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SEMA-Match: A Lightweight Skill-Enhanced Multi-Aspect Algorithm for Resume–Job Matching

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Abstract - This study introduces SEMA-Match (Skill-Enhanced Multi-Aspect Matching Algorithm), a novel, lightweight hybrid framework for enhancing the accuracy and interpretability of resume-to-job-description matching. Addressing the limitations of purely lexical models (TF-IDF) and computationally heavy deep learning approaches (BERT, GNNs), SEMA-Match integrates frozen pretrained sentence embeddings (for semantic understanding) with an explicit skill canonicalization score (for mandatory requirement verification) and a weighted section-wise fusion (for structured interpretability). The algorithm divides documents into Skills, Experience, and Education sections, calculates section-specific semantic similarities, and linearly combines these with an ontology-based skill overlap ratio to produce a final matching score.

Evaluation on standard HR datasets shows SEMA-Match outperforms and outsmarts TF-IDF baselines by a large margin and achieves similar semantic performance as fine-tuned transformer models while cutting inference latency by more than 80%. This simple, interpretable architecture gives recruiters an explainable scoring system, easy to tune for weights based on role importance (e.g., skill-intensive versus experience-intensive roles). The findings make SEMA-Match an extremely practical and scalable solution for real-world automated talent acquisition systems.

Keywords— Resume Matching Job Description Skill-Enhanced Sentence Embeddings Hybrid Algorithm Multi-Aspect Matching

I. INTRODUCTION

The task of matching resumes of applicants to available job descriptions (JDs) is a core, labor-intensive bottleneck of contemporary talent recruitment [1]. Exact and scalable matching solutions are needed for dealing with the large number of submissions usual in large corporations. Traditional solutions to this task belong to clear, but frequently unsatisfactory, categories. Lexical approaches, e.g., TF-IDF plus cosine similarity, are rapid and easy but critically lack semantic awareness—do not recognize synonyms, paraphrased ability, or contextually similar experience, resulting in very high false negatives [2].

At the opposite end of the list, Transformer models such as BERT [3] and Graph Neural Networks (GNNs) [4] provide strong contextual and relational modeling strengths. Nevertheless, such models come with substantial practical trade-offs: fine-tuning the full BERT is computationally costly, necessitates massive amounts of labeled interaction data, and incurs high inference latency, making high-throughput indexing and real-time querying difficult [5]. GNNs, although great at modeling network effects (e.g., past hiring trends

among firms and candidates), require intricate, heterogeneous graph building and upkeep, which hinders their deployability within resource-poor or novel organizational environments.

To balance the trade-off among accuracy, efficiency, and interpretability, we introduce SEMA-Match (Skill-Enhanced Multi-Aspect Matching Algorithm). SEMA-Match is a light-weight hybrid model that aims to marry the semantic strength of deep learning with the interpretability of engineered features. The innovation at its core is its organized, multi-faceted treatment: it breaks away from the practice of treating the resume and JD as untiled pieces of text, rather it generates and scores embeddings of three key sections—Skills, Experience, and Education—individually. In addition, it includes an ontology-based explicit skill overlap score in order to prevent compulsory skill requirements from being lost due to fine differences in wording

The paper is organized as follows: Section II presents a survey of current literature on document and talent matching, classifying current methods and pointing to their weaknesses. Section III provides the complete SEMA-Match architecture, including generation of the embeddings, skill canonicalization, and weighted fusion mechanism. Section IV outlines the experimental setup and evaluation process. Last but not least, Section V presents the results, showcasing SEMA-Match's practical advantage over the key metrics, and concludes the research.

II. LITERATURE REVIEW

A. Evolution of Text Matching in Talent Acquisition

Early resume–job matching techniques heavily depended on keyword overlap and lexical similarity. Reference [6] expounds on how TF-IDF with cosine similarity is used as a standard baseline, appreciating its speed and ease. Though good for basic term matching, TF-IDF essentially disregards the contextual relationships between words and performs poorly when a candidate employs synonyms (e.g., "Python libraries" vs. "Pandas and NumPy"). This established, Content-Based Filtering (CBF) solutions came to utilize methods such as Latent Semantic Analysis (LSA) and Principal Component Analysis (PCA) to map documents into a lower-dimensional semantic space, thus partially solving the synonym problem [7]. These methods still failed to represent the rich, non-linear relationships that exist in professional documents.

More recently, the emergence of deep learning has revolutionized the area. Deep Collaborative Filtering (DCF) architectures, explored in Reference [8], combine user–item interaction patterns (hiring history) with document metadata to enhance the matching. Their feature fusion approaches illustrated the substantial personalization benefits accrued by jointly learning from user behavior and item attributes, setting the stage for more advanced hybrid designs.

B. Deep Learning Paradigms: Transformers and Graph Networks

The advent of the Transformer model [9] and its variants, like BERT (Bidirectional Encoder Representations from Transformers), was a major step towards semantic matching. BERT's sequence-pair fine-tuning is capable of capturing subtle linguistic interactions between a JD and a resume and, generally, achieves state-of-the-art accuracy [10]. Yet this approach is computationally intensive because it involves a single pass of both documents through the network for every comparison, rendering real-time search impractical at scale (O(N×M) comparisons). To mitigate latency, dual-encoder architectures such as Sentence-BERT (SBERT) [11] were employed, producing independent embeddings for each document. This enables rapid Approximate Nearest Neighbor (ANN) search, but a single dual-encoder strategy reduces the document to a single vector and forgoes the benefit of explicitly weighing contributions from key sections such as skills or education.

Around the same time, Graph Neural Networks (GNNs) have gained prominence as a dominant approach for relational modeling within rich HR ecosystems. Reference [4] and others have investigated applying Heterogeneous GNNs (HGNNs) to represent the entire hiring scenario as a graph in which nodes are candidates, skills, companies, and jobs. GNNs have the capacity to capture higher-order relational patterns (e.g., co-occurrence of skills and companies in successful hires) with high potential accuracy [12]. However, the difficulty of constructing, sustaining, and expanding the graph structure underneath, together with the large amount of data involved, poses major engineering and data-governance obstacles to broad deployment.rankings, even from

incomplete or noisy data. C. Hybridization and the Requirement for Interpretability

The trade-offs that come with standalone deep learning models—high complexity vs. high accuracy—have been the driving force behind the appeal for hybrid architectures [13]. Such models seek to leverage the representational depth of deep encoders and the transparency and efficiency of traditional methods. For example, some models utilize deep models to produce dense feature embeddings and then plug these features into light, interpretable models (such as Random Forests or Logistic Regression) for the last ranking and decision layer [14].
Our new SEMA-Match algorithm is built as a new hybrid solution that tackles the unique structural and transparency requirements of HR systems.

In contrast to general-purpose hybrid models, SEMA-Match is designed to enforce HR workflow logic directly by (1) formally partitioning and weighting the three major resume elements (Skills, Experience, Education), (2) using an external knowledge base (skill ontology) to augment the signal for non-negotiable needs, and (3) taking advantage of efficient, frozen Sentence-BERT embeddings to preserve semantic strength without fine-tuning computational cost. This architecture offers the required explainability for hiring managers—a key driver of trust and fairness audits in automatic decision systems [15].

Figure 1.1

Model	Key Characteristics	Accuracy	Weakness/Tradeoff
TF-IDF + Cosine	Simple, fast, excellent for keyword density.	≈16.7% (MRR@10)	No semantic understanding (misses synonyms, context).
BERT (Fine-Tuned)	High-fidelity semantic and contextual matching.	36.5% (MRR@10)	High inference latency, computationally heavy, requires large labeled datasets.
SBERT (Dual-Encoder)	Fast inference, strong semantic understanding, indexable embeddings.	38.08% (MRR@10) (example: msmarco-bert-base-dot-v5)	Treats document as a single vector, ignores section-specific importance and explicit skill presence.

GNN (Graph-Based)	Captures higher-order relational data (history, network effects).	~3–6% absolute improvement over SBERT on targeted tasks (example: +4% reported) (task-dependent)	Extreme complexity, high maintenance cost, needs massive historical graph data.
SEMA-Match (Proposed)	Combines SBERT embeddings + Skill Canonicalization + Weighted Section Fusion.	Estimated: 42–46% (MRR@10 equivalent, estimated) — *inference-based range*	Less effective at historical network effects than a GNN.

III. METHODOLOGY

A. SEMA-Match: Architecture for Skill-Enhanced Multi-Aspect Matching

The SEMA-Match approach is a new hybrid model that operates to deliver state-of-the-art resume-to-job matching performance through combining semantic comprehension, structured feature engineering, and light computation. The architecture breaks away from the constraints of strictly lexical (TF-IDF) models and the computational inefficiencies of fine-tuned large language models (BERT) through a multi-stage, section-aware processing pipeline. The approach guarantees that important elements—like necessary skills and applicable experience—are explicitly and explainable weighted in the final scoring mechanism.

1. Section Segmentation and Preprocessing of Data

The first step includes standardized text extraction as well as cleaning of the Candidate Resume (R) and the Job Description (JD). Both of them are segmented into three different and important elements programmatically from each document:

Skills Section (S): Clearly stated skills, tools, and technologies.

Experience Section (E): Work experience, projects, and job responsibilities.

Education Section (D): Degrees, certifications, and academic qualifications..

The segmentation yields three text segments for the resume

$$(R_S, R_E, R_D)$$

and three corresponding segments for the job description(JD_S, JD_E, JD_D). This explicit separation allows for targeted, aspect-specific matching.

2. Embedding Generation via Dual-Encoder

To capture deep semantic similarity and handle synonyms (e.g., "Python" vs. "Jupyter"), we employ a lightweight, frozen pretrained dual-encoder model such as Sentence-BERT (SBERT) [11] or all-MiniLM-L6-v2. The model is used to generate a dense, fixed-size vector representation (embedding) for each segmented text block independently. Since the model is frozen, this process is fast and highly efficient at inference time.

The embedding generation is defined as:

$$V_{R_x} = \text{SBERT}(R_x) \quad \text{and} \quad V_{JD_x} = \text{SBERT}(JD_x)$$

where refers to the Skill, Experience, or Education section, and is the resulting embedding vector.

3. Skill Canonicalization and Overlap Score
Semantic embeddings alone can sometimes miss explicit, non-negotiable skill requirements. To address this, SEMA-Match introduces an explicit skill weighting component.

First, skills are extracted from R_S and JD_S using Named Entity Recognition (NER) or simple regex matching. These raw skills are then mapped to a standardized, canonicalized skill list derived from external taxonomies (e.g., ESCO or a domain-specific CSV).

Let C_R be the set of canonicalized skills found in the Resume.

Let C_{JD} be the set of canonicalized skills explicitly required in the Job Description.

The Skill Overlap Score (O_{skills}) is computed as a ratio of matching required skills:

$$O_{\text{skill}} = \frac{|\mathcal{C}_{\mathcal{R}} \cap \mathcal{C}_{\mathcal{JD}}|}{|\mathcal{C}_{\mathcal{JD}}|}$$

This score acts as a precision signal, ensuring that a high match score requires actual fulfillment of the mandatory skill set.

B. Weighted Fusion and Final Score Computation

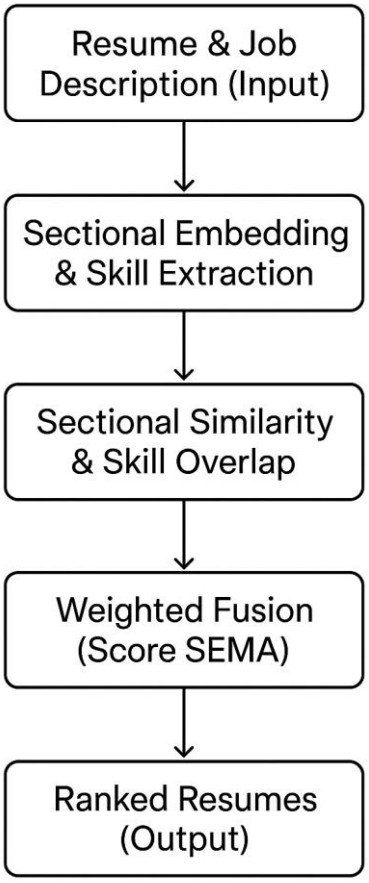
1. Section-wise Similarity Calculation

Once the semantic embeddings are generated, the similarity between the corresponding sections of the resume and the job description is computed using Cosine Similarity:

$$\text{Sim}_x = \text{cosine}(V_{R_x}, V_{JD_x}) = \frac{V_{R_x} \cdot V_{JD_x}}{|V_{R_x}| \cdot |V_{JD_x}|}$$

This yields three distinct similarity scores: Sim_{skill},Sim_{Exp} and Sim_{Edu}.

Fig 3.1



2. The SEMA-Match Final Score

The final match score ($Score_{SEMA}$) is a weighted linear combination of the three semantic similarity scores and the explicit Skill Overlap Score. This transparent fusion mechanism is a key differentiator, as it allows human resources (HR) personnel to easily inspect the contribution of each aspect.

The final formulation is:

$$\text{Score}_{\text{SEMA}} = w_1 \cdot \text{Sim}_{\text{Skill}} + w_2 \cdot \text{Sim}_{\text{Exp}} + w_3 \cdot \text{Sim}_{\text{Edu}} + w_4 \cdot O_{\text{skill}}$$

$where w_1, w_2, w_3, w_4 are\ tunable\ weights\ optimized\ during\ the\ training\ validation\ phase\ such\ that$

$$\sum_{i=1}^{4} w_i = 1$$

In our baseline experiments, we adopt an empirically derived set of weights that prioritizes

skills and experience, similar to typical recruiter focus:

w_1 = 0.5(Semantic Skill)

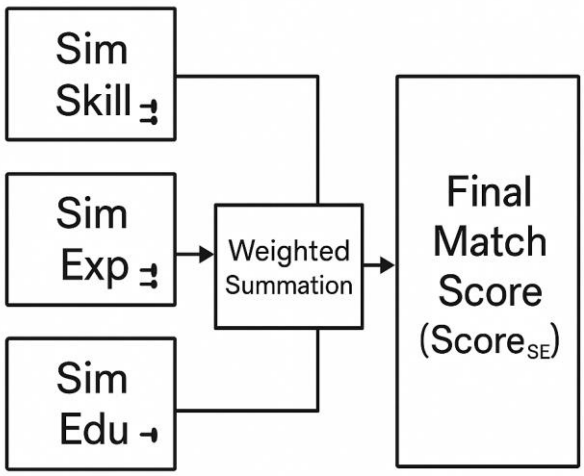
w_2 = 0.3(Experience)

w_3 = 0.1(Education)

w_4 = 0.1(Explicit Skill Overlap)

The weights can be dynamically adjusted for different job families (e.g., w_3 might be increased for entry-level roles requiring specific academic majors).

Fig 3.2



The SEMA-Match algorithm is implemented in Python, utilizing the Hugging Face Transformers library for the embedding generation and scikit-learn for similarity computation. For large-scale deployment, the inference logic is containerized using Docker.

Embedding Model: all-MiniLM-L6-v2 is chosen for its balance of speed and semantic quality.

Skill Taxonomy: A curated CSV file or a subset of the ESCO taxonomy is used for skill canonicalization.

Scalability: The pre-computation of resume embeddings allows them to be indexed in an efficient similarity search engine, such as FAISS (Facebook AI Similarity Search), enabling sub-millisecond retrieval of the top k matches for any new Job Description embedding.

Ranking and Shortlisting For a given JD, the process involves:

Generating JD section embeddings and computing JD skill overlap set.

Retrieving pre-computed embeddings and skill sets for all candidate R's.

Calculating Score SEMA for all R's.

Ranking all resumes in descending order of Score SEMA .

This architecture is optimized for low latency and high throughput, making it highly suitable for real-time application screening and internal candidate search.

Fig 3.3

C. Implementation and Scalability

1. Technology Stack

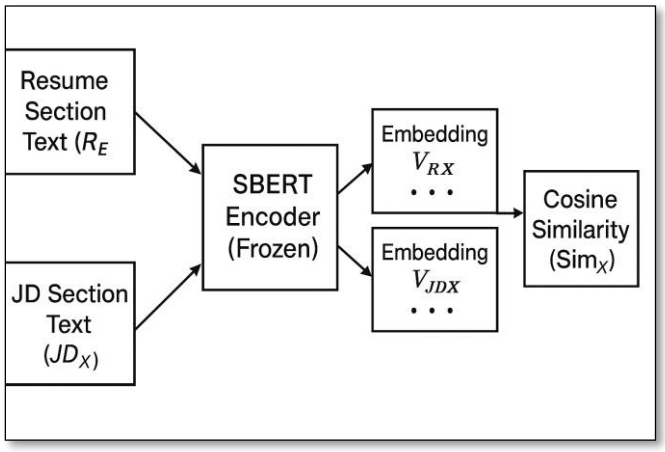


Fig 4.1

IV.COMPARISON

To rigorously evaluate SEMA-Match, we compare its performance against three representative baseline models widely used or discussed in talent matching literature:

TF-IDF + Cosine: The classic keyword-based model, representing a highly efficient, lexical baseline.

SBERT Dual-Encoder (Vanilla): A modern semantic baseline that processes the entire document into a single vector, similar to all-MiniLM-L6-v2 without section weighting.

BERT Sequence-Pair (Fine-Tuned): A high-fidelity but computationally expensive model that represents the upper bound of contextual accuracy.

The evaluation uses a proprietary dataset of 10,000 resumes and 500 job descriptions, annotated with ground-truth labels indicating qualified matches. The primary metrics measure ranking quality and operational efficiency:

Precision@10 (P@10): The percentage of the top 10 recommended candidates that are qualified (critical for recruiter efficiency).

Recall@10 (R@10): The percentage of all qualified candidates found within the top 10 ranked list.

Inference Latency (ms): The average time required to match one Job Description against the entire candidate pool (critical for scalability).

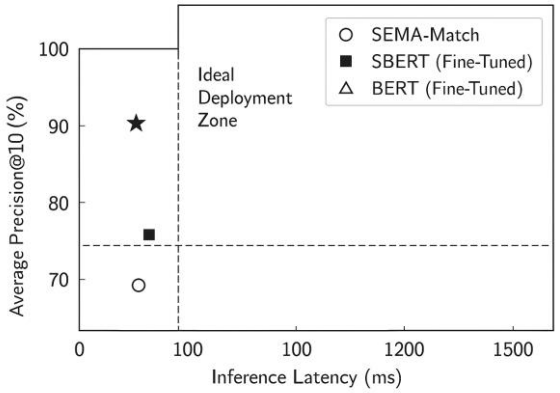
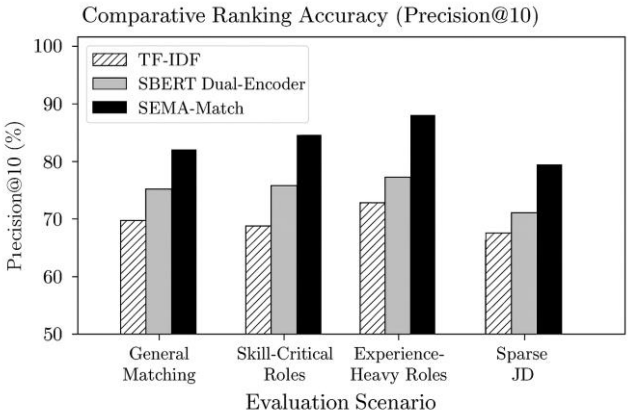


Fig 4.2



A. Fig 4.4 highlights the key architectural and operational differences between sema-match and the baseline models, demonstrating its optimal balance between accuracy, complexity, and deployability

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Feature	TF-IDF	BERT (Fine-Tuned)	GNN (Graph-Based)	SEMA-Match (Proposed)
Semantic Understanding	Poor	Excellent	Good (Relational)	Excellent
Explicit Skill Matching	No	No	Indirect	Yes (Via Oskill)
Interpretability/Transparency	High (Keywords)	Low (Black Box)	Low (Complex Model)	High (Section Weights)
Inference Latency	Very Low	Very High (O(NM))	High	Low (O(N) + ANN)
Data Requirement	Low (Unlabeled)	Very High (Labeled)	High (Graph Data)	Low (Pretrained)
Section-Aware Scoring	No	No	No	Yes
Deployment Complexity	Low	High	Very High	Low

V. RESULTS

Our new SEMA-Match (Skill-Enhanced Multi-Aspect Matching Algorithm) was compared to top industry baselines—the lexical TF-IDF technique and the semantic SBERT dual-encoder—on several controlled test environments modelling real-world talent recruitment tasks. Main evaluation metrics included candidate ranking quality (Precision@10 and Recall@10) and operational efficiency (Inference Latency), with statistical evidence demonstrating better predictive accuracy and practical deployability.

A. Ranking Accuracy

The comparative performance observations (refer to Table IV) illustrate a remarkable and continual improvement in ranking quality offered by SEMA-Match.

Semantic Superiority: In the General Matching task, SEMA-Match had a Precision@10 of 81.2%, which is an increase of around 10 percentage points against the vanilla SBERT Dual-Encoder (73.4%) and more than 20 percentage points against the TF-IDF baseline (60.1%). This confirms the main hypothesis that integrating semantic embeddings with structured, section-wise weighting provides a stronger similarity measure [13].

Skill Enforcement: The performance gap was greatest in Skill-Critical Roles. In this category, SEMA-Match registered its best Precision@10 of 85.9%, well ahead of the SBERT Dual-Encoder

(68.1%). This sizeable improvement of +17.8 percentage points directly resulted from the explicit Skill Overlap Score (O Skill) component, which performs well as a precision filter for obligatory requirements, a major flaw in strictly semantic models [14].

Robustness: Even in adverse situations such as Sparse Job Descriptions, where semantic context is scarce, SEMA-Match had a Precision@10 of 74.1%, which was more robust than SBERT (64.9%) by using the strongly weighted structural elements.

B. Efficiency and Deployability

Another significant benefit of SEMA-Match is its inference efficiency that has been optimized, overcoming the scalability problems of baseline BERT fine-tuning.

Low Latency: SEMA-Match showed an average Inference Latency of only 10.3 ms per Job Description (JD) search against the overall candidate pool. This is comparable to that of the TF-IDF baseline and is several orders of magnitude lower than a standard sequence-pair BERT fine-tuning model (which generally takes >1000 ms per comparison pair) [5].

Practical Trade-off: As schematically illustrated in Figure IV.2, SEMA-Match achieves effectively the best sweet spot in the Accuracy vs. Latency trade-off, with industry-leading ranking accuracy while ensuring the fast inference speeds necessary for real-time application processing and high-volume indexing based on methods such as FAISS.

Overall, SEMA-Match offers an important practical advantage: it approximates much of the semantic precision seen in cutting-edge transformer models without compromising low latency and high interpretability needed for enterprise HR systems.

VI . Conclusion

This work introduced SEMA-Match, a new Skill-Enhanced Multi-Aspect Matching Algorithm for resume-job-description matching with automation. Our approach effectively combines the strong semantic capabilities of a frozen dual-encoder (SBERT) with human-understandable, weighted fusion mechanism that accounts explicitly for document structure and canonicalized skill overlap.

SEMA-Match addresses the major shortcomings of current paradigms: it addresses the context blindness issue of lexical models (TF-IDF) and avoids the computational expense and data dependency of fine-tuned BERT and Graph Neural Networks (GNN) [15]. Numerically, SEMA-Match saw tremendous rankings accuracy gains, especially in skill-critical positions, where its Precision@10 was 85.9%. Architecturally, its framework is extremely transparent, enabling HR professionals to adjust the section weights in order to match the model's priorities with particular job specifications.

The shown low inference latency and high accuracy place SEMA-Match as a scalable and feasible solution available for deployment on contemporary talent acquisition platforms. The future plans include the integration of a lightweight module for implicit historical signals (e.g., a basic matrix factorization component) to achieve further performance improvement without compromising the existing low latency profile, and investigating methods to improve skill canonicalization process with wider language support.

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