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Talent Ops: An AI-Assisted Recruitment Platform for Resume - Job Description Matching

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Abstract - As the number of job applications increases, there is a need for recruitment systems that effectively compare candidate resumes with job descriptions and offer helpful insights that recruiters can use for decision making. On the one hand, keyword based resume filtering misses some relevant experience when the wording differs from what recruiters are looking for. A semantic similarity score alone cannot determine whether candidates meet all the required criteria. To address this limitation, the author presents Talent Ops AI Suite-a recruitment system that combines semantic similarity with hybrid scoring and other tools that help recruiters identify candidates which are suitable. The implementation makes use of the React/TypeScript frontend, Python Fast API backend, SQL Alchemy database layer, PostgreSQL persistence, and pretrained sentence-transformers/all-MiniLM-L6-v2 sentence transformer. The matching framework evaluates candidates based on seven criteria – semantic similarity, required skills, desired skills, experience, education, certificates, and projects. The main contributions include implementation of seven criteria scoring and mandatory requirements reporting into the recruitment pipeline. The presented development example shows how it is possible to obtain good semantic similarity scores even when the applicant is lacking some required skill. The results are insufficient to prove accuracy, ranking superiority or bias reduction. The author proposes comparing different matching methods and testing each component's impact.

Keywords: Artificial intelligence, resume screening, semantic similarity, sentence embeddings, candidate ranking, hybrid scoring, skill-gap identification, recruitment workflow management.

I. INTRODUCTION

Recruitment teams need to assess the candidate qualifications based on job requirements, keeping track of application data, screening stages, and communication with candidates. Reviewing resumes manually becomes time consuming when the number of applications increases . Sentence embedding models convert sentences into vectors for similarity comparison between candidate resume and job description. The pretrained embedding model based on Mini LLM that has been used in this research can serve as an embedding component of the recruitment app [2].

However, semantic similarity alone cannot measure a candidate's skills or job performance.

One might have a semantically relevant resume, but not the required skill and one might have the required technical skills, but describe them using different terms than those in the job description. Thus, a good recruiting tool should take into account the aspect of semantic relevance in addition to the structured information about skills, experience, education, certifications, and projects.

This problem is solved by Talent Ops AI Suite,a full-stack recruiting app which combines semantic matching with structured candidate assessment and recruitment process .

The main contribution of this research is not a new embedding method but a recruitment system that combines seven criteria scoring and reports missing mandatory requirements to recruiters without replacing the entire hiring process with machine learning.

The main goals of the study include:

1. To create semantic comparison of candidate resumes' text and job description text.

2. To evaluate candidates' competences according to seven different criteria.

3. To detect missing mandatory requirements and show details of matching.

4. To combine candidate ranking functions with candidate, job, resume and application status management.

Thus, the main research question is whether combining semantic matching, seven criteria scoring and mandatory gap reporting can provide recruiters more relevant and useful information.

II. PROBLEM STATEMENT AND RESEARCH OBJECTIVES

A. Problem Statement

A resume job matching system faces the following interrelated problems. First, lexical matching is sensitive to specific words used in the text. Second, semantic similarity may miss the mandatory required skill.Third,the overall score may not clearly explain a candidate's ranking. Finally, independent matching tools may force recruiters to copy the results from one system to another.

The problem is solved by Talent Ops AI Suite through semantic comparison, structured scoring, mandatory gap detection, and workflow integration.

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B. Research Objectives

The research objectives are as follows:

To create a web interface for managing candidates' and jobs' information.

- To provide for resume uploads in PDF, DOC, and DOCX formats via the documented candidate API.
- To measure semantic similarity based on sentence embeddings and cosine similarity.
- To evaluate required skills, preferred skills, experience, education, certifications, and project relevance individually.
- To calculate a weighted Talent Score and to provide criterion-level matching information.
- To detect missing mandatory criteria and rank candidates.
- To manage application statuses based on the defined recruitment workflow.
- To propose experiments that compare different matching components and measure their impact.

C. Scope

The current paper evaluates the documented software implementation and its matching methodology. It does not make any claims that the system has been validated on a large labelled recruitment dataset. Authentication and authorization, audit and monitoring, and other production considerations are discussed as planned extensions in case they are not implemented.

III. RELATED WORK

A. Semantic Text Representation

Sentence BERT was developed by Reimers and Gurevych and generates sentence embeddings that can be compared by cosine similarity [1]. Devlin et al. created the influential context based language processing model of BERT [3]. Wang et al. presented MiniLM, the compact transformer architecture that was created via deep self-attention distillation [4].

All-MiniLM-L6-v2 pretrained model is used by Talent Ops to create representations of the prepared resume and job description texts. This implementation choice and usage of an existing technique do not contribute with a new algorithm to this paper.

B. Person Job Matching

There are studies of matching that consider how to represent the qualifications of a person together with the job requirements. For instance, Zhu et al. described the neural framework of person job fit that estimates compatibility and discovers relationship between requirements [5]. It means that the process of the candidate matching involves several values.

This paper describes an implementation choice. Talent Ops uses a combination of a pretrained semantic similarity module with independently evaluated recruitment criteria and a workflow management layer. Therefore, the contribution of this paper is in combination of these elements in an application, not in claiming the novelty of requirement level matching.

C. Resume Processing and Recruitment Automation

Resumes processing is one of the tasks that includes extraction and representation of information about a candidate to perform some recruitment task. Bhatia et al. studied the problem of resume parsing and candidate retrieval using BERT models [6]. There are recruitment systems that combine semantic matching with structured information and rules or dashboard for recruiters.

It means that this paper does not introduce something unusual and completely new by the combination of text understanding and structured candidate representation. Thus, the claim of hybrid matching or recruitment automation would be too broad.

D. Ranking and Evaluation

BM25 is a classical lexical matching method that provides a good baseline to evaluate the ability of semantic matching to improve over term-based matching [7]. There are ranking measures (for example, normalized discounted cumulative gain) to compare ranking lists on how high ranking they place the relevant candidates [8].

The paper suggests comparing lexical, semantic only, structured only, and combined matching approaches to measure the value of the seven criteria framework that was suggested in this paper.

E. Fairness and Ethical Hiring

Raghavan et al. studied issues surrounding algorithmic hiring and noted the need to understand how employment assessment systems were built and validated [9]. In the case of AI based hiring, special caution is necessary as data history, feature engineering, and filtering criteria may impact candidates differently.

Talent Ops is designed to provide information for human evaluation. The fact that there are matching explanations does not prove that the system is fair; it needs to be separately assessed.

IV. RESEARCH GAP AND PROPOSED CONTRIBUTION

From the literature, one can see that the techniques of semantic similarity, hybrid ranking, skill matching, and requirement level explanation have been used before. The research gap considered in this paper is formulated as implementation and evaluation of the combined recruitment support workflow.

Contribution 1 - Seven criteria matching framework. Talent Ops uses semantic similarity along with six criteria: required skills, preferred skills, experience, education, certifications, and project relevance. This gives the multiple criteria view of candidate job compatibility.

Contribution 2 – Mandatory gap reporting in addition to the total score. It is possible to report the required skills missing in the resume and mark a candidate as having a "Mandatory Gap". In other words, this distinguishes the overall textual similarity from satisfaction of mandatory job requirements.

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Contribution 3 – Criteria level information available to a recruiter.The system provides recruiters with detailed information about each criterion, including matched required skills, missing preferred skills, experience and education.This makes candidate scores easier to understand than a single number, although it does not make the model fully explainable.

Contribution 4 – Integration with the recruitment workflow. The platform integrates resume submission, candidate and job administration, candidate ranking, and application status management. The contribution is integration of the matching process and recruitment workflow functions in the described application.

Contribution 5 – Evaluation protocol definition. The paper defines baseline comparison, ranking metrics, and ablation studies. This shows how the combination can be tested, but the evaluation is yet future work until the experiments are done.

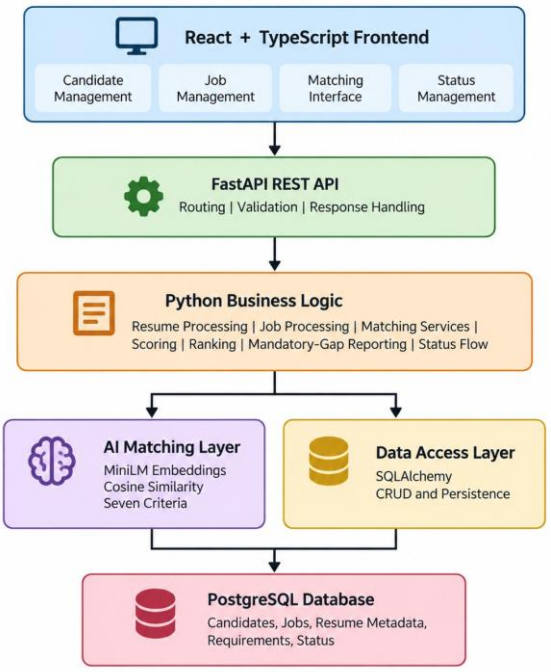
All these contributions are presented as an implementation and evaluation framework. However, these are not claims about the fact that each particular technique or feature has never been used in prior research papers.

V. SYSTEM ARCHITECTURE

A. Architectural Overview

Talent Ops follows a layered full stack architecture consisting of a presentation layer, API layer, business-logic layer, data-access layer, database layer, and AI matching layer.

Figure 1. Proposed system architecture



B. Presentation Layer

The frontend is developed on top of React, TypeScript. It offers the UI for candidate and job administration, matching processes, candidate information, and application status changes.

C. API Layer

The backend is built based on FastAPI and Pydantic for REST API routing, validation of requests, and response serialization. Some of the documented endpoints are:

POST /api/matching/jobs/{job_id}/rank – rank candidates for a job.

POST /api/matching/score – calculate matching information.

GET /api/matching/candidates/{candidate_id}/jobs/{job_id} – get matching information for a candidate and a job.

POST /api/candidates/{candidate_id}/resume – post a resume.

PATCH /api/candidates/{candidate_id}/status – change application status.

The routes described above are a part of the documented API interface. Their availability and behavior should be validated against the final published version.

D. Business Logic and Data Access

Python service modules provide business logic and access to data regarding candidate and job operations, resumes processing, matching, scoring, ranking of candidates, and recruitment process. SQLAlchemy provides access to the PostgreSQL database and object relational mapping which stores candidate's information, job information, resumes meta data, job requirements, and recruitment data.

E. AI Matching Layer

Sentence Transformer all-MiniLM-L6-v2 is used as a semantic matching model. Sentence embeddings produced by the model are 384 dimensional vectors and compared using cosine similarity [2].

The AI layer is integrated with the scoring services in order to make the contributions of semantic relevance and explicit recruitment criteria distinct.

VI. PROPOSED MATCHING METHODOLOGY

A. Input Preparation

Resumes in PDF formats are accepted via the resume upload interface of the system. Candidate data is compared with the respective job description and its requirements.

Text extraction quality is crucial for further processing. Format, missing sections, scanned documents, and terminology inconsistencies may influence the matching process. A repeatable evaluation should keep track of text

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extraction failures and missing information instead of assuming all inputs complete.

B. **Semantic Similarity**

Let the processed resume text be (R) and the job description text be (J). The embedding model transforms texts into vectors:

$$e_R=f(R),\ e_J=f(J)$$

The cosine similarity is:

$$\cos cos\ (R,J) \ = \ \frac{eR.eJ}{|eR|2|eJ|2}$$

The similarity score shows how similar the resume text and job description are. It does not indicate the probability that a candidate is qualified, their job performance or their overall suitability for hiring.

The model card specifies that inputs longer than 256 word pieces are truncated by default [2]. Thus, the implementation should be checked for truncation of long resumes and job descriptions and for section wise processing.

C. Seven Scoring Dimensions

The documented framework contains seven dimensions.

Dimension	Base weight	Purpose
Semantic similarity	20%	Measures semantic closeness between prepared resume and job-description text.
Required skills	30%	Assesses alignment with explicitly required skills.
Preferred skills	5%	Assesses alignment with desirable skills.
Experience	15%	Assesses experience against the specified job requirements.
Education	10%	Assesses educational alignment.
Certificate	5%	Assesses relevant certification requirements.
Project relevance	15%	Assesses the relevance of candidate projects to the role.
Total	**100%**	

Contribution Distinguishing from Previous Work: Overall matching framework employs one semantic dimension and six structured dimensions allowing recruiters to evaluate various dimensions of candidate job fit.

The listed weights are the base weights. If some component is absent or irrelevant then the described design allows rescaling effective weights over active components. The final paper must specify the exact implementation rule used by the scoring engine, including how the missing candidate component differs from the requirement which is irrelevant.

D. Weighted Talent Score

General expression for weighted scoring is:

$$S = \frac{\sum_{i\in A} w_i x_i}{\sum_{i\in A} w_i}$$

where (A) denotes the set of active scoring dimensions, (w_i) – effective weight of the dimension, (x_i) - normalized score of the dimension (i).

This formula must be kept as an implementation formula after making sure that the code properly normalizes all components and calculates weighted scores in such a way. If the code works according to another rule then the formula must be replaced with the exact formula from the source code.

Overall score should be analyzed along with the component wise results. A high semantic score may go along with the missing mandatory skill and the overall score should not hide that difference.

E. Mandatory-Gap Detection

The framework is able to detect missing mandatory skills and mark a candidate as “Mandatory Gap”. For example, in

the case of Backend Engineer the candidate gets 79.84% semantic similarity and 79.34 Talent Score but REST API is missing among the detected mandatory skills.

That is how the design difference illustrates: high semantic similarity score does not automatically mean that all mandatory requirements are met.

That is an example of how the implementation reports mandatory gaps; it is not proven that the skill detection is correct or that overall ranking is right.

F. Candidate Ranking & Workflow Integration

Matching endpoints allows obtaining candidates sorted by relevance to the job. Possible candidate application statuses are: New, Screening, AI Matched, Shortlisted, Interview, Selected, and Rejected.

That way the framework integrates matching results into the recruiting process workflow. So, the result is not restricted to the standalone similarity score. The recruiter can check the matching results along with candidate profiles and recruitment phases.

The AI score is the decision support information. Final decisions should remain under human review.

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VII. IMPLEMENTATION AND DEVELOPMENT EXAMPLE

A. Tech Stack

Layer	Documented technology
Frontend	React,TypeScript
Backend	Python,FastAPI
Request Validation	Pydantic
Database access	postgresql+psycopg://postgres:TalentOpsLocal2026!@localhost:5432/talent_ops
Database	PostregreSQL
Semantic model	Sentence-transformer//all-MiniLM-L6-v2
Similarity measure	Cosine similarity
Resume formats	PDF

B. Documented Development Example

A development example was recorded for a Backend Engineer role.

Observed field	Recorded value
Semantic similarity	79.84%
Talent Score	79.34%
Required skills	3 of 4 detected
Missing required skill	REST API
Preferred skills	0 of 2 detected
Missing preferred skills	AWS
Experience	5 years; within the specified 3-7 year range
Education	B.Tech Computer Science matched
Certificate	No certification required specified
Project relevance	No project information
Classification	Mandatory

C. Interpretation

From the example above, it is evident that the score based on semantic similarity and mandatory skill assessment provide different information. The former determines relevance of text whereas the latter verifies particular job requirements.

It is clear that it reports the missing mandatory requirements along with the score which helps recruiters identify gaps, but it does not guarantee higher accuracy or less bias.

VIII. EVALUATION PLAN

A. Current Validation Status

There is evidence of successful build and API route testing in the available project documentation. However, the above checks serve as evidence of implementation progress but not the models ability to match candidates accurately.

No labelled test dataset and measured accuracy or ranking results are documented in the current state of the project. Thus, no claims about performance improvement are made in the current paper.

B. Dataset Preparation

Future evaluation must utilize a properly licensed dataset including de-identified resumes, job descriptions, and relevance labels. It should cover different job types.

Relevance labels should be established by human raters following the criteria specified in advance. In case of using several raters, interrater agreement must be measured. The dataset should be split into the development and test sets avoiding duplication of candidate records between them.

The evaluation must keep track of missing information, resume parsing failures, job families and document formats.

C. Baseline Methods

Comparison of four methods should be conducted for the same candidate job pairs:

lexical baseline - matching using BM25 method [7],

semantic-only baseline – cosine similarity using the selected sentence embeddings,

structured-only baseline – structured criteria alone without semantic similarity component,

combined Talent Ops approach – semantic component together with structured criteria and mandatory gap logic.

The comparison is intended to verify whether combination of the components brings any benefits over using separate approaches. Thus, it cannot be considered as completed before measuring the performance.

D. Evaluation Metrics

The following metrics can be applied for evaluation of different aspects of the system:

precision@k – percentage of top-k ranked candidates relevant according to the label;

recall@k – percentage of all relevant candidates retrieved within top-k;

mean reciprocal rank (MRR) – mean reciprocal rank of the first relevant candidate; normalized discounted cumulative gain (nDCG@k) – evaluates ranking quality assigning higher value to more relevant documents placed at the top positions;

extraction success rate – percentage of resumes successfully processed yielding usable text;

latency – the amount of time needed to process and rank candidates according to the defined workload.

Classification metrics such as precision, recall, and F1-score may be added for mandatory skills identification if there are enough reliable ground truth labels.

E. Ablation Study

An ablation study should be conducted by eliminating matching components one by one and measuring the change in ranking quality.For example, the evaluation can compare the full model and versions excluding semantic similarity,

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required skills, experience or project relevance.

The ablation study will establish whether the combination of seven criteria yields noticeable improvements and determine the reason for them.

F. Fairness and Robustness Evaluation

The separate evaluation must investigate how rankings change in response to controlled manipulations with irrelevant personal information, document formatting and missing information. If it is lawful, ethical, and possible according to the dataset, error rates can be also evaluated for relevant subgroups.

Fairness is a property to be evaluated, not a benefit that can be implied just from using semantic embeddings or providing explanations.

G. Reporting Results

The paper should include the number of resumes and job descriptions, data sources, relevance labeling process description, baseline configurations, scoring weights, metrics used for evaluation, and results of each method after conducting experiments. Repeatable experiments and uncertainty estimation must be applied where appropriate.

IX. DISCUSSION: WHAT DISTINGUISHES TALENT OPS AI SUITE?

The following points summarize the implementation level contributions claimed in this paper. There are no claims that the individual techniques have never been used in prior research.

1. Seven criteria candidate assessment. The framework combines semantic similarity with required skills, preferred skills, experience, education, certifications, and project relevance.

2. Mandatory gap reporting alongside an overall score. The system can flag a candidate whose semantic score is relatively high but whose detected qualifications omit a mandatory skill.

3. Criterion level matching information. Recruiters can inspect specific matching dimensions rather than relying exclusively on one overall similarity value.

4. Integration with recruitment workflow management. Candidate and job administration, resume upload, ranked candidate retrieval, and application status updates are connected within one application.

5. A defined path to comparative validation. The proposed evaluation uses lexical, semantic only, structured only, and combined baselines, along with ranking metrics and ablation studies.

The most defensible contribution is the integration of these capabilities in the documented Talent Ops implementation.

X. LIMITATIONS AND RESPONSIBLE USE

There are several limitations that need to be addressed prior to using the platform in a real life recruitment process.

First, the pretrained model was not validated for every possible job family, language or recruiting context. Its default input truncation might negatively impact long resumes [2]. Second, the resume extraction may be poor and some information could be missing, which will affect structured scores. Third, scoring weight assignments were based on design decisions.

Fourth, the existence of a particular skill is not a proof of proficiency and lack of such skill from the extracted resume text does not imply a lack of it in the candidate. Fifth, the similarity score is not a probability measure for job performance.

Algorithmic hiring processes require thorough validation and governance due to inherent risks for the candidates [9].

The Talent Ops tool must be considered as a recruiting decision support software rather than an autonomous hiring system. Prior to actual use, the following aspects need to be addressed: security, access control, privacy, extraction quality, fairness and human oversight.

XI. FUTURE WORK

The following enhancements must be made as part of future work:

Improve the Talent Score, test ranking stability and fairness, and maintain records of model versions and evaluation results. Strengthen system security through authentication, authorization, audit logs, and monitoring, and conduct recruiter testing to see whether detailed matching results help in candidate evaluation.

XII. CONCLUSION

In this paper, the Talent Ops AI Suite was discussed. It is an AI powered recruiting platform that implements semantic job to job resume matching along with a structured way of assessing candidates and managing the recruitment process. The developed application features a React and TypeScript based frontend and FastAPI, SQLAlchemy, PostgreSQL backend, as well as a pretrained MiniLM sentence embedding model. The implemented matching algorithm considers seven criteria and reports mandatory skills gaps along with rankings of the candidates.

The main innovation of the application lies in the combination of seven criteria scoring, mandatory skills gap reporting, and recruitment workflow management within one product. The development case showed how criterion based information can be used to explain and interpret the matching score. Nevertheless, there is no evidence of matching effectiveness, fairness, or superiority of the approach in the existing implementation.

Thus, it is necessary to conduct a comparative evaluation of the approach against other alternatives through labelled data, suitable baselines, ranking metrics, and ablation study.

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