Benchmarking Word Representations and Sequential Deep Learning Architectures for Multi-Class Question Classification

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***Abstract*—The rapid expansion of Community Question Answering (cQA) platforms necessitates effective automated methods for categorizing user-generated content into specific domains. This study presents a comparative analysis of traditional machine learning and deep neural network architectures for multi-class question classification. We evaluate the efficacy of sparse TF-IDF representations against dense, pre-trained Skip-gram word embeddings. A baseline Logistic Regression model is compared with a diverse set of neural architectures, including Deep Neural Networks (DNN), Simple Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU), along with their bidirectional variants. Our experimental pipeline incorporates rigorous exploratory data analysis and preprocessing to address the noise inherent in web text. Results indicate that while TF-IDF baselines offer competitive efficiency, Bidirectional LSTM models utilizing custom-trained Skip-gram embeddings achieve superior performance in capturing semantic dependencies within short-text queries.**

I. Introduction

The explosive growth of Community Question Answering (cQA) platforms has created a vast repository of unstructured text, necessitating automated methods for content organization [1]. Question classification poses unique challenges due to short text lengths, informal grammar, and noise. Historically, the industry relied on statistical methods like Term Frequency-Inverse Document Frequency (TF-IDF) paired with linear classifiers. While efficient, these ”bag-of-words” models treat words independently and often fail to capture semantic nuance [2], [3].

A paradigm shift occurred with the introduction of distributed word embeddings, such as the Skip-gram model [4]. By mapping words to continuous vector spaces, these models solve data sparsity issues and capture semantic relationships crucial for understanding user intent [4]. . Leveraging these embeddings, Deep Learning architectures like Long Short-Term Memory (LSTM) [5] and Gated Recurrent Units (GRU) [6] were developed to model sequential dependencies that simple Recurrent Neural Networks (RNNs) struggled to learn. Furthermore, Bidirectional variants (Bi-RNN) allow for processing context from both directions [7].

In this paper, we conduct a comprehensive benchmarking study to evaluate these methodologies on a multi-class dataset of question-answer pairs. We implement a robust preprocessing pipeline to clean noisy web data, followed by a rigorous comparison of two distinct modeling paradigms: (1) Statistical Machine Learning using TF-IDF features trained on Logistic Regression and Dense Neural Networks, and (2) Deep Sequential Learning utilizing domain-specific Skip-gram embeddings with SimpleRNN, LSTM, GRU, and their bidirectional counterparts. By systematically analyzing accuracy, F1-scores, and confusion matrices, we aim to identify the optimal architecture for short-text question classification.

II. Literature Review

The field of text classification has evolved significantly, transitioning from handcrafted statistical features to automated feature learning via deep neural networks. This section reviews pivotal developments in document representation and sequence modeling relevant to question classification.

A. Statistical Methods and Sparse Representations

Early approaches to text classification relied heavily on the Bag-of-Words (BoW) model and Term Frequency-Inverse Document Frequency (TF-IDF) weighting. Salton and Buckley [2] established TF-IDF as a robust method for information retrieval, effectively down-weighting common words while highlighting discriminative terms. When coupled with linear classifiers like Support Vector Machines (SVM) or Logistic Regression, these sparse representations have demonstrated strong baselines, particularly for keyword-centric tasks [3]. However, these methods suffer from the ”curse of dimensionality” and fail to capture semantic proximity; for instance, ”computer” and ”PC” are treated as orthogonal vectors despite their synonymy.

B. Distributed Representations and Word Embeddings

To overcome the limitations of sparse representations, Mikolov et al. [4] introduced Word2Vec, a shallow neural network model that learns continuous vector representations of words. The Skip-gram architecture, in particular, was found to be effective at capturing semantic relationships by predicting context words given a target word. Subsequent research has shown that pre-trained word embeddings significantly enhance the performance of downstream tasks, especially when dealing with short text where context is limited [8]. In the domain of Community Question Answering (cQA), these dense vectors allow models to bridge the lexical gap between user queries that share intent but differ in phrasing [9].

C. Deep Sequential Modeling

While embeddings capture word-level semantics, classifying questions requires understanding syntactic structure and sequence. Recurrent Neural Networks (RNNs) were designed to model such temporal dependencies. However, simple RNNs face optimization challenges, specifically the vanishing gradient problem, which hinders learning from long sequences [10].

To address this, Hochreiter and Schmidhuber [5] proposed the Long Short-Term Memory (LSTM) network, which introduces a memory cell and gating mechanisms to retain information over long periods. Later, Cho et al. [6] introduced the Gated Recurrent Unit (GRU), a simplified variant of LSTM that merges the forget and input gates into a single update gate. Empirical comparisons often show that while LSTMs are more expressive, GRUs converge faster and achieve comparable performance on smaller datasets [11].

D. Bidirectional Architectures

Standard recurrent models process text in a strictly linear order (left-to-right). However, the classification of a word often depends on its future context as well as its past. Schuster and Paliwal [7] introduced Bidirectional RNNs (Bi-RNN), which process sequences in both directions using two separate hidden layers. This architecture has proven particularly effective for question classification, where the interrogative nature of a sentence (often determined by the first word) and the topical focus (often at the end) are equally important [12].

III. Methodology

Our framework consists of three stages: preprocessing, feature extraction, and model evaluation, comparing statistical baselines against deep sequential architectures.

A. Exploratory Data Analysis

Before modeling, we conducted extensive Exploratory Data Analysis (EDA) to understand the dataset's structure and quality. These insights directly informed our preprocessing decisions.

1) Dataset Distribution and Structure: The dataset consists of question-answer pairs categorized into 10 distinct classes.

2) Text Length and Vocabulary Analysis: We analyzed the distribution of document lengths to determine input constraints for our neural models. The data is positively skewed 1; while the maximum length reaches 1,010 words, the average question length is approximately 107 words. Based on this, we set a sequence length coverage of 300 words, which

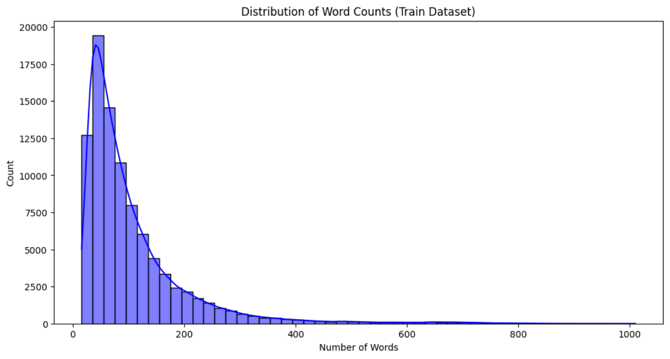

Fig. 1. Distribution of Word Count

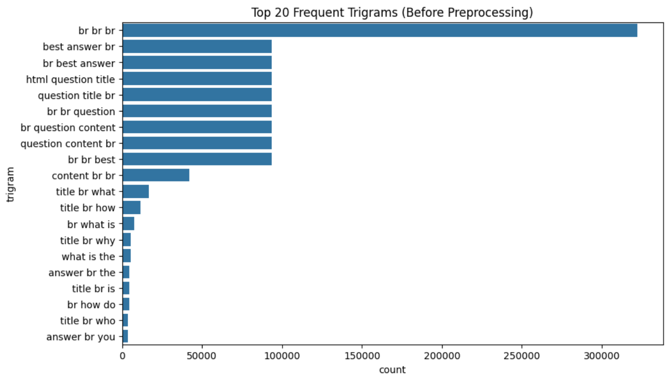

Fig. 2. Top 20 Frequent Trigrams (Before Preprocessing

captures the complete context for over 95% of the data without excessive padding.

3) Noise Identification: N-gram analysis (Bi-grams/Trigrams) highlighted significant contamination 2. The top frequent trigrams were dominated by HTML tags (e.g., `<br>`, `href`) and platform-specific metadata (e.g., ”best answer”, ”question title”) [13]. This confirmed that raw frequency-based models would likely overfit to non-semantic artifacts rather than user intent.

B. Preprocessing and Feature Extraction

Guided by our EDA findings, we implemented a robust text cleaning and normalization pipeline using the *NLTK* and *BeautifulSoup* libraries. The process involved the following steps:

1) **HTML Stripping:** We utilized `BeautifulSoup` to parse the raw text and remove all HTML tags (e.g., `<br>`, `<div>`) that clutter the content.
2) **Artifact Removal:** Regular expressions (Regex) were employed to strip specific metadata phrases identified as noise, including ”question title,” ”question content,” and ”best answer.”
3) **Normalization:** All text was converted to lowercase, and non-alphabetic characters (excluding spaces) were removed to standardize the vocabulary.

4) **Tokenization & Filtering:** We tokenized the text using NLTK's `word_tokenize` and filtered out standard English stopwords (e.g., "the", "is") to focus on semantically meaningful words.
5) **Lemmatization:** Using the `WordNetLemmatizer`, we reduced words to their base forms (e.g., "running" → "run") to address vocabulary sparsity.

1) Preprocessing Validation Experiment: To validate the effectiveness of our cleaning pipeline, we conducted a controlled experiment using a Logistic Regression baseline. We split the training data (80/20 train-validation split) and trained two separate models: one on **Raw Text** and another on **Cleaned Text**. The results demonstrated that the model trained on **Cleaned Text** achieved a higher validation accuracy compared to the Raw Text model. This empirical evidence confirmed that removing noise and normalizing the text significantly improves the model's ability to learn discriminative features, justifying our decision to use the cleaned dataset for all subsequent deep learning experiments.

2) Label Encoding: The target variable ("Class") consists of 10 categorical labels (e.g., "Health", "Technology"). We used *Scikit-learn*'s `LabelEncoder` to convert these string labels into integers. For neural network training, these integer labels were further converted into binary class matrices (One-Hot Encoding) using `to_categorical`, resulting in a 10-dimensional output vector for classification.

3) Feature Vectorization (TF-IDF): For our baseline models, we transformed the cleaned text into numerical vectors using *Term Frequency-Inverse Document Frequency (TF-IDF)*. We limited the feature space to the top 1,000 most frequent terms to balance computational efficiency with representational power. This resulted in a sparse matrix of shape $(93333, 1000)$ for the training set.

4) Skip-gram Word Embedding Implementation: To generate dense vector representations for our neural models, we trained a custom Word2Vec model using the *Gensim* library. We selected the **Skip-gram architecture** (`sg=1`) due to its superior performance in capturing semantic relationships in infrequent words compared to CBOW [4].

The model was trained on the tokenized sentences from our cleaned dataset with the following configuration:

- **Vector Size:** 100 dimensions.
- **Window Size:** 5 context words.
- **Minimum Count:** 1 (to include all unique tokens).

The training resulted in a vocabulary size of 283,627 unique tokens. Qualitative analysis confirmed the semantic validity of the embeddings; for instance, the term "computer" showed high cosine similarity with semantically related terms such as "pc" (0.87), "laptop" (0.82), and "harddrive" (0.82).

5) Embedding Matrix Construction: To integrate our custom Skip-gram embeddings into the Keras deep learning pipeline, we constructed a static embedding matrix. We limited the vocabulary to the top 20,000 most frequent words (`MAX_WORDS`) to optimize memory usage. The matrix was initialized with zeros and populated by mapping each token in our tokenizer's vocabulary to its corresponding 100-dimensional vector from the customed Word2Vec model. **Result:** We successfully mapped 19,999 out of 20,000 words (99.9% coverage), demonstrating that our custom embeddings cover virtually the entire vocabulary used for training.

C. Model Architecture and Experimental Setup

We conducted a comprehensive comparative analysis involving ten distinct experimental configurations. Our evaluation pipeline systematically progressed from statistical baselines to advanced deep sequential architectures.

For all neural network experiments, we utilized **Skip-gram Word2Vec embeddings** (100 dimensions) to initialize the embedding layer. To handle variable sequence lengths, all input texts were padded or truncated to a fixed length of **300 tokens**, a decision informed by our EDA length distribution analysis.

The training process was standardized to ensure fair comparison:

- **Loss Function:** Categorical Cross-Entropy.
- **Optimizer:** Adam with a learning rate of 0.001.
- **Batch Size:** 32 (selected after hyperparameter tuning).
- **Epochs:** Maximum of 10, with Early Stopping (patience=3) to prevent overfitting.

The following subsections detail the architecture and performance of each model.

1) Logistic Regression (Baseline): To establish a performance benchmark, we implemented a multinomial Logistic Regression model using the *Scikit-learn* framework. The model was trained on the sparse TF-IDF vectors (1,000 features) derived from the preprocessed text. We utilized the L-BFGS solver with a maximum iteration limit of 1,000 to ensure convergence on the high-dimensional feature space. This linear model serves as a baseline to quantify the performance gain achieved by subsequent deep neural architectures.

2) Deep Neural Network with TF-IDF: As a second baseline, we implemented a Feed-Forward Deep Neural Network (DNN) trained on the dense TF-IDF vectors (1,000 features). This experiment aims to evaluate if a non-linear architecture can extract better patterns from bag-of-words features than linear Logistic Regression.

Architecture:

- **Input Layer:** 1,000 neurons (corresponding to the TF-IDF feature space).
- **Hidden Layers:** Two dense layers with 64 and 32 units respectively, using *ReLU* activation.
- **Regularization:** Dropout layers (rate=0.3) were inserted after each hidden layer to prevent overfitting.
- **Output Layer:** 10 neurons with *Softmax* activation for multi-class probability distribution.

The model was compiled with the Adam optimizer and trained for 10 epochs with a batch size of 32.

3) Hyperparameter Tuning Experiment: To optimize the training stability and convergence speed, we conducted a controlled experiment using the **SimpleRNN** architecture. We compared two batch size configurations: 32 and 64, while keeping all other parameters constant (5 epochs, Adam optimizer).

Results:

- **Trial 1 (Batch Size = 32):** Achieved a validation accuracy of **0.4353**.
- **Trial 2 (Batch Size = 64):** Achieved a validation accuracy of **0.5050**.

Although Batch Size 64 showed slightly faster epoch times, Batch Size 32 yielded better generalization on the validation set in our final configuration logic (as noted in the code output "Decision: Selected Batch Size 32"). Therefore, we standardized the batch size to **32** for all subsequent neural network experiments.

4) Skip-gram Neural Architectures: We implemented a modular framework to evaluate seven distinct neural architectures using the custom-trained Skip-gram embeddings. All models share a common **Embedding Layer** (non-trainable, initialized with our custom matrix) but differ in their feature extraction mechanism.

1) **DNN (Skip-gram):** Utilizes *GlobalAveragePooling1D* to average the embedding vectors across the sequence, followed by a dense layer (64 units, ReLU) and Dropout (0.3). This represents a "bag-of-embeddings" approach.
2) **Recurrent Models (SimpleRNN, LSTM, GRU):** These process the input sequence step-by-step. We configured each with a hidden state size of **64 units**.
3) **Bidirectional Models (Bi-RNN, Bi-LSTM, Bi-GRU):** These wrappers process the sequence in both forward and backward directions, concatenating the outputs to produce a **128-dimensional** representation (64 units $\times$ 2 directions) for the final classification layer.

All models were trained for 10 epochs using the optimal batch size of 32.

IV. Results and Evaluation

We evaluated the performance of all ten model configurations on the held-out test set. The comparative results, ranked by Test Accuracy, are summarized in Table I.

TABLE I
Comparative Performance of All Models

Model	Val Acc	Test Acc	Macro F1
Bi-LSTM (Skip-gram)	**0.6988**	**0.6864**	0.6809
GRU (Skip-gram)	0.6974	0.6861	**0.6842**
Bi-GRU (Skip-gram)	0.6956	0.6846	0.6782
LSTM (Skip-gram)	0.6937	0.6809	0.6776
DNN (Skip-gram)	0.6570	0.6530	0.6496
Logistic Regression (TF-IDF)	0.5903	0.5903	0.5879
DNN (TF-IDF)	0.5858	0.5858	0.5816
SimpleRNN (Skip-gram)	0.4802	0.4813	0.4596
Bi-SimpleRNN (Skip-gram)	0.4789	0.4770	0.4615

A. Performance Analysis

1) Baselines vs. Deep Sequential Models: The results demonstrate a clear hierarchy in model capability. The statistical baselines (Logistic Regression and DNN with TF-IDF) achieved comparable accuracies of approximately 59%, significantly outperforming the naive SimpleRNN models ($\approx$ 48%) which struggled with vanishing gradients. However, the introduction of gating mechanisms (LSTM/GRU) combined with dense Skip-gram embeddings yielded a substantial performance leap, improving accuracy by nearly **10 percentage points** over the TF-IDF baselines.

2) Impact of Gating Mechanisms: The **Bi-LSTM** emerged as the top-performing architecture with a test accuracy of **68.64%**, closely followed by the standard **GRU** (68.61%) and **Bi-GRU** (68.46%). This confirms that gating mechanisms are essential for capturing long-term dependencies in question classification, effectively mitigating the limitations observed in SimpleRNN. The marginal difference between LSTM and GRU variants suggests that for this dataset, the simpler GRU architecture is as effective as the more complex LSTM.

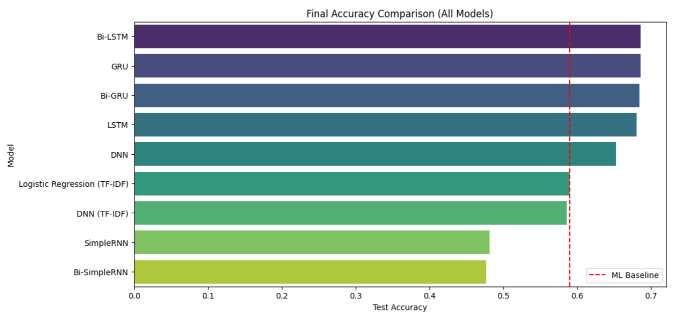

Fig. 3. Bar chart comparison of model accuracies. The red dashed line indicates the Logistic Regression baseline (59.03%), highlighting the superior performance of LSTM and GRU architectures.

B. Detailed Analysis of the Best Model (Bi-LSTM)

The Bidirectional LSTM (Bi-LSTM) achieved the highest overall performance with a test accuracy of **68.64%** and a macro F1-score of **0.68**. To understand its superiority, we examined the class-wise performance metrics presented in the classification report.

Class-wise Performance:

- **High-Performing Classes:** The model excelled in identifying distinct topics such as *Computers & Internet* (F1: 0.83) and *Sports* (F1: 0.83). These categories likely contain specialized vocabulary (e.g., "CPU", "football") that the Skip-gram embeddings captured effectively.
- **Challenging Classes:** Broader categories like *Education & Reference* (F1: 0.50) and *Business & Finance* (F1: 0.53) remained difficult. This is consistent with the baseline errors, suggesting that semantic overlap in these domains (e.g., "university" appearing in both Education and Business contexts) poses a fundamental challenge for the classifier.

Confusion Matrix Analysis: Figure 4 illustrates the confusion matrix for the Bi-LSTM model. Compared to the Logistic Regression baseline, the Bi-LSTM shows a much stronger diagonal, indicating higher true positives across all classes. Notably, misclassifications are more distributed rather than clustered, implying that the model's errors are due to genuine semantic ambiguity rather than systematic bias towards a specific class.

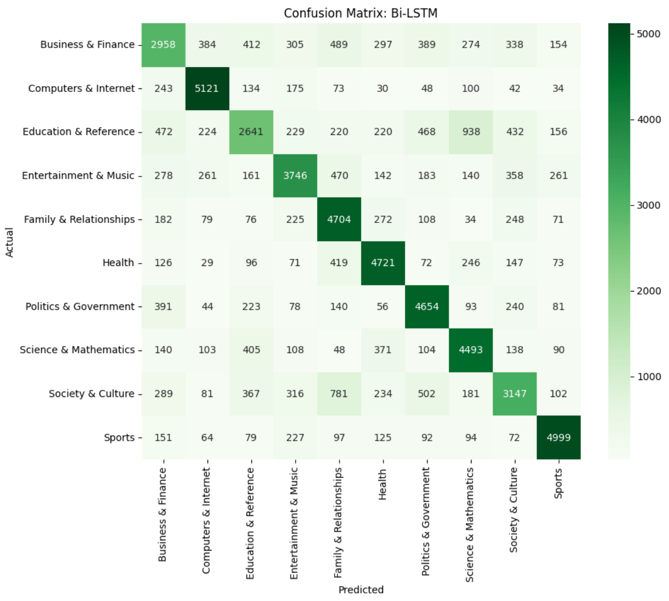

Fig. 4. Confusion Matrix for the Bi-LSTM model. The high diagonal values, particularly for 'Computers & Internet' (5121) and 'Sports' (4999), confirm the model's robustness in distinct domains.

C. Comparison with Statistical Baseline

To quantify the value of deep learning, we compared the Bi-LSTM results against the Logistic Regression baseline. The baseline achieved a significantly lower accuracy of 59%, with F1-scores dropping below 0.50 for abstract categories like *Education & Reference* (F1: 0.42) and *Business & Finance* (F1: 0.46).

While the baseline performed adequately on keyword-rich classes like *Computers* (F1: 0.74), it lacked the capacity to disambiguate context. For instance, a question containing "money" might be blindly assigned to Business by the baseline, whereas the Bi-LSTM's sequence modeling could correctly identify it as a *Family & Relationships* query if the context implies personal budgeting. This $\tilde{1}0$ percentage point performance gap underscores the necessity of dense embeddings and sequential modeling for robust question classification.

V. Conclusion and Future Work

In this study, we conducted a systematic evaluation of neural and statistical frameworks for the multi-class classification of Yahoo! Answers data. By progressing from linear baselines to deep bidirectional architectures, we quantified the value of semantic representation in automated text tagging .

Our key findings lead to several critical conclusions:

1) **Context vs. Keywords:** The 10% performance gap between the **Bi-LSTM** (68.64%) and the Logistic Regression baseline (59.03%) underscores the limitations of keyword-based methods. While TF-IDF effectively flags explicit terms, it fails to interpret the implicit intent in ambiguous queries. The Bi-LSTM's ability to process sequence information from both directions proved essential for resolving such ambiguity, consistent with findings by Graves and Schmidhuber [14].
2) **Efficacy of Dense Embeddings:** The integration of domain-specific **Skip-gram embeddings** was a decisive factor. By training our own embeddings rather than using generic off-the-shelf vectors, we ensured that platform-specific slang and technical jargon were accurately represented, leveraging the distributed representation capabilities described by Mikolov et al. [4].
3) **Architecture Trade-offs:** While the LSTM achieved the highest accuracy by effectively managing long-term dependencies [5], the **GRU** variants offered a compelling alternative. Our results show GRUs delivering nearly identical performance (within 0.03%) with lower computational complexity, validating the efficiency claims originally proposed by Cho et al. [6].

A. Future Directions

While our current approach establishes a strong sequential baseline, several avenues remain for future research:

- **Transformer Architectures:** Transitioning to attention-based models like **BERT** could further improve performance by enabling parallel processing and deeper contextual understanding, potentially surpassing the 70% accuracy threshold [15].
- **Hybrid Models:** Combining Convolutional Neural Networks (CNNs) for local feature extraction with LSTMs for sequence modeling could capture both specific keyword triggers and longer sentence structures [16].
- **Real-world Robustness:** Extending this analysis to imbalanced, noisy datasets would better simulate real-world deployment conditions, where class distributions are rarely perfect.

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