Machine Learning Assignment Group 71 (18CS10021) Hardik Aggarwal and (18CS30040) Sriyash Poddar

Assignment - 2 - Naive Bayes

Procedure:

- 1. Preprocess Data Drop the id column as it is not a feature.
- 2. Fill the missing value in the data, using the mode *viz*. max frequency element of the corresponding feature, and encode the discrete features using an inbuilt function from sklearn.
- 3. Train the Naive Bayes classifier across 5-folds and report the average accuracy across different folds.
- 4. Finding out the class probability using the formula:

$$P(C \mid i) = (No. \ of \ samples \ classified \ as \ C \mid i)/(Total \ no. \ of \ samples)$$

5. Find out the probability matrix using the formula:

 $P(X_j \mid C_i) = (No. of samples classified as C_i, having feature j = X_j)/(No. of samples classified as C_i)$ For continuous features, however, we use :

 $P(X \mid C \mid i) \sim N(m, var)$; m, var = Mean and Variance of feature j, across all samples classified as $C \mid i$

6. For test data, find out the probability of sample $X = (X \ j1, X \ j2, X \ j3 \)$ by the formula :

$$P(C_{-}i \mid X) = \{ [P(X_{-}j1 \mid C_{-}i) * P(X_{-}j2 \mid C_{-}i)...] * P(C_{-}i) \} / (\Sigma_{-}i \mid P(X_{-}j1 \mid C_{-}i) * P(X_{-}j2 \mid C_{-}i)...] * P(C_{-}i) \} / (\Sigma_{-}i \mid P(X_{-}j1 \mid C_{-}i) * P(X_{-}j2 \mid C_{-}i)...] * P(C_{-}i) \} / (\Sigma_{-}i \mid P(X_{-}j1 \mid C_{-}i) * P(X_{-}j2 \mid C_{-}i)...] * P(C_{-}i) \} / (\Sigma_{-}i \mid P(X_{-}j1 \mid C_{-}i) * P(X_{-}j2 \mid C_{-}i)...] * P(C_{-}i) \} / (\Sigma_{-}i \mid P(X_{-}j1 \mid C_{-}i) * P(X_{-}j2 \mid C_{-}i)...] * P(C_{-}i) \} / (\Sigma_{-}i \mid P(X_{-}j1 \mid C_{-}i) * P(X_{-}j2 \mid C_{-}i)...] * P(C_{-}i) \} / (\Sigma_{-}i \mid P(X_{-}j1 \mid C_{-}i) * P(X_{-}j2 \mid C_{-}i)...] * P(C_{-}i) \} / (\Sigma_{-}i \mid P(X_{-}j1 \mid C_{-}i) * P(X_{-}j2 \mid C_{-}i)...] * P(C_{-}i) \} / (\Sigma_{-}i \mid P(X_{-}j1 \mid C_{-}i) * P(X_{-}j2 \mid C_{-}i)...] * P(C_{-}i) \} / (\Sigma_{-}i \mid P(X_{-}j1 \mid C_{-}i) * P(X_{-}j2 \mid C_{-}i)...] * P(C_{-}i) \} / (\Sigma_{-}i \mid P(X_{-}j1 \mid C_{-}i) * P(X_{-}j2 \mid C_{-}i)...] * P(C_{-}i) \} / (\Sigma_{-}i \mid P(X_{-}j1 \mid C_{-}i) * P(X_{-}j2 \mid C_{-}i)...] * P(C_{-}i) \} / (\Sigma_{-}i \mid P(X_{-}j1 \mid C_{-}i) * P(X_{-}j2 \mid C_{-}i)...] * P(C_{-}i) \} / (\Sigma_{-}i \mid P(X_{-}j1 \mid C_{-}i) * P(X_{-}j2 \mid C_{-}i)...] * P(C_{-}i) \} / (\Sigma_{-}i \mid P(X_{-}j1 \mid C_{-}i) * P(X_{-}j2 \mid C_{-}i)...] * P(C_{-}i) \} / (\Sigma_{-}i \mid P(X_{-}j1 \mid C_{-}i) * P(X_{-}j2 \mid C_{-}i)...] * P(C_{-}i) \} / (\Sigma_{-}i \mid P(X_{-}j1 \mid C_{-}i) * P(X_{-}i1 \mid C_{-}i) * P(X_{-}i1 \mid C_{-}i) * P(X_{-}i1 \mid C_{-}i) * P(X_{-}i1 \mid C_{-}i1 \mid C$$

Predicted class =
$$max i P(C i | X)$$

- 7. For performing Principal Component Analysis on the given data, keeping 95% of the variance, we calculated the no. of components with explained variance ratio less just above or equal to 95%.
- 8. Transform the given data to the found components using an inbuilt function, plot the cumulative sum of explained variance ratios and eigenvalues of the components.
- 9. Trained the classifier on the transformed data and reported the test accuracy. (Repeat steps 3-6)
- 10. Remove outliers from the sample, using the following rule: Samples having max feature values beyond +-3*std of a feature are outliers.
- 11. Using the sequential backward selection process to remove features, i.e., given the accuracy of given features set F, on the test data(= acc_prev) calculate:

$$acc_i = Test \ accuracy \ of features \ F-f_i$$

Remove feature, where acc i - acc prev is maximum.

- 12. Run the process, starting from all features till the point where no improvement is possible i.e., acc i acc prev is negative for all present features.
- 13. Trained the classifier on the transformed data and reported the test accuracy. (Repeat steps 3-6)

14. Observations:

Split Number	Accuracy
1	0.5019364833462432
2	0.4965143299767622
3	0.5243996901626646
4	0.5058094500387297
5	0.49147286821705427

Fig (a): Accuracy across different splits

Results: On kfold:-

Average train accuracy = 0.5041800419121046

On Test set :-

Test accuracy = 0.5012391573729864

Part (b) Principal Component Analysis:-

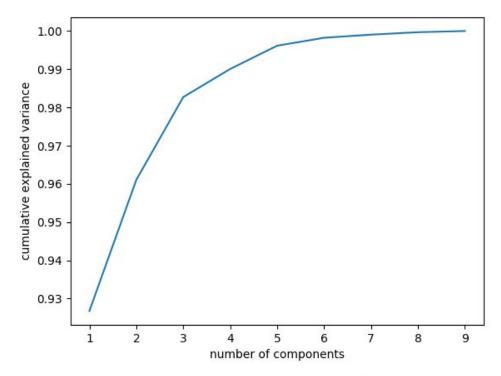


Fig (c) Explained variance plot during PCA.

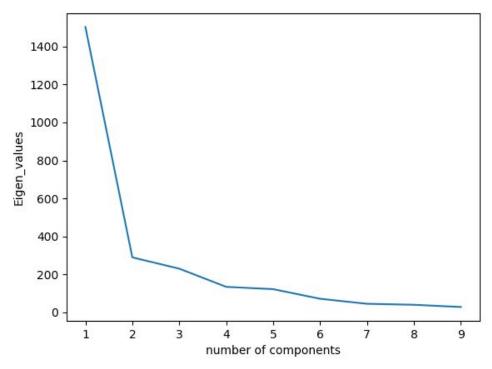


Fig (c) Eigenvalue plot during PCA

Observations after PCA

Split Number	Accuracy
1	0.3996901626646011
2	0.3756777691711851
3	0.418280402788536
4	0.37412858249419056
5	0.3875968992248062

Fig (a): Accuracy across different splits

Results: On kfold:-

Average train accuracy = 0.39107476326866386

On Test set :-

Test accuracy = 0.3990086741016109

Part (c)

(i) Removal of feature outliers :-

-> Samples before removal: 8068 -> Samples after removal: 7927

(ii) Sequential backward selection

Initial features: Gender, Ever_Married, Age, Graduated, Profession, Work_Experience, Spending Score, Family Size, Var 1

Remaining features: Ever_Married, Age, Graduated, Profession, Spending_Score, Family_Size, Var_1

Observations:

Split Number	Accuracy
1	0.46887312844759654
2	0.5157728706624606
3	0.48974763406940064
4	0.5299684542586751
5	0.47712933753943215

Fig (a): Accuracy across different splits

Results: On kfold:-

Average train accuracy = 0.496298284995513

On Test set :-

Test accuracy = 0.5044136191677175