Exploring industrial safety knowledge via Zipf law

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Abstract: The hazard and operability analysis (HAZOP) report contains precious industrial safety knowledge (ISK) with expert experience and process nature, which is of great significance to the development of industrial intelligence.

Subject to the attributes of ISK, existing researches mine them through sequence labeling in deep learning. Yet, there are two thorny issues: (1) Uneven distribution of ISK: for various processes, the consequence and the state are common, but the material and the equipment are not. (2) Consistent importance of ISK: for safety review, the material and the equipment, as the industrial substances, should be endowed with higher attention.

In this study, we propose a novel generative mining strategy called CRGM to explore ISK. Inspired Zipf law in linguistics, CRGM consists of common-rare discriminator, induction-extension generator and ISK extractor. Firstly, the common-rare discriminator divides HAZOP descriptions into common words and rare words, and obtains the common description and the rare description, where the latter contains more industrial substances. Then, they are operated by the induction-extension generator in the way of deep text generation, the common description is induced and the rare description is extended, the material knowledge and the equipment knowledge can be enriched. Finally, the ISK extractor processes the material knowledge and equipment knowledge from the generated description through the rule template method, the additional ISK is regarded as the supplement of the training set to train the proposed sequence labeling model.

We conduct multiple evaluation experiments on two industrial safety datasets. The results show that CRGM has promising and gratifying aptitudes, greatly improves the performance of the model, and is efficient and generalized. Our sequence labeling model also shows the expected performance, which is better than the existing research. Our research provides a new perspective for exploring ISK, we hope it can contribute support for the intelligent progress of industrial safety.

Keywords: Industrial safety knowledge; Zipf law; Deep learning; Text mining; Text generation; HAZOP

1. INTRODUCTION

The industrial safety knowledge (ISK) contained in the HAZOP report has profound, broad and practical value, it can assist staff to locate the source of faults and anomalies, analyze the path of the hazard propagation, explore the consequence involved, implement effective measures, plan safety precautions, infer the lurking peril of process units, and predict potential risks, etc., which is of irreplaceable significance to the stability and sustainability of industry and promotes the vigorous progress of intelligent industrial safety (He et al., 2020; Feng et al., 2021; Wang et al., 2022). Moreover, ISK can popularize and enhance risk prevention awareness for non-professionals. There is no doubt that how to efficiently explore ISK from HAZOP reports is a meaningful and valuable research.

ISK carries the experience and decision-making of experts and is embedded in HAZOP reports with rigorous and sophisticated process nature. For example, the Fischer Tropsch reactor is a kind of equipment in the coal process; the node reaction "hexamethylene diisocyanate produced by the reaction of hexamethylene diamine hydrochloride and phosgene" recorded in HAZOP consists of three different material knowledge; the reported "ethylene glycol recovery tower overhead knockout drum" has four types of knowledge nesting: "ethylene glycol", "knockout drum", "ethylene glycol recovery tower" and "ethylene glycol recovery tower overhead knockout drum". In addition, the consequence knowledge and the state knowledge reflect the transmission trend of the hazard, such as "high liquid level" and "insufficient oxygen content", etc.

Currently, ISK is explored in the form of sequence labeling to treat the above characteristics (He et al., 2020; Feng et al., 2021; Peng et al., 2021; Wang et al., 2021; Wang et al., 2022; Zhao et al., 2022), which can improve the ability of the ISK mining model with the help of the generalization and expansibility of deep learning from different aspects. Unfortunately, there are additionally two thorny issues that impede this research topic.

(1) Uneven distribution of ISK. The state knowledge and the consequence knowledge are frequently common, for example, "low temperature" and "valve blockage" occur in various processes. But the material knowledge and the equipment knowledge are scattered, they are affected and determined by the type of process, in terms of the glass manufacturing process and the diesel hydrogenation process, the former focuses on the glass related knowledge, while the latter focuses on the diesel related knowledge, there is little commonality between them.

(2) Consistent importance of ISK. The risk analysis is launched based on the specific unit, obviously, the material and the equipment, as the industrial substances, should be given higher attention to the knowledge that they carry.

To conquer these challenges, inspired by the Zipf law in linguistics, we consider that the risk analysis description initiated by the expert group is a combination of words in language used by people, and should follow the Zipf distribution (Piantadosi, 2014). The curve fitted by Zipf potential mechanism can be divided into head part and tail part, they reflect significantly different characteristics (Newman, 2005). In general, the head part contains common and gathered
events, while the tail part contains rare and scattered events (Xiao and Zeng, 2022).

From the perspective of HAZOP, the head part implies the node analysis that occurs repeatedly in the industry, which is more about the state and the consequence in the hazard propagation. The tail part more reflects the equipment and materials that change with the change of specific process. Further, the head part is relatively complete through multiple brainstorming conducted by the expert group, and the undetected potential risk is often low, while the tail part is not.

Therefore, the work on Zipf law provides a fine foundation for this research. In this paper, we present a novel generative mining strategy termed CRGM to explore ISK. CRGM consists of common-rare discriminator, induction-extension generator and ISK extractor. Firstly, the common-rare discriminator regards the measurement of ISK as a binary discrimination through Zipf mechanism, scatters the HAZOP description into common words and rare words through maximum curvature, and classifies HAZOP descriptions into common descriptions and rare descriptions through a proportional algorithm, which correspond to head part and tail part respectively. Then, we train two GPT2 (Radford, 2019) models with different objectives for the induction-extension generator, namely GPT2-I and GPT2-E, which are respectively leveraged to induce the common description and extend the rare description in the way of text generation, so as to enrich the material knowledge and the equipment knowledge as relevant as possible. Finally, the ISK extractor processes and labels the material knowledge and the equipment knowledge in the generated description through the rule template, which are regarded as the supplement of the training set to train our XLNet-CNN-BiLSTM-CRF sequence labeling model.

We conduct multiple trial experiments on two HAZOP datasets that enjoy different types of process backgrounds. The evaluation results present that CRGM can greatly improve the performance of various models, is efficient and reliable, and has a promising prospect. Our sequence labeling model also demonstrates the expected and advanced performance, which is better than the existing research. Our research pushes the exploration of ISK to a new level, we hope it can contribute added value to the daily practice in industrial safety and provide support for the intelligence of industrial safety.

The main highlights are as follows.

1. We propose a generative mining strategy termed CRGM via Zipf law to explore ISK.
2. We contribute a discriminant algorithm to treat HAZOP that enjoy expert experience and process nature.
3. We present the GPT2 model in the field of industrial safety.
4. We raise a new sequence labeling model for ISK.
5. Experiments demonstrate that CRGM is effective and generalized, and our model is advanced.

Section 2 is the related work, which mainly reviews Zipf distribution and HAZOP. Section 3 is the methodology, we elaborate CRGM and its three components. In Section 4, we conduct a series of evaluation experiments and present a detailed analysis. The conclusion is expounded in Section 5.

2. RELATED WORK

It is a meaningful and challenging research to explore industrial safety knowledge through Zipf law. To better understand this work, we introduce Zipf distribution and HAZOP.

2.1. Zipf distribution

Zipf distribution is a universal law about the quantitative attribute of items, which was first found in linguistics. The frequency $F$ of words is inversely proportional to its frequency rank $R$. That is, $F \cdot R = C$ (C is a constant), which indicates that only a few words are popular, while the vast majority of words are rarely used (Newman, 2005; Piantadosi, 2014).

At present, Zipf distribution has been widely used in urban planning (Bee et al., 2019), government administration (Van, 2020), social network (Kak, 2017), economics (Bottazzi, 2015), natural disaster prediction (Rossi, 2019), and so on (Contreras, 2021; Xiao and Zeng, 2022; Yang, 2022). For example, Ramos et al. (2020) described the regularity of complex social systems through football game interaction according to the Zipf theorem, and revealed the predefined strategic constraints of teams. Wang (2021) benefited from the variational theory in basic disciplines, and demonstrated the Zipf law in the form of the maximum efficiency principle through the thermodynamic efficiency of the engine. Bee et al. (2017) described the size distribution and growth of enterprises in French economy and business through the Zipf law. Rossi et al. (2019) used the Zipf distribution to model the landslide risk of the landform and administrative divisions in the whole Italy, which is helpful to determine the coexistence of multiple hazards and enhance the risk management of the government.

The above researches manifest the potential of the Zipf law in various fields. Therefore, how to enable Zipf theorem to explore industrial safety knowledge is a promising prospect.

2.2. HAZOP

HAZOP is an efficient concept for safety analysis, and also a risk decision-making methodology based on brainstorming of expert team, which has been popularized in various industry fields. HAZOP takes the node of the process unit as the starting point, concentrates on the deviation of the node, retroactively traces its causes, infers its consequences in forward, and gives practical suggestions and measures. The node generally refers to the specific equipment, such as electrolytic cell and stripper, etc., and the deviation refers to the state of the node, such as countercurrent and high liquid level. An intuitive example is "补水泵 P0101A/B 桶电；换热器 E0102A/B 液位低；管程 氮气降温不足，下游流程 PSA 工段超温，氮气从法兰密封泄漏，发生闪爆，重大人员安全隐患、财产和企业声誉影响，较小的环境影响：采用备用泵 & 回路供电 （Electricity shaking of feed-water pump P0101A/B; low liquid level of heat exchanger E0102A/B; insufficient cooling of hydrogen on the
tube side, overt temperature of downstream process and PSA section, hydrogen leakage from the flange seal, flash explosion, major impact on personnel safety, property and corporate reputation, and minor environmental impact; setting of standby pump & dual circuit power supply.

Where, PSA refers to the hydrogen production from methanol cracking. Each HAZOP description records the risk propagation of each node, that is, a complete risk flow path given by the expert group. The expert team exhausts all nodes in the system for logical and meticulous evaluation, which can greatly enhance the stability of the system. At present, many countries including China stipulate that HAZOP must be carried out before each factory is put into production, and the analysis results are recorded in the HAZOP report. Therefore, the HAZOP description contains critical and golden industrial safety knowledge (ISK) with expert experience and process nature. The management and reuse of ISK can complete and optimize HAZOP, and promote the intelligent development of industrial safety, which has great research prospects and application value (He et al., 2020; Feng et al., 2021; Wang et al., 2022).

It should be noted that the HAZOP report is the achievement of the expert team and is protected and encrypted by intellectual property rights. It is a scarce resource that can only be accessed by experts and staff participating in the HAZOP project, so that HAZOP data cannot be obtained in large quantities.

3. METHODOLOGY

Motivated by Zipf law and driven by artificial intelligence, and the descriptions used by experts follow the underlying logic of linguistics, we present a novel generative mining strategy for ISK called CRGM. CRGM includes three modules: common-rare discriminator, induction-extension generator and ISK extractor, see Fig.1. The operation procedure of CRGM is briefly as follows.

(1) Common-rare discriminator. Firstly, it reads the HAZOP report, calculates the frequency of each HAZOP word, and fits the Zipf distribution. Then, HAZOP words are divided into common words and rare words through the maximum curvature value of Zipf.

Discriminant #2: \[ h_j = \begin{cases} 1, & \tau > 0 \\ 0, & \tau \leq 0 \end{cases} \]

where \( \tau \) is the curvature value of Zipf distribution, and \( h_j \) is the frequency of word \( j \). If \( \tau > 0 \), the word is a common word; otherwise, it is a rare word.
curve. Finally, the HAZOP descriptions are classified into common descriptions and rare descriptions through a proportional algorithm.

(2) Induction-extension generator. It consists of GPT2-I and GPT2-E, which manage the common description and the rare description respectively.

(3) ISK extractor. It filters and labels the equipment knowledge and the material knowledge from the generated descriptions through the rule template, which are regarded as the supplement of the training set to train the proposed XLNet-CNN-BiLSTM-CRF.

Section 3.1 introduces our HAZOP projects, and Sections 3.2, 3.3 and 3.4 detail the three modules respectively.

### 3.1. HAZOP report

We cooperate with different enterprises to carry out HAZOP for various processes, which can be divided into four types: petroleum, sulfur, coal and gas. Table 1 provides information about HAZOP reports, where, the column "Process" refers to the specific process, and the column "Net total words" only records the Chinese words of all reports in each type.

| Type | Process                                      | Net total words |
|------|----------------------------------------------|-----------------|
| petroleum | diesel hydrogenation | 278910          |
|       | solvent regeneration |                |
|       | heavy oil catalytic cracking |        |
|       | naphtha isomerization |                |
| sulfur | sulfur recovery | 306147          |
|       | desulfurization and sulfur foam |          |
|       | sulfur production |                 |
| coal  | indirect coal liquefaction | 135460         |
|       | coal washing |                    |
|       | coal cracking |                       |
| gas   | natural gas cracking | 242173          |
|       | water electrolysis |                        |
|       | nitrogen |                                     |
|       | formic acid |                                     |

These different types of process reports have various descriptions with ISK, which lay a good foundation for the operation of subsequent modules.

### 3.2. Common-rare discriminator

This section is a detailed introduction of the common-rare discriminator. The input is the HAZOP description, and the output is the common description and the rare description, see Fig.2.

We start from calculating the equation of HAZOP distribution.

HAZOP description is the combination of words in the language communicated by human and society, the frequency $f$ of the HAZOP word and its rank $r$ are considered to be consistent with Zipf distribution, see Equ.1.

$$f(r) = \frac{C}{r^\alpha}$$

(1)

Where, $\alpha$ and $C$ are constants, which are determined by the type of process. We can estimate the values of $\alpha$ and $C$ by using linear regression, see Table 2 for $\alpha$ and $C$ in different types of processes.

| Type          | $\alpha$ | $C$  |
|---------------|----------|------|
| petroleum     | 0.965    | 51756|
| sulfur        | 0.932    | 50040|
| coal          | 0.773    | 10829|
| gas           | 0.726    | 14194|
the common-rare discriminator obtains the curvature equation of Zipf distribution by calculating Eq.2, where \( \kappa(r) \) represents the curvature of \( f(r) \).

\[
\kappa(r) = \frac{|f''(r)|^3}{1 + [f'(r)]^2} \tag{2}
\]

\( r_0 \) can be obtained by calculating Eq.3.

\[
r_0 = \operatorname{argmax} \kappa(r) \tag{3}
\]

Fig.3 is the curvature curve of frequency-rank function of the HAZOP word, and see Table 3 for information on \( r_0 \).

![Curvature curve of HAZOP words](image)

Fig.3: The curvature curve of HAZOP words with log-scaled rank of HAZOP words.

The common-rare discriminator takes the HAZOP word that the rank of its frequency higher than \( r_0 \) as the common word and that lower than \( r_0 \) as the rare word. Note that \( r_0 \) is the only curvature extreme point of the HAZOP word distribution when \( C > 0 \) and \( \alpha > 0 \), the following is the proof.

Bring Eq.1 into Eq.2, we have Eq.4:

\[
\kappa(r) = \frac{C\alpha(\alpha + 1)r^{-\alpha-2}}{[1 + (C\alpha \cdot r^{-\alpha-1})^2]^2} \tag{4}
\]

Note that \( r \) is the rank of the HAZOP word frequency, that is, \( r > 0 \). We calculate the first derivative of Eq.4 to analyze that \( \kappa(r) \) has only one maximum point, see Eq.5.

\[
\kappa'(r) = \eta(r) \cdot \lambda(r)
\]

\[
\eta(r) = \frac{C\alpha(\alpha + 1)r^{-\alpha-3}}{[1 + C^2 \alpha^2 \cdot r^{-2\alpha-2}]^2} \tag{5}
\]

\[
\lambda(r) = [C^2 \alpha^2 \cdot r^{-2\alpha-2} (1 + 2\alpha) - \alpha - 2]
\]

when \( C > 0 \) and \( \alpha > 0 \), for the item \( \eta(r) \), it is obviously a positive value. For term \( \lambda(r) \), we calculate its derivative, see Eq.6.

\[
\lambda'(r) = -2C^2\alpha^2 (1 + 2\alpha)(\alpha + 1) \cdot r^{-2\alpha-3} \tag{6}
\]

Obviously, \( \lambda(r) \) is the negative, so \( \lambda(r) \) decreases monotonically when \( 0 < r < +\infty \). We have: \( r \to 0^+ \), \( \lambda(r) \to +\infty \), and \( r \to +\infty \), \( \lambda(r) = -\alpha - 2 < 0 \). Hence, there is a definite point \( r_0 \) such that \( \lambda(r_0) = 0 \), \( 0 < r < r_0 \), \( \lambda(r) > 0 \), and \( r_0 < r < +\infty \), \( \lambda(r) < 0 \).

Since \( \eta(r) \) is the positive, we have: when \( 0 < r < r_0 \), \( \kappa'(r) > 0 \), when \( r_0 < r < +\infty \), \( \kappa'(r) < 0 \), and when \( r = r_0 \), \( \kappa'(r) = 0 \). Therefore, \( r_0 \) is the only maximum point for \( \kappa(r) \).

This ends the proof, which ensures that the common-rare discriminator can work well. Fig.4 is an illustration on petroleum type.

![HAZOP word division](image)

Fig.4: An illustration of HAZOP word division on petroleum type. Here \( r_0 = 239 \), and HAZOP words whose rank in \([1, 239]\) are classified as common word, and the rest are rare word.

After the common-rare discriminator has determined the common words and rare words, Eq.7 is executed to divide the HAZOP descriptions into common descriptions and rare descriptions, where, "1" refers to the common description, "0" refers to the rare description and "\( c_w \)" refers to common words. That is, for each HAZOP description \( h_d \) containing \( h_w \) HAZOP words, if the proportion of \( c_w \) contained in it is higher than the proportion of \( r_0 \) in the overall rank \( r \), it is a common description, otherwise it is a rare description.

\[
h_d = \begin{cases} 1, & \tau > 0 \\ 0, & \tau \leq 0 \end{cases}, \quad \tau = \frac{h_w \cap c_w}{h_w} - \frac{r_0}{r_t} \tag{7}
\]

Table 3

| Type       | \( r_0 \) | Common descriptions | Rare descriptions |
|------------|-----------|---------------------|-------------------|
| petroleum  | 239       | 1603                | 3122              |
| sulfur     | 253       | 1585                | 3249              |
| coal       | 153       | 756                 | 1481              |
| gas        | 199       | 1377                | 2051              |

Algorithm 1 is the overall workflow of the common-rare discriminator, where, "\( r_w \)" refers to rare words. Finally, we have obtained common descriptions and rare descriptions in each type of process, the discrimination results are shown in Table 3.
Algorithm 1: Common-rare discriminator

Input: HAZOP descriptions $H_d$
Parameter: HAZOP words $H_w$ (in descending order of frequency), the distribution $\kappa(r)$ of $H_w$
Output: common descriptions $c_d$, rare descriptions $r_d$

1. $c_w, r_w, c_d, r_d = \emptyset, \emptyset, \emptyset, \emptyset$
2. $\kappa(r) \leftarrow$ Equ. 2
3. $r_0 \leftarrow$ Equ. 3
4. for $i \leftarrow 1$ to $r_0$ do
5.   $c_w = c_w \cup H_d[i]$
6. for each HAZOP description $h_d$ in $H_d$ do
7.   $h_d \leftarrow$ Equ. 4
8. if $h_d = \emptyset$ do
9.   $r_d = r_d \cup h_d$
10. $r_d = H_d - c_d$
11. return $c_d, r_d$

Next, CRGM with the above HAZOP descriptions starts the induction-extension generator.

3.3. Induction-extension generator

What we want to reiterate is that common descriptions often contain ISK that is common to all processes, and the analysis is relatively complete, while the more critical material knowledge and equipment knowledge exist in rare descriptions, and vary with the change of processes. This imbalance is not conducive to knowledge mining, and it is unrealistic to make up for it by carrying out more HAZOP, and the method of constructing an external dictionary fails to ensure its relevance. A natural idea is that this dilemma can be alleviated by text generation. Considering that each description has its potential characteristics, we not only extend the rare description, but also induce the common description to enrich the material knowledge and the equipment knowledge as relevant as possible.

\[\text{The induction description} \quad \downarrow \quad \text{The extension description} \quad \downarrow \quad \text{The common description}\]

Fig.5: The architecture of the induction-extension generator. It consists of GPT2-I for induction and GPT2-E for extension, which generate words in turn over time step. Here, the common description is “流量过小...排放大气 (too small flow... discharge into the atmosphere)”, which can be generated verbatim "大气|污染 (air pollution)" by GPT2-I, and the extension generation mechanism of GPT2-E is the same.

Specifically, we propose an induction-extension generator and embed it into CRGM. It consists of two GPT2 models (Radford et al., 2019; Anaby et al., 2020), GPT2-I and GPT2-E, which can generate the induction description and the extension description respectively, see Fig.5. GPT2 employs the next word prediction pattern for training, and can predict the subsequent sequences by conditional probability modeling for the known sequences. It is an efficient language model, which has been widely used in various generation tasks, such as: text-to-speech synthesis (Saeki, 2021), event detection (Veyseh et al., 2021), AI brainwave opera (Pearlman, 2021), etc. GPT2-I and GPT2-E are trained with different datasets, objectives and optimizations respectively. The following are the details.

3.3.1. GPT2-I

Considering that HAZOP description is a series of expert terms, its logical structure is fixed, its linguistic diversity is often insufficient, and it has no corresponding label. So, GPT2-I is trained with the help of the Weibo data. The Weibo data consists of massive and diverse topics, users can make comments, spread news and record events based on some topics. Fig. 6 is an example under the topic "oral ulcer should be vigilant against oral cancer if it is not cured for a long time", users interested in this topic can post their own content, such as the “人民网” (People's Daily) and the "生命时报" (Life Times) in Fig.6. Therefore, each Weibo content naturally carries the topic title, which is very suitable for the research of this section, that is, the content and the title correspond to the common description and the induction description respectively.

Fig.6: An example under the topic “oral ulcer should be vigilant against oral cancer if it is not cured for a long time”.

We first grab raw data from Weibo through crawlers. Next, we clean them to remove the emoji, "HTML", "#" symbols and so
on. Then we integrate the cleaned data to remove the data that is duplicate, the data with content words less than 100 and the data with title words less than 2. Finally, we employ Equ.8 to construct the training dataset with 24000 contents.

\[
\{(x_i, y_i)\}_{i=1}^n = \ y_1 \mid \text{SEP} \mid x_1 \mid \text{EOS} \mid y_2 \mid \cdots \mid y_n \mid \text{SEP} \mid x_n \mid \text{EOS}
\]

(8)

Where, \(x_i\) represents the title, \(y_i\) represents the content, \(\text{SEP}\) separates the title and content, and \(\text{EOS}\) terminates a sentence.

\[
\text{Loss} = -\sum_i \log P(\omega_i | \omega_{i-1}, \ldots, \omega_{i-1})
\]

(9)

After preprocessing the Weibo data, we draw lessons from the GPT2 network (Radford et al., 2019) and employ the loss function in the form of Equ.9 to train our GPT2-1, where \(\omega\) represents the token. In addition, we apply Adam optimizer with learning rate of 0.0001, the batch with size of 16, GELU activation function, Transformer decoder with 6 parallel layers and attention with 12 parallel headers.

After 10 epochs of training, we call the prediction ability of GPT2-1 to generate one induction description for each common description in the way of top-1. Note that GPT2 is only a functional tool in this paper, and evaluating its performance is considered a great research problem on its own that is out of the scope of our discussion, hence, GPT2-1 does not need to care about this, so does GPT2-E.

**Table 4**

| common descriptions | induction descriptions |
|---------------------|------------------------|
| 流量过小－故障停，空气顺管道 |  |  
| 进入炉膛，炉膛温度降低，严重 |  |  
| 时流量中断－停车、联锁启动， |  |  
| 低温警，备用风机尾气焚烧炉。 |  |  
| 溢位高－回路故障，开度小或关 |  |  
| 一罐液位升高，压力升高，严重 |  |  
| 高温，大气污染 |  |  
| 时气相突破水封排放至大气。 |  |  

Table 4 presents two generated induction descriptions, where, the common description #1 means “too small flow - fault shutdown, air enters the furnace along the pipeline, the furnace temperature decreases, and in case of serious flow interruption - stop the machine, start the interlock, prepare the low alarm, and start the standby fan tail gas incinerator.”, its corresponding induction description means “stop the machine when the flow is too small”. It can be seen that the induction description #1 retains “too small flow” and “stop the machine”, which are two state knowledge. The common description #2 means “high liquid level - circuit fault, reduce or close - opening, tank liquid level rises, pressure rises, and in serious cases, the gas phase breaks through the water seal and is discharged to the atmosphere.”, its corresponding induction description means "high temperature, atmosphere pollution", which are the state knowledge and the consequence knowledge respectively. Interestingly, the two knowledge do not belong to the common description #2, but are created additionally, which can enrich relevant ISK. In addition, as expected, the knowledge in induction description is often the state knowledge and the consequence knowledge, which conforms to the attribute of the common description.

It should be noted that although the overall meaning of the induction description is inevitably vague, it doesn't matter, since what we need is the relevant knowledge provided. Besides, for some induction descriptions without ISK, the ISK extractor can get rid of them.

### 3.3.2. GPT2-E

Considering that HAZOP corpus is too small to support GPT2-E training alone, the dataset we use is the concatenation between CLUECorpus2020 corpus and HAZOP corpus. CLUECorpus2020 an open source corpus with a total of about 5 billion words, which is sufficient to extend rare descriptions.

Before the training, we attach the "MASK" mark to the beginning of each article in the dataset, use "CLS" to distinguish different articles, and embed "SEP" between lines, see Equ.10, where, \(a\) represents the article, and \(l\) represents the paragraph line.

We use the tokenizer of BERT for word preprocessing, and build the structure of GPT2-E through the decoder in Transformer with 12 parallel layers and attention with 12 parallel headers, the dimensions of token embedding and positional vector are 768 and 1024 respectively. In addition, we apply Adam optimizer with learning rate of 0.0001, the batch with size of 8, GELU activation function.

\[
D[a,l] = [\text{MASK} \mid l^a_1 \mid \text{SEP} \mid l^a_2 \mid \cdots \mid \text{SEP} \mid l^a_n \mid \text{CLS}]
\]

(10)

We use unsupervised training for GPT2-E and autoregressive n-gram method to predict the current word. That is, the word at the current time step is inferred from the information before the current time step, and the gap between the predicted word and the real word is minimized, as shown in Fig.5 and Equ.9.

We call the GPT2-E trained by 10 iterations to perform text extended prediction, and each rare description is generated in the way of top-16 into two descriptions with a length of 500.

Considering the length of the extension description, we show the example in the form of illustration, see Fig.7.
通过扩展描述的生成，我们可以获取到如下的信息：

- 原料油缓冲罐伴热给水管泄漏可能造成原料油带水进入反应器，造成催化剂破碎，严重时装置停工。
- 若出现水管堵塞情况，导致泄漏将严重影响供油管道的寿命。
- 第四节燃气泄漏防范措施燃气泄漏发生后，应及时发现并及时处理。若出现水管堵塞严重的情况，导致泄漏将严重影响供油管道的寿命。

通过扩展描述的生成，我们可以获取到如下的信息：

- 原料油缓冲罐伴热给水管泄漏可能造成原料油带水进入反应器，造成催化剂破碎，严重时装置停工。
- 若出现水管堵塞情况，导致泄漏将严重影响供油管道的寿命。

Note that the above knowledge is not combined and arranged like HAZOP, so we can mine them roughly through the method of rule template to supplement the subsequent tasks.

### 3.4. ISK extractor

通过扩展描述的生成，我们可以获取到如下的信息：

- 原料油缓冲罐伴热给水管泄漏可能造成原料油带水进入反应器，造成催化剂破碎，严重时装置停工。
- 若出现水管堵塞情况，导致泄漏将严重影响供油管道的寿命。

图7: 生成扩展描述的例子

Where, the rare description used for generation is "破裂泄漏原料油缓冲罐伴热给水管泄漏可能造成原料油带水进入反应器，造成催化剂破碎，严重时装置停工。"
etc. It has become the paradigm of knowledge exploration (Li et al., 2020; Goyal et al., 2018).

The starting position of each verb, set...

...Fig. 9 is an illustration of sequence labeling in ISK.

The sequence labeling refers to the supervised learning of a function $F$ from the labeled training set to map the sequence $X = \{x_1, x_2, \ldots, x_n\}$ composed of text into the sequence $Y = \{y_1, y_2, \ldots, y_n\}$ composed of labels, where labels represent the type of knowledge. Fig. 9 is an illustration of sequence labeling in ISK, where, the text sequence is "ammonia sour gas enters non-hydrogenated sour water stripping ... cause personnel poisoning ....", which is mapped into the ISK label sequence by $F$. "M" means the material knowledge, "E" means the equipment knowledge, "C" means the consequence knowledge and "O" is not knowledge, besides, the starting position of each ISK is represented by "B" and the rest by "I".

The sequence labeling model needs HAZOP dataset for training. Yet, as emphasized, the problems existing in HAZOP dataset can impede the performance of the model. Fortunately, our ISK extractor can benefit from the generated description to overcome this dilemma.

### 3.4.2. Processing of generated description

Thanks to the mechanism of Zipf law and the common-rare discriminator, there is additional equipment knowledge and material knowledge in the generated description. Furthermore, the combination and the arrangement of words given by the induction-extension generator are not the coupling of the HAZOP attribute. Therefore, we can take the additional ISK from generated descriptions through the method of rule template to adjust the HAZOP dataset. Note that what the rule template can pursue here is their correctness, not quantity, to avoid introducing additional errors in the sequence labeling.

We mainly use part of speech processing in the Jieba tool, supplementary trigger word matching and other regularities, which has been widely used in natural language processing. It is normal that most knowledge is not available since industrial safety is obviously different from the general field, which is one of the reasons why this method is rarely used in previous studies. We take the induction descriptions in Table 4 as an example, for the state knowledge "流量过小 (too small flow)", it involuntarily combines with the word "时 (when)", and then is parsed into three parts: noun "流量 (flow)", tense particle "过 (too)" and noun "小时 (hour)". "大气污染 (air pollution)" is regarded as an idiom, but most consequence knowledge is not the idiom. Other uncontrollable results are also universal, see table 5. In addition, considering that the purpose of CRGM is to enrich the material knowledge and equipment knowledge as relevant as possible, we decide to abandon the state knowledge and the consequence knowledge in the whole process of parsing the generated descriptions.

### Table 5 An example of part of speech analysis of induction description, where, "n", "ug", "x", "v", "i" stand for the noun, the tense particle, the non-morpheme, the verb and the idiom respectively.

| Induction descriptions | part of speech analysis |
|------------------------|------------------------|
| 流量过小时, 停车开启。高 | (x) | 停车 (v) | 开启 (v) | (x) |
| 湿，大气污染         | (n) | 过小 (ug) | 时 (n) |

For the equipment knowledge and material knowledge in the induction description, they are faced with the obstacle of semantic nesting that cannot be parsed, for example, the "高报警制硫余热锅炉液位过低 (high alarm low liquid level of sulfur waste heat boiler)", where the "制硫余热锅炉 (sulfur waste heat boiler)" is a kind of equipment, but it is treated as three nouns, besides, the "报警 (alarm)" and "液位 (liquid level)" are also separately recognized as nouns. This is a fact that the equipment knowledge cannot be completely mined by part of speech analysis directly, see Table 6. Therefore, we build a series of rules or templates to deal with them, for example, a rule expression is that when multiple nouns are adjacent, nouns connected with other parts of speech are excluded.

### Table 6: An example of part of speech analysis of the material knowledge and equipment knowledge.

| Induction descriptions | part of speech analysis |
|------------------------|------------------------|
| 高报警制硫余热锅炉液位过低 | (a) | 报警 (n) | 制硫 (n) | 余热 (n) |
| 锅炉 (n) | 液位 (n) | 过 (ug) | 低 (a) |

In addition, the equipment knowledge and material knowledge in the extension description are scattered. Some of them can be analyzed in the form of the proper noun, such as "聚乙烯 (polyethylene)". Some can be treated with the pattern combination, such as the pattern between "verb + noun + verb + noun" and idioms. Others are abandoned due to the irregularity.

Note that the two kinds of knowledge are processed separately and further verified by a series of auxiliary trigger words, such as "罐 (tank)" and "管 (pipe)". When all the generated descriptions are processed, we invite several experts to correct them, and then automatically attach knowledge labels to them respectively. Finally, we obtain 9588 material knowledge and 7659 equipment knowledge, they serve as incentives for HAZOP training dataset.

### 3.4.3. Architecture of sequence labeling model

Our sequence labeling model is an end-to-end deep learning architecture composed of a pre-training layer, an encoding layer and a decoding layer, see Fig. 10.
1. The pre-training layer

We call XLNet (Yang et al., 2019) to extract the semantic information from the sequence, since the semantics of the text is conducive to enhance the understanding ability of the model, which can improve the efficiency of knowledge mining. XLNet is a pre-training language model that adopts the permutation language mechanism based on the combination of the autoregressive mechanism and the autoencoding mechanism. Its backbone is the Transformer-XL with the two-stream self-attention.

\[ X = XLNet(h_s) \]  

(11)

XLNet maps the HAZOP sequence \( h_s \) to the embedding \( X \) with semantic features, see Equ.11, and passes it to the encoding layer.

2. The encoding layer

In order to further characterize the features of HAZOP sequences, we leverage CNN and BiLSTM to encode the semantic embedding \( X \). Specifically, we consider the max pooling operation in CNN to extract character-level features from \( X \), which is conducive to selecting prominent features. In addition, the contextual features of sequences are critical, we build a pair of bidirectional LSTMs to treat them. See Equ.12, where, \( t \) represents each time step, \( Conv(\cdot) \) refers to the convolution operation, \( \text{max}(\cdot) \) is the max pooling operation, \( \sigma(\cdot) \) indicates the splicing operation.

\[ G = \sigma[LSTM(X_t, X_{t}), \text{max}(Conv(X_t))] \]  

(12)

We concatenate these two sets of feature vectors into \( G \), and passes it to the decoding layer.

3. The decoding layer

We use a CRF as the decoder to assign the feature vectors \( G \) as the label sequence, see Equ.13.

\[ l_s = \text{argmax} \left[ \frac{1}{T(G)} \prod_{t=1}^{N} \mathcal{G}(l_{t-1}, l_t, G; \theta) \right] \]  

(13)

where \( T(G) \) implies the normalization of the \( \sigma(\cdot) \) for the possible label sequence, \( \sigma(\cdot) \) is a potential expression with the parameters \( \Theta \) and manages the label sequences on different time steps based on \( G \). The label sequence \( l_s \) with maximum probability can be solved by dynamic programming.

4. EXPERIMENT & ANALYSIS

To verify the effectiveness of our proposed exploration, we perform extensive experiments on two HAZOP datasets belonging to different process types. In this part, we first briefly introduce HAZOP datasets, then show the baseline model and its integration with our CRGM strategy, then present the parameter setting, and finally report and analyze the evaluation results, the evaluation metrics used according to the convention are F1, precision, recall.

4.1. HAZOP dataset

We have constructed two HAZOP datasets from a series of HAZOP reports through data preprocessing operations such as text integration and data cleaning. One is based on projects of the coal type and the petroleum type in cooperation with Shenhua Group, Yanshan Group and Brunei group, which is called CPSYB dataset, and the other is based on projects of the gas type and the sulfur type in cooperation with Sichuan Petrochemical and Liaoyang Petrochemical, which is called GSSL dataset. CPSYB and GSSL contain the state knowledge, the consequence knowledge, the material knowledge and the equipment knowledge, which are manually marked with "BIO". CPSYB and GSSL have 78315 and 72189 lines of data, respectively, they are divided into training set, test set and validation set in the ratio of 8:1:1.

4.2. Comparison

Common sequence labeling models are considered as baselines (see Section 1):

1. BiLSTM-CNN-CRF (base#1): Before the emergence of the pre-training language model, it once became the mainstream by integrating the operation of RNN and CNN.

2. BERT-BiLSTM-CRF (base#2): BERT is a powerful pre-training model for language understanding, which can extract the semantic information of text. It cooperates with BiLSTM to become the default model of knowledge mining in many domains.
(3) BERT-CNN-BiLSTM-CRF (base#3): It is based on the base#2 model and adds convolution operation to extract additional features of text.

(4) ALBERT-CNN-BiLSTM-CRF (base#4): ALBERT is a variant of BERT, which improves the efficiency by factoring word embedding and sharing cross-layer parameters.

To evaluate the performance gain brought by our CRGM to the baselines:

(5) base#1 + CRGM
(6) base#2 + CRGM
(7) base#3 + CRGM
(8) base#4 + CRGM

Ablation experiments to verify the effectiveness of our CRGM:

(9) (our) XCBC#1: For convenience, XLNet-CNN-BiLSTM-CRF is abbreviated as XCBC. XCBC#1 is a form in which XCBC is not attached to any components of CRGM.
(10) (our) XCBC#2: It is not guided by the common-rare discriminator with Zipf mechanism, that is, the HAZOP description for subsequent operations is random, and the amount of generated descriptions and knowledge processed by the rule template is not change.
(11) (our) XCBC#3: The proposed complete method.

4.3. Parameter setting

The parameters of each trial experiment are consistent. For example, we choose Adam optimizer with 0.0003 learning rate, the activation function is ReLU, the batch size is 64, the size of the pre-training language model is base, that is, XLNet_base, BERT_base, ALBERT_base, and the epoch is 50. The training parameters of GPT2-I and GPT2-E have introduced in the respective sections, which will not be repeated here.

4.4. Evaluation analysis

Tables 7-10 present the evaluation results on different data sets. In addition, for more intuitive analysis and discussion, we have prepared a series of figures. There are the following major observations.

From a macro point of view, compared with CPSYB, the knowledge in GSSL seems more obscure and difficult to understand. On GSSL, especially for the four base models, their F1 performance hovers around 40% on the validation set and less than 69% on the test set. For CPSYB, the model can better draw the knowledge from it. Whether on the validation set or the test set, their F1 performance exceeds 83%, and even the that of XCXC series models reach more than 90%.

Figure 11: Performance comparison between our model and the base series on GSSL / test set.
Further, for the base series, in all trial experiments, our model is optimal, which far exceeds their performance on GSSL (see Fig.11 and Fig.12) and is significantly ahead of the that on CPSYB (see Fig.13 and Fig.14). These figures reflect the performance improvement of our model compared with the base series. Take "XCBC#3 / base#1" as a case, which refers to the difference between the performance of XCBC#3 and that of base#1. The same is true for subsequent figure.

Specifically, on GSSL, the F1 performance of our model on the validation set is at least 10 percentage points higher than that of the base series, and for base#1 without pre-training language model, it seems more confused to understand the knowledge in GSSL, the F1 is only 34.28%. On the test set, this situation has been alleviated, but it is still 11.69% F1 lower than XCBC#3. Compared with base#2, base#3 and base#4 with pre-training language model, although their performance has been improved, they are still defeated by XCBC#3. On CPSYB, although the performance of XCBC#3 is not overwhelmingly ahead, it is still considerable, at least 3 F1 percentage points higher than base#2, base#3 and base#4.

These phenomena demonstrate the progressiveness of our method. The CRGM strategy brings a priori to the model, that is, the relevant material knowledge and equipment knowledge, which improves the proportion of key knowledge and alleviates the uneven distribution. In addition, XLNet seems to be more suitable than BERT and ALBERT.

Table 9: Evaluation results (%) on CPSYB / validation dataset.

| model               | precision | recall  | F1     |
|---------------------|-----------|---------|--------|
| base#1              | 83.71     | 85.10   | 84.40  |
| base#2              | 86.03     | 87.71   | 86.86  |
| base#3              | 87.45     | 87.03   | 87.24  |
| base#4              | 86.36     | 86.50   | 86.43  |
| base#1 + CRGM       | 85.25     | 87.11   | 86.17  |
| base#2 + CRGM       | 87.83     | 89.30   | 88.56  |
| base#3 + CRGM       | 88.42     | 91.47   | 89.92  |
| base#4 + CRGM       | 88.04     | 88.38   | 88.21  |
| XCBC#1              | 87.64     | 86.43   | 87.03  |
| XCBC#2              | 88.77     | 92.44   | 90.57  |
| XCBC#3              | 89.59     | 92.15   | 90.85  |

We analyze the exploration of industrial safety knowledge (ISK) by the pre-training model, that is, the evaluation between base#3, base#4 and XCBC#1. Fig.14 shows the performance of the three models on different datasets, where, the abscissa is the validation set and test set of GSSL and CPSYB in turn, and the ordinate is F1. We can find that the performances of BERT, ALBERT and XLNet are very close on CPSYB that is relatively easy to understand, while XLNet is superior on GSSL that is relatively complex, especially in the face of validation set. We speculate that the permutation language mechanism of XLNet is relatively consistent with the layout of ISK under HAZOP, the next sentence prediction mechanism in BERT may not conform to the HAZOP description with strong logic, and the parameter reduction under factorization in ALBERT seems to limit the extraction of some semantic features.

Therefore, choosing XLNet is effective for our method, and this also provides the additional empirical evidence for the
processing of ISK semantic in other studies, that is, XLNet is a relatively appropriate decision.

Table 10: Evaluation results (%) on CPSYB / test dataset.

| model          | precision | recall  | F1   |
|----------------|-----------|---------|------|
| base#1         | 84.03     | 85.16   | 84.59|
| base#2         | 85.44     | 87.83   | 86.62|
| base#3         | 87.88     | 87.88   | 87.88|
| base#4         | 85.92     | 87.17   | 86.54|
| base#1 + CRGM  | 85.90     | 86.24   | 86.07|
| base#2 + CRGM  | 88.76     | 89.34   | 89.05|
| base#3 + CRGM  | 89.31     | 89.53   | 89.42|
| base#4 + CRGM  | 88.65     | 89.01   | 88.83|
| XCBC#1         | 88.50     | 87.03   | 87.76|
| XCBC#2         | 90.87     | 90.01   | 90.44|
| XCBC#3         | 91.52     | 91.08   | 91.30|

We evaluate the benefits brought by Zipf mechanism to our model, that is, the performance comparison of XCBC#3 and XCBC#2. The only difference between the two is that XCBC#2 is not guided by the common-rare discriminator with Zipf law, and the strategy of the generated description is random (the amount generated is consistent). Fig.16 records the performance gain from Zipf mechanism. It can be seen that the Zipf mechanism supports encouragement for the model on all datasets except for the recall under the validation set of CPSYB. Zipf can provide a slight boost on the test set of CPSYB, and the increase of F1 and precision is less than 1%. It can win praise on the verification set of GSSL, and F1 is promoted by 2.39 percentage points. The performance on the test set of GSSL is also commendable, and the improvement of the three indicators is more than 1 percentage point.

Fig.15: Incentive of our CRGM strategy.

We discuss the incentive of our CRGM strategy in depth. Fig. 15 shows the evaluation results of the F1 performance gain given by CRGM to the base series models and the XCBC model (see table 7-10 for more information). Obviously, the incentive on each dataset is impressive and gratifying. The growth rate of different models on the first three dataset is about 2%, and some are more than 3%. Especially for the validation set of GSSL, the performance of the last four models is improved by about 10%, which can imply that CRGM has more significant stimulation under complex conditions and often brings greater feedback. This proves the generalization and effectiveness of CRGM.

Consistent with our expectations, with the efforts of CRGM, the common-rare discriminator guides decision-support to the HAZOP description, and provides good adjustment and supplement for ISK under Zipf constraints. The induction-extension generator alleviates the symptoms of uneven distribution of ISK subjected to different processes. The ISK extractor enriches the equipment knowledge and material knowledge, and indirectly improves the weight of relatively more important ISK. Undoubtedly, CRGM provides a feasible and novel viewpoint for exploring ISK and studying HAZOP.

Fig.14: evaluation of pre-training.

Fig.16: Benefit of Zipf mechanism.

We speculate that the random generation strategy does not accord with the potential language distribution of HAZOP, since the uneven distribution of ISK embedded in HAZOP description is objective. In addition, not all potential distributions of HAZOP / ISK have a positive stimulus to the subject of this study. This seems interesting, but it is considered
a research problem on its own that is beyond the scope of this paper, we don’t demonstrate it here.

Zipf distribution does provide a fine support for exploring ISK. It conforms to linguistics in HAZOP report with a certain scale, is relatively consistent with the analysis logic of the expert group, and its attributes fit the distribution of HAZOP description and the arrangement of ISK, that is, the head part and the tail part of Zipf curve are the common words and the rare words respectively from the perspective of HAZOP.

All in all, CRGM has promising and gratifying aptitudes, greatly improves the exploration of ISK, and is efficient and generalized. Our sequence labeling model also shows the expected performance, which is better than others. Undoubtedly, our research launches a new perspective and pushes the exploration of ISK to a new level, we hope it can contribute added value to the daily practice in industrial safety and provide support for the intelligence of industrial safety.

5. CONCLUSION

The industrial safety knowledge (ISK) embedded in the hazard and operability analysis (HAZOP) report is of crucial significance to the intelligent progress of industrial safety. The existing researches mine and explore ISK through the sequence labeling. However, there are two thorny issues, one is the uneven distribution of ISK, and the other is the consistent importance of ISK.

In this study, inspired Zipf law, we propose a novel generative mining strategy called CRGM to explore ISK. CRGM consists of the following three modules.

1. Common-rare discriminator. Firstly, it reads the HAZOP report, calculates the HAZOP word frequency and its rank, and fits the Zipf distribution. Then, HAZOP words are discriminated into common words and rare words through the maximum curvature value of Zipf curve. Finally, the HAZOP descriptions are classified into common descriptions and rare descriptions through a proportional algorithm, where the latter embodies more industrial substances.

2. Induction-extension generator. It is a pair of GPT2 modules we trained, which contains two models with different optimization objectives and training data, namely, GPT2-I and GPT2-E. They respectively induce common descriptions and extend rare descriptions to enrich the material knowledge and the equipment knowledge.

3. ISK extractor. It filters and labels the equipment knowledge and the material knowledge from the generated descriptions through the rule template, which are regarded as the supplement of the training set to train the proposed XLNet-CNN-BiLSTM-CRF.

We conduct multiple trial experiments on two HAZOP datasets (CPSYB and GSSL) that enjoy different types of process backgrounds. The base models subject to comparison are BiLSTM-CNN-CRF, BERT-BiLSTM-CRF, BERT-CNN-BiLSTM-CRF and ALBERT-CNN-BiLSTM-CRF. We assess the benefits of CRGM on these baselines. In addition, we evaluate the incentives of our XLNet-CNN-BiLSTM-CRF and the that of Zipf mechanism.

The results show that CRGM has satisfactory and delightful aptitudes, greatly promotes the exploration of ISK, and is efficient and generalized. Our model also presents the expected and advanced performance. Our research launches a new perspective for exploring ISK, there is no doubt that it can push the research topic to a new level, we hope it can contribute added value to the daily practice in risk decision-making and provide support for the orderly development of industrial safety.

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