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Bayesian Regularized Artificial Neural Network for Sentiment Classification of Amazon Customer Reviews

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Abstract
Sentiment classification plays a vital role in extracting customer opinions from online reviews and supporting intelligent decision-making in e-commerce. Conventional machine learning techniques often experience reduced performance due to high-dimensional textual features and limited generalization capability. This paper proposes a Bayesian Regularized Artificial Neural Network (BRANN) for sentiment classification of Amazon customer reviews. The proposed approach integrates text preprocessing, TF–IDF feature representation, Bayesian regularization, and Levenberg–Marquardt optimization to improve classification accuracy while minimizing overfitting. The Bayesian learning strategy estimates probabilistic network parameters instead of deterministic weights, leading to improved model stability and prediction reliability. Experimental evaluation on the Amazon Customer Review dataset demonstrates an accuracy of **99.34%**, precision of **99.18%**, recall of **99.12%**, and F1-score of **99.15%** after **45 training epochs**. Comparative analysis indicates that the proposed BRANN outperforms several conventional and deep learning models in terms of classification accuracy and convergence efficiency.

Keywords: Bayesian Regularization, Artificial Neural Network, Sentiment Classification, Opinion Mining, Amazon Reviews, TF–IDF.

1. Introduction

Online customer reviews significantly influence purchasing behavior and product reputation. Automatic sentiment classification helps businesses analyze customer opinions efficiently and improve product quality. Traditional classifiers such as Decision Trees, Naïve Bayes, and Support Vector Machines provide reasonable performance but often require extensive feature engineering and may struggle with complex nonlinear relationships.

Artificial Neural Networks improve representation learning but can suffer from overfitting when trained on moderate-sized datasets. Bayesian Regularized Artificial Neural Networks address this limitation by incorporating Bayesian inference during optimization, automatically balancing prediction accuracy with model complexity.

The main contributions of this paper are:

- Development of a Bayesian Regularized Artificial Neural Network for sentiment classification.
- Integration of TF–IDF feature extraction with Bayesian learning.
- Automatic complexity control through Bayesian regularization.
- Comprehensive comparison with conventional classifiers.
- High classification accuracy with rapid convergence.

2. Related Work

Machine learning algorithms such as Naïve Bayes, Decision Trees, and Support Vector Machines have been widely used for sentiment classification. More recent approaches employ CNNs, LSTMs, and transformer-based architectures such as BERT to improve contextual understanding. However, these deep learning models require substantial computational resources and large labeled datasets.

Bayesian learning provides probabilistic parameter estimation and naturally incorporates uncertainty into the training process. Bayesian Regularized Artificial Neural Networks improve generalization by preventing unnecessary weight growth and reducing overfitting. Although Bayesian methods have been explored in several domains, their application to Amazon customer review sentiment classification remains relatively limited, motivating the proposed approach.

3. Proposed Brann Model

A. Dataset

The experiments utilize the Amazon Customer Review dataset containing **4,915 reviews**, divided into **3,440 training samples (70%)** and **1,475 testing samples (30%)**.

B. Preprocessing

The preprocessing pipeline includes:

- Lowercase conversion
- URL removal
- HTML tag removal
- Tokenization
- Stop-word removal
- Lemmatization

C. TF–IDF Feature Extraction

Use the same TF–IDF equations from your first paper to represent review text numerically.

D. Bayesian Regularized Neural Network

Describe the BRANN architecture, Bayesian inference, and the regularized objective function, emphasizing the model rather than the end-to-end framework.

4. Experimental Results

Table I. Experimental Configuration

Parameter	**Value**
Dataset	Amazon Customer Reviews
Samples	4,915
Training	3,440

Parameter	Value
Testing	1,475
Features	TF–IDF
Hidden Layers	3
Epochs	45
Optimizer	Levenberg–Marquardt

(These values are taken from your manuscript.)

Table II. Classification Performance

Metric	Value
Accuracy	99.34%
Precision	99.18%
Recall	99.12%
F1-score	99.15%
MAE	0.67%

(Based on the reported experimental results.)

Table III. Comparison with Existing Methods

Method	Accuracy (%)
Decision Tree	60.54
Naïve Bayes	79.84
SVM	82.48
PSO-SVM	89.00
CNN	92.59
CNN-LSTM	93.00
CNN-SVM	93.50
Proposed BRANN	**99.34**

(Adapted from your comparison table.)

5. Conclusion

This paper presented a Bayesian Regularized Artificial Neural Network for sentiment classification of Amazon customer reviews. Experimental evaluation demonstrated that Bayesian regularization effectively improves model generalization while reducing overfitting. The proposed BRANN achieved high classification accuracy with efficient convergence, making it suitable for intelligent e-commerce analytics and customer feedback analysis. Future work may investigate multilingual sentiment analysis, transformer-based feature extraction, and explainable AI techniques.

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