

Introduction to Machine Learning

Logistic Regression, Multi-class Classification

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Overview

- Classification: predicting a discrete-valued target
 - Binary classification: predicting a binary-valued target
 - Multiclass classification: predicting a discrete (> 2)-valued target
- Examples of binary classification:
 - predict whether a patient has a disease, given the presence or absence of various symptoms
 - classify e-mails as spam or non-spam
 - predict whether a financial transaction is fraudulent

Overview

- Binary linear classification

- classification: given a D -dimensional input $\mathbf{x} \in \mathbb{R}^D$ predict a discrete-valued target
- binary: predict a binary target $t \in \{0, 1\}$
 - Training examples with $t = 1$ are called positive examples, and training examples with $t = 0$ are called negative examples.
 - $t \in \{0, 1\}$ or $t \in \{+1, -1\}$ is for computational convenience.
- linear: model prediction y is a linear function of \mathbf{x} , followed by a threshold r

$$z = \mathbf{w}^\top \mathbf{x} + b \quad (1)$$

$$y = \begin{cases} 1 & z \geq r \\ 0 & z < r \end{cases} \quad (2)$$

Some Simplification

- Eliminating the threshold

- We can assume without loss of generality (WLOG) that the threshold $r = 0$:

$$\mathbf{w}^\top \mathbf{x} + b \geq r \iff \mathbf{w}^\top \mathbf{x} + b - r \geq 0 \quad (3)$$

- Eliminating the bias

- Add a dummy feature x_0 which always takes the value 1. The weight $w_0 = b$ is equivalent to a bias (same as linear regression)

- Simplified model

- Receive input $\mathbf{x} \in \mathbb{R}^{D+1}$ with $x_0 = 1$:

$$z = \mathbf{w}^\top \mathbf{x} \quad (4)$$

$$y = \begin{cases} 1 & z \geq r \\ 0 & z < r \end{cases} \quad (5)$$

Some Examples

- Let's consider some simple examples to examine the properties of our model
- Let's focus on minimizing the training set error, and forget about whether our model will generalize to a test set.

Some Examples

NOT

x_0	x_1	t
1	0	1
1	1	0

- Suppose this is our training set, with the dummy feature x_0 included
- Which conditions on w_0, w_1 guarantee perfect classification?
 - When $x_1 = 0$, need: $z = w_0x_0 + w_1x_1 \geq 0 \iff w_0 \geq 0$
 - When $x_1 = 1$, need: $z = w_0x_0 + w_1x_1 < 0 \iff w_0 + w_1 < 0$
- Possible solution: $w_0 = 1, w_1 = -2$
- Is this the only solution?

Some Examples

AND

x_0	x_1	x_2	t
1	0	0	0
1	0	1	0
1	1	0	0
1	1	1	1

$$z = w_0x_0 + w_1x_1 + w_2x_2$$

$$\text{need: } w_0 < 0$$

$$\text{need: } w_0 + w_2 < 0$$

$$\text{need: } w_0 + w_1 < 0$$

$$\text{need: } w_0 + w_1 + w_2 \geq 0$$

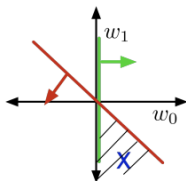
Example solution: $w_0 = -1.5$, $w_1 = 1$, $w_2 = 1$

The Geometric Picture

- Training examples are points
- Weights (hypotheses) \mathbf{w} can be represented by half-spaces.
 $H_+ = \{\mathbf{x} : \mathbf{w}^\top \mathbf{x} \geq 0\}$, $H_- = \{\mathbf{x} : \mathbf{w}^\top \mathbf{x} < 0\}$
 - The boundaries of these half-spaces pass through the origin (why?)
 - Decision boundary: $\{\mathbf{x} : \mathbf{w}^\top \mathbf{x} = 0\}$
 - In 2-D, it's a line, but in high dimensions it is a hyperplane
- If the training examples can be perfectly separated by a linear decision rule, we say data is linearly separable.

The Geometric Picture

- Weight space



$$w_0 \geq 0$$

$$w_0 + w_1 < 0$$

- Weights (hypotheses) \mathbf{w} are points
- Each training example \mathbf{x} specifies a half-space \mathbf{w} must lie in to be correctly classified: $\mathbf{w}^\top \mathbf{x} \geq 0$ if $t = 1$.
- For NOT example:
 - $x_0 = 1, x_1 = 0, t = 1 \implies (w_0, w_1) \in \mathcal{W} : w_0 \geq 0$
 - $x_0 = 1, x_1 = 1, t = 0 \implies (w_0, w_1) \in \mathcal{W} : w_0 + w_1 < 0$
- The region satisfying all the constraints is the feasible region; if this region is nonempty, the problem is feasible, otherwise it is infeasible.

Summary — Binary Linear Classifiers

- Summary: Targets $t \in \{0, 1\}$, inputs $\mathbf{x} \in \mathbb{R}^{D+1}$ with $x_0 = 1$, and model is defined by weights \mathbf{w} and

$$z = \mathbf{w}^\top \mathbf{x} \tag{6}$$

$$y = \begin{cases} 1 & z \geq r \\ 0 & z < r \end{cases} \tag{7}$$

- How can we find good values for \mathbf{w} ?
- If the training set is linearly separable, we could solve for \mathbf{w} using linear programming
 - We could also apply an iterative procedure known as the perceptron algorithm (but this is primarily of historical interest).
- If it's not linearly separable, the problem is harder
 - Data is almost never linearly separable in real life.

Towards Logistic Regression

Loss Function

- Instead: define loss function then try to minimize the resulting cost function
 - Recall: cost is loss averaged (or summed) over the training set
- Seemingly obvious loss function: 0-1 loss

$$\mathcal{L}_{0,1}(y, t) = \begin{cases} 1 & y = t \\ 0 & y \neq t \end{cases} \quad (8)$$

$$\mathcal{L}_{0,1}(y, t) = \mathbb{I}(y \neq t) \quad (9)$$

Attempt 1: 0-1 loss

- Usually, the cost \mathcal{J} is the averaged loss over training examples; for 0-1 loss, this is the misclassification rate:

$$\mathcal{J} = \frac{1}{N} \sum_{i=1}^N \mathbb{I}(y^{(i)} \neq t^{(i)}) \quad (10)$$

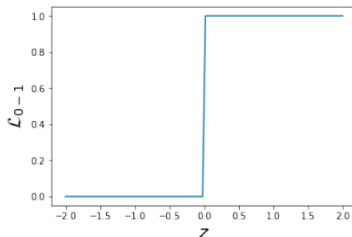
- Problem: how to optimize? In general, a hard problem (can be NP-hard)
- This is due to the step function (0-1 loss) not being nice (continuous/smooth/convex etc)

Attempt 1: 0-1 loss

- Minimum of a function will be at its critical points.
- Let's try to find the critical point of 0-1 loss
- Chain rule:

$$\frac{\partial \mathcal{L}_{0,1}}{\partial w_j} = \frac{\partial \mathcal{L}_{0,1}}{\partial z} \frac{\partial z}{\partial w_j} \quad (11)$$

- But $\frac{\partial \mathcal{L}_{0,1}}{\partial z}$ is zero everywhere it's defined!



- $\frac{\partial \mathcal{L}_{0,1}}{\partial w_j} = 0$ means that changing the weights by a very small amount probably has no effect on the loss \implies Almost any point has 0 gradient!

Attempt 2: Linear Regression

- Sometimes we can replace the loss function we care about with one which is easier to optimize. This is known as relaxation with a smooth surrogate loss function.
- One problem with $\mathcal{L}_{0,1}$: defined in terms of final prediction, which inherently involves a discontinuity
- Instead, define loss in terms of $\mathbf{w}^\top \mathbf{x}$ directly
 - Redo notation for convenience: $z = \mathbf{w}^\top \mathbf{x}$

Attempt 2: Linear Regression

- We already know how to fit a linear regression model. Can we use this instead?

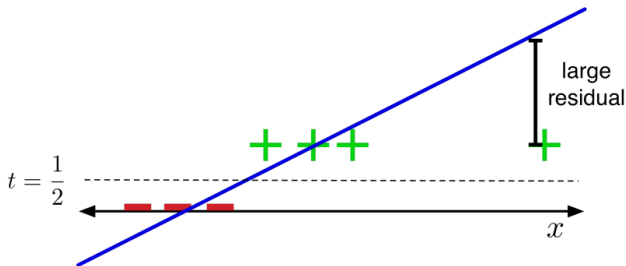
$$z = \mathbf{w}^\top \mathbf{x} \quad (12)$$

$$\mathcal{L}_{SE} = \frac{1}{2}(z - t)^2 \quad (13)$$

- Doesn't matter that the targets are actually binary. Treat them as continuous values.
- For this loss function, it makes sense to make final predictions by thresholding z at 0.5

Attempt 2: Linear Regression

- The problem:



- The loss function hates when you make correct predictions with high confidence!
- If $t = 1$, it's more unhappy about $z = 10$ than $z = 0$.

Attempt 3: Logistic Activation Function

- There's obviously no reason to predict values outside $[0, 1]$. Let's squash y into this interval.
- The logistic function is a kind of sigmoid, or S-shaped function:

$$\sigma(z) = \frac{1}{1 + e^{-z}} \quad (14)$$

- A linear model with a logistic nonlinearity is known as log-linear:

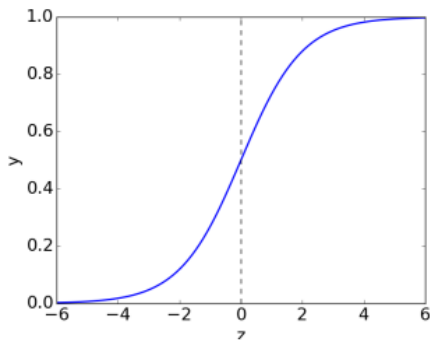
$$z = \mathbf{w}^\top \mathbf{x} \quad (15)$$

$$y = \sigma(z) \quad (16)$$

$$\mathcal{L}_{SE} = \frac{1}{2}(y - t)^2 \quad (17)$$

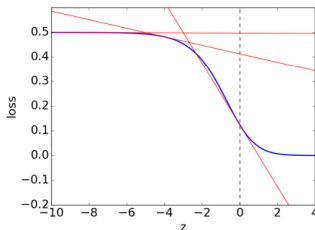
- Used in this way, σ is called an activation function.

Attempt 3: Logistic Activation Function



Attempt 3: Logistic Activation Function

- The problem: (plot of \mathcal{L}_{SE} as a function of z , assuming $t = 1$)



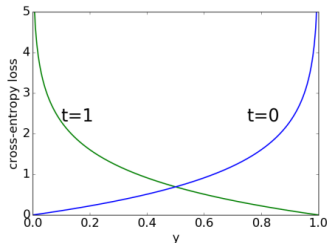
$$\frac{\partial \mathcal{L}}{\partial w_j} = \frac{\partial \mathcal{L}}{\partial z} \frac{\partial z}{\partial w_j}$$

- For $z \ll 0$, we have $\sigma(z) \approx 0$.
- $\frac{\partial \mathcal{L}}{\partial z} \approx 0$ (check!) $\implies \frac{\partial \mathcal{L}}{\partial w_j} \approx 0 \implies$ derivative w.r.t. w_j is small $\implies w_j$ is like a critical point
- If the prediction is really wrong, you should be far from a critical point (which is your candidate solution).

Logistic Regression

- Because $y \in [0, 1]$, we can interpret it as the estimated probability that $t = 1$. If $t = 0$, then we want to heavily penalize $y \approx 1$.
- The people who were 99% confident a certain presidential candidate would win were much more wrong than the ones who were only 90% confident, given that the person didn't win.
- Cross-entropy loss (aka log loss) captures this intuition:

$$\begin{aligned}\mathcal{L}_{\text{CE}}(y, t) &= \begin{cases} -\log y & \text{if } t = 1 \\ -\log(1 - y) & \text{if } t = 0 \end{cases} \\ &= -t \log y - (1 - t) \log(1 - y)\end{aligned}$$

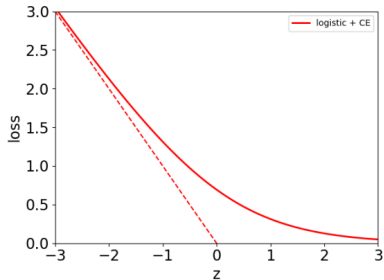


Logistic Regression

- Logistic regression:

$$\begin{aligned}z &= \mathbf{w}^\top \mathbf{x} \\y &= \sigma(z) \\&= \frac{1}{1 + e^{-z}} \\\mathcal{L}_{\text{CE}} &= -t \log y - (1 - t) \log(1 - y)\end{aligned}$$

Plot is for target $t = 1$.



Logistic Regression - Numerical Instabilities

- If we implement logistic regression naively, we can end up with numerical instabilities.
- Consider: $t = 1$ but you're really confident that $z \ll 0$
- If y is small enough, it may be numerically zero. This can cause very subtle and hard-to-find bugs.

$$y = \sigma(z) \Rightarrow y \approx 0 \quad (18)$$

$$\mathcal{L}_{CE} = -t \log y - (1 - t) \log(1 - y) \quad (19)$$

Logistic Regression - Numerical Stable Version

- Instead, we combine the activation function and the loss into a single logistic-cross-entropy function

$$\mathcal{L}_{LCE} = \mathcal{L}_{CE}(\sigma(z), t) = -t \log\left(\frac{1}{1 + e^{-z}}\right) - (1 - t) \log\left(1 - \frac{1}{1 + e^{-z}}\right) \quad (20)$$

$$\mathcal{L}_{LCE} = t \log(1 + e^{-z}) - (1 - t)(-z - \log(1 + e^{-z})) \quad (21)$$

$$\mathcal{L}_{LCE} = z - zt + \log(1 + e^{-z}) \quad (22)$$

- Equivalently,

$$\mathcal{L}_{LCE} = t \log(1 + e^{-z}) + (1 - t) \log(1 + e^z) \quad (23)$$

Gradient Descent for Logistic Regression

- How do we minimize the cost \mathcal{J} for logistic regression? No direct solution.
 - Taking derivatives of \mathcal{J} w.r.t. \mathbf{w} and setting them to 0 doesn't have an explicit solution.
- However, the logistic loss is a convex function in \mathbf{w} , so let's consider the gradient descent method/
 - Recall: we initialize the weights to something reasonable and repeatedly adjust them in the direction of the steepest descent.
 - A standard initialization is $\mathbf{w} = \mathbf{0}$.

Gradient of Logistic Loss

- Back to logistic regression:

$$\mathcal{L}_{CE}(y, t) = -t \log y - (1 - t) \log(1 - y) \quad (24)$$

$$y = \frac{1}{1 + e^{(-z)}}, z = \mathbf{w}^\top \mathbf{x} \quad (25)$$

$$\frac{\partial \mathcal{L}_{CE}}{\partial w_j} = \frac{\partial \mathcal{L}_{CE}}{\partial y} \frac{\partial y}{\partial z} \frac{\partial z}{\partial w_j} \quad (26)$$

$$\frac{\partial \mathcal{L}_{CE}}{\partial w_j} = \left(-\frac{t}{y} + \frac{1-t}{1-y} \right) \cdot y(1-y) \cdot x_j = (y-t)x_j \quad (27)$$

- Gradient descent update to find the weights of logistic regression:

$$w_j \leftarrow w_j - \alpha \frac{\partial \mathcal{J}}{\partial w_j} = w_j - \frac{\alpha}{N} \sum_{i=1}^N (y^{(i)} - t^{(i)}) x_j^{(i)} \quad (28)$$

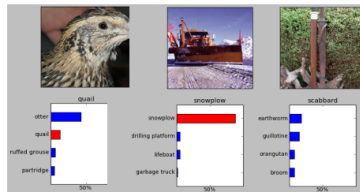
Multiclass Classification and Softmax Regression

Overview

- Classification: predicting a discrete-valued target
 - Binary classification: predicting a binary-valued target
 - Multiclass classification: predicting a discrete $v(> 2)$ -valued target
- Examples of multi-class classification
 - predict the value of a handwritten digit
 - classify e-mails as spam, travel, work, personal

Multiclass Classification

- Classification tasks with more than two categories:



Multiclass Classification

- Targets form a discrete set $\{1, \dots, K\}$.
- It's often more convenient to represent them as one-hot vectors, or a one-of-K encoding:
 - Entry k is 1, the other entries are all 0's.
 - k is not to be confused with K .

$$\mathbf{t} = (0, \dots, 0, 1, 0, \dots, 0) \in \mathbb{R}^K \quad (29)$$

Multiclass Linear Classification

- We can start with a linear function of the inputs.
- Now there are D input dimensions and K output dimensions, so we need $K \times D$ weights, which we arrange as a weight matrix W .
- Also, we have a K -dimensional vector b of biases.
- A linear function of the inputs:

$$z_k = \sum_{j=1}^D w_{kj}x_j + b_k \text{ for } k = 1, 2, \dots, K \quad (30)$$

- We can eliminate the bias b by taking $W \in \mathbb{R}^{K \times (D+1)}$ adding a dummy variable $x_0 = 1$. So, vectorized:

$$\mathbf{z} = \mathbf{W}\mathbf{x} + \mathbf{b}, \text{ or with dummy } x_0 = 1, \mathbf{z} = \mathbf{W}\mathbf{x} \quad (31)$$

Multiclass Linear Classification

- How can we turn this linear prediction into a one-hot prediction?
- We can interpret the magnitude of z_k as a measure of how much the model prefers k as its prediction.
- If we do this, we should set

$$y_i = \begin{cases} 1 & i = \underset{k}{\operatorname{argmax}} z_k \\ 0 & \text{otherwise} \end{cases} \quad (32)$$

- Exercise: how does the case of $K = 2$ relate to the prediction rule in binary linear classifiers?

Softmax Regression

- We need to soften our predictions for the sake of optimization.
- We want soft predictions that are like probabilities, i.e., $0 \leq y_k \leq 1$ and $\sum_k y_k = 1$.
- A natural activation function to use is the softmax function, a multivariable generalization of the logistic function:

$$y_k = \text{softmax}(z_1, \dots, z_K)_k = \frac{e^{z_k}}{\sum_{k'} e^{z_{k'}}} \quad (33)$$

- Outputs can be interpreted as probabilities (positive and sum to 1)
- If z_k is larger than the others, then $\text{softmax}(z)_k \approx 1$ and it behaves like argmax .
- The inputs z_k are called the logits.

Softmax Regression

- If a model outputs a vector of class probabilities, we can use cross-entropy as the loss function, where the log is applied elementwise.

$$\mathcal{L}_{CE}(\mathbf{y}, \mathbf{t}) = - \sum_{k=1}^K t_k \log y_k = -\mathbf{t}^\top (\log \mathbf{y}) \quad (34)$$

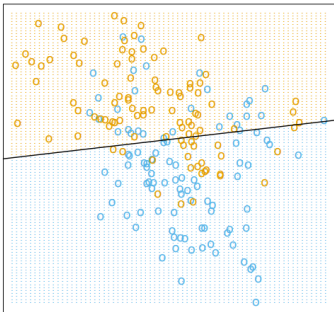
- Just like with logistic regression, we typically combine the softmax and cross-entropy into a softmax-cross-entropy function

Linear Classifiers vs. KNN

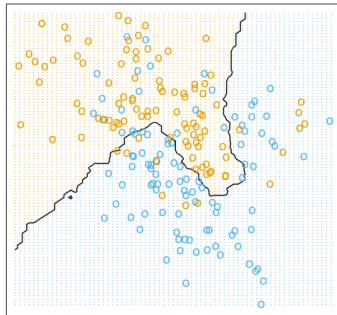
Linear Classifiers vs. KNN

- Linear classifiers and KNN have very different decision boundaries:

Linear Classifier



K Nearest Neighbours



Linear Classifiers vs. KNN

- Advantages of linear classifiers over KNN?

- Robustness to irrelevant features
 - Linear classifiers are generally robust to irrelevant or redundant features.
- Scalability
 - Linear classifiers can handle high-dimensional feature spaces efficiently and are more scalable as the number of features increases.
 - The curse of dimensionality!
- Easy updates of the model

- Advantages of KNN over linear classifiers?

- No assumption of data distribution
 - It is a non-parametric method, which means it does not assume any specific functional form for the decision boundaries.
- Non-linearity
 - KNN can capture complex, non-linear decision boundaries
- Robustness to imbalanced data
 - It relies on the local neighborhood and not global statistics.

Limitations of Linear Classification

A Few Basic Concepts

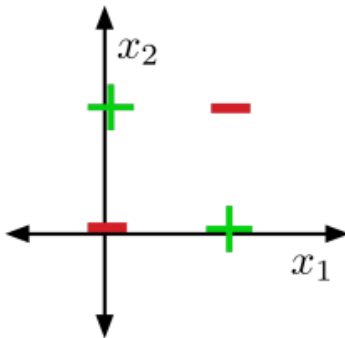
- A hypothesis is a function $f : \mathcal{X} \rightarrow \mathcal{T}$ that we might use to make predictions (recall \mathcal{X} is the input space and \mathcal{T} is the target space).
- The hypothesis space \mathcal{H} for a particular machine learning model or algorithm is a set of hypotheses that it can represent.
 - E.g., in linear regression, \mathcal{H} is the set of functions that are linear in the data features
 - The job of a machine learning algorithm is to find a good hypothesis $f \in \mathcal{H}$
- The members of \mathcal{H} , together with an algorithm's preference for some hypotheses of \mathcal{H} over others, determine an algorithm's inductive bias.
 - Inductive biases can be understood as general natural patterns or domain knowledge that helps our algorithms to generalize;
 - E.g., linearity, continuity, simplicity (L_2 regularization) ...
 - The so-called No Free Lunch (NFL) theorems assert that if datasets/problems were not naturally biased, no ML algorithm would be better than another

A Few Basic Concepts

- If an algorithm's hypothesis space \mathcal{H} can be defined using a finite set of parameters, denoted θ , we say the algorithm is parametric.
 - In linear regression, $\theta = (\mathbf{w}, b)$
 - Other examples: logistic regression, neural networks, k-means and Gaussian mixture models
- If the members of \mathcal{H} are defined in terms of the data, we say that the algorithm is non-parametric.
 - In k -nearest neighbors, the learned hypothesis is defined in terms of the training data
 - Other examples: Gaussian processes, decision trees, support vector machines, kernel density estimation
 - These models can sometimes be understood as having an infinite number of parameters

Limits of Linear Classification

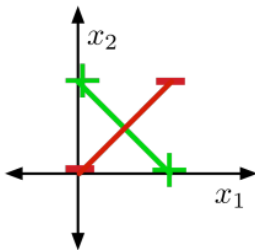
- Some datasets are not linearly separable, e.g. XOR,



- Visually obvious, but how to show this?

Showing that XOR is not linearly separable (proof by contradiction)

- If two points lie in a half-space, the line segment connecting them also lies in the same half-space.
- Suppose there were some feasible weights (hypothesis). If the positive examples are in the positive half-space, then the green line segment must be as well.
- Similarly, the red line segment must lie within the negative half-space



- But the intersection can't lie in both half-spaces. **Contradiction!**

Limits of Linear Classification

- Sometimes we can overcome this limitation using feature maps, just like for linear regression. E.g., for XOR:

$$\psi(\mathbf{x}) = \begin{pmatrix} x_1 \\ x_2 \\ x_1 x_2 \end{pmatrix}$$

x_1	x_2	$\psi_1(\mathbf{x})$	$\psi_2(\mathbf{x})$	$\psi_3(\mathbf{x})$	t
0	0	0	0	0	0
0	1	0	1	0	1
1	0	1	0	0	1
1	1	1	1	1	0

- This is linearly separable.

In the Future

- Feature maps are hard to design well, so next time we'll see how to learn nonlinear feature maps directly using neural networks...
- The basics of NN will be covered in this class.

...

