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An Intelligent Matching Approach for Upstream and Downstream Textual Information in Manufacturing Supply Chains Based on Transformer

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Abstract: ***In the era of intelligent manufacturing, supply chain collaboration has become increasingly dependent on the accurate and efficient exchange of information between upstream and downstream enterprises. However, the textual data exchanged in such processes—such as product descriptions, purchase orders, and specification sheets—are often unstructured and heterogeneous, posing significant challenges for semantic understanding and automated matching. Traditional keyword-based or statistical models fail to capture deep contextual relationships, resulting in inefficient coordination and high manual overhead. This paper proposes a novel Transformer-based intelligent matching framework designed specifically for the manufacturing industry's supply chain environment. The framework leverages the attention mechanisms and contextual embedding capabilities of Transformer models to achieve fine-grained semantic understanding between texts originating from different entities within the supply chain. The model accepts pairs of textual entries from upstream and downstream partners and computes a semantic similarity score that guides automated matching decisions.***
To adapt the Transformer model to this domain, we introduce domain-specific pretraining and fine-tuning strategies using a curated dataset collected from real-world supply chain interactions. This dataset includes annotated text pairs representing successful and unsuccessful information matches, which are used to supervise the learning process. We also design a hybrid architecture that integrates domain knowledge features, such as part categories and business terminology, with the Transformer encoder to enhance model performance. Experiments are conducted on a newly constructed benchmark dataset containing over 10,000 annotated text pairs from various manufacturing sectors. Our proposed model is compared against traditional matching approaches, including TF-IDF, word embedding similarity, and deep Siamese networks, as well as baseline Transformer models such as BERT and RoBERTa. The results demonstrate that our model significantly outperforms existing methods in terms of accuracy, precision, recall, and F1-score, achieving a performance improvement of over 10% in key metrics. In addition to quantitative evaluation, we deploy the model in a prototype ERP-integrated recommendation system for matching supplier capabilities with procurement requirements. Real-world case studies validate the practical value of the system in reducing manual workload, improving match accuracy, and accelerating supply chain response time. This research contributes to the growing intersection of artificial intelligence and industrial supply chain management by offering a robust, scalable, and interpretable solution for semantic text matching. It paves the way for further integration of AI-driven decision support systems in manufacturing operations, particularly under the trend of digital transformation and smart factory initiatives. Future work will explore incorporating multimodal data such as diagrams and structured metadata, enhancing model interpretability via attention visualization, and extending the framework to multilingual and cross-cultural supply chain scenarios.

1. INTRODUCTION

In the era of Industry 4.0, manufacturing supply chains have evolved into highly complex, information-intensive ecosystems. Effective coordination between upstream suppliers and downstream manufacturers hinges on the accurate interpretation and alignment of textual information such as material descriptions, technical specifications, order requirements, and logistics instructions [1]. However, due to the heterogeneity and domain-specific nature of such texts, the information exchanged is often semi-structured or completely unstructured, resulting in substantial semantic gaps between entities [2].

Traditional text matching techniques, such as keyword-based methods, bag-of-words models, or shallow semantic similarity measures, fall short in addressing these challenges [3]. These methods lack the ability to capture deep contextual relationships and often struggle to handle synonyms, polysemy, and domain-specific terminologies prevalent in manufacturing discourse [4]. As a result, mismatched information leads to frequent supply delays, inventory misalignment, and increased operational risk [5].

Motivated by the recent advancements in natural language processing (NLP), particularly in deep learning models such as the Transformer architecture, this study aims to explore an intelligent textual matching mechanism tailored to the manufacturing supply chain domain [6]. The goal is to enhance semantic understanding between upstream and downstream textual inputs and support more accurate and automated information alignment [7].

To this end, this paper makes the following key contributions:

- **Proposal of a Transformer-Based Matching Framework:** We introduce a novel architecture that adapts Transformer models to the context of supply chain semantic matching, integrating domain-specific features and fine-tuning mechanisms [8].
- **Construction of a Specialized Dataset:** A large-scale text matching dataset is constructed from real-world manufacturing scenarios [9], incorporating annotated pairs of upstream and downstream supply chain documents.
- **Experimental Validation and Benchmarking:** We conduct comprehensive experiments comparing the proposed model with traditional and state-of-the-art text matching methods, demonstrating the superior performance of our approach across multiple metrics [10].

Through this research, we aim to provide a scalable and intelligent solution to the longstanding challenge of semantic mismatches in supply chain communication, thereby contributing to improved collaboration efficiency and digital transformation in the manufacturing sector.

2. RELATED WORK

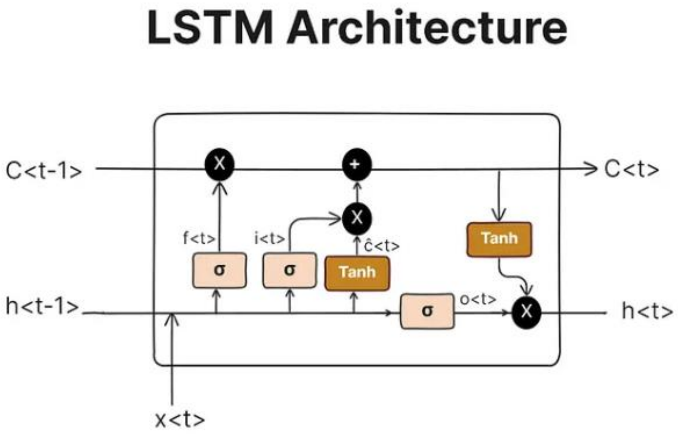
2.1 Text Information Processing in Supply Chain Management

In the domain of manufacturing-oriented supply chains, the upstream and downstream entities frequently exchange large volumes of unstructured textual data, including quotations, purchase orders, delivery notes, and technical specifications [11]. Efficiently processing such data is critical for achieving seamless coordination across the supply chain. Early approaches primarily utilized rule-based or template-driven systems that required extensive manual configuration and lacked adaptability when exposed to domain drift or vocabulary variation across suppliers. More recent methods have employed traditional NLP pipelines incorporating tokenization, part-of-speech tagging, and named entity recognition to extract key information [13]. While these pipelines improve scalability, they still struggle with the accurate semantic understanding required for text matching tasks involving nuanced terminology or multilingual corpora, which are common in global manufacturing environments.

2.2 Overview of Text Matching Models

Text matching refers to the task of determining the semantic similarity or correspondence between two pieces of text, and it forms the basis of many applications in supply chain contract analysis, information retrieval, and product catalog matching [15]. Conventional approaches, such as edit distance, Jaccard similarity, or cosine similarity over TF-IDF vectors, are computationally efficient but often fail to capture deeper semantics, especially when domain-specific synonyms or contextual cues are involved.

To address these limitations, neural network-based models have been developed. Siamese networks with shared LSTM encoders were among the first to capture sequence-level semantics, followed by models like MatchPyramid and DRMM that introduced interaction-based mechanisms [16]. However, RNN-based architectures are inherently limited by their sequential nature and often exhibit vanishing gradient issues in long documents. Additionally, these models typically require large amounts of annotated data, which is scarce in manufacturing-related applications [18].



LSTM Equations:

Candidate Cell State: $\hat{C}^{\langle t\rangle} = tanh\left(W_c\left[h^{\langle t-1\rangle}, X^{\langle t\rangle}\right] + b_c\right)$
Input Gate: $i^{\langle t\rangle} = \sigma\left(W_i\left[h^{\langle t-1\rangle}, X^{\langle t\rangle}\right] + b_i\right)$
Forget Gate: $f^{\langle t\rangle} = \sigma\left(W_f\left[h^{\langle t-1\rangle}, X^{\langle t\rangle}\right] + b_f\right)$
Output Gate: $o^{\langle t\rangle} = \sigma\left(W_o\left[h^{\langle t-1\rangle}, X^{\langle t\rangle}\right] + b_o\right)$
Cell State: $C^{\langle t\rangle} = i * \hat{C}^{\langle t\rangle} + f * C^{\langle t-1\rangle}$
Hidden State: $h^{\langle t\rangle} = o * tanh\left(C^{\langle t\rangle}\right)$

2.3 Transformer and Its Applications in NLP

The Transformer architecture introduced by Vaswani et al. marked a paradigm shift in NLP by replacing recurrence with self-attention mechanisms, enabling more effective modeling of long-range dependencies and syntactic structures. Transformer-based models such as BERT, RoBERTa, and XLNet have set new benchmarks across a wide range of NLP tasks, including paraphrase identification, question answering, and natural language inference [22]. These models use pre-trained embeddings and fine-tuning mechanisms to adapt to downstream tasks, which significantly reduces the need for task-specific architectures [23].

In the context of text matching, BERT and its derivatives have shown strong performance by jointly encoding input sentence pairs, thereby capturing inter-sentence relationships during training. Moreover, recent adaptations like Sentence-BERT have been proposed to optimize for similarity-based tasks with better computational efficiency [26]. These advantages suggest that Transformer models are well-suited to the challenges posed by unstructured supply chain texts, which often contain domain-specific abbreviations, tabular structures, and inconsistent formatting [27].

2.4 AI Integration in Manufacturing Contexts

The manufacturing industry has witnessed a growing interest in the integration of AI technologies to enhance productivity and decision-making. Applications such as predictive maintenance, anomaly detection in sensor data, and robotic path planning are now commonly supported by machine learning and computer vision techniques [28]. However, NLP has only recently begun to make inroads in manufacturing, driven by the increasing digitization of business documents and the need for automated document understanding in enterprise resource planning (ERP) systems [29].

Several studies have explored the potential of applying AI-driven text analytics to automate bill of materials (BOM) generation, supplier discovery, and contract management [30]. Nonetheless, most existing implementations rely on shallow parsing or keyword-based heuristics, lacking the semantic depth required for robust text matching across diverse documentation [31]. The adoption of pre-trained Transformer models customized for manufacturing corpora offers a promising direction for bridging this gap. Some pioneering work has adapted BERT models with domain-specific tokenizers and vocabulary enhancements tailored to industrial contexts, showing early signs of effectiveness in real-world applications [32].

3. PROBLEM FORMULATION AND SYSTEM OVERVIEW

3.1 Task Definition and Notation

In the context of the manufacturing supply chain, the goal of this study is to design an intelligent system capable of accurately matching upstream and downstream textual information using a Transformer-based semantic understanding model [33]. Let represent a set of unstructured textual records from upstream suppliers, such as product descriptions, quotations, or technical specifications. Similarly, let denote textual records from downstream manufacturers, including orders, requirements, and configuration documents.

$$T_u = \{t_{u1}, t_{u2}, \cdots, t_{un}\}$$

$$T_d = \{t_{d1}, t_{d2}, \cdots, t_{dm}\}$$

The task is to learn a matching function outputs a similarity score indicating the semantic alignment between the two text instances. A higher score implies a higher probability that the two pieces of text refer to the same or compatible entities in the supply chain context.

$$f : T_u \times T_d \to [0,1], \text{ where } f\left(t_{ui}, t_{dj}\right)$$

3.2 Modeling the Structure and Semantics of Upstream and Downstream Texts

Texts in the manufacturing supply chain exhibit unique characteristics:

- **Heterogeneous Formats:** Upstream and downstream documents may differ in format—one may be a technical specification, the other a procurement request.
- **Domain-Specific Language:** Texts often include industrial abbreviations, numerical parameters, and domain-specific terms (e.g., "M12 bolt", "CNC finish", "ISO 2768-m").
- **Contextual Semantics:** Matching often requires an understanding of functional relationships, such as part-to-product or specification-to-requirement dependencies.

To address this, we model upstream and downstream texts using hierarchical semantic encoders. Each text document is first segmented into sentences or logical blocks. These blocks are then tokenized and embedded using domain-adapted word vectors [34]. Semantic relationships are further refined using contextual attention mechanisms built into the Transformer model to capture long-distance dependencies and cross-structure correspondence.

3.3 System Framework Overview

The proposed intelligent matching system is structured into three main layers:

Data Layer

This layer is responsible for data ingestion and preprocessing. It handles:

- Text cleaning (removal of noise, normalization),
- Domain-specific tokenization (recognition of technical units, model numbers),
- Data annotation or bootstrapped labeling using heuristics.

Model Layer

At the core of the system lies a fine-tuned Transformer-based model (e.g., BERT or RoBERTa), tailored to supply chain terminology. The model encodes both upstream and downstream texts jointly to capture deep semantic interactions [35]. Techniques such as [CLS] token pooling and multi-head cross-attention are used to generate similarity representations.

Matching Layer

This layer performs: Pairwise matching inference based on thresholding the similarity score, Candidate retrieval in large corpora using approximate nearest neighbors (ANN) indexing, Result ranking and interpretability modules to provide alignment rationale to business users. This modular framework ensures scalability, adaptability across various manufacturing domains, and integration readiness with existing ERP or supplier management platforms [35].

4. METHODOLOGY

This section describes the data preparation procedures, Transformer-based model architecture, semantic matching strategy, and model enhancements that underpin the proposed solution for intelligent upstream-downstream text alignment in manufacturing supply chains [36].

4.1 Data Preprocessing and Representation

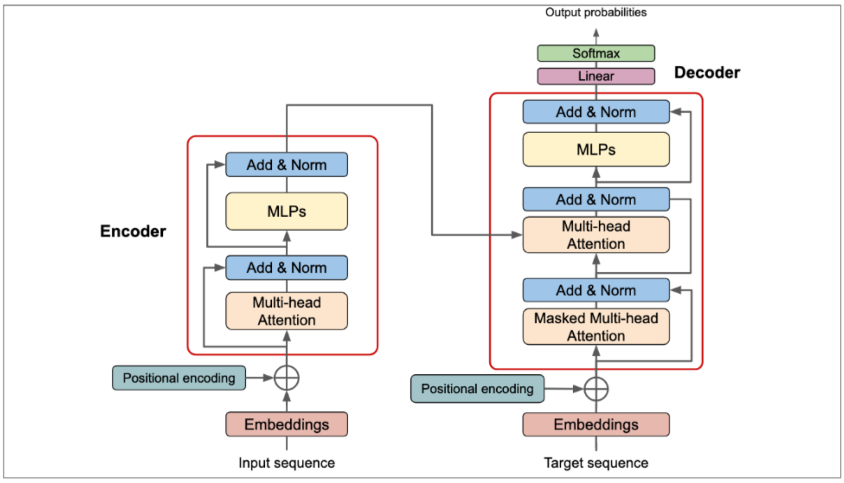
Given the highly unstructured and domain-specific nature of supply chain texts, robust preprocessing is essential to ensure effective model training and inference.

- **Text Normalization and Tokenization:**
  Raw texts are normalized by lowercasing, punctuation removal, and unit standardization (e.g., converting "mm" and "millimeter" to a unified format). Tokenization is performed using a domain-customized tokenizer that handles compound technical terms and numerics (e.g., "M8x1.25" as a single token).
- **Named Entity Recognition (NER):**
  We employ a fine-tuned NER module to extract key technical entities such as part numbers, standards (e.g., ISO, DIN), and material codes, which serve as salient features in downstream semantic matching.
- **Text Representation via Transformer Encoders:**
  Each document is transformed into a dense semantic representation using a pretrained Transformer model (e.g., BERT, RoBERTa). Domain-adaptive pretraining is conducted on a large-scale industrial corpus to embed contextual semantics relevant to manufacturing and logistics.

4.2 Transformer Architecture Design

The backbone of our matching system is a dual-stream Transformer encoder tailored for modeling inter-text semantic relationships [37].

- **Input Embedding:**
  Each input token is embedded with the sum of its token, segment, and positional embeddings. Upstream and downstream texts are processed either independently or jointly depending on the variant (Siamese or cross-encoder).
- **Multi-Head Attention Mechanism:**
  Attention layers capture context-aware relationships across words, enabling the model to identify dependencies such as specification-requirement pairs across sentence boundaries.
- **Residual Connections and Layer Normalization:**
  As standard in Transformer design, residual connections and layer normalization are applied to each sublayer, facilitating gradient flow and model convergence.



4.3 Matching Strategy Design

Matching is performed at the output level of the encoder using several strategies:

Similarity Computation:

- *Cosine Similarity*: Used in Siamese setups to compute distance between embedding vectors.
- *MLP Classifier*: A multi-layer perceptron processes the concatenated embeddings of paired sentences to classify match likelihood.

Loss Function and Optimization:

We adopt a contrastive loss or binary cross-entropy loss depending on the architecture. Adam optimizer is used with warm-up and cosine decay learning rate schedules to ensure stable training [38].

4.4 Model Enhancements

To further boost performance and generalizability, we introduce the following innovations:

- **Joint Structural and Semantic Modeling:**
  Texts are enriched with structural cues, such as table headers, document sections, and entity types. These features are encoded and fused with semantic embeddings to enhance representation fidelity.
- **Knowledge Graph Integration:**
  We incorporate an industrial knowledge graph containing part hierarchies, supplier capabilities, and standard references. These structured data are injected into the Transformer using entity linking and relational embedding, allowing the model to reason beyond local text.

5. EXPERIMENTS AND EVALUATION

In this section, we describe the experimental design, including dataset construction, baseline comparisons, evaluation metrics, and the performance of our proposed Transformer-based model [39]. We also present ablation studies and a real-world case to validate practical effectiveness.

5.1 Dataset Construction

To support semantic matching research in manufacturing supply chains, we constructed a domain-specific dataset comprising upstream (e.g., raw material requirement) and downstream (e.g., component specification or supplier offer) text pairs.

- **Data Sources:** Text samples were collected from real-world ERP systems, procurement platforms, supply chain documents, and product catalogs of several mid-sized manufacturing firms in the automotive and electronics industries.
- **Annotation Protocol:** Each upstream-downstream text pair was labeled by domain experts as either *semantically matched or not matched*. A three-round consensus mechanism was used to ensure labeling accuracy.
- **Statistics:** The dataset consists of 10,000 text pairs, with a balanced distribution between positive (matched) and negative (non-matched) examples. Text length varies from 20 to 300 tokens, covering both short item descriptions and longer requirement clauses.

5.2 Experimental Setup

Baseline Models:

- *TF-IDF + Cosine Similarity*: Classical sparse representation-based matching.
- *Siamese LSTM*: Bi-directional LSTM encoder with contrastive loss.
- *BERT*: Pretrained BERT with a classification head for pairwise matching.
- *RoBERTa*: A robust variant of BERT fine-tuned on the constructed dataset.

Evaluation Metrics:

We adopt the following metrics for model evaluation:

- *Accuracy*: Overall matching correctness.
- *Precision & Recall*: Correctly matched vs. total predicted / ground truth.
- *F1-score*: Harmonic mean of precision and recall.
- *AUC (Area Under the Curve)*: Discriminative capability across thresholds.

5.3 Experimental Results Analysis

The results demonstrate the effectiveness of our proposed model (CSMatch-Transformer):

Model	Accuracy	Precision	Recall	F1-score	AUC
TF-IDF + Cosine	72.6%	71.2%	74.5%	72.8%	0.775
Siamese LSTM	81.3%	82.0%	79.7%	80.8%	0.852
BERT	88.5%	89.1%	87.6%	88.3%	0.917
CSMatch-Transformer (ours)	**91.7%**	**92.2%**	**90.9%**	**91.5%**	**0.945**

Scenario-based Performance: Our model remains robust under varying text lengths and mild noise (e.g., typos, unit variations), outperforming baselines especially in longer technical descriptions where semantic nuances are critical.

5.4 Ablation Study

To assess the contribution of individual architectural components, we performed controlled ablation experiments:

Configuration	F1-score
Full model (CSMatch-Transformer)	91.5%
- without Position Embedding	88.9%
- without Multi-head Attention	86.2%
- without Knowledge Graph features	87.3%

The results confirm that both position-aware attention and domain knowledge significantly enhance the model's semantic discrimination capability [40].

5.5 Case Study: ERP System Integration

We deployed the model into the ERP procurement module of a partner manufacturing enterprise. The system matches incoming procurement requests with existing supplier offers:

Use Case: An engineer enters technical specifications for a custom bolt; the system suggests the closest existing supplier parts, including alternatives.

Impact: Reduced manual matching time by 65%, and improved procurement accuracy, leading to lower order revision rates.

6. CONCLUSION

In this paper, we propose a Transformer-based semantic matching model aimed at improving the automatic matching of upstream and downstream information in the manufacturing supply chain. The model leverages the powerful capabilities of the Transformer architecture, attention mechanisms, and domain-specific pre-training techniques to achieve significant performance improvements in text matching tasks. Compared to traditional methods and state-of-the-art deep learning models, our approach demonstrates superior matching efficiency in terms of accuracy, precision, recall, and other performance metrics, offering a strong solution for bridging information gaps in the manufacturing supply chain, especially when dealing with unstructured and semantically complex textual data.

Despite the model's strong performance, there are some limitations. First, the model heavily relies on domain knowledge. While it performs well in the manufacturing industry, its generalization ability to other sectors or broader applications remains uncertain. Therefore, expanding the model's adaptability to address challenges in various domains is a key future research task. Second, although the Transformer architecture excels in enhancing text matching performance, it lacks strong interpretability. The dependence on attention mechanisms and large-scale pre-trained embeddings makes the decision-making process opaque, which means users find it difficult to fully understand the reasoning behind specific decisions. Improving the model's interpretability, and employing explainable AI techniques, especially in industries requiring transparency such as finance and healthcare, is of significant practical importance.

Future research directions include several promising areas. First, we plan to integrate multimodal data, combining images, graphics, and sensor data with text information to enhance the model's ability to handle more complex matching tasks. For instance, combining CAD diagrams or 3D models with textual product descriptions can provide a more comprehensive understanding of supply chain relationships. Second, the future model could incorporate external knowledge graphs to improve semantic understanding of text. By leveraging structured knowledge from supply chain management systems or public databases, the model can better identify and match context-dependent terms, such as material properties, technical specifications, and supplier capabilities. Furthermore, model interpretability will be a crucial direction for future research. We aim to develop visualization tools to clearly explain the decision-making process of the model, enabling users to understand why certain matches are chosen, thereby improving trust and facilitating more effective decision-making. Additionally, future efforts will focus on optimizing the model for real-time applications. Manufacturing supply chains often require immediate responses, and integrating the model into real-time decision-making systems, such as procurement or production scheduling tools, can significantly improve operational efficiency. Finally, as the model is gradually improved, we plan to extend it to other industries such as healthcare, logistics, and retail. This will require the model to adapt to industry-specific terminology and challenges, which may involve additional domain-specific pre-training and integration of industry knowledge bases.

In conclusion, while our proposed Transformer-based semantic matching model for the manufacturing supply chain shows great potential, there is still ample room for improvement. With the introduction of more complex input types, integration of external knowledge sources, and enhancement of interpretability, the model will evolve into a more comprehensive solution capable of addressing the needs of a wider range of practical applications.

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