GENERAL ASSEMBLY

NAÏVE BAYES

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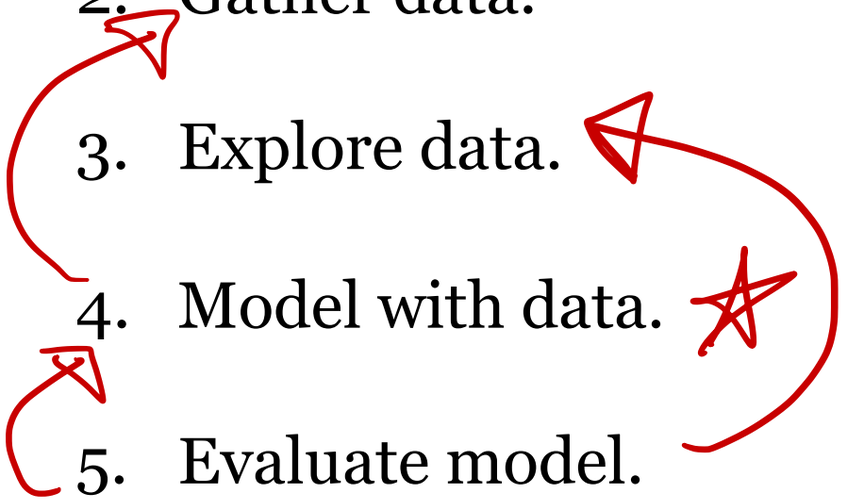
DATA SCIENCE PROCESS

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.

"P of A"

- If we want to describe the probability that A occurs given that we know something else to be true, we use $P(A|B)$.

"P of A given B"

A = roll a 2

B = roll an even

P(A) = 1/6

P(A|B) = 1/3

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

↳ 1/3

↳ 1

BAYES' THEOREM

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

$$P(A \text{ and } B) = P(B \text{ and } A)$$

$$P(A|B)\,P(B) = P(B|A)\,P(A)$$

multiplication rule for probabilities

divided both sides by $P(B)$

Bayes' Theorem

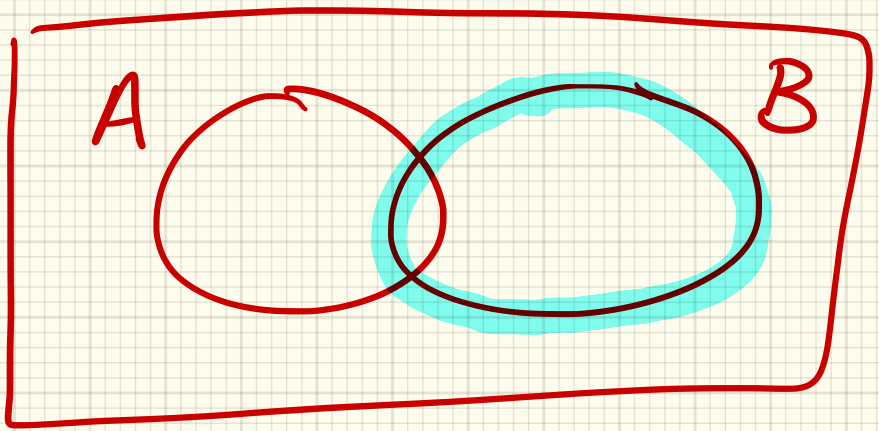
$$P(A|B) = \frac{P(B|A)\,P(A)}{P(B)}$$

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.
  ↳ prior prob. of A
- $P(B|A)$ is the probability of B given 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.



S = sample space

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

APPLYING BAYES' THEOREM TO SPAM CLASSIFICATION

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

- 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!

APPLYING BAYES' THEOREM TO SPAM CLASSIFICATION

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

$Y = \begin{cases} 1 & \text{if spam} \\ 0 & \text{else} \end{cases}$

given the words in my email, what is the prob. that my email is spam?

APPLYING BAYES' THEOREM TO SPAM CLASSIFICATION

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

words = $w_1 \cap w_2 \cap w_3 \cap \cdots$ (and)

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

Yes! But we have to make an assumption.

$$P(w_{100}|w_{99} \cap w_{98} \cap w_{97} \cap \cdots w_1)$$

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.**

↳ words

APPLYING BAYES' THEOREM TO SPAM CLASSIFICATION

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

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

$$P(w_2|w_1) = P(w_2)$$

NAÏVE BAYES

- **Advantages** of making this assumption of feature independence:
  - Easier to calculate probabilities. → model is faster
  - Empirically, our classifications are surprisingly accurate.
    ↳ b/c model performs well on test data, we're willing to make this assumption
- **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.

use .predict()

.predict_proba() is less reliable

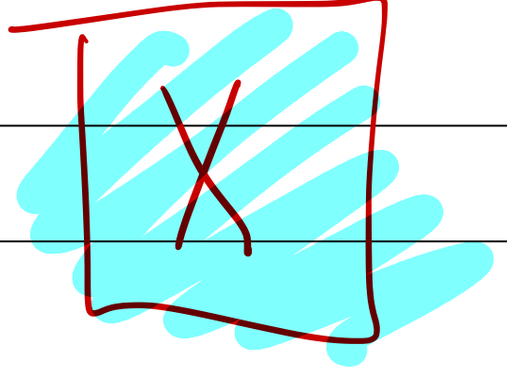
PROCESS OF NAÏVE BAYES

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
  - ↳ if columns of X are 1/0, use Bernoulli NB
    - ↳ dummy variables
- MultinomialNB
  - ↳ if columns of X are integer counts, use Multinomial
    - ↳ CountVectorizer, Likert scale columns + TF-IDF Vectorizer
- GaussianNB
  - ↳ if columns of X are Normal
    - ↳ realistically — anything that isn't 1/0 or integer.

WHAT SHOULD MY PRIORS SHOULD BE?

Posterior

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

Prior

- Estimated from data.

default

what you should do.

- Manually set.

only do this w/ subject-matter expertise

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3. `.fit()`, `.predict()`!

INTERVIEW QUESTION

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

legit

1 0

1. Define problem. ✓
2. Gather data. .csv SQL API ← Google scrape* ask Amazon proxy Yelp eBay
3. Explore. missing outliers valid Y
4. Model

NB
- fast
- spam

Log Reg
- fast
- interpretable

(NNs CARTs)
↳ data?

KNN
↳ slow
↳ variance

5. Evaluate
6. Answer: minimize false positives $\frac{TN}{TN+FP}$ = specificity