Naïve Bayes Leaner for Adult Database

COMP30027 2022 Assignment 1

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Purpose of Project

Developing Engineering Skills: Machine Learning (ML) Capabilities

- Problem Solving (build Naïve Bayes Learner)
 - ► (Data) Analytics: read and understand assignment spec and adult.csv
 - Computer Modeling: build and evaluate a Naïve Bayes Learner, How?

Python coding? Yes, but more ML skills

- Troubleshooting (Analytical Skills): guided by questions Q1 to Q4 (Q1&2 for individual), beyond code debugging
 - * Interpret and explain the results: expected/unexpected, good/bad,
 - ★ More Importantly, how.....why..... (other choices)

 → Improvement
- <u>Communication skills</u>: disseminate your discovery/innovation (to us), clean code (w/ proper comments), concise answers, ...

(Data) Analytics

Database: Adult.csv: 11 attributes, a binary class label, 1,000 records

age	work class	education	education num		label
68	?	1st-4th	2		<= 50K
39	State-gov	Bachelors	13		<= 50K
50	Self-emp-not-inc	Bachelors	13		<= 50K
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Assignment Spec/Project Description (excl. question part): Naïve Bayes Learner,

$$\hat{c} = rg \max_{c_j} P(c_j) \prod_{i=1}^m P(X_i | c_j)$$

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to be implemented and evaluated by preprocess(), train(), test() and evaluate()

Computer Modeling

Training train(): using attribute values (a_1, \ldots, a_m) 's and their labels c_j 's in training set to lean Naïve Bayes Learner f (a formal expression):

$$\hat{c} = f(a_1, \dots, a_m)$$

$$= \mathop{\mathrm{arg\,max}}_{c_j} \Pr(C = c_j) \prod_{i=1}^m \Pr(X_i = a_i | C = c_j)$$

m=11, attribute X_i (e.g., 'age', 'education'), label C ($c_1='<=50$ K', $c_2='>50$ K')

- kowning all parameters that determine f: prior $Pr(C = c_j)$ and conditional probs. $Pr(X_i = a_i | C = c_j)$ for all attribute values a_i 's and c_j 's, for each attribute X_i
- a mixture of numeric and nomial attributes
- $Pr(X_i = a_i | C = c_j)$: numeric (Gaussian in four functions and KDE in Q2(a)) and nominal attributes, refer to (Thu lecture in week 2 and Tue lecture in week 3)
- issues/concerns: data structure, missing values (see spec, e.g., Q3),

Computer Modeling

Testing test(): using attribute values (t_1, \ldots, t_m) 's in testing set to get \hat{c} :

$$\hat{c} = f(t_1, \dots, t_m)$$

$$= \underset{c_j}{\operatorname{arg \, max}} \Pr(C = c_j) \prod_{i=1}^m \Pr(X_i = t_i | C = c_j)$$

issues/concerns? e.g., missing values: decide by yourself that makes the most sense.

Evaluating evaluate(): comparring true label c^* and predicted label \hat{c} to get accuracy, confusion matrix

		Predicted		
		Positive	Negative	
Lue	Positive	TP	FN	
	Negative	FP	TN	

and F1 score (Thu lecture in week 3)

Q1: interpreting, analyzing and reasoning the output of evaluate()

Keyword Extraction

Sensitivity and specificity.....should have both sensitivity and specificity high.....calculate the sensitivity and specificity.....see a difference.....what causes this difference.....suggestions to improve the model performance.....

- ▲ Expectation ⟨ red ⟩
- ▲ To do ⟨ purple ⟩
 - Observation: values of sensitivity and specificity, (mis)align w/ expectation?
 - Reasoning: why the observation, thinking of possibilities and justify
 - Suggestion: based on your reasoning. ⇒ completes troubleshooting!

Q2: exploring other choices for train() and test()

Sub-task (a)

Gaussian vs. KDE for modeling $P(X_i|c_j)$, aka $Pr(X_i=a_i|C=c_j)$, for numeric X_i

 \blacktriangle Suitability of two probabilistic models for each numeric X_i : **Justify**

Sub-task (b)

Different m in m-fold cross-validation: $m \in \{2, 10\}$

- \triangle Observation and Interpreting (some reasoning): the changes in evaluation metrics (e.g., accuracy, see spec) for different m and over all folds, why difference (Thu lecture in week 3)
- ▲ Conclusion: summerize and answer the quesion

Q3: exploring different methods for handling missing values for nominal X_i

Options

- 1. Missing value '?' ⇒ new category
- 2. Ignore missing value: how to ignore
- ▲ Try both large and small datasets; what you should look at to compare
- ▲ Observation-conclusion (incl. reasoning) approach: justify!

Q4: exploring how to use information gain (IG) and gain ratio (GR) in Naïve Bayes (in fact beyond) The most Interesting part!

Sub-task (a)

Obtain GR: attributes vs. class

- throwing out attributes X_i 's one by one according to ascending order of GRs
- ▲ Observe the change of accuracy; justify and reason the observatons.

Sub-task (b)

Obtain IG: for each pair of attributes X_i and $X_{i'}$, for all $i, i' \in \{1, ..., m\}$ such that $i \neq i'$

- predict one by another.
- ▲ Justify, alwasy justify!......

Finally

Good Luck!