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A Semantic Embedding Approach for Peer-to-Peer Skill Exchange Networks

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Abstract

Acquiring new skills has been a issue for many students which we attribute to high costs associated with educators and also to few opportunities for practical teaching. In a traditional model which is lecture based we see little to no interaction from the student, which in turn produces a very passive learning environment. Also we see inactivity, a lack of interaction and low motivation from this approach. To fix this we put forth the idea of a peer to peer skill exchange system. In order to maintain participants long-term engagement, elements of gamification such as leaderboards, rankings, and rewards are included. The platform also encourages users to gain personal attributes such as confidence, effective communication, and collaborative participation in addition to technical skills development. Overall, the methodology leads to enhanced interactivity in the learning process and moves away from the traditional paradigms of learning, providing empowerment in the development of skills more than a personal gain.

Introduction

Folks are using digital education more these days - yet plenty still check out because classes feel like endless talks with no back-and-forth, making it tough to stay involved [4]. On top of that, clunky tools or sites offering little real help tend to push people away even faster [7]. Peer learning thrives when there's honesty along with open replies - otherwise, teamwork drops off [3]. Abilities often show up in chunks tied to real tasks, which means setting beats just spotting keywords [8]. Choosing each other boosts fit quality, whereas blind pairings tend to weaken drive and results [7,10]. Smart tech that adjusts keeps people involved and prevents system hiccups [1].Persistent problems involve keyword-driven systems failing to grasp meaning [10], spotty engagement from weak confidence [3], also absence of organized elements such as game-like incentives or real-time coaching that lowers user stay rates [6,9].SkillXchange fills these holes by letting users swap skills - SBERT pulls out key abilities, cosine similarity finds good matches, live chat keeps talks flowing smoothly, while two-way reviews keep things honest.

Literature Survey

Knowledge Sharing Architectures and Foundational Constraints

Knowledge builds up from well-ordered details, yet holes show up if setups don't get steady handling [1]. Solid frameworks depend on straightforward guidelines along with ongoing tweaks to keep things fair [2]. Confidence plays a big role in getting involved, particularly where checks and responsibility fall short [3]. People take part more once they see actual results together with individual benefits in gaining skills [4].

Participation Stability, Peer-Learning Structures, and Incentive Mechanisms

Time banks tend to fail when trades aren't balanced or people take advantage, especially if no one's watching [5]. Casual feedback from peers doesn't do much, whereas organized engagement boosts how well people learn [6]. Groups work better when everyone knows their role and meetings happen often - without these, things get messy fast [7]. Online systems that offer solid ways to communicate help keep members involved while cutting down on disorganized attempts [9].

Semantic Skill Modelling, Expert Identification, and Matching Algorithms

Early systems for spotting experts used keyword tricks - better at hitting targets yet still narrow [12]. Next-phase research shifted to tracking how users act, uncovering hidden layers in skill signals [13]. Ideas were bundled using meaning-aware grouping, sharpening focus on subject areas [14]. Today's graph-driven methods spot faint traces within tangled datasets, lifting both detection quality and pairing success rates [15,16].

Methodology

This study uses hands-on tests alongside side-by-side comparisons to check whether pulling meaning from words works better than just matching keywords [17]. Because old-school keyword systems struggle with varied contexts and need precise word hits, smarter embedding techniques link similar skill ideas instead - capturing deeper connections [18].

Dataset and Experimental Setup

The actual skill tags came from real resumes checked by people - these were usually messy, disorganized, or written freely. The models tested were:

- Starting point: pulling info using keywords
- Semantic Model: SBERT/MiniLM (384-dim embeddings)

Skill Extraction and Embedding

The uploaded resumes stay safe before getting sorted. Check out these tools listed here instead:

- PyPDF2 grabs text from PDFs
- NLTK helps clean text while spotting key skills in candidates
- Use SBERT or MiniLM so skills become embedding
- Scikit-learn handles similarity calculations

This step grabs jumbled text, then shapes it into clean, organized meaning bits.

$$sim(s_i, s_j) = \frac{s_i \cdot s_j}{\|s_i\| \|s_j\|} = \frac{\sum_{l=1}^{n} s_{il} s_{jl}}{\sqrt{\sum_{l=1}^{n} s_{il}^2} \sqrt{\sum_{l=1}^{n} s_{jl}^2}} \quad (1)$$

Computation of Skill Similarity

Every person gets shown as a set of skills. It checks how well folks match up through cosine similarity. The closer they match, the better their abilities fit to- gether, so the tool removes anyone under that line.

$$Sim(A, B) = \frac{A.B}{\|A\|\|B\|} \quad (2)$$

Weighted Recommendation Score

Making a match looks at your skills, yet it weighs trust just as much - availability matters too. So the last score you get will reflect all three

$$R_{ij} = \alpha \cdot sim(s_i, s_j) + \beta \cdot T_j + \gamma \cdot A_j \quad (3)$$

This way, role models feel real to those involved - yet still reliable and down-to- earth. **FIGURE 1**, shows that the system consists of resume ingestion, skill embedding, similarity computation, and recommendation scoring modules.

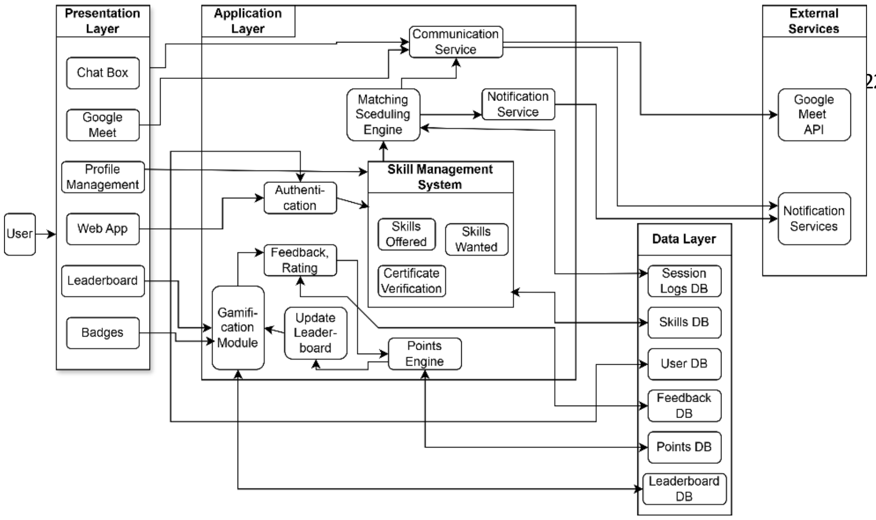

Figure 1. System Architecture Diagram

Algorithms

Skill Extraction Algorithm

This algorithm analyses a profile to remove non-essential words and extract skills for semantic similarity and recommendations.

Steps:

1. Accept unstructured profile text (experiences, education, keywords).
2. Convert text to lowercase for uniformity.
3. Tokenize sentences into words.
4. Remove stopwords (e.g., “and,” “with,” “for”).
5. Match remaining tokens to a predefined list of hard and soft skills.
6. Store matched skills in the database for further embedding and analysis.

SBERT Embedding Generation Algorithm

SBERT generates context-aware embeddings, identifying semantic relation- ships beyond keyword matches (e.g., “Machine Learning” vs “Deep Learning”).

Steps:

1. Input skills extracted from the Skill Extraction module.
2. Load the SBERT model.
3. Encode each skill/sentence to obtain a 384-dimensional vector.
4. Store embeddings in the database for matchmaking.

User Streak Calculation Algorithm

This gamified algorithm encourages consistent engagement by rewarding regu- lar logins.

Steps:

1. Compute diff = current date – last login date.
2. If diff = 0, streak remains the same.
3. If diff = 1, increment streak by 1.
4. If diff > 1, reset streak to 1.
5. Store and display updated streak.

Results

The evaluation of mentor recommendation showed a considerable gap between the baseline keyword extraction and the semantic similarity-based approaches:

• Keyword Extraction: Shown moderate precision with low recall, where some skills were identified, but many relevant contextually matching ones were missed. F1 score reflects insufficient skills being recognized for effective matching[19].

• SBERT/MiniLM Semantic Similarity: The objective is to outperform keyword extraction on all metrics, hence capturing essential contextually relevant skills. Improving recall and F1 scores and better-matching mentors for user skill requirements.

• Method Comparison: Keyword-based methods are faster but error-prone, while semantic embeddings are more accurate but heavier in terms of computation. The differences between resumes and skills were correlated with the number of recommended relevant mentors [20] .

TABLE 1 shows alignment scores between resume embeddings and skill embeddings. Higher scores are better. By using paraphrased skill descriptions. And **TABLE 2** showcases tests on various resumes.

Table 1. Cosine Similarity Scores Between Document Representation and Skill Vectors

Resume ID	Top Matched Skill	Cosine Similarity Score	Other Relevant Skills (Score)
R1	Python	0.92	SQL (0.87), Docker (0.81)
R2	Excel	0.89	Power BI (0.86), SQL (0.78)
R3	AWS	0.91	Linux (0.84)
R4	TensorFlow	0.93	Python (0.90), NumPy (0.88), Pandas (0.87)

Table 2. SBERT Skill Extraction Efficiency

Resume ID	Actual Skills Present	Skills Extracted by SBERT	Extraction Accuracy (%)
R1	Python, SQL, HTML	Python, SQL, HTML	99.01%
R2	Java, PHP, Docker	Java, PHP	98.09%
R3	Python, Machine Learning, C++	Python, ML, C++	99.28%
R4	React, Node.js, JavaScript	JavaScript, React	99.33%

Conclusion

The SkillXchange platform enhances conventional and digital learning through semantic skill modeling and gamification in real time. According to the results of the experiments, SBERT/MiniLM embeddings greater outperform keyword-based methods as per more precise metrics like precision/recall/F1 score and context- based skill ranking. In addition, it shows the relations among the skills that could not have been inferred just by matching skills with keywords. The system offers an adaptable and flexible model by combining the use of semantic embeddings with P2P interaction and reward system for research and real-life skills across other contexts.

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