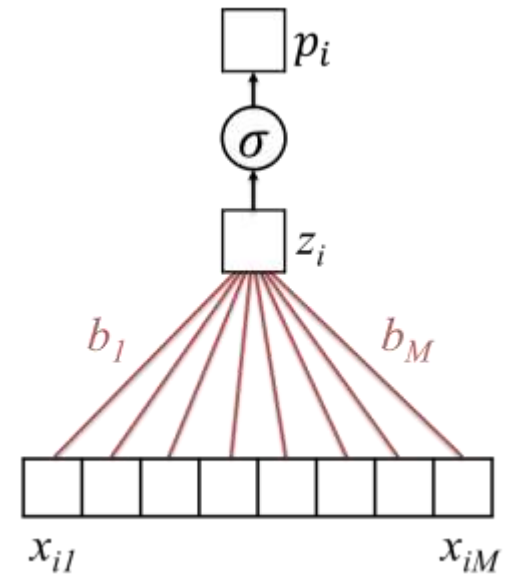


Training Set



$$p_i = \sigma(b_0 + b_1x_{i1} + b_2x_{i2} + \dots + b_Mx_{iM})$$

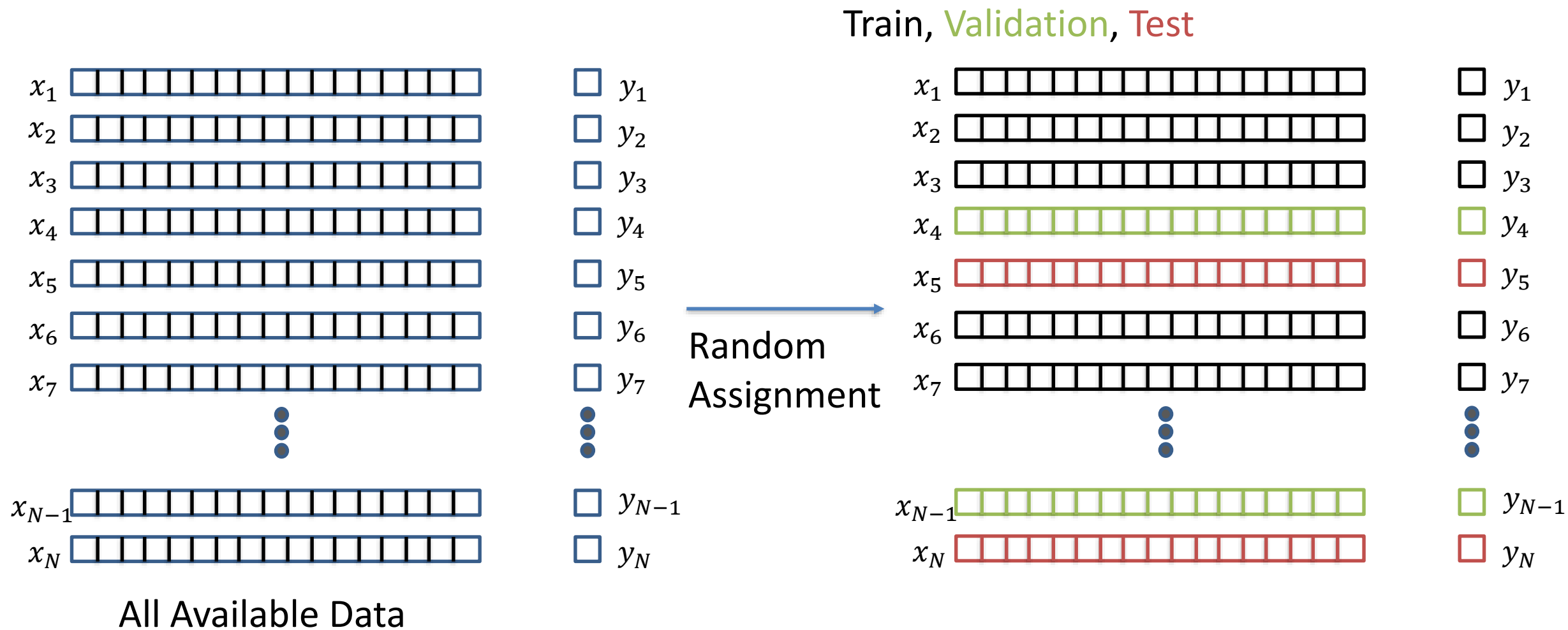
Untrained Logistic Regression
Model (or "Network")



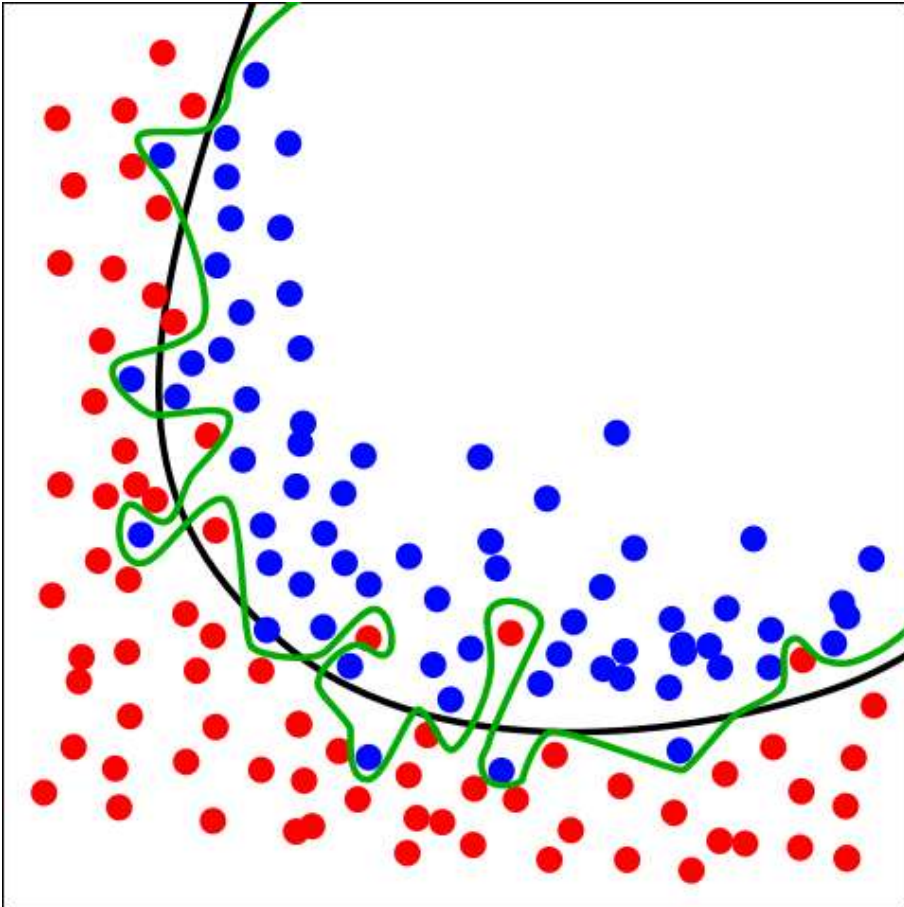
$$b = (b_0, \dots, b_M)$$

Trained Model (with
learned parameters)

Split Data into Separate Groups



But some models can be *too* flexible.



Green boundary:

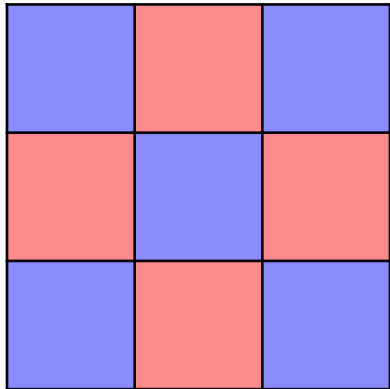
- This is overfitting

Black boundary:

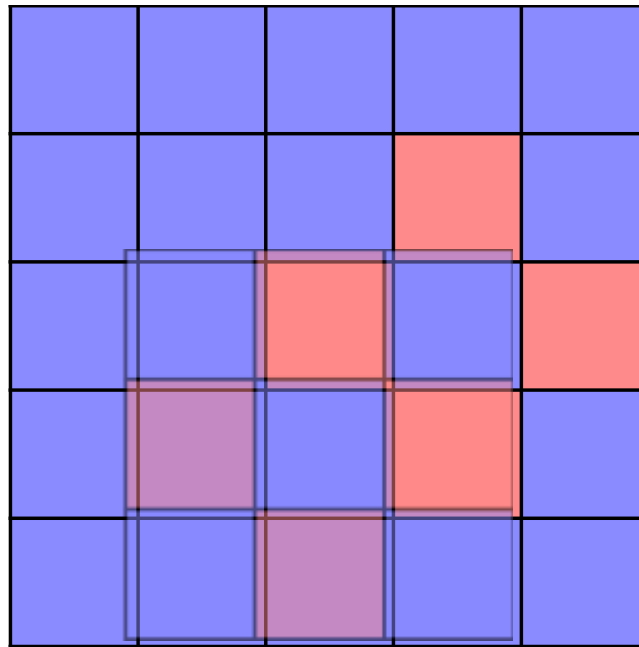
- Balance between fit and model complexity

-> The black boundary is likely to perform better on new data

An Example...



filter



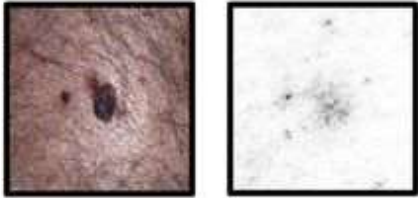
image

-1	5	-5
3	-5	9
-1	5	

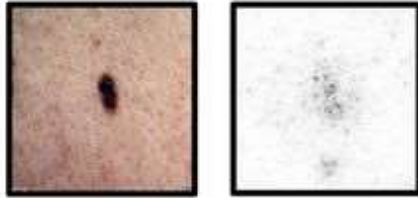
$$x_i^R \odot b$$

Saliency maps for example images

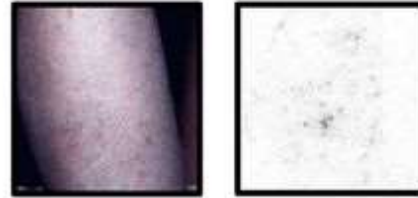
a. Malignant Melanocytic Lesion



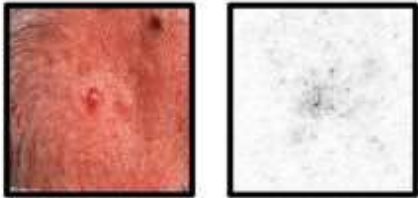
d. Benign Melanocytic Lesion



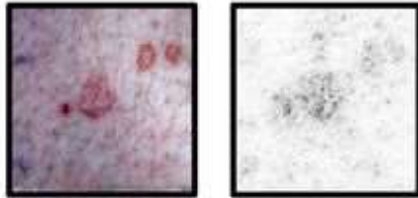
g. Inflammatory Condition



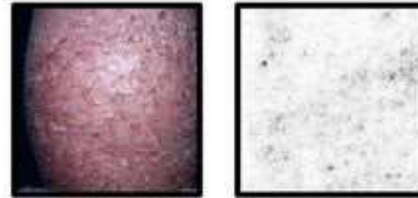
b. Malignant Epidermal Lesion



e. Benign Epidermal Lesion



h. Genodermatosis



c. Malignant Dermal Lesion



f. Benign Dermal Lesion



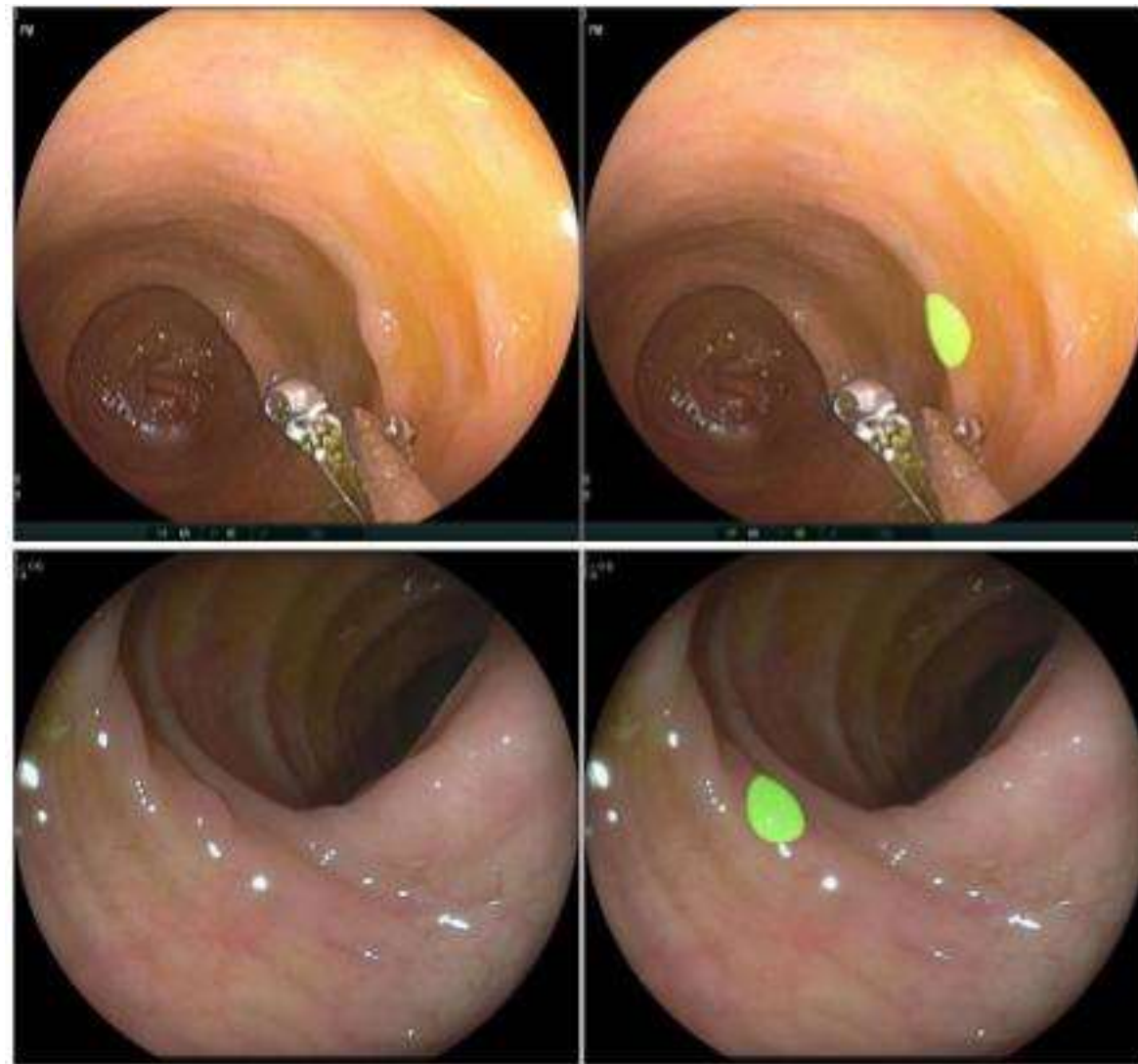
i. Cutaneous Lymphoma



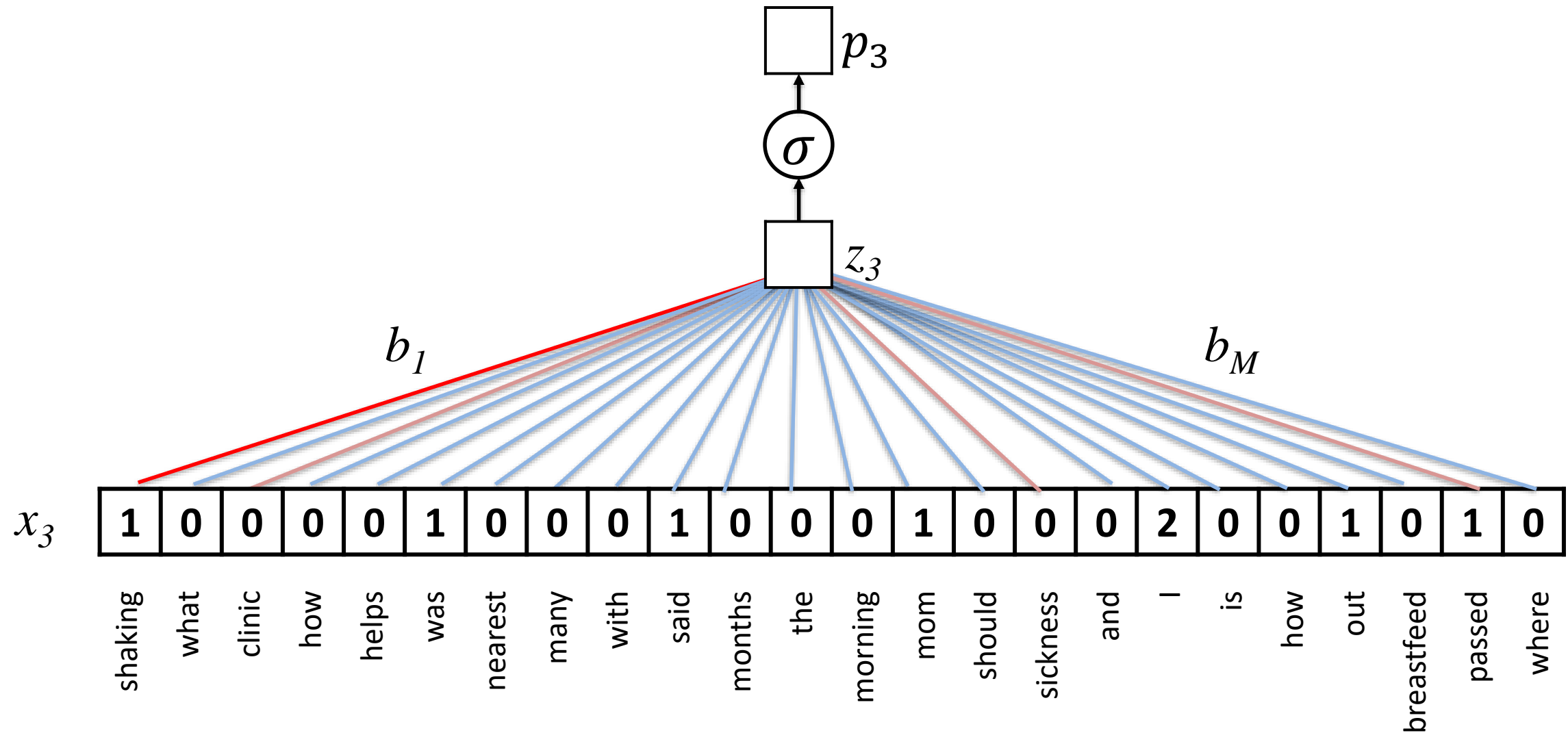
Saliency maps show gradients for each pixel with respect to the CNN's loss function. Darker pixels represent those with more influence.

Q: How much does this visualization help us understand the model?

Precisely Identify Boundaries

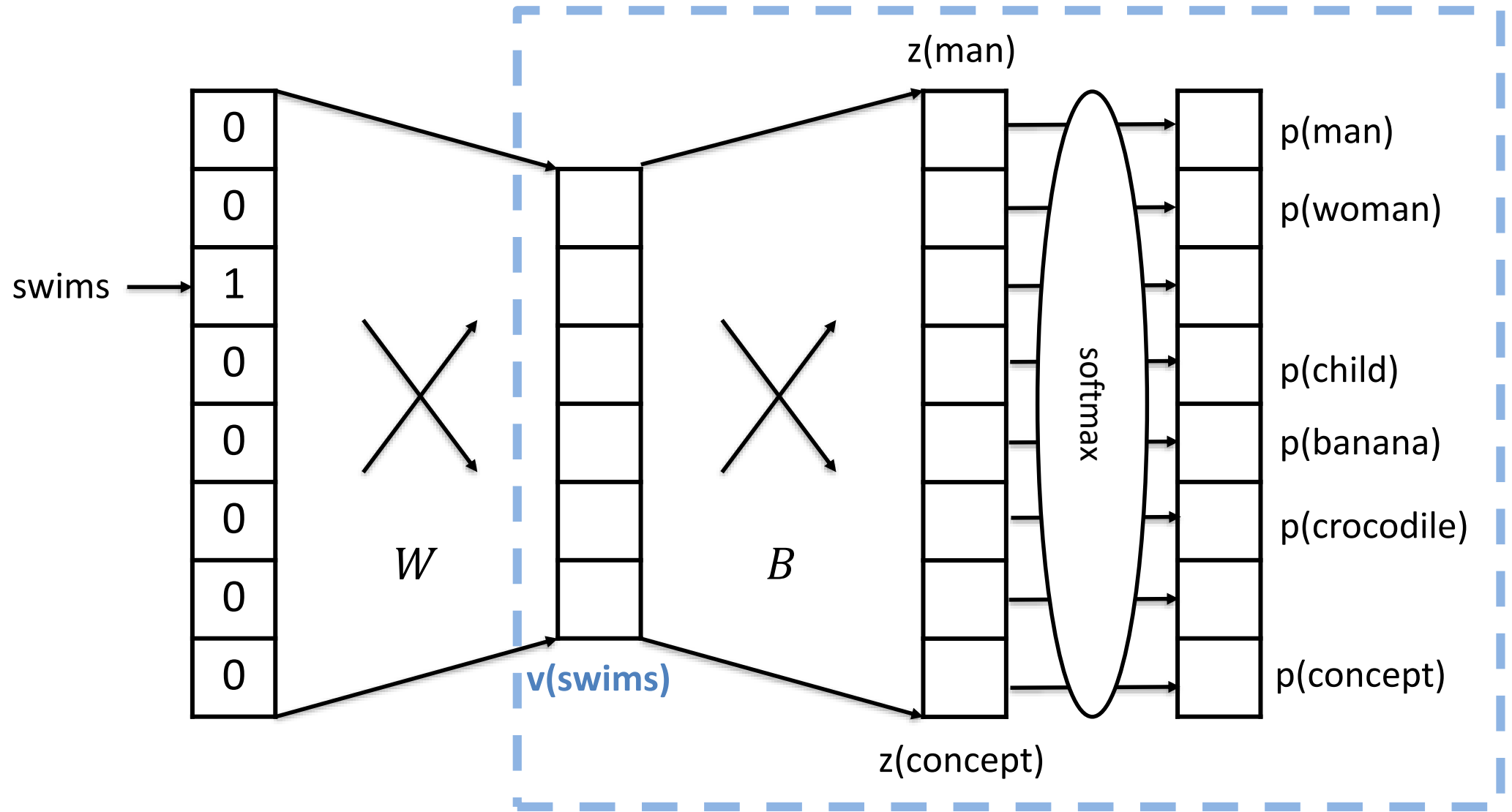


Logistic Regression for Text Classification

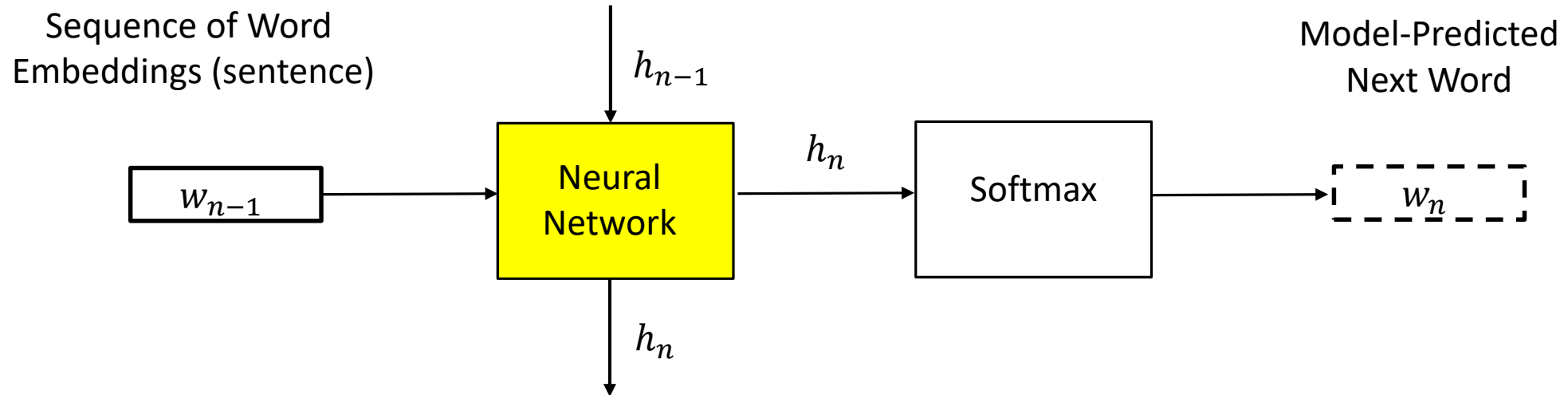


I passed out and Mom said I was shaking

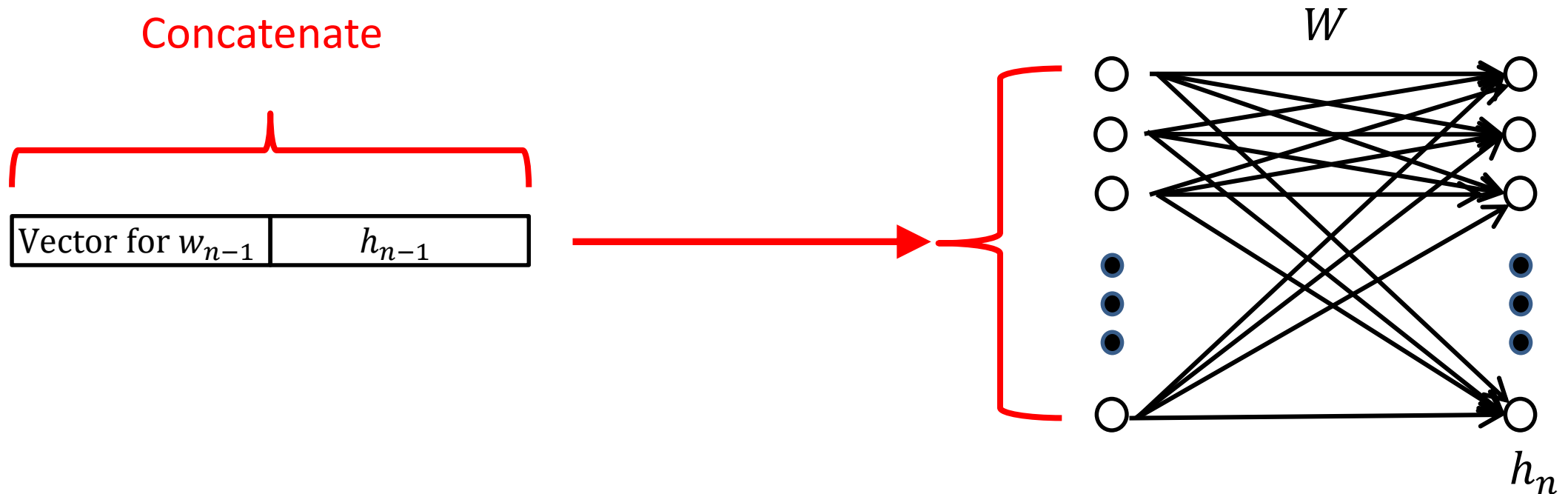
We now have a distributed representation of word *meaning* based on *context*



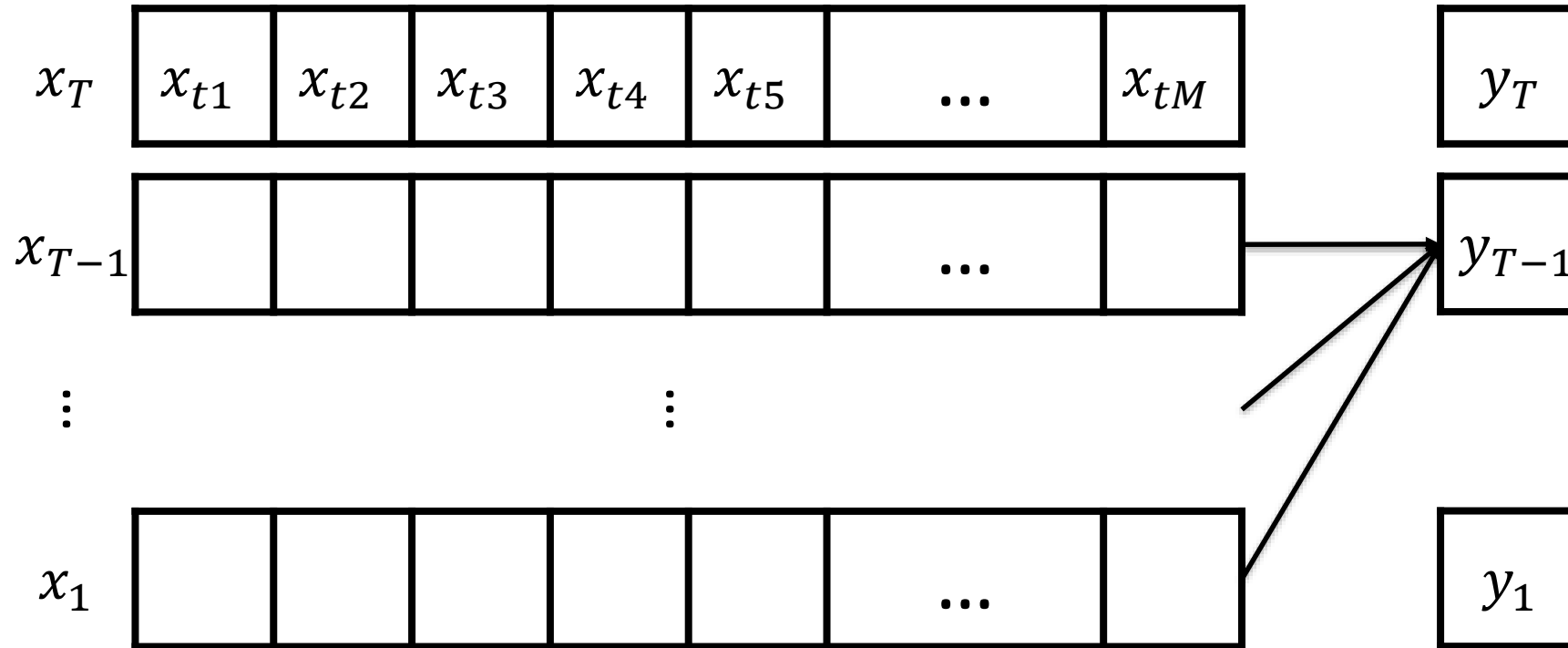
Recurrent Neural Network



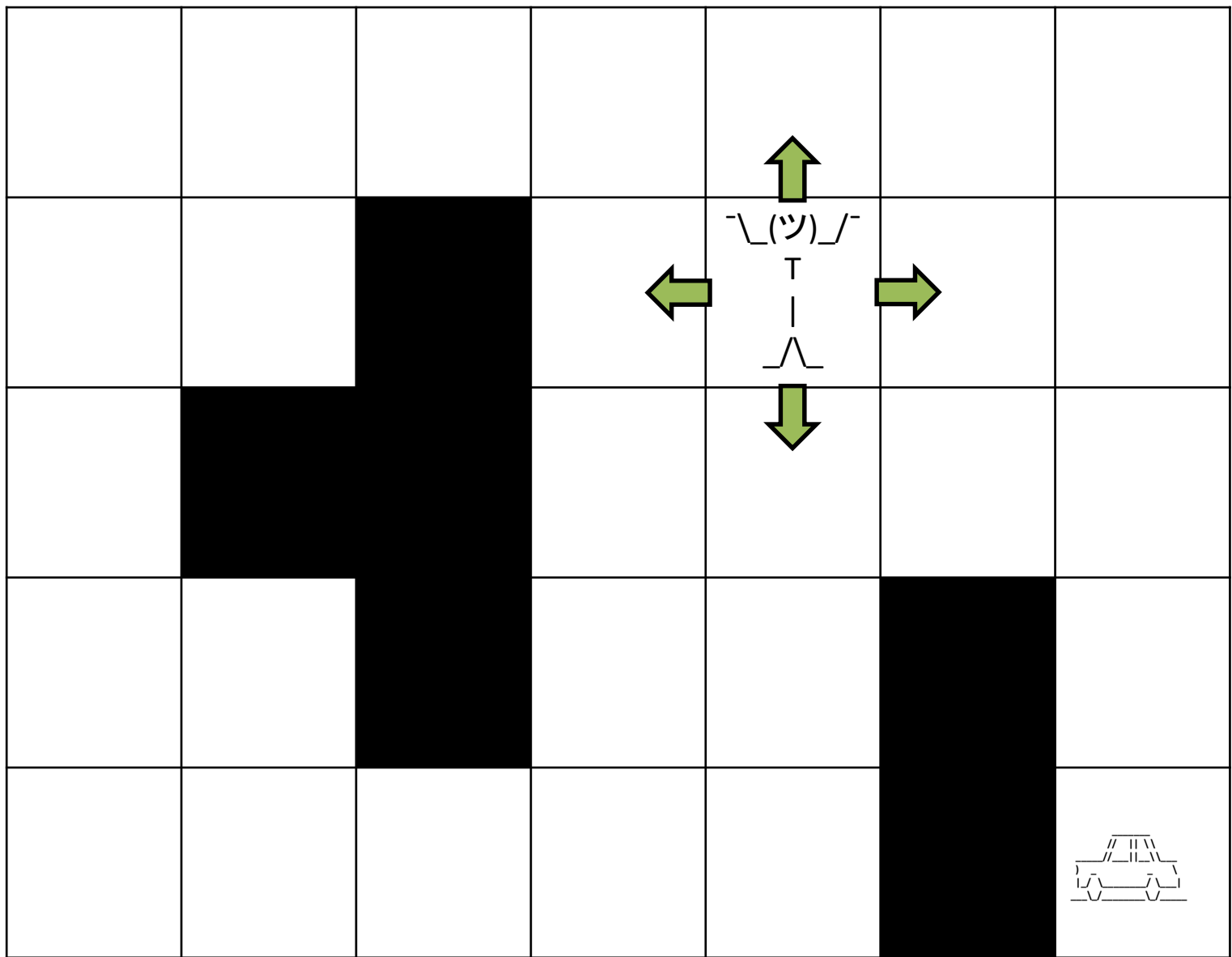
Concatenate



Prediction task B: one label per time step



Goal: predict whether pt will become hypoxemic during the next 5 minutes



GOAL:

Learn a policy $\pi: S \rightarrow A$

that **maximizes expected reward over time**

HOW?

Learn the value $Q(s, a)$ of action a when in state s

$Q(\text{current square, down})$

Sequential Medical Decision-Making: Sepsis Management

An agent

takes actions

based on the state of a system

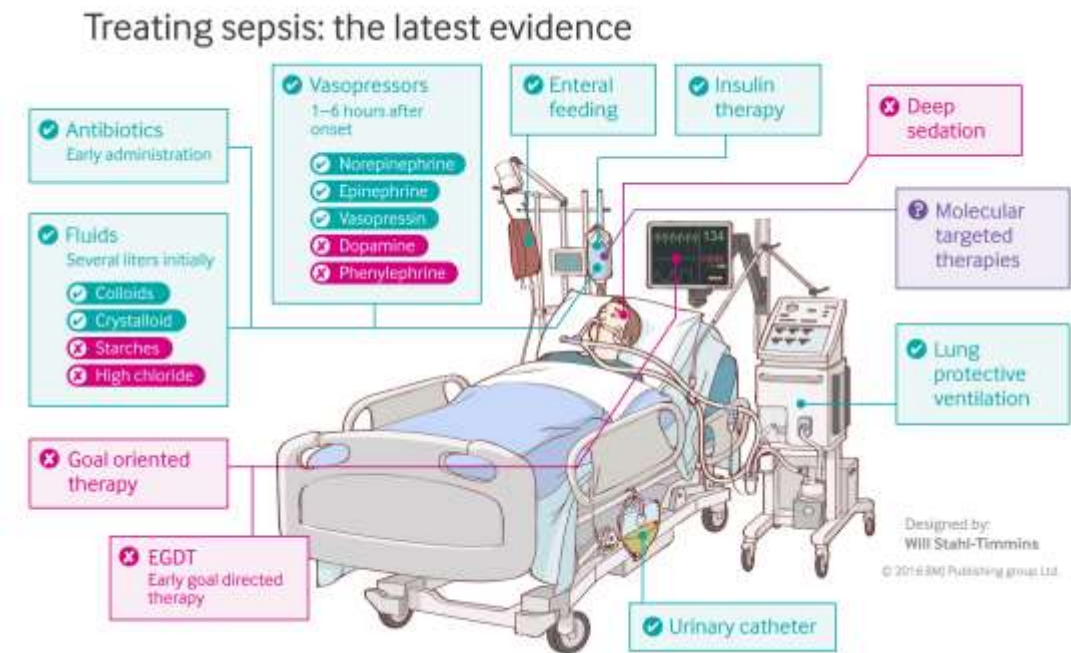
to maximize reward

A clinician

gives fluid and/or vasopressor

based on the patient's physiologic status

to maximize chance of survival



Be in touch: m.engelhard@duke.edu

THANK YOU!