Engineering and Technology Journal e-ISSN: 2456-3358

Volume 09 Issue 12 December-2024, Page No.- 5659-5664

DOI: 10.47191/etj/v9i12.14, I.F. – 8.227

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Product Matching using Sentence-BERT: A Deep Learning Approach to E-Commerce Product Deduplication

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ABSTRACT: Product matching in e-commerce platforms presents a significant challenge due to variations in product titles, descriptions, and categorizations across different vendors. This paper presents a lightweight yet effective approach to product matching using Sentence-BERT (SBERT), specifically the all-MiniLM-L6-v2 variant. Our method combines efficient text preprocessing, strategic training pair generation, and threshold-based similarity matching to achieve high-accuracy product matching while maintaining computational efficiency. The system was evaluated on the Pricerunner dataset, achieving exceptional results with 98.10% accuracy, 100% precision, and 91.84% recall. The implementation includes a modular architecture that facilitates maintenance and updates, while the threshold-based matching strategy allows fine-tuned control over precision-recall trade-offs. Our results suggest that carefully designed preprocessing and training strategies, combined with lightweight transformer models, can achieve state-of-the-art performance in product matching without requiring complex model architectures or extensive computational resources.

KEYWORDS: Product Matching, Sentence-BERT, E-commerce, Semantic Similarity

I. INTRODUCTION

The explosive growth of e-commerce platforms has led to an unprecedented challenge in managing and organizing product data across multiple vendors and marketplaces. A critical aspect of this challenge is the accurate identification and matching of identical or similar products listed under different names, descriptions, and categorizations. Traditional approaches based on string matching and rule-based systems often fall short in capturing the semantic similarities between product listings, particularly when dealing with variations in terminology, formatting, and descriptive styles [1].

Recent advances in natural language processing (NLP) and deep learning have opened new avenues for addressing this challenge. In particular, Sentence-BERT (SBERT), a modification of the BERT architecture optimized for generating semantically meaningful sentence embeddings, has shown remarkable promise in various semantic similarity tasks [2]. While BERT models have revolutionized NLP tasks through their contextual understanding of language [3], their computational complexity and the need for pair-wise comparisons make them impractical for large-scale product matching scenarios. SBERT addresses these limitations by generating fixed-size sentence embeddings that can be compared using simple similarity metrics, making it particularly suitable for product matching applications.

This paper presents a novel approach to product matching that leverages the semantic understanding capabilities of SBERT. Our method combines the power of transformer-based language models, specifically the all-MiniLM-L6-v2 SBERT model, with domain-specific training data to create a robust system capable of identifying matching products across different e-commerce platforms. We demonstrate that this lightweight yet effective approach achieves exceptional performance on real-world product matching tasks, with 98.10% accuracy and 100% precision, while maintaining computational efficiency suitable for production environments [4].

The primary contributions of this work are:

1. A comprehensive framework for applying SBERT to the product matching domain, including efficient training pair generation and similarity threshold-based matching strategies
2. An effective text preprocessing pipeline that handles common variations in product titles while maintaining semantic meaning
3. A practical implementation that balances accuracy with computational efficiency, suitable for real-world e-commerce applications
4. Empirical evaluation demonstrating the effectiveness of our approach using the Pricerunner dataset

The remainder of this paper is organized as follows: Section 2 reviews related work in product matching and semantic similarity modeling. Section 3 describes our methodology and implementation details. Section 4 presents experimental results and analysis. Finally, Section 5 discusses conclusions and future research directions.

II. RELATED WORK

The challenge of product matching has been extensively studied in both academia and industry, with approaches evolving from simple string matching techniques to sophisticated deep learning methods. This section reviews the key developments in this field, focusing on three main areas: traditional approaches, deep learning methods, and specific applications of transformer-based models in e-commerce.

A. Traditional Product Matching Approaches

Early attempts at product matching primarily relied on string similarity metrics and rule-based systems. Köpcke et al. [5] provided a comprehensive survey of these methods, highlighting the use of techniques such as Levenshtein distance, Jaccard similarity, and TF-IDF vectors. While these approaches proved effective for exact matches and minor variations, they struggled with semantic similarities and contextual understanding. Cohen et al. [6] introduced more sophisticated string matching algorithms, including hybrid approaches that combined multiple similarity metrics, but these still faced limitations with heterogeneous product descriptions and varying attribute formats.

B. Deep Learning in Product Matching

The advent of deep learning brought significant improvements to product matching accuracy. Word embeddings, particularly Word2Vec [7] and GloVe [8], enabled better semantic understanding of product descriptions. These approaches demonstrated superior performance compared to traditional string-based methods by capturing word-level semantic relationships. Fu et al. [9] extended this concept by incorporating product attributes and hierarchical category information into the embedding space, achieving notable improvements in matching accuracy.

C. Transformer-based Approaches and SBERT

The introduction of BERT [3] marked a paradigm shift in NLP tasks, including product matching. Several studies have explored BERT's application in e-commerce scenarios. Wang et al. [10] demonstrated BERT's effectiveness in product title matching, while Zhang et al. [11] proposed a modified BERT architecture specifically for e-commerce search and matching tasks. However, these approaches often faced scalability challenges due to BERT's computational requirements for pair-wise comparisons.

Sentence-BERT [2] addressed many of these computational limitations while maintaining strong semantic understanding capabilities. Its architecture, optimized for generating sentence embeddings, has shown particular promise in e-commerce applications where efficient computation of similarity scores is crucial. Recent work by Liu et al. [12] demonstrated that lightweight SBERT models like MiniLM can achieve competitive performance while significantly reducing computational overhead.

D. Similarity Metrics and Matching Strategies

A critical aspect of product matching systems is the choice of similarity metrics and matching strategies. Recent work has shown that cosine similarity applied to transformer-based embeddings can effectively capture semantic relationships between product titles [13]. Additionally, research has demonstrated the importance of appropriate similarity thresholds in balancing precision and recall for product matching tasks [14]. Our work builds on these findings by implementing a threshold-based matching strategy with cosine similarity measures.

E. Cross-lingual and Multi-modal Product Matching

An emerging area of research focuses on cross-lingual and multi-modal product matching. Studies by Martinez-Gil et al. [13] explored the challenges of matching products across different languages and markets, while Chen et al. [14] investigated the integration of visual and textual features for more robust product matching. These approaches highlight the increasing complexity of product matching in global e-commerce platforms and the need for more sophisticated solutions.

F. Gaps in Current Research

Despite these advances, several challenges remain unaddressed in the current literature. First, most existing approaches focus on specific product categories or marketplaces, limiting their generalizability. Second, the handling of noisy and incomplete product descriptions remains problematic. Third, the trade-off between computational efficiency and matching accuracy continues to be a significant concern for large-scale applications. Our work aims to address these gaps through a novel application of SBERT that combines efficient computation with robust semantic understanding.

III. METHODOLOGY

This section presents our approach to product matching using Sentence-BERT, detailing the model architecture, preprocessing pipeline, training strategy, and matching algorithm.

A. Model Architecture

Our system is built upon the all-MiniLM-L6-v2 variant of Sentence-BERT, chosen for its optimal balance between performance and computational efficiency. This model is a distilled version of BERT that maintains strong semantic understanding capabilities while requiring significantly fewer computational resources. The architecture generates fixed-size embeddings (384 dimensions) for product titles, enabling efficient similarity computations through cosine similarity measures.

B. Data Preprocessing Pipeline

The preprocessing pipeline is designed to handle common variations in product titles while preserving semantic meaning. Our implementation includes the following steps:

1. Text normalization:

   - Conversion to lowercase
   - Removal of special characters and punctuation
   - Whitespace normalization
2. Missing value handling through empty string conversion
3. Regular expression-based cleaning to retain only alphanumeric characters

This pipeline is implemented through the following function:

```
def preprocess_text(text: str) -> str:
    if pd.isna(text):
      return ""
    text = str(text).lower()
    text = re.sub(r'[^a-z0-9\s]', ' ', text)
    text = ' '.join(text.split())
    return text
```

C. Training Strategy

Our training approach focuses on efficient fine-tuning of the SBERT model for product matching, achieving high precision through careful pair generation and loss optimization.

We implement a strategic pair generation process that creates both positive and negative examples:

- Positive pairs: Products from the same cluster (matching products)
- Negative pairs: Products from different clusters (non-matching products)
- Balanced sampling to prevent class imbalance

The model is trained using cosine similarity loss, optimizing for the following objectives:

- Maximizing similarity between matching products
- Minimizing similarity between non-matching products
- Batch-wise training with a size of 32 samples
- Training duration of 3 epochs, empirically determined for optimal performance

D. Matching Algorithm

Our matching algorithm implements an efficient similarity-based approach with a carefully tuned threshold of 0.8, which was empirically determined to achieve optimal precision:

1. Embedding Generation:
   - Convert preprocessed product titles to fixed-size embeddings (384 dimensions)
   - Utilize batch processing for computational efficiency
2. Similarity Computation:
   - Calculate cosine similarity between query and candidate embeddings
   - Implementation using efficient matrix operations
3. Match Selection:
   - Apply similarity threshold (0.8)
   - Select highest similarity matches above threshold
   - Return detailed match information including product IDs and similarity scores

E. Implementation Details

The system is implemented in Python, utilizing key libraries including:

- sentence-transformers for SBERT implementation
- PyTorch for deep learning operations
- pandas for data handling
- scikit-learn for similarity computations
- logging for system monitoring

The implementation prioritizes modularity and maintainability while ensuring efficient processing of large product catalogs.

IV. EXPERIMENTAL RESULTS

This section presents the empirical evaluation of our product matching system, demonstrating its effectiveness on real-world e-commerce data.

A. Experimental Setup

The experiments were conducted using the Pricerunner dataset, which contains product listings from various e-commerce platforms. The dataset was split into training (80%) and testing (20%) sets, ensuring a balanced representation of different product categories and cluster sizes.

We evaluated our system using standard classification metrics:

- Accuracy: Proportion of correct predictions (both true positives and true negatives)
- Precision: Proportion of correct positive predictions
- Recall: Proportion of actual positives correctly identified
- F1-Score: Harmonic mean of precision and recall

B. Results and Analysis

Our system achieved exceptional performance across all evaluation metrics:

Accuracy:	0.9810 (98.10%)
Precision:	1.0000 (100.0%)
Recall:	0.9184 (91.84%)
F1-Score:	0.9574 (95.74%)

The results demonstrate several key strengths of our approach:

1. **Perfect Precision**: The system achieved 100% precision, indicating that when it identifies a match, it is always correct. This is crucial for e-commerce applications where false positives can be particularly costly.
2. **High Accuracy**: The overall accuracy of 98.10% shows the system’s robust performance across both matching and non-matching cases.

3. **Strong Recall**: The recall of 91.84% indicates that the system successfully identifies the vast majority of true matches, though there is still room for improvement in catching all potential matches.
4. **Balanced Performance**: The F1-score of 95.74% demonstrates that the system maintains a good balance between precision and recall, making it suitable for real-world applications.

The gap between precision and recall (100% vs 91.84%) suggests that the system's conservative threshold of 0.8 successfully prioritizes precision over recall, preferring to miss some potential matches rather than make incorrect predictions. This behavior aligns with our design goals for e-commerce settings where the cost of false positives (incorrectly matched products) typically exceeds the cost of false negatives (missed matches). The high accuracy of 98.10% demonstrates that this trade-off effectively balances the overall system performance.

C. Comparative Analysis

Our results compare favorably with previous approaches reported in the literature:

1. Traditional string-matching approaches typically achieve 70-80% accuracy [5]
2. Word embedding methods report 85-90% accuracy [7]
3. Standard BERT-based approaches achieve 93-95% accuracy [10]

Our system's performance (98.10% accuracy) represents a significant improvement over these baselines while maintaining computational efficiency through the use of the lightweight MiniLM architecture.

D. Performance Considerations

The system's high precision and computational efficiency make it particularly suitable for production environments where:

- False positives must be minimized to maintain data quality
- Processing time and resource usage need to be optimized
- Large-scale product catalogs need to be matched efficiently

These results validate our approach of combining efficient preprocessing, strategic training pair generation, and threshold-based matching using the lightweight SBERT model.

The challenge of product matching has been extensively studied in both academia and industry, with approaches evolving from simple string matching techniques to sophisticated deep learning methods. This section reviews the key developments in this field, focusing on three main areas: traditional approaches, deep learning methods, and specific applications of BERT-based models in e-commerce.

CONCLUSIONS

This paper presented a highly effective approach to product matching using Sentence-BERT, specifically designed for real-world e-commerce applications. Our implementation successfully addresses several key challenges in the product matching domain:

1. **High Accuracy and Precision**: The system achieved exceptional performance metrics (98.10% accuracy, 100% precision) while maintaining computational efficiency through the use of a lightweight transformer model. These results demonstrate that carefully designed preprocessing and training strategies can achieve state-of-the-art performance without requiring complex model architectures.

2. **Practical Implementation**: Our approach prioritizes production readiness through:
   - Efficient preprocessing pipelines that handle common variations in product titles
   - Strategic training pair generation that balances positive and negative examples
   - Threshold-based matching that allows for fine-tuned control over precision-recall trade-offs
   - Modular implementation that facilitates maintenance and updates

3. **Computational Efficiency**: By utilizing the all-MiniLM-L6-v2 variant of SBERT, our system achieves high performance while maintaining reasonable computational requirements, making it suitable for deployment in production environments with large-scale product catalogs.

While our current implementation demonstrates strong performance, with 98.10% accuracy and perfect precision, several promising directions for future research emerge:

1. **Dynamic Threshold Optimization**
   - Improve upon our current fixed threshold of 0.8 through adaptive thresholding based on product categories or market segments
   - Explore machine learning approaches for automatic threshold tuning
   - Develop category-specific matching strategies to potentially improve recall while maintaining precision
2. **Cross-lingual Product Matching**
   - Extend the current approach to handle product titles in multiple languages
   - Investigate zero-shot cross-lingual transfer capabilities of multilingual SBERT models
   - Develop language-agnostic preprocessing strategies for improved generalization

3. **Enhanced Feature Integration**
   - Incorporate additional product attributes beyond titles (e.g., descriptions, specifications)
   - Develop multi-modal matching capabilities by integrating image features
   - Explore graph-based approaches for leveraging product relationship information
4. **Scalability Improvements**
   - Investigate efficient indexing strategies for faster similarity search
   - Optimize the current 384-dimensional embeddings for large-scale deployments
   - Enhance batch processing for improved throughput
5. **Model Robustness**
   - Develop techniques for handling emerging product categories
   - Improve resilience to adversarial product listings
   - Enhance performance on long-tail products with limited training data

The success of our implementation has several important implications for the e-commerce industry:

1. **Data Quality**: The perfect precision achieved by our system makes it particularly valuable for maintaining high-quality product databases, crucial for modern e-commerce platforms.
2. **Cost Efficiency**: The combination of high accuracy and computational efficiency suggests that effective product matching can be achieved without requiring extensive computational resources.
3. **Scalability**: The modular nature of our implementation allows for easy adaptation to different product categories and market segments, making it a versatile solution for various e-commerce applications.

These findings suggest that practical, efficient approaches to product matching can achieve exceptional performance when carefully designed and implemented. As e-commerce continues to grow and evolve, the need for accurate and efficient product matching solutions becomes increasingly critical. Our work provides a solid foundation for future developments in this important area.

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