Article

Learning Job Competency Models from Historical Recruitment Data Using Supervised Machine Learning

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Abstract: Based on the structured representation of job responsibilities, qualification requirements, and skill information within historical recruitment texts, this study investigates data-driven learning methods for job competency models. The research focuses on feature representation of recruitment texts, construction of job competency labels, and training mechanisms for supervised learning. It details the processes of identifying competency elements, learning structural patterns, and constructing hierarchical structures. Experimental validation using a multi-position recruitment dataset yielded an accuracy of 0.851 on test samples and a macro-average F1 score of 0.832. Technical R&D positions achieved 0.892 accuracy, while operational management positions reached a macro-average recall of 0.842. Results demonstrate that the supervised learning framework reliably reconstructs job competency combinations.

Keywords: supervised machine learning; recruitment data analysis; job competency model; text mining; competency identification

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1. Introduction

Job competency models serve as a crucial foundation linking recruitment demand identification, talent screening, and job matching. Their construction quality directly impacts the precision and interpretability of human resource allocation. Historical recruitment data continuously records job responsibilities, qualification requirements, and skill demands, offering strong practical relevance and providing actionable foundations for data-driven learning of job competency models.

Related research indicates that integrating LSA, BERT, and SVM can enhance text recognition and job screening efficiency in recruitment processes [1]. It has also been suggested that combining skill classification systems with online data can effectively support career decision-making [2]. In addition, knowledge graph-based approaches have been applied to talent capability prediction and the organization of competency relationships [3]. Evidence further shows that machine learning techniques can improve measurement accuracy and predictive performance in personnel selection [4]. Moreover, machine learning frameworks have been shown to optimize recruitment screening processes and improve decision efficiency [5].

While existing research provides methodological foundations for recruitment analytics, several challenges remain. These include unclear standards for constructing recruitment text competency tags, insufficient alignment between supervised learning methods and the structural representation of job competencies, and difficulties in translating model outputs into hierarchical competency models. Consequently, this paper investigates job competency tagging, supervised learning model training, and job competency structure representation methods based on historical recruitment data, establishing a competency model construction pathway for data-driven job analysis.

2. Historical Recruitment Data and Job Competency Information Representation

Historical recruitment data comprises four core fields: job title, job description, qualification requirements, and skill requirements. These fields collectively define the boundaries for expressing job competency information. The data processing module first performs noise removal, word segmentation, term merging, and field alignment on raw recruitment texts. It then reorganizes the "education-experience-skills-responsibilities" structure into a competency semantic sequence to minimize semantic drift caused by variations in corporate terminology. The set of job competency units is denoted as $C=\{c_1,c_2,\ldots,c_m\}$, the job text sequence as $D=\{w_1,w_2,\ldots,w_n\}$, and the competency association strength is characterized by the following equation:

$$r_{ij}=\frac{f(c_i,w_j)\times\log\left(\frac{N}{n_j+1}\right)}{\sum_{k=1}^{n} f(c_i,w_k)} \quad (1)$$

Where r_{ij} represents the normalized association weight between capability unit c_i and term w_j , $f(c_i,w_j)$ denotes co-occurrence frequency, N indicates the total number of positions in the corpus, and n_j represents the number of positions containing term w_j . The weight matrix $R=[r_{ij}]$ is further compressed into a capability representation vector. This process unifies the explicit skill terms and implicit responsibility semantics from the recruitment corpus into a unified representation space, enabling subsequent semantic embedding to maintain consistent correspondence between job capability boundaries and position text semantics.

3. Supervised Machine Learning-Based Job Competency Learning Model

3.1. Modeling the Job Competency Learning Problem

The job competency learning problem requires transforming semantic representations from historical recruitment data into a supervised mapping task. The job sample set is denoted as $S=\{(\mathbf{x}_1,\mathbf{y}_1),(\mathbf{x}_2,\mathbf{y}_2),\ldots,(\mathbf{x}_q,\mathbf{y}_q)\}$, where the feature vector $\mathbf{x}_i\in\mathrm{R}^d$ represents the field-fused semantic representation of the $j_{th}job_i$, and the label vector $\mathbf{y}_i\in\{0,1\}^{\mathrm{h}}$ indicates the job's membership states across the kth competency dimension h . The learning objective requires the classifier $g(\mathbf{x}_i;\theta)$ to output a competency probability vector $\hat{\mathbf{y}}_i$ and minimize the empirical risk via the following equation:

$$J(\theta)=-\frac{1}{q}\sum_{i=1}^{q}\sum_{u=1}^{h}\left[y_{iu}\ln\hat{y}_{iu}+(1-y_{iu})\ln(1-\hat{y}_{iu})\right]+\lambda\|\theta\|_2^2 \quad (2)$$

Where y_{iu} denotes the true label of the i_{th} position on the u_{th} competency dimension, $\hat{y}_{iu}$ represents the predicted probability, and λ indicates the regularization coefficient. This job modeling process transforms the single-position matching problem into a multidimensional competency identification problem. Job responsibilities, skills, and qualifications within recruitment texts are constrained by a unified loss function into the same discriminative space, thereby establishing a verifiable statistical foundation for the learnability of competency boundaries.

3.2. Vectorization of Recruitment Text Features

The feature vectorization process for recruitment texts requires uniformly mapping job descriptions, qualification requirements, and skill phrases into a computable space. The preprocessing module first performs word segmentation, term merging, and low-frequency noise filtering on job titles, responsibility sentences, and requirement sentences. Differentiated weights are then assigned based on field functionality, as shown in Table 1. Skill fields exhibit higher discriminative strength than experience fields, while the semantic coverage of responsibility fields better facilitates competency boundary localization. The weighted representation of term v_t in the job corpus is defined as:

Table 1. Vectorization Processing Attributes for Recruitment Text Fields

Field Type	Primary Content Format	Weight Coefficient $\alpha_{g(t)}$	Representation Function
Position Title	Position Abbreviation, Functional Identifier	1.10	Provides semantic anchors for positions, limiting vector topic drift
Job Responsibilities	Work Tasks, Process Description	1.25	Expand applicable scenarios for capabilities and enhance semantic coverage
Qualifications	Education, Experience, and Qualifications	0.95	Provide threshold information for filtering and strengthen constraint boundaries
Skill Requirements	Tools, Languages, and Specialized Skills	1.40	Highlight capability identification signals to improve category separability

$$\omega_{it}=\alpha_{g(t)}\cdot\frac{n_{it}}{\sum_{b=1}^{p}n_{ib}}\cdot\log\left(\frac{M+1}{m_t+1}\right) \quad (3)$$

where ω_{it} represents the final weight of term v_t in the i_{th} job, $\alpha_{g(t)}$ denotes the weight coefficient of the term's field, n_{it} indicates the term frequency, p signifies the total number of terms in the job text, M represents the total number of job samples, and m_t denotes the number of jobs containing term v_t .The vector construction module generates feature vectors $\mathbf{z}_i=[\omega_{i1},\omega_{i2},\ldots,\omega_{is}]$ based on these parameters. The distribution differences of job competency-related terms in high-dimensional space are expanded by field weights and inverse document frequency constraints, enabling subsequent classifiers to distinguish job samples with similar role descriptions but differing competency requirements [6].

3.3. Job Competency Tag Construction Methodology

Building competency tags for job roles requires addressing the annotation challenge in recruitment texts where "expressions are scattered yet competencies are homogeneous, and terms appear similar but point to different meanings. "Job descriptions typically embed competency requirements within action items, tool names, qualification criteria, and experience thresholds. Relying solely on keyword matching risks misclassifying "familiarity with project processes" as managerial capability or conflating "communication and coordination experience" with generic role descriptions. Thus, annotation must first identify the semantic role of each term before assessing its strength of support for specific competency categories [7]. As shown in Figure 1, the label generation pipeline comprises term extraction, semantic merging, conflict resolution, and threshold determination. The term extraction stage retains four high-information-density segments: job titles, responsibility phrases, skill nouns, and qualification restrictions. The semantic merging stage uses domain glossaries to map synonyms like "data modeling," "statistical analysis," and "report development" to unified competency clusters. The conflict resolution stage distinguishes between "tool usage" and "competency requirements" based on contextual position and field weighting. Report development" to unified competency clusters. The conflict resolution phase distinguishes between "tool usage" and "competency requirements" based on contextual position and field weighting. For a job sample s_i , the membership score for competency label l_k is defined as:

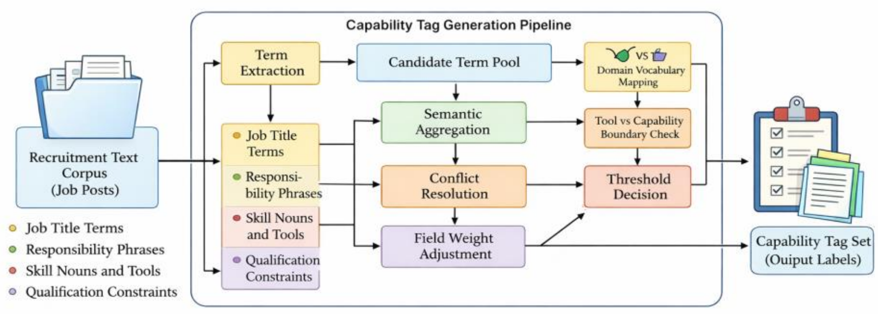

Figure 1. Job Competency Label Construction Flowchart

$$\psi_{ik}=\frac{\sum_{r=1}^{u_i}\rho_{ir}\eta_{rk}\gamma_{ir}}{\sum_{r=1}^{u_i}\rho_{ir}\gamma_{ir}} \qquad (4)$$

Where ψ_{ik} represents the overall strength of job s_i belonging to tag l_k , ρ_{ir} denotes the statistical weight of candidate term r in the job text, η_{rk} indicates the semantic mapping coefficient between the term and the tag, γ_{ir} represents the structural correction factor of the field containing the term, and u_i signifies the total number of candidate terms for job s_i .The annotation module then generates binary labels via a discriminative function $y_{ik}=I(\psi_{ik}\geq\delta_k)$, where δ_k denotes the minimum confirmation threshold for the capability label k . Generalized statements that appear frequently in the responsibilities field but lack sufficient discriminative power are suppressed due to low γ_{ir} , while terms in the skills field that reliably indicate professional capabilities receive higher retention weights. This process converges label noise in subsequent training samples.

3.4. Supervised Learning Model Construction and Training

The supervised learning model construction requires the aforementioned position vectors and competency labels as unified input-output interfaces, transforming job competency identification into an iteratively optimized multi-label classification task. Training samples are first stratified by job category into training, validation, and test sets. Texts with significantly varying field lengths are mapped into a common feature space via normalized vectorization. Categories with skewed skill label distributions employ inverse frequency weighting to correct learning bias. The model layer selects linear support vector machines and logistic regression as baseline classifiers, incorporating gradient-boosted trees to handle non-linear composite features. This aims to simultaneously preserve linear separability on high-dimensional sparse text and capture the interactive expression capabilities of composite skill terms. The predicted probability of sample a_i across the first j competency dimensions is denoted as $\hat{p}_{ij}$. The overall objective function is formulated as:

$$Q(\Theta)=-\frac{1}{R}\sum_{i=1}^{R}\sum_{j=1}^{L}\omega_j\left[z_{ij}\ln\hat{p}_{ij}+(1-z_{ij})\ln(1-\hat{p}_{ij})\right]+\xi\|\Theta\|_2^2 \qquad (5)$$

Where R denotes the number of samples, L represents the number of skill labels, z_{ij} indicates the true label, ω_j signifies the category weight, Θ denotes the model parameter, and ξ represents the regularization coefficient. The training process jointly adjusts parameter scale and threshold position based on the validation set F1 score and Hamming loss. This progressively expands the decision boundary between job samples with similar job descriptions but differing skill requirements.

4. Data-Driven Construction of Job Competency Models

4.1. Job Competency Factor Identification Method

Identifying job competency elements requires realigning supervised learning-derived label probabilities with explicit terms in recruitment texts, thereby converting classification results into foundational building blocks for competency models [8]. The identification process begins by using the predicted probability vectors of job samples to trace back high-contribution terms within job responsibilities, skill terminology, and qualification requirements. It then filters out generic expressions serving only a descriptive function based on field position and co-occurrence strength, ensuring low-distinctiveness descriptions like "familiar with office software" or "possesses good qualities" do not enter the core competency set. The identification score for candidate element e_q in job b_i is defined as:

$$\chi_{iq}=\frac{\sum_{v=1}^{K}\hat{p}_{iv}\,\kappa_{qv}\,\tau_{iq}}{\sum_{v=1}^{K}\hat{p}_{iv}} \quad (6)$$

Where χ_{iq} represents the comprehensive confirmation strength of element e_q for position b_i, $\hat{p}_{iv}$ denotes the predicted probability of the nth capability label (v), κ_{qv} indicates the correlation coefficient between the element and the label, and τ_{iq} represents the contextual consistency weight of the element within the job text. The identification module then generates the job capability element set using the threshold function $g_{iq}=I(\chi_{iq}\geq\varepsilon_q)$. Consequently, professional skills, analytical abilities, and collaborative competencies are no longer confined to label names but are restored as structured capability units supported by specific terms and constrained by context.

4.2. Learning Job Competency Structural Patterns

Learning job competency structural patterns requires extracting stable combinatorial relationships from the identified competency set, rather than merely listing individual elements statically. Competency requirements in recruitment corpora are typically organized around job tasks. Frequently occurring technical terms within a single position do not inherently constitute structural patterns. Only when sustained synergistic constraints emerge among job actions, skill tools, and qualification requirements do competency units acquire transferable organizational significance [9]. The learning process first quantifies the co-occurrence strength of competency elements within similar job samples. It then determines hierarchical relationships between elements by considering field positions and task semantics, distinguishing continuous competency chains like "data processing-statistical analysis-visual representation" from generalized statements such as "communication skills-sense of responsibility." The structural correlation between competency elements e_a and e_b is defined as:

$$\phi_{ab}=\frac{\nu_{ab}}{\sqrt{\nu_a\nu_b}}\cdot\log\left(1+\frac{H\cdot\nu_{ab}}{\nu_a+\nu_b-\nu_{ab}+1}\right) \quad (7)$$

Where ϕ_{ab} represents the structural coupling strength between elements, ν_{ab} denotes the co-occurrence frequency, ν_a and ν_b indicate the number of independent occurrences respectively, and H represents the total sample size of similar positions. The pattern learning module constructs a competency relationship network based on ϕ_{ab} . Competencies with strong task-driven characteristics and cross-field recurrence gradually consolidate into core nodes, while competencies tied to specific tools, scenarios, or qualification requirements form peripheral support clusters. This preserves the intrinsic organizational contours of positional competencies.

4.3. Construction of the Job Competency Hierarchy

Constructing the hierarchical structure of job competencies requires identifying the hierarchical organizational relationships between competency units on the acquired competency relationship network, rather than remaining at a flat associative description. Core competencies within job corpora typically exhibit high frequency, cross-role reusability, and a unifying influence over supporting competencies. Supporting competencies primarily fulfill methodological implementation, tool operation, and scenario adaptation functions. As illustrated in Figure 2, competency nodes progressively distribute from inner to outer layers as "Core Task Competencies-Specialized Execution Competencies-Supporting General Competencies." This distribution reflects the constraint path from job objectives to implementation conditions in recruitment requirements [10]. During hierarchical determination, the level index for capability elements (e_r) is defined as:

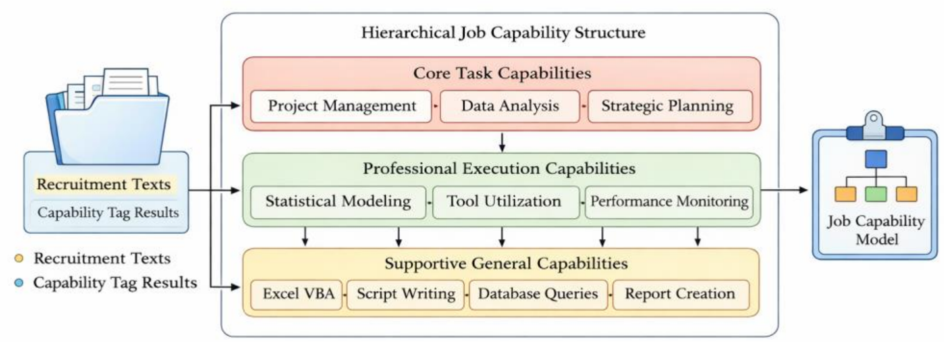

Figure 2. Schematic Diagram of Job Competency Hierarchy Structure

$$\lambda_r=\omega_1 \frac{d_r^{in}+d_r^{out}}{\max\limits_{t\in E}(d_t^{in}+d_t^{out})}+\omega_2 \frac{f_r}{\max\limits_{t\in E} f_t}-\omega_3 \frac{h_r}{\max\limits_{t\in E} h_t} \quad (8)$$

Among these, λ_r represents the hierarchical score of the competency element e_r , d_r^{in} and d_r^{out} denote the in-degree and out-degree of a node respectively, f_r indicates the cross-role replication frequency, h_r signifies the dependency depth on higher-level competencies, while ω_1 , ω_2 , and ω_3 denote the structural weight coefficients. The hierarchical generation module completes node stratification based on the interval distribution from λ_r . High-level competencies such as data analysis and business judgment are assigned to upper tiers, while capabilities like tool application and standard execution are allocated to middle and lower tiers. This process establishes an expandable and aggregable hierarchical framework for the job competency model.

5. Experimental Design and Results Analysis

5.1. Experimental Dataset and Setup

The experimental dataset was sourced from historical job postings continuously published on a public recruitment platform over the past three years. Data screening retained five core fields: job title, responsibilities, qualifications, skill requirements, and education/experience. Templated duplicate postings, samples with severe field deficiencies, and abnormally short texts were excluded. After corpus cleaning, job texts were uniformly mapped into trainable vectors. Competency labels underwent manual review and multi-label correction based on the aforementioned semantic consolidation rules. As shown in Table 2, the sample distribution spans major job categories including technical, operations, marketing, finance, and general management. This structure enables simultaneous evaluation of both specialized competency recognition accuracy and generic competency extraction stability. During the experimental phase, hierarchical sampling was employed to partition the training, validation, and test sets, preventing classification boundary shifts caused by job category imbalance. The training environment uniformly configured random seeds, batch sizes, and early stopping iterations, enabling comparative analysis of different models' recognition performance under identical data conditions.

Table 2. Experimental Dataset Composition and Partitioning

Job Category	Original Sample Count	Cleaned Samples	Number of Capability Labels	Training Set	Validation Set	Test set
Technology R&D	3,420	3,108	18	2,174	467	467
Operations Management	2,860	2,531	15	1,772	379	380
Market Sales	2,415	2,176	14	1,523	326	327
Financial Audit	1,986	1,742	13	1,219	261	262
General Functions	1,754	1,563	12	1,094	234	235
Total	12,435	11,120	-	7,782	1,667	1,671

5.2. Job Competency Recognition Accuracy Testing

The job competency identification accuracy test focuses on the stability of multi-label classification results and inter-job variations. Evaluation metrics include accuracy, macro-average precision, macro-average recall, and macro-average F1 score to verify whether the preceding feature representation, label correction, and training constraints effectively support job competency identification. As shown in Table 2, the technical R&D position achieved an accuracy of 0.892 and a macro-average F1 score of 0.874, demonstrating significantly superior recognition performance compared to the 0.811 and 0.786 scores for general administrative positions. This disparity indicates that roles with concentrated professional terminology and clear semantic boundaries are more conducive to stable classification. The macro-average precision for finance and audit roles was 0.861, higher than the 0.834 for marketing and sales roles, indicating that strongly rule-based qualification requirements reduce label misclassification. The macro-average recall for operations management roles reached 0.842, demonstrating that duty-driven expressions provide robust coverage during the label backtracking phase. Overall averages show the model achieved an accuracy of 0.851 on the test set and a macro-average F1 score of 0.832. The job competency identification results provide a stable input foundation for subsequent competency structure extraction, though low-frequency generic competency labels still exhibit some recognition shrinkage (As shown in Table 3).

Table 3. Job Competency Recognition Accuracy Test Results

Job Category	Accuracy	Macro-Precision Macro-P	Macro-Recall	Macro-F1
Technology R&D	0.892	0.881	0.867	0.874
Operations Management	0.846	0.839	0.842	0.840
Market Sales	0.829	0.834	0.807	0.820
Financial Audit	0.857	0.861	0.828	0.844
General Functions	0.811	0.798	0.775	0.786
Overall Mean	0.851	0.843	0.824	0.832

5.3. Comparative Experiments of Different Machine Learning Models

The comparative experiments of different machine learning models focus on the discriminative stability and generalization capability for the task of job competency identification. As shown in Figure 3, the Linear Support Vector Machine achieved 0.851 accuracy, 0.843 macro-average precision, and 0.832 macro-average F1 score, outperforming Naive Bayes, Decision Tree, and K-Nearest Neighbors models overall. This indicates that high-dimensional sparse recruitment texts are better characterized by category boundaries using interval maximization mechanisms. Logistic regression achieved a macro-average recall of 0.821, approaching the 0.824 of linear SVM, indicating that field-weighted term representations can stably support multi-label regression. The accuracy of Random Forest was 0.829, but its macro-average F1 score dropped to 0.807. This indicates that while tree models can capture local nonlinear relationships, they are susceptible to perturbations from the discrete distribution of low-frequency capability labels. The recall of Naive Bayes was 0.756, reflecting the difficulty of the conditional independence assumption in fully characterizing the compound dependencies between job responsibility statements and skill terms.

Figure 3. Experimental results comparing different machine learning models

5.4. Analysis of Feature Variables' Impact on Model Performance

The impact of feature variables on model performance manifests primarily in two dimensions: field information completeness and semantic distinctiveness. Experimental results show that when retaining all feature variables, the linear support vector machine achieves an accuracy of 0.851 and a macro-average F1 score of 0.832. After removing the skill requirement field, accuracy dropped to 0.816, macro-average F1 score decreased to 0.791, and recall for R&D positions fell from 0.867 to 0.804, indicating that professional skill terms remain the dominant information for identifying competency boundaries. After removing the job description field, the overall accuracy dropped to 0.823, and the macro-average recall for operations management positions decreased from 0.842 to 0.781. This demonstrates that task process semantics significantly support the identification of managerial and collaborative competencies. After removing the qualification requirements field, the overall accuracy decreased by only 0.011. However, the macro-average precision for financial audit positions dropped from 0.861 to 0.826, indicating that educational background, experience, and qualification constraints play a more critical role in suppressing misclassification for rule-based positions. After field weight standardization, the model's macro-average F1 score further declined to 0.803, revealing the sensitivity of job competency recognition to variations in heterogeneous fields.

5.5. Analysis of Job Competency Model Learning Effectiveness

The learning effectiveness of the job competency model is primarily reflected in three aspects: completeness of competency unit recovery, stability of competency combination recognition, and consistency of hierarchical structure mapping. Test results show that for technical R&D positions, the model stably identifies the core competency combination "Programming Development-Data Processing-Tool Application," achieving a combination matching rate of 0.884 and a competency level mapping consistency rate of 0.861.For operational management roles, the model achieved a 0.842 recovery rate for the "Process Coordination-Task Advancement-Communication Organization" combination, indicating that role-driven semantics can be converted into relatively stable competency structures. The competency cross-recognition rate for marketing and sales roles was 0.137, higher than the 0.082 rate for financial auditing roles, suggesting that positions with stronger behavioral expressions still exhibit some semantic overlap. Across all test samples, the model achieved an average competency coverage rate of 0.847, with core competency recognition accuracy at 0.873, supporting competency recognition accuracy at 0.826, and generic competency recognition accuracy at 0.791. The role competency model demonstrates more thorough learning of high-frequency specialized competencies, while boundary contraction persists for low-distinctiveness generic competencies.

6. Conclusion

By integrating job semantics, competency labels, and structural relationships from historical recruitment data into a unified learning framework, this study comprehensively demonstrates a data-driven approach to constructing job competency models. It establishes a coherent analytical chain linking competency identification, structural extraction, and hierarchical representation. However, limitations such as variations in recruitment text expression, ambiguous boundaries of low-frequency generic competencies, and insufficient cross-industry semantic transfer suggest room for improvement in the model's generalization capabilities for complex roles. Future research should incorporate cross-platform corpora, fine-grained label correction mechanisms, and dynamic update strategies.

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