Classification

Read Chapter 4 in the text by Bishop, except omit
Sections 4.1.6, 4.1.7, 4.2.4, 4.3.3, 4.3.5, 4.3.6, 4.4, and 4.5.
Also, review sections 1.5.1, 1.5.2, 1.5.3, and 1.5.4.

Classification Problems

Many machine learning applications can be seen as classification problems — given a vector of D “inputs” describing an item, predict which “class” the item belongs to. Examples:

- Given anatomical measurements of an animal, predict which species the animal belongs to.
- Given information on the credit history of a customer, predict whether or not they would pay back a loan.
- Given an image of a hand-written digit, predict which digit (0-9) it is.
- Given the proportions of iron, nickel, carbon, etc. in a type of steel, predict whether the steel will rust in the presence of moisture.

We assume that the set of possible classes is known, with labels $C_1, \ldots, C_K$.

We have a training set of items in which we know both the inputs and the class, from which we will somehow learn how to do the classificaton.

Once we’ve learned a classifier, we use it to predict the class of future items, given only the inputs for those items.

Approaches to Classification

Classification problems can be solved in (at least) three ways:

- Learn how to directly produce a class from the inputs — that is, we learn some function that maps an input vector, x, to a class, C_k.
- Learn a "discriminative" model for the probability distribution over classes for given inputs — that is, learn $P(C_k|x)$ as a function of x. From $P(C_k|x)$ and a "loss function", we can make the best prediction for the class of an item.
- Learn a "generative" model for the probability distribution of the inputs for each class — that is, learn $P(x|C_k)$ for each class k. From this, and the class probabilities, $P(C_k)$, we can find $P(C_k|x)$ using Bayes' Rule.

Note that the last option above makes sense only if there is some well-defined distribution of items in a class. This isn't the case for the example of determining whether or not a type of steel will rust.

Loss functions and Classification

Learning $P(C_k|x)$ allows one to make a prediction for the class in a way that depends on a "loss function", which says how costly different kinds of errors are.

We define L_{kj} to be the loss we incur if we predict that an item is in class C_j when it is actually in class C_k. We'll assume that losses are non-negative and that $L_{kk} = 0$ for all k (ie, there's no loss when the prediction is correct). Only the relative values of losses will matter.

If all errors are equally bad, we would let L_{kj} be the same for all $k \neq j$.

Example: Giving a loan to someone who doesn't pay it back (class C_1) is much more costly than not giving a loan to someone who would pay it back (class C_0). So for this application we might define $L_{01} = 1$ and $L_{10} = 10$.

Note that we should define the loss function to account both for monetary consequences (money not repaid, or interest not earned) and other effects that don't have immediate monetary consequences, such as customer dissatisfaction when their loan isn't approved.

Predicting to Minimize Expected Loss

A basic principle of decision theory is that we should take the action (here, make the prediction) that minimizes the *expected* loss, according to our probabilistic model.

If we predict that an item with inputs x is in class C_j, the expected loss is

$$\sum_{k=1}^{K} L_{kj} P(C_k|x)$$

We should predict that this item in the class, C_j, for which this expected loss is smallest. (The minimum might not be unique, in which case more than one prediction would be optimal.)

If all errors are equally bad (say loss of 1), the expected loss when predicting C_j is $1 - P(C_j|x)$, so we should predict the class which highest probability given x.

For binary classification ($K = 2$, with classes labelled by 0 and 1), minimizing expected loss is equivalent to predicting that an item is in class 1 if

$$\frac{P(C_1|x)}{P(C_0|x)} \frac{L_{10}}{L_{01}} \quad > \quad 1$$

Classification from Generative Models Using Bayes' Rule

In the generative model approach to classification, we learn models from the training data for the probability or probability density of the inputs, x, for items in each of the possible classes, C_k — that is, we learn models for $P(x|C_k)$ for $k = 1, \ldots, K$.

To do classification, we instead need $P(C_k|x)$. We can get these conditional class probabilities using Bayes' Rule:

$$P(C_k|x) \quad = \quad \frac{P(C_k)\, P(x|C_k)}{\sum_{j=1}^{K} P(C_j)\, P(x|C_j)}$$

Here, $P(C_k)$ is the prior probability of class C_k. We can easily estimate these probabilities by the frequencies of the classes in the training data. Alternatively, we may have good information about $P(C_k)$ from other sources (eg, census data).

For binary classification, with classes C_0 and C_1, we get

$$\begin{aligned} P(C_1|x) \quad &= \quad \frac{P(C_1)\, P(x|C_1)}{P(C_0)\, P(x|C_0) \;+\; P(C_1)\, P(x|C_1)} \\ &= \quad \frac{1}{1 \;+\; P(C_0)\, P(x|C_0)\, /\, P(C_1)\, P(x|C_1)} \end{aligned}$$

Naive Bayes Models for Binary Inputs

When the inputs are binary (ie, x is a vectors of 1's and 0's) we can use the following simple generative model:

$$P(x|C_k) \;=\; \prod_{i=1}^{D} \mu_{ki}^{x_i}\,(1-\mu_{ki})^{1-x_i}$$

Here, μ_{ki} is the estimated probability that input i will have the value 1 in items from class k.

The maximum likelihood estimate for μ_{ki} is simply the fraction of 1's in training items that are in class k.

This is called the *naive Bayes* model — "Bayes" because we use it with Bayes's Rule to do classification, an "naive" because this model assumes that inputs are independent given the class, which is something a naive person might assume, though it's usually not true.

It's easy to generalize naive Bayes models to discrete inputs with more than two values, and further generalizations (keeping the independence assumption) are also possible.

Binary Classification using Naive Bayes Models

When there are two classes (C_0 and C_1) and binary inputs, applying Bayes' Rule with naive Bayes gives the following probability for C_1 given x:

$$
\begin{aligned}
P(C_1|x) &= \frac{P(C_1)\,P(x|C_1)}{P(C_0)\,P(x|C_0) \;+\; P(C_1)\,P(x|C_1)} \\
&= \frac{1}{1 \;+\; P(C_0)\,P(x|C_0)\,/\,P(C_1)\,P(x|C_1)} \\
&= \frac{1}{1 \;+\; \exp(-a(x))}
\end{aligned}
$$

where

$$
\begin{aligned}
a(x) &= \log\left(\frac{P(C_1)\,P(x|C_1)}{P(C_0)\,P(x|C_0)}\right) \\
&= \log\left(\frac{P(C_1)}{P(C_0)} \prod_{i=1}^{D} \left(\frac{\mu_{1i}}{\mu_{0i}}\right)^{x_i} \left(\frac{1-\mu_{1i}}{1-\mu_{0i}}\right)^{1-x_i}\right) \\
&= \log\left(\frac{P(C_1)}{P(C_0)} \prod_{i=1}^{D} \frac{1-\mu_{1i}}{1-\mu_{0i}}\right) \;+\; \sum_{i=1}^{D} x_i \log\left(\frac{\mu_{1i}/(1-\mu_{1i})}{\mu_{0i}/(1-\mu_{0i})}\right)
\end{aligned}
$$

Gaussian Generative Models

When the inputs are real-valued, a Gaussian model for the distribuiton of inputs in each class may be appropriate. If we also assume that the covariance matrix for all classes is the same, the class probabilities for binary classification turn out to depend on a linear function of the inputs.

For this model,

$$P(x|C_k) \quad = \quad (2\pi)^{-D/2}\,|\Sigma|^{-1/2}\,\exp\Big(-\,(x-\mu_k)^T\Sigma^{-1}(x-\mu_k)\,/\,2\Big)$$

where μ_k is an estimate of the mean vector for class C_k, and Σ is an estimate for the covariance matrix (same for all classes).

As shown in Bishop's book, the maximum likelihood estimate for μ_k is the sample means of input vectors for items in class C_k, and the maximum likelihood estimate for Σ is

$$\sum_{k=1}^{K} \frac{N_k}{N} S_k$$

where N_k is the number of training items in class C_k, and S_k is the usual maximum likelihood estimate for the covariance matrix in class C_k.

Classification using Gaussian Models for Each Class

For binary classification, we can now apply Bayes' Rule to get the probability of class 1 from a Gaussian model with the same covariance matrix in each class:

As for the naive Bayes model:

$$P(C_1|x) \;=\; \frac{1}{1 \;+\; \exp(-a(x))}$$

where

$$a(x) \;=\; \log\left(\frac{P(C_1)\,P(x|C_1)}{P(C_0)\,P(x|C_0)}\right)$$

Substituting the Gaussian densities, we get

$$\begin{aligned} a(x) \;&=\; \log\left(\frac{P(C_1)}{P(C_0)}\right) \;+\; \log\left(\frac{\exp(-(x-\mu_1)^T\Sigma^{-1}(x-\mu_1)\,/\,2)}{\exp(-(x-\mu_0)^T\Sigma^{-1}(x-\mu_0)\,/\,2)}\right) \\ &=\; \log\left(\frac{P(C_1)}{P(C_0)}\right) \;+\; \frac{1}{2}\left(\mu_0^T\Sigma^{-1}\mu_0 - \mu_1^T\Sigma^{-1}\mu_1\right) \;+\; x^T\left(\Sigma^{-1}(\mu_1-\mu_0)\right) \end{aligned}$$

The quadratic terms of the form $x^T\Sigma^{-1}x^T/2$ cancel, producing a linear function of the inputs, as was also the case for naive Bayes models.

Logistic Regression

We see that binary classification using either naive Bayes or Gaussian generative models leads to the probability of class C_1 given inputs x having the form

$$P(C_1|x) \quad = \quad \frac{1}{1 \; + \; \exp(-a(x))}$$

where $a(x)$ is a linear function of x, which can be written as $a(x) \; = \; w_0 + x^T w$.

Rather than start with a generative model, however, we could simply start with this formula, and estimate w_0 and w from the training data. Maximum likelihood estimation for w_0 and w is not hard, though there is no explicit formula.

This is a discriminative training procedure, that estimates $P(C_k|x)$ without estimating $P(x|C_k)$ for each class.

Which is Better — Generative or Discriminative?

Even though logistic regression uses the same formula for the probability for C_1 given x as was derived for the earlier generative models, maximum likelihood logistic regression does *not* in general give the same values for w_0 and w as would be found with maximum likelihood estimation for the generative model.

So which gives better results? It depends...

If the generative model accurately represents the distribution of inputs for each class, it should give better results than discriminative training — it effectively has more information to use when estimating parameters. (The discussion of this in Bishop's book, bottom of page 205, is misleading.)

However, if the generative model is not a good match for the actual distributions, using it might produce very bad results, even when logistic regression would work well. The independence assumption for naive Bayes and the equal covariance assumption for Gaussian models are often rather dubious.

Similarly, logistic regression may be less sensitive to outliers than a Gaussian generative model.

Non-linear Logistic Models

As we saw earlier for neural networks, the form $P(C_1|x) = 1/(1 + \exp(-a(x)))$ for the probability of class C_1 given x can be used with $a(x)$ being a non-linear function of x.

If $a(x)$ can equally well be any non-linear function, the choice of this form for $P(C_1|x)$ doesn't really matter, since *any* function $P(C_1|x)$ could be obtained with an approporiate $a(x)$.

However, in practice, non-linear models are biased towards some non-linear functions more than others, so it does matter that a logistic model is being used, though not as much as when $a(x)$ must be linear.

Probit Models

An alternative to logistic models is the *probit* model, in which we let

$$P(C_1|x) \;=\; \Phi(a(x))$$

where Φ is the cumulative distribution function of the standard normal distribution:

$$\Phi(a) \;=\; \int_{-\infty}^{a} (2\pi)^{-1/2} \exp(-x^2/2)\, dx$$

This would be the right model if the class depended on the sign of $a(x)$ plus a standard normal random variable. But this isn't a reasonable model for most applications. It might still be useful, though.