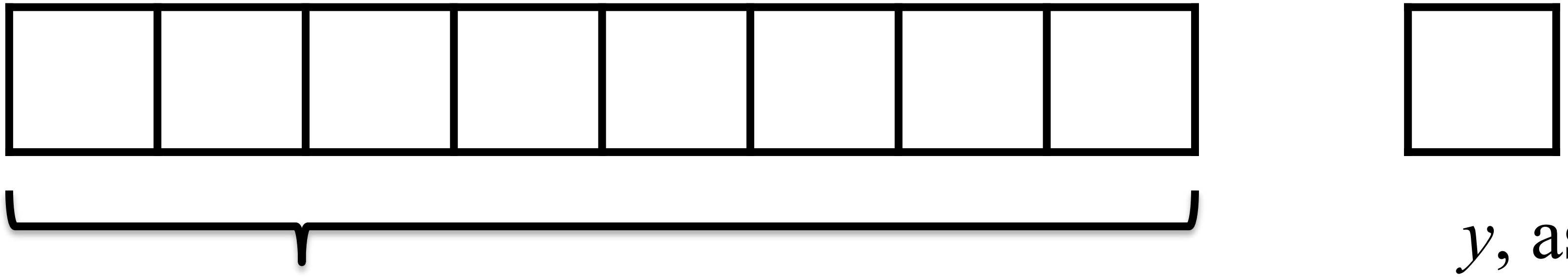
Beyond Supervised Learning

August 8, 2020

Applied Data Science
MMCi Term 4

Matthew Engelhard

Supervised Learning

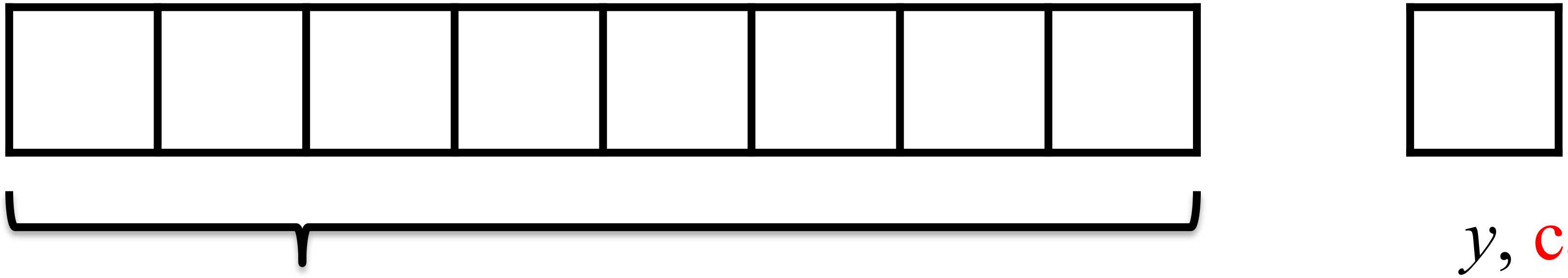


x, data/features for
a subject or patient

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
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y, categorical
label

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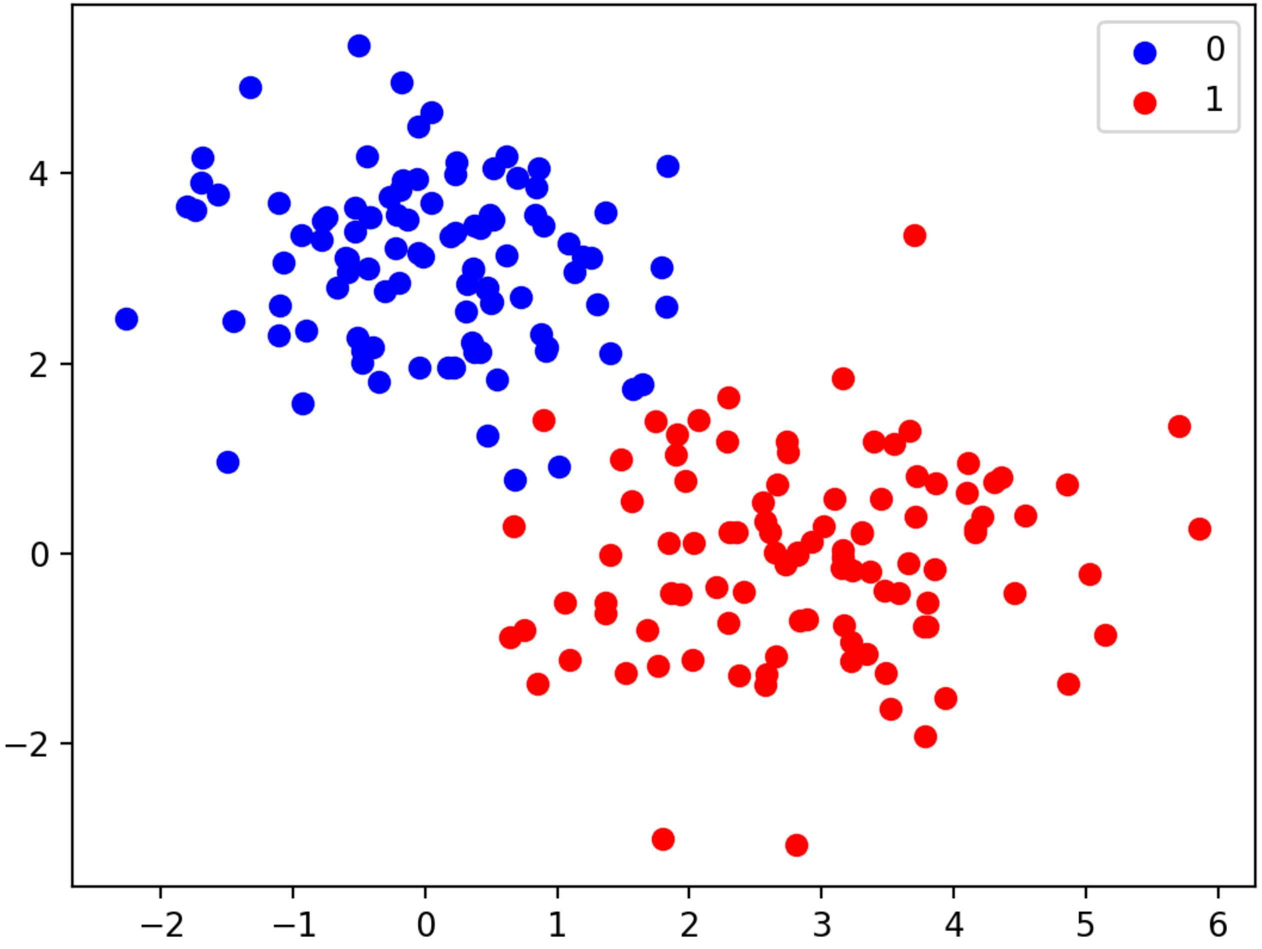
Supervised Learning: Classification

<u>Goal</u>:

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



Supervised Learning: Classification

Goal:

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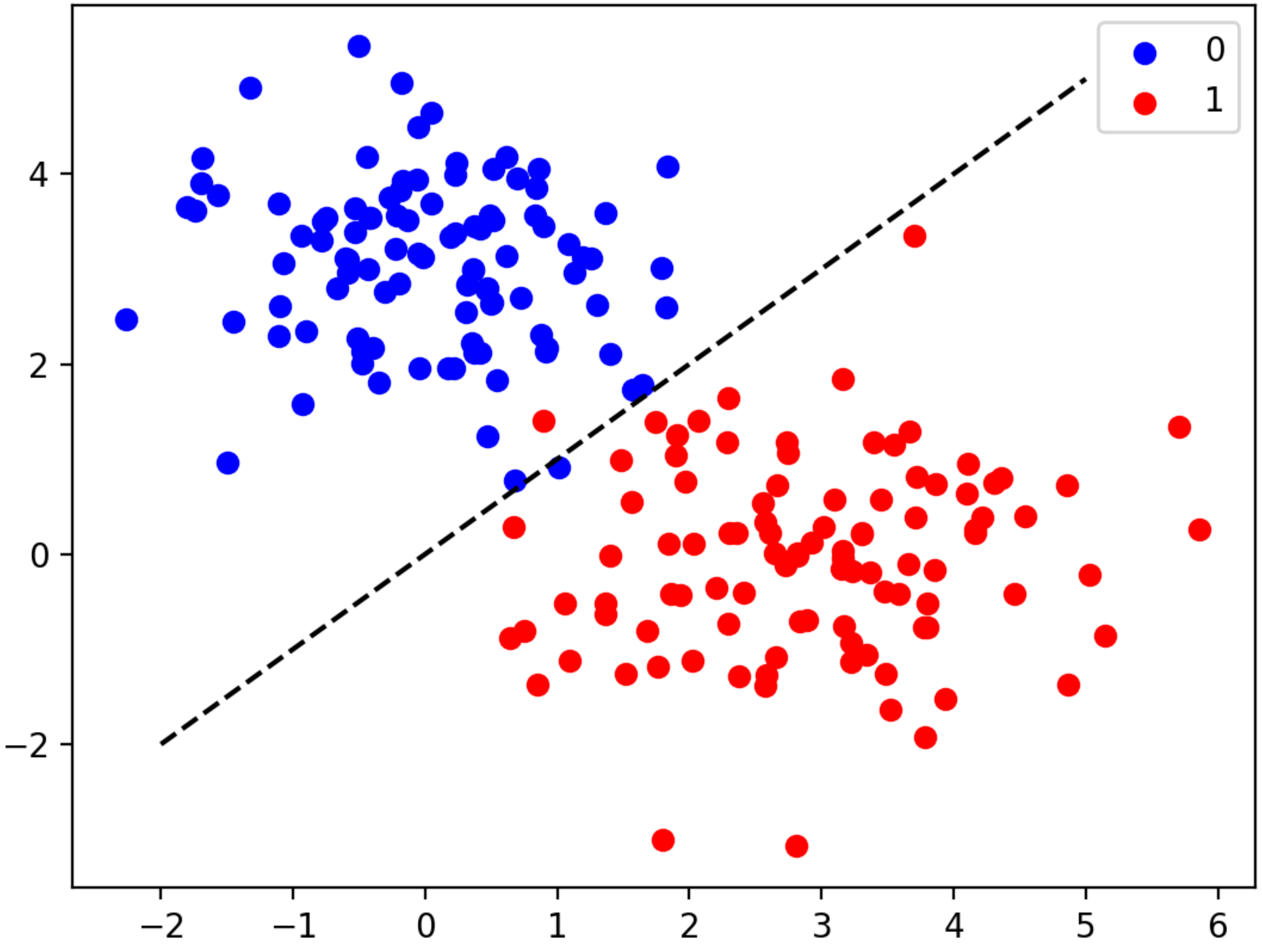
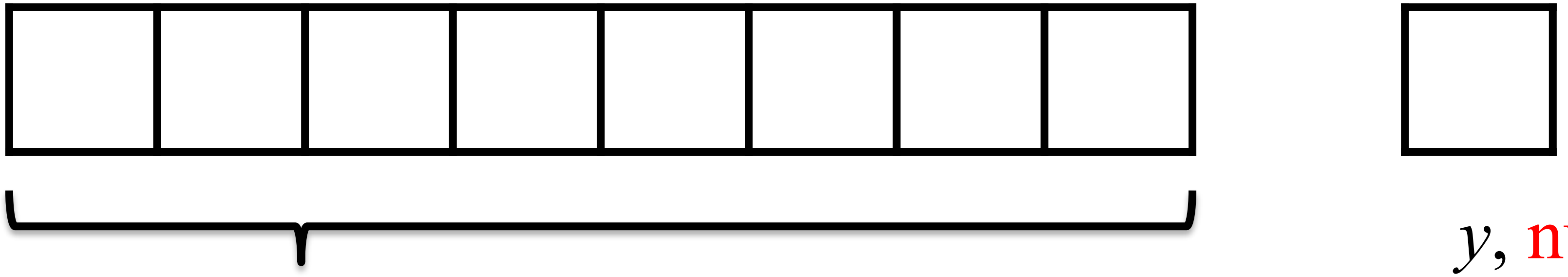


Supervised Learning: Regression



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y, numeric value

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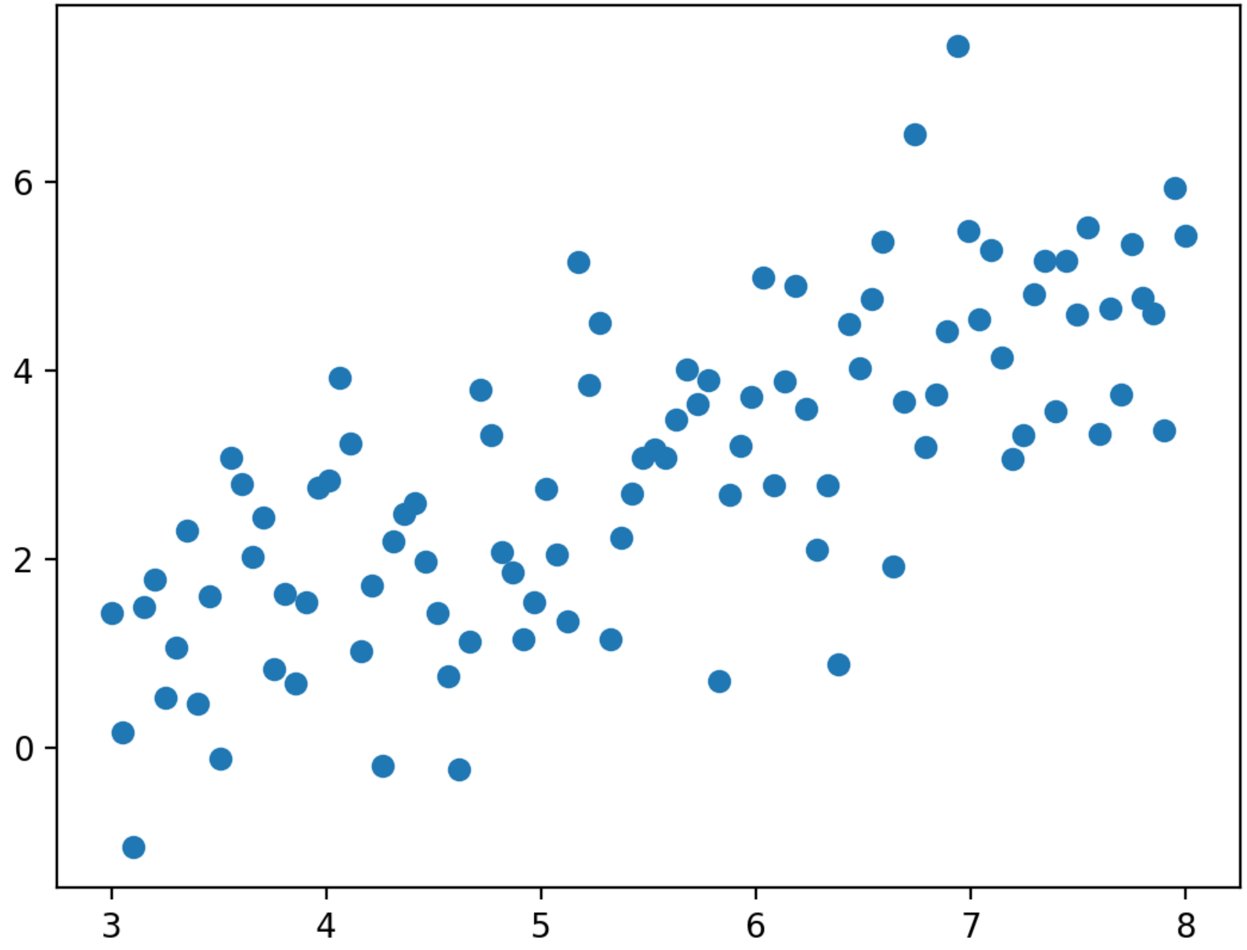
Supervised Learning: Regression

<u>Goal</u>:

Learn a function that predicts y based on x



Supervised Learning: Regression

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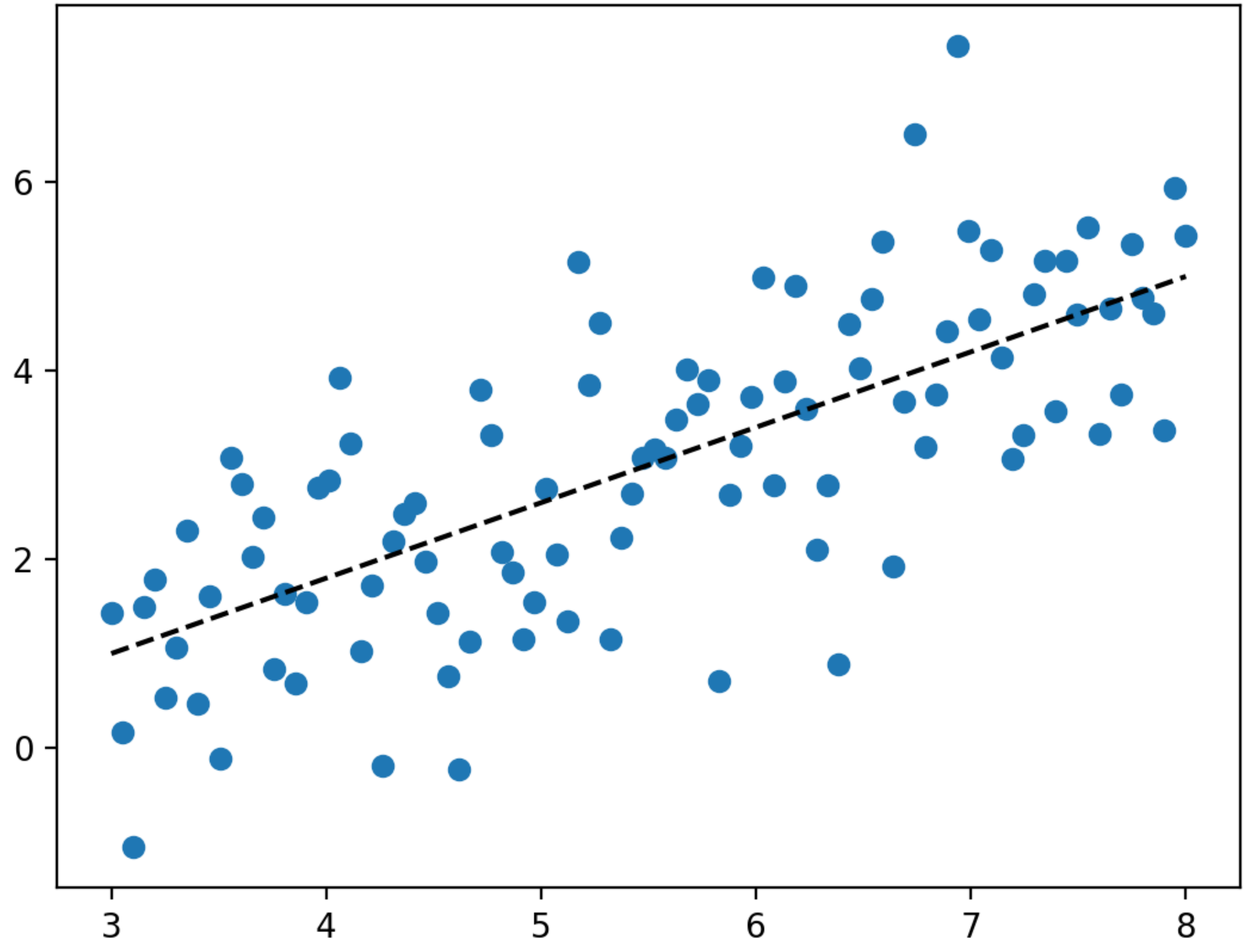
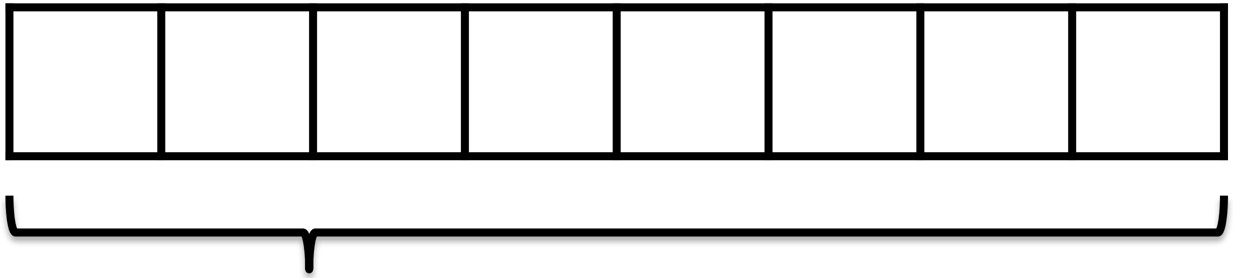


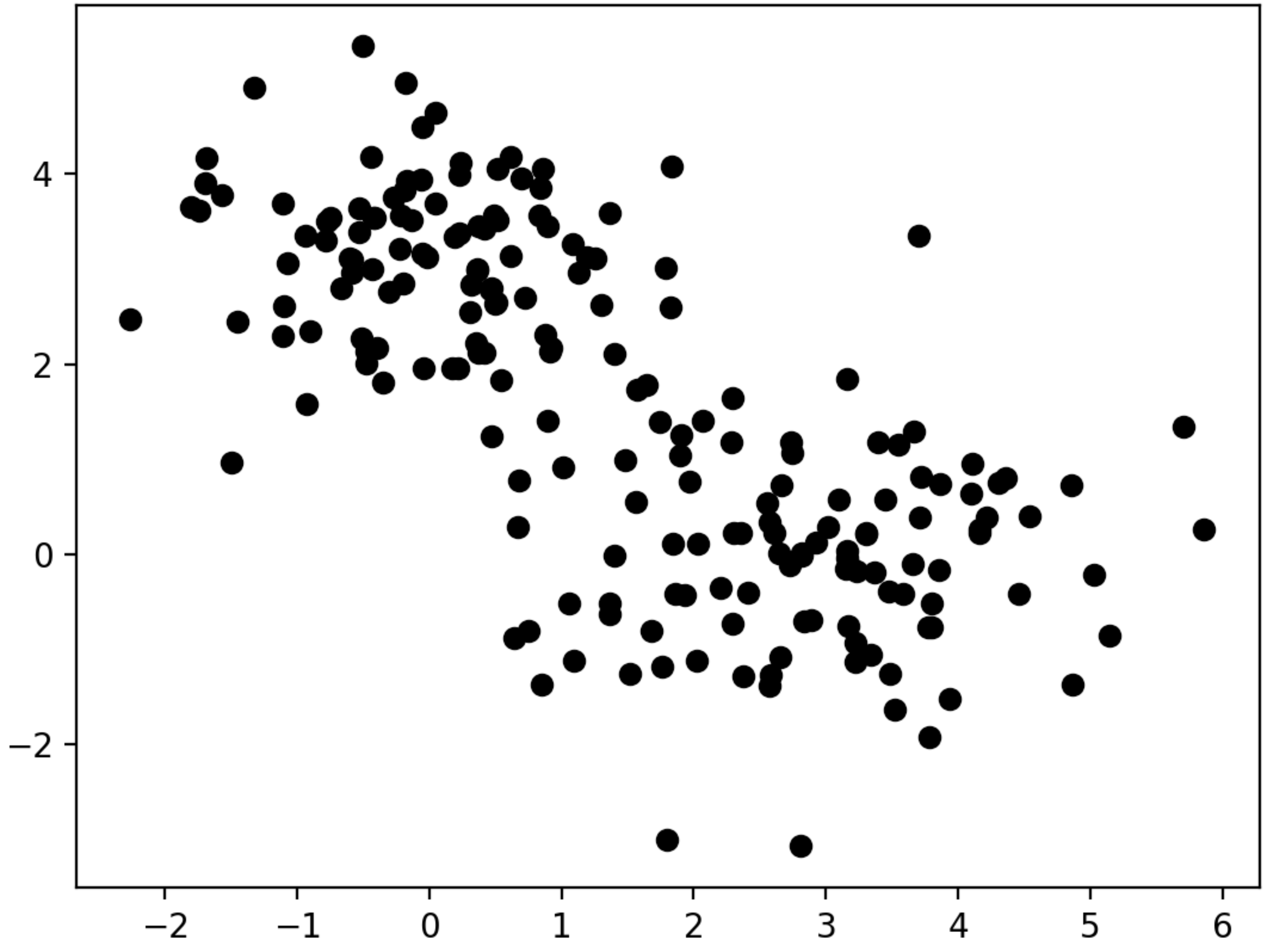
Unsupervised Learning



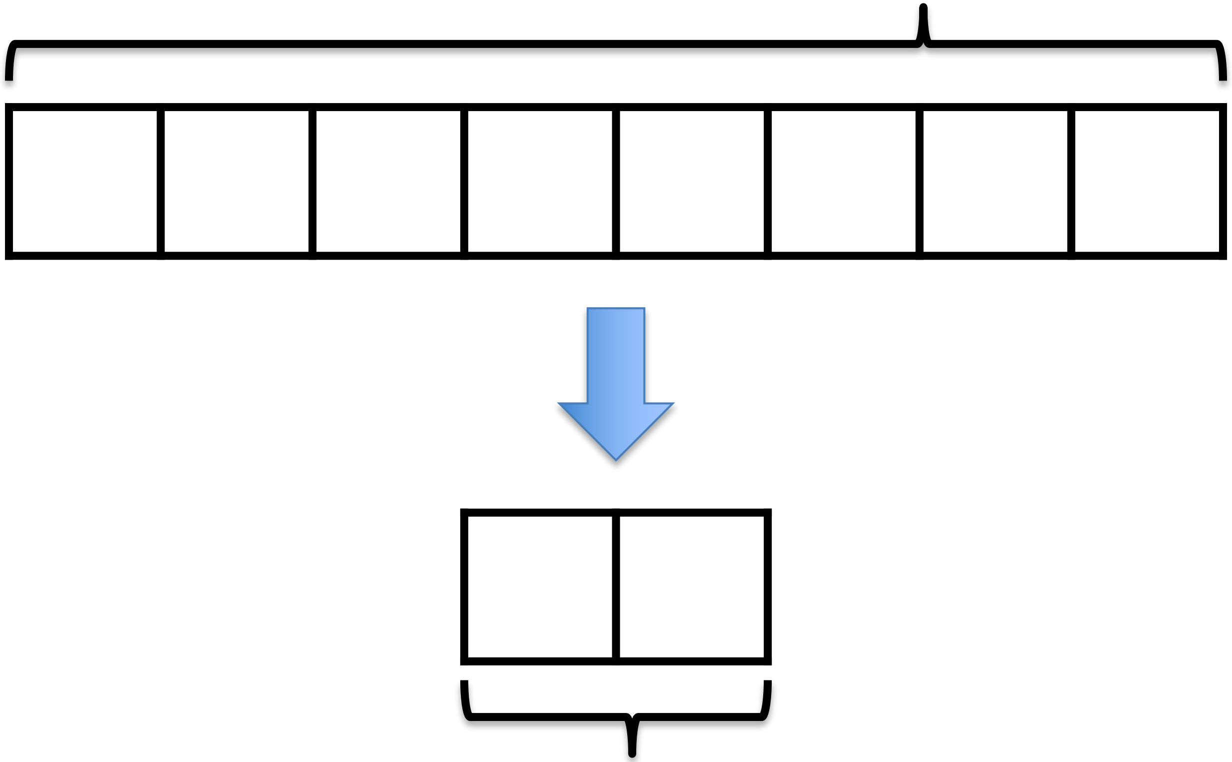
x, data/features for
a subject or patient

The learning process: - find structure or patterns in the data
- describe the data or create new, similar data

Unsupervised Learning



Unsupervised Learning: Dimensionality Reduction



<u>Goal</u>:

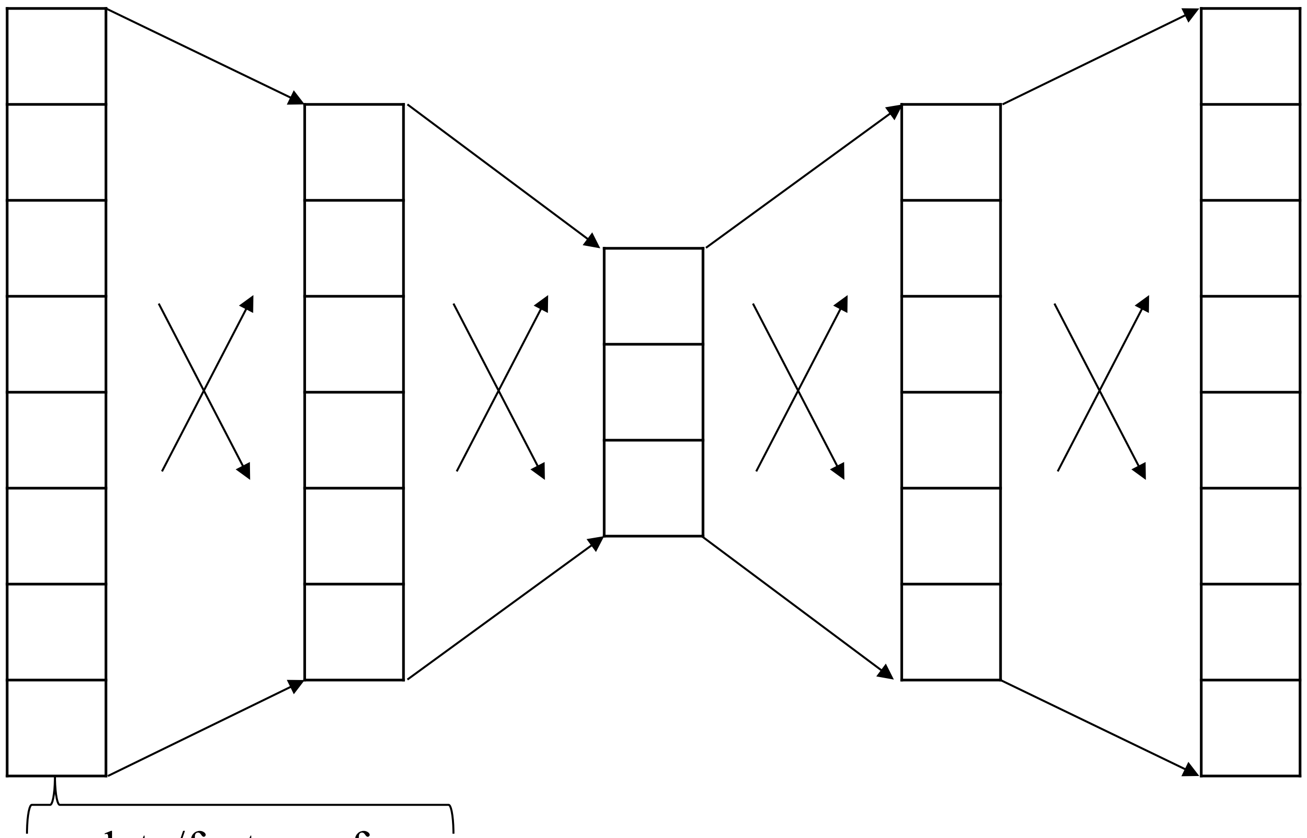
Describe a large number of features in terms of a smaller number of features

Dimensionality Reduction Example: Autoencoder

Goal:

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

- Train to minimize **reconstruction loss**



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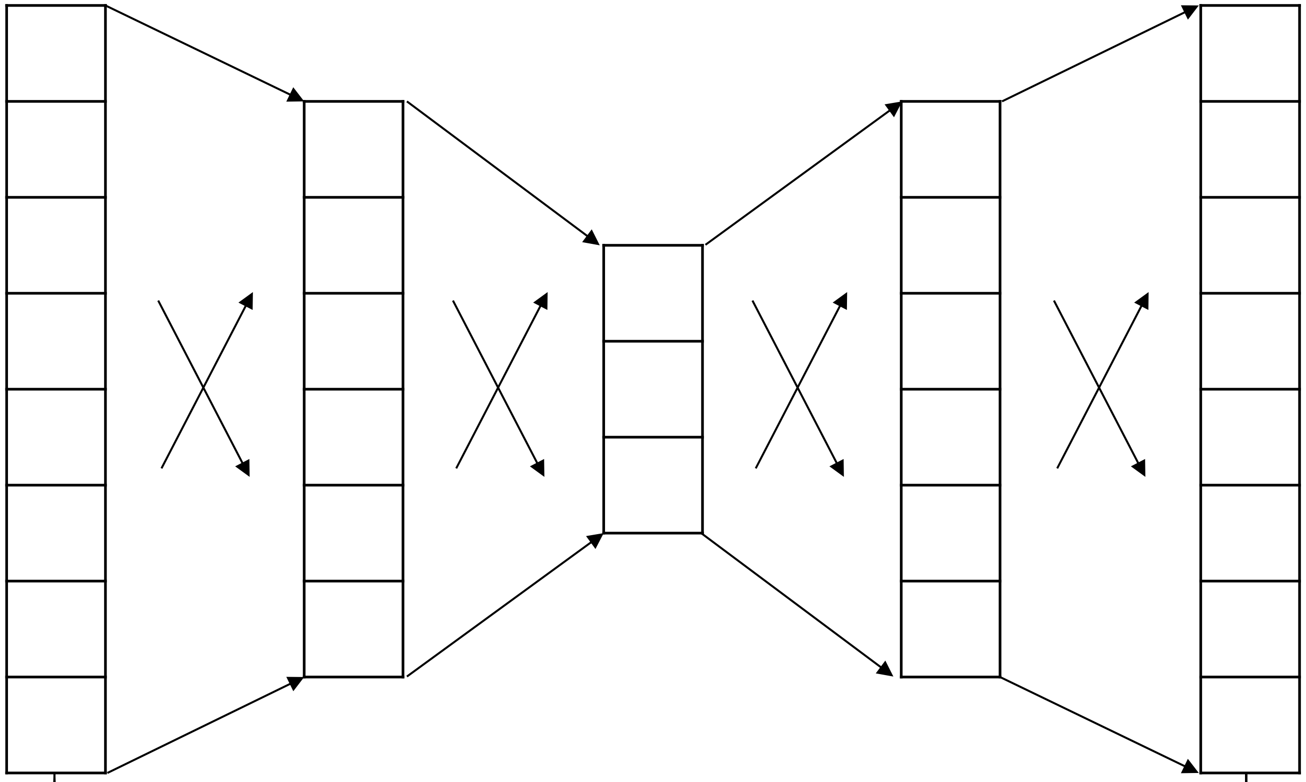

x, data/features for a subject or patient

$\hat{x}$, predicted data/features for a subject or patient

Dimensionality Reduction Example: Autoencoder

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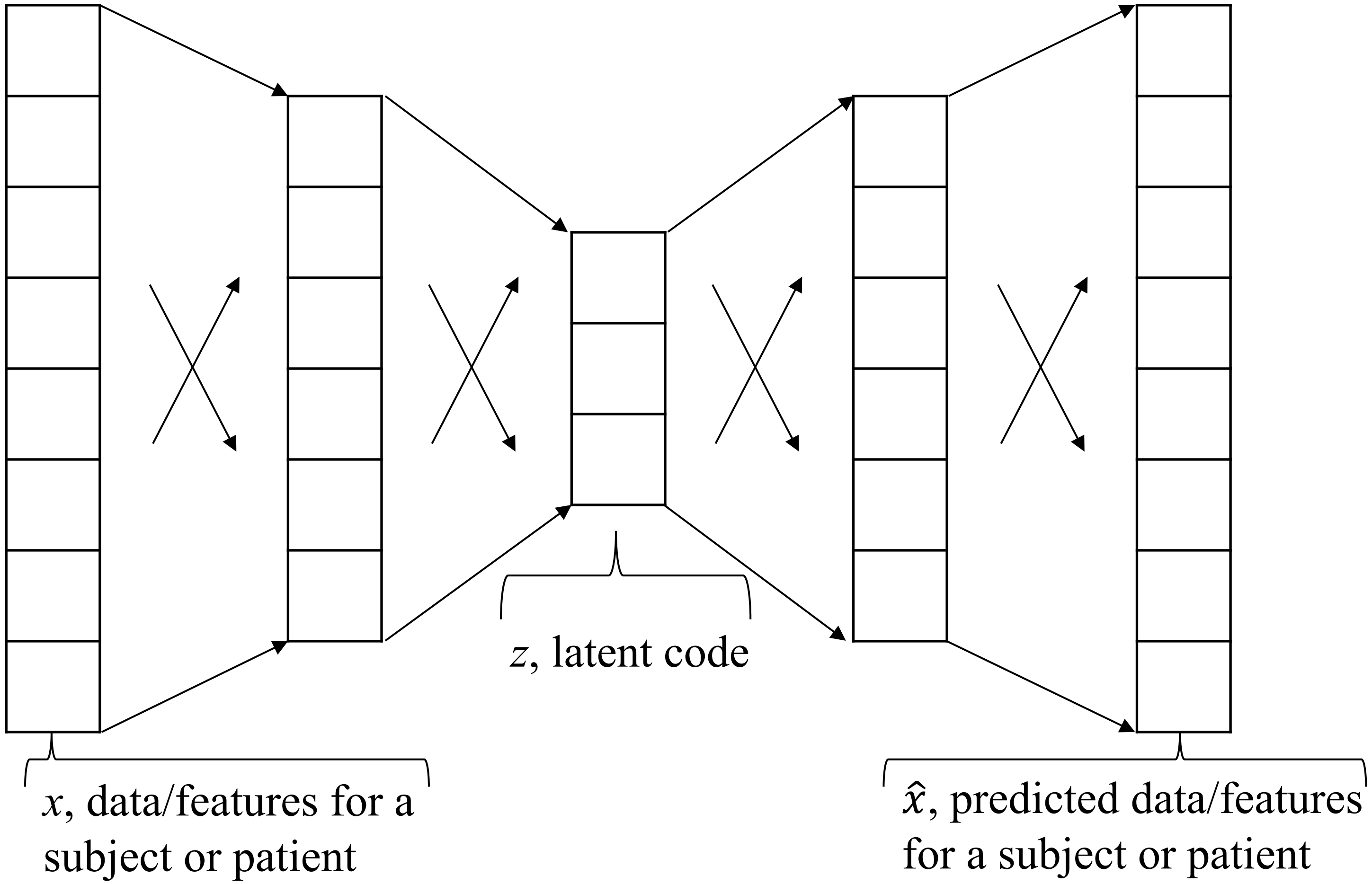
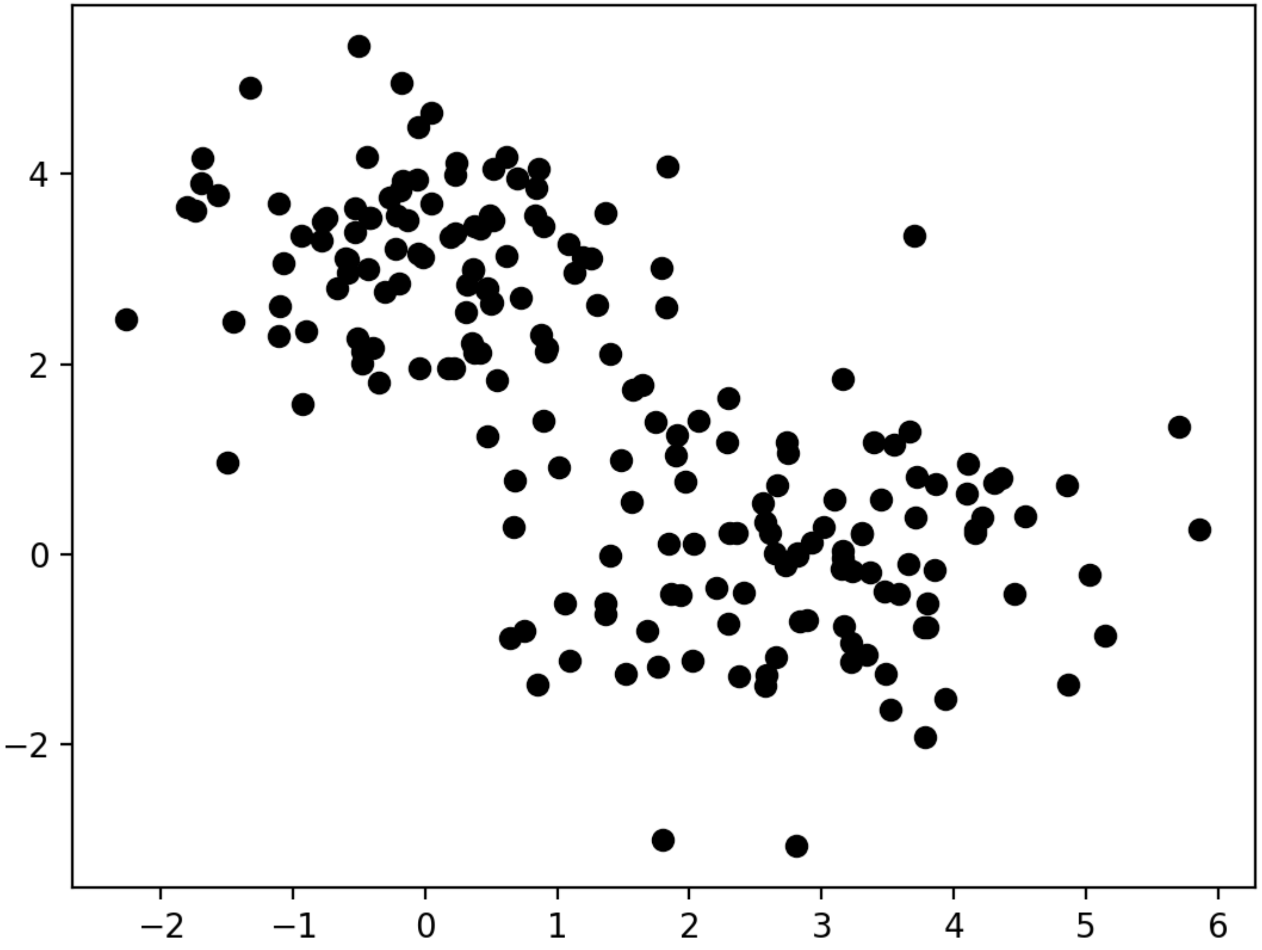


Unsupervised Learning: Clustering

Goal:

Assign points to distinct groups with shared characteristics



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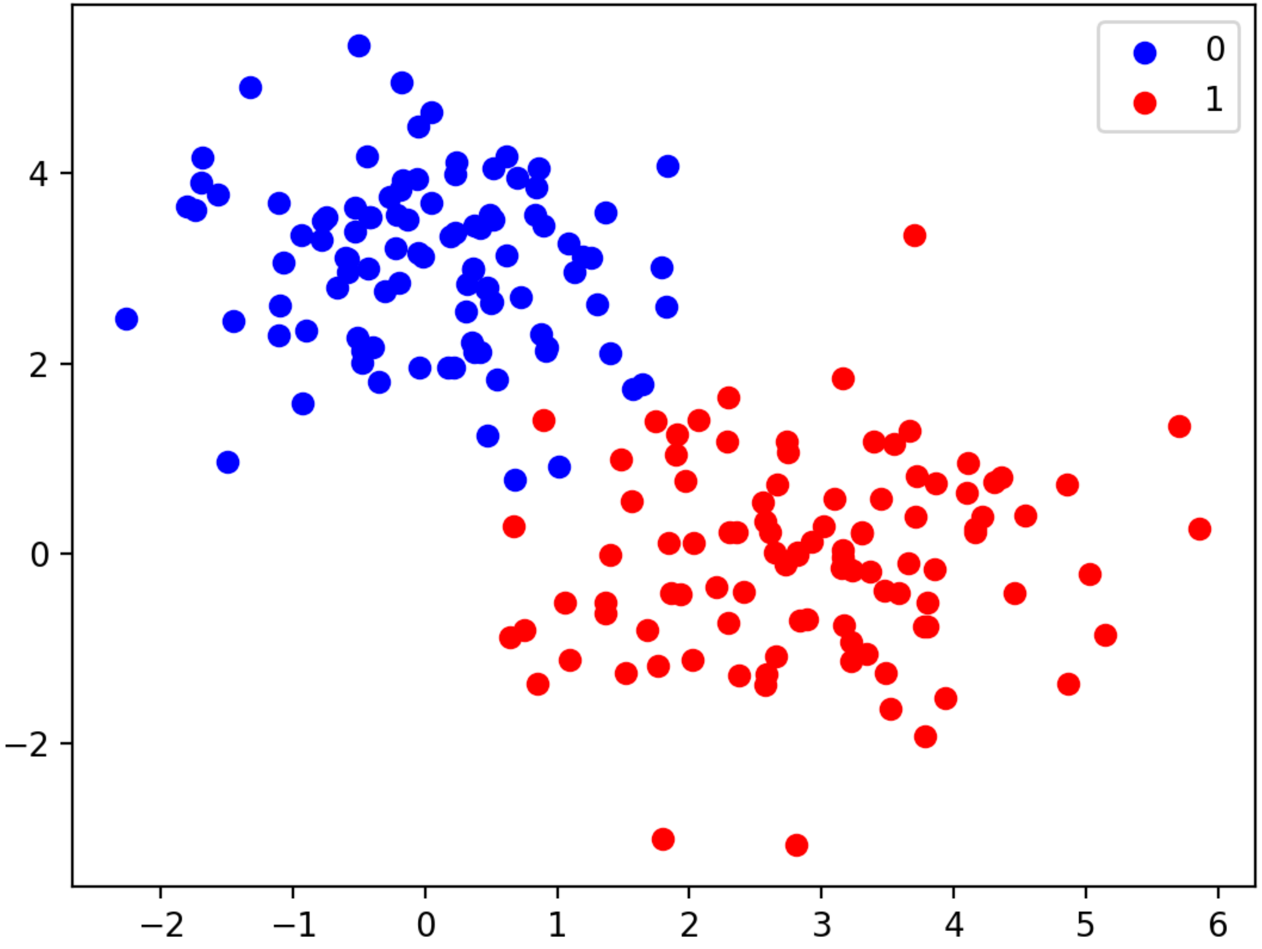
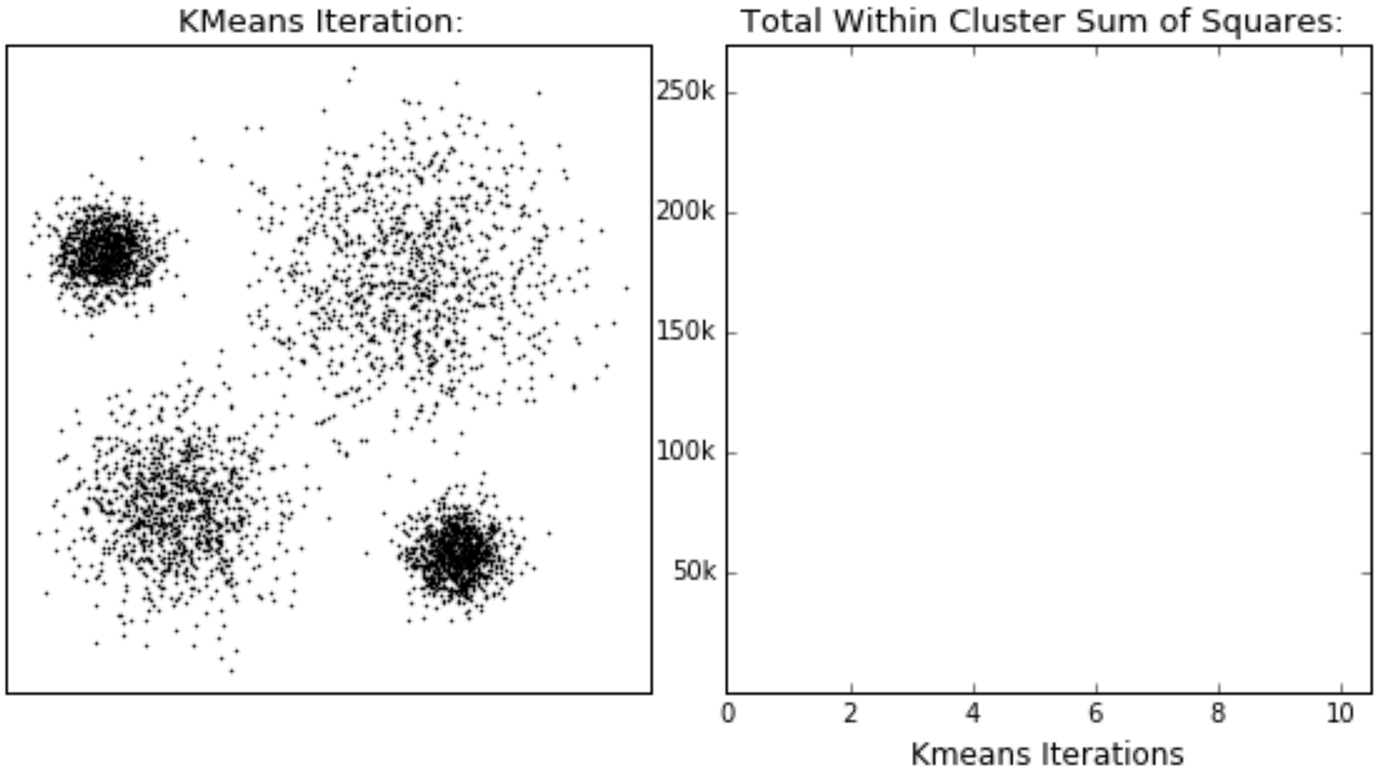


Example of K-Means Clustering

<u>Goal</u>:

Assign points to distinct groups with shared characteristics

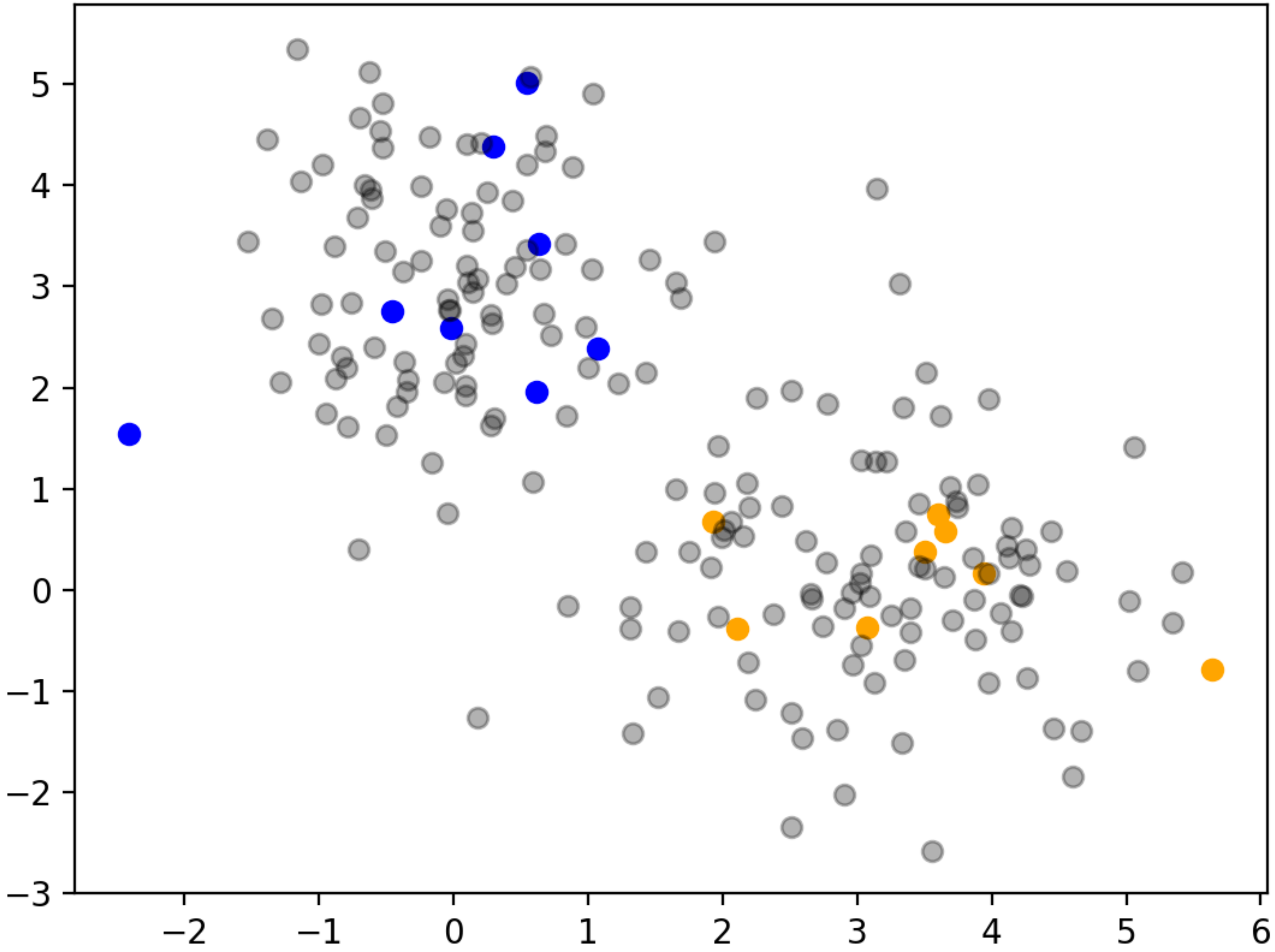


- sensitive to initialization
- minimize Σdistance^2 from points to centers

Semi-Supervised Learning

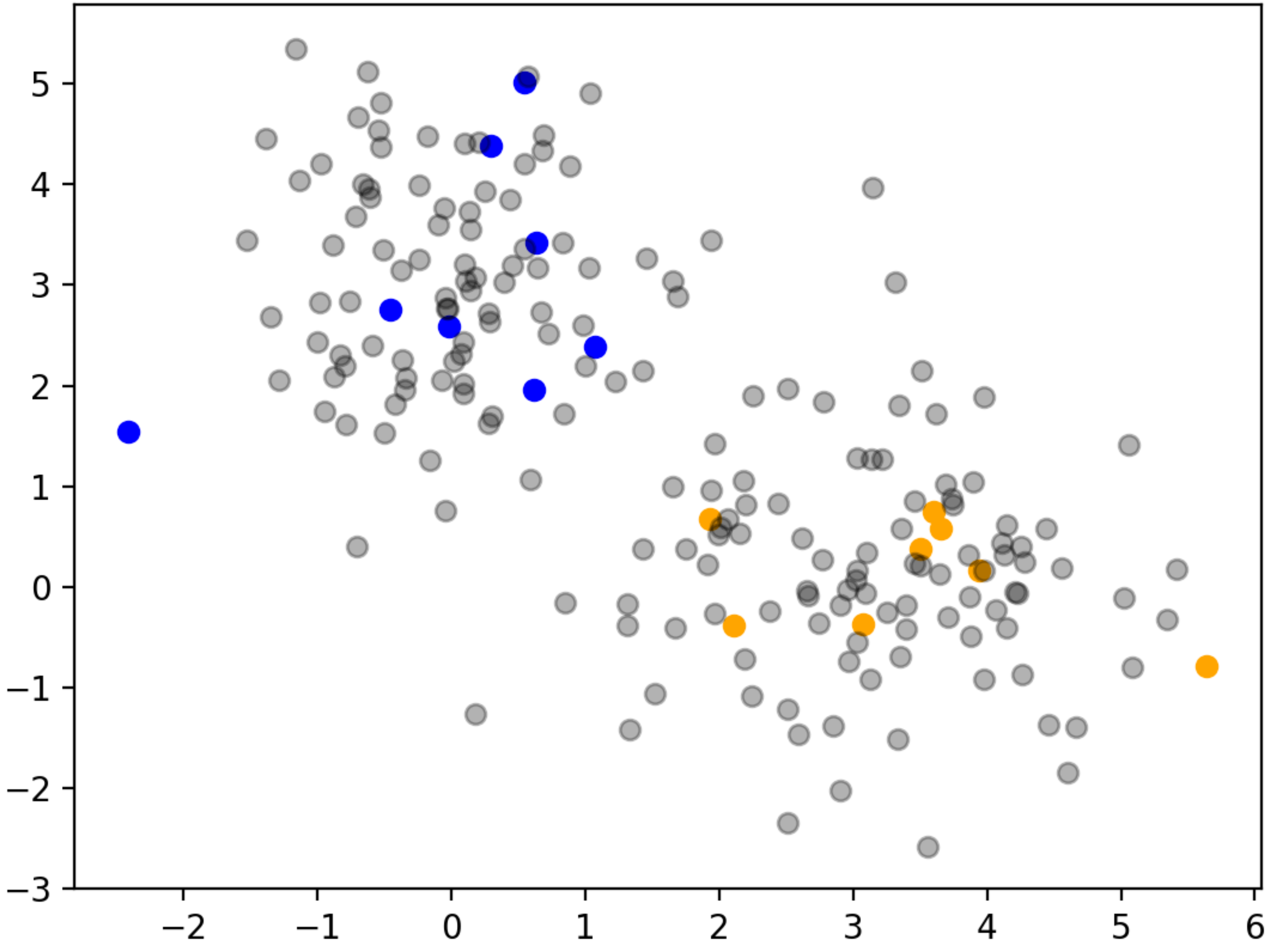
- Some points are labeled, some are not

- Try to use the unlabeled data to help us reason about the labeled data



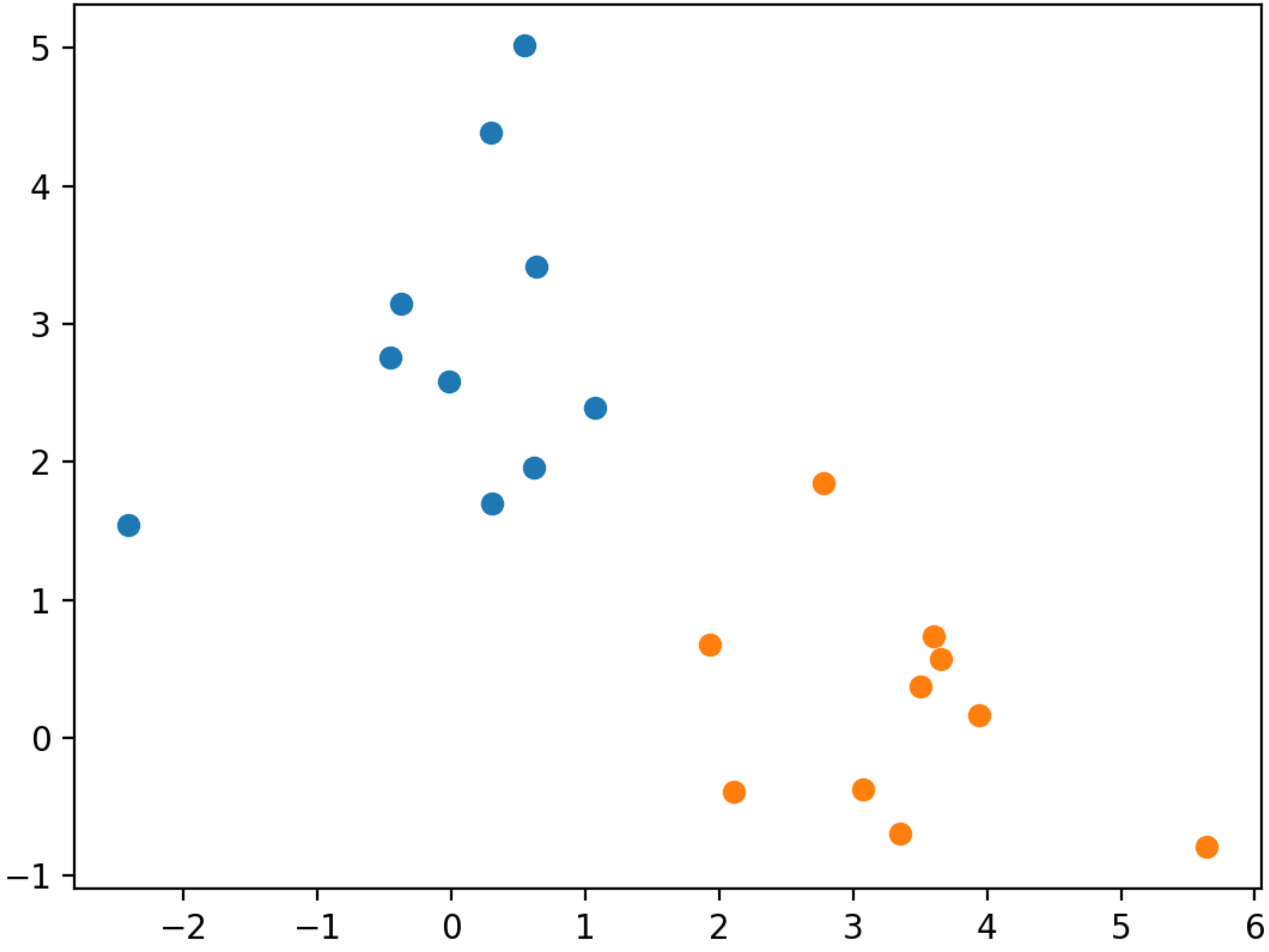
Active Learning

- 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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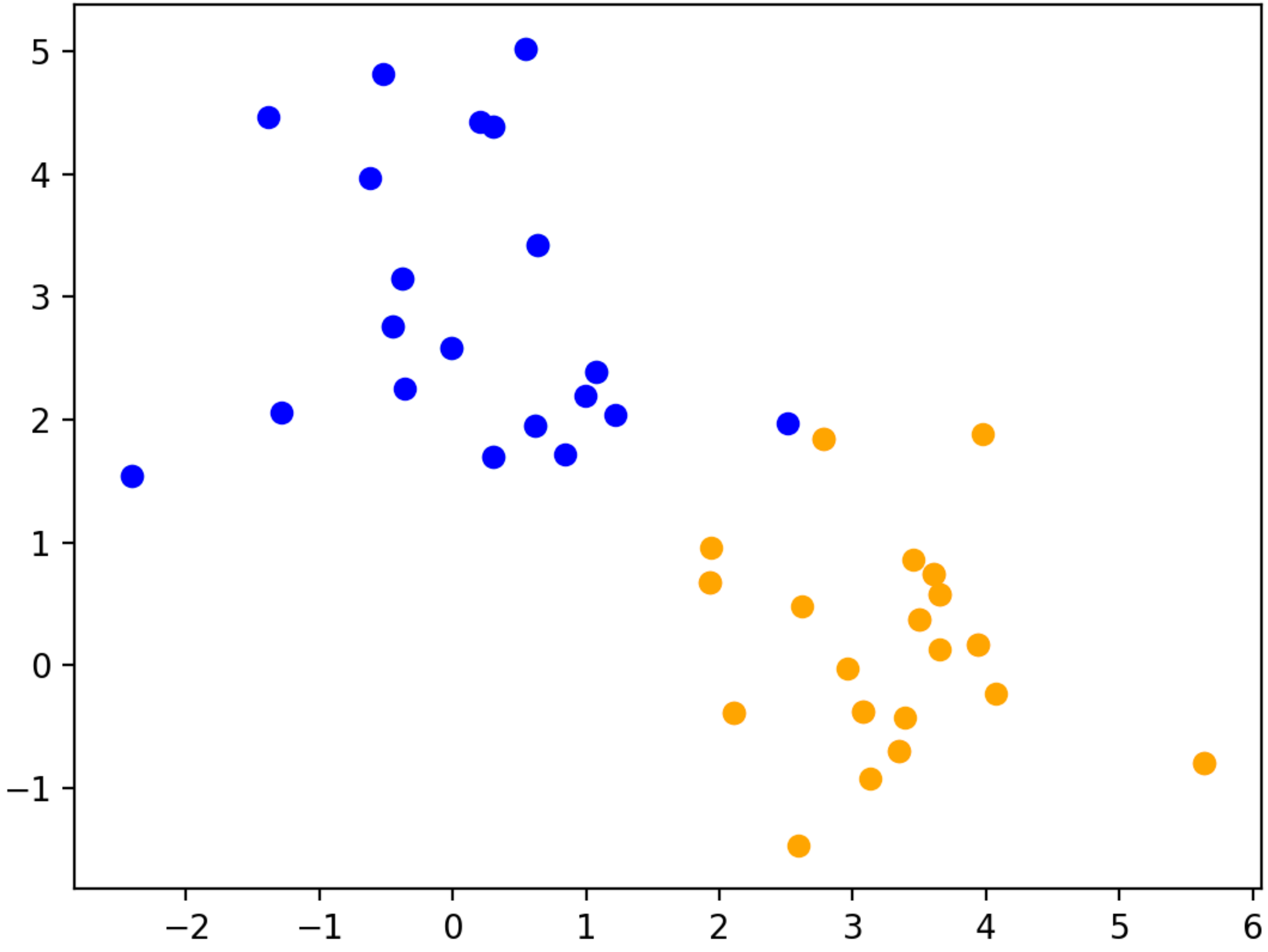

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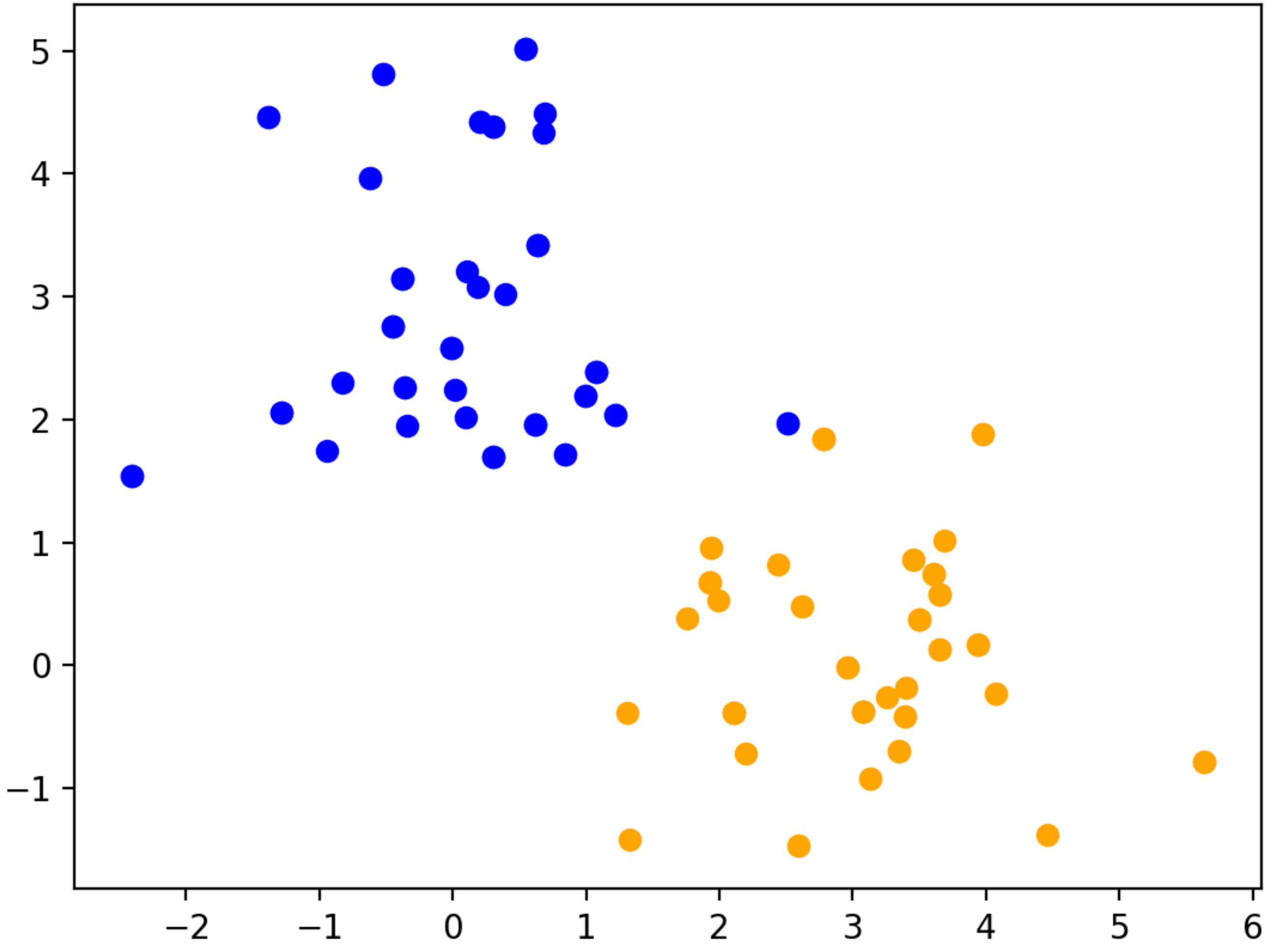

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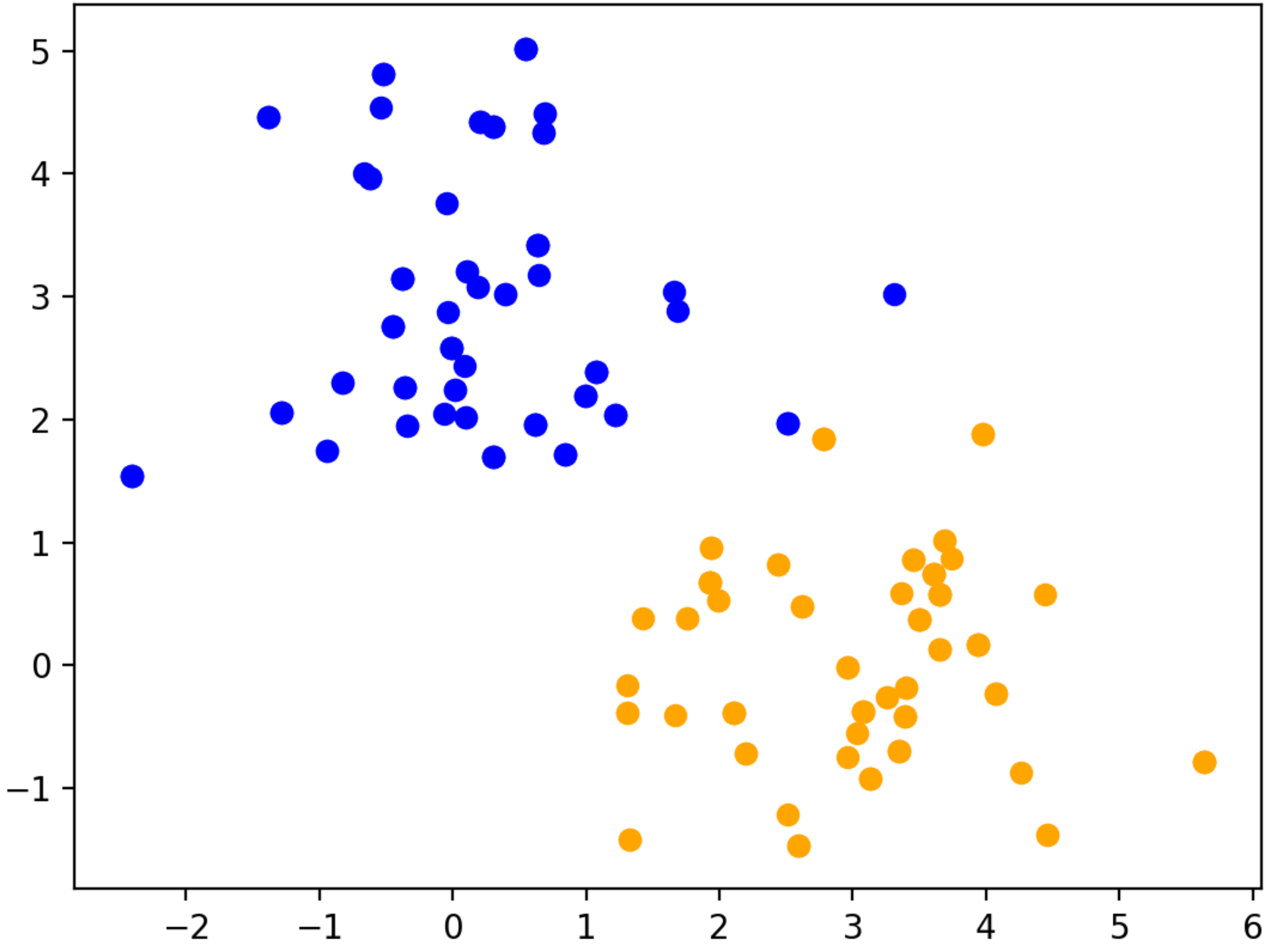
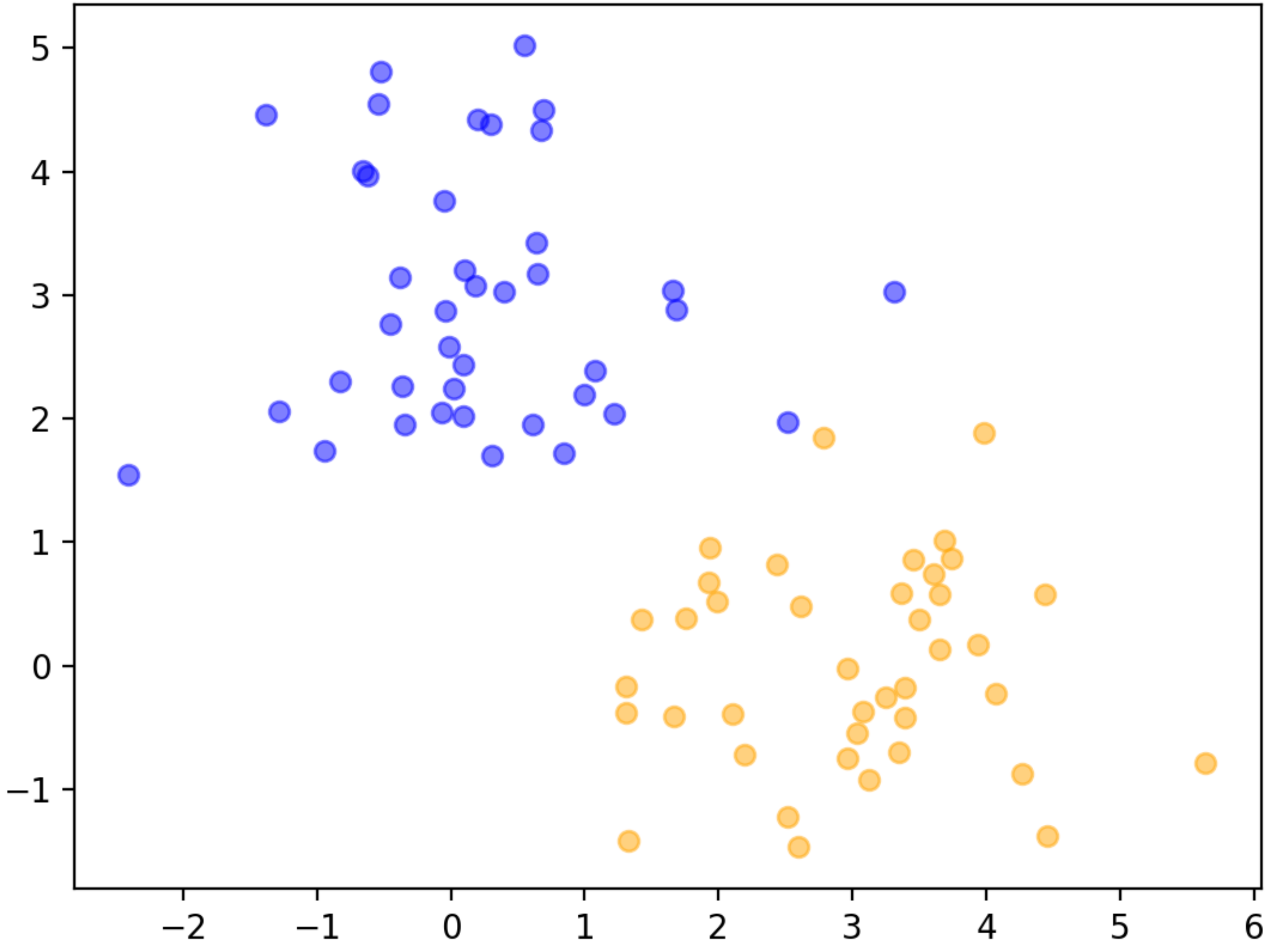


Lifelong Learning

- Similar to lifelong learning; also uses a learning rate

- Data characteristics change over time

- Continually refine our classifier to adjust to these changing characteristics



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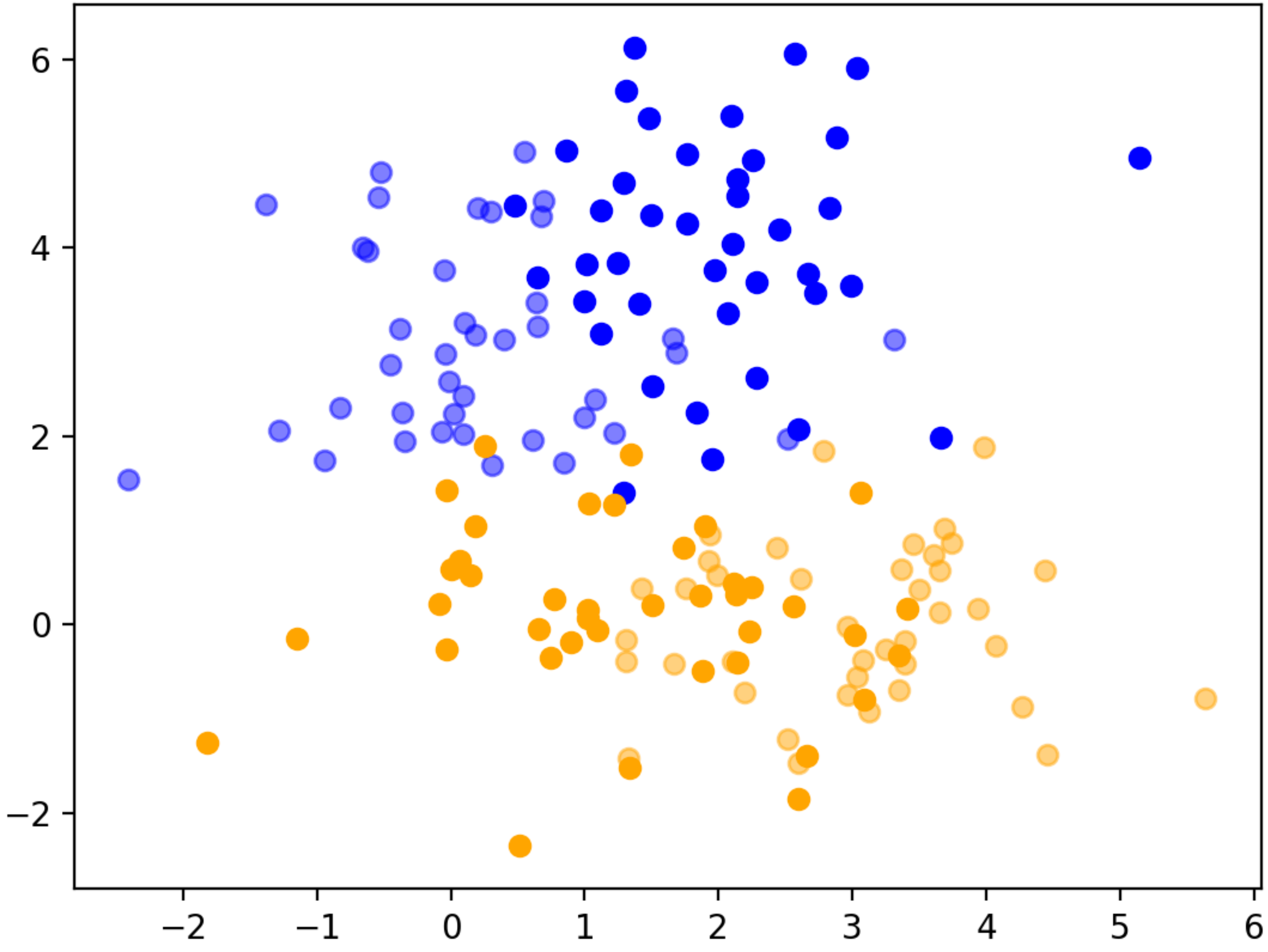
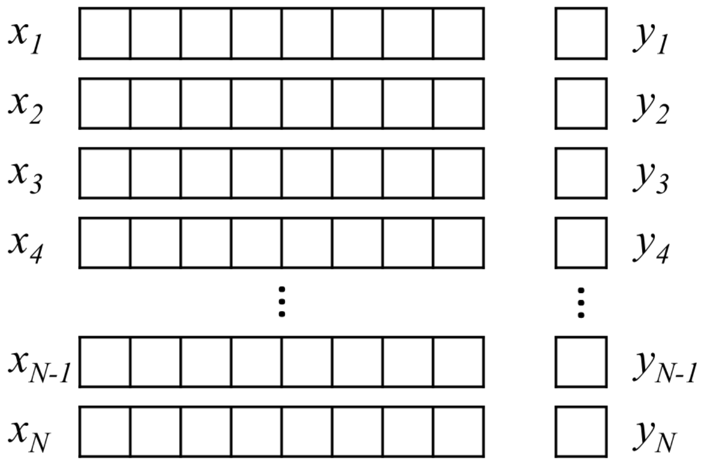
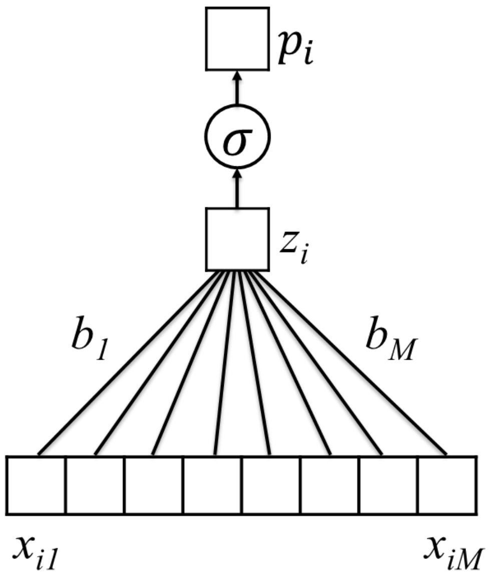


WE HAVE COVERED A LOT!

Learning Model Parameters

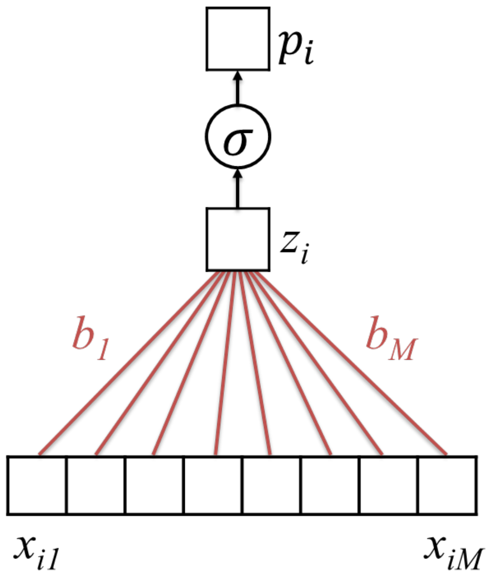


Training Set



$$p_i = \sigma(b_0 + b_1 x_{i1} + b_2 x_{i2} + \cdots + b_M x_{iM})$$

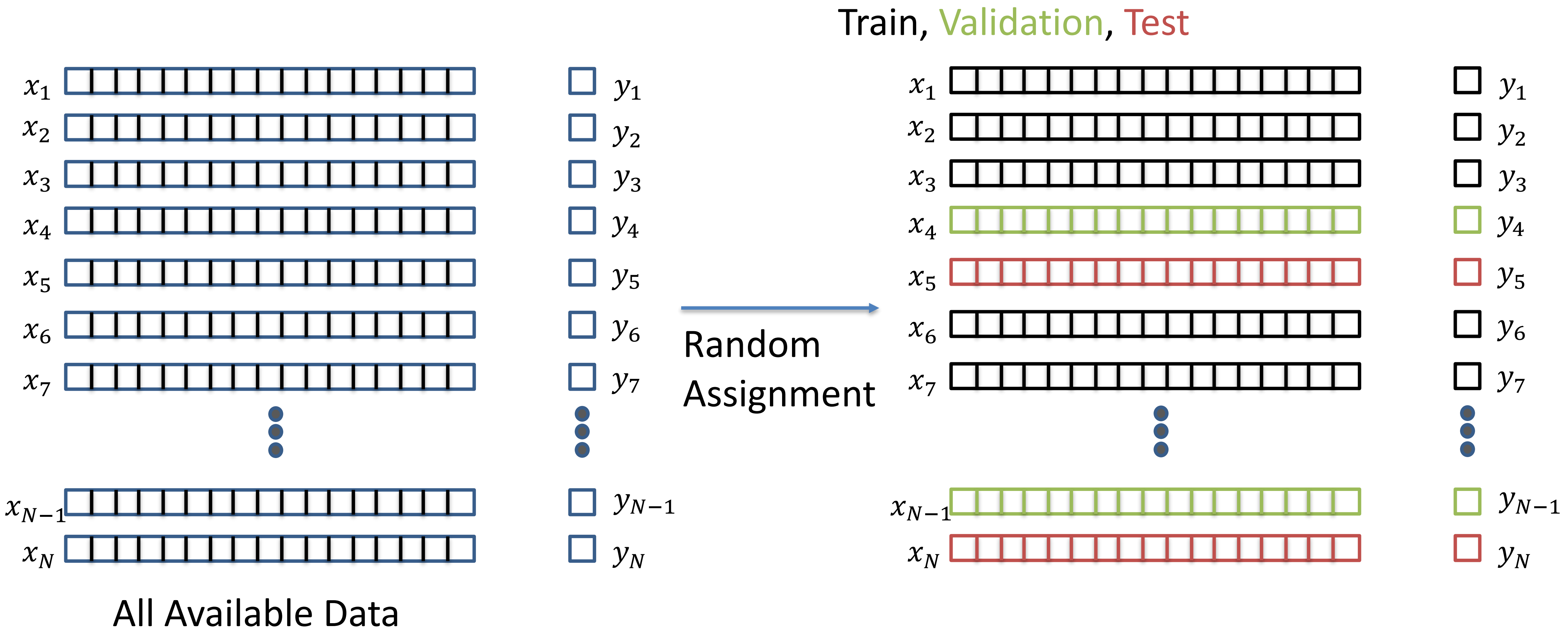
Untrained Logistic Regression Model (or “Network”)



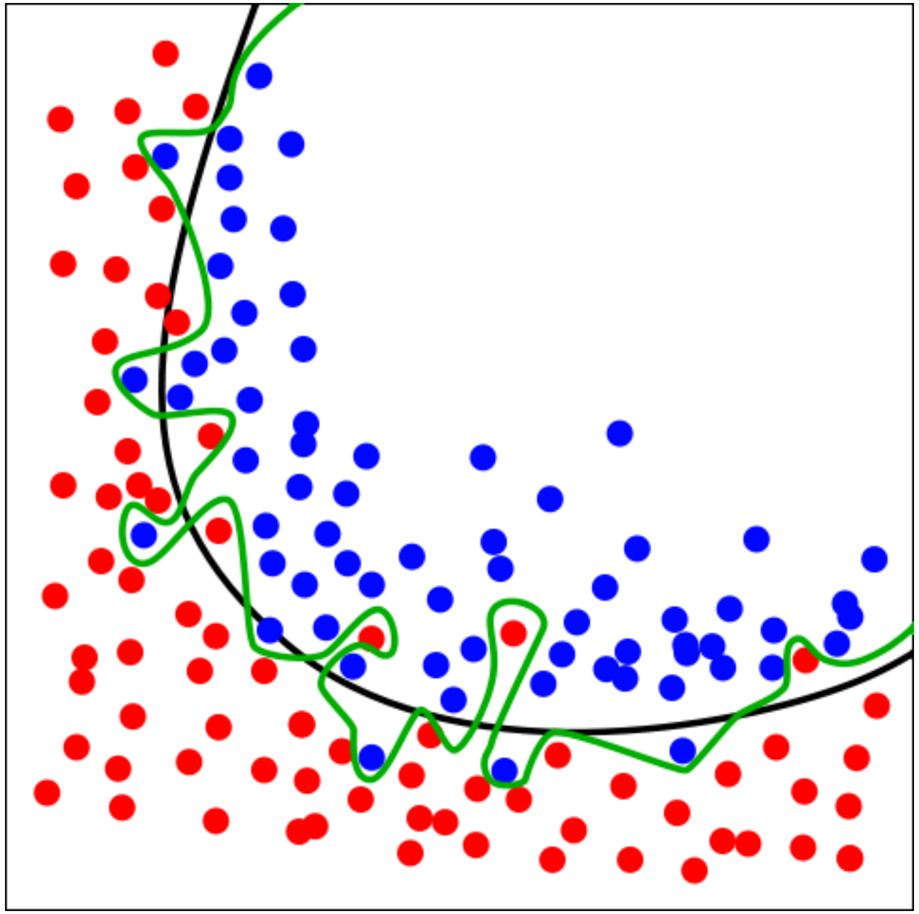
$$b = (b_0, \ldots b_M)$$

Trained Model (with learned parameters)

Split Data into Separate Groups



But some models can be *too* flexible.

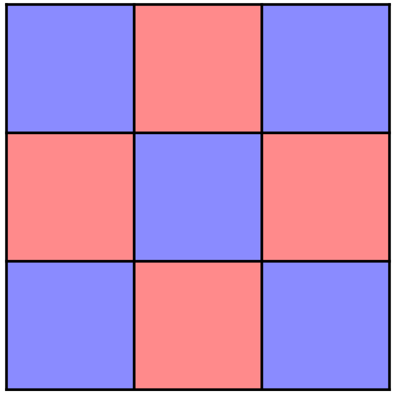


Green boundary:
- This is overfitting

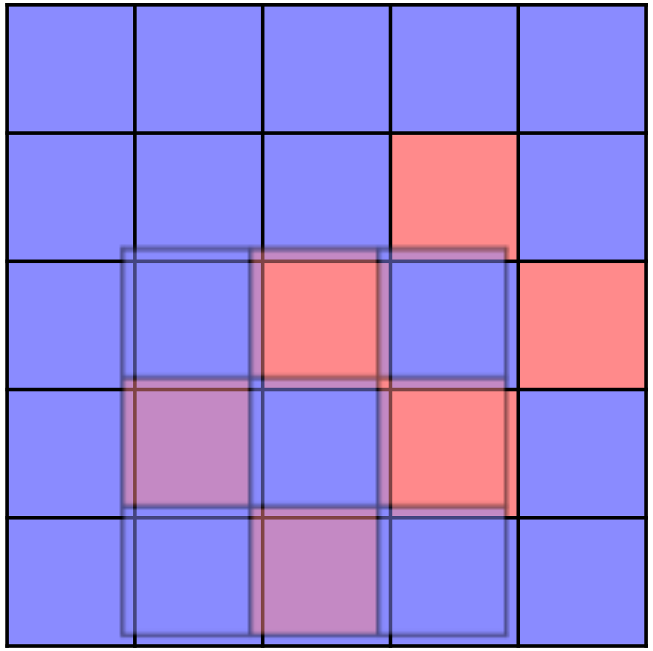
Black boundary:
- Balance between fit and model complexity

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

An Example…



filter

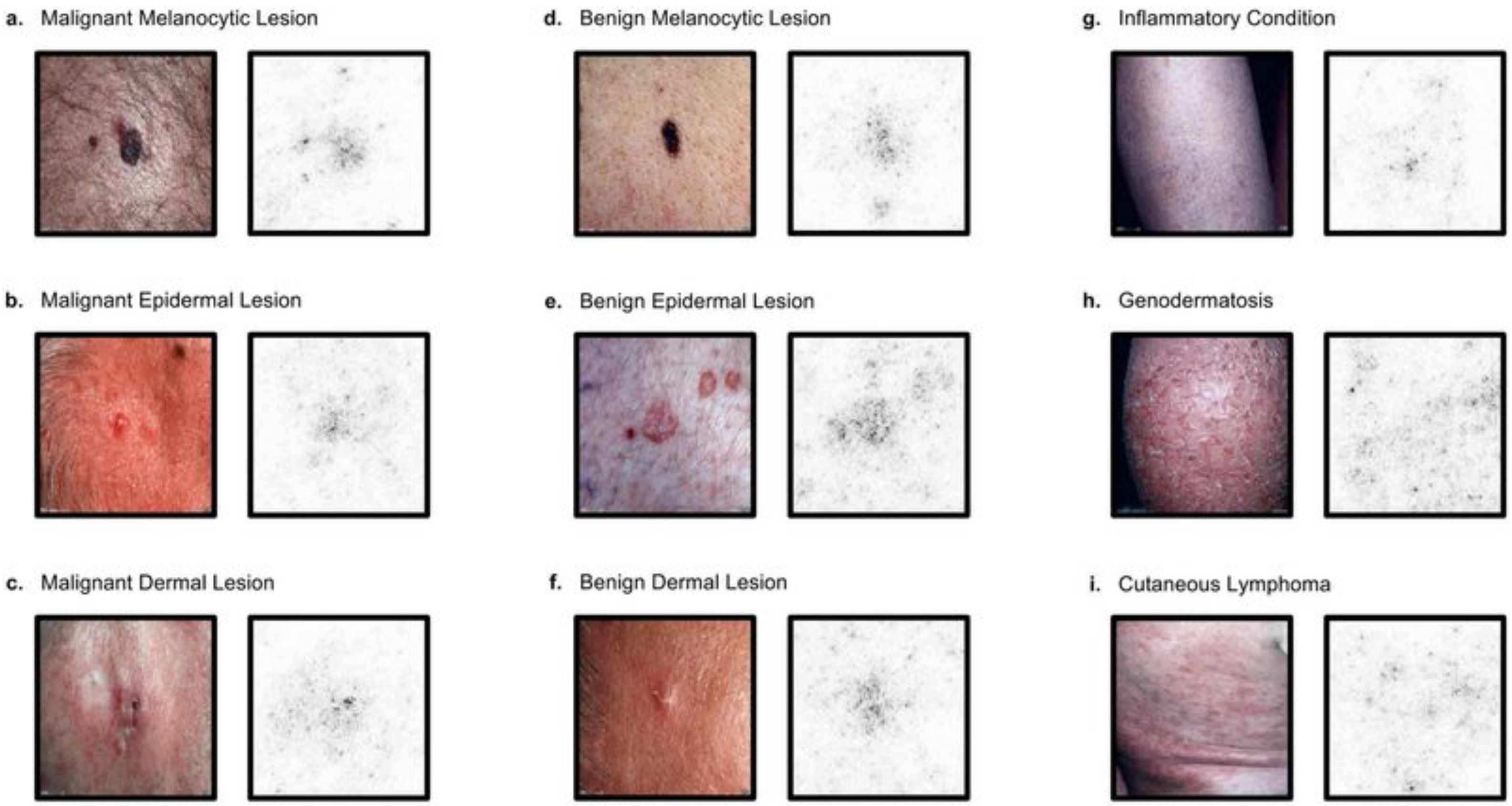


image

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

$x_i^R \odot b$

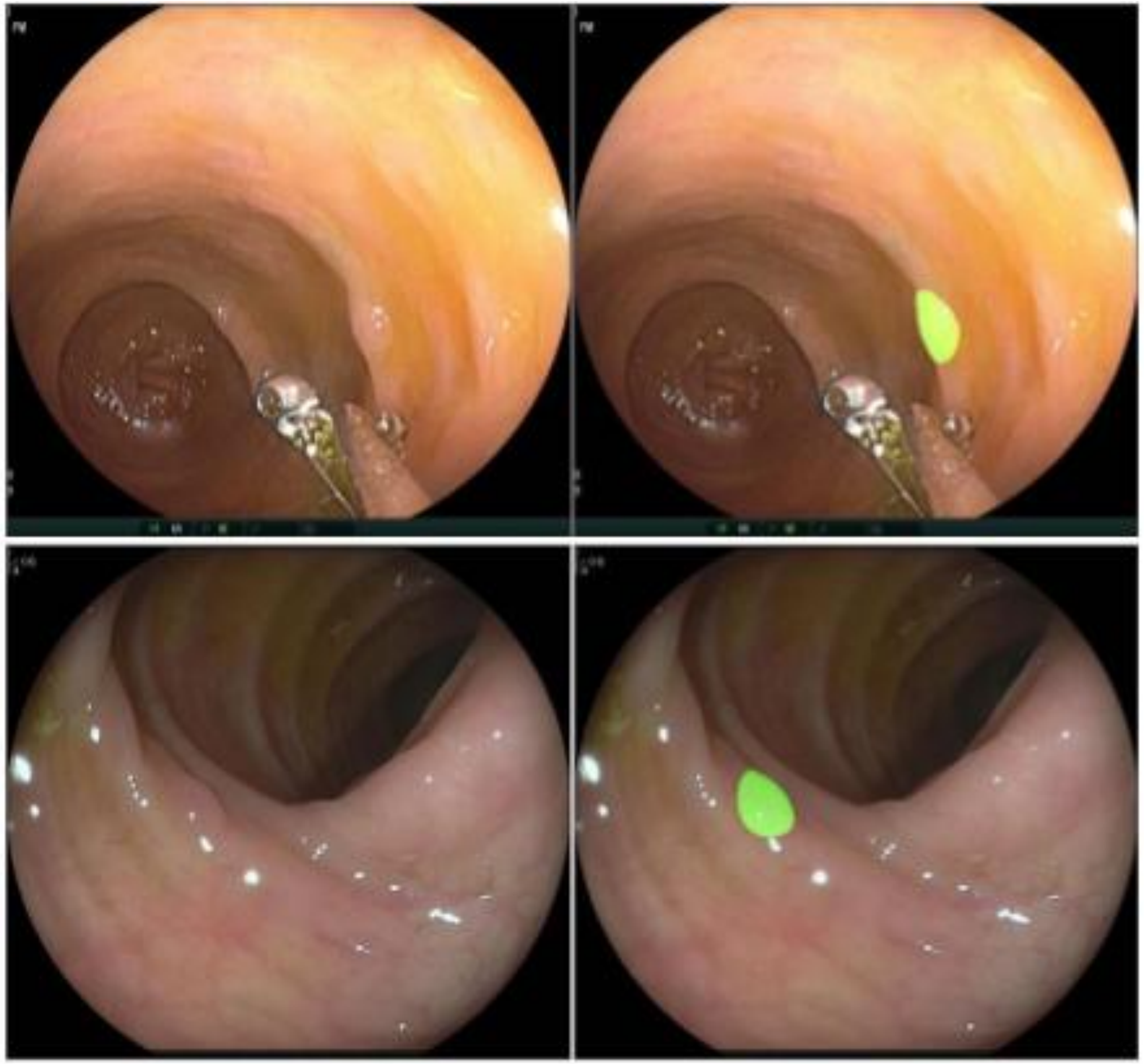
Saliency maps for example images



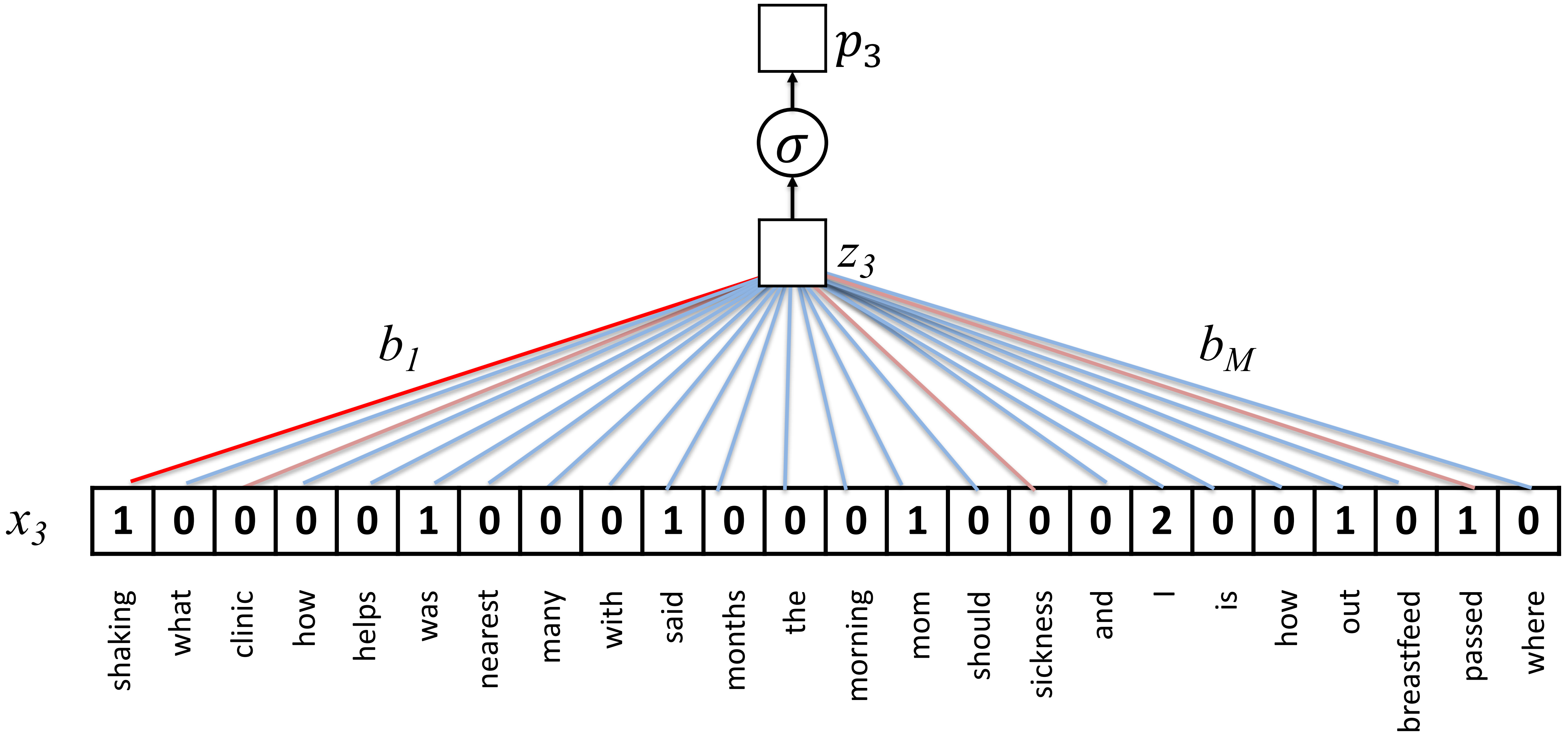
Saliency maps show gradients for each pixel with respect to the CNN's loss function. Darker pixels represent those with more influence.

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

Precisely Identify Boundaries

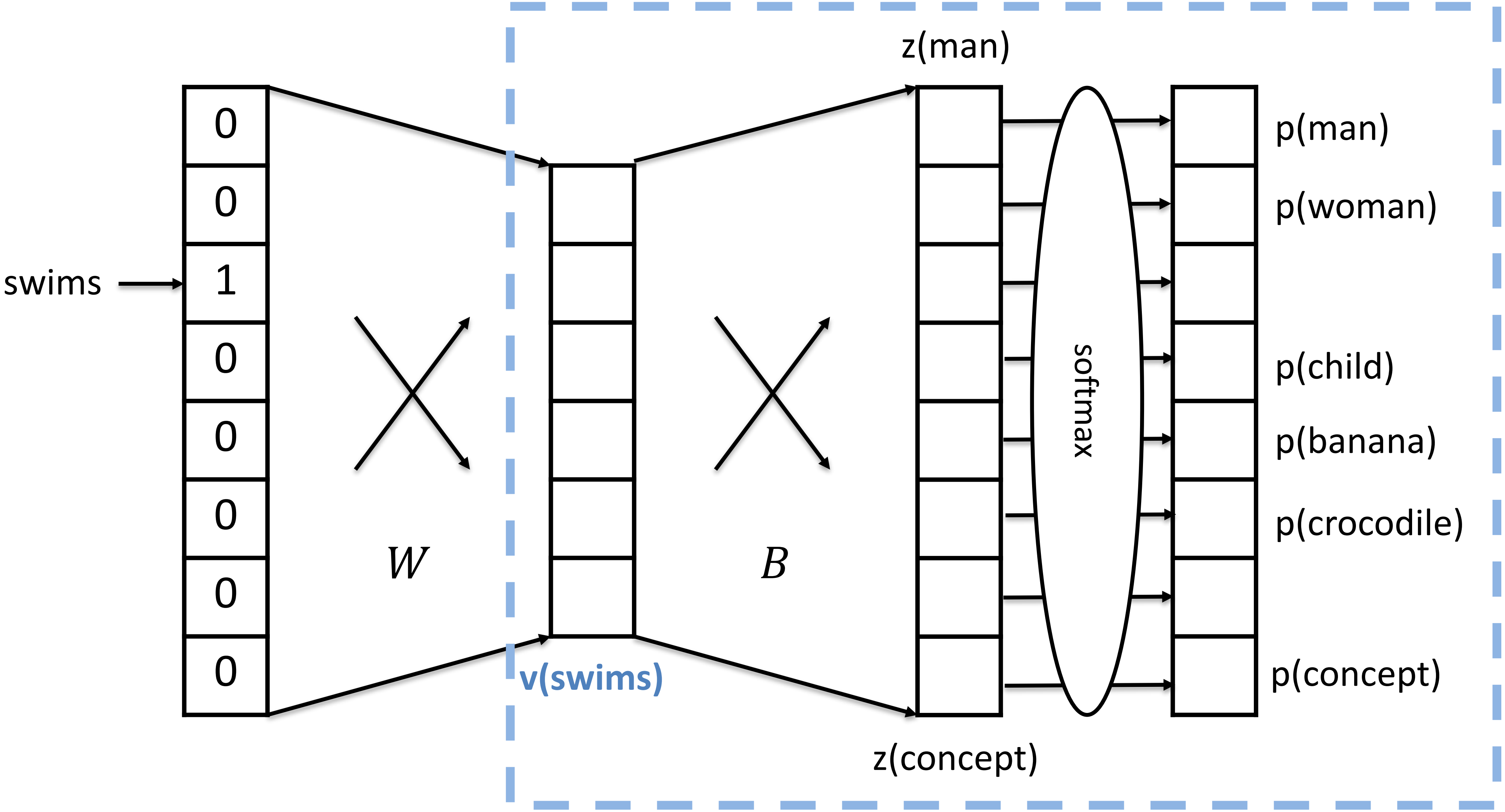


Logistic Regression for Text Classification

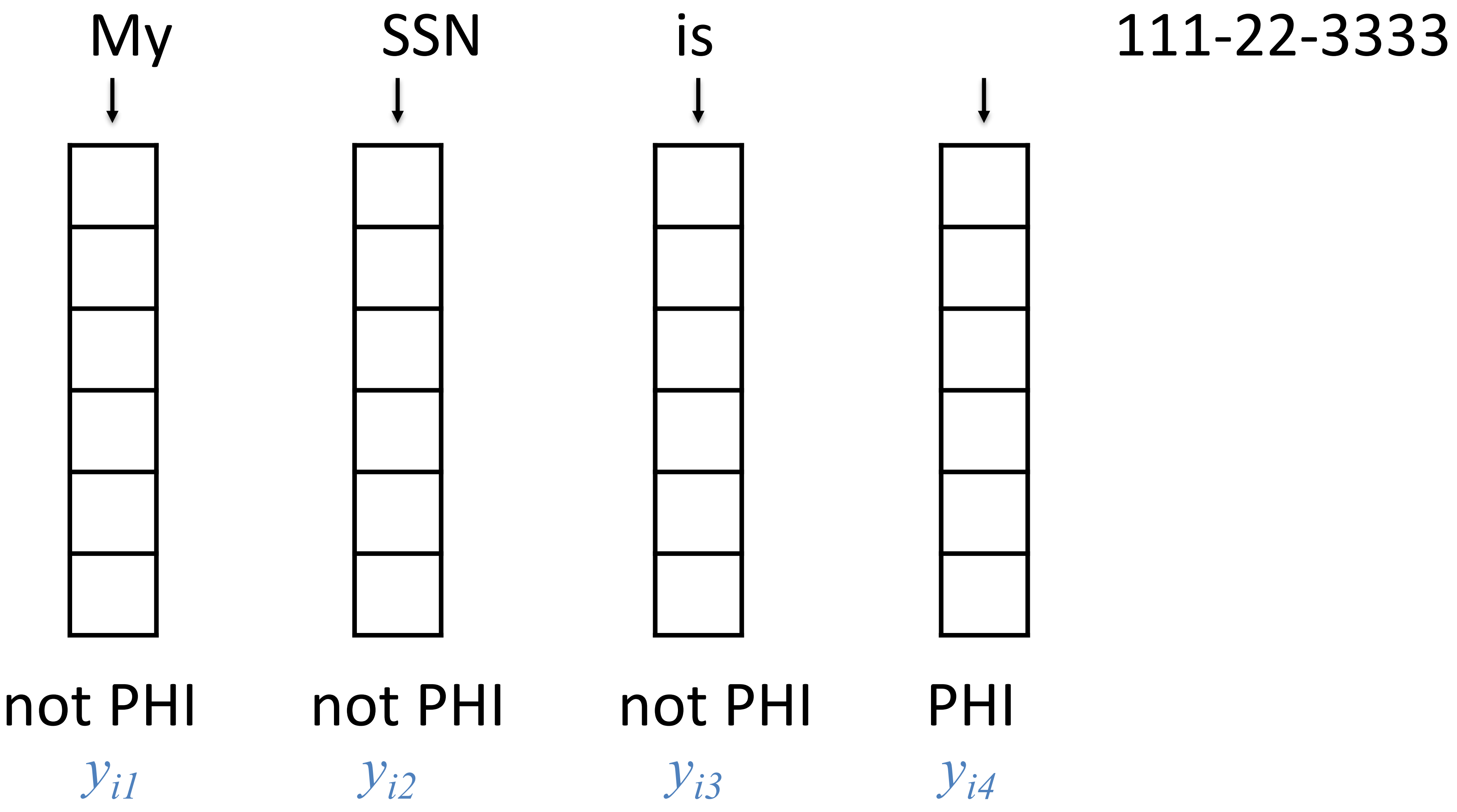


I passed out and Mom said I was shaking

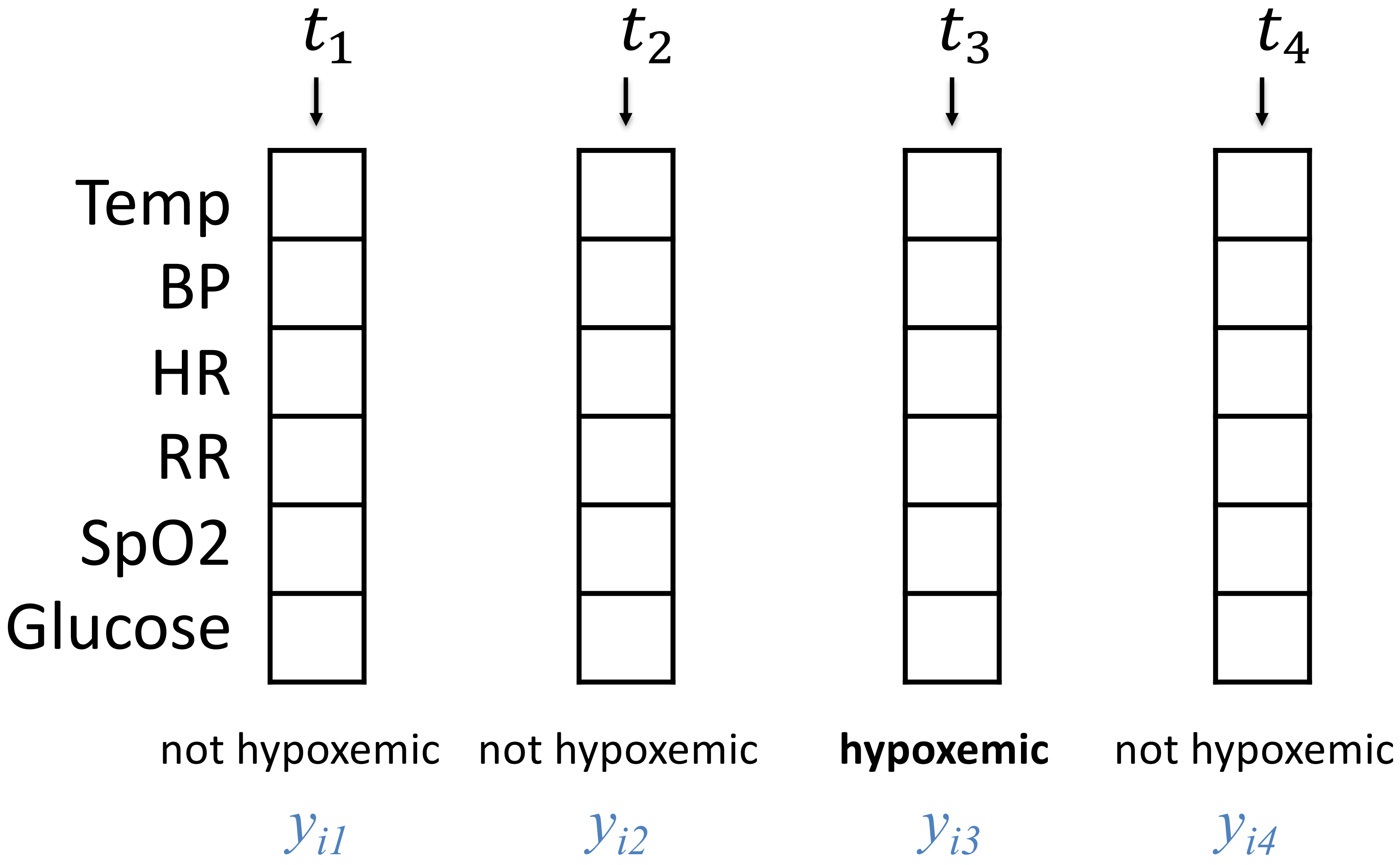
We now have a distributed representation of word ***meaning*** based on ***context***



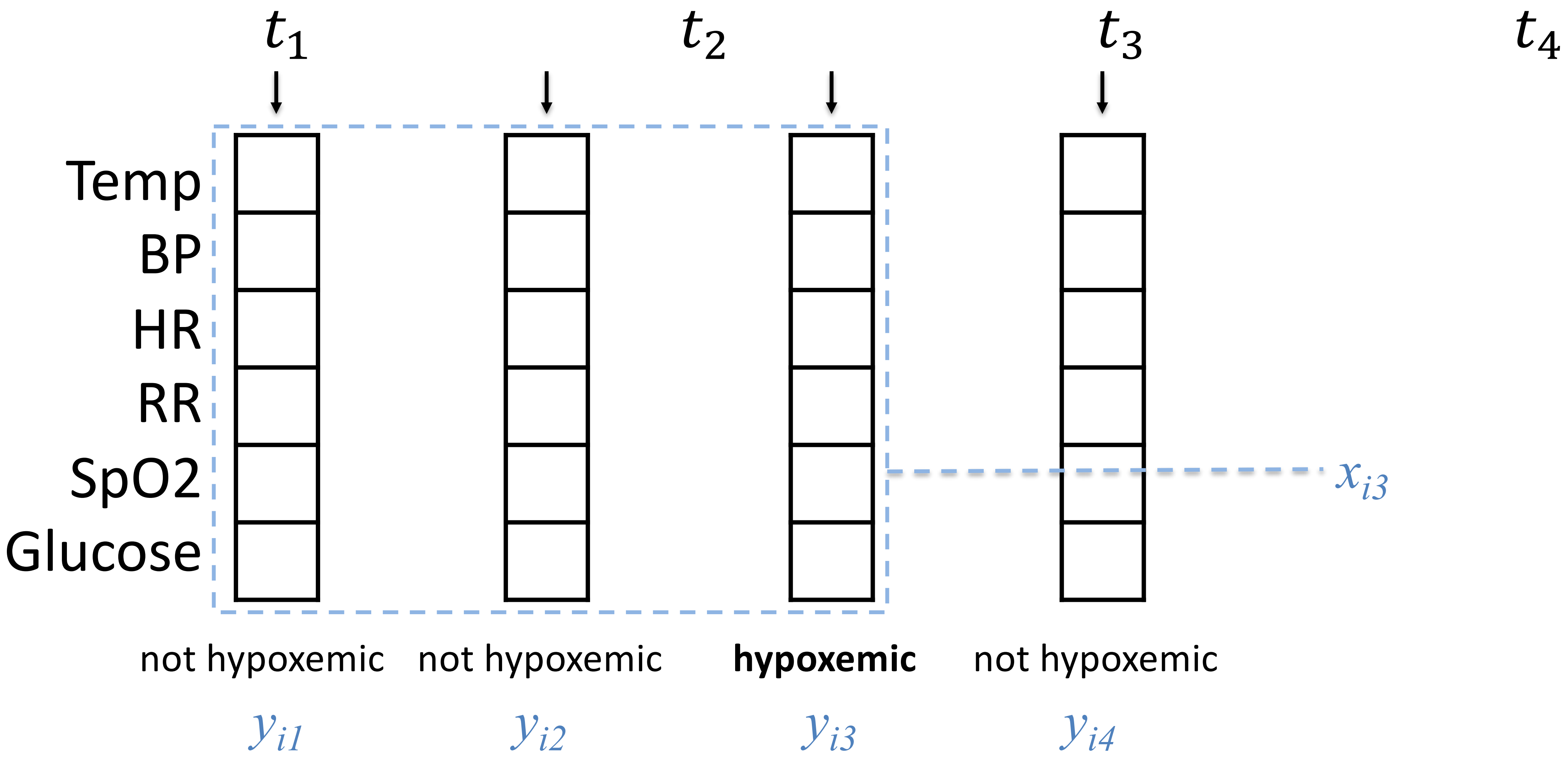
Task 2: Predict a label associated with each word



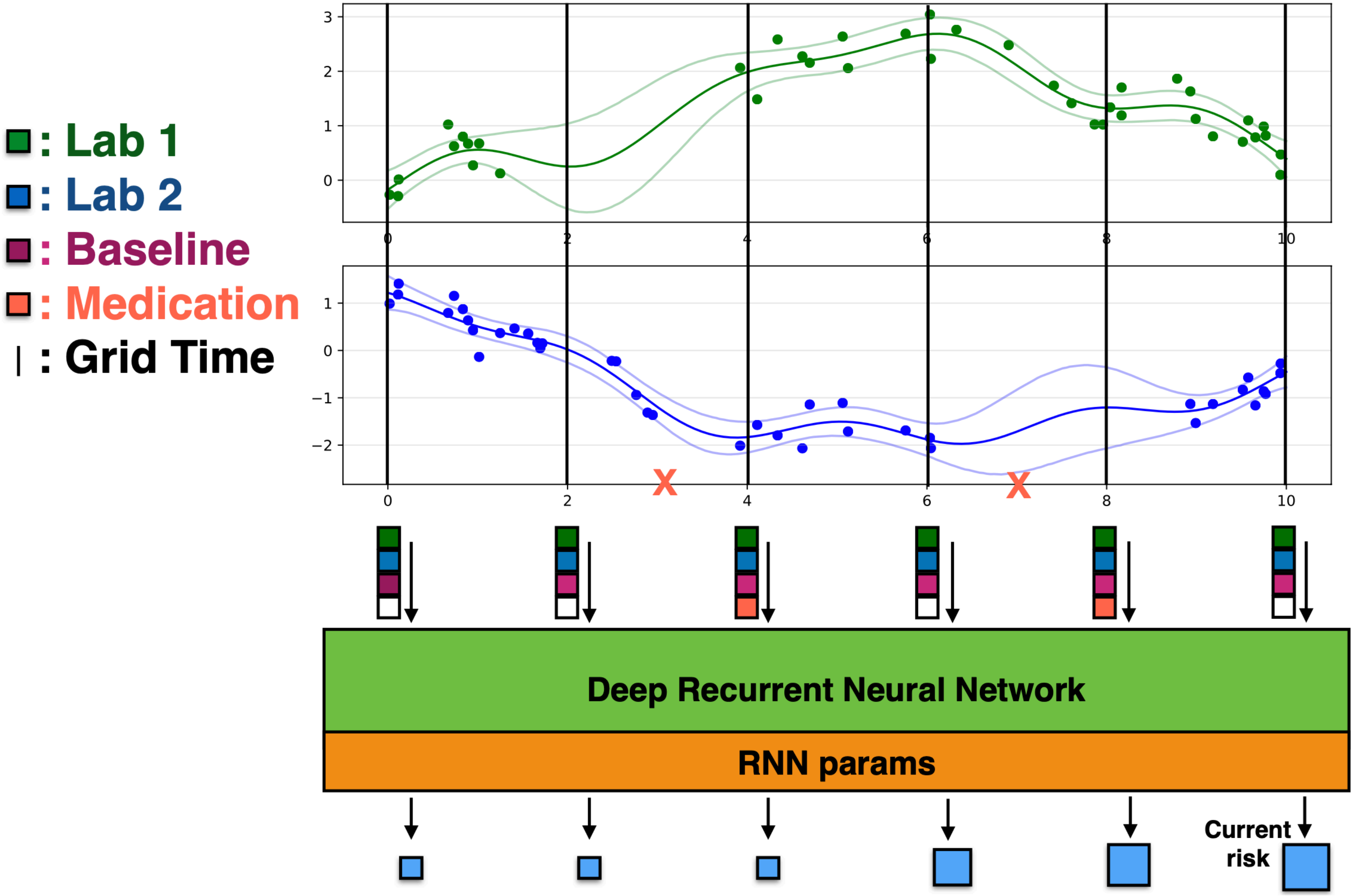
Task 2: Predict label assoc. with each time point



Similarly, we can aggregate measurements in a time-series



DIHI Sepsis Watch



<- Use GP regression to predict measurements at regular intervals

<- Predict sepsis risk using an RNN

Sequential Decision-Making

Make a series of decisions

based on a set of features (state)

to maximize reward over time

Sequential Medical Decision-Making

Make a series of decisions

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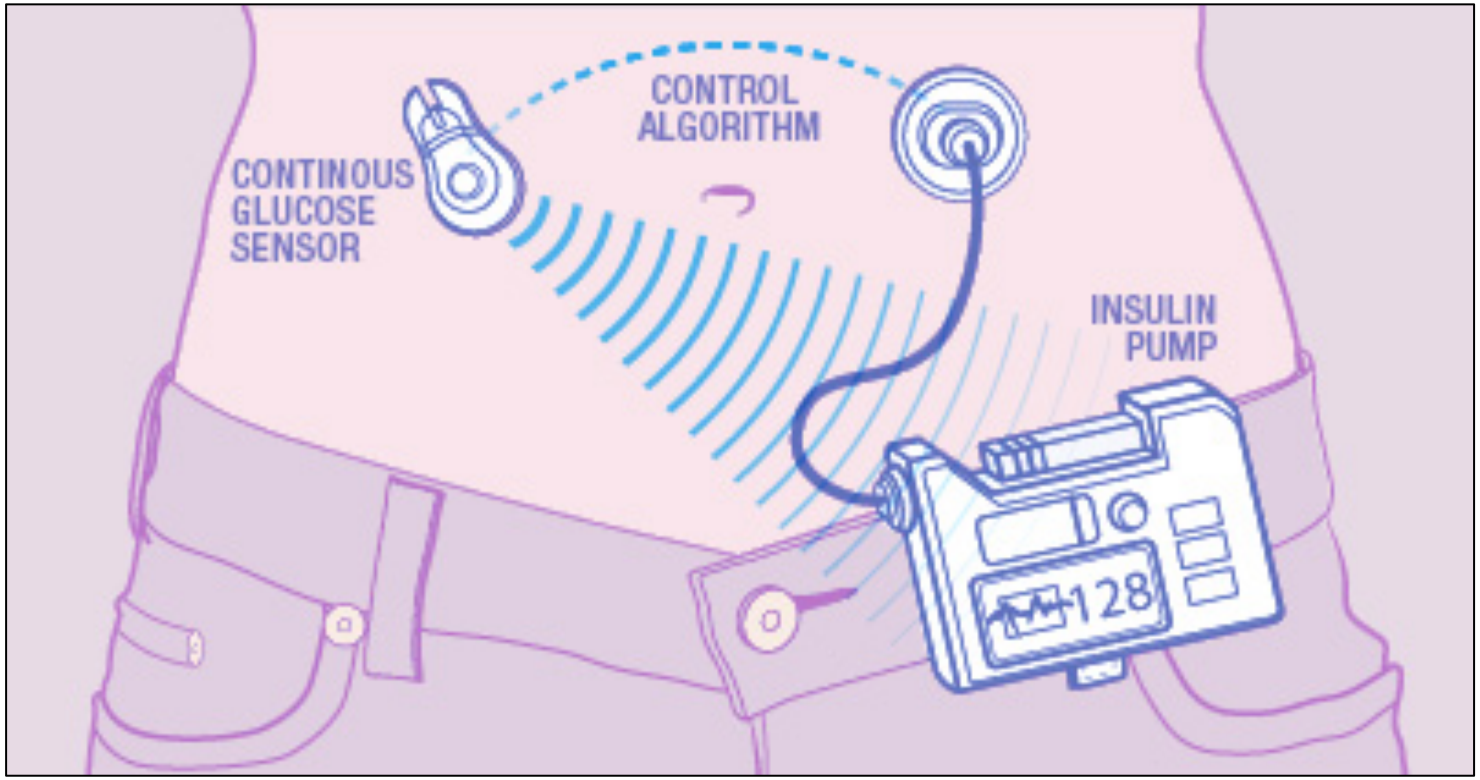

Be in touch: m.engelhard@duke.edu

THANK YOU!