

NAÏVE BAYES

Matt Brems
Data Science Immersive, GA DC

DATA SCIENCE PROCESS

- 1. Define problem.
- 2. Gather data.
- 3. Explore data.
- 4. Model with data.
- 5. Evaluate model.
- 6. Answer problem.

LEARNING OBJECTIVES

- By the end of this lesson, students should be able to:
 - Intuitively explain how Bayes' Theorem can be used as a modeling tactic.
 - Implement Naive Bayes in scikit-learn.
 - **Discuss** assumptions, advantages, and disadvantages of Naive Bayes as a classifier.

CONDITIONAL PROBABILITY

- Recall that we use P(A) to refer to the probability that A occurs, where A is some event.
- If we want to describe the probability that A occurs given that we know something else to be true, we use P(A|B).

• Note that P(A|B) is usually not the same as P(B|A)!

BAYES' THEOREM

• Bayes' Theorem (Bayes' Rule) relates P(A|B) to P(B|A).

BREAKING DOWN BAYES' THEOREM

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

- P(A) is the probability that A occurs given no supplemental information.
- P(B|A) is the likelihood of seeing evidence (data) B assuming that A is true.
- P(B) is the probability that B occurs given no supplemental information.
 - P(B) what we scale P(B|A)P(A) by to ensure we are only looking at A within the context of B occurring.

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

- Bayes' Theorem is really neatly set up as a classification model.
- We can estimate the probability -.predict_proba() that an observation falls into a specific class, then classify that observation -.predict() accordingly!

$$P(\text{spam}|\text{words in email}) = \frac{P(\text{words in email}|\text{spam})P(\text{spam})}{P(\text{words in email})}$$

$$P(\text{spam}|\text{words}) = \frac{P(w_1|\text{spam})P(w_2|w_1 \cap \text{spam})P(w_3|w_2 \cap w_1 \cap \text{spam}) \cdots P(\text{spam})}{P(w_1)P(w_2|w_1)P(w_3|w_2 \cap w_1) \cdots}$$

• This gets **really** complicated. Can we simplify this?

NAÏVE BAYES

- The Naïve Bayes classification algorithm is a:
 - classification modeling technique
 - that relies on Bayes Theorem
 - that makes one simplifying assumption.

We assume that our features are independent of one another.

$$P(\text{spam}|\text{words}) = \frac{P(w_1|\text{spam})P(w_2|w_1 \cap \text{spam})P(w_3|w_2 \cap w_1 \cap \text{spam}) \cdots P(\text{spam})}{P(w_1)P(w_2|w_1)P(w_3|w_2 \cap w_1) \cdots}$$

$$P(\text{spam}|\text{words}) = \frac{P(w_1|\text{spam})P(w_2|\text{spam})P(w_3|\text{spam})\cdots P(\text{spam})}{P(w_1)P(w_2)P(w_3)\cdots}$$

NAÏVE BAYES

- Advantages of making this assumption of feature independence:
 - Easier to calculate probabilities.
 - Empirically, our classifications are surprisingly accurate.

- **Disadvantages** of making this assumption of feature independence:
 - · It's incredibly unrealistic, especially in the case of text data.
 - While our classifications are accurate, our predicted probabilities are usually quite bad.

PROCESS OF NAÏVE BAYES

- 1. Decide which Naïve Bayes model to use.
 - BernoulliNB
 - MultinomialNB
 - GaussianNB
- 2. Decide what your priors will be.
 - Based on your data. (default)
 - Manually set.
- 3. .fit(), .predict()!

WHICH NAÏVE BAYES MODEL SHOULD I USE?

BernoulliNB

MultinomialNB

GaussianNB

WHAT SHOULD MY PRIORS SHOULD BE?

$$P(\text{spam}|\text{words in email}) = \frac{P(\text{words in email}|\text{spam})P(\text{spam})}{P(\text{words in email})}$$

Estimated from data.

Manually set.

PROCESS OF NAÏVE BAYES

- 1. Decide which Naïve Bayes model to use.
 - BernoulliNB
 - MultinomialNB
 - GaussianNB
- 2. Decide what your priors will be.
 - Based on your data. (default)
 - Manually set.
- 3. .fit(), .predict()!



INTERVIEW QUESTION

• Suppose we want to detect whether Amazon reviews are spam or ham. How would you do this?