Naïve Bayes Classifiers

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Introduction to Data Mining, 2nd Edition
Chapter 5.3

Motivation

- Relationship between attributes and class lables may not be deterministic but probabilistic
- Reasons:
  - Noise in the data
  - Confounding factors affecting the classification and not in the data
- Bayesian Classifier exploit the Bayes Theorem that combines prior knowledge on the class labels with knowledge derivable from data

Bayes Classifier

- A probabilistic framework for solving classification problems.
- Let ***P*** be a probability function that assigns a number between 0 and 1 to events.
- **X = x** an events is happening - **data tuple**
- **Goal:** we are looking for **the probability that tuple X belongs to class C**, given that we know the attribute description of X.
- P(X = x) is the probability that events X = x --- **Prior probability of X**
- Joint Probability P(X = x, Y = y)
- Conditional Probability P(Y = y | X = x)
- Relationship: P(X,Y) = P(Y|X) P(X) = P(X|Y) P(Y)
- Bayes Theorem: P(Y|X) = P(X|Y)P(Y) / P(X) --- **Posterior Probability of Y**
- Another Useful Property: P(X =x) = P(X=x, Y=0) + P(X=x, Y=1)

Bayes Theorem

- Consider a football game. Team 0 wins 65% of the time, Team 1 the remaining 35%. Among the game won by Team 1, 75% of them are won playing at home. Among the games won by Team 0, 30% of them are won at Team 1's field.
- **If Team 1 is hosting the next match, which team will most likely win?**
- Team 0 wins: $P(Y = 0) = 0.65$
- Team 1 wins: $P(Y = 1) = 0.35$
- Team 1 hosted the match, Team 1 wins: $P(X = 1 | Y = 1) = 0.75$
- Team 1 hosted the match Team 0 wins: $P(X = 1 | Y = 0) = 0.30$
- Objective $P(Y = 1 | X = 1)$

Bayes Theorem

Team 1 hosted the match, Team 1 wins

Team 1 wins

Team 1 hosted the match

- $P(Y = 1 | X = 1) = P(X = 1 | Y = 1) P(Y = 1) / P(X = 1) =$

$= 0.75 \times 0.35 / (P(X = 1, Y = 1) + P(X = 1, Y = 0))$

$= 0.75 \times 0.35 / (P(X = 1 | Y = 1)P(Y=1) + P(X = 1 | Y = 0)P(Y=0))$

$= 0.75 \times 0.35 / (0.75 \times 0.35 + 0.30 \times 0.65)$

$= 0.5738$

- Therefore Team 1 has a better chance to win the match

Bayes Theorem for Classification

- X denotes the attribute sets, $X = \{X_1, X_2, \dots X_d\}$
- Y denotes the class variable
- We treat the relationship probabilistically using P(Y|X)

Likelihood

Prior Probability

- $P(Y|X) = \frac{P(X|Y)P(Y)}{P(X)}$

Posterior Probability

Evidence

Bayes Theorem for Classification

- Learn the posterior P(Y | X) for every combination of X and Y.
- By knowing these probabilities, a test record X' can be classified by finding the class Y' that maximizes the posterior probability P(Y'|X').
- This is equivalent of choosing the value of Y' that maximizes P(X'|Y')P(Y').
- How to estimate it?

Naïve Bayes Classifier

- It estimates the class-conditional probability by **assuming that the attributes are conditionally independent** given the class label y.
- The conditional independence is stated as:

$$P(X|Y=y) = \prod_{i=1}^{d} P(X_i|Y=y)$$

where each attribute set $X = \{X_1, X_2, \ldots X_d\}$

Conditional Independence

- Given three variables Y, X_1, X_2 we can say that Y is conditionally independent from X_1 given X_2 if the following condition holds:

$$P(Y \mid X_1, X_2) = P(Y|X_2)$$

- With the conditional independence assumption, instead of computing the class-conditional probability for every combination of *X* we only need to estimate the conditional probability of each X_i given *Y*.

- Thus, to classify a record the naive Bayes classifier computes the posterior for each class *Y* and takes the maximum class as result

$$P(Y|X) = P(Y)\prod_{i=1}^{d} P(X_i|Y=y)\,/P(X)$$

How to estimate ?

How to Estimate Probability From Data

- Class $P(Y) = N_y / N$
- N_y number of records with outcome y
- N number of records
- **Categorical attributes**

  $$P(X = x \mid Y = y) = N_{xy} / N_y$$

- N_{xy} records with value x and outcome y
- P(Evade = Yes) = 3/10
- P(Marital Status = Single|Yes) = 2/3

Tid	Refund	Marital Status	Taxable Income	Evade
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
6	No	Married	60K	No
7	Yes	Divorced	220K	No
8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

How to Estimate Probability From Data

Continuous attributes:

- Discretize the range into bins
  - Continuous vs nominal
  - Estimation: count records with class y and falling in the range
- Probability density estimation:
  - Assume attribute follows a normal distribution
  - Use data to estimate parameters of distribution (e.g., mean and standard deviation)
  - Once probability distribution is known, can use it to estimate the conditional probability P(X|y)

How to Estimate Probability From Data

- Normal distribution

$$P(X_i = x_i \mid Y = y) = \frac{1}{\sqrt{2\pi}\sigma_{ij}} e^{-\frac{(x_i - \mu_{ij})^2}{2\sigma_{ij}^2}}$$

- μ_{ij} can be estimated as the mean of X_i for the records that belongs to class y_j.
- Similarly, σ_{ij} as the standard deviation.
- P(Income = 120|No) = 0.0072
  - mean = 110
  - std dev = 54.54

Tid	Refund	Marital Status	Taxable Income	Evade
1	Yes	Single	125K	No
2	No	Married	100K	No
3	No	Single	70K	No
4	Yes	Married	120K	No
5	No	Divorced	95K	Yes
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8	No	Single	85K	Yes
9	No	Married	75K	No
10	No	Single	90K	Yes

M-estimate of Conditional Probability

- If one of the conditional probability is zero, then the entire expression becomes zero.
- For example, given X = {Refund = Yes, Divorced, Income = 120k}, if P(Divorced|No) is zero instead of 1/7, then
  - P(X|No) = 3/7 x 0 x 0.00072 = 0
  - P(X|Yes) = 0 x 1/3 x 10^{-9} = 0
- M-estimate $P(X|Y) = \frac{N_{xy}+mp}{N_y+m}$ (if $P(X|Y) = \frac{N_{xy}+1}{N_y+|Y|}$ is Laplacian estimation)
- m is a parameter, p is a user-specified parameter (e.g. probability of observing x_i among records with class y_j.
- In the example with m = 3 and p = 1/m = 1/3 (i.e., Laplacian estimation) we have

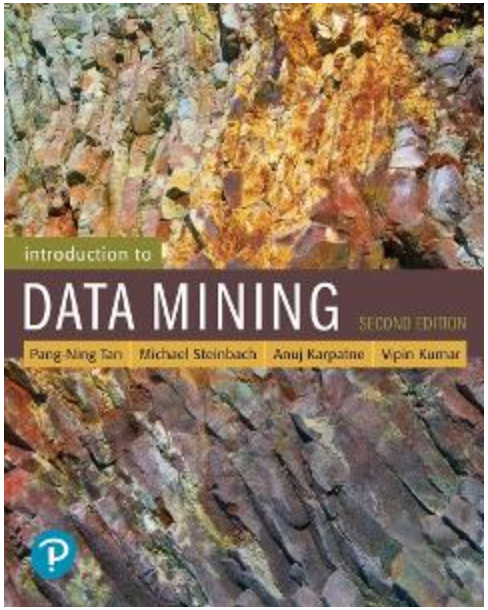
P(Married |Yes) = (0+3x1/3)/(3+3) = 1/6

Naïve Bayes Classifier

- Robust to isolated noise points
- Handle missing values by ignoring the instance during probability estimate calculations
- Robust to irrelevant attributes
- Independence assumption may not hold for some attributes
  - Use other techniques such as Bayesian Belief Networks (BBN)

References

- Bayesian Classifiers. Chapter 5.3. Introduction to Data Mining.



EXERCISE - NBC

Play-tennis example. estimating $P(x_i|C)$

Outlook	Temperature	Humidity	Windy	Class
sunny	hot	high	false	N
sunny	hot	high	true	N
overcast	hot	high	false	P
rain	mild	high	false	P
rain	cool	normal	false	P
rain	cool	normal	true	N
overcast	cool	normal	true	P
sunny	mild	high	false	N
sunny	cool	normal	false	P
rain	mild	normal	false	P
sunny	mild	normal	true	P
overcast	mild	high	true	P
overcast	hot	normal	false	P
rain	mild	high	true	N

P(p) = 9/14	
P(n) = 5/14	

outlook	
P(sunny|p) =	P(sunny|n) =
P(overcast|p) =	P(overcast|n) =
P(rain|p) =	P(rain|n) =
temperature	
P(hot|p) =	P(hot|n) =
P(mild|p) =	P(mild|n) =
P(cool|p) =	P(cool|n) =
humidity	
P(high|p) =	P(high|n) =
P(normal|p) =	P(normal|n) =
windy	
P(true|p) =	P(true|n) =
P(false|p) =	P(false|n) =

Play-tennis example. estimating $P(x_i|C)$

Outlook	Temperature	Humidity	Windy	Class
sunny	hot	high	false	N
sunny	hot	high	true	N
overcast	hot	high	false	P
rain	mild	high	false	P
rain	cool	normal	false	P
rain	cool	normal	true	N
overcast	cool	normal	true	P
sunny	mild	high	false	N
sunny	cool	normal	false	P
rain	mild	normal	false	P
sunny	mild	normal	true	P
overcast	mild	high	true	P
overcast	hot	normal	false	P
rain	mild	high	true	N

P(p) = 9/14
P(n) = 5/14

outlook	
P(sunny|p) = 2/9	P(sunny|n) = 3/5
P(overcast|p) = 4/9	P(overcast|n) = 0
P(rain|p) = 3/9	P(rain|n) = 2/5
temperature	
P(hot|p) = 2/9	P(hot|n) = 2/5
P(mild|p) = 4/9	P(mild|n) = 2/5
P(cool|p) = 3/9	P(cool|n) = 1/5
humidity	
P(high|p) = 3/9	P(high|n) = 4/5
P(normal|p) = 6/9	P(normal|n) = 1/5
windy	
P(true|p) = 3/9	P(true|n) = 3/5
P(false|p) = 6/9	P(false|n) = 2/5

Play-tennis example. estimating $P(x_i|C)$

P(p) = 9/14	
P(n) = 5/14	

Outlook	Temeprature	Humidity	Windy	Class
rain	hot	high	false	?

outlook	
P(sunny|p) = 2/9	P(sunny|n) = 3/5
P(overcast|p) = 4/9	P(overcast|n) = 0
P(rain|p) = 3/9	P(rain|n) = 2/5
temperature	
P(hot|p) = 2/9	P(hot|n) = 2/5
P(mild|p) = 4/9	P(mild|n) = 2/5
P(cool|p) = 3/9	P(cool|n) = 1/5
humidity	
P(high|p) = 3/9	P(high|n) = 4/5
P(normal|p) = 6/9	P(normal|n) = 1/5
windy	
P(true|p) = 3/9	P(true|n) = 3/5
P(false|p) = 6/9	P(false|n) = 2/5

$P(X|p) \cdot P(p) =$

$P(X|n) \cdot P(n) =$

Play-tennis example. estimating $P(x_i|C)$

P(p) = 9/14	
P(n) = 5/14	

Outlook	Temeprature	Humidity	Windy	Class
rain	hot	high	false	**N**

outlook	
P(sunny|p) = 2/9	P(sunny|n) = 3/5
P(overcast|p) = 4/9	P(overcast|n) = 0
P(rain|p) = 3/9	P(rain|n) = 2/5
temperature	
P(hot|p) = 2/9	P(hot|n) = 2/5
P(mild|p) = 4/9	P(mild|n) = 2/5
P(cool|p) = 3/9	P(cool|n) = 1/5
humidity	
P(high|p) = 3/9	P(high|n) = 4/5
P(normal|p) = 6/9	P(normal|n) = 1/5
windy	
P(true|p) = 3/9	P(true|n) = 3/5
P(false|p) = 6/9	P(false|n) = 2/5

$\mathbf{P(X|p) \cdot P(p)} = P(rain|p) \cdot P(hot|p) \cdot P(high|p) \cdot P(false|p) \cdot P(p) = 3/9 \cdot 2/9 \cdot 3/9 \cdot 6/9 \cdot 9/14 = 0.010582$

$\mathbf{P(X|n) \cdot P(n)} = P(rain|n) \cdot P(hot|n) \cdot P(high|n) \cdot P(false|n) \cdot P(n) = 2/5 \cdot 2/5 \cdot 4/5 \cdot 2/5 \cdot 5/14 = 0.018286$

a) Naive Bayes (**3 points**)

Given the training set below, build a Naive Bayes classification model (i.e. the corresponding table of probabilities) using (i) the normal formula and (ii) using Laplace formula. What are the main effects of Laplace on the models?

A	B	class
no	green	N
no	red	Y
yes	green	N
no	red	N
no	red	Y
no	green	Y
yes	green	N

Answer:

Normal

	Y	N		Y	N
	3	4		0.43	0.57
	A | Y	A | N		A | Y	A | N
yes	0	2	yes	0.00	0.50
no	3	2	no	1.00	0.50
	B | Y	B | N		B | Y	B | N
green	1	3	green	0.33	0.75
red	2	1	red	0.67	0.25

Laplace

	Y	N		Y	N
	3	4		0.43	0.57
	A | Y	A | N		A | Y	A | N
yes	0	2	yes	0.20	0.50
no	3	2	no	0.80	0.50
	B | Y	B | N		B | Y	B | N
green	1	3	green	0.40	0.67
red	2	1	red	0.60	0.33