

데이터 상호 운용성 제공을 위한 딥 러닝 활용 시맨틱 정렬 적용 평가: 웹 오브젝트 기반 우울증 온톨로지 사례

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Deep Learning Utilized Semantic Alignment Evaluation for Data Interoperability Provisioning: Use Case of Web Objects based Depressive Disorder Ontologies

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Abstract

This paper focuses the evaluation mechanism to support the semantic interoperability provisioning in healthcare applications with the experiments of emotion and depressive disorder symptom data. We develop the ontology model of depression states in WoO framework to enrich depressive disorder symptoms data with the semantics. The paper delivers a proof of concept to carry out the semantic interoperability evaluation of healthcare application of depressive disorder using hybrid deep learning for base ontology model and shared data representations.

I. Introduction

In today's healthcare environments, depressive disorder assistance is one of the important issue. To support depressive disorder (DD) healthcare service, its symptoms can be monitored with IoT enabled, wearable sensor devices and questionnaire activities. Web Objects based ontology model simplifies object representations and provides effective way to utilize virtualization environment shown in [3] and [4]. In the use case of Web of Objects(WoO) platform [4], a VO has been linked to an information resource, and a CVO provides the rules to represent a functional feature aggregated by multiple VOs.

Preparing the data for the analytics in the DD healthcare applications it has been semantically aligned through mediation procedure first. This involves aligning the different data models from heterogeneous sources to be mapped to the base ontology model following a shared vocabulary. The deep learning mechanism has been incorporated as a process to perform analytic procedures on the data aggregated by the ontologies composed by VOs and CVOs. In order to evaluate the semantic interoperability provisioning for DD healthcare applications has been designed. To realize the DD conditions, the ontologies of affective human health conditions have been implemented. To support the integration and semantic harmonization of the data models a base ontology, and shared data model and vocabulary have been applied.

This is to evaluate the ontology models in different settings considering the nature of time series data. In the developed model of CNN with LSTM, an extra layer has been cascaded with CNN model. In this setting the fully connected dense layer output is fed in the cell of LSTM. The models are trained on the shared data with integration of the data from three well known datasets.

II. Semantic Ontology Alignment Model on Deep Representation Learning Process

To deploy the automatic semantic ontology alignment model, a base ontology catalog has been setup to provide the repositories and data processing and management mechanism based on Web Objects framework [1][2][3]. The learning mechanism has been designed in microservice process. Depending the semantic matches entries are stored in the base ontology instances. These instances collectively form an interoperable shared data model to provide semantic coherence of multiple data models. The representation of the ontology graphs is developed using deep learning method to provide the semantic alignment. The alignment process is performed using the semantic association algorithm based on the ontology graph structure. In the last step, it combines the results of both alignments and perform semantic interoperability checking and then provide the final semantic interoperability provisioning as shown in Figure 1.

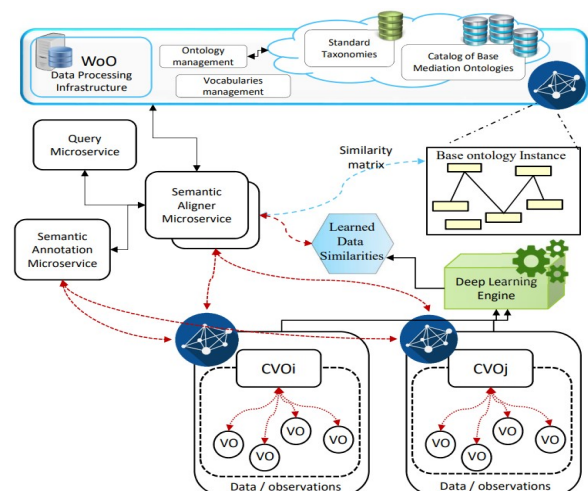


Figure 1. Deep semantic interoperability provisioning process

It is important to note that all the entity names and profile vectors are combined to form the integrated embedding. As the input to the three sub-networks, the embedding is executed based on the

mutual parameters for semantic similarity predictions. The networks are designed using three layers which comprise CNN along with the ReLU attachments. More importantly the resultant output of the sub-networks is combined together along with the features computed earlier. The network probabilities for source and target entities shown in Figure 2 have been defined as follows:

- (1) $Z_{source} = \text{Act}_{ReLU}(\text{Act}_{ReLU}(\text{Act}_{ReLU}(V_{source}, \theta_{eta_1}); \theta_{eta_2}); \theta_{eta_3})$
- (2) $Z_{target} = \text{Act}_{ReLU}(\text{Act}_{ReLU}(\text{Act}_{ReLU}(V_{source}, \theta_{eta_1}); \theta_{eta_2}); \theta_{eta_3})$
- (3) $P(Z_{source}, Z_{target}) = \text{SIGM}(\text{Act}_{ReLU}(Z_{source}, Z_{target}); \theta_{eta_4}); \theta_{eta_5})$

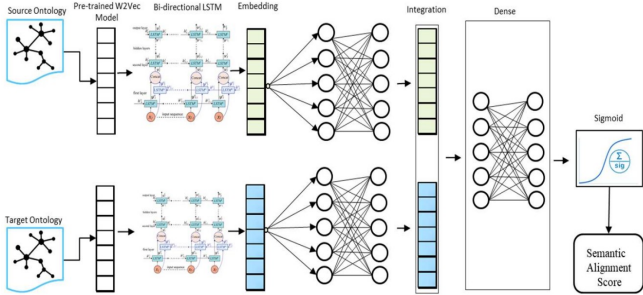


Figure 2. Deep semantic alignment architecture with enhanced embedding

In the developed model of CNN LSTM, an extra layer has been cascaded with CNN model. The model configuration has been kept same with addition of layer of the LSTM. In the Hybrid LSTM shown in Figure 3, cell parts learns the resultant output by updating their memory depending on their input and past history of the states. The model developed with 3 learning layers, has been trained on the data from the shared data representation model sharing the modalities of the different sensors.

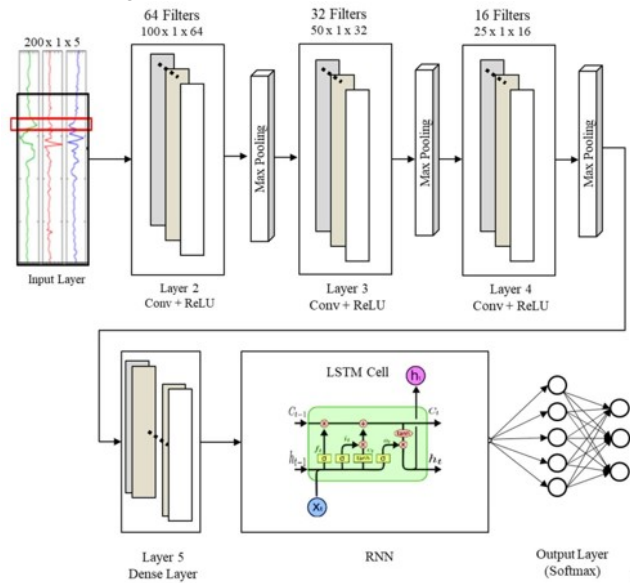


Figure 3. Hybrid LSTM based learning network

III. Experimental Results and Conclusion

The experiment on DEAP dataset is introduced to show the performance of DEAP dataset in terms of 2 learning based CNN model and 3 learning based Hybrid LSTM model. DEAP data sets based on sensor data as explained earlier. We have compared the accuracy achieved of our developed models (CNN and Hybrid model) with recent state of the art methods who utilize the AMIGOS, DEAP and ACGM dataset [8][9] shown in Table 1.

Moreover, in order to implement semantic interoperability features in DD healthcare application, Web Objects

reference architecture [4] has been implemented, and the accuracy of the Hybrid LSTM deep learning model applied in this paper to provide semantic interoperability in DD healthcare applications was found to be relatively good as shown in Table 1 and figure 4. It has been also shown that the semantic data representation based on Web Objects contributes to achieve a better accuracy to support semantic interoperability provisioning. The Web Objects (VOs, CVOs and Microservice) to represent semantic ontology models should be well fitted with required performance enhancement of DD healthcare applications.

Based on this analysis, further development to support practical applications environment will be necessary to enhance semantic interoperability provisioning capability in real DD healthcare application environment.

Table 1. State of the art approaches comparison of accuracy measure for AMIGOS, DEAP and ACGM datasets

	AMIGOS	DEAP	ACGM
CNN	86.92 %	88.23 %	92.56 %
Hybrid(CNN+LSTM)	90.66 %	91.24 %	94.56 %



Figure 4. Achieved Accuracy for Training and Testing with respect to DEAP, AMIGOS Dataset

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