



IMPROVING SEMANTIC ANALYSIS IN VISUALIZATION WITH META NETWORK REPRESENTATION AND PARSING ALGORITHM

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Abstract. This article aims to advance semantic analysis models, particularly in visualization, by proposing a novel semantic representation method utilizing the semantic Meta Network (MNet). MNet is a complex framework comprising semantic elements, internal and external relationships, and feature attributes, defined hierarchically through recursive processes, aiming to depict the comprehensive semantic space from phrase-level components to complete texts. The methodology involves the development of a general construction algorithm for MNet, encompassing meta relationships, tree structures, and network structures, and a Parsing method for specific semantic analysis problems, including a bottom-up specification-based MNet semantic dependency tree construction algorithm and a network construction algorithm tailored for natural language interface parsing. Empirical experiments confirm the effectiveness of these algorithms, particularly in parsing natural language control interface instructions in Supervisory Control and Data Acquisition (SCADA) systems, bridging specific semantic analysis problems with the general construction and parsing processes of MNet, accounting for internal semantics concerning language unit structures and foreign language meanings in the linguistic context, thereby contributing significantly to the field of natural language semantic analysis.

Key words: Natural language processing, SCADA, Natural language interface, MNet, Parsing algorithm

1. Introduction and examples. SCADA technology, also known as Computer for Remote Sensing (telemetry, remote control, remote signalling, remote adjustment), is an automated system founded on the Computer, Communication, Control, Sensor (3C+S) framework. It seamlessly integrates monitoring, control, and data acquisition functionalities. Communication technology enables data communication within cross-regional and long-distance SCADA systems. To address the distribution of SCADA systems, the complexity of regulating control objects, and the concurrent data collection and real-time demands of automatic control, advanced computer network communication technology is essential for constructing a distributed SCADA system [6].

The authors introduced a VLAN-based distributed SCADA system implemented within the overall automation system of the Yellow River Diversion Project. They explored its system architecture, distributed data acquisition, and regulation control algorithms, all based on parallel databases. Nonetheless, it is evident that China's manufacturing industry currently faces challenges in attaining a high level of sophistication, particularly when harnessing information technology for industrial production. In this regard, a considerable gap exists between China and industrialized developed nations. One prominent technology that stands out in industrial production is SCADA, a prevalent and indispensable industrial information system [15].

The full potential of SCADA systems in China's manufacturing industry is yet to be realized, leaving substantial room for growth and advancement. Closing this technological gap and fully integrating SCADA technology into the industrial production landscape is essential for China's progress in this arena and its efforts to compete globally. Currently, traditional SCADA systems predominantly rely on copper wires. However, as the industry transitions towards IP-based massive data collection SCADA systems, it confronts two significant challenges. The first challenge pertains to the adaptability of data collection protocols. This issue arises due to multiple IP-based data collection and transmission protocols, each characterized by substantial variations. Notably, there is a unified industry standard for the IP data transmission protocols used by sensors [9].

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The different IP sensors employ a range of protocols such as HTTP, FTP, SNMP, SSH, TELNET, and MODBUS, each presenting distinct formats for the transmitted data messages. This diversity poses a formidable obstacle for SCADA systems seeking to integrate many sensors into their infrastructure seamlessly. This results in substantial pressure for the widespread adoption of IP-based SCADA systems [5].

Distributed processing of massive data collection is a primary advantage of IP-based SCADA systems, as it allows for nearly unlimited system capacity, facilitating the creation of large-scale data acquisition and monitoring control systems encompassing up to 100,000 points. However, such extensive systems' scalability introduces challenges in efficiently managing SCADA systems' substantial influx of data. Failure to address this issue could potentially hinder the widespread adoption of SCADA systems in large enterprises, posing significant hurdles to their application [8].

Semantic analysis, a fundamental process in natural language processing, encompasses various tasks depending on the language unit under consideration. These tasks encompass word sense disambiguation at the word level, role labelling at the sentence level, and referential disambiguation at the discourse level. Recent years have seen semantic analysis primarily focus on two major approaches: rule-based and statistical methods. Rule-based methods rely on a series of language rules rooted in generative linguistics, often beginning with establishing "predicate-argument relationships", featuring concepts like first-order predicate calculus, semantic networks, concept dependency graphs, and frame-based representations. On the other hand, statistical methods draw insights from extensive corpora analysis, employing probabilistic and data-driven techniques. Advancements in deep semantic analysis have given rise to concepts such as semantic dependency analysis trees, dependency analysis graphs, Abstract Semantic Representation (AMR), combinatorial category logic, and knowledge graphs. Deep networks, primarily founded on distributed learning, including word embeddings and sub-embeddings, have delivered promising outcomes in shallow semantic analysis tasks like named entity recognition, word relationship extraction, text classification, and automatic term extraction. Notably, practical applications have seen a continuous integration of rule-based and empirical statistical methods, yielding favourable results [3, 4].

2. MNet Methodology. This section presents an abstract definition of the semantic analysis model, MNet. Subsequently, we investigate a comparative analysis, highlighting the similarities and distinctions between MNet and other relevant methods. Conclusively, we explain the conceptual framework for constructing MNet and underscore that the construction of MNet inherently represents the process of semantic analysis and its corresponding solution [2].

2.1. Definitions. DEFINITION 2.1. *Meta network (MNet) is an ordered group, $MNet=(n_1, n_2, \dots, n_m; r, R, P)$, among them, n_i ($i = 1, \dots, m$) is also a semantic network, which is a sub semantic network of N (this is a recursive definition, this is particularly important, and it is also an important feature to distinguish other semantic networks), $m \geq 1$, for example, under the framework of natural language description, n_i can be any form from words, phrases, phrases to sentences and texts [14].*

R is the set of internal relationships of N , $r = r_{ij}, j = 1, \dots, m$, and $i \neq j$;

R is the set of external relationships of N , $R = R_{ik} = 1, \dots, m, k = 1, \dots, \infty$;

The set of P attributes, $P = p_i = 1, \dots, \infty$;

DEFINITION 2.2. *The internal relationship of the semantic MNet: r_{ij} is a quaternion ($\eta_i, n_j, relation, P$), among them, relationship is the name of the relationship where n_i points to n_j , where $\eta_i \in MNet$ and $n_j \in MNet$.*

DEFINITION 2.3. *The external relationship of the semantic MNet: R_{ik} is a quaternion ($\eta_i, n_k, relation, P$), the relationship is η_i points to η the relationship name of k , among them, $\eta_i \in MNet$, $n_k \in MNet$.*

DEFINITION 2.4. *Attribute set P : p_i is a binary (AttriName, AttriValue) consisting of attribute names and values.*

DEFINITION 2.5. *Meta relationship: If n_i, n_j are independent words, then r_{ij} or R_{ik} are meta relationships.*

Here are a few clarifications within the MNet framework: firstly, MNet suggests that the smallest semantic unit is a word, with the connections between words referred to as meta relationships. Secondly, MNet exclusively defines binary relations, even though real semantic units often involve multiple relationships; for instance, in the natural language interface parsing for SCADA instructions, ternary relationships are commonplace but can

generally be simplified into binary relations for shortness. However, the precise transformation details are not expounded here [11].

2.2. Comparative Analysis. When MNet’s target object is a sentence, similar methods predominantly centre around sentence dependency analysis, represented by dependency analysis trees and diagrams. Semantic dependency analysis’s primary objective is to define the genuine or logical semantic connections among words within a sentence’s structure. In a broader context, these connections encompass syntactic functional relationships within sentence components, thereby encompassing syntactic dependency analysis within the purview of semantic dependency analysis [16].

From Definition 2.1, it can be seen that the semantic dependency tree is a special form of semantic meta-network. When semantic meta-network N meets the following restrictions, it is simplified into a natural language semantic dependency tree:

- 1) $S = n_1, n_2, \dots, n_m$ is a complete natural language sentence composed of words;
- 2) R satisfies the following qualifications related to the semantic dependency tree:

The directed acyclic tree composed of r as an edge and n_1, n_2, \dots, n_m as nodes, is a single root node; $N_i (i = 1, \dots, m)$ has only one parent node; If the word n_i depends on n_j , then all words between n_i and n_j belong to n_j , which means there are no edge intersections in the dependency tree.

- 3) R and P are empty sets.

The semantic dependency graph represents a significant advancement by overcoming the limitations of semantic dependency trees, particularly in terms of edge crossing and multiple parent nodes. This expansion of functionality contributes to a richer semantic description. AMR transcends traditional syntactic tree structures by abstracting a sentence into a semantically coherent, single-rooted, directed acyclic graph. Comparable methods for sentence-level semantic analysis include semantic networks, which essentially depict the conceptual relationships among words in a graphical network format. When the focus extends to sets of words as language units within a specific natural language, the functionalities of the Italian Meta Network (MNet) align with those of ConceptNet, WordNet, and HowNet, as well as knowledge base tools like Knowledge Graph. Various internet companies and organizations have introduced their knowledge base tools, including Google Knowledge Graph, BabelNet, DBpedia, DBary, and Microsoft Concept Graph. But, the widespread adoption of these tools is currently limited [12, 10, 18].

In essence, MNet unifies various expression methods, including knowledge base tools like WordNet, semantic dependency trees (graphs), and semantic networks to represent semantic relationships comprehensively. A noteworthy aspect of MNet is its incorporation of external relationship definitions and recursive structures, pivotal features of this unified model.

2.3. MNet Construction Ideas. The cognitive process is facilitated by MNet, using Figure 2.1 as an illustrative example. It provides insight into the thought process guided by common sense and perception. Hypothetical evaluation is incorporated to shed light on the natural language processing tasks involved in reading comprehension. The sentence “someone smiles and walks towards a table with apples and water cups” serves as an overarching description of a particular real-life scenario, necessitating the prediction of the subsequent actions of the individual involved. According to common-sense reasoning, these actions could encompass “eating apples” or “drinking water”. Regarding the static features of the semantic analysis model, the internal and external relationships inherent to each layer of elements within the scene correspond to the internal and external relationships of the semantic units within the sentence [7].

While speech transmission typically follows a chronological sequence from left to right, creating the impression that the brain processes speech and text linearly, word by word and sentence by sentence, the actual relationships between semantic units in language are fundamentally grounded in the objective scene. Each semantic unit represents a distinct element of the dynamic natural scene, independent in time and space. Consequently, constructing and deducing these relationships can be orchestrated and interconnected through these semantic units. In other words, establishing relationships need not adhere strictly to a word-by-word sequential order as per sentence input; it can instead unfold in a bottom-up, parallel manner akin to the processing of visual imagery [17].

Modern cognitive neuroscience posits that the brain can convert language into visual information, with the cortex processing auditory signals like visual inputs from the eyes.

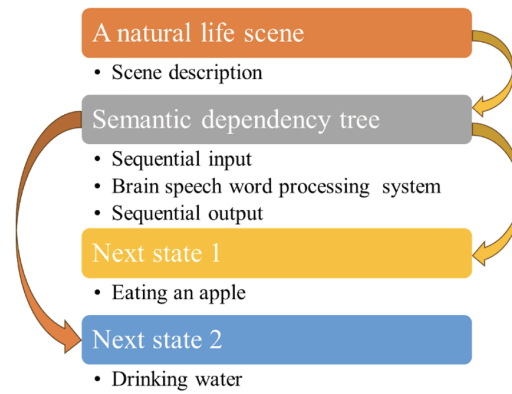


Fig. 2.1: Natural language understanding task.

In analysis and reasoning, the leverage of external relations, often manifested as contextual connections and background knowledge embedded within language and text, proves invaluable. In natural language processing, semantic dependency trees are valuable for delineating internal and external relationships among scene elements facilitating logical reasoning. However, these trees alone do not provide a comprehensive view. The interplay between the intrinsic relationships inherent to a sentence itself and the extrinsic relationships governed by contextual knowledge engenders a complex network structure within the semantic units of the sentence.

Consider the sentence “someone smiles and walks towards a table with apples and water cups”. Internal relationships encompass actions such as “walking towards the table” and “smiling”, intertwined with external relationships like “apples and water cups may be food” and “people can eat food and drink water”. Navigating this intricate web of relationships allows us to deduce that the potential next state involves “eating apples” and “drinking water”.

In light of this analysis, the author employs MNet to investigate the composition and relationships of elements that characterize objective scenes. The construction of MNet adopts a bottom-up self-organizational approach, with the ultimate goal of addressing specific practical challenges in natural language processing. The subsequent steps employed in the process of constructing MNet are as follows [1]:

1) Meta-relationship construction involves establishing a foundational semantic relationship library among words, serving as a cornerstone for resolving Met’s internal relationships. A deep learning approach leveraging bidirectional GRU and an attention mechanism was employed to construct the meta-relationship library between words, accompanied by corresponding experimental investigations.

2) Tree construction primarily encompasses the development of internal relationships based on these meta-relationships. This is achieved through a parallel bottom-up self-organization method to induce and construct a comprehensive semantic dependency tree. The author introduced a bottom-up specification-based MNet semantic dependency tree construction algorithm supported by an accompanying experimental analysis.

3) Conversely, Web construction primarily deals with external relationships. Given the impracticality of exhaustively constructing all external relationships of semantic units within sentences, a selective approach is adopted. Tailored to specific natural language computing tasks, the semantic tree established in the preceding step is extended to encompass external relationships. As an illustrative example, the natural language control interface of the smart home SCADA system is considered, with the objective being to map the relationships between nodes in the MNet semantic dependency tree and target instructions. Algorithmic details and experimental outcomes are presented separately to explain this process.

Given current cognitive limitations, our exploration of the MNet method has not delved into a rigorous mathematical framework. Rather, our focus has centred on refining the MNet approach for semantic analysis within the context of solving natural language manipulation interfaces, approaching it primarily from a design perspective.

Table 2.1 provides an overview of the MNet method, evaluating it from various dimensions of semantic

Table 2.1: Assessment of the MNet semantic analysis model.

Index	Description
Visualization	The relationship between semantic units expressed in network graphics
Concurrency	Each language unit can independently and parallelly calculate its relationship with others.
Complexity	Recursive definition reduces model complexity.
Uniformity	Consistent with natural reading habits and good consistency
Variability	Support incremental semantic parsing from meta-relationship tree relationships to graph relationships with good model variability.

representation modelling. MNet exhibits strong concurrency, variability, visualization, and consistency characteristics in many respects and maintains low complexity.

3. Structure of MNet.

3.1. MNet Relationship. MNet meta relationships can leverage existing knowledge base tools such as WordNet and HowNet. However, it becomes imperative to pre-construct bidirectional GRU and word vectors through sample training when addressing domain-specific challenges. This process, in combination with sub-character level and sentence-level attention mechanisms, facilitates the training of word relationships based on sample data.

Character embedding and position embedding information vectors of word pairs involved in the prediction relationship are employed to represent the input. This approach incorporates a word-level attention mechanism and combines bidirectional GRU with a character attention mechanism to create the embedding vector representation of the sentence.

For instance, consider a set of n sentences encompassing relational pairs (word1, word2), denoted as $s_i (i = 1, \dots, n)$. The embedded expression vector within each sentence carries information about whether it includes the relationship r . We incorporate a sentence-level attention mechanism to leverage information from all these sentences when predicting relationship r for the pairs (word1, word2). This mechanism enables us to represent these n sets of sentences using feature vectors encapsulating embedded expression information from all the sentences. Subsequently, we conduct comprehensive training, a strategy that offers the advantage of justifying the noise impact from inaccurate standard data.

3.2. Tree Construction. The analysis of semantic dependency trees typically encompasses both transfer-based and graph-based methods. To align more closely with human language thought patterns and accommodate concurrent execution, we have integrated both transfer-based and graph-based approaches. Building upon the probabilistic assessment of relationships between words within a sentence, our method employs a bottom-up approach involving neighbouring word competition and a dependency mechanism to construct a semantic dependency tree. This approach differs from traditional transfer-based methods in several key ways:

- 1) It is no longer constrained by the input order of the sentence, irrespective of whether left-associative or right-associative dependencies take precedence.
- 2) When dealing with words that have not yet determined their dependent objects, it considers the dependency relationships with adjacent words and those of the words upon which the adjacent words rely.
- 3) We have implemented optimizations to address the occurrence of multi-subtree phenomena during the construction process.

3.3. MNet Construction. The construction of the MNet network varies based on the specific semantic understanding tasks at hand. Fundamentally, it revolves around tree construction, where we re-label words and their relationships to align with the diverse requirements of downstream natural language processing tasks. This secondary annotation process can occur either after the completion of semantic dependency tree parsing or concurrently during the parsing process. Consequently, MNet can iteratively optimize natural language parsing, thereby continually deepening its grasp of semantics. This adaptability and incremental refinement distinguish it from neural network models, providing distinct advantages in the field [13].

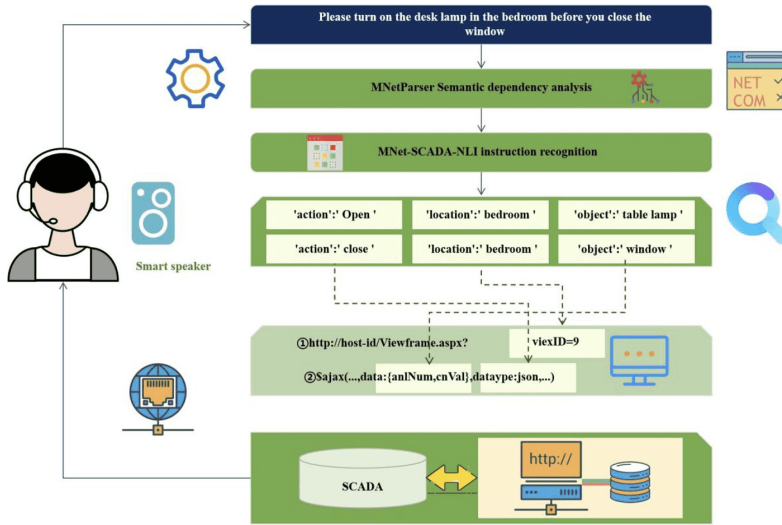


Fig. 3.1: MNet SCADA-Natural Language Interface (NLI) analysis algorithm.

To illustrate the process of constructing a specific MNet network, let’s consider the application of a natural language interaction interface in a SCADA system. In the SCADA system’s control mode, there are primarily two types of commands: query and control. Query commands retrieve status data from on-site processes or equipment, while control commands modify on-site equipment or process parameters. Control commands in the SCADA system typically consist of three key components: actions, objects, and parameters. Among these, the parameter often includes the position, indicating the specific location of the controlled object.

For instance, a natural language instruction like “turn on the desk lamp in the bedroom” can be transformed into an intermediate language representation with a data structure such as “{Object=desk lamp, Location=bedroom, Action=turn on}” using a natural language processing program. Subsequently, formal rules can be applied to generate the SCADA system’s command instructions. Figure 3.1 illustrates the parsing principle of the SCADA system’s natural language control instructions. This example highlights the process of adapting natural language input into actionable commands within the SCADA system.

To enhance the efficiency of accomplishing the intended tasks, it is possible to seamlessly integrate the construction of specific MNet networks into the MNet tree construction process. This approach allows for the modification of STEP3 within “MNetSParser” to align with specific application requirements. Subsequently, the processed data can undergo further processing using the MNet-SCADA-NLI algorithm. This integration streamlines the task execution process and enhances overall efficiency.

4. Experiments and Applications.

4.1. Building MNet Relationships with Word Relationship Knowledge Base. There is a lack of standardized definitions for word relationships, even in resources such as WordNet, HowNet, ConceptNet, and others, which are customized and incomplete. The original word relationship samples are constructed to address this issue using the “evsam05.zip” Chinese semantic dependency analysis and evaluation dataset published by the Natural Language Processing and Chinese Computing Conference (NLP & CCC 2013). The training data follows the CoNLL format for a Chinese dependency corpus, while the experimental data is sourced from the Tsinghua database. The data samples have been uniformly converted to facilitate model training, as detailed in Table 4.1. This approach establishes a more comprehensive and tailor-made understanding of word relationships.

The Tsinghua semantic dependency tree database enumerates 69 types of word dependency relationships, as presented in Table 4.2. For example, in the sentence “The Eighth Wonder of the World Appears”, the relationship between “the world” and “the miracle” is “limited”. At the same time, negative samples were

Table 4.1: Semantic relationships in sample sentences.

Word 1	Word 2	Relationship Type	Sentence
World	Miracle	Limit	The eighth wonder of the world appears
Within	Hall	Locative word dependency	The hall is carpeted with red carpet
Red	Carpet	Describe	The hall is carpeted with red carpet
World	Appear	Null	The eighth wonder of the world appears

Table 4.2: Serial numbers and their associated types.

Serial Number	Type	Serial Number	Type
0	The word 'dependent' on '	9	Connection Dependency
1	Original state	10	quantity
2	content	11	degree
3	Process Period	12	result
4	Relationship subject	13	possessor
5	source	14	objective
6	comment	15	Final state
7	reason	16	Tone dependency
8	result event	17	Comparative quantity

added, and the relationship type was NULL, indicating that there was no dependency relationship between the group of words, the data was divided into training and testing sets.

Two cases were tested separately, one without negative samples and the other with negative samples, among them, 80% of the training set with negative samples included the addition of negative samples, which significantly improved the efficiency and accuracy of training. Figure 4.1 and Figure 4.2 show the changes in loss function and accuracy rate during the training process of adding negative samples using the TensorboardX tool. Finally, select the model with the training fitting accuracy acc of 0.98 and the accuracy of this model in predicting word relationships on the test set is 89.9

4.2. MNet Parser Semantic Dependency Analysis for Tree Construction. The MNet implies utilizing the MNet parser to perform semantic dependency analysis in tree construction. The proposed method suggests that the MNet parser plays a pivotal role in dissecting semantic relationships, which are the meaningful connections between words, and this analysis is crucial for creating tree-like structures.

In the data source and analysis process, the evaluation indicators test set uses the Chinese semantic dependency analysis and evaluation data package published by the NLP & CCC 2013 to evaluate the tested system using three indicators, namely: Labeled Attachment Score (LAS); Unlabeled Attachment Score (UAS); Labeled Accuracy (LA). Assuming that the total Number of words in the entire test corpus is N , the dependency of any word is represented by a triplet $\langle \text{word}_i, \text{word}_j, \text{Depreij} \rangle$ represents. Among them, 'word_i' is the word itself, and 'word_i' is dependent on 'word_j' with a relationship of 'deprej', the correct Number of words 'for all word_j is 'Nuas', the correct word data for all deprij is 'Nla', and the correct Number of words for all word_j and deprij is 'Nlus'. So, the calculation method for testing indicators using Equations (4.1) to (4.3):

$$LAS = \frac{N_{las}}{N} \quad (4.1)$$

$$UAS = \frac{N_{uas}}{N} \quad (4.2)$$

$$LA = \frac{N_{la}}{N} \quad (4.3)$$

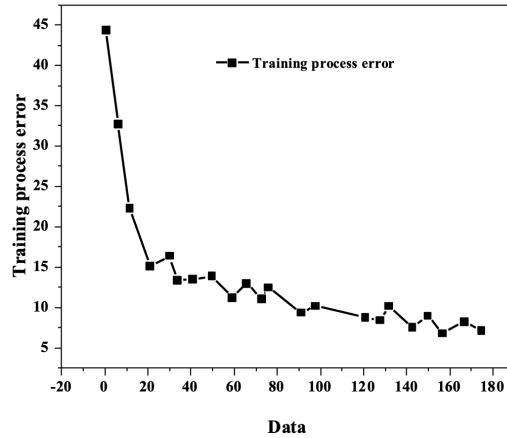


Fig. 4.1: Evolution of training process errors.

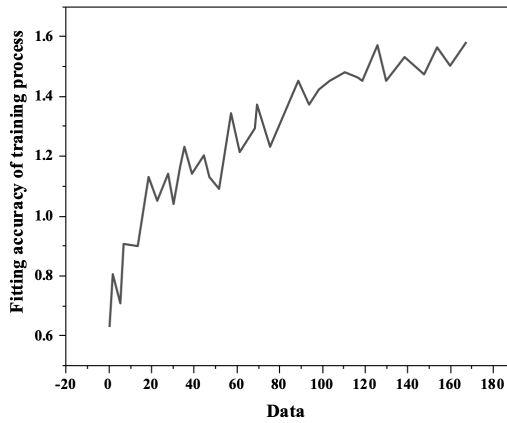


Fig. 4.2: Training process fitting accuracy.

Regarding computational complexity analysis, “MNet Parser” can efficiently construct semantic dependency trees in $O(n \log n)$ time, similar to the straightforward edge-first approach. Evaluating accuracy using the same word relationship calculation model and comparing it with the effective transfer-based edge-first algorithm reveals certain advantages of MNet Parser, with an improvement of approximately 2-3 percentage points, as demonstrated in Table 4.3. However, the overall accuracy remains somewhat modest, primarily attributed to a relatively small sample size and up to 70 dependency categories. It is anticipated that enhancing accuracy can be achieved by reducing the Number of dependency categories and increasing the sample size. Factors such as part-of-speech and dependency category prioritization introduced during the parsing process can improve accuracy.

4.3. MNet-SCADA-NLI Methodology. In the context of natural language interaction within smart homes, a limited-scale questionnaire survey was conducted to compile a dataset comprising roughly 100 frequently utilized language manipulation commands. TF-IDF51 and the proposed MNet-SCADA-NLI were employed for intermediate language recognition within the SCADA system.

The algorithm’s performance is assessed by measuring accuracy (P), recall (R), and F-values, which are defined by Equations (4.4) to (4.6):

Accuracy (P) quantifies the fraction of accurately parsed parameters within the predicted intermediate

Table 4.3: Comparative analysis of test results for MNet parser.

Method	LAS	UAS	LA	Time complexity
MNet Parser	59%	72%	79%	$o(n \log n)$
Edge First Algorithm	57%	69%	77%	$o(n \log n)$

Table 4.4: Comparison of natural language manipulation instructions in SCADA system.

Method	Precision (P)	Recall (R)	F value
TF-IDF	0.71	0.52	0.6
Proposed MNet-SCADA-NLI	0.90	0.90	0.90

language results.

$$P = \frac{N}{Total_P} \quad (4.4)$$

Recall rate (R): It reflects the proportion of correctly parsed parameters in natural manipulation language samples.

$$R = \frac{N}{Total_R} \quad (4.5)$$

F-value: It is calculated as the harmonic mean of precision and recall and is defined as:

$$F = \frac{2 \times P \times R}{P + R} \quad (4.6)$$

where N = Number of correctly parsed parameter indicators; $Total_P$: Number of parameter indicators in the algorithm prediction results; $Total_R$: The Number of parameter indicators in the expected results of the original natural manipulation language sample.

Table 4.4 displays the comparative outcomes between the TF-IDF method and the proposed MNet-SCADA-NLI algorithm in terms of instruction recognition within the intermediate language of the SCADA system. The experimental findings show that the proposed MNet-SCADA-NLI holds notable advantages, particularly when dealing with small sample training sets. TF-IDF primarily relies on keyword extraction for sorting and differentiation based on part of speech and category. While TF-IDF performs well in straightforward natural language instruction parsing, its performance notably diminishes when tackling complex natural language instructions. In some cases, it may fail to parse certain instructions altogether.

For instance, when presented with a sentence like ‘Please turn on the desk lamp in the bedroom before closing the window,’ TF-IDF often struggles to parse a comprehensive set of commands. Alternative approaches like Seq2Seq are attempted but yield less-than-ideal results due to the limited sample size. Seq2Seq typically demands substantial-high-quality training data to achieve favourable outcomes.

In contrast, the proposed MNet-SCADA-NLI method excels in handling complex natural language instructions. It yields high accuracy when coupled with domain-specific rules and dependency analysis results. However, it’s important to acknowledge that this method has certain limitations, particularly regarding question formulation and openness. Furthermore, there is a prerequisite to enhance the accuracy of semantic dependency analysis to achieve superior results for intricate language sequences.

5. Conclusion. A comprehensive semantic analysis methodology called the MNet is introduced from the Semantic Web, deep web, and dependency analysis. MNet is designed to encompass various semantic elements, internal and external relationships, and feature attributes, all structured hierarchically to capture semantic

nuances from individual phrases and sentences to entire texts. Developing a general MNet construction algorithm involves three pivotal processes: Meta relationship, tree structure, and network structure. A novel bottom-up specification-based MNet semantic dependency tree construction algorithm, demonstrating its effectiveness through experiments, is introduced in resolving challenges related to semantic dependency analysis and natural language control interfaces, particularly within the context of SCADA system interfaces. The proposed approach effectively translates the semantic analysis procedure used in SCADA system natural language manipulation interfaces into the broader construction framework of MNet, presenting a promising path for advancing natural language semantic analysis. Potential areas for exploration include utilizing established knowledge bases like WordNet and HowNet to extract word vector features, positions, and parts of speech for MNet meta-relationship construction integrating deep reinforcement learning into the dependency selection process of the MNetParser algorithm.

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