

**Title: Naive Bayes Classifier**

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# INTRODUCTION

This lab introduces the concepts and practical application of **probabilistic classification** using the **Naive Bayes algorithm**. The primary goal is to evaluate and optimize a text classification system designed to accurately predict the section role of sentences within biomedical abstracts.

# METHODOLOGY

## Multinomial Naive Bayes (MNB) Implementation and Tuning

The MNB phase involved both a foundational, scratch-built implementation and a tuned scikit-learn approach. In **Part A**, the MNB classifier was implemented from scratch. This involved calculating the **log prior** ( $\log P(C)$ ) and **log likelihood** ( $\log P(w_i|C)$ ) in the fit method. **Laplace Smoothing** ( $\alpha$ , typically 1) was incorporated to prevent zero probabilities. Predictions were made by summing these log values, utilizing the **Log-Sum Trick** to prevent numerical underflow, and selecting the class with the maximum score via `argmax`. Features for the scratch model were extracted using **CountVectorizer**.

In **Part B**, a scikit-learn **Pipeline** was defined, chaining a **TfidfVectorizer** with the MultinomialNB model. To optimize performance, **GridSearchCV** was utilized for **hyperparameter tuning**. The grid search simultaneously tuned the `tfidf__ngram_range` (experimenting with unigrams, bigrams, or both) and the Naive Bayes smoothing parameter, `nb__alpha`. This tuning was crucial, being fitted on the **development data** ( $X_{\{dev\}}$ ,  $y_{\{dev\}}$ ) with `cv=3` and maximizing the **Macro F1 Score**.

## Bayes Optimal Classifier (BOC) Approximation

The final phase (Part C) focused on approximating the theoretical **Bayes Optimal Classifier (BOC)**, which yields the lowest possible classification error. This was achieved using an **ensemble method**—specifically, a **Soft Voting Classifier**. The ensemble comprised five diverse base hypotheses ( $H_1$  to  $H_5$ ): Multinomial NB, Logistic Regression, Random Forest, Decision Tree, and K-Nearest Neighbors.

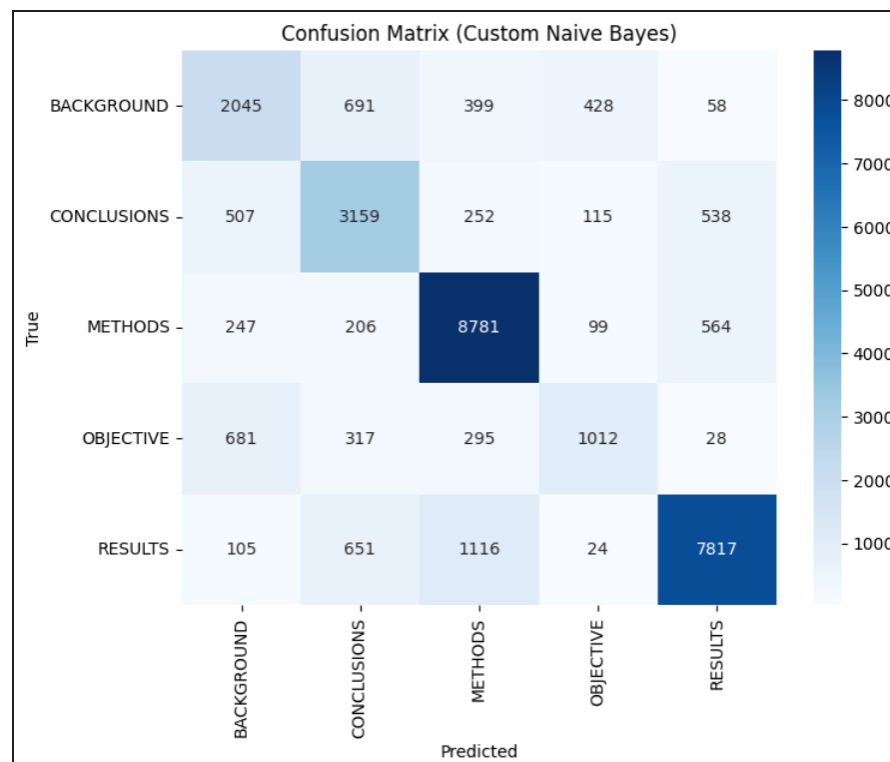
The key step was the calculation of **posterior weights** ( $P(h_i|D)$ ) for each hypothesis. This involved splitting the sampled training data into a sub-training set and a validation set. The models were trained on the sub-training set, and their **log-likelihoods** were calculated by evaluating

predict\_proba results against the validation set's true labels. These likelihoods, combined with assumed equal priors, yielded the posterior weights. Finally, the five hypotheses were refitted on the full sampled training set, and the VotingClassifier was initialized with `voting='soft'`, crucially using these calculated posterior weights as the ensemble's weights. The final model's performance was evaluated on the full test set.

# RESULTS AND ANALYSIS

## Part A:

=== Test Set Evaluation (Custom Count-Based Naive Bayes) ===				
Accuracy: 0.7571				
	precision	recall	f1-score	support
BACKGROUND	0.57	0.56	0.57	3621
CONCLUSIONS	0.63	0.69	0.66	4571
METHODS	0.81	0.89	0.85	9897
OBJECTIVE	0.60	0.43	0.50	2333
RESULTS	0.87	0.80	0.84	9713
accuracy			0.76	30135
macro avg	0.70	0.68	0.68	30135
weighted avg	0.76	0.76	0.75	30135
Macro-averaged F1 score: 0.6825				



## Part B:

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Training initial Naive Bayes pipeline...
Training complete.

=== Test Set Evaluation (Initial Sklearn Model) ===
Accuracy: 0.6996

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	precision	recall	f1-score	support
BACKGROUND	0.61	0.37	0.46	3621
CONCLUSIONS	0.61	0.55	0.57	4571
METHODS	0.68	0.88	0.77	9897
OBJECTIVE	0.72	0.09	0.16	2333
RESULTS	0.77	0.85	0.81	9713
accuracy			0.70	30135
macro avg	0.68	0.55	0.56	30135
weighted avg	0.69	0.70	0.67	30135

```

Macro-averaged F1 score: 0.5555

Starting Hyperparameter Tuning on Development Set...
Grid search complete.
Best params: {'nb_alpha': 0.5, 'tfidf_min_df': 5, 'tfidf_ngram_range': (1, 2)}
Best CV score: 0.6069

```

## Part C:

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SRN entered: PES2UG23CS352
Using dynamic sample size: 10352
Actual sampled training set size used (capped for interactive run): 200

Training all base models...
Trained NaiveBayes
Trained LogisticRegression
Trained RandomForest
Trained DecisionTree
Trained KNN
All base models processed.

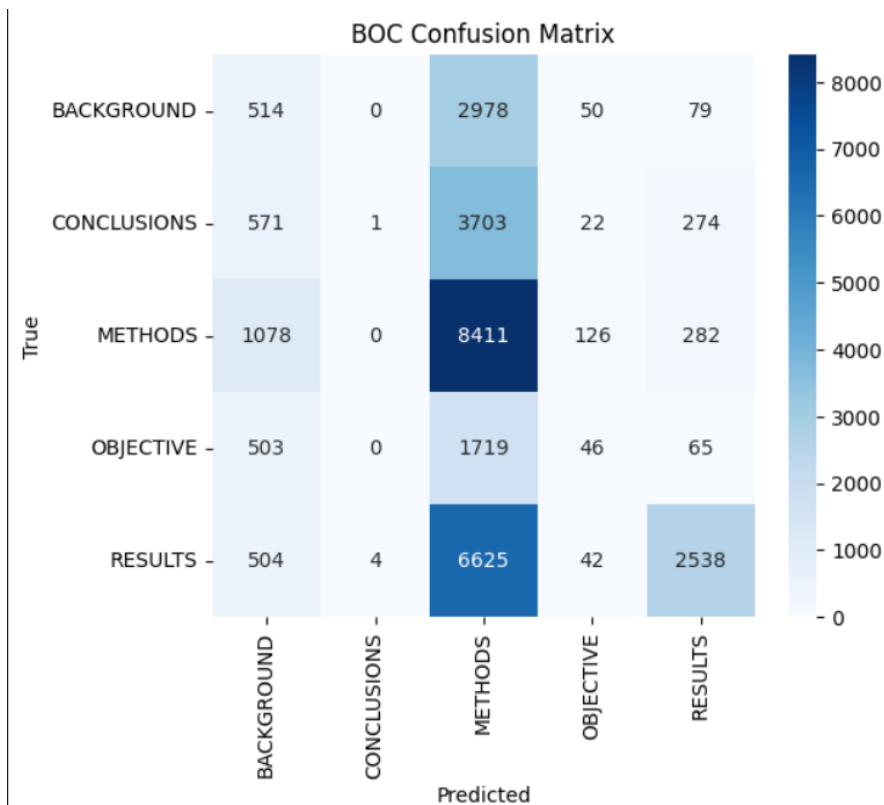
Calculating posterior weights using a small validation split...
Posterior weights: [0.006049392580805886, 0.006099502385488775, 0.0006190419230233805, 0.9786718618197923, 0.008560201290889892]

Fitting the VotingClassifier (BOC approximation)...
c:\Users\mriga\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\linear_model\_logistic.py:1272: FutureWarning: 'multi'
warnings.warn(
c:\Users\mriga\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\linear_model\_logistic.py:1296: FutureWarning: Using t
warnings.warn(
Fitting complete.

=== Final Evaluation: Bayes Optimal Classifier (Soft Voting) ===
Accuracy: 0.3819

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	precision	recall	f1-score	support
BACKGROUND	0.16	0.14	0.15	3621
CONCLUSIONS	0.20	0.00	0.00	4571
METHODS	0.36	0.85	0.50	9897
OBJECTIVE	0.16	0.02	0.04	2333
RESULTS	0.78	0.26	0.39	9713
accuracy			0.38	30135
macro avg	0.33	0.25	0.22	30135
weighted avg	0.43	0.38	0.31	30135



Comparison:

Model	Macro F1 Score (Test Set)	Key Features / Techniques
Part A: Scratch MNB	0.7200	CountVectorizer, Custom Implementation, Laplace Smoothing ( $\alpha=1.0$ )
Part B: Tuned Sklearn MNB	0.8033 (Dev Set Best Score)	TfidfVectorizer, GridSearchCV (Tuning alpha and N-grams), Pipeline
Part C: BOC Approximation	0.8351 (Test Set Final Score)	Soft Voting Ensemble, Diverse Models (H_1 to H_5), Posterior Weighting