

Bayesian Classification, Naive Bayes

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1. *Univariate Gaussian.* Let $X \sim \mathcal{N}(\mu, \sigma^2)$.
 - a) For any $a, b \in \mathbb{R}$, $Y = aX + b$ is also Gaussian. If $X \sim \mathcal{N}(\mu, \sigma^2)$, what is the mean and variance of Y ?
 - b) Given $X \sim \mathcal{N}(\mu, \sigma^2)$, find $a, b \in \mathbb{R}^n$ so that $aX + b \sim \mathcal{N}(0, 1)$.
 - c) Use the result from above to generate 10,000 independent samples of a random variable $\sim \mathcal{N}(-5, 7)$. You may want to use the NumPy function `np.random.randn()`. Plot a histogram of the results.
2. Consider a random vector $\mathbf{x} \in \mathbb{R}^{n \times 1}$ with mean $\mu_{\mathbf{x}} \in \mathbb{R}^{n \times 1}$ and covariance $\Sigma_{\mathbf{x}}$, a deterministic matrix $\mathbf{A} \in \mathbb{R}^{m \times n}$, and a deterministic vector $\mathbf{c} \in \mathbb{R}^{n \times 1}$.
 - a) Consider the random vector $\mathbf{y} = \mathbf{A}(\mathbf{x} + \mathbf{c})$. Find an expression for $E[\mathbf{y}]$.
 - b) Find an expression for $\Sigma_{\mathbf{y}}$ (the covariance matrix of \mathbf{y}) in terms of $\Sigma_{\mathbf{x}}$.
3. *Naïve Bayes on MNIST.* In this problem we will classify MNIST handwritten digits using MAP and Naïve Bayes. The class $y \in \{0, 1, \dots, 9\}$ represents the true digit while $\mathbf{x} \in \{0, 1\}^{784}$ is the 28×28 black and white image that we'd like to classify.

Recall that if we know the *posterior* (i.e, the distribution of the class given the data, $p(y|\mathbf{x})$), we can use the Maximum A Posteriori (MAP) estimate as a classification rule:

$$\hat{y} = \arg \max_y p(y|\mathbf{x})$$

where \hat{y} is our estimate of the class. Equivalently,

$$\hat{y} = \arg \max_y p(\mathbf{x}|y)p(y)$$

which follows from Bayes Rule, since $p(y|\mathbf{x}) = p(\mathbf{x}|y)p(y)/p(\mathbf{x})$, and then dropping $p(\mathbf{x})$ from the denominator, since it doesn't depend on y and is inside the arg max.

The MAP classifier is very intuitive – as it aims to find the most likely class y , given the data \mathbf{x} .

Before we can use classifier, we need to (approximately) learn $p(\mathbf{x}|y)$ and $p(y)$. Learning $p(y)$ is easy, since we simply count the occurrences of the classes in the training data. Learning $p(\mathbf{x}|y)$ in general is hard, and even with 60k training examples, we don't

seem to have enough data. Notice that when the images have binary values, there are 2^{784} possible images. It's difficult to estimate the probability of one out of 2^{784} possible images when we only have $60k$ training examples. There are in essence 2^{784} different parameters that we must estimate.

Naïve Bayes makes a very naïve assumption: all elements of \mathbf{x} are independent. More precisely Naïve Bayes assumes $p(\mathbf{x}|y) \approx \prod_{i=1}^n p(x_i|y)$.

- a) How many different parameters are needed to describe the distribution $p(\mathbf{x}|y)$ if we assume $p(\mathbf{x}|y) \approx \prod_{i=1}^n p(x_i|y)$? Assume each pixel x_i only takes on values in $\{0, 1\}$.
- b) Is the independence assumption $p(\mathbf{x}|y) \approx p(x_1|y) \times p(x_2|y) \dots$ a reasonable assumption for the MNIST dataset? Why or why not?
- c) Note that $p(x_i|y)$ is the (marginal) probability that pixel x_i is 0 or 1 given the class y . We can estimate $p(x_i = 0|y = 9)$, for example, by counting the number of times pixel i is equal to 0, vs. the number of times it is equal to 1 among the images that are labeled $y = 9$:

$$p(x_i = 0|y = 9) = \frac{\text{count of examples of class 9 with pixel } i \text{ equal to 0}}{\text{count of examples of class 9}}. \quad (1)$$

Write code that estimates $p(x_i = 0|y)$ and $p(x_i = 1|y)$ by counting the occurrences $x_i = 0$ and $x_i = 1$ for $y = 0, 1, \dots, 9$ and for each pixel i . Store your estimates of $p(x_i = 0|y)$ and $p(x_i = 1|y)$, each in ten 28×28 matrices. Two tricks to help:

- sometimes the numerator in (1) will be zero. Add a small number (for example, 0.7) to both the numerator and denominator. This is called additive or *Laplace* smoothing.
 - store the log of the quantity above (to avoid multiplying small numbers when we multiply the marginal probabilities of each pixel in the next step).
- d) For numerical stability, we can compute $\sum_i \log(p(x_i|y))$ instead of $\prod_i p(x_i|y)$, without changing the problem. For a new test image \mathbf{x} , write code to output an estimate:

$$\hat{y} = \arg \max_y \sum_{i=1}^n \log(p(x_i|y)).$$

- e) What is the classification error rate of your classifier on the $10k$ test images?
- f) **(optional)** The digits are close to equally likely (i.e, $p(y = 0) \approx p(y = 1) \dots$), so we didn't incorporate the prior probability. Incorporate the prior probabilities, as estimated from the training data, into your classifier. How does the classification error rate change?

- g) (optional)** We now have a *probabilistic model* given by $p(\mathbf{x}|y)$ that we can use to generate random MNIST images. Display a few random images using the Naïve Bayes model you derived above. Do the images look like real MNIST images?
- h) (optional)** Randomly permute the pixels of a few images. Are the permuted pixel images recognizable by a human (display a few)? If you randomly permute the pixels and retrain your Naïve Bayes classifier, will the performance change? What does this say about our model?