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Economic Granularity Interval in Decision Tree Algorithm Standardization from an Open Innovation Perspective: Towards a Platform for Sustainable Matching

Tao Li [1] , Lei Ma [2],*, Zheng Liu [3],* and Kaitong Liang [1]

[1] School of Intellectual Property, Nanjing University of Science and Technology, Nanjing 210094, China; taolee@njust.edu.cn (T.L.); liangktong@njust.edu.cn (K.L.)
[2] School of Public Affairs, Nanjing University of Science and Technology, Nanjing 210094, China
[3] Cardiff School of Management, Cardiff Metropolitan University, Cardiff CF5 2YB, UK
* Correspondence: maryma2009@njust.edu.cn (L.M.); ZLiu@cardiffmet.ac.uk (Z.L.)

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Abstract: In the context of the application of artificial intelligence in an intellectual property trading platform, the number of demanders and suppliers that exchange scarce resources is growing continuously. Improvement of computational power promotes matching efficiency significantly. It is necessary to greatly reduce energy consumption in order to realize the machine learning process in terminals and microprocessors in edge computing (smart phones, wearable devices, automobiles, IoT devices, etc.) and reduce the resource burden of data centers. Machine learning algorithms generated in an open community lack standardization in practice, and hence require open innovation participation to reduce computing cost, shorten algorithm running time, and improve human-machine collaborative competitiveness. The purpose of this study was to find an economic range of the granularity in a decision tree, a popular machine learning algorithm. This work addresses the research questions of what the economic tree depth interval is and what the corresponding time cost is with increasing granularity given the number of matches. This study also aimed to balance the efficiency and cost via simulation. Results show that the benefit of decreasing the tree search depth brought by the increased evaluation granularity is not linear, which means that, in a given number of candidate matches, the granularity has a definite and relatively economical range. The selection of specific evaluation granularity in this range can obtain a smaller tree depth and avoid the occurrence of low efficiency, which is the excessive increase in the time cost. Hence, the standardization of an AI algorithm is applicable to edge computing scenarios, such as an intellectual property trading platform. The economic granularity interval can not only save computing resource costs but also save AI decision-making time and avoid human decision-maker time cost.

Keywords: open innovation; AI standardization; edge computing; intellectual property platform

1. Introduction

Culture controls open innovation complexity [1], whereas machine learning algorithms in open innovation communities or in corporations have probably been trapped in pursuing brute computing power, which requires micro- and macro-dynamics with a quadruple helix [2] to enhance the sustainability of human-machine collaborative artificial intelligence. In the context of the application of AI, the number of suppliers and demanders in intellectual property information and trading platforms is surging. Improvement of matching efficiency highlights the sustainable competitiveness of a platform, that is, the ability to quickly search massive information and matching demands to reduce the operating

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cost of the platform. The standardization of artificial intelligence involves the definition of the application scope, the solution framework adopted, data exchange and privacy, algorithm standards in various scenarios, and compatibility between modules, among others. The TinyML paradigm aims to integrate machine learning within microcontroller units (MCUs) [3]. Large-scale information and communications technology components such as Internet of Things (IoT) are implementing edge-to-cloud architecture through distributed networks [4]. Given that the computing power of edge IoT components is limited due to volume design and cost control, the ultra-low-power concept considers integrated circuit design and energy saving algorithms [5,6]. The reduced instruction set computer—fifth generation (RISC-V), system on a chip (SoC), and Raspberry Pi are typical examples of hardware in autonomous driving and smart cities [7]. Classical algorithms such as decision trees, K nearest neighbors (KNNs), and convolutional neural networks (CNNs) lack standardization, which is unmatched with open source hardware computing power. The ecosystem of AI-scale data machine learning can be improved through algorithm standardization research. A decision tree is a classical and popular machine learning algorithm in the theory and practice of AI, and the advantages of a decision tree algorithm have been confirmed by existing studies [8]. The functions of an intellectual property platform include promotion of the underlying asset, information release, pledge financing, ownership transfer, matching of the supply and demand, maintenance of the relationship between the supply and demand of the underlying asset of intellectual property, and reduction in the cost of supply and demand and supervision of intellectual property. The matching function of supply and demand is not only a technical problem to be improved in industrial organization practice but also a theoretical problem to be studied by academia. However, a large number of AI algorithms used in practice are generated through open source and open innovation, and the performance and cost of algorithms are always the difficulties in the standardization of industrial applications. In this work, the maximum information gain principle in a decision tree was used to study the depth and time cost of the decision tree caused by the increase in candidate matching opportunities brought by the granularity of evaluation language and delayed matching at different quantity levels. This research provides a quantifiable solution to the problem of AI algorithm standardization.

The open innovation paradigm demonstrates a novel open business model [9,10] that can encourage diversified knowledge to be transformed into innovative results [11–13]. The combination of innovation strategy and the open innovation paradigm stimulates the innovation will of collective wisdom [14,15], thus giving rise to a large number of intellectual properties underlying assets in the form of patents or copyrights, which need to be confirmed in the transaction of their market value, and an intellectual property platform is a platform-based organization to meet such needs [16]. The platform provides a place for the information exchange of intellectual property assets. Park et al. demonstrated the delay caused by technological innovation to economic growth through empirical evidence [17], so the innovation results need to realize their own value in the exchange of information, which conforms to the characteristics of the sharing economy [18]. Rasiah proposed that innovation synergy in open communities is realized through the construction of information exchange networks [19]. Kim studied 21 platform-based enterprises and found that organizations rebuilt value streams in their platforms to gain sustainable growth capacity. Kim likened the participants in platform-based organizations to tailors and facilitators [20]. Eremina et al. stated that the sustainable competitiveness of stock price performance brought by the maturity of the digital platform transformation of organizations may not be synchronized [21]. Although this asynchronous pattern widely exists, the transition to a digital platform is bound to be the cornerstone of future financial performance and market value performance.

One of the most important functions of the platform is to provide information sharing [22]. Information is the representation of knowledge in the forms of explicit or implicit. Alos-simo et al. demonstrated that a large number of small and family enterprises have weak intellectual property capitalization and marketization capabilities [23], while the platform can help enterprises achieve sustainable development. Krejcar took universities which provide technology transfer for intellectual property platforms as an example, and proved the importance of platforms to obtain market recognition

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and market value of the underlying assets of intellectual property [24]. On a typical intellectual property platform, there are the supply and demand sides of the underlying asset of intellectual property. They constitute the matching subject, while the underlying asset of intellectual property is the object of matching activities. The functions of the platform include promotion of the underlying assets of intellectual property, information release of the underlying assets, pledge financing of the underlying assets, ownership transfer of the underlying assets, matching of the supply and demand of the underlying assets of intellectual property, maintenance of the relationship between the supply and demand of the underlying assets of intellectual property, and reduction in the cost of supply and demand and supervision of intellectual property. The supplier of the underlying asset transfers the right to use or ownership of the intellectual property for financing purposes, while the demander acquires the right by providing cash flow. The efficiency and effect of matching functions play a crucial role in the sustainable development of the platform. Battula, Xu, and Gu et al. studied the industry segmentation of matching theory from the resource allocation perspective [25–27]. It is necessary to match supply and demand in the intellectual property platform, in order to realize reasonable resource allocation. In the matching activities, there are many fund providers competing for an intellectual property asset, and it is also possible for many intellectual property assets to compete for a fund provider. Thus, it is a mixed two-sided match in a one-to-many or many-to-many platform organization. There are two matching approaches, manual matching and automatic matching. Manual matching is suitable for sporadic financing application and has the advantages of situational driving and detail. However, once the number of applications in the platform increases alongside the diffusion effect and scale effect, manual matching becomes unsuitable for the exponential growth of financing needs. In order to cope with the increasing scale of suppliers in the platform, artificial intelligence technology can improve matching efficiency and eliminate artificial matching mis-operation [28–33]. Based on the studies of big data and AI in line with matching theory, platform-matching activity parameters tuning covers two issues: (a) particle size optimization matching the evaluation language, which can improve the accuracy of the decision tree branch and matching accuracy; (b) in participating in the match of the two sides of a small number of cases, whether participants should choose to delay or immediately match is a debatable issue. Delayed matching may bring more matching opportunities, which improve the satisfaction of both parties. A habitual domain can be used to describe the organizational capability [34], and intellectual property can be separated from the organization that created it. The evaluation of intellectual property can still use the methodology of a habitual domain to evaluate organizational capability, that is, to mine the evaluation granularity. This paper will answer two questions: (1) Will the increase in matching language evaluation granularity and the number of candidate matches lead to significant changes in the depth of the decision tree used for matching? (2) Will the increase in matching language evaluation granularity and the number of candidate matches lead to a significant increase in time cost? In summary, fine tuning can not only improve the matching efficiency, reduce the error of artificial judgement, and save unnecessary human resources costs within the platform, but it can also take the fairness of the screening and matching of a large number of candidate intellectual property assets into account. Therefore, this study also aims to solve the following two problems: (1) How much tree depth is needed for human–machine collaborative matching activities on a centralized trading platform using decision trees? (2) Is the search depth cost–benefit balanced? (Table 1).

Table 1. Advantages and Disadvantages of Matching Activities via Manual or AI.

	Fixed Costs	Variable Costs	Training Expenses	Efficiency	Scale Effect	Reproducible (Traceability)	Impartiality (Anti-Intervention)	Compliance
Manual	LOW	HIGH	HIGH	LOW	LOW	LOW	LOW	LOW
AI	HIGH	LOW	LOW	HIGH	HIGH	HIGH	HIGH	HIGH

2. Model Analysis

2.1. Establishing Maximum Information Gain

Proposed by Clausius in 1985, the concept of entropy is a material state parameter that reflects the irreversibility of a spontaneous process according to the second law of thermodynamics. In an isolated system, there is no energy exchange between the system and environment. The system always changes spontaneously in the direction of increasing chaos, which increases the entropy value of the whole system. This is the principle of entropy increase. The universe as a whole can be seen as an isolated system, evolving in the direction of increased entropy. Originally proposed by Claude Shannon in 1948, Shannon entropy was later on named to measure the degree of information uncertainty in a system [35]. Entropy in thermodynamics measures the degree of chaos in a system, while Shannon entropy measures the degree of uncertainty in a source. It can be expressed as the total amount of information in a system. The greater the amount of information in a system becomes, the greater the Shannon entropy is, meaning the greater the uncertainty of the system is. Shannon entropy can be calculated by the following formula:

$$H = -\sum_{i=1}^{n} p(x_i) \log_2 p(x_i) \tag{1}$$

In the expected value of information of any system expressed in the above formula, the information is classified by language granularity annotation, that is, classification x_i, $i \in \mathbb{N}$, where i is a language granularity annotation. $p(x_i)$ is the posterior probability of classification after granularity annotation, then a single classification x_i, and the Shannon entropy of $i \in \mathbb{N}$ is

$$l(x_i) = -\log_2 p(x_i) \tag{2}$$

For an individual waiting to be paired in a platform, the higher the Shannon entropy, the higher the diversity of the pairing results. Further, the individual is likely to get a better match or a worse match than expected. In other words, if an individual in the platform takes an active or passive waiting strategy, the uncertainty of the matching results will increase with the increase in the waiting time, so that it is more likely that the actual trading results are deviated from the players' expectation. Shannon entropy changes in the decision tree composed of language granularity. Since the decision tree splits the language granularity node from top to bottom, in this study, the information gain of the ID3 algorithm is used to represent the difference between Shannon entropy and variable Shannon entropy under the conditions of an original deferred interval and language granularity. The maximum information gain can be expressed as

$$Maximize: \ \Delta H = -\sum_{i=1}^{n} p(x_i) \log_2 p(x_i) - \sum_{j=1}^{m} p(x_j) \log_2 p(x_j), \ i, j \in \mathbb{N} \tag{3}$$

Under the condition of taking the variable delay interval into account, the above equation can be expressed as

$$Maximize: \ \Delta H = \ -\sum_{i=1}^{n} p(x_i(t)) \log_2 p(x_i(t)) \\ -\sum_{j=1}^{m} p(y_j(t+\Delta t)) \log_2 p(y_j(t+\Delta t)), \ i, j \in \mathbb{N} \tag{4}$$

$y_j(t+\Delta t)$ represents the $x_i(t)$ information classification with a language granularity of $j \in [1, m]$ under the condition of a variable recurrence interval Δt. $p(y_j(t+\Delta t))$ is the corresponding probability.

2.2. Vectorization of Language Granularity and Tree Depth

Since the matching transaction provided by the intellectual property platform is essentially a transaction of information data (Figure 1), the matching process is a screening process. The description and evaluation of the attributes and characteristics of the supplier and demanders of the underlying assets of intellectual property are fuzzy and complex. Language granularity is the evaluation information, which can intuitively represent the characteristics of the object. The language granularity feature set can be expressed as $F = \{F_1, F_2 \dots F_n\}$, where F_i represents the ith granularity characteristic. Fuzzy features can be transformed into granularity classification features by vectorization, with the matrix form as

$$F_{matrix} = \begin{vmatrix} F_1 \\ F_2 \\ \dots \\ F_n \end{vmatrix} \tag{5}$$
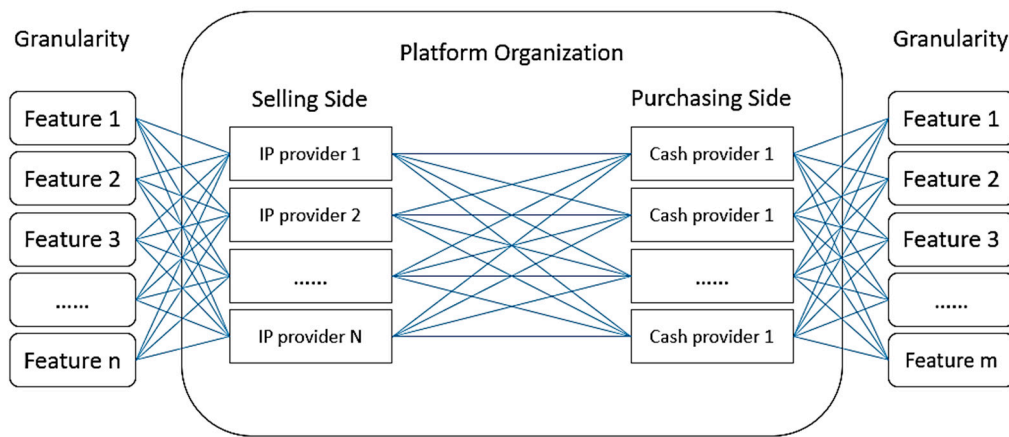
Figure 1. Information Transaction in an Intellectual Property Platform Organization.

Language granularity is initially defined in textual form, for example, pledge, transferable, quote, future cash flow, need for secondary development, industry of the subject, and duration of patent sleep. When the granularity features are pawnable, transferable, and other logical text evaluation features, the language granularity vectorization can be converted to 0–1 logical values. When the industry of the IP target asset needs to be represented with granular features, the industry segmentation can be converted into one-hot-coded eigenvalues through enumeration, and one-hot coding can be further transformed into 0–1 logical values. For example, one-hot coding features with k features can be transformed into 0–1 logical values with combination number C(k,2). The text evaluation with granularity characteristics of the quotation range can be divided into at least two independent numerical characteristics of the lowest quotation and the highest quotation.

In any decision tree process, the vectorized language granularity can be converted into 0–1 logical values. After the text evaluation granularity characteristics are vectorized, the matching process of the IP target asset supply and demand is equivalent to the decision tree process (Figure 2). The language granularity characteristics after vectorization are regarded as the original data set, and they are divided based on the granularity characteristics. If the number of granularity is greater than two, the classification process starts from the root node and reaches the leaf node or the termination node along the bifurcation of the decision tree. A node corresponds to a granularity characteristic, and the algorithm of single-granularity segmentation is presented in Algorithm 1.

Algorithm 1. Partitioning Data Sets by Granularity

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(1) Input Raw Dataset
(2) Define granularity features
(3) Partition Dataset
(4) Create branch nodes based on selected granularity features
(5) For each granularity feature in Dataset:
(6)   If the *i*th granularity feature = TRUE:
(7)   Remove *i*th granularity feature
(8)   Endif
(9) End Loop
(10) Return the split Dataset

	Ownership Transfer	Licensing Authorize	Industry Type	Expected Cashflow per year	Residual Life(years)	......
1	1	0	1	20000	3	...
2	0	1	2	7000	10	...
3	1	1	4	15300	5	...
4	1	0	3	10010	7	...
...	...	...	...	...		...
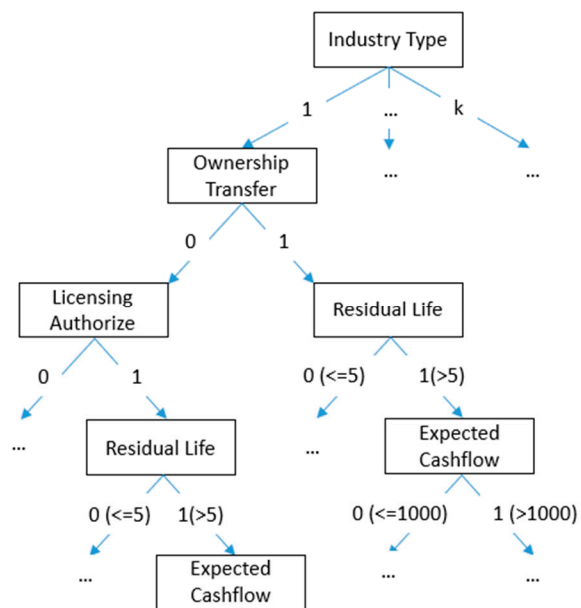
Figure 2. Matching Process Equivalent to Decision Tree Process by Granularity Partitioning.

Since a complete granularity segmentation is traversed through continuous bifurcation of the decision tree, this process is a recursive traversal process, and the algorithm is given in Algorithm 2.

Algorithm 2. Recursive Computation of Max Information Gain

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(1) Collect granularity classification names
(2) Calculate frequencies of each granularity & initial_entropy
(3) For each granularity feature in classification names:
(4)　　　If the *i*th granularity feature is not used:
(5)　　　　　Proceed tree with *i*th granularity feature
(6)　　　　　Probability = number of counts in *i*th granularity feature
(7)　　　　　Entropy = − log2(probability)
(8)　　　　　Entropy_update = − log2(probability) + entropy
(9)　　　Endif
(10)　　　Information_gain = initial_entropy − entropy_update
(11)　　　If info_gain > initial_entropy
(12)　　　　　Max_info_gain = info_gain
(13)　　　　　Return the *i*th granularity feature
(14)　　　Endif
(15)　　　Return loop
(16) End loop
(17) Build tree (granularity nodes, dataset)
(18) n = number of subnodes
(19) If n > 0
(20)　　　Get the *i*th granularity feature with max_info_gain
(21)　　　n = n − 1
(22)　　　Build tree (n, dataset)
(23) Endif
(24) End

2.3. Concerns of Privacy Desensitization

Data privacy in platform-based organizations has long been a problem for platform participants. Agrawal and Srikant suggested adding noise to the data mining method to protect data privacy [36], but it cannot avoid the risk of removing noise and restoring clean data. Decision trees have better data desensitization and privacy governance advantages. To make full use of the advantages of distributed computing, in this study, it is believed that the right approach is to slice and shard clean decision data. Since the bifurcation process of decision trees is the filtering process based on the granularity characteristics, the evaluation language granularity characteristics (columns) with privacy sensitivity are replaced with the data record name (rows) when the decision target is unchanged, that is, the process of "peeling-encrypting-combining". Without adding noise to the 0–1 logical value in the data, information distortion caused by adding noise is avoided. In data privacy, the control data fragmentation process is adopted in different nodes of a host for storage and processing, in order to achieve the effect of the separation of duties (Figures 2 and 3). Based on the perspective of Industry 4.0, Sun et al. proposed distributed accounting to solve the problem of data privacy [37], which is also a method worthy of reference for the protection and governance of data privacy.
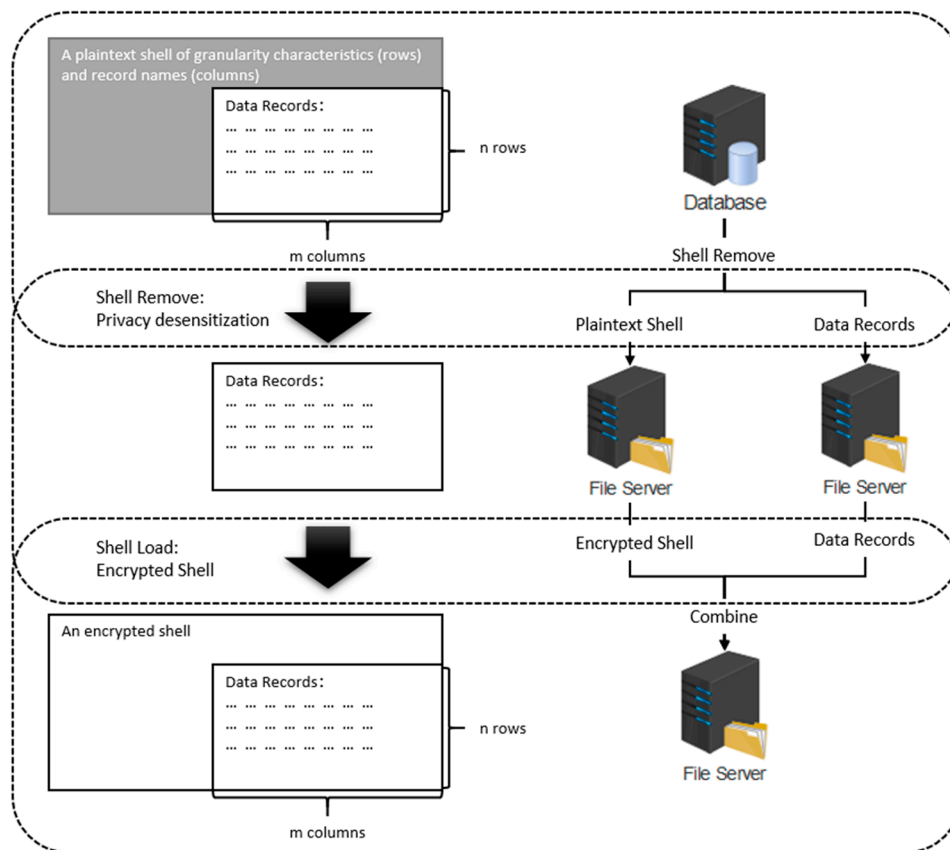
Figure 3. A Procedure for Data Privacy Desensitization.

3. Simulation Analysis and Validation

3.1. Experiment Objective

(A) Given the number of matches, the optimal tree depth interval and the corresponding time cost with increasing language granularity.

(B) If there is a delay matching opportunity, the change in optimal tree depth and the change in evaluation language granularity under the maximum information gain algorithm will bring the corresponding time cost.

3.2. Experiment Setup

Since k (k > 2) decision tree bifurcations under any node can be converted into the combined number C(k,2) leaf nodes, the experimental hypothesis in this paper has completed the transformation of evaluation language granularity with k branching trees to binary decision trees. In order to simulate various data combinations in the platform as far as possible, 01 bifurcation under the random generated granularity is adopted in the experiment. The number of simulation times under each change condition is set to 10~100 times. When the search condition meets the maximum information gain, the decision tree bifurcation stops searching and returns the tree depth and search time.

The following is hardware and software (OS) information:

System = "Windows", Release = "10", Version = "10.0.18362";
Machine = "AMD64";
Processor = "Intel(R) Core(TM) i5-7300U CPU@2.6 GHz";
Software = "Python", Version = "3.7";
Packages = "math, log, operator, random, string, NumPy, seaborn, matplotlib, pandas, etc."

The source code referred to Appendix A.

3.3. Experiment

(A) The experimental results are shown in Figure 4a–d: given the number of candidate matches, the increase in the granularity of the evaluation language causes the decrease in the tree depth and gradually converges. When the number of candidate matches is at a low level, the tree search depth decreases slowly with the increase in the evaluation language granularity. However, when the number of candidate matches is at a high level, the increase in language granularity can accelerate the decline in the tree search depth. The experimental results also show that the yield of decreasing tree search depth brought by the increase in evaluation language granularity is not linear. With a given number of candidates matches, there is an economic interval from the number of 40 to 80 granularity characteristics, and a smaller tree depth can be obtained by selecting the specific evaluation language granularity in this interval.
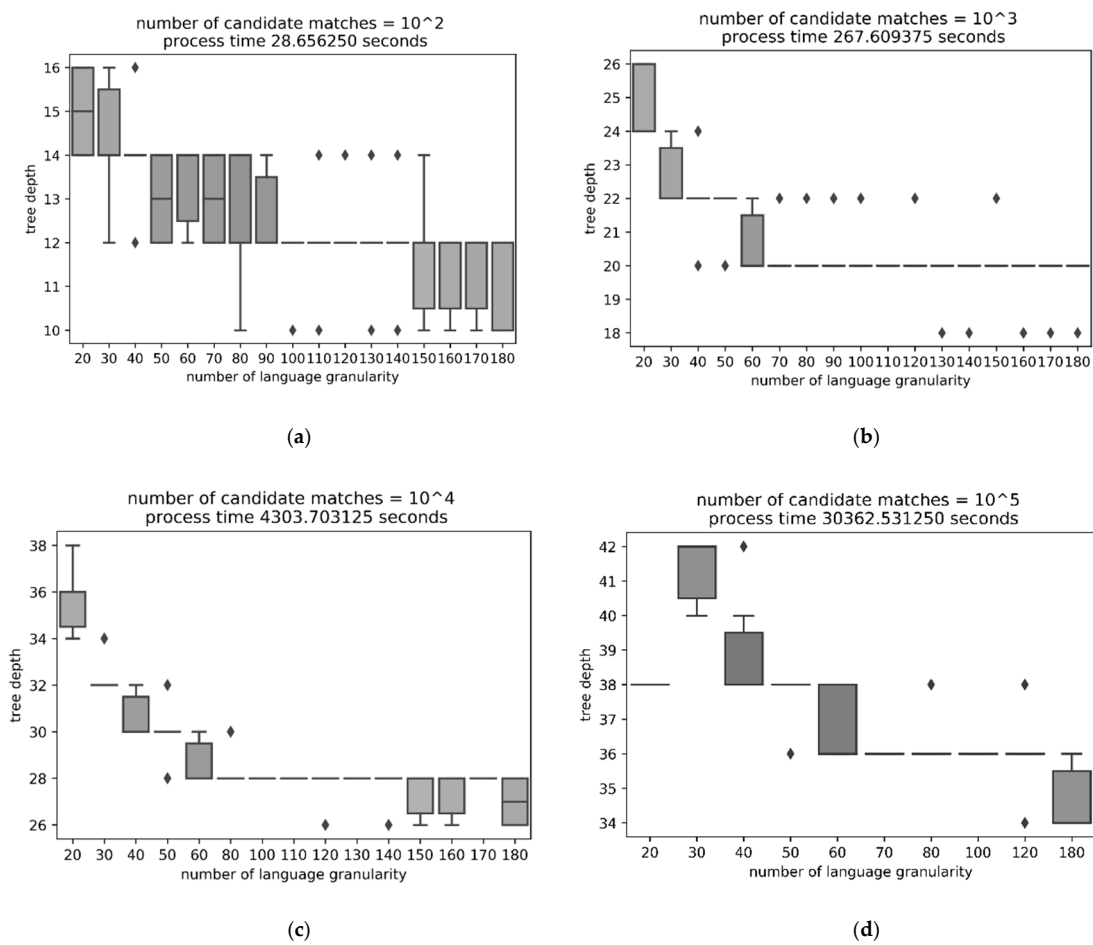
Figure 4. Tree Depth Reduction Based on Different Levels of Granularity and Candidate Matching. (**a**) Simulation on the order of magnitude of 10^2; (**b**) Simulation on the order of magnitude of 10^3; (**c**) Simulation on the order of magnitude of 10^4; (**d**) Simulation on the order of magnitude of 10^5.

(B) At the same time, the order of magnitude of growth in candidates due to the waiting delay is considered. Thus, it simulates the orders of magnitude of 10^2, 10^3, 10^4, and 10^5, when the candidate matching tree depth changes. Figure 4a–d show that when orders of magnitude of the matching candidates increase (such as order of magnitude increases to 10^2, 10^3, 10^4, and 10^5), at a given granularity size, the tree depths obtained with the maximum information gain rule result in an average increase of 8 tree depths. It also results in an exponential increase in the search time.

From the perspective of cost and benefit, if demanders and suppliers adopt the decision of delayed matching, though the number of candidate matches may increase considerably, the number of granularity that reduces the depth of the search tree to a stable interval is still between 60 and 80, and the time cost brought by the searches increases exponentially. Therefore, there may be no deterministic optimal combination between the increase in candidate orders of magnitude brought by the decision of delay matching and the exponential time cost increment of searching.

4. Conclusions and Prospect

The benefit of decreasing the tree search depth brought by the increase in evaluation language granularity is not linear. In a given number of candidate matches, the number of language granularity features has a definite and relatively economical range. Meanwhile, the selection of specific evaluation language granularity in this range can obtain a smaller tree depth and avoid the occurrence of low efficiency, that is, excessively increasing the time cost of the tree search brought by evaluation language granularity. Under the decision of waiting for delayed matching, the quantity level on both sides of the supply and demand of the candidate-matched intellectual property asset may increase. In terms of cost and benefit, the granularity of evaluation language whose search tree depth drops to a stable interval is still between 60 and 80, while the time cost brought by the search increases exponentially. Therefore, there may not be a deterministic optimal combination between the increase in candidate orders of magnitude brought by the decision of waiting for delay matching and the exponential increase in the search time cost. This is a problem to be actively weighed by both the supply and demand in practice. Compared with other machine learning methods, the decision tree method can still consider a small data volume and an accurate decision. As a reproducible "white box" process, it is conducive to man-machine collaboration in platform-matching activities and sustainable development of the platform.

The advantage and contradiction of the cooperation between the method of industrial intelligence and human become increasingly more prominent. In the practice of intellectual property pledge financing and trading platforms, the decision tree method can improve the matching efficiency of the supply and demand in the platform and save human resource cost. However, AI technology cannot completely replace human decision making [38]. Machine learning-based methods in the industrial application of artificial intelligence often require a huge amount of data training machine learning models. Although the decision tree using cascading leaf nodes and branch-building binary tree data to filter data can be exempted from the training process, the implementation process of the decision tree classification evaluation language granularity is still set manually in advance according to the experience. To evaluate language granularity, word vectors should be constructed by word segmentation. Mikolov applied an efficient method for constructing word vectors [39]. Bengio adopted a probabilistic neural language model [40] to solve the problem of generating word sequences. Combining the studies of Mikolov, Bengio et al., and ELMo (Embeddings from Language Models) [41], Peters proposed the text feature extraction method. The language granularity feature evaluation is based on the intellectual property underlying assets of natural language description texts of high- and low-mixed contexts and generates 0–1 logical granularity characteristics satisfying the number of decisions. As an asset, intellectual property is characterized by its evaluation granularity [34]. Human intervention in AI decision-making processes is an integral part of human-machine collaboration. Thus, in the determination of an economic range of evaluation granularity considering the computing power of equipment, the standardization of AI algorithms helps in applying edge computing scenarios, such as an intellectual property platform. The economic interval of evaluation granularity can not only save the cost of computing resources, but also save AI decision-making time and reduce human decision-making cost.

Appendix A

The source code for this study selects MIT License:

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The source code written with Python3.7 for this study can be viewed and the result can be reproduced. Please visit or download in the GitHub repository below:

https://github.com/dogfaraway/tree_depth_MIG/blob/master/tree_depth_search_and_economic_language_granularity_based_on_MIG.ipynb

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