International Journal of Mathematics and Computer Science
Volume **20,** Issue no. 2, (2025), 689–693
DOI: https://doi.org/10.69793/ijmcs/02.2025/khairullaev

Neural Network Model for Automated Task Assignment

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(Received February 27, 2025, Revised April 7, 2025,
Accepted April 8, 2025, Published April 9, 2025)

Abstract

In this paper, we present a neural network model for optimizing the allocation of project tasks among performers based on their skills, experience, and other relevant characteristics. The proposed approach relies on deep learning, employing a method of vector representation of skills and tasks within a unified semantic space. Experimental results demonstrate a 27% improvement in the quality of performer selection compared to traditional methods, as well as a 68% reduction in the time required for task allocation.

1 Introduction

Let $S = \{s_1, s_2, \ldots, s_m\}$ be the set of all possible skills in the system and let $E = \{e_1, e_2, \ldots, e_n\}$ be the set of performers. For each performer e_i, we

Key words and phrases: Neural networks, machine learning, personnel selection, task allocation, project management.
AMS (MOS) Subject Classifications: 68T07, 90B70, 90C35.
ISSN 1814-0432, 2025, https://future-in-tech.net

define a skill vector $\mathbf{v}_{e_i} = (w_{i1}, w_{i2}, \ldots, w_{im})$, where w_{ij} is a weight reflecting the proficiency level of performer e_i in skill s_j.

The matching function between a performer e and a task t is defined as $f(t, e) \in [0, 1]$, where higher values indicate a better match.

Efficient task allocation among performers is a key challenge in project management. Traditional methods often fail to optimize human resource utilization due to their inability to capture complex skill-task relationships. In this work, we propose a neural network model to automate task assignment based on performers' skills and experience, inspired by recent advances in algebraic structures and topological optimization techniques [1, 2].

2 Methodology

Definition 2.1. *The vector representation of a performer's skills e_i is defined as a vector $\mathbf{v}_{e_i} = (w_{i1}, w_{i2}, \ldots, w_{im})$, where $w_{ij} \in [0, 1]$ is a quantitative assessment of proficiency in skill s_j.*

Definition 2.2. *The vector representation of a task's requirements t_k is defined as a vector $\mathbf{v}_{t_k} = (r_{k1}, r_{k2}, \ldots, r_{km})$, where $r_{kj} \in [0, 1]$ is the importance of skill s_j for completing task t_k.*

2.1 Neural Network Architecture

The proposed neural network architecture consists of the following key components [5]:

1. Task Representation Module: Transforms the initial task description into a vector of required skills.

2. Performer Representation Module: Transforms the performer's profile into a competency vector.

3. Matching Module: Evaluates the compatibility between a task and a performer.

Formally, for a task t and a performer e, the matching function is defined as:

$$f(t, e) = \sigma\left(W_2 \cdot \mathrm{ReLU}(W_1 \cdot [\mathbf{v}_t; \mathbf{v}_e] + b_1) + b_2\right) \tag{2.1}$$

where $[\mathbf{v}_t; \mathbf{v}_e]$ is the concatenation of the task and performer representation vectors, W_1, W_2, b_1, b_2 are trainable network parameters, and σ is the sigmoid function [3] .

Theorem 2.1. *If the vector representations of performers' skills and task requirements reside in the same semantic space of dimension m, then there exists a neural network with architecture (2.1) that can approximate the optimal matching function with accuracy $\varepsilon > 0$.*

Proof. By the universal approximation theorem [4], a multilayer perceptron can approximate any continuous function on a compact set. Since $\mathbf{v}_t$, $\mathbf{v}_e \in [0,1]^m$ and $[\mathbf{v}_t; \mathbf{v}_e] \in [0,1]^{2m}$, the network approximates the optimal matching function with accuracy $\varepsilon > 0$. □

2.2 Model Training

The model is trained using a combination of several loss functions:

$$\mathcal{L}_{match} = -\frac{1}{N} \sum_{i=1}^{N} [y_i \log(f(t_i, e_i)) + (1 - y_i) \log(1 - f(t_i, e_i))] \tag{2.2}$$

where y_i is a binary label indicating whether performer e_i was successful in completing task t_i.

$$\mathcal{L}_{rank} = \frac{1}{|D|} \sum_{(t, e_+, e_-) \in D} \max(0, \gamma - f(t, e_+) + f(t, e_-)) \tag{2.3}$$

where D is a set of triplets (t, e_+, e_-) such that performer e_+ is more suitable for task t than performer e_-, and γ is a margin parameter.

The final loss function is:

$$\mathcal{L} = \mathcal{L}_{match} + \lambda \cdot \mathcal{L}_{rank} + \alpha \cdot \|W\|_2^2 \tag{2.4}$$

where λ is a hyperparameter controlling the contribution of the ranking loss, and the last term represents L2 regularization with coefficient α.

Lemma 2.1. *If the dataset contains a sufficient number of examples for each type of task and performer profile, minimizing the loss function (2.4) leads to the model converging to the optimal matching function [4].*

Proof. The loss function (2.4) combines convex matching loss (2.2) and ranking loss (2.3), with L2 regularization preserving convexity. With sufficient data and optimization (e.g., stochastic gradient descent), the model converges to the optimal matching function. □

3 Experimental Results

We used three datasets: an IT company database (1,250 tasks, 175 executors, 2020–2023), GitHub data (5,000 tasks), and synthetic data for controlled testing. Performance was assessed via Matching Accuracy (percentage of optimal assignments), Mean Rank (average rank of the correct executor), and Completion Success Rate (proportion of successful tasks).

Method	**Accuracy**	**Mean Rank**	**Success Rate**
Manual Selection	62.3%	4.7	76.8%
Neural Network Model	89.4%	1.7	91.3%

Table 1: Comparison of Methods

Theorem 3.1. *The model significantly ($p < 0.01$) outperforms baselines across all metrics.*

Proof. A paired t-test gave $p < 0.01$ for all comparisons, rejecting the null hypothesis of equal means. A bootstrap with 1,000 iterations confirmed stability, with a 95% confidence interval for accuracy improvement of [10.2%, 18.9%].Improvement reaches 34% for complex tasks with rare skills. $\square$

4 Conclusion

This neural network model enhances task allocation, improving selection quality by 27% and reducing time by 68%. Future work may explore explainability and temporal dynamics, leveraging topological and cosmological frameworks.

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