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A deep learning approach for relationship extraction from interaction context in social manufacturing paradigm

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ABSTRACT

There is an increasing unstructured text data produced in cross-enterprise social interaction media, forming a social interaction context that contains massive *manufacturing relationships*, which can be potentially used as decision support information for cross-enterprise manufacturing demand-capability matchmaking. How to enable decision-makers to capture these relationships remains a challenge. The text-based context contains high levels of noise and irrelevant information, causing both highly complexity and sparsity. Under this circumstance, instead of exploiting man-made features carefully optimized for the relationship extraction task, a *deep learning* model based on an improved *stacked denoising auto-encoder* on sentence-level features is proposed to extract manufacturing relationships among various *named entities* (*e.g.*, enterprises, products, demands, and capabilities) underlying the text-based context. Experiment results show that the proposed approach can achieve a comparable performance with the state-of-the-art learning models, as well as a good practicality of its' web-based implementation in social manufacturing interaction context. The ultimate goal of this study is to facilitate knowledge transferring and sharing in the context of enterprise social interaction, thereby supporting the integration of the resources and capabilities among different enterprises.

1. Introduction

Social manufacturing [1,2] has recently attracted significant attention, as a novel paradigm for supporting cross-enterprise manufacturing demand-capability matchmaking through extensive Information and Communication Technology (ICT) deployment. The successful deployment of ICT-enabled processes has motivated enterprises to reduce inter-organizational production processes inefficiencies, and also enable enterprises to match manufacturing demands, services, resources and capabilities in a wide range network for manufacturing insourcing or outsourcing [3]. Consequently, the growing use of ICT-enabled cross enterprise communication devices, media and platforms has resulted in explosion of the quantity of interaction text data forming *Manufacturing Service Interaction Contexts* (MSIC), which contain highly flexible, multi-dimensional, and cooperative *manufacturing relationships* among partners.

This situation consequently leaves a challenge for analysts and decision makers (DMs), which is the capture and maintenance of relationships and interactions that occur across enterprises. This information can be used by DMs to understand how manufacturing resources and capabilities are distributed in the network, and identify potential partners so as to outsource manufacturing operations to them. However, retrieving and processing this information is difficult due to the lack of formal structure in the natural language narrative MSIC.

The study bridges this gap by automatically mining and extracting manufacturing relationships from text-based MSIC, holding the promise of easily consolidating large amounts of underlying knowledge in computer-accessible form. The task of relationship extraction is to predict semantic relationships between pairs of *named entities* (*e.g.*, enterprises, product, demand, and capability) and can be defined as follows: given a sentence *S* with the annotated pairs of entities *e1* and *e2*, the goal is to identify the relationships between *e1* and *e2*.

To identify the relationships between pairs of entities, it is necessary to a skillfully use of sentence level clues from diverse syntactic and semantic structures in a sentence. For example, in the sentence "$\langle We\rangle_{e1}$ *are specialized in* $\langle rapid\ prototyping\rangle_{e2}$", to identify that an *enterprise* and a *manufacturing method* are in a *specialty* relationship, the marked entities and the meanings of the entire sentence should be leveraged. In this study, instead of exploiting man-made features carefully optimized for the relationship extraction task, a deep learning approach to extract sentence level features for relationships extraction is exploited. As shown in Fig. 1, the proposed approach takes all of the word tokens as input

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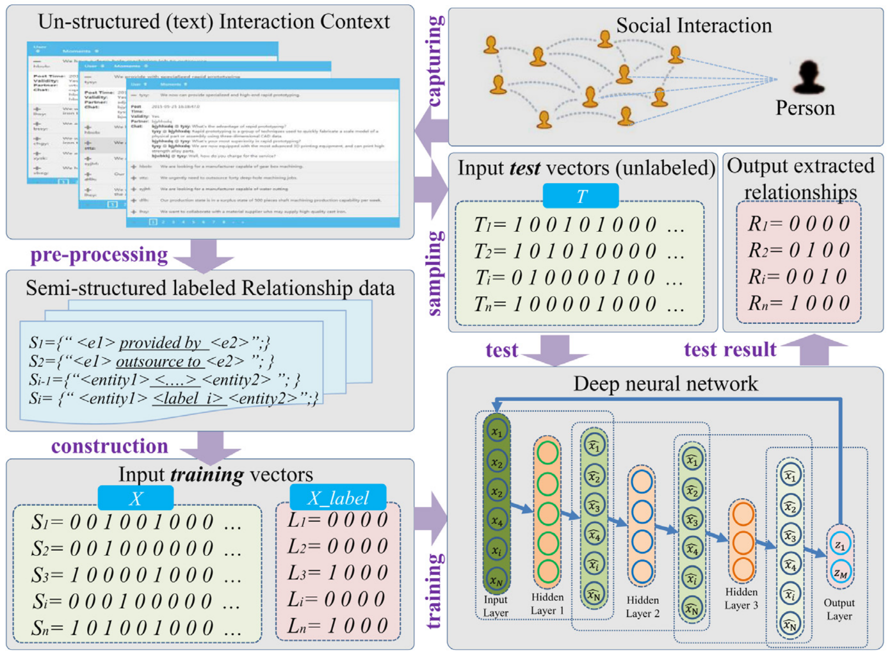

Fig. 1. Logic flow of the deep learning approach based relationship extraction in the MSIC.

without complicated pre-processing, neither Part-of-Speech (POS) nor syntactic parsing. First, all the word tokens are transformed into training vectors by looking up word embeddings, which is a collection of all words in the context under study. Then, sentence level features are obtained using a *stacked denoising auto-encoder* based deep learning approach. These learned features are concatenated to form the final extracted feature vector. Finally, on the basis of the trained deep neural network, the extracted features can be viewed as the relationships between two marked entities. With proper further processing, these relationships results can finally enable the demand-capability matchmaking in the cross-enterprise outsourcing decision-making progress.

The rest of this paper is organized as follows. Section 2 reviews some of the related work in data mining in cross-enterprise manufacturing, and relationships extraction from text-based context. Section 3 discusses the deep learning methodology for manufacturing relationship extraction from the context. Section 4 gives the comparisons between the proposed approach and the state-of-the-art learning models, and also evaluates the practicality of a web-based software implementation based on the proposed approach in the MSIC. Section 5 concludes with the main contributions and future research directions.

2. Related work

This section is to survey the advancements in two research directions related to manufacturing relationship extraction, and identify the current hiatus that must be overcome.

2.1. Data mining in cross-enterprise manufacturing interaction context

Data mining in cross-enterprise manufacturing context is to extract useful information and knowledge for demand and capability management [4]. Most of existing research focused on the data mining from structured context database. For examples, Hui and Jha [5] integrated neural network, case-based and rule-based reasoning techniques to extract knowledge from the database to support service decision and fault diagnosis. Agard and Kusiak [6] used association rule-based clustering for customer functional requirements segmentation in the design of product families from customer response data. However, nowadays, in the paradigm of social and cloud manufacturing, large amount of context data from the social media were produced in un-structured plain text form rather than a predefined formal exchanging framework or model [7].

Text-based context data is the main knowledge source from cross-enterprise social interaction context [8,9]. Many text mining studies have been conducted in text classification [10,11], terminology extraction [12], entity recognition [13], relationship extraction [14], hypothesis generation [15], and opinion mining [16]. Two strategies have been reported in the literature for these text mining applications. The first strategy is a two-phase process. It proposes the pre-processing phase of noise elimination from text, and then proceeds with analysis on cleaned or formulated form such as ontology [12,14–16]. The second strategy processes the noisy text directly using machine learning techniques which can learn patterns from the underlying text [10,11,13]. The adopted strategies usually depend on the ultimate information extraction task. This study focuses on the manufacturing relationship extraction from the text-based context data, and adopts the second strategy to deal with the big-data and high sparsity nature of the MSIC.

2.2. Techniques for features and relationships extraction in text data

Significant progress of text mining applications has been made in the relationship extraction aspect, which is to detect instances of pre-specified types of relationships between a pair of entities of given types. Several approaches have been reported in the literature: (1) *statistical methods* identify relationships that predicted by chance or probability [17], (2) *template-based methods* define patterns manually by domain experts to extract relationships [18], (3) *NLP (i.e., Natural Language Processing) based methods* perform sentence parsing to decompose the text into layered-structure from which relationships can be extracted [19], and (4) *automatic or supervised methods* create similar templates by learning patterns of interest [20]. Supervised methods can be further categorized into feature-based methods and kernel-based methods. Feature-based methods utilize a set of features that are obtained by