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

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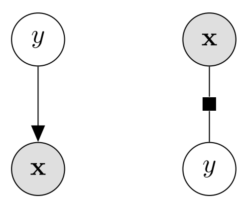
Abstract

In statistical classification, there are two main approaches to learning: *generative* and *discriminative*. In computer vision, *image interpolation* is a method to rescale images analgous to dimensionality reduction. We explore the generalization ability of *generative-discriminative pairs* when interpolating images to smaller sizes.

1 Introduction

2 Statistical Classification

Classification is the task of assigning a label y to a set of observed features $\mathbf{x}$. Yet the way we approach modeling these relationships can be broken down into either the *generative* or the *discriminative* approach.



Generative Discriminative

The generative approach models the joint distribution $p(y, \mathbf{x})$, and can assign labels through Bayes rule [3].

$$\hat{y} \;=\; \underset{y}{\text{argmax}}\; p(y, \mathbf{x}) \;=\; \underset{y}{\text{argmax}}\; p(y) \cdot p(\mathbf{x}|y) \tag{1}$$

Generative models are attractive in that distributions are learned over the feature space for each indvidual class. However, an important limitation mentioned by Callum et. al [2] is that modeling a distribution *per feature* quickly becomes intractable as the dimensionality of our observed variables $\mathbf{x}$ grows. While simple models can mitigate these issues by assuming independence among the features, allowing complex dependencies between inputs offers the ability to increase performance.

An alternative approach is to model the conditonal probabilities directly, ignoring the feature distributions. This is the discriminative approach, and is sometimes referred to as a *distribution-free classifier*. By ignoring the feature distributions, parameters are learned only on the conditional likelihood $p(y|\mathbf{x})$, resulting in a compact model that can handle large feature spaces, as dependencies are ignored [2].

To compare generative and discriminative modeling, one can experiment with pairs of classifiers that can be considered analgous to each other. More formally, a *generative-discriminative pair* is

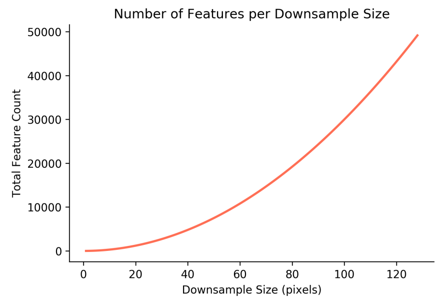


Figure 2: Exponentional growth in the number features quickly makes modeling intractable.

a parametric family of probabilistic models that can either be fit to maximize the joint probability $p(y, \mathbf{x})$ or the conditional likelihood $p(y|\mathbf{x})$ [3]. The simplest pairing is the Naive Bayes classifier (generative) and Logistic Regression (discriminative). This paradigm can be extended to sequential and general models to form more pairs. We discuss our experimental pairs in Section **??**.

3 Image Interpolation

The most common problem encountered in machine learning is the *curse of dimensionality*. Esssentially, as our feature space $\mathbf{x}$ grows in size, we require a larger number of parameters to estimate. This can quickly become intractable in complex models, and reasonably difficult in simple ones. We can see the growth in features as we increase the image size in Figure 2. One method to reduce the number of features for a data set is Principle Component Analysis, which projects data to a smaller dimension while maximining the variance. However, interapibility is lost, and the structure of the painting is unitnelligble.

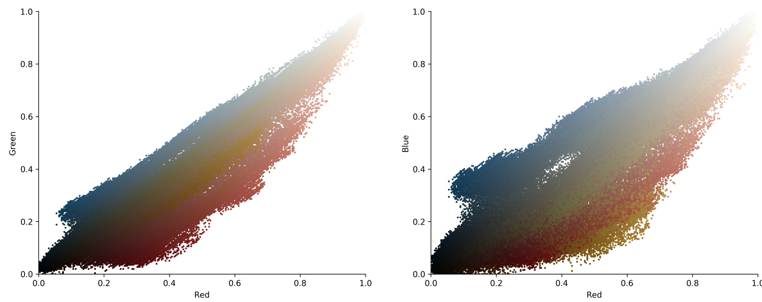
Image interpolation offers a convient way to downsample images according to their local neighborhood, aggregating otherwise noisy estimates into a single value. This may be beneficial for classification tasks, as we combine a method analgous to dimsionality reduction while preserving the fundamental structure of the orignal content. We use OpenCV's implementation of interpolation [1].

Formally, image interpolation is the task of rescaling an image of one size to another. This can be used to both decimate and expand the image. Several methods exists for this task, including linear, bicubic, nearest neighbor, and *area relation*.

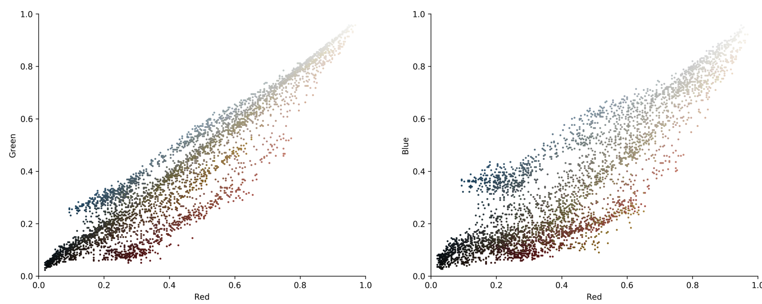
The perferred method for image decimation, or downsampling, is to resampling using pixel area relation as it gives moire'-free results. We can see in Figure 3 that the general space of the pixels in relation to there values is replicated, albeit with information loss.

(a) Original Image (498x500) (b) Decimated Image (64x64)



(c) Pixel Plot for the Original Image



(d) Pixel Plot for the Decimated Image

Figure 3: Results of Interpolating a 249,000 pixel image to a 4,096 pixel image.

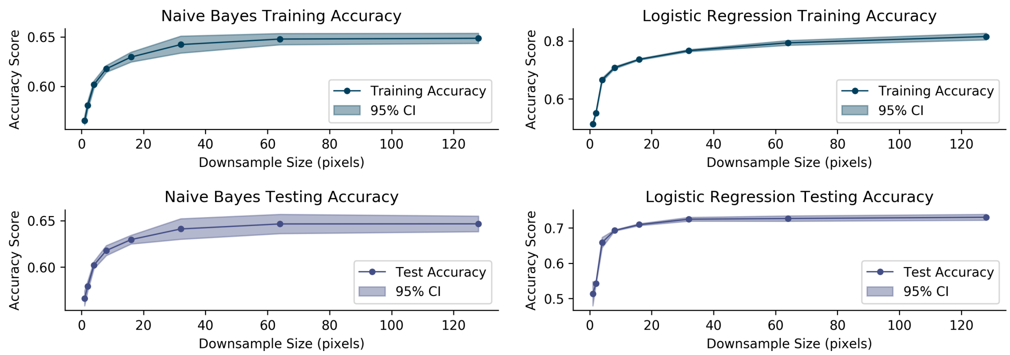


Figure 4: Training/Testing Accuracy Results for Baseline Models.

4 Data

4.1 Descriptive Statistics

4.2 Preprocessing Pipeline

5 Baseline Models

5.1 Naive Bayes

5.2 Logistic Regression

6 General Models

6.1 Bayesian Networks

6.2 Conditonal Random Fields (CRFs)

7 Experimental Task

8 Results: Parameter Estimation

8.1 Baseline

8.2 General

9 Results: Inference

9.1 Baseline

9.2 General

10 Conclusion

References

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[3] A. Y. Ng and M. Jordan. On discriminative vs. generative classifiers: A comparison of logistic regression and naive bayes. *Adv. Neural Inf. Process. Sys*, 2, 04 2002.