Tele-Knowledge Pre-training for Fault Analysis

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Abstract-In this work, we share our experience on teleknowledge pre-training for fault analysis. Fault analysis is a vital task for tele-application, which should be timely and properly handled. Fault analysis is also a complex task, that has many sub-tasks. Solving each task requires diverse tele-knowledge. Machine log data and product documents contain part of the tele-knowledge. We create a Tele-KG to organize other teleknowledge from experts uniformly. With these valuable teleknowledge data, in this work, we propose a tele-domain pretraining model KTeleBERT and its knowledge-enhanced version KTeleBERT, which includes effective prompt hints, adaptive numerical data encoding, and two knowledge injection paradigms. We train our model in two stages: pre-training TeleBERT on 20 million telecommunication corpora and re-training TeleBERT on 1 million causal and machine corpora to get the KTeleBERT. Then, we apply our models for three tasks of fault analysis, including root-cause analysis, event association prediction, and fault chain tracing. The results show that with KTeleBERT, the performance of task models has been boosted, demonstrating the effectiveness of pre-trained KTeleBERT as a model containing diverse tele-knowledge.

Index Terms—telecommunication, model pre-training, knowledge graph, numeric encoding, fault analysis

I. INTRODUCTION

Faults in telecommunication networks directly affect the availability and effectiveness of the network, causing a huge amount of maintenance cost for the operating company. Thus quick elimination of faults and preventing causes generating the faults are essential for and of special interest for operating companies. Fault analysis is a complex task composed of many sub-tasks, and requires rich tele-knowledge, such as network architecture and dependence between products. In the past, these knowledge are stored in the mind of experts. While in now-days, massive product data and expert experience in this field are accumulated, which is helpful for fault analysis.

Some of the knowledge is already recorded in different forms. For example, the **machine log data** (e.g., abnormal events like the alarms or normal indicator like the KPI score) is raised continuously no matter in real tele-environment or simulation scenes from the laboratories. Log data is valuable first-hand data that could be used for fault analysis. Apart from log data, **product documents** are often created for a specific product in the network, in which product profile, event description, fault case, solutions to particular issues, etc., are described mainly in natural language, as detailed as possible.

Some of the knowledge is not uniformly recorded, such as types of faults and their hierarchy. Considering the diversity of such knowledge, Knowledge Graph (KG) is a common choice to represent them. It represents facts as triples, such as (China, capitalIs, Beijing). Recent years, KGs have been widely applied in the industry [1]–[3] due to their flexibility and convenience of fusing data from various sources. To uniformly represent the recorded tele-knowledge, we built a tele-product knowledge graph (a.k.a. Tele-KG). For example, the triple ([Alm] ALM-100072 The NF destination service is unreachable, trigger, [KPI] 1929480378 The number of initial registration requests increases abnormally) It represents that alarm 100072 showing that NF (Network Function) destination service being unreachable always results in the number of initial registration requests increasing captured by a KPI. Most knowledge in Tele-KG comes from experts and engineers. Tele-KG helps us build an integrated view of the tele-knowledge and accumulated experience.



Fig. 1: Workflow for our KTeleBERT.

These recorded knowledge and Tele-KG are widely used for tasks related to fault analysis.

With Tele-KG, experts and engineers often regard it as a knowledge base and get knowledge in Tele-KG by executing

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SPARQL [4] queries. The knowledge, namely the triples, retrieved from Tele-KG will be used as background knowledge or constrains in fault analysis tasks. However, supporting tasks in this way requires carefully selecting knowledge to be retrieved, which is inflexible. Meanwhile, these expert system-based approaches have limitations in generalization capabilities, which ignore massive telecommunication domain textual corpus. Another way to utilize Tele-KG is by applying Knowledge Graph Embedding methods to learn embeddings of entities and relations, and using embeddings in the fault analysis model rather than using triples data. Recently, a variety of knowledge graph embedding (KGE) methods are proposed for knowledge completion [5]-[8], which aims to learn an embedding representation for each entity and relation in the continuous vector space. The embeddings are then utilized for knowledge inference like the link prediction or triple classification task in a KG. However, those technologies always suffer from knowledge inconsistency, i.e., the same entity or noun in the real world may have different surfaces like the "Alm" v.s. "Alarm"), and the textual knowledge and semantic information in entity surfaces or attributes are abandoned during training.

With product documents represented in natural language, apart from regarding it as a handbook, another way is to pre-train a domain-specific language model. Language model pre-training [9]–[12] is a good recipe for learning implicit semantic knowledge with self-supervised text reconstruction as the training objective in a vast amount of language data, but they are constantly struggling to exploit the structured knowledge for explicit intellectual reasoning.

With machine log data, as far as we know, no efficient and effective algorithm has been proposed to encode and understand them automatically.

In this work, we propose to pre-train all data containing teleknowledge, including machine log data, tele-corpus from product documents, and triples from Tele-KG, and use the pre-train model to fault analysis tasks, as shown in Fig. 1. We expect the pre-trained model containing diverse tele-knowledge could aid the downstream tasks in a conveniently and effectively manner and boost their performances, especially those tasks with limited data (a.k.a. low resource tasks).

During pre-training model designing, firstly, we observe that multi-source and multi-modal data (e.g., sequential log data, textual documents, and semi-structured KG) always distract the model from efficient learning. In order to remedy this defect, in this work we refer to the **prompt engineering** [13]–[15] for modal unification and provide relevant **template hints** to the model for modalities unification.

Secondly, we find that numerical data is an essential component of the telecommunications field data which frequently appears in the machine log data (e.g., KPI score). This data format is similar to tabular data, sharing the characteristic of: (*i*) The text part is short; (*ii*) The Numerical values always have different meanings and ranges under different circumstances; (*iii*) Data stretches from both vertically and horizontally which is hierarchical. However, existing table pre-training methods mainly study the hierarchical structure of tabular data [16]– [21] and the numerical information is rarely studied in depth. Those methods that target at learning numerical features [22]– [24] focus on learning field embedding for each numerical field or transforming numerical features to categorical features through heuristic discretization strategies. But these methods always consider the task with limited fields (e.g., user attribute in Click-Through Rate, CTR) but fail when migrated to our tele-scenario where the field number (e.g., KPI name) is numerous and new fields are often generated. Thus, we propose an adaptive numeric encoder (ANEnc) in tele domain for name-aware numeric encoding.

Thirdly, we are aware of different volumes between machine log data, tele-corpus, and triples. Thus we adopt a multistage training mode for multi-level knowledge acquisition: (*i*) **TeleBERT**: in stage one we follow ELECTRA [25] pretraining paradigm and data augmentation method SimCSE [26] for large-scale (about 20 million) textual tele-corpus pretraining; (*ii*) **KTeleBERT**: In stage two, we extract those causal sentences which contain relevant causal keywords and re-train TeleBERT together with the numeric-related machine log data, where a knowledge embedding training objective and multi-task learning method are introduced for explicit knowledge integration.

With our pre-trained model, we apply the model-generated service vectors to enhance three tasks of fault analysis, rootcause analysis (RCA), event association prediction (EAP), and fault chain tracing (FCT). The experimental results show that our TeleBERT and KTeleBERT successfully improve the performance of these three tasks.

In summary, the contributions of this work are as follows:

- We propose a uniform encoding method that could encode not only text and triples, but also machine log data.
- We propose a tele-domain pre-training model TeleBERT and its knowledge-enhanced version KTeleBERT, which could fuse and encode diverse tele-knoweldge in different forms.
- We prove that our proposed models could serve multiple fault analysis task models and successfully boost their performance.

II. BACKGROUND

A. Corpus in Telecommunication

1) Machine Log Data: The machine (log) data (e.g., abnormal events like the alarms, or normal indicators like the KPI score) is often raised continuously in both real teleenvironment or simulation scenes. Typically, those abnormal events are always accompanied by the anomalies that exist in some of the current subnet points (e.g., service interruption), which have various importance levels. The normal indicators are cyclical and persistent in character, which accounts for the vast majority of all automatically generated machine data.

Most abnormal events could be recovered by themselves (e.g., network congestion), and the correlate / causal relationships are sometimes exist across the abnormal events or



Fig. 2: Tele-product Knowledge Graph (Tele-KG).

abnormal indicator, e.g, the alarm "(*NF destination service is unreachable*)", always lead to abnormal KPI score "*the number of initial registration requests increases abnormally*)".

2) Product Document: Those engineers or experts in telecommunications field are constantly recording and iterating on the telecommulication **product documentation**. Particularly, each scenario may contain one or more product documents, which are maintained by different departments and may involve nearly all relevant explanations in this field, e.g., event descriptions, fault cases, and solutions to all already occurred or potential cases.

3) Tele-product Knowledge Graph (Tele-KG): We build the Tele-KG, as shown in Fig. 2, which integrates massive information about events / resources on our platform. Our motivation is intuitive: hoping that such a fine-grained Tele-KG could refine and purify the domain knowledge, where the semi-structured KG is more flexible in use than traditional structured databases and has higher knowledge density than unstructured product documents. Specifically, we define a hierarchical **tele-schema** as the guidance for KG construction where the top-down modeling method is adopted for design. The concept classes across different levels are inherited via "subclassOf", and those classes within the same levels are connected via common relations like "provide".

We note that two top superclasses, "*Event*" and "*Resource*", are defined as the root in our field. Other top tele-concept are the subdivisions for them, which are the upper abstract classes to other specific subclasses. As the instantiation of the tele schema, the instance level contains the interaction among different instance, forming the major part of Tele-KG. Those case triples mentioned before are involved in this part.

B. Task of Fault Analysis

1) Root-Cause Analysis: In modern telecommunication systems, a large number of abnormal events happen every day with various causes and one of the biggest challenges for maintaining telecommunication systems is to fix such abnormal events, which is vital for reducing the financial loss for operators of telecommunication systems. The most important step of abnormal event fixing is finding what is the cause of a large number of abnormal events. The traditional method of analyzing root causes is conducted by experts with some summarized documents based on a mass of manual work. However, such manual work costs a lot of financial and human resources. With the increasing size and complexity of telecommunication systems, the difficulty of analyzing root causes by experts increases. Thus, how to find root causes in telecommunication systems automatically is a vital problem in modern telecommunication systems.

2) Event Association Prediction: Generally, one solution for finding the root cause of an emerging fault is to utilize prior trigger relationships between fault events, that is, a kind of fault pattern revealing that some fault events are caused by some other events. For example, the triple (Alarm A, triggers, Alarm B) indicates that the Alarm B is caused by the Alarm A, when we observe a fault event represented by Alarm B, its root cause can be further located by analyzing the root cause of Alarm A. By traversing the trigger relation chain, we can induce the root cause of the current fault observation. These prior trigger relationships largely support the requirement of finding the root cause and are naturally explainable. However, in traditional fault diagnosis solutions, such trigger relationships are often summarized from a large number of fault cases by tele experts, which is rather inefficient and usually has the following limitations: i) the experiences are humancentric and are not easily shared; ii) quite a few human efforts may be required to update some existing relationships or summarize new relationships when the tele-network evolves; and *iii*) some trigger relationships are important but have lower frequencies of fault cases, which are not easily covered by experts. Therefore, we hope to develop a deep learningbased algorithm that learns to automatically predict the trigger relationship between events, so as to quickly mine the fault patterns behind fault cases and quickly adapt to new cases.

3) Fault Chain Tracing: In modern telecommunication field, the failure of network element occurs all the time because of huge running pressure. In the specific failure scenario, some broken equipment will have a warning called alarms, which will have a knock-on effect and cause damage to the entire system. Therefore, how to trace the source of the failure is an important question for machines in the field of telecommunication. For this problem, the traditional approach is dependable on experts to trace and locate the failed network equipment through their experience. However, this will consume a lot of manpower and time, and the accuracy usually does not meet the requirements. Therefore, it is extremely valuable and

meaningful to automatically find the root cause.

III. PRE-TRAINING ON TELE-COMMUNICATION CORPORA

In this section we introduce our TeleBERT, a tele-domain specific PLM which is pretrained in large-scale textual telecorpus via ELECTRA [25] pre-training paradigm and data augmentation method SimCSE [26].

A. Telecommunication Corpus Integration

We note that massive textual tele corpora are collected to constitute the training data in sentence form, where all the product documents, entity surfaces within the knowledge graph are contained. Specifically, two data augmentation techniques in NLP community are adopted: (*i*) Explicit data augmentation. We take a range of paragraphs (e.g., those adjacent sentences in the same document) for splicing to expand the dataset and constitute 20 million sentences as the final textual pre-training data (a.k.a. **Tele-Corpus**). (*ii*) Implicit data augmentation. Following SimCSE [26], we utilize the dropout strategy to introduce the noise. This method could enhance our model's robustness.

B. TeleBERT

Following the vanilla mask language model (MLM) [9], each of the textual sentence is fed to the model with special token [CLS] prepended and [SEP] rearward. Taking the Chinese pre-trained language model (PLM) MacBERT [27] as the backbone, we adopt the whole word masking (WWM) strategy during TeleBERT pre-training with a tele-domain vocabulary as the "whole word" segmentation collection. Concretely, this vocabulary contains about 372k Chinese or English elements which are all proper nouns (e.g., "QoS" which refs to "Quality of Service") or phrases (e.g., "network congestion points" and "dedicated control channel").

Moreover, the simple contrastive learning on sentence embeddings (SimCSE) [26] is employed to alleviate the collapse of representation learning on large models, i.e., most sentences are represented by similar embeddings. The ELECTRA [25] pre-training paradigm is used for increasing pre-training difficulty, where a MLM generator is equipped for mask reconstruction and makes the TeleBERT a discriminator with a selfsupervised objective replaced token detection (RTD) applied. Note that we define the TeleBERT pre-training progress as the stage one, aiming to let the PLM understand the general semantic knowledge in tele domain.

IV. RE-TRAINING ON CAUSAL AND MACHINE CORPORA

This section is mainly about the details of the stage two. We claim that our KTeleBERT is the re-training version of TeleBERT. Specifically, we first provide the rules for causal sentences extraction and how to efficiently unify those multimodal data for re-training the TeleBERT (in Sec. IV-A). Then we elaborate our proposed numerical data encoding module which contains an adaptive numeric encoder, numeric decoder, and tag classifier in each layer (in Sec. IV-B). Next, we illustrate different strategy we consider for mask reconstruction in Sec. IV-C. Finally, in Sec. IV-D we introduce our method for explicit expert knowledge injection, and introduce the training policy for task integration (in Sec. IV-E).

A. Unifying Modalities and Patterns

1) Causal sentences extraction: Firstly, we remove all those IDs like " [KPI] 1929480378" which are simply unique identifiers. Then, (i) we manually select those words and phrases which have the causal meaning (e.g., "affect" and "lead to"), as the causal keywords. Then we heuristically customize extraction rules (e.g., min length) to get about 200k sentences from Tele-Corpus which both contain part of these causal keywords and satisfy the rule constraints. Besides, (ii) we serialize all relational triples and part of the attribute triples (which contain significant attribute after evaluated) in Tele-KG via simply concatenating the surfaces of entity/attribute and relation to uniform the format into a sentence. This protocol is a manner for implicit knowledge injection [28], [29].

2) Prompt template construction: Different from the typical natural language sequences that have strict language order, the structured machine (log) data is always disordered, similar to attribute triples in KG where an entity may have multifaceted attributes. Since it has been proved that the PLMs benefit from the prompt in knowledge utilizing and crossmodal learning [13]–[15], [30], we introduce special special prompts (tokens) for representing the category of immediately following content, e.g., [ATTR] indicates that the following contexts are the attribute together with its value, and [ALM] illustrates the alarm data type. Then we wrap the input with our prompt template to unify the data modality meanwhile alleviate the disorderly disturbance brought by structured machine / attribute data [17]. Besides, special symbol "|" is employed for splitting the type names with their values. The details of the pre-defined prompt templates are shown in Fig 3.

3) Tele special token construction: Considering that these domain specific corpora contain massive special words, in order to promote model's understanding in these domain words, we adopt the wordpiece method BPE (Byte Pair Encoding) [31] to merge the characters and learn a collection of tele tokens. Concretely, BPE iteratively counts all symbol pairs to get the most frequent symbol oc-currence pair with a predefined symbol vocabulary size as the constraint. According to our statistic and analysis, those candidate tokens that satisfy the following two constraints are mostly significant abbreviations of domain-specific phrases or nouns: (i) The length of the character sequence between $2 \sim 4$; (ii) Appearing enough times (e.g., ≥ 8000) in Tele-corpus and is not included in original MacBERT / BERT vocabulary; "RAN", "MML", "PGW", "MME", "SGW", "NF" are some filtered examples. Then, these tokens together with the prompt tokens are all inserted into the vocabulary of KTeleBERT as special tokens with newly learnable token embeddings added in.

B. Numerical Data Encoding

We claim that structured machine data's major information comes from its numerical value together with the paired tag



Fig. 3: Prompt template for KTeleBERT. Those corpora are all wrapped with our pre-defined prompt template to unify the input modality. The meaning and full names of these special tokens are as follows: Alarm ([ALM]); Relation ([REL]); Entity ([ENT]); Location ([LOC]); Document ([DOC]); Attribute ([ATTR]); Numeric ([NUM]); KPI ([KPI]).

name, which indicates the meaning of corresponding numeric. Different numerical data generally have some implied associations, which are reflected in their synergistic changes in value. For example, when the message number of "*PDU Session Establishment Reject*" abnormally increases in interface "*N11*" of network element (NE) "*SMF*", the successful rate for "*5G SA Session Establishment*" will suddenly decrease. Since the tele machine data are constantly generated, those **correlations among various numerical information are a plentiful supplement knowledge toward the expert experience in Tele-KG**. Moreover, some numerical data also lies in Tele-KG which mainly comes from the value within attribute triples.

As elaborated in Sec. IV-A, we unify the modalities and patterns of the input to alleviate the problems caused by inconsistent input formats. It is worth noting that the alarm and KPI are import parts of the machine data, but not the whole collection of machine data in tele field. Other data sources like signaling flow and configuration data are temporarily not considered in this paper. We leave it as the future work.

We noticed that existing numerical learning methods [22]– [24] always fail when migrated to our tele-scenario where the field number (e.g., KPI name) is numerous and new names are often generated. In this work, we design an **adaptive numeric encoder** (ANEnc) module to achieve the fine-grained numerical data encoding meanwhile being adaptive to numerous fields, which works as part of the KTeleBERT as shown in Fig. 4.

As the details shown in Fig. 5(a), the whole process for adaptive numeric encoding model are composed of L stacked ANEnc layers together with a numeric decoder (NDec) module. Each of the ANEnc layer contains two types of sub-layers: attention-based numeric projection (ANP) and a fully connected feed-forward network (FFN).

Specifically, we construct N learnable field aware meta embeddings $\boldsymbol{E} \in \mathbb{R}^{N \times (d/N)}$. Each of the meta embedding $e^{(i)}$ is paired with a *value* conversion function parameterized by

TABLE I: Part of the notation and symbols used in Sec. IV.

Symbols	Description				
t	d-dimensional tag name embedding				
v^{tag}	Numerical value v with tag as the tag name				
N	Number of field aware meta embedding in each layer				
\hat{h}	Output for attention-based numeric projection (ANP)				
h^l	Output for <i>l</i> -th adaptive numeric encoder (ANEnc) layer				
x	Input numerical embedding for each ANEnc layer				
$oldsymbol{E}$	$N \times (d/N)$ Matrix collection for meta embeddings				
$e^{(i)}$	The <i>i</i> -th meta embedding in E				
$oldsymbol{W}_q$	$d \times (d/N)$ matrix for Query conversion				
$oldsymbol{W}_v^{(i)}$	$d \times d$ matrix for numeric transformation				
q	query embedding which equals to $t W_q$				



Fig. 4: Numerical value encoding in KTeleBERT.

 $\boldsymbol{W}_{v}^{(i)} \in \mathbb{R}^{d \times d}$. Note that the meta embedding $e^{(i)}$ denotes one decoupled aspect of the domain knowledge and the conversion matrix $W_v^{(i)}$ represent the numerical embedding transformation manner in this meta domain. Moreover, we define the Query projection as $W_q \in \mathbb{R}^{d \times (d/N)}$, which converts the d-dimensional tag name embedding t into a (d/N)-dimension query embedding q. Then the attention score $s_{attn}^{(i)}$ for each meta domain *i* is calculated by attention function using $(q, e^{(i)})$, and the output of each projection matrix $W_{v}^{(i)}$ are summed by attention-based fractional weighting to get the domain-adaptive embedding h. Note that the embedding t remains unchanged across all ANEnc layer, which is tag name's pooling output embedding from the former embedding layer, as shown in Fig. 5. We following previous works [22]-[24] to put a single fully connected network with $\boldsymbol{W}_{fc} \in \mathbb{R}^{1 \times d}$ prepended for numerical value mapping. Note that all numerical values across the same tag name should be normalized via Min-max normalization to smooth the learning process of the model. The above process could be represented as:

 $\hat{h} = softmax(\frac{tW_q E^T}{\sqrt{d/N}})V, \qquad (1)$

where

$$V = (x \boldsymbol{W}_v^{(i)} \cdots x \boldsymbol{W}_v^{(N)}).$$
⁽²⁾

Note that in the *l*-th ANEnc layer $(l \leq L)$:

$$x = \begin{cases} \text{ACT_FN}(v \boldsymbol{W}_{fc}) & l = 1\\ h^{(l-1)} & otherwise \,, \end{cases}$$
(3)



Fig. 5: Framework for adaptive numeric encoding process.

where

$$h = Norm(FFN(\hat{h}) + \alpha \cdot xW_{down}W_{up}), \qquad (4)$$

which is the output hidden state of the following FFN sublayer with trainable low-rank matrices injected to approximate the weight updates, following LoRA [32]. Concretely, $W_{down} \in \mathbb{R}^{d \times r}$, and $W_{up} \in \mathbb{R}^{r \times d}$ are both turnable parameters where $r \leq d$, and $\alpha \geq 1$ is a turnable scalar hyperparameter. Then, the output embedding h^L (represented by h in following context) is fed into the stacked transformers layer together with those normal token embeddings.

1) Numeric regression: In order to make ANEnc compatible with typical self-supervised pre-training mode, we further introduce a numeric decoder (NDec) module to match the ANEnc and form an autoencoder-like framework. Concretely, we let the output embedding of the final transformer layers as the input of NDec, where the semantic interactive information across multiples transformer layers can be well involved. Assuming NDec's 1-dimensional embedding output as v_p . As shown in Fig. 4(b), we present the numeric regression loss \mathcal{L}_{reg} :

$$\mathcal{L}_{reg} = \mathbb{E} \| v_p - v \|_2^2 \,, \tag{5}$$

which encourages the embedding output h to retain the original numerical information.

2) Tag name classification: As shown in Fig. 4(c), a tag classifier (TGC) is introduced to enforce the numerical representation to maintain original tag name's knowledge with h as the input:

$$\mathcal{L}_{cls} = \mathbb{E}\left[-y_{tag} \cdot \log \mathrm{TGC}(h)_{tag}\right],\tag{6}$$

where y_{tag} is the ground truth label for target numerical value's tag name and $TGC(h)_{tag}$ denotes the probabilistic output for model TGC in label y_{tag} . Note that this objective

is optional, since sometimes there could be **newly unseen tag name during the development of specific field**.

3) Numerical contrastive learning: To further strengthen the alignment between the numerical interval and the embedding distance, we propose a numerical contrastive loss \mathcal{L}_{nc} . Given a target sample, traditional supervised contrastive learning defines those samples which share labels with the target one as positive and those samples with distinct labels inside the mini-batch as negative. Differently, we define the sample whose **numerical value is the most closed to** v **as positive and the rest as negative within each min-batch**. Particularly, given numerical a value v,

$$\mathcal{L}_{nc} = \mathbb{E}\left[-\log \frac{\exp\left(Sim\left(h, h^{+}\right)/\tau\right)}{\sum_{h' \in \mathcal{N}(v)} \exp\left(Sim\left(h, h'\right)/\tau\right)}\right], \quad (7)$$

where τ is the temperature hyper-parameter, $\mathcal{N}(v)$ is the inbatch negative embedding set, h^+ denotes the in-batch positive embedding and $Sim(\cdot, \cdot)$ refs to the cosine similarity function here. Additionally, we observe that this objective also helps a lot which smooths the numerical value changing process and stabilizes our model (See Fig 10).

4) Automatically weighted loss: Considering that three training objectives are involved for numerical encoder learning, we exploit an automatically loss weighted strategy [33] for multi-task fusion, which weighs multiple loss functions by considering the homeostatic uncertainty of each task. This allows us to simultaneously learn various quantities with different units or scales in both classification and regression settings. Let μ_i be a learnable observation noise parameter toward task *i* which captures how much noise contained in the outputs, we formulate the numerical loss function as follow:

$$\mathcal{L}_{num} = \frac{1}{2} \left(\frac{1}{\mu_1^2} \mathcal{L}_{reg} + \frac{1}{\mu_2^2} \mathcal{L}_{cls} + \frac{1}{\mu_3^2} \mathcal{L}_{nc} \right) + \sum_{i=1}^3 \log(1 + \mu_i^2) \, .$$

5) Orthogonal regularization for Parameters: In addition to the default weight decay regularization, which is applied to the weights of the whole network, we introduce an orthogonal regularization for parameters in numeric transformation functions to mitigate the gradient explosion phenomenon when the network is deep [34]. The final loss is:

$$\mathcal{L}_{num} \leftarrow \mathcal{L}_{num} + \lambda \sum_{i=1}^{N} \left(\left\| I - W_{v}^{(i)\top} W_{v}^{(i)} \right\|_{F}^{2} \right), \quad (8)$$

where λ is a weight hyperparameter and I is the identity matrix.

C. Mask Reconstruction

Since firstly being proposed in BERT [9], mask reconstruction gradually becomes a general self-supervised pre-training strategy in large scale data [12], [27], [35].

Not that the common objective for mask loss is:

$$\mathcal{L}_{mask} = \mathbb{E}\left[-\sum_{i=1}^{Len(w)} \log P(w_i \,|\, \mathcal{S}_{\backslash w})\right],\tag{9}$$

where w represents the target token sequence to be predicted in PLM's vocabulary, $S_{\setminus w}$ denotes the input sentence with subsequence w being masked, and the cross-entropy objective is adopted for masked token reconstruction in $P(w_i | S_{\setminus w})$. In our work, we exclude those pre-defined prompt special tokens and numerical values from the candidate set of w. The original data is wrapped by prompt template, as introduced in Sec. IV-A, to make up the candidates for an input sentence S.

1) Masking Rate: Masking rate refers to the proportion of masked tokens to the total number of tokens. Most previous works follow the standard ratio (i.e., 15%) in BERT. Nevertheless, recent researchers prove that those higher masking rates benefit training via adding discrepancy [36]. Thus, in this work we increase the masking rates from 15% to 40% during re-training.

2) *Masking Strategy:* We consider the following masking strategy in our work in re-training stage:

- The dynamic masking strategy in RoBERTa [12] which dynamically changing the masking pattern applied to the training data in each step.
- Chinese WWM strategy in MacBERT [27]. we use the LTP tool [37] for Chinese whole word split.

D. Expert Knowledge Injection

To enhance PLM's ability on explicit reasoning, we follow KEPLER [38] to introduce a text-enhanced knowledge embedding (KE) objective for tele expert knowledge injection, as shown in Fig. 6. Specifically, we warp entities / relations into the textual sentences using the templates in Fig. 3, and encode them with KTeleBERT as their embeddings.

Let e_h , e_r , e_t , respectively denotes the embedding of given head entity, relation, and tail entity, we formulate the KE loss function \mathcal{L}_{ke} as follow:

$$\mathcal{L}_{ke} = -\log \sigma \left(\gamma - d_r(\mathbf{h}, \mathbf{t})\right) - \sum_{i=1}^{n} p\left(h'_i, r, t'_i\right) \log \sigma \left(d_r\left(\mathbf{h}'_i \mathbf{t}'_i\right) - \gamma\right),$$
(10)



Fig. 6: Text-enhanced KE progress in KTeleBERT.

where (h'_i, r, t'_i) are negative samples, γ is the margin, σ is the sigmoid function. Let d_r as the scoring function from TransE [5]:

$$d_r(\mathbf{h}, \mathbf{t}) = \|e_h + e_r - e_t\| \tag{11}$$

Note that we define the negative sampling policy as fixing the head entity and randomly sample a tail entity, and vice versa.

E. Training Strategy for Multi-source Data

In order to achieve co-training for KTeleBERT, we define it as a multi-task learning (MTL) progress that combines different tasks across multi-source data. Concretely, two strategies are considered to avoid forgetting the learned knowledge:

- Iterative training (IMTL). We follow ERNIE2 [35], a continual multi-task pre-training framework from Baidu, to apply a iterative training method across tasks.
- Cooperative parallel training (PMTL). The loss from different tasks are simply summed in each of the step.

In addition, we also consider single-task learning (STL), i.e., using only the causal sentences for mask reconstruction. The details are recorded in Table II where we unify the total training step to 60k for strategy comparison.

V. EXPERIMENT

In this section, we firstly introduce the implementation details for our model, including pre-training / re-training datasets, experiment environment and parameter sets. Then, we validate the TeleBERT and KTeleBERT on three downstream tasks: root-cause analysis (RCA), event association prediction (EAP), and fault chain tracing (FCT). Experiment results demonstrate our model's superiority in all tele-domain tasks where MacBERT is used as the strong baseline to initialize the representation for those task's input.

A. Pre-training Details

1) TeleBERT Pre-training: **Datasets**: Tele-Corpus used for TeleBERT pre-training involves multiple aspects of the teledomain data, including tele question answering, software parameter description, daily maintenance cases, etc, which all come from the product documents. As elaborated in Sec. III-A, data augmentation methods are used to generate totally 20, 330 k sentences (1.4GB). **Environment**: About 269 hours are spent to pre-train TeleBERT on 8*8 32G NVIDIA V100 cluster for 30 epochs with batchsize 4096.

Strategy	Re-training task	Training iterations (steps)		s (steps)	Training objective	
		Stage	1 Stage 2	Stage 3	8	
Single-task Learning (STL)	Masking Reconstruction		60k		$ $ $\mathcal{L}_{num} + \mathcal{L}_{mask}$	
Parallel Multi-task Learning (PMTL)	Masking Reconstruction		50k		$\mathcal{L}_{mum} + \mathcal{L}_{mash} + \mathcal{L}_{ha}$	
	Knowledge Embedding		60k			
Iterative Multi-task Learning (IMTL)	Masking Reconstruction	40k	10k	10k	$ $ $\mathcal{L}_{num} + \mathcal{L}_{mask}$	
	Knowledge Embedding	-	40k	20k	$ $ \mathcal{L}_{ke}	

TABLE II: Details about different learning strategy, including multi-task learning and single task learning.

2) *KTeleBERT Re-training:* **Datasets**: As described in Sec. IV-A and Sec. IV-D, the datasets for KTeleBERT re-training consist of the causal sentences, numeric-relate machine log data, and triples in Tele-KG. In order to balance the data scale, we select 434K causal sentences, 429K machine logs (alarms and KPI information), and 130K knowledge triples.

Environment and Parameters For those coefficients, we set λ to 1e-4, temperature τ to 0.05, the number of negative samples for each entity in \mathcal{L}_{ke} as 10, margin γ to 1.0, learning rate to 4E-5, and accumulation steps to 6. About 8 hours are spent to re-train KTeleBERT on four 24G NVIDIA RTX 3090 for 60K steps with batchsize 256.

3) Service Delivery Paradigm: Given a target name in teledomain from related tasks, we state three kind of data types: (*i*) "only name": pure literal name for the target. (*ii*) "Entity mapping w/o Attr.": The target name is mapped to entity in Tele-KG by surface. (*iii*)"Entity mapping w/ Attr.": The target name is mapped to entity in Tele-KG with attributes provided by downstream tasks concatenated behind.

Particularly, the details for data formats all follow the basic templated rule shown in Fig. 3, and our model encodes the content for those wrapped names with [CLS]'s output embeddings as the representations, which work as service embeddings for those tasks of fault analysis.

B. Task1: Root-Cause Analysis

1) Task Description: In this task, we formulate the problem of finding the root cause of a telecommunication system as a node ranking problem in a graph, since a telecommunication system consisting of a number of network elements (nodes) and their connections (edges) can be formulated as a graph naturally. A telecommunication system can be represented by $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathbf{X})$, where \mathcal{V} is a set of nodes (i.e., network elements (NEs)), and $\mathcal E$ is a set of edges (i.e., connections between NEs). Furthermore, $X \in \mathbb{R}^{|\mathcal{V}| \times n}$ is the node feature matrix where each row i describes the abnormal event feature on corresponding node v_i , and n is the number of all abnormal events. Specifically, for example, $x_{ij} = 3$ denotes that the abnormal event j occurs three times on network element i. In real-world applications, analysts usually collect all information including abnormal events in a specific time slot when abnormal events occur, and we term a telecommunication system in a time slot as a state. When and how to collect a state is not the subject of this task. The goal of this task is to design a model f that can map a state of a telecommunication system



Fig. 7: Method overview for root-cause analysis.

to a score vector of nodes, $s = f(\mathcal{G})$, where $s \in \mathbb{R}^{|\mathcal{V}|}$ is a score vector representing the scores of nodes, and the higher the score, the more likely it is that the corresponding node is the root cause.

2) Method: The method for handling root-cause analysis is mainly based on KTeleBERT and Graph Convolutional Networks (GCNs) [39]. The overview can be found in Figure 7. First, for a graph \mathcal{G} , we use our proposed KTeleBERT to obtain the representations of abnormal events, and use them to initialize representations for nodes based on the node feature matrix **X**. This step is referred to as Node Initialization, where we first obtain the representations of abnormal events:

$$\mathbf{E}_i = \mathrm{KTeleBERT}(seq_i), \tag{12}$$

where seq_i is the input sequence for the *i*-th abnormal event, and its format is described in Section V-A3. $\mathbf{E}_i \in \mathbb{R}^{1 \times d}$ is the representation vector for abnormal event *i*, and $\mathbf{E} \in \mathbb{R}^{n \times d}$ is the representation matrix for all abnormal events where *d* is the dimension.

To initialize input node representations for GCN, we use the average summation on representations of abnormal events for each node:

$$\mathbf{H}_j = \frac{\mathbf{x}_j \mathbf{E}}{\sum \mathbf{x}_j},\tag{13}$$

where $\mathbf{x}_j \in \mathbb{R}^{1 \times n}$ is the node feature for node j and it is a vector indicating how many times an abnormal event happens on node j. $\mathbf{H} \in \mathbb{R}^{|\mathcal{V}| \times d}$ is the representation matrix for all nodes used as the input of the following GCN.

We use L GCN layers to update the node representation:

$$\mathbf{H}^{l} = \sigma \left(\widetilde{\mathbf{D}}^{-\frac{1}{2}} \widetilde{\mathbf{A}} \widetilde{\mathbf{D}}^{-\frac{1}{2}} \mathbf{H}^{l-1} \Omega^{l} \right) , \qquad (14)$$

where \mathbf{A} is the adjacency matrix of a graph \mathcal{G} , $\widetilde{\mathbf{A}} = \mathbf{A} + \mathbf{I}$ is the adjacency matrix with self-loop, $\widetilde{\mathbf{D}}$ is the degree matrix of $\widetilde{\mathbf{A}}$, σ is an activation function, Ω is a layer-specific trainable parameter. More precisely, $\mathbf{H}^0 = \mathbf{H}$ and \mathbf{H}^L is the output node representations.

Finally, the output node representations are passed through a 2-Layer MLP to calculate the final score for nodes:

$$s = f_s(\mathbf{H}^L) \,. \tag{15}$$

We use the logistic loss to train our model, and we treat the labeled root cause node as positive samples (y = 1) and others as negative samples (y = -1). The parameters in GCN and MLP are optimized by minimizing the following loss:

$$\mathcal{L}_{rca} = \sum_{\mathcal{G}_i} \sum_{j \in \mathcal{V}_i} \log(1 + \exp(-y_j s_j)).$$
(16)

3) Evaluation: In this part, we describe the dataset, baselines, implementation details, and results in root-cause analysis. We use a dataset containing different states of the telecommunication system with labeled root causes. Table III shows the data statistics, specifically, we present the number of graphs (#Graphs), the number of features (#Features), and the average number of nodes (#Nodes) and edges (#Edges) in graphs. As mentioned above, each graph is a state of a telecommunication system, and nodes are network elements. Furthermore, features can represent the abnormal situations of nodes. Moreover, we use random valued vectors drawn from a uniform distribution to represent abnormal events as a baseline.

TABLE III: Data statistics for root-cause analysis.

#Graphs	#Features	#Nodes	#Edges
127	349	10.96	51.15

Implementation Details. For baselines Random and MacBERT, and our proposed method TeleBERT and KTele-BERT, we use 768-dimensional representations. We use 2-layers GCNs, and the hidden dimensions are 1024 and the output dimensions are 512. For transforming output representations from GCNs to scores for nodes, we use 2-Layer MLPs with 128-dimensional hidden layers. In our evaluation, we use K-Fold Validation. Specifically, we split all graphs into 5 folds, we select 1 fold as the testing set, the next 1 fold as the validation set, and others as the training set. Finally, we report average results. We use Mean Rank (i.e., mean rank of labeled root causes on the node ranking lists by predicted scores in graphs) and Hits at N (Hits@N) (i.e., the proportion of labeled root causes ranked in top N in graphs) to evaluate our model.

Results Analysis. The results of root-cause analysis are shown in Table IV. From these results, we find that the model using abnormal event representations from KTeleBERT achieves the best performance. Specifically, the best Hits@1 of KTeleBERT obtains 5.28% relative improvements compared with TeleBERT on Hits@1 and that figure is 10.60% compared with MacBERT. The results indicate the effectiveness of our proposed TeleBERT and KTeleBERT.

TABLE IV: Evaluation results for root-cause analysis.

Method	$\mathrm{MR}\downarrow$	Hits@1	Hits@3	Hits@5
Random	2.47	54.88	75.00	88.67
MacBERT	2.16	59.64	82.68	90.85
TeleBERT KTeleBERT-STL w/o ANEnc	$\frac{2.09}{2.06}$ 2.13	62.65 63.66 60.72	83.52 83.21 82.96	<u>92.46</u> 91.87 90.80
KTeleBERT-PMTL	2.03	65.96	84.98	92.63
KTeleBERT-IMTL	2.02	64.78	85.65	91.13

C. Task2: Event Association Prediction

1) Motivation and Problem Formulation: With the development of deep learning techniques, which aim to embed the targets into low-dimensional spaces with their information and associations with other targets in the original space preserved, one of our objectives is to represent each event as a low-dimensional vector (i.e., event embedding) and learn the associations between events based on the embedding computation. Moreover, motivated by many methods which model the relationship between targets by embedding similarity, we propose a *trigger* relation specific space, where events are represented in this space and the similarities between these embedded events are measured to predict the trigger relationships between target event pairs. Formally, let e_i and e_j be a pair of input events, their similarity score s_{ij} is

$$s_{ij} = f(\boldsymbol{e}_i, \boldsymbol{e}_j), \qquad (17)$$

where e_i and e_j are the vector representations of the pair of events, and f represents the similarity measurement function. If there exists a trigger relationship between e_i and e_j , the embeddings are similar in the *trigger* relation space, otherwise are dissimilar.

Next, the question is how to represent the event. One naive idea is random initialization like most deep learningbased algorithms, and the embeddings are further optimized by a number of labeled training event pairs. However, the quality of the learned event embeddings will be greatly limited by the number of labeled data. Regarding some additional information about the event, such as its textual information, its machine data, and the topological environment of the network element it depends on, that can be utilized, we try to represent each event using the following information:

- its literal name, which shortly and abstractly describes the event in text, and reveals some fault patterns such as by word co-occurrence;
- the topological environment of the network element it depends on, in general, a fault event is generated from a network element and the topological connections between the network elements decide the information flow in a network, that is to say, two events whose network

elements that are adjacent are more likely to have the trigger relationship;

• its log machine data, which reflects the running context that causes the fault event, such as its occurrence time.



Fig. 8: Method overview for event association prediction.

2) Method: Therefore, the further objective is how to vectorize the information listed above and fuse them to represent a target event. To achieve this goal, we apply different strategies to embed different kinds of information. The overview of the method is shown in Fig. 8. Specifically, given a target event pair (e_i, e_j) , we first embed their corresponding literal names seq_i and seq_j in a way analogous to the task of *Root-Cause Analysis*, i.e., according to the equation Eq. (12), we have $\mathbf{E}_i = \text{KTeleBERT}(seq_i)$ and $\mathbf{E}_j = \text{KTeleBERT}(seq_j)$. Next, to encode the topological environment, for the network elements n_i and n_j on which these two events depend, we aggregate their one-hop neighbors in the network graphs, formally, for n_i , we have

$$\boldsymbol{n}_{i} = \frac{1}{\mathcal{N}_{i}} \sum_{k \in \mathcal{N}_{i}} \boldsymbol{n}_{k} , \qquad (18)$$

where n_i denotes its aggregated embedding and \mathcal{N}_i is its one-hop neighbor set including itself. Here, we adopt a sum pooling to aggregate the topological features. Finally, for the occurrence time of these two events from the log machine data, we wish to compute and encode the time difference that indicates the sequential features between events. Formally, for the occurrence time t_i and t_j of e_i and e_j , we first compute the D-value and pass it into a fully connected network with a weight parameter of W_1 , as

$$\boldsymbol{d}_{ij} = \boldsymbol{W}_1(t_i - t_j) \,. \tag{19}$$

In the end, we concatenate these vectors to generate a final representation for the input event pair and pass it into another fully connected network by the weight parameter of W_2 to predict the similarity score as

$$s_{ij} = \boldsymbol{W}_2[\mathbf{E}_i; \mathbf{E}_j; \boldsymbol{n}_i; \boldsymbol{n}_j; \boldsymbol{d}_{ij}], \qquad (20)$$

where $[\cdot; \cdot]$ means the concatenation operation for vectors.

To learn the similarity and dissimilarity of the input event pairs, a standard binary cross-entropy loss with softmax activation function is minimized for all the event pairs in the datasets:

$$\mathcal{L}_{eap} = -\frac{1}{|\mathcal{P} \wedge \mathcal{P}'|} \sum_{(e_i, e_j) \in \mathcal{P} \wedge \mathcal{P}'} y_{ij} \cdot log(softmax(s_{ij})) + (1 - y_{ij}) \cdot log(1 - softmax(s_{ij})),$$
(21)

where \mathcal{P} in the set of positive event pairs, i.e., there exists a trigger relationship between events in the pair. For each positive pair, we generate a negative pair by randomly replacing one of the two events with other events to constitute the negative set \mathcal{P}' , each of them not exists in the current positive set. y_{ij} is the label of the given event pair (e_i, e_j) , whose value is 1 when the pair is positive and 0 otherwise. During prediction, given a candidate event pair, we will input it into the model to obtain the similarity score.

TABLE V: Data statistics for event association prediction.

# Events	# Event Pairs	# Event Pairs	# MDAF	# Nework
	(positive)	(negative)	packages	Elements
86	2141	2141	104	31

3) Evaluation: We use some event pairs that are known to have trigger relationships and have been validated by the tele experts. To conveniently evaluate the designed algorithm, we split them into two disjoint sets – 80% of them are used for training and the rest 20% are used for testing. Meanwhile, for each event pair, we collect MDAF packages to provide the log machine data and a graph of network elements to provide their topological environment. The detailed statistics are shown in Table V. Moreover, we use word embeddings as a baseline where the literal name sequence is cut into multiple separated words, each of which is randomly initialized with a 768-dimensional vector and is represented by averaging the word embeddings.

Implementation Details. The whole model is implemented with PyTorch and uses Adam as the optimizer with a learning rate of 0.01 and batch size of 32. The shapes of matrices used for mapping the time difference W_1 and the event pair representations W_2 are set to 1×2 and 540×2 , respectively. For more robust results, we perform multiple random data splits for 5-fold cross-validation. Since the task is modeled as a binary classification task, we report the evaluation results with widely used metrics of Accuracy, Precision, Recall, and F1-score.

Result Analysis. The results compared with baselines are shown in Table VI. As we can see, the representations of event literal names by our designed PLMs perform better than those generated by the solutions raised as baselines. Moreover, MacBERT has poor performance compared with those domain-specific methods, i.e., Word Embeddings learned by known event pairs and TeleBERT trained using telecommunication corpora, showing the important domain-specific features. Also, in most situations, our models show their superiority of encoding event literals.

Methods	Accuracy	Precision	Recall	F1-score
Word Embeddings MacBERT	64.9 64.3	66.4 65.9	96.8 96.1	78.7 78.2
TeleBERT	70.4	71.4	95.1	81.5
KTeleBERT-STL	77.3	76.6	96.6	85.4
w/o ANEnc	76.0	76.1	95.1	84.5
KTeleBERT-PMTL	68.5	68.8	99.1	81.3
KTeleBERT-IMTL	73 5	73.8	95.6	83.2

TABLE VI: Evaluation results for event association prediction.



Fig. 9: Method overview for fault chain tracing.

D. Task3: Fault Chain Tracing

1) Task Description: For fault chain tracing task, the input is the fault alarm network which consists of lots of incomplete fault chains. The key point in finding root cause is the completion of the fault propagation chain.

2) Problem Formulation: In our work, we formulate the problem of the fault chain tracing problem as the Knowledge Graph Completion (KGC) task. The telecommunication network can be represented by the heterogeneous graph \mathcal{G} = $(\mathcal{V}, \mathcal{E}, Q, \mathcal{P})$, where \mathcal{V} is a set of nodes consisting of alarms. \mathcal{E} is a set of edges, which is the relations between two alarms in the network element instances. Q is the fact set which is represented by a quadruple q = (h, r, t, s), where $h, t \in \mathcal{V}$, $r \in \mathcal{E}, \ s \in \mathbb{R}_{[0,1]}$ The fact is generated by the records of experts and automatic algorithms, so it is probabilistic triplet. Specifically, s indicates the probabilities and entities h and t are connected by a relation r with confident score. A higher s means it is more likely h and t are connected by r. $\mathcal{P} = \{p_1, p_2, ...\}$ denotes the fault propagation path (fault chain), which consists of a set of alarms. In the real world, fault chains are sometimes incomplete and the model needs to predict the associations among candidate alarm nodes in the range of one-hop or two-hop steps. So the fault chain completion problem is actually the link prediction task in the knowledge graph completion. It should be noted that the heterogeneous graph \mathcal{G} is built by the paths in \mathcal{P} . The goal of this task is to design a model f that can complete the incomplete fault chain, $\mathcal{P}' = f(\mathcal{G})$, where \mathcal{P}' the completed path.

3) *Method:* In order to complete the fault chain tracing task, our approaches are made up of the following three procedures.

Rules Lightning. In real scenarios, there are complex teleproduct fault networks. Therefore, the first step is to filter the irrelevant alarms and network elements

$$\mathcal{G}' = Filter(\mathcal{G}, rules).$$
 (22)

The filtered graph \mathcal{G}' consists of the filtered alarms and their instanced relations.

Initialization of Pre-training Knowledge. For the filtered graph \mathcal{G}' , an important procedure is the initialization of pretraining Knowledge. For each node (alarm) in \mathcal{G}' , the properties or descriptions contain significant information in the potential associations between alarms and network elements. We use KTeleBERT to replace the original randomly initialization and obtain more informative embeddings for each node in the graph.

$$\mathbf{V}_i = \mathrm{KTeleBERT}(V_i), \qquad (23)$$

Note that some edges in the the filtered graph share the same embedding since they connect the same network element type.

Training and Prediction. To model the probabilistic knowledge, we leverage a generalizing translation-based method for uncertain knowledge graph embedding. Since uncertain KG contains confidence of quadruples, the influence of each quadruple is not uniform when learning embeddings. We follow the paradigm in [40] for probabilistic knowledge representation learning.

$$\mathcal{L}_{fct} = \sum_{(h,r,t,s)\in Q} \sum_{(h',r,t',s)\in Q'} [d_r(h,r,t) - d_r(h',r,t') + s^{\alpha}M]_+,$$
(24)

where d_r is the score function for (h, r, t) of the fact quadruple q, [x]+ denotes the positive part, M is the margin hypeparameter. s is the probabilistic confidence of the quadruple, and α is an adjusting hyper-parameter.

After the self-supervised representation learning process, our approach will predict the missing links in the incomplete paths. Our method are shown in Fig. 9.

4) Evaluation: We use fault chain paths which are masked the first-hop relation between alarms to build the dataset. To evaluate the designed algorithm, we split the into three sets – train, valid and test dataset. The detailed statistics is shown in Table VII. Moreover, we random initialize the embeddings of entities and relations in the knowledge graph for comparisons.

TABLE VII: Data statistics for fault chain tracing.

#Nodes	#Edges	#Train	#Valid	#Test
243	100	232	33	32

Implementation Details. The whole model is implemented with PyTorch and framework NeuralKG [41]. We set the training batch size, evaluation batch size and number of negative samples as $\{1024, 1024, 1000\}$ The learning rate and regularization value is set as 10^{-5} and the hidden embedding size is set as 2000.

TABLE VIII: Evaluation results for fault chain tracing.

Method	MRR	Hits@1	Hits@3	Hits@10
Random	58.2	56.2	56.2	62.5
MacBERT	65.9	62.5	65.6	68.8
TeleBERT	69.0	$-\frac{65.6}{7\overline{1.9}}$	71.9	71.9
KTeleBERT-STL	73.6		71.9	78.1
w/o ANEnc	67.5		65.6	71.9
KTeleBERT-PMTL	87.3	84.4	87.5	93.8
KTeleBERT-IMTL	94.8	93.8	93.8	100.0

Results Analysis. From the results in Table VIII, we find that the representations provided by our KTeleBERT models obtain the best performance and obtain a large increase compared with baseline methods.

E. Ablation Study

As the result shown in Table IV, VI, and VIII, our KTele-BERT not only exceeds the simple baseline like random embedding initialization, TeleBERT model, but also performs better than the strong baseline TeleBERT and MacBERT. Moreover, we observe that our proposed ANEnc module also could steadily improve performance in multiple downstream tasks with STL version KTeleBERT as the control group model. In addition, we uniformly collect those generated numerical from ANEnc and visualize them through dimension reduction. As shown in Fig. 10(a) and Fig. 10(b) where the depth of the color represents the size of the value (between 0. and 1.), we find that the continuous changes in values from small to large can be mapped into vector spaces via our proposed numerical contrastive learning method, proving that this method could help the model well understand the magnitude relationship among various numerical values.



Fig. 10: Visualization for numerical embedding when applying the \mathcal{L}_{nc} loss or not.

VI. RELATED WORK

A. Pre-trained Language Model

In order to enhance the semantic understanding of the PLMs, works like ERNIE [10], spanBERT [42] and Struct-BERT [43] try to extend BERT [9] by employing novel token-level and sentence-level pre-training tasks.

Compared with those methods pre-trained on sentence-like corpora, recent knowledge enhanced PLMs begin to focus on

structured data (e.g., KG) for explicit knowledge injection. Specifically, KEPLER [38] plugs a text-enhanced knowledge embedding (KE) module without modifying the model structure. KG-BERT [30] treats triples in knowledge graphs as textual sequences, taking entity and relation descriptions of a triple as a spliced input. K-BERT [44] involves soft position and visible matrix to limit the impact scope for each knowledge triple.

Moreover, recently a series of table pre-training frameworks are proposed to follow the pre-training paradigm in the NLP community. TaBERT [17] combines a row-wise transformer with column-wise vertical attention layers to deal with the hierarchy structure of tabular data. TableFormer [21] introduces a structurally aware table-text encoding architecture, where tabular structural biases are incorporated completely through learnable attention biases. To enable model the ability for numeric learning, Tapas [45] devised the rank embedding for column-wise number comparison, and TUTA [46] distinguishes those numerical values via embedding over various discrete numerical features. We find that fine-grained numerical information encoding is rarely studied in depth in these pre-trained works, making it hard for models to analyze the relationships among close values.

B. Numerical Information Encoding

Existing specialized numerical learning methods [22]–[24] mainly focus on learning limited numerical field features to distinguish different numerical meanings where the field number is limited. In addition, there are also works in the KG community that define the numerical value encoding in KG attribute as a n-gram encoding [47] problem or use a convolutional neural network (CNN) to extract features from the attributes and values of entities [48]. However, they seldom consider the fine-grained encoding for numerical data, which makes it hard for the model to analyze the relationships among values from different fields.

VII. CONCLUSION

In this paper we propose a tele-domain pre-trained language model named TeleBERT to learn the general semantic knowledge in the telecommunication field. Meanwhile, we also introduce its improved version KTeleBERT, which incorporates those implicit information in machine log data and explicit knowledge contained in our Tele-product Knowledge Graph (Tele-KG). Experiences are summarized as causal sentence extraction, tele special token selection and prompt templates construction for unifying multi-source and multi-modal data. Besides, we design an adaptive numeric encoder (ANEnc) for encoding fine-grained numerical data like tele indicators or attribute values. Moreover, three key tele downstream fault analysis tasks are introduced with corresponding solutions attached: root-cause analysis (RCA), event association prediction (EAP), and fault chain tracing (FCT). All those experiment results demonstrate the robustness and effectiveness of our models.

REFERENCES

- W. Zhang, C. M. Wong, G. Ye, B. Wen, W. Zhang, and H. Chen, "Billion-scale pre-trained e-commerce product knowledge graph model," in *ICDE*. IEEE, 2021, pp. 2476–2487.
- [2] W. Zhang, S. Deng, M. Chen, L. Wang, Q. Chen, F. Xiong, X. Liu, and H. Chen, "Knowledge graph embedding in e-commerce applications: Attentive reasoning, explanations, and transferable rules," in *IJCKG*. ACM, 2021, pp. 71–79.
- [3] Y. Zhu, H. Zhao, W. Zhang, G. Ye, H. Chen, N. Zhang, and H. Chen, "Knowledge perceived multi-modal pretraining in e-commerce," in ACM Multimedia. ACM, 2021, pp. 2744–2752.
- [4] M. Schmidt, M. Meier, and G. Lausen, "Foundations of SPARQL query optimization," in *ICDT*, ser. ACM International Conference Proceeding Series. ACM, 2010, pp. 4–33.
- [5] A. Bordes, N. Usunier, A. García-Durán, J. Weston, and O. Yakhnenko, "Translating embeddings for modeling multi-relational data," in *NIPS*, 2013, pp. 2787–2795.
- [6] Z. Wang, J. Zhang, J. Feng, and Z. Chen, "Knowledge graph embedding by translating on hyperplanes," in AAAI. AAAI Press, 2014, pp. 1112– 1119.
- [7] T. Trouillon, J. Welbl, S. Riedel, É. Gaussier, and G. Bouchard, "Complex embeddings for simple link prediction," in *ICML*, ser. JMLR Workshop and Conference Proceedings, vol. 48. JMLR.org, 2016, pp. 2071–2080.
- [8] Z. Sun, Z. Deng, J. Nie, and J. Tang, "Rotate: Knowledge graph embedding by relational rotation in complex space," in *ICLR (Poster)*. OpenReview.net, 2019.
- [9] J. Devlin, M. Chang, K. Lee, and K. Toutanova, "BERT: pre-training of deep bidirectional transformers for language understanding," in NAACL-HLT (1). Association for Computational Linguistics, 2019, pp. 4171– 4186.
- [10] Y. Sun, S. Wang, Y. Li, S. Feng, X. Chen, H. Zhang, X. Tian, D. Zhu, H. Tian, and H. Wu, "ERNIE: enhanced representation through knowledge integration," *CoRR*, vol. abs/1904.09223, 2019.
- [11] A. Radford, K. Narasimhan, T. Salimans, I. Sutskever *et al.*, "Improving language understanding by generative pre-training," 2018.
- [12] Y. Liu, M. Ott, N. Goyal, J. Du, M. Joshi, D. Chen, O. Levy, M. Lewis, L. Zettlemoyer, and V. Stoyanov, "Roberta: A robustly optimized BERT pretraining approach," *CoRR*, vol. abs/1907.11692, 2019.
- [13] P. Liu, W. Yuan, J. Fu, Z. Jiang, H. Hayashi, and G. Neubig, "Pretrain, prompt, and predict: A systematic survey of prompting methods in natural language processing," *CoRR*, vol. abs/2107.13586, 2021.
- [14] T. Gao, A. Fisch, and D. Chen, "Making pre-trained language models better few-shot learners," in ACL/IJCNLP (1). Association for Computational Linguistics, 2021, pp. 3816–3830.
- [15] X. Chen, N. Zhang, X. Xie, S. Deng, Y. Yao, C. Tan, F. Huang, L. Si, and H. Chen, "Knowprompt: Knowledge-aware prompt-tuning with synergistic optimization for relation extraction," in WWW. ACM, 2022, pp. 2778–2788.
- [16] H. Dong, Z. Cheng, X. He, M. Zhou, A. Zhou, F. Zhou, A. Liu, S. Han, and D. Zhang, "Table pre-training: A survey on model architectures, pretraining objectives, and downstream tasks," in *IJCAI*. ijcai.org, 2022, pp. 5426–5435.
- [17] P. Yin, G. Neubig, W. Yih, and S. Riedel, "Tabert: Pretraining for joint understanding of textual and tabular data," in ACL. Association for Computational Linguistics, 2020, pp. 8413–8426.
- [18] Q. Liu, B. Chen, J. Guo, M. Ziyadi, Z. Lin, W. Chen, and J. Lou, "TAPEX: table pre-training via learning a neural SQL executor," in *ICLR*. OpenReview.net, 2022.
- [19] H. Iida, D. Thai, V. Manjunatha, and M. Iyyer, "TABBIE: pretrained representations of tabular data," in *NAACL-HLT*. Association for Computational Linguistics, 2021, pp. 3446–3456.
- [20] H. Gong, Y. Sun, X. Feng, B. Qin, W. Bi, X. Liu, and T. Liu, "Tablegpt: Few-shot table-to-text generation with table structure reconstruction and content matching," in *COLING*. International Committee on Computational Linguistics, 2020, pp. 1978–1988.
- [21] J. Yang, A. Gupta, S. Upadhyay, L. He, R. Goel, and S. Paul, "Table-former: Robust transformer modeling for table-text encoding," in ACL (1). Association for Computational Linguistics, 2022, pp. 528–537.
- [22] H. Guo, R. Tang, Y. Ye, Z. Li, and X. He, "Deepfm: A factorizationmachine based neural network for CTR prediction," in *IJCAI*. ijcai.org, 2017, pp. 1725–1731.

- [23] W. Song, C. Shi, Z. Xiao, Z. Duan, Y. Xu, M. Zhang, and J. Tang, "Autoint: Automatic feature interaction learning via self-attentive neural networks," in *CIKM*. ACM, 2019, pp. 1161–1170.
- [24] H. Guo, B. Chen, R. Tang, W. Zhang, Z. Li, and X. He, "An embedding learning framework for numerical features in CTR prediction," in *KDD*. ACM, 2021, pp. 2910–2918.
- [25] K. Clark, M. Luong, Q. V. Le, and C. D. Manning, "ELECTRA: pretraining text encoders as discriminators rather than generators," in *ICLR*. OpenReview.net, 2020.
- [26] T. Gao, X. Yao, and D. Chen, "Simcse: Simple contrastive learning of sentence embeddings," in *EMNLP (1)*. Association for Computational Linguistics, 2021, pp. 6894–6910.
- [27] Y. Cui, W. Che, T. Liu, B. Qin, and Z. Yang, "Pre-training with whole word masking for chinese BERT," *IEEE ACM Trans. Audio Speech Lang. Process.*, vol. 29, pp. 3504–3514, 2021.
- [28] Z. Chen, Y. Huang, J. Chen, Y. Geng, Y. Fang, J. Z. Pan, N. Zhang, and W. Zhang, "Lako: Knowledge-driven visual question answering via late knowledge-to-text injection," *CoRR*, vol. abs/2207.12888, 2022.
- [29] Z. Zhang, X. Han, Z. Liu, X. Jiang, M. Sun, and Q. Liu, "ERNIE: enhanced language representation with informative entities," in ACL (1). Association for Computational Linguistics, 2019, pp. 1441–1451.
- [30] L. Yao, C. Mao, and Y. Luo, "KG-BERT: BERT for knowledge graph completion," *CoRR*, vol. abs/1909.03193, 2019.
- [31] R. Sennrich, B. Haddow, and A. Birch, "Neural machine translation of rare words with subword units," in ACL (1). The Association for Computer Linguistics, 2016.
- [32] E. J. Hu, Y. Shen, P. Wallis, Z. Allen-Zhu, Y. Li, S. Wang, L. Wang, and W. Chen, "Lora: Low-rank adaptation of large language models," in *ICLR*. OpenReview.net, 2022.
- [33] A. Kendall, Y. Gal, and R. Cipolla, "Multi-task learning using uncertainty to weigh losses for scene geometry and semantics," in CVPR. Computer Vision Foundation / IEEE Computer Society, 2018, pp. 7482– 7491.
- [34] A. Brock, T. Lim, J. M. Ritchie, and N. Weston, "Neural photo editing with introspective adversarial networks," in *ICLR (Poster)*. OpenReview.net, 2017.
- [35] Y. Sun, S. Wang, Y. Li, S. Feng, H. Tian, H. Wu, and H. Wang, "ERNIE 2.0: A continual pre-training framework for language understanding," in *AAAI*. AAAI Press, 2020, pp. 8968–8975.
- [36] A. Wettig, T. Gao, Z. Zhong, and D. Chen, "Should you mask 15% in masked language modeling?" CoRR, vol. abs/2202.08005, 2022.
- [37] W. Che, Y. Feng, L. Qin, and T. Liu, "N-LTP: an open-source neural language technology platform for chinese," in *EMNLP (Demos)*. Association for Computational Linguistics, 2021, pp. 42–49.
- [38] X. Wang, T. Gao, Z. Zhu, Z. Zhang, Z. Liu, J. Li, and J. Tang, "KEPLER: A unified model for knowledge embedding and pre-trained language representation," *Trans. Assoc. Comput. Linguistics*, vol. 9, pp. 176–194, 2021.
- [39] T. N. Kipf and M. Welling, "Semi-supervised classification with graph convolutional networks," in *ICLR (Poster)*. OpenReview.net, 2017.
- [40] N. Kertkeidkachorn, X. Liu, and R. Ichise, "Gtranse: Generalizing translation-based model on uncertain knowledge graph embedding," in *JSAI*, ser. Advances in Intelligent Systems and Computing, Y. Ohsawa, K. Yada, T. Ito, Y. Takama, E. Sato-Shimokawara, A. Abe, J. Mori, and N. Matsumura, Eds., vol. 1128. Springer, 2019, pp. 170–178.
- [41] W. Zhang, X. Chen, Z. Yao, M. Chen, Y. Zhu, H. Yu, Y. Huang, Y. Xu, N. Zhang, Z. Xu, Z. Yuan, F. Xiong, and H. Chen, "Neuralkg: An open source library for diverse representation learning of knowledge graphs," in *SIGIR*, E. Amigó, P. Castells, J. Gonzalo, B. Carterette, J. S. Culpepper, and G. Kazai, Eds. ACM, 2022, pp. 3323–3328.
- [42] M. Joshi, D. Chen, Y. Liu, D. S. Weld, L. Zettlemoyer, and O. Levy, "Spanbert: Improving pre-training by representing and predicting spans," *Trans. Assoc. Comput. Linguistics*, vol. 8, pp. 64–77, 2020.
- [43] W. Wang, B. Bi, M. Yan, C. Wu, J. Xia, Z. Bao, L. Peng, and L. Si, "Structbert: Incorporating language structures into pre-training for deep language understanding," in *ICLR*. OpenReview.net, 2020.
- [44] W. Liu, P. Zhou, Z. Zhao, Z. Wang, Q. Ju, H. Deng, and P. Wang, "K-BERT: enabling language representation with knowledge graph," in *AAAI*. AAAI Press, 2020, pp. 2901–2908.
- [45] J. Herzig, P. K. Nowak, T. Müller, F. Piccinno, and J. M. Eisenschlos, "Tapas: Weakly supervised table parsing via pre-training," in ACL. Association for Computational Linguistics, 2020, pp. 4320–4333.

- [46] Z. Wang, H. Dong, R. Jia, J. Li, Z. Fu, S. Han, and D. Zhang, "TUTA: tree-based transformers for generally structured table pre-training," in
- tree-based transformers for generally structured table pre-training," in *KDD*. ACM, 2021, pp. 1780–1790.
 [47] B. D. Trisedya, J. Qi, and R. Zhang, "Entity alignment between knowledge graphs using attribute embeddings," in *AAAI*. AAAI Press, 2019, pp. 297–304.
 [48] Q. Zhang, Z. Sun, W. Hu, M. Chen, L. Guo, and Y. Qu, "Multi-view knowledge graph embedding for entity alignment," in *IJCAI*. ijcai.org, 2019, pp. 5429–5435.