ARTIFICIAL INTELLIGENCE

Assignment 2

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Question

Write a note on Bayesian Decision Theory. Your answer should include (but not limited to) the following questions.

- **How do you we find the optimal decision boundary?**
- **What does Bayes decision theory optimize when making decisions?**
- **What are the tradeoffs in Bayes decision theory**?

Bayesian decision theory is a basic statistical method to solve the problem of image classification; if the probability structure on which the category is based is known, consider the ideal situation; although this situation rarely occurs in practice, it allows us to determine the optimal probability structure. A classifier that we can use to compare all other classifiers. In addition, in the case of certain problems, it allows us to predict the errors we will receive. If we generalize to the new model. The method is based on quantifying the tradeoffs between different categories. Decisions based on the possibility and cost of such decisions. It is assumed that the problem to be solved is expressed in terms of probability and all related probability values.

if both bass and salmon are caught, we will say that the next Ash may also be bass or salmon. Generally speaking, we assume that the perch will be the next fish with the prerequisite probability P (w1). , And it is a certain prior probability P (w2) of salmon. Assuming there are no other suitable fish species, then P (w1) + P (w2) = 1. These probabilities resect our prior knowledge of the probability that we should catch bass or salmon before the fish appears. If we are forced to select the next fish species only by using the value of the previous probability, we define w1, if P(w1)>P(w2), otherwise define w2. This rule makes sense when we judge only one fish, but if we judge many fish based on this rule over and over again, we will always make the same decision, even if we know that both fish will appear. So, it does not work depending on the value of the previous probability. In most cases, they will not be asked to make a decision with little information.

This form of decision rule emphasizes the role of posterior probability. As equivalent, the same rule can be expressed in the form of prior probability and conditional probability as follows: If p (x w1) P (w1)> p (x w2) P (w2), then find w1; otherwise, do Decision w2. Enabling the use of multiple functions only requires replacing the scalar x with the feature vector x, where x Rd is in the d-dimensional Euclidean space, is called the feature space. The assumption of more than two natural states provides us with a useful generalization, namely the low cost of symbols such as {w1 ... wc}. Allowing actions other than classification, such as {a1...aa}, allows the possibility of rejection, that is, rejection of a decision in a narrow situation.

The loss function accurately describes the cost of each action and is used to transform the Definition of probability into a decision. The cost function allows us to deal with situations where certain types of misclassifications are more expensive than others. Then the posterior probability can be calculated using the Bayesian formula. Let us assume that we observe a certain x and consider the possibility that ai works. If by definition, the true natural state is wj, we suffer a loss l (ai wj), because P (wj x) is the probability that the true natural state is equal to wj, that is, the expected loss related to the action ai. The expected loss is called Is risk, R (ai x) is called contingent risk. Whenever we face a particular observation of x, we can minimize the expected loss by choosing stocks that minimize the unexpected risk. The general decision rule a(x) tells us which actions should be taken for each possible observation x, and the total risk R is given by formula. Therefore, the Bayesian decision rule says that in order to minimize the overall risk, the formula for calculating conditional risk is as follows10 for i = 1... a, and then select the action ai with the smallest R (ai x).

Find the optimal decision boundary:

The decision boundary can be an intuitive description of the answer to the classification question. Solution boundaries can help us understand which solution might be suitable for a problem. You can also help us understand how different machine learning classifiers come up with the same solution. Optimal Solution Limit represents the "best possible" solution to this problem. Therefore, by looking at the complexity of this constraint and the number of errors generated, we can understand the inherent complexity of the problem. The learning classifier tries to get as close as possible to the optimal limit of the problem. Data scientists can use many classification algorithms: regression, discriminant analysis, decision trees, neural networks, etc. It is important to understand that the algorithm is suitable for the task at hand. One solution to the classification problem is to separate the features and assign all the features of a part to the same class of rules.

The "limit" in this section is the judgment limit of the rule. It can happen those two observations have exactly the same properties but belong to different classes. In terms of probability, this means that P (C = 0|X)> 0 and P (C = 1|X)> 0In. In other words, we cannot classify observations with complete certainty. However, we can classify observations into the most probable category. This gives us the decision rule C ^ = argmax (C = c|X). The restriction created by this rule is the restriction of the optimal solution. This is the MAP level of the class label. The rule minimizes the classification error with a zero-one loss function. We will see more errors and losses in future posts. We consider the problem of binary classification, ie. H. There are only two possible categories, 0 or 1. For binary classification problems, the best limit value appears at the point where the probability of each category is equal: P (C = 0|X) = P (C = 1|X)

Optimize when making decisions

Bayesian decision-making involves making a decision based on the probability of a successful outcome, which is determined by information previously obtained from the decision maker and new evidence. The main statistical analysis for these probability calculations is Bayesian analysis and Tradeoffs in Bayesian call theory may be a basic statistical procedure to unravel the matter of pattern classification. This approach depends on exploitation the chances and prices related to such selections to quantify the trade-offs between totally different ranking decisions.

Conclusion

What you have just learned is a simple, univariate application of Bayesian Decision Theory that can be expanded onto a larger feature space by using the multivariate Gaussian distribution in place of the evidence and likelihood. Although this article focused on tackling the problem of cancer detection, Bayes' Theorem is used in a variety of disciples including investing, marketing, and systems engineering.

https://github.com/Enggadil/-AI-LAB-_BSSE-5-M-