GENERAL ASSEMBLY

INTRO TO DATA SCIENCE LESSON 7: NAÏVE BAYES

LOGISTIC REGRESSION

QUESTIONS?

I. NAIVE BAYES
II. LAB: IMPLEMENT NAIVE BAYES IN PYTHON
III. LAB: USE NAIVE BAYES IN SKLEARN

I. BAYESIAN INFERENCE

Bayes' theorem. *Here it is again:*

$$P(A|B) = P(B|A) * P(A) / P(B)$$

Some facts:

- This is a simple algebraic relationship using elementary definitions.

- It's interesting because it's kind of a "wormhole" between two different "interpretations" of probability.

- It's a very powerful computational tool.

This term is the **likelihood function**. *It represents the joint probability of observing features* $\{x_i\}$ *given that that record belongs to class* C.

$$P(\text{class } C \mid \{x_i\}) = \frac{P(\{x_i\} \mid \text{class } C) \cdot P(\text{class } C)}{P(\{x_i\})}$$

This term is the **prior probability** *of C. It represents the probability of a record belonging to class C before the data is taken into account.*

$$P(\text{class } C \mid \{x_i\}) = \frac{P(\{x_i\} \mid \text{class } C) \cdot P(\text{class } C)}{P(\{x_i\})}$$

This term is the **normalization constant.** *It doesn't depend on* C*, and is generally ignored until the end of the computation.*

$$P(\text{class } C \mid \{x_i\}) = \frac{P(\{x_i\} \mid \text{class } C) \cdot P(\text{class } C)}{P(\{x_i\})}$$

This term is the **posterior probability** *of C. It represents the probability of a record belonging to class C after the data is taken into account.*

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The goal of any Bayesian computation is to find ("learn") the posterior distribution of a particular variable.

Maximum likelihood estimator (MLE):

*What parameters **maximize** the likelihood function?*

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Maximum a posteriori estimate (MAP):

*What parameters **maximize** the likelihood function **AND** prior?*

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Problem:

We observe the following coin flips:

HTHH

What is $P(X = \text{Heads})$?

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What is P(X = Heads) ? 3/4, Why?

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*What parameters **maximize** the likelihood function?*
Let P(X = Heads) = q, and write Bayes Theorem

P(q | observations) = P (observations | q) * P (q) / constant

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P(q | observations) = P (observations | q) * P (q) / constant

P(observations | q) = Binomial Distribution
P(q) = ????

Binomial Distribution:

$$\Pr(X = k) = \binom{n}{k} p^k (1-p)^{n-k}$$

P (HTHHTHT | q) = P (X = 4, n = 7) =

= (7 choose 4) * q^4 * (1-q) ^ 3

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After optimizing, the **MLE is 4/7**

A prior distribution is known as **conjugate prior** if its from the same family as the posterior for a certain likelihood function

For the binomial distribution, the conjugate prior is the **Beta distribution**

$$= \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1}(1-x)^{\beta-1}$$

$$= \frac{1}{\mathrm{B}(\alpha,\beta)} x^{\alpha-1}(1-x)^{\beta-1}$$

The **MAP estimate** is the value that maximizes both the likelihood function and prior - the product of the two.

In the coin flip setting is the value that optimizes

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After optimizing, the **MAP is (4 + a -1) / (7 + a + b - 2)**

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Sample 100 people and ask if they support a politician?

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Sample 100 people and ask if they support a politician?
23 say Yes - Is the correct prediction 23/100?
What’s the prior?

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Need to choose between multiple categories to present (for ads, products, news).

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But each should have a unique prior - **unique psuedo counts**

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Suppose we have a dataset with features $x_1, \ldots, x_n$ and a class label C. What can we say about classification using Bayes' theorem?

$$P(\text{class } C \mid \{x_i\}) = \frac{P(\{x_i\} \mid \text{class } C) \cdot P(\text{class } C)}{P(\{x_i\})}$$

Bayes' theorem can help us to determine the probability of a record belonging to a class, given the data we observe.

The idea of Bayesian inference, then, is to **update** *our beliefs about the distribution of* C *using the data ("evidence") at our disposal.*

$$P(\text{class } C \mid \{x_i\}) = \frac{P(\{x_i\} \mid \text{class } C) \cdot P(\text{class } C)}{P(\{x_i\})}$$

Then we can use the posterior for prediction.

Q: What piece of the puzzle we've seen so far looks like it could intractably difficult in practice?

Remember the likelihood function?

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Observing this exactly would require us to have enough data for every possible combination of features to make a reasonable estimate.

Q: What piece of the puzzle we've seen so far looks like it could intractably difficult in practice?

A: Estimating the full likelihood function.

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This "naïve" assumption simplifies the likelihood function to make it tractable.

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Q: Given that we can compute this value, what do we do with it?

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A: In our training phase, we 'learn' the probability of seeing our training examples under each class.

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Q: Given that we can compute this value, what do we do with it?

A: In our training phase, we 'learn' the probability of seeing our training examples under each class.

Then we use Bayes Theorem to compute P(class | inputs)

$$P(\text{class } C \mid \{x_i\}) = \frac{P(\{x_i\} \mid \text{class } C) \cdot P(\text{class } C)}{P(\{x_i\})}$$

Maximum a posteriori estimate (MAP):

*What **LABEL maximizes** the likelihood function **AND** prior?*

$$P(\text{class } C \mid \{x_i\}) = \frac{P(\{x_i\} \mid \text{class } C) \cdot P(\text{class } C)}{P(\{x_i\})}$$

Example: Text Classification

Does this news article talk about politics?

Training Set: Collection of New Articles

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Training Set: Collection of New Articles

Article 1: The computer contractor who exposed....
Article 2: The parents of a missing U.S. journalist in Syria...

Q: What are my features?

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A: The text in the documents.

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Q: How to I represent them?

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Q: How to I represent them?
A: Binary occurrence? Word counts?

the,	computer,	contractor,	exposed,	parents,	missing,	Syria,	U.S.
1	1	1	1	0	0	0	0
1	0	0	0	1	1	1	1

computer,	contractor,	exposed,	parents,	missing,	Syria,	U.S.
1	1	1	0	0	0	0
0	0	0	1	1	1	1

We can make some alterations

1) Drop stop words (commonly occurring words that don't have meaning)

computer,	contractor,	exposed,	parents,	missing,	Syria,	U.S.,	**POL**
1	1	1	0	0	0	0	0
0	0	0	1	1	1	1	1

Our goal is to compute compute P (POL = T | words in the text)

We need to ***learn*** *P(word | POL) i.e. P (Syria | POL)*

computer,	contractor,	exposed,	parents,	missing,	Syria,	U.S.,	**POL**
1	1	1	0	0	0	0	0
0	0	0	1	1	1	1	1

Once we've learned P(computer | POL), P(U.S. | POL) on our training set, we want to label our test set

computer,	contractor,	exposed,	parents,	missing,	Syria,	U.S.,	**POL**
1	1	1	0	0	0	0	0
0	0	0	1	1	1	1	1

The correct label, POL = True or POL = False is the one that maximize our posterior.

computer,	contractor,	exposed,	parents,	missing,	Syria,	U.S.,	**POL**
1	1	1	0	0	0	0	0
0	0	0	1	1	1	1	1

Compute probability in each class:

$$P\,(\,POL = T \mid \{x\}\,) = P\,(\,\{x\} \mid POL = T) * P(POL{=}T)$$

$$P\,(\,POL = F \mid \{x\}\,) = P\,(\,\{x\} \mid POL = F) * P(POL{=}F)$$

computer,	contractor,	exposed,	parents,	missing,	Syria,	U.S.,	**POL**
1	1	1	0	0	0	0	0
0	0	0	1	1	1	1	1

Article 2: The parents of a missing U.S. journalist in Syria...

$$P(POL = T \mid \{x\}) = P(\{x\} \mid POL = T) * P(POL=T)$$
$$= P(Syria \mid POL=T) * P(journalist \mid POL=T) * P(parents \mid POL=T) \ldots$$
$$* P(POL=T)$$

LAB