The Effect of Image Interpolation on the Generalization of Generative and Discriminative Graphical Models

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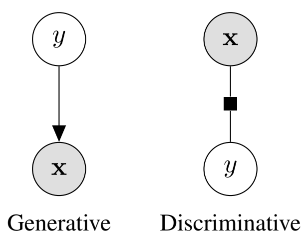
Abstract

In statistical classification, there are two main approaches to learning: *generative* and *discriminative*. In computer vision, *image interpolation* is a method to rescale images. This proposal will outline a procedure to explore the generalization ability of graphical models when downsampling images to various sizes.

1 Generative and Discriminative Modeling

For a classification task, we are interested in the probability distribution of a class label y conditioned on the sample features $\mathbf{x}$, written as $p(y \mid \mathbf{x})$. We can approach modeling this distribution in two ways: *generative* or *discriminative*.



1.1 Generative Approach

Generative classifiers seek to model the joint probability $p(\mathbf{x},\, y)$ from our data [5]. Predictions can be made with Bayes rule as follows:

$$\hat{y} \;=\; \operatorname*{argmax}_{y}\; p(\mathbf{x},\, y) \;=\; \operatorname*{argmax}_{y}\; p(y \mid \mathbf{x})\, p(\mathbf{x}) \;=\; \operatorname*{argmax}_{y}\; p(\mathbf{x} \mid y)\, p(y) \tag{1}$$

1.2 Discriminative Approach

For discriminative classifiers, the latent variables are class labels y, and model the posterior distribution $p(y \mid \mathbf{x})$ directly [5]. Hence, prediction becomes:

$$\hat{y} \;=\; \operatorname*{argmax}_{y}\; p(y \mid \mathbf{x}) \tag{2}$$

2 Data

I will use the Rijkmuseum Dataset [3] to perform type categorization. There will be 4 classes (print, drawings, paintings, photos) to make the problem difficult yet not intractable. There are 9,077 images for this sub-task, split evenly between classes, and we will use image interpolation to test various downsampling sizes and how well our models can learn the underlying distributions.

3 Models

In order to compare generative and discriminative approaches to classification, I will explore their static and general versions, as outlined in Figure 2.

3.1 Baseline

The baseline model will consist of a *Naive Bayes* classifier, a simple generative Bayesian network that assumes all the features $x_i \in \mathbf{x}$ are independent from one another and the sole parent is the class label y.

The discriminative analog to Naive Bayes is *Logistic Regression*, which is also a naive classifier, yet models the conditional probability directly.

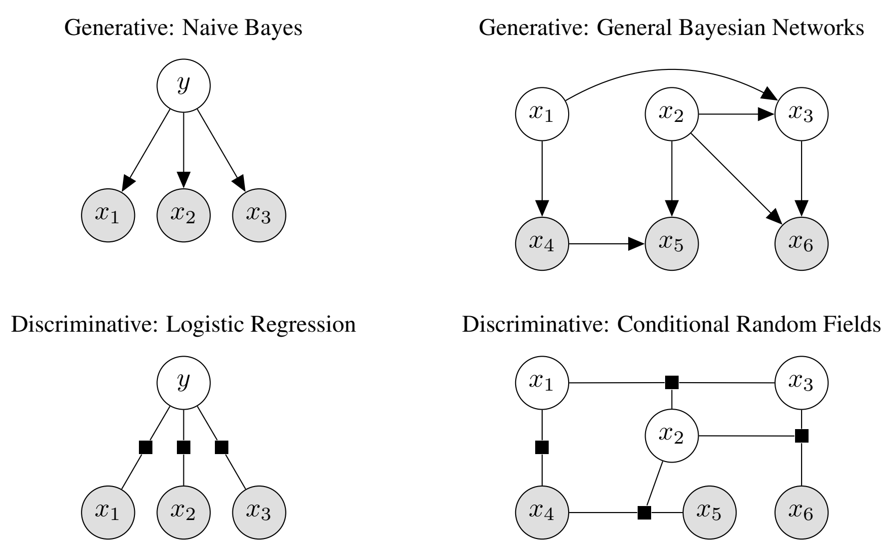
3.2 General

The general counterparts to the baseline models are the generative *General Bayesian Network* and its discriminative analog *Conditional Random Fields (CRFs)*.

General Bayesian Networks are probabilistic models that encode the conditional dependencies of its variables via a directed acyclic graph. Each variable is dependent only on its parents, allowing for more complex interactions between the features.

CRFs are an undirected probabilistic graphical model whose nodes can be partitioned into two disjoint sets: $\mathbf{x}$ and $\mathbf{y}$, and models the conditional distribution $p(\mathbf{y} \mid \mathbf{x})$ directly.

Figure 2: Generative vs. Discriminative Models



4 Parameter Estimation

Parameter estimation for generative models will use Maximum Likelihood Estimation. Logistic Regression will optimize its parameters via the L-BFGS algorithm. CRFs will use an approach depending on the library used (Section 7).

5 Inference

Inference for generative models will use belief propagation, if tractable. Otherwise, variational or sampling methods [2] will be used to approximate the conditional posterior.

CRF inference will use loopy belief propagation or sampling techniques, since exact inference is intractable in general graphs. However, since Logistic Regression is a tree, message passing algorithms yield exact solutions.

6 Experiment

To measure the generalization ability of our models, we plan to train each one on different sets of downsampled images. For instance, we plan to examine the errors in training and test of a 1x1 downsampled image, and increment in powers of 2. This will provide details on the effect of the number of features required to get good accuracy.

7 Software

This project will use OpenCV [1] for image processing. Our bayesian networks will use pgmpy[1]. Naive Bayes and Logistic Regression can be learned with scitkit-learn [4]. CRFs will use R's CRF library[2].

References

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[1]http://pgmpy.org

[2]https://cran.r-project.org/web/packages/CRF/index.html