Perceptrons

Basic Linear Classifiers

- Assumess 2 classes of labels (binary classification)
  - Will work to recognize if diabetes or not
  - Will not work to recognize 10 handwritten digits
  - Looking ahead: will see how to "spoof" multi-class classifiers from binary classifiers

- Assumes a linear decision boundary
  - Looking ahead: will see how to manipulate linear classifiers to get arbitrary decision boundaries

Linear Classifiers

- Training: find a dividing "hyperplane" between two classes
- Testing: check which side of hyperplane the new point falls

There are several algorithms to learn linear classifiers

Hyperplane

A hyperplane in $\mathbb{R}^1$ is a point
A hyperplane in $\mathbb{R}^2$ is a line
A hyperplane in $\mathbb{R}^3$ is a 2D plane

A hyperplane in $\mathbb{R}^n$ is an $n-1$ dimensional subspace
What is a hyperplane?

- Parameterized by a “weight” vector \( \mathbf{w} \) orthogonal to the hyperplane, centered at origin
- What is the dimensionality of \( \mathbf{w} \) in an \( n \)-dimensional space?
- What range is
  - The dot product of \( \mathbf{w} \) with any of the blue points?
  - The dot product of \( \mathbf{w} \) with any of the red points?

Perceptron Motivation

Perceptron Learning Algorithm

Two classes: one is +1 and the other is -1
Training data comes as vectors \( \mathbf{x} \) and labels \( y \)

Start with vector \( \mathbf{w} = \) all zeros
1. For each training datapoint \( \mathbf{x} \) with label \( y \):
   - If \( \mathbf{w} \cdot \mathbf{x} > 0 \) and \( y = +1 \), do nothing
   - If \( \mathbf{w} \cdot \mathbf{x} < 0 \) and \( y = -1 \), do nothing
   - If \( \mathbf{w} \cdot \mathbf{x} \leq 0 \) and \( y = +1 \), \( \mathbf{w} = \mathbf{w} + \mathbf{x} \)
   - If \( \mathbf{w} \cdot \mathbf{x} \geq 0 \) and \( y = -1 \), \( \mathbf{w} = \mathbf{w} - \mathbf{x} \)
2. Repeat step 1 until no more misclassified datapoints, or until \textsf{num\_epochs} (where the number of epochs is a hyperparameter)

Perceptron Algorithm In Action

Two classes: one is +1 and the other is -1
Training data comes as vectors \( \mathbf{x} \) and labels \( y \)

Start with vector \( \mathbf{w} = \) all zeros
1. For each training datapoint \( \mathbf{x} \) with label \( y \):
   - If \( \mathbf{w} \cdot \mathbf{x} > 0 \) and \( y = +1 \), do nothing
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   - If \( \mathbf{w} \cdot \mathbf{x} \leq 0 \) and \( y = +1 \), \( \mathbf{w} = \mathbf{w} + \mathbf{x} \)
   - If \( \mathbf{w} \cdot \mathbf{x} \geq 0 \) and \( y = -1 \), \( \mathbf{w} = \mathbf{w} - \mathbf{x} \)
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Perceptron Algorithm In Action

Two classes: one is +1 and the other is -1
Training data comes as vectors \( x \) and labels \( y \)

Start with vector \( w = \text{all zeros} \)

1. For each training datapoint \( x \) with label \( y ⟹ \)
   - If \( w \cdot x > 0 \) and \( y = +1 \), do nothing
   - If \( w \cdot x < 0 \) and \( y = -1 \), do nothing
   - If \( w \cdot x ≤ 0 \) and \( y = +1 \), \( w = w + x \)
   - If \( w \cdot x ≥ 0 \) and \( y = -1 \), \( w = w - x \)

2. Repeat step 1 until no more misclassified datapoints, or until \( \text{num\_epochs} \) (where the number of epochs is a hyperparameter)

Perceptron Algorithm - Condensed Pseudocode

Start with vector \( w = \text{all zeros} \)

1. For each training datapoint \( x \) with label \( y \):
   - If \( w \cdot x > 0 \) and \( y = +1 \), do nothing
   - If \( w \cdot x < 0 \) and \( y = -1 \), do nothing
   - If \( y \cdot (w \cdot x) > 0 \), do nothing
   - If \( w \cdot x ≤ 0 \) and \( y = +1 \), \( w = w + x \)
   - If \( w \cdot x ≥ 0 \) and \( y = -1 \), \( w = w - x \)

2. Repeat step 1 until no more misclassified datapoints, or until \( \text{num\_epochs} \) (where the number of epochs is a hyperparameter)
What if the hyperplane is not centered at the origin?

\[ \mathbf{w} \cdot \mathbf{x} + b = 0 \] represents a hyperplane orthogonal to \( \mathbf{w} \), translated by \( -b / ||\mathbf{w}|| \) in the direction of \( \mathbf{w} \).

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**Perceptron Motivation**

- **Perceptron Learning Algorithm**

Two classes: one is +1 and the other is -1
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Start with vector \( \mathbf{w} = \) all zeros

1. For each training datapoint \( \mathbf{x} \) with label \( y \):
   - If \( \mathbf{w} \cdot \mathbf{x} > 0 \) and \( y = +1 \), do nothing
   - If \( \mathbf{w} \cdot \mathbf{x} < 0 \) and \( y = -1 \), do nothing
   - If \( \mathbf{w} \cdot \mathbf{x} \leq 0 \) and \( y = +1 \), \( \mathbf{w} = \mathbf{w} + \mathbf{x} \)
   - If \( \mathbf{w} \cdot \mathbf{x} \geq 0 \) and \( y = -1 \), \( \mathbf{w} = \mathbf{w} - \mathbf{x} \)

2. Repeat step 1 until no more misclassified datapoints, or until \text{num\_epochs} \ (where the number of epochs is a hyperparameter)
Perceptron Learning Algorithm with bias term

Two classes: one is +1 and the other is -1
Training data comes as vectors \( x \) and labels \( y \)

Start with vector \( w = \text{all zeros}, \) and a bias term \( b = 0 \)

1. For each training datapoint \( x \) with label \( y \):
   - If \( w \cdot x + b > 0 \) and \( y = +1 \), do nothing
   - If \( w \cdot x + b < 0 \) and \( y = -1 \), do nothing
   - If \( w \cdot x + b \leq 0 \) and \( y = +1 \), \( w = w + x \) and \( b = b+1 \)
   - If \( w \cdot x + b \geq 0 \) and \( y = -1 \), \( w = w - x \) and \( b = b-1 \)

2. Repeat step 1 until no more misclassified datapoints, or until \( \text{num\_epochs} \) (where the number of epochs is a hyperparameter)

Perceptron Algorithm with bias term Condensed

Start with vector \( w = \text{all zeros}, \) and a bias term \( b = 0 \)

1. For each training datapoint \( x \) with label \( y \):
   - If \( w \cdot x + b > 0 \) and \( y = +1 \), do nothing
   - If \( w \cdot x + b < 0 \) and \( y = -1 \), do nothing
   - If \( y \cdot (w \cdot x + b) > 0 \), do nothing
   - If \( w \cdot x + b \leq 0 \) and \( y = +1 \), \( w = w + x \) and \( b = b+1 \)
   - If \( w \cdot x + b \geq 0 \) and \( y = -1 \), \( w = w - x \) and \( b = b-1 \)
   - If \( y \cdot (w \cdot x + b) \leq 0 \), \( w = w + y \cdot x \) and \( b = b+y \)

2. Repeat step 1 until no more misclassified datapoints, or until \( \text{num\_epochs} \) (where the number of epochs is a hyperparameter)

Perceptron Algorithm with bias term in Action

What happens if we change to order of the training data?

Order of data affects training time!
To be safe, shuffle order on each epoch.
Perceptron Algorithm - no Linear Boundary

Once the perceptron has been trained and the parameters $w$ and $b$ (i.e., the hyperplane) have been learned, we predict the class of a new datapoint $x$ by determining which side of the hyperplane it falls on, i.e., by computing the weighted sum (i.e., dot product) followed by the activation function:

$$\text{predicted class} = \begin{cases} 1 & \text{if } w \cdot x + b > 0 \\ -1 & \text{otherwise} \end{cases}$$

Recap

- **Training**
  - Training data: labeled points $x, y$
  - Perceptron Learning Algorithm
  - Hyperplane parameters $w, b$

- **Testing**
  - Testing data: $x$
  - Dot product: $w \cdot x + b$
  - Prediction: $+1$ or $-1$

Complexity of Perceptron

- **Training** (as a function of $n$ datapoints, $d$ dimensions, and number of epochs)

- **Testing**
What does the trained hyperplane give us?

- Most importantly: a classifier to predict labels for new datapoints
- Also indicates which features are most important for each label
  - Given dataset of Twitter users, where each feature is a word and the value is the number of times a user writes that word
  - Train perceptron to classify gender
    - Resulting \( w \) shows which dimensions (aka features aka words) are most indicative of female or male
  - Given dataset of movie/product/restaurant reviews, where each feature is a word and the value is the number of times a review uses that word
    - Train perceptron to classify sentiment (positive or negative)
    - Resulting \( w \) shows which dimensions (aka features aka words) are most indicative of positive or negative sentiment

Danger of Vanilla Perceptron

- Last few points have too much influence
- May result in a hyperplane that’s “bad” even if it separates the training data

Solution 1: Voted Perceptron

- **Training**: Cache every hyperplane seen during training history, i.e., store every \( w \) and \( b \) and the number of times it occurs
- **Testing**: Given a new point \( x \), have every one of these cached hyperplanes vote with the number of times it occurs

**Problem:**

1. Need to store 1000s of hyperplanes after training
2. Testing time goes up drastically

Solution 2: Averaged Perceptron

- **Idea:**
  During training, compute the average hyperplane. During testing, use this average hyperplane to classify a new point.

- **Training**: Rather than store every intermediate hyperplane seen during training (too expensive), instead keep track of a running sum of each hyperplane, i.e., a running sum of each \( w \) and \( b \)
- **Testing**: Given a new point \( x \), use the average hyperplane (based on \( u \) and \( \beta \)) to classify the point

\[
\begin{align*}
\mathbf{u} &= \mathbf{u} + \mathbf{w} \\
\beta &= \beta + b
\end{align*}
\]

\[
\begin{align*}
\mathbf{u} &= \mathbf{u} / (n \times \text{epochs}) \\
\beta &= \beta / (n \times \text{epochs})
\end{align*}
\]