# Life-long Learning for Reasoning-based Semantic Communication

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Abstract—Semantic communication is an emerging paradigm that focuses on understanding and delivering semantics or meaning of messages. Most existing semantic communication solutions define semantic meaning as the labels of objects recognized from a given form of source signal, while ignoring intrinsic information that cannot be directly observed. Since the models for recognizing labels need to be pre-trained with labelled dataset, the total number of semantic objects are often limited by a fixed set. In this paper, we propose a novel reasoning-based semantic communication architecture in which the semantic meaning is represented by a graph-based knowledge structure in terms of semantic-entity, relationships, and reasoning rules. An embedding-based semantic interpretation framework is proposed to convert the high-dimensional graph-based representation of semantic meaning into a low-dimensional representation, which is efficient for channel transmission. We develop a novel inference function-based approach that can automatically infer hidden information such as missing entities and relations that cannot be directly observed from the message. Finally, we introduce a life-long model updating approach in which the receiver can learn from previously received messages and automatically update the rules for reasoning the hidden information when new unknown semantic entities and relations have been discovered. Extensive experiments are conducted based on a real-world knowledge database and numerical results show that our proposed solution achieves 76% interpretation accuracy of the hidden meaning at the receiver when some entities are missing in the transmitted message.

## I. Introduction

Recent development in communication systems witnesses a surging demand in diverse services and new applications targeting at enhanced human-oriented experience with stringent and highly personalized requirements. This motivates a new communication paradigm, referred to as the semantic communication, which draws inspiration from human communication whose focus lies in understanding and delivering the semantic meaning of the message as opposed to mere a data reconstruction task [1]–[3].

Most of the existing works in semantic communication exploit recent advances in machine learning, especially deep learning-based solutions, to detect and communicate object labels extracted from source signals. For example, in [4], the authors defined the individual word recognized from the source signal as semantic meaning. Similarly, the authors in

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[5] considered the text of a communication message as semantic meaning and adopt a deep learning-based algorithm to recognize the text transcript of a voice signal. These solutions have the potential to significantly reduce the volume of traffic and improve the reliability for transporting and delivering the intended meaning under certain conditions.

Unfortunately, it is known that the semantic meaning of a communication message can be much more intricate than simple object labels. More specifically, traditional semantic communication solutions suffer from the following drawbacks: (1) Relations between objects are often ignored: Communication content may consist of many complex relations that are essential for the understanding of semantic meaning. Also, different objects in the same message and the context of messages received across different times may exhibit strong correlations which can be utilized to recover important hidden information, e.g., human users would be able to recover some missing information of received messages through inference. How to design a simple and effective solution for both transmitters and receivers to learn these correlations within a communication context and imitate human recognition and reasoning mechanism to infer the missing information in the communication message is still an open problem.

- (2) Different users can have different interpretations of semantic meaning when observing the same signal: It is known that the semantic meaning of the signal can be closely related to user's personality, context, and environment [6], e.g., the term "Apple" can be interpreted by different users as different concepts (fruit or smart phone manufacturer). It is therefore of critical importance for each transmitter and receiver pair to learn and coordinate their personalized semantic concepts and collections of rules for knowledge inference.
- (3) Recognizable semantic meaning is limited by a pre-defined closed set: Most existing models can only identify a limited number of object labels, each of which needs to be trained based on a large volume of manually-labeled data samples. Unfortunately, possible semantics expressed by human users can be complex and highly dynamic, it is possible that users associated with transmitters can use some new terms, facts, and concepts unknown to the receivers. How to continuously learn new knowledge and automatically update the model for semantic interpretation at the receiver is still an open problem.

In this paper, we propose a novel reasoning-based seman-

tic communicator (R-SC) architecture to address the above challenges. More specifically, to address the first two challenges, we adopt a graph-based structure to represent the semantic meaning of a communication message. Our proposed structure consists of three key components: (i) entities are the concepts and knowledge terms, (ii) relations are the relationships between entities; and (iii) reasoning rules specify the most likely combination of entities and relations. Our proposed graph-based structure can model the complex relations between diverse knowledge concepts and take into account scenarios in which the same sets of entities and relations can represent different meanings when combined in different ways due to differences in users' personal preference, backgrounds, environments, etc. To address the problem that high-dimensional feature sets of graph-based representations and highly correlated information are not suitable for efficient communication, we propose an embedding-based semantic interpretation (ESI) framework in which an embedding-based function is proposed to map the graphical representation of semantic meaning into a low-dimensional embedding space. We develop a novel inference function to characterize the transitional relationship between different entities and relations as well as their combination likelihoods in the embedding space. Our proposed framework can not only characterize the complex relationship among entities but also infer hidden information such as incomplete entities and missing relations that cannot be directly observed from the message. To address the third drawback, we introduce a life-long learning approach based on model updating in which the receiver can sequentially learn from the past messages sent by the users at the transmitter side and automatically update the reasoning rule models when new semantic entities and relations have been observed. Extensive experiments have been conducted based on real-world knowledge databases. Numerical results show that the proposed solution achieves 76% accuracy in semantic meaning recovery with incomplete entity information. II. RELATED WORK

Semantic Communication: Most existing works on semantic communications consider the labels of objects as as the semantics and adopt mature machine learning approaches, especially the deep learning based solutions, to identify semantics from various forms of source signal (e.g., image or voice signals). In particular, in [7], the authors adopted a transformer-based deep learning algorithm into semantic encoding and decoding. The authors in [8] also adopted a deep learning-based solution for image signal recognition and transmission in wireless channels.

Life-long Learning: As an emerging machine learning approach, life-long learning has attracted significant interest due to its capability to autonomously learn and accumulate knowledge over different tasks [9]. The authors in [10] proposed a reinforcement learning-based approach that is rooted in lifelong learning. The authors in [11] adopted a Bayesian optimization framework based on stochastic gradient descent to retain the knowledge learned from past tasks and use it to assist future sentimental classification tasks.

Currently, there are still lacking simple and effective solutions leveraging life-long learning in communication systems.

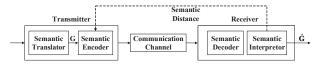


Fig. 1: A generic semantic communication system.

To the best of our knowledge, this is the first work that applies life-long learning to semantic communication.

## III. SYSTEM MODEL

A generic semantic communication system consists of the following key components as illustrated in Fig. 1.

#### **Transmitter Side:**

- (1) Semantic Translator: recognizes the semantic meaning from the source signal and converts the recognized meaning into a suitable form, denoted as G, to characterize key semantic elements and the associated relationships. For example, the semantic translator includes a machine learning model to identify the labels of key objects.
- (2) Semantic Encoder: converts the semantic representation of the source signal into an appropriate form for efficient transmission in the physical channel. Generally speaking, the semantic encoder should include two functions that are implemented separately or jointly: (1) removing the redundancy of the semantic representation and (2) protecting the information from being corrupted in the channel.

#### **Receiver Side:**

- (1) Semantic Decoder: decodes the received signal back into a representable form, and can be considered as an inverse process of the semantic encoder. However, due to the propagation loss of the communication channel, the decoded semantic representation can be different from the semantic meaning observed by the transmitter.
- (2) Semantic Interpreter: recovers the semantic meaning and presents it into the original form as observed by the transmitter. One of the key differences between traditional communication and semantic communication systems is that the result of the message delivery in the former tends to be a binary solution, e.g., either success or failure of delivery. The semantic meaning delivery result, however, is usually evaluated by a continuous value, called semantic distance (or dissimilarity), specifying the divergence of the meaning interpreted by the receiver from the true meaning of the user. Let G and G be the semantic meaning at the transmitter and the one recovered by the receiver, respectively. We denote the semantic distance between G and  $\hat{G}$  as  $\Omega(G_t, \hat{G}_t)$ . The receiver may feedback a performance indicator that can be used by the transmitter to evaluate the semantic distance between the meaning interpreted by the receiver and the true meaning. In this case, a certain action (e.g., retransmission of signal) may be triggered if the semantic distance between the received meaning and the transmitted one is above a certain threshold.

In this paper, we focus on the life-long learning process in which the communication process between a transmitter and receiver spans a long time period and the receiver can learn from the communication history and improve the understanding of the transmitter's message throughout the process. We assume the communication process can be considered as a slotted process. We use subscript t to denote the transmission

parameters in time slot t for  $t=1,2,\ldots$  The optimization problem for life-long learning-enabled semantic communication can be written as follows:

$$\min \sum_{t=1}^{\infty} \Omega(G_t, \hat{G}_t). \tag{1}$$

#### IV. AN R-SC ARCHITECTURE

Before presenting the details of our architecture, we introduce the following key concepts of R-SC.

# A. Semantic Representation

As mentioned earlier, finding an appropriate representation of semantic meaning is essential for the semantic communication system. In this paper, we adopt a graph-based structure to represent the semantic meaning of the message, i.e., the message received in time slot t can be represented as  $G_t = \langle \mathcal{E}_t, \mathcal{R}_t \rangle$  where  $\mathcal{E}_t$  and  $\mathcal{R}_t$  are sets of entities and relations, respectively. Our proposed semantic representation is composed of the following three key elements:

- (1) Entities: are objects and concepts as well as their associated properties such as "apple", "fruit", "Steve Jobs", etc.
- (2) **Relations:** specify the relationship between entities. Generally speaking, relations have directions and different directions between the same pair of entities will result in different meanings.
- (3) Rules: correspond to reasoning rules. Theses can be rules for deciding the possible relations between any given pair of entities, or deciding the most relevant hidden entities and relations of a given entity recognized from the source signal. A graphical representation of knowledge is considered as a set of triplets, each of which corresponds to the combination of a head entity, a connecting relation, and a tail entity, to denote subject-predicate-object information. Let  $\Phi_t$  be the set of all the triplets in the message arrived at time slot t. The ith triplet arrived at time slot t can be written as  $\phi_t^i = \langle e_{i,t}^s, r_{i,t}, e_{i,t}^o \rangle$ where  $\phi_t^i \in \Phi_t$ ,  $e_{i,t}^s$ ,  $r_{i,t}$ , and  $e_{i,t}^o$  correspond to the head (subject), relation (predicate), and tail (object) entities respectively for  $e_{i,t}^s, e_{i,t}^o \in \mathcal{E}_t$  and  $r_{i,t} \in \mathcal{R}_t$ . One of the key unique features of R-SC is to learn the relationships between observable and hidden entities as well as that between entities and relations, so it can automatically infer the missing or hidden information of messages. For example, the message "I love apple" may mean the user's favorite fruit or his/her favorite smart phone brand. A complete representation of this message should contain some hidden knowledge entities and/or relations, e.g., a more specific semantic interpretation of the message should be "I love apple which is a fruit". In R-SC, the reasoning rule can be considered as a function that takes the incomplete entities and relations directly identified from the source message as input and outputs the sets of completed triplets. Let  $\Pi_t$  be the reasoning rule learned by the receiver at time slot t. Suppose  $\phi_t^i$  is an incomplete triplet with one or two missing elements arrived at the receiver, e.g.,  $\tilde{\phi}^i_t = \langle e^s_{i,t}, r_{i,t}, - \rangle$  or  $\langle -, -, e^o_{i,t} \rangle$  where - denotes the missing elements of the triplet. We have  $\Pi_t \left( \tilde{\phi}_t^i \right) = \hat{\phi}_t^i$  where  $\hat{\phi}_t^i$  is the complete triplet recovered by the semantic interpreter based on the learned reasoning rule.

#### B. Semantic Distance

As per (1) finding an appropriate metric to measure semantic distance is of critical importance for optimizing semantic communication system. Most existing works in semantic communication adopt the meaning similarity of words identified by dictionaries and/or thesaurus.

However, these metrics have several drawbacks when being adopted in semantic communication. First, the semantic meaning of messages may consist of complex relations as well as some hidden entities and relationships that cannot be measured by simply combining the meaning of the words. Meaning of messages can be closely related to the transmitter's personal background information such as personal preference, past experience, and understanding of the entities and relations, none of which are pre-defined in the dictionary. It is known that human users' understanding of concepts and facts can change with their age, personal experience, and accumulation of knowledge. Simply interpreting the meaning of words based on an existing dictionary cannot reflect these changes.

The graphical representation of semantic meaning adopted in this paper captures the meaning of many different words, concepts, facts, as well as their complex relations taking into account the users' personal preference and backgrounds. To measure the difference between graphs, we propose a novel embedding-based solution to evaluate and calculate the semantic distance between two graphical representations of meanings. The main idea of our proposed solution is to learn a mapping function that maps the entities and relations in the high-dimensional graphical representation space into a low-dimensional embedding space. The low-dimensional representations of the entities and relations, also called entity embeddings and relation embeddings, should possess two ideal features: (1) easy to recognize and infer and (2) highly efficient for physical channel transmission. We use the bold font to denote the embeddings of entities and relations, i.e., the embeddings of  $e_t^s$  and  $r_t$  are denoted by  $e_t^s$  and  $r_t$ , respectively, and  $\phi_t^i$  denotes the triplet of embeddings. For the first feature, we introduce a carefully designed inference function  $f(\phi_t^i)$  to measure the likelihood (truthfulness) of the triplet, i.e., the closeness of the meaning specified by  $\phi_t^i = \langle e_{i,t}^s, r_{i,t}, e_{i,t}^o \rangle$  and the real meaning of user. We would like to design an inference function  $f(\phi_t^i)$  with the following desirable conditions:

- (1) If  $\phi_t^i = \langle e_t^s, r_t, e_t^o \rangle$  is in coordination with the intended meaning of the user, the value of  $f\left(\phi_t^i\right)$  should be minimized (e.g., approach zero).
- (2) If  $\phi_t^{i'} = \langle e_t^{s'}, r_t', e_t^{o'} \rangle$  does not reflect the meaning of the user, the value of  $f\left(\phi_t^{i'}\right)$  should be much larger than  $f\left(\phi_t^{i}\right)$ . Also the difference between  $f\left(\phi_t^{i'}\right)$  and  $f\left(\phi_t^{i}\right)$  should be proportional to their meaning difference.
- (3) The difference between any given pair of triplets is only related to their meaning difference, i.e.,  $\Delta f\left(\phi_t^{i'},\phi_t^{i''}\right) = f\left(\phi_t^{i'}\right) f\left(\phi_t^{i''}\right)$  depends only on the meaning difference of  $\phi_t^{i'}$  and  $\phi_t^{i''}$ .

If all the above conditions are satisfied, the value of  $f\left(\phi_t^i\right)$ 

is an ideal metric to reflect the difference of meaning between a given triplet  $\phi_t^i$  and the true meaning of the user. As will be shown later in this paper, for a given number of dimensions of embedding space, the inference function  $f\left(\phi_t^i\right)$  can determine the mapping function between a graph and its corresponding entity and relation embeddings. By extending this observation into a graphical structure consisting of a set of triplet embeddings  $\Phi_t$ , we can define  $F\left(\Phi_t\right) = \sum_{\phi_t^i \in \Phi_t} f\left(\phi_t^i\right)$  as the main metric to measure the distance between a set of triplets  $\Phi_t$  and the real meaning of messages transmitted in time slot t. We can then define the semantic distance between two messages represented by  $\Phi_t$  and  $\Phi_t'$  as

 $\Omega\left(\mathbf{\Phi}_{t}, \mathbf{\Phi}_{t}^{\prime}\right) = F\left(\mathbf{\Phi}_{t}\right) - F\left(\mathbf{\Phi}_{t}^{\prime}\right). \tag{2}$ 

For the second ideal feature of the embedding function which requires the converted entity and relation embeddings to be efficient in channel transmission and interpretation at the receiver side, we will allow the receiver to calculate the inference function based on its received embeddings that can be corrupted by the channel and coordinate with the transmitter to optimize the mapping between the graphical representation and the corrupted embedding values. In this way, the receiver can always obtain the best interpretation of the meaning based on its received message.

#### C. Life-long Model Updating

In this paper, we focus on modeling and optimizing the life-long learning process of semantic knowledge between a transmitter and a receiver. The transmitter and receiver cannot observe all the knowledge entities and relations at the beginning of the communication process but can observe from the past communication and sequentially learn and update an inference function  $f\left(\phi_t^i\right)$  to convert the graphical representation of semantic meaning into a low-dimensional embedding space. The inference function will only be updated when unknown new knowledge terms, i.e., new entities, relations, or triplets have been discovered in the currently received message. The main objective for R-SC is to minimize the semantic distance between the transmitted meaning and the meaning interpreted by the receiver through the learning process, i.e., we can rewrite the problem (1) into the following equivalent form:

$$\min \sum_{t=1}^{\infty} \Omega\left(\mathbf{\Phi}_t, \hat{\mathbf{\Phi}}_t\right). \tag{3}$$

#### V. AN ESI FRAMEWORK FOR R-SC OPTIMIZATION

In this section, we present a novel framework, called embedding-based semantic interpretation (ESI), to solve (3). The proposed framework consists of two key functional modules: reasoning rule learning and life-long model updating.

#### A. Reasoning Rule Learning

**Inference Function:** Our proposed rule learning solution relies on a carefully designed inference function to differentiate the positive (most possible) and negative (less unlikely) combinations of entities and relations in the embedding space.

More specifically, the inference function should be able to map the plausibility of any given pair of entities and relations to a single value. The receiver will then be able to use the mapped value to decide whether these entities and relations are likely to be combined when interpreting the meaning of the user. To map the possible combinations of entity and relation embeddings into a single value, we introduce three possible forms of functional basis to characterize the additive, linear, and multiplicative relationships between the various entities and relations in the embedding space. In particular, we introduce the following generalized inference function:

$$f\left(\phi_{t}^{i}\right) = g\left(\phi_{t}^{i}\right) + h\left(\phi_{t}^{i}\right) + l\left(\phi_{t}^{i}\right),\tag{4}$$

where  $g(\cdot)$ ,  $h(\cdot)$ ,  $l(\cdot)$  correspond to the additive, linear, and multiplicative relations of entity and relation embeddings defined in the following forms:

$$g\left(\phi_{t}^{i}\right) = ae_{i\,t}^{s} + br_{t} + ce_{i\,t}^{o} + d,\tag{5}$$

$$h(\phi_t^i) = a' r_t^T e_{i,t}^s + b' r_t^T e_{i,t}^o + c' (e_{i,t}^s)^T e_{i,t}^o + d', (6)$$

$$l\left(\boldsymbol{\phi}_{t}^{i}\right) = a''\left(\boldsymbol{e}_{i,t}^{s}\right)^{T} \operatorname{diag}\left(\boldsymbol{r}_{t}\right) \boldsymbol{e}_{i,t}^{o} + b'', \tag{7}$$

where a, a', a'', b, b', b'', c, c', and d are constants decided based on the range and Euclidean distance between entities and relations with different meanings in the embedding space.  $(\cdot)^T$  denotes the transpose of vector/matrix. diag  $(\cdot)$  is the diagonal operation with all the elements of a vector listed in the diagonal of the matrix. We assume entities and relations will be mapped into the same embedding space. However, our model can be directly extended into the scenarios that relations and entities are mapped into different embedding spaces [12].

The inference function in (4) is general enough to cover various possible ways to differentiate the positive and negative entity and relation combinations in the embedding space. For example, in the simplest case, if the inference function uses a single additive functional basis to evaluate the plausibility of entity and relation combinations, i.e., we have  $f(\phi_t^i) =$  $e_{i,t}^s + r_t - e_{i,t}^o$  which is in the same form as the TransE, one of the most commonly adopted graph embedding models, with the L1-norm-based solution [13]. For any positive triplet, we will train the embedding outcome of inference function  $f(\phi_t^i)$  to approach zero and, for the negative triplet, the output of the inference function should be a positive value that is proportional to the semantic distance with the positive triplet. In another example, if the inference function is set to include the linear functional basis, we can adopt the following form of inference function  $f\left(\phi_t^i\right) = \|\boldsymbol{e}_t^s + \boldsymbol{r}_t - \boldsymbol{e}_t^o\|_{L^2} =$  $2\mathbf{r}^T\mathbf{e}^s - 2\mathbf{r}^T\mathbf{e}^o - 2(\mathbf{e}^s)^T\mathbf{e}^o + d''$  which is equivalent to the L2-norm version of TransE embedding [13]. In this case, the output of the inference function will again approach zero if the triplet combination of entities and relations is positive and will also be close to a semantic distance-related large positive value if the combination of entities and relations is negative. Finally, the multiplicative relation-based inference function is also applicable and, in this case, the inference function can be defined as  $f(\phi_t^i) = -e_t^s \operatorname{diag}(r_t^T) e_t^o$  where the positive triplet will result in a small negative value and, for the negative triplet, the resulting output of the inference function will be a much higher value. It can be observed that this case is equivalent to DistMult [14] another popular graphbased embedding model.

Our proposed inference function-based solution can be used to evaluate the likelihood of any given triplet and also recover the missing information of the semantic meaning based on the relative locations of relations and entities in the embedding space. More specifically, suppose  $\tilde{\phi}_t^i$  is an incomplete triplet arrived at time slot t. We can write the reasoning rule based on our proposed inference function  $f(\cdot)$  as follows:

$$\Pi_t \left( \tilde{\phi}_t^i \right) = \tilde{\phi}_t^i \oplus \varphi_t^i, \tag{8}$$

where  $\varphi_t^i$  denotes the recovered missing components in triplet  $\phi_t^i$  calculated by

$$\varphi_t^i = \underset{e^s, e^o \in \mathcal{E}_t, r \in \mathcal{R}_t}{\arg \min} f\left(\tilde{\boldsymbol{\phi}}_t^i\right), \tag{9}$$

and  $\oplus$  is the triplet completion function.  $\mathcal{E}_t$  and  $\mathcal{R}_t$  are possible entities and relations observed during the first t time slots of communication.  $e^s$ ,  $e^o$  and r are the missing entities and relations in  $\phi_t^i$ .

Model Training: In R-SC, the embeddings sent by the transmitter may be corrupted in the physical channel and the receiver can only observe the corrupted version of embedding to interpret the semantic meaning. We use  $Y(\cdot)$  to denote the impact of the channel corruption on the reception of the embedding, e.g., the ith triplet embeddings observed by the receiver in time slot t can be written as  $Y(\phi_t^i)$ .

The main objective for the transmitter and receiver is to learn the embedding of entities and relations based on our proposed inference function, so the receiver will be able to evaluate and recover the missing entities and relations based on their relative distance in the embedding space.

Following the same line as most existing machine learning solutions, the transmitter and receiver must construct their models based on two non-overlapping training sample sets: a set of positive samples (with labels intended to be recognized) and a set of negative samples (without labels or with labels that should be differentiated). In the R-SC, the positive samples (positive triplets) can be directly obtained from the communication message and the samples (triplets) without being observed will be considered as negative.

We give a more detailed description of the model training procedure as follow: at the beginning of the communication process (e.g., time slot t=1), the transmitter will convert the arrived message into a graphical representation with a set  $\Phi_1$  of triplets consisting of both complete and incomplete triplets. The transmitter will collect the subset of completed triplets into a positive training set, denoted as  $\Phi_1^+$ , and will randomly generate a negative training set  $\Phi_1^-$  with triplets composed of unobserved combinations of the relations and entities. The transmitter will then calculate the embeddings of the entities and relations based on these two training sets. Both embeddings and labels will be sent to the receiver. The transmitter will also rank the meaning difference between positive and negative triplets in these two training sets and set a list of ranked constants  $c''(\phi, \phi')$  to the receiver. We assume the embedding can be corrupted by the communication channel. The labels of the embedding however can always be correctly decoded by the receiver. Let  $\hat{\Phi}_t^+$  and  $\hat{\Phi}_t^-$  the sets of positive embeddings and negative embeddings corrupted by the physical channel transmission. Once received the embeddings and labels from the transmitter, the receiver will establish the positive and negative training sets based on the

received embedding given by  $\hat{\Phi}_t^+$  and  $\hat{\Phi}_t^-$ , respectively. Then,

the receiver will calculate the following loss function 
$$\mathcal{L} = \sum_{\phi \in \hat{\Phi}_t^+} \sum_{\phi' \in \hat{\Phi}_t^-} \max\{0, f(\phi) - f(\phi') + c''(\phi, \phi')\}, \quad (10)$$

where  $c''(\phi, \phi')$  is a constant depending only on the labels of  $\phi$  and  $\phi'$ . c'' should be decided by the transmitter at the beginning of the training process and will remain as a constant during the rest of the process. The receiver will feedback the value of the loss function to the transmitter. The transmitter will update the embedding using the standard stochastic gradient descent (SGD) approach and send the updated embedding values to the receiver. Following the same line as [13], the above process will converge to a stationary solution with the relative distances between the embedding values of different entities and relations approach fixed values. **Life-long Model Updating:** In the life-long learning process, the transmitter and receiver may observe new entities and relations in the arrived communication message. In this case, new complete triplets will be added to the positive training set and if some newly observed positive triplets are also in the negative training set, these triplets will be removed and replaced with some newly generated negative triplets. Once positive and negative training sets have been updated, the model training process will be repeated. It can be observed that as more and more messages can be communicated between the transmitter and receiver, the chances for discovering new unknown entities and relations will be decreased and the model training will be less frequent. Suppose the transmitter and receiver have already observed most of the commonly used entities and relations of the users, the receiver in this case will be able to directly apply reasoning rule in (8) to infer the missing meaning information of the message.

# VI. EXPERIMENTAL RESULT

Dataset and Simulation Setup: To evaluate the accuracy of the reasoning rules in (8), we adopt a dictionary and thesaurusbased knowledge dataset WordNet-WN18 which is a subset of WordNet consisting of 18 types of relations and 40,943 entities. We use 141,442 triplets given in the dataset as the positive training set and the rest 5000 triplets as test set. We generate the negative training set by replacing the (head or tail) entity in triplets of the positive set with invalid entity. **Numerical Results:** In Fig. 2, we evaluate the communication reliability improvement that can be achieved by using our proposed semantic reasoning solutions. Motivated by the fact that in most knowledge graph dataset, the number of relation types are limited and therefore instead of always transmit all the embedding features to the receiver, the transmitter only needs to send the full embedding features of relations at one time and then send only a small label message to the receiver during the rest of the communication process. We therefore mainly focus on the received error probability of the packets, each corresponds to an entity embedding with 2800 bits of data size. We evaluate the packet error rate when the packets (entities) corrupted during the physical channel transmission can be recovered from other successfully received entities and relations using our proposed semantic reasoning solutions

with additive and multiplicative inference functions. We can observe that our proposed solutions can significantly reduce the packet error rate for wireless channel transmission under different SNR. Also, when transmitting entity packets of our considered dataset, the additive inference function offers a better performance than the linear inference solution.

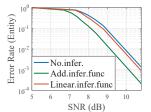
In Fig. 3, we evaluate the impact of different forms of inference functions on the convergence rate of model training. We present the values of loss when two inference functions, additive and linear functions, are adopted to train the embedding models. We can observe that during the first few rounds of training iterations, the linear inference function offers a faster convergence rate than the additive function. However, as the number of iterations continues to grow, the additive function has a much faster convergence speed than the linear function. Compared to the linear function, the additive function is much easier to compute and offers a better convergence performance which makes it an ideal inference function for WordNet-based dataset. This however may not always be the case since in some other datasets with more complex relations between entities, the linear function may exhibit a faster convergence rate than the additive function.

We next evaluate the accuracy of semantic meaning interpretation when the model is trained with different number of training samples. In Fig. 4, we evaluate the semantic meaning recovery performance when head or tail entities are missing in the received message. In this case, the receiver uses the reasoning rule in (8) to infer missing semantic information. Our solution achieves 76% and 48% of accuracy in recovering missing information when using additive and linear inference functions, respectively.

As mentioned earlier, the semantic distance between different entities and relations will reflect their meaning difference. In the ideal scenario, we want the entities in the same category to have relatively short distance, compared to those in different categories. In Fig. 5, we randomly choose two categories of entities, categories "city" and "drug" from the dataset to compare their relative distance in the embedding space. We can observe that entities from the considered categories of entities form two clusters. There are however some overlaps between two categories of entities since some entities can have close connections with each other in some embedding space dimensions, e.g., some drugs are produced in some cities. This verifies that our proposed embedding-based semantic distance is a useful metric to measure the meaning difference between graph-based representations of semantic meaning.

#### VII. CONCLUSION

This paper introduced an R-SC architecture in which the semantic meaning is represented by a graph-based structure. An embedding-based semantic interpretation framework was proposed to convert the high-dimensional graphical representation of semantic meaning into a low-dimensional representation for efficient communication. We developed a novel inference function-based approach that can infer hidden information such as incomplete entities and relations that cannot be directly observed from the message. A life-long model updating approach was introduced in which the receiver can learn from



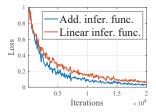
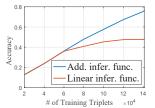


Fig. 2: Packet error rate of pro- Fig. 3: Loss based on different posed reasoning-based entity re- inference functions under difcovery solutions compared with no ferent training iterations. reasoning under different SNRs.



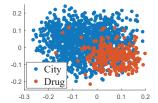


Fig. 4: Accuracy of missing information recovery when using different numbers of training triplets.

Fig. 5: The distribution of entities in categories of 'city' and 'drug' in a two-dimensional embedding space.

the past messages sent by the users and automatically update the reasoning rule models when new semantic entities and relations have been discovered. Extensive experiments were conducted and our results showed that the proposed solution achieves 76% of accuracy in meaning recovery.

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