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Implementing Supervised Bayesian approach for mining facial images

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ABSTRACT

In this paper I introduce a Bayesian supervised approach for weakly-labeled data of a web facial images.I assume supervision in the form of a tag dictionary, and it prior encourages the use of cross linguistically common category structures as well as transitions between tags that can combine locally according to combinatory. It is theoretically appealing since it is motivated by language independent, universal properties of the formalism. Empirically, It shows that it yields substantial improvements over previous work that used similar biases to initialize a Bayesian based learner. Additional gains are obtained by further shaping the prior with corpus-specific information that is extracted automatically from raw text and a tag dictionary.

Keywords: Image mining, facial detection, Bayesian classification, supervised learning

1. INTRODUCTION

Unsupervised part-of-speech induction is a classic problem in NLP. Many proposed solutions are based on Hidden Markov models, with various improvements obtainable through: inductive bias in the form of tag dictionaries, sparsely constraints careful initialization of parameters, feature based representations and priors on model parameters. In this popular World, High Mega pixel cameras and the development of tools in media for internet-based photo sharing have witnessed an explosion of the vast number of digitalized photos which are clicked and stored by consumers. A Huge part of photos shared by users in the web are human images mainly their faces. Many of these images were tagged with names, but some of this were not tagged properly. This results in auto face annotation, which is a significant technique, focus to annotate facial images automatically. Currently Auto face annotation are beneficial in many applications Besides, face annotation techniques can also used in video news domain to find important persons seen in the videos. Classical face annotation techniques are frequently used as an extended face recognition problem, in which the different classification models were trained from a collection of well named facial pictures by using the supervised or

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Semi-supervised machine learning techniques. Normally, the "model-based face annotation" approaches are few in several aspects.

2. BACKGROUND DATA

Supervised learning (machine learning) takes a known set of input data and known responses to the data, and seeks to build a predictor model that generates reasonable predictions for the response to new data. Suppose you want to predict if someone will have a heart attack within a year. You have a set of data on previous , including age, weight, height, blood pressure, etc. You know if the previous had heart attacks within a year of their data measurements. So the problem is combining all the existing data into a model that can predict whether a new person will have a heart attack within a year. Supervised learning splits into two broad categories:

Classification for responses that can have just a few known values, such as 'true' or 'false'. Classification algorithms apply to nominal, not ordinal response values.

Regression for responses that are a real number such as miles per gallon for a particular car. You can have trouble deciding whether you have a classification problem or a regression problem. In that case, create a regression model first, because they are often more computationally efficient. While there are many Statistics and Machine Learning Toolbox algorithms for supervised learning, most use the same basic workflow for obtaining a predictor model. (Detailed instruction on the steps for ensemble learning is in Framework for Ensemble Learning.) The steps for supervised learning are:

As early work on image annotation, many researchers resort to users' relevance feedback (RF) to assign labels to a given image. For example, asked the user to label an image in the RF stage and then propagate these labels to all the positive images suggested by the retrieval system. Improved it by calculating the propagation likelihood based on internet synonym sets as well as image low-level features, and presenting those images that are most ambiguous to the user for relevance feedback.

All supervised learning methods start with an input data matrix, usually called X here. Each row of X represents one observation. Each column of X represents one variable, or predictor. Represent missing entries with NaN values in X. Statistics and Machine Learning Toolbox supervised learning algorithms can handle NaN values, either by ignoring them or by ignoring any row with a NaN value. You can use various data types for response data Y. Each element in Y represents the response to the corresponding row of X. Observations with missing Y data are ignored.

For regression, Y must be a numeric vector with the same number of elements as the number of rows of X. For classification, Y can be any of these data types. This table also contains the method of including missing entries.

3. PROPOSED METHOD

The typical characteristics of the various supervised learning algorithms. The characteristics in any particular case can vary from the others. Use these characteristics as a guide for your initial choice of algorithms, but be aware that the table can be inaccurate for some problems.

SVM prediction speed and memory usage are good if there are few support vectors, but can be poor if there are many support vectors. When you use a kernel function, it can be difficult to interpret how SVM classifies data, though the default linear scheme is easy to interpret. Naive Bayes speed and memory usage are good for simple distributions, but can be poor for kernel distributions and large data sets. Nearest Neighbor usually has good predictions in low dimensions, but can have poor predictions in high dimensions. For linear search, Nearest Neighbor does not perform any fitting. For *k*d-trees, Nearest Neighbor does perform fitting. Nearest Neighbor can have either continuous or categorical predictors, but not both Discriminate Analysis is accurate when the modeling assumptions are satisfied (multivariate normal by class). Otherwise, the predictive accuracy varies.

The Naive Bayes classifier is designed for use when predictors are independent of one another within each class, but it appears to work well in practice even when that independence assumption is not valid. It classifies data in two steps:

1. Training step: Using the training data, the method estimates the parameters of a probability distribution, assuming predictors are conditionally independent given the class.
2. Prediction step: For any unseen test data, the method computes the posterior probability of that sample belonging to each class. The method then classifies the test data according the largest posterior probability.

The class-conditional independence assumption greatly simplifies the training step since you can estimate the one-dimensional class-conditional density for each predictor individually. While the class-conditional independence between predictors is not true in general, research shows that this optimistic assumption works well in practice. This assumption of class-conditional independence of the predictors allows the naive Bayes classifier to estimate the parameters required for accurate classification while using less training data than many other classifiers. This makes it particularly effective for data sets containing many predictors.

4. ALGORITHM

This example shows how to make Bayesian inferences for a logistic regression model using slice sample. Statistical inferences are usually based on maximum likelihood estimation (MLE). MLE chooses the parameters that maximize the likelihood of the data, and is intuitively appealing. In MLE, parameters are assumed to be unknown but fixed, and are estimated with some confidence. In

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Bayesian statistics, the uncertainty about the unknown parameters is quantified using probability so that the unknown parameters are regarded as random variables.

4.1 BAYESIAN INFERENCE

Bayesian inference is the process of analyzing statistical models with the incorporation of prior knowledge about the model or model parameters. The root of such inference is Bayes' theorem: For example, suppose we have normal observations

$$X|\theta \sim N(\theta, \sigma^2)$$

where sigma is known and the prior distribution for theta is

$$\theta \sim N(\mu, \tau^2)$$

In this formula mu and tau, sometimes known as hyper parameters, are also known. If we observe n samples of X, we can obtain the posterior distribution for theta as

$$\theta|X \sim N\left(\frac{\tau^2}{\sigma^2/n+\tau^2}\bar{X} + \frac{\sigma^2/n}{\sigma^2/n+\tau^2}\mu, \frac{(\sigma^2/n)\times\tau^2}{\sigma^2/n+\tau^2}\right)$$

The following graph shows the prior, likelihood, and posterior for theta. The Sample algorithm as follows

```
rng(0,'twister');
n = 20;
sigma = 50;
x = normrnd(10,sigma,n,1);
mu = 30;
tau = 20;
theta = linspace(-40, 100, 500);
y1 =
normpdf(mean(x),theta,sigma/sqrt(n)
);
y2 = normpdf(theta,mu,tau);
postMean =
tau^2*mean(x)/(tau^2+sigma^2/n) +
sigma^2*mu/n/(tau^2+sigma^2/n);
postSD =
sqrt(tau^2*sigma^2/n/(tau^2+sigma^
2/n));
y3 = normpdf(theta,
postMean,postSD);
plot(theta,y1,'-', theta,y2,'--',
theta,y3,'-
```

Sample Algorithm

And the executed results are plotted in the graphical form as described in figure

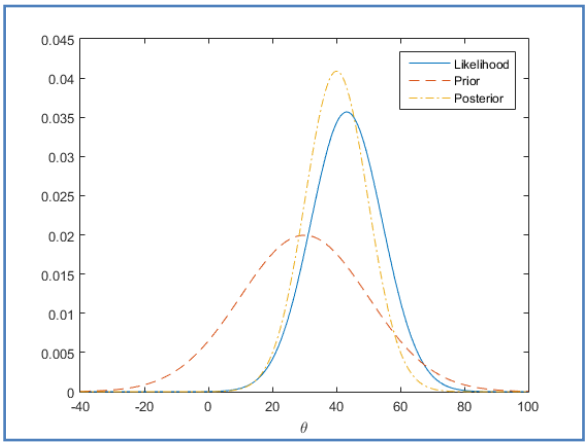

FIGURE 1-RESULT VIEW

5. CONCLUSION

This paper presents a generative Bayesian transfer learning algorithm particularly well-suited for the face verification problem. This is possible in large part because large web-based facial databases contain a variety of relevant information that can be used to bias estimation in smaller, more nuanced, application-specific domains. Although admittedly quite simple, our extensive theoretical and empirical analysis suggests that it nonetheless represents a viable candidate for many practical, real-time systems.

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