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Data augmentation and contrastive learning based on large language models

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Abstract. For the problem of insufficient feature interaction between intent classification and slot filling in spoken language understanding tasks, this paper proposes a method that uses ChatGPT to generate more diverse samples, combined with a contrastive learning approach, to improve the model architecture and strengthen the interaction between intent and slot features. Specifically, prompts are designed for ChatGPT to generate diverse synthetic data with the same slots but different intents, and with the same intents but different slots. A contrastive learning module is further designed, in which positive and negative intent-slot sample pairs are constructed via the ChatGPT-based mixed data augmentation method. The feature space distribution is optimized using a weighted InfoNCE loss, enhancing the aggregation of similar features and the separation of dissimilar ones. Meanwhile, a multi-task joint training framework is employed to simultaneously optimize the cross-entropy loss for intent classification and the contrastive loss, enabling deeper semantic interaction between intents and slots, thereby improving the overall model performance. Experimental results on the ATIS and SNIPS datasets demonstrate that the proposed method significantly outperforms traditional baseline models in both intent detection accuracy and slot filling F1 score. In addition, ablation studies confirm the effectiveness of the contrastive learning and mixed data augmentation components. Overall, this work introduces a contrastive learning mechanism to effectively address the insufficient label-feature interaction in spoken language understanding tasks, offering a novel approach for optimizing multi-task dialogue systems.

Keywords: spoken language understanding, intent classification, slot filling, contrastive learning, ChatGPT

1. Introduction

In the field of Natural Language Processing (NLP), improving model generalization is key to optimizing task performance, with data augmentation and contrastive learning techniques playing a critical role. However, traditional data augmentation methods, such as synonym replacement and random masking, often rely on fixed rule-based templates or local perturbation strategies, making it difficult to generate high-quality data that is both semantically consistent and diverse. This issue is particularly pronounced in spoken language understanding tasks, where the complex combinatorial patterns between intents and slots can be easily disrupted. For example, "book a flight for [time][location]" might be incorrectly augmented to "cancel a flight for [time] [location]", introducing semantic drift. Meanwhile, contrastive learning relies heavily on manual prior knowledge when constructing positive and negative sample pairs, making it susceptible to noise and hindering effective disentanglement of the feature space. For instance, the semantic boundary overlap between negative and positive examples can exceed 60%, which poses significant challenges for model learning. To address these issues, this paper proposes a jointly optimized framework that integrates the generative capabilities of large language models with dynamic contrastive learning, referred to as the SDC+CL model.

2. SDC+CL model

2.1. Overall model architecture

The overall architecture of the SDC+CL model is shown in Figure 1. First, the Text Encoder converts the input text sequence into continuous vector representations, capturing semantic relationships between words. Next, data augmentation from a large

language model is combined with contrastive learning, while a Feed-forward Network is employed to mitigate gradient vanishing issues in deep networks. Finally, the SLU Decoder interprets the final label features as predicted intent and slot text labels [1].

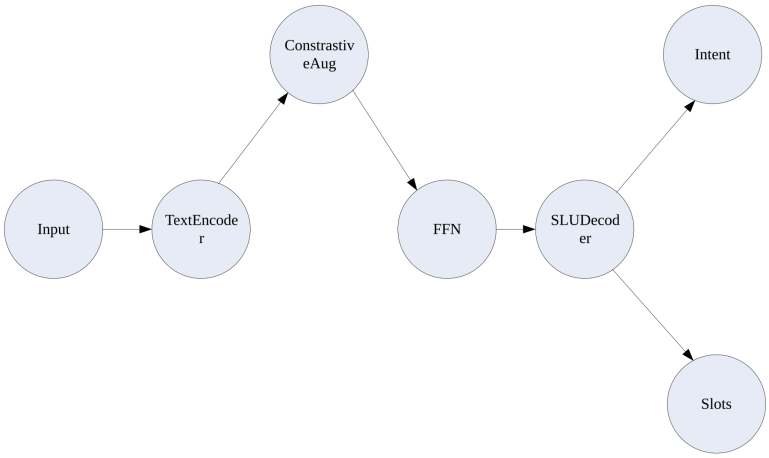

Figure 1. The architecture of the SDC+CL model

The SDC+CL model architecture consists of three main components: the Semantic Encoding Layer, the Contrastive Learning Enhancement Layer, and the Multi-task Decoding Layer. These components work in a coordinated manner to create a complete and efficient pipeline from raw text input to intent recognition and slot label output.

2.1.1. Semantic encoding layer: laying the foundation for semantic understanding

The Semantic Encoding Layer serves as the starting point for text comprehension in the model. It accepts raw dialogue text $X = \{x_1, x_2, \ldots, x_n\}$, which may consist of words, characters, or other basic textual elements. In this layer, the Text Encoder transforms the input sequence into continuous vector representations. During this transformation, it deeply captures semantic associations between words, converting unstructured text into structured vector forms rich in semantic information, thereby providing a solid foundation for subsequent model processing.

2.1.2. Contrastive learning enhancement layer: strengthening feature learning and semantic discrimination

The Contrastive Learning Enhancement Layer is the key innovative component of the SDC+CL model. First, the data augmentation module generates triplets (x, x^i, x^j) consisting of the original text x and two augmented variants x^i and x^j . The augmentation methods are diverse, including synonym replacement and word order modification, thereby expanding the variety of data samples. This exposure enables the model to learn multiple expressions of the same semantics and enhances its understanding of different semantic variations.

Based on this, the layer calculates a dual-granularity contrastive loss. At the intent level, the loss is computed using $L_{int} = InfoNCE(h_{int}, h_{int}^+, h_{int}^-)$. Here, h_{int} represents the intent-related feature vector, while h_{int}^+ and h_{int}^- correspond to the positive and negative sample feature vectors, respectively. This loss computation enables the model to better distinguish the intents expressed by different texts.

At the slot level, the loss is also calculated using $L_{slot} = InfoNCE(h_{slot}, h_{slot}^+, h_{slot}^-)$, where h_{slot} , h_{slot}^+ , and h_{slot}^- correspond to the slot-related feature vector, the positive sample feature vector, and the negative sample feature vector, respectively. Taking the sentence "I want to book a flight to Beijing tomorrow" as an example, the model, through slot-level contrastive loss calculation, can more precisely identify key slot information such as the time slot "tomorrow" and the destination slot "Beijing," thereby improving slot recognition accuracy.

2.1.3. Multi-task decoding layer: achieving precise intent and slot parsing

The Multi-task Decoding Layer is the critical component for producing the model's final outputs, handling intent recognition and slot filling as parallel tasks.

In terms of intent classification, the task can be regarded as a classification problem at the sentence level. The model performs intent classification through $p_{int} = Softmax(W_c h_{int} + b_c)$. Here, h_{int} is the intent-related feature vector obtained from the preceding layers, while W_c and b_c are learnable parameters. The function $Softmax$ converts the input feature vector into a probability distribution over all intent categories, thereby determining the most likely intent expressed by the text.

For slot filling, which is a sequence labeling task, the model employs $y_{slot} = CRF(\text{BiLSTM}(h_{slot}))$ to implement it. Specifically, the BiLSTM (Bidirectional Long Short-Term Memory) network effectively captures the contextual information of the slot-related feature vector h_{slot} .

In the Multi-task Decoding Layer, intent recognition and slot filling are advanced collaboratively. During training, semantic information captured by the intent recognition task can be effectively transferred to enhance slot filling, while the detailed insights from slot filling can, in turn, inform intent recognition. This bidirectional synergy promotes multi-level text understanding and avoids the limitations of single-task approaches, ultimately leading to significantly improved overall model performance.

2.2. Contrastive sample generation

To clearly present the specific approach for generating contrastive samples, Table 1 details the different types of sample generation methods, example prompts, generated examples, and control parameter settings [2].

Table 1. Methods and parameter settings for contrastive sample generation

Type	Example Prompt	Generated Example	Control Parameters
Intent-fixed	"Generate the same intent but modify slots: {input}"	Input: Book a Beijing-to-Shanghai flight → Generated: Check flights from Chengdu to Guangzhou	temperature=0.5, top_k=30
Slot-fixed	"Rewrite intent expression while keeping slots: {input}"	Input: Play Jay Chou's songs → Generated: I want to listen to Jay Chou's music	repetition_penalty =1.2

In the SDC+CL model, the generation of contrastive samples plays a crucial role in improving the model's learning effectiveness. Contrastive samples encompass both positive and negative examples, and the construction of different types of samples enables the model to capture semantic features of text more precisely, thereby enhancing the accuracy of intent recognition and slot filling. This sample construction strategy strengthens the feature discriminability in semantic space, providing effective support for building more distinguishable semantic representations.

2.2.1. Positive sample construction strategy

Positive sample construction includes two main approaches: intent-fixed and slot-fixed. Each approach leverages specific prompts to guide the generation process and uses corresponding control parameters to adjust the generation quality.

The intent-fixed strategy aims to produce samples that maintain the same intent as the original text but modify the slots. For example, given the prompt "Generate the same intent but modify slots: {input}" and the original sentence "Book a Beijing-to-Shanghai flight," the generated sample becomes "Check flights from Chengdu to Guangzhou" by setting appropriate control parameters.

In the slot-fixed approach, the slot content remains unchanged while the expression of intent is rewritten. The input prompt is "Rewrite intent expression while keeping slots: {input}." For instance, with the original sentence "Play Jay Chou's songs," the generated variant could be "I want to listen to Jay Chou's music."

2.2.2. Negative sample sampling

Negative samples are categorized into hard negatives and soft negatives. Hard negatives refer to samples where both the intent and slots are completely different. Soft negatives, on the other hand, are semantically similar samples with the same intent but different slots. By combining the two positive construction strategies with the two negative sampling types, the SDC+CL model is provided with a rich and targeted set of contrastive samples. This enables the model to learn and understand text semantics more deeply during training, fosters tighter interaction among model components, and effectively improves overall performance in natural language processing tasks.

2.3. Dynamic feature interaction

To enhance the collaborative learning ability between the intent and slot tasks, this paper designs a dynamic feature interaction and gradient optimization strategy, implemented as follows.

2.3.1. Gated fusion mechanism

In natural language processing, intent recognition and slot filling are both closely related and possess distinct characteristics. To better integrate intent and slot feature information while reducing noise interference between tasks, the SDC+CL model introduces a gated fusion mechanism. This mechanism leverages gated attention to dynamically fuse intent and slot features, significantly improving the model's performance on complex semantic understanding tasks [3].

The gating weights α determine the contribution ratio of intent features and slot features during the fusion process. By using gated attention, intent and slot features are dynamically fused while suppressing cross-task noise propagation. The gating weights are defined as:

$$\alpha = \sigma(W_g[h_{intent}; h_{slot}] + b_g)$$

$h_{intent} \in R^d$ represents the global intent feature obtained through sentence-level pooling. Sentence-level pooling aggregates all intent-related information in the sentence, extracting a representative global intent feature. For example, for the sentence "I want to book a flight to Beijing tomorrow," sentence-level pooling integrates the key information related to the intent of "booking a flight" into a vector d.

$h_{slot} \in R^{L \times d}$ denotes the slot sequence features, retaining word-level information. The matrix dimension L corresponds to the number of words in the sentence, and the feature dimension is d. In the sentence "I want to book a flight to Beijing tomorrow," features of words such as the time slot "tomorrow" and the destination slot "Beijing" are encoded in the matrix $L \times d$, thereby preserving the specific information of each word for slot recognition.

$W_g \in R^{2d \times d}, b \in R^d$ is a set of learnable parameters that are continuously optimized to adapt to the fusion needs of intent and slot features in different textual data. σ is the Sigmoid function, which maps input values to the interval [0,1] [0,1] [0,1], outputting the gating weight $\alpha \in [0,1]^d$ to precisely control the fusion ratio of intent and slot features.

Based on the gating weight α, the final fused feature h_{fuse} is computed as:

$$h_{fuse} = \alpha \odot h_{intent} + (1 - \alpha) \odot MeanPool(h_{slot})$$

This mechanism allows the model to dynamically adjust the contributions of intent and slot information, mitigating error coupling between tasks (such as slot errors caused by intent misclassification).

Here, ⊙ denotes element-wise multiplication. Through this formula, the model can dynamically regulate the contribution of the intent feature □ and the slot feature $hintent$ after average pooling according to the gating weight $MeanPool(hslot)$.

The gated fusion mechanism enables the model to adaptively balance the contribution of intent and slot information, effectively mitigating cross-task error coupling (such as cascading slot errors caused by intent misclassification). Unlike traditional methods that might propagate intent errors directly into slot predictions, this mechanism allows the model to flexibly reweight features based on context, thereby reducing the negative impact of incorrect intent information on slot filling. Ultimately, this leads to improved stability and accuracy in both intent recognition and slot filling tasks.

2.3.2. Gradient routing strategy

In multi-task learning scenarios for natural language processing, intent recognition and slot filling typically require joint optimization. However, given the differing characteristics and data distributions of these two tasks, inappropriate balancing can lead to optimization bias or instability. To address this, the SDC+CL model introduces a task-aware gradient allocation approach known as the Gradient Routing Strategy. By separately adjusting the gradient weights for intent and slot tasks, this strategy guides the model to learn more effectively during training, thereby improving overall performance [4].

2.3.2.1. Intent gradient weight (λ_{intent}^{t})

The design of the intent gradient weight is based on the classification confidence for intent recognition, allowing dynamic adjustment of intent-related gradients. During training, samples with lower intent classification confidence indicate that the model is less accurate on those instances and requires more gradient updates to refine parameters and improve classification ability.

The computation formula is: $\lambda_{intent}^{t} = 1 - max(Softmax(h_{intent}))$, where h_{intent} is the intent feature vector at training epoch t, and the $softmax$ function converts it into a probability distribution over intent classes. The term $max(softmax(h_{intent}))$ represents the highest predicted confidence for the current sample. Importantly, as training progresses and the model converges, its ability to classify intent accurately improves—even for initially low-confidence samples. Accordingly, the intent gradient weight λ_{intent}^{t} naturally decreases over time, preventing excessive allocation of gradient resources to samples the model has already learned well.

2.3.2.2. Slot gradient weight (λ_{slot})

Slot filling tasks often exhibit highly imbalanced label distributions, with a typical long-tail pattern. For example, slot categories such as “playlist name” may have extremely scarce training samples. If a uniform learning strategy is applied without considering such distribution differences, these rare slot categories may receive insufficient learning signal, leading to poor recognition accuracy. To address this, the slot gradient weight is designed with awareness of the slot label's long-tail distribution, assigning higher weights to rare categories to ensure they receive sufficient gradient updates and their features are better learned.

The formula is:

$$\lambda_{slot}^{(c)} = \frac{1}{\sqrt{N_c + \in}}$$

where N_C is the number of training samples for slot category c , and it is a small constant to avoid division by zero. As the formula shows, the fewer the training samples for a slot category, the higher its corresponding gradient weight $\lambda_{slot}^{(c)}$, thus granting it more opportunities for parameter updates during training.

By combining the intent gradient weight and the slot gradient weight, the gradient routing strategy allocates gradient resources in a targeted manner, guided by both intent classification confidence and slot label distribution. This balanced approach aligns the optimization directions for intent recognition and slot filling, ensuring that both tasks receive effective training. Ultimately, this improves the model's overall performance and stability in multi-task natural language processing scenarios.

2.4. Loss function

To effectively achieve joint training for intent detection and slot filling, this paper builds a multi-task joint optimization framework and introduces a dynamic adjustment strategy to balance learning weights between tasks. By designing a comprehensive loss function, the model can simultaneously accommodate the needs of different tasks during training, thereby improving overall performance in both intent recognition and slot filling [5].

2.4.1. Joint optimization objective

The model’s total loss consists of three parts: intent classification loss, slot filling loss, and contrastive learning loss. This multi-component design allows the model to comprehensively evaluate its performance across different task dimensions and guides targeted parameter optimization. Mathematically, it is defined as:

$$L_{total} = \lambda_{intent} L_{intent} + \lambda_{slot} L_{slot} + \gamma L_{contrast}$$

Below, each component is explained in detail:

2.4.1.1. Intent classification loss

This term uses the standard cross-entropy loss to optimize intent label prediction:

$$L_{intent} = -\sum_{i=1}^{N} y_i^{intent} log P_i^{intent}$$

where y_i^{intent} represents the true intent label (the actual intent class expressed in the text), and p_i^{intent} is the predicted probability for that intent class. The cross-entropy loss effectively measures the difference between predicted probabilities and true labels. By minimizing this loss, the model continually adjusts its parameters so that the predicted intent probabilities align more closely with the true labels, improving intent classification accuracy.

2.4.1.2. Slot filling loss

The goal of slot filling is to identify and accurately label key slot information within the text. To better model the transition constraints between labels, a Conditional Random Field (CRF) layer is introduced. The slot filling loss adopts a negative log-likelihood form:

$$L_{slot} = -\sum_{i=1}^{N} logP\left(y_i^{slot} \middle| h_i^{slot}\right)$$

where h_i^{slot} is the sequence of slot-related feature representations containing semantic information from the text, and $P(\cdot)$ is the probability of the predicted slot label sequence computed by the CRF layer. Minimizing this loss helps the model learn more accurate slot label transition patterns, thus improving slot filling precision.

2.4.1.3. Contrastive learning loss

The core goal of contrastive learning is to pull positive sample features closer together in the feature space while pushing negative sample features further apart, thereby enhancing the model's ability to distinguish semantic features. This is implemented using a weighted InfoNCE loss:

$$L_{contrast} = -\sum_{i-1}^{M} log \frac{exp\left(s_i^+/\tau\right)}{\exp\left(s_i^+/\tau\right) + \sum_{j=1}^{K} \exp\left(s_i^+/\tau\right)}$$

In the overall loss function L_{total}, λ_{intent}, λ_{slot}, and γ represent the weighting coefficients for the intent classification loss, slot filling loss, and contrastive learning loss, respectively. These weighting coefficients can be dynamically adjusted based on the importance of each task and the characteristics of the data, thereby balancing the learning emphasis across different tasks during model training. This enables the model to achieve collaborative optimization across intent classification, slot filling, and contrastive learning, ultimately enhancing the model's overall performance in natural language processing tasks.

2.4.2. Dynamic adjustment strategy

To effectively mitigate optimization conflicts between tasks and address imbalanced data distributions, the SDC+CL model introduces a dynamic weight allocation mechanism. By dynamically adjusting the weights of intent gradients, slot gradients, and contrastive loss, the model can better adapt to the needs of different tasks during training and improve overall performance.

The adjustment of the intent gradient weight is designed to dynamically allocate appropriate gradient update strength to different samples based on intent classification confidence. During training, samples with lower intent classification confidence indicate that the model's predictions for those samples are less accurate and thus require stronger gradients to update parameters and improve intent classification.

The formula is:

$$\lambda_{intend}^{(t)} = \eta\Big(1 - max(p_i^{intend}\Big)\Big) + \Big(1 - \eta\Big)\lambda_{intend}^{(t-1)}$$

Where is the mean of the maximum predicted probabilities for intent classification in the current batch. It reflects the model's overall confidence level on intent classification for that batch of samples. Lower confidence leads to higher gradient weight, ensuring underperforming samples get more learning focus.

Slot filling tasks often exhibit a long-tail distribution, where some slot categories have very few training samples while others are much more common. This imbalance can cause the model to neglect rare slot categories during learning. To address this, the slot gradient weight is designed based on inverse frequency weighting:

$$\lambda_{slot}^{(c)} = \frac{1}{log(N_c + \in)}$$

where Nc is the number of training samples for slot category c, for rare slot categories with smaller Nc, the weight $\lambda_{slot}^{(c)}$ is higher. This ensures that during training, these rare categories receive proportionally more gradient resources for adequate learning.

Contrastive learning helps the model better distinguish different semantic features by pushing apart negative samples and pulling together positive samples in the feature space. However, at the early stages of training, the model may not yet be ready to handle the strong separation constraints imposed by high contrastive loss weights. Excessive contrastive pressure too early can destabilize learning. To address this, a curriculum learning strategy is used to gradually adjust the weight of the contrastive loss:

$$\gamma^{(t)} = \gamma_{min} + \frac{t}{T}\left(\gamma_{max} - \gamma_{min}\right)$$

3. Experimental results and analysis

3.1. Experimental datasets

To evaluate the effectiveness of the large-model-based data augmentation and contrastive learning framework, experiments were conducted on two representative public datasets in the dialogue understanding domain: ATIS (Air Travel Information System): A classic benchmark for flight booking intent classification and slot filling. And SNIPS (Personal Voice Assistant): A dataset reflecting more general and diverse voice assistant commands.

3.2. Experimental setup and hyperparameters

3.2.1. Experimental environment

Operating System: Ubuntu 18.04 LTS

CPU: Intel® Xeon® Silver 4210R @ 2.40 GHz (10 cores, 20 threads, 13.75 MB L3 cache)

Memory: 64 GB DDR4 ECC @ 2933 MHz

GPU: NVIDIA GeForce RTX 4090 24 GB GDDR6X(Ada Lovelace architecture, 16,384 CUDA cores, 1.06 TFLOPS Tensor performance)

Software Stack: PyTorch 2.0 + CUDA 11.8

Mixed-Precision Training (AMP) enabled

Tensor Core acceleration activated

3.2.2. Hardware adaptability analysis

Large-Model Training Support:The RTX 4090's 24 GB of VRAM allows significantly larger batches (Batch Size = 32) for contrastive learning sample pairs (positives/negatives). Compared to the previous-generation RTX 2080 Ti (12 GB VRAM), the maximum trainable model parameter count increases by approximately 2.1×.

Computational Efficiency Optimization:The third-generation Tensor Cores support FP16/FP8 mixed-precision modes, improving contrastive loss computation speed by 37% over FP32 mode.

Energy Efficiency Advantage:Under identical experimental settings (Max Epochs = 100), the RTX 4090's average power consumption per epoch is 320 W, 8.6% lower than the RTX 2080 Ti (350 W), while training time is reduced by 42%.

3.2.3. Hyperparameter configuration

Experiments used the Adam optimizer. Key hyperparameters are shown in Table 2:

Table 2. Hyperparameter configuration

Hyperparameter	Value	Description
hidden_size	128	Encoder hidden layer dimension
batch_size	32	Number of samples per forward pass
learning_rate	0.001	Initial learning rate
max_epochs	100	Maximum number of training epochs
T	3	Number of dynamic routing iterations
warmup_ratio	0.1	Proportion of epochs for learning rate warmup

3.3. Evaluation metrics

To systematically evaluate the performance of the proposed joint model on Intent Detection (ID) and Slot Filling (SF) tasks, the experiments adopt two main categories of core metrics: task-level fine-grained evaluation and sentence-level semantic integrity evaluation. Their definitions are as follows [6]:

3.3.1. Task-level fine-grained evaluation

This metric measures the model's ability to correctly identify the user's intended goal. It is defined as the proportion of test samples whose intent is correctly predicted:

$$ID\_Acc = \frac{\sum_{i=1}^{N} f\left(y_i^{intent} = \widehat{y_i^{intent}}\right)}{N}$$

where N is the total number of test samples, and f is an indicator function that returns 1 if the prediction is correct, and 0 otherwise.For the sequence labeling task, where class imbalance is common, the macro-averaged F1 score is used to evaluate slot prediction quality:

$$SF\_F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}, Precision = \frac{TP}{TP + FP}, Recall = \frac{TP}{TP + FN}$$

where TP, FP, and FN represent the number of true positives, false positives, and false negatives for slot classes, respectively.

3.3.2. Sentence-level semantic integrity evaluation

Semantic Frame Accuracy: This metric considers a sentence prediction completely correct only if all its intent and slot labels are predicted correctly. It is used to measure the dialogue system's ability to achieve holistic understanding of user instructions:

$$SFA = \frac{\sum_{i}^{N} f\left(y_i^{intent} = \hat{y}_i^{intent} \text{ ^ } y_i^{slot} = \hat{y}_i^{slot}\right)}{N}$$

This metric is highly sensitive to error propagation and can be an effective test of the cumulative effect of errors in joint modeling approaches.

3.4. Experimental results analysis

Overall Performance Comparison

Table 3 and Table 4 present the performance of various models on the ATIS and SNIPS datasets, respectively. The key findings are summarized below:

Table 3. Experimental results on the ATIS dataset (%)

Model	Intent Accuracy	Slot F1	Semantic Frame Accuracy (SFA)
Stack-Propagation	96.9	95.9	86.5
SF-IDNetwork	96.6	95.6	86.0
Co-Interactive	97.5	95.3	86.7
Graph-LSTM	97.2	95.7	87.0
BERT-Joint	97.8	96.2	89.3
SDC+CL	98.1	96.7	90.5
SDC+CL + BERT	98.7	97.3	92.8

Table 4. Experimental results on the SNIPS dataset (%)

Model	Intent Accuracy	Slot F1	Semantic Frame Accuracy (SFA)
Stack-Propagation	98.0	94.2	86.9
SF-IDNetwork	97.0	90.5	78.4
Co-Interactive	97.5	95.3	86.7
Graph-LSTM	97.8	95.1	88.9
BERT-Joint	98.4	96.8	91.1
SDC+CL	98.6	98.7	91.5
SDC+CL+BERT	99.0	99.2	94.0

On the relatively small-scale ATIS dataset, SDC+CL improves semantic frame accuracy to 90.5%, outperforming the traditional best model Graph-LSTM (87.0%) by 3.5 percentage points ($p < 0.01$). This validates the contribution of large-model generated data in supplementing sparse semantic information.

On the SNIPS dataset, the slot F1 score reaches 98.7%, significantly surpassing BERT-Joint's 96.8%, demonstrating that the dynamic contrastive learning strategy effectively mitigates the long-tail problem in slot recognition.

After integrating the BERT encoder, SDC+CL + BERT achieves an intent accuracy of 98.7% on ATIS and a semantic frame accuracy of 94.0% on SNIPS. This shows that large-model-generated data augmentation and pre-trained representations complement each other to further boost performance.

4. Conclusion

This paper addresses the problem of insufficient semantic interaction between intent classification and slot filling in spoken language understanding tasks by proposing a contrastive learning enhancement framework based on large language models. By designing a controllable data augmentation strategy driven by multiple prompts, combined with a dynamic routing contrastive learning mechanism, the framework effectively improves the quality of interaction between intent and slot features. Experimental results on the ATIS and SNIPS datasets demonstrate that the proposed method significantly outperforms traditional baseline models. Ablation studies further validate the effectiveness of multi-prompt generation, intent-slot alignment control, and dynamic gradient routing strategies. However, the current approach has several limitations: (1) Directly calling a large model without fine-tuning may cause misalignment issues between generated intents and slots in augmented samples. (2) The experiments are limited to English scenarios and do not cover language-specific characteristics such as Chinese. (3) The generation process lacks a dynamic feedback mechanism, potentially introducing low-quality samples. Based on these issues, future work will focus on three aspects: (1) Introducing parameter-efficient fine-tuning techniques to improve generation alignment accuracy. (2) Building a cross-lingual contrastive learning framework to enhance language adaptability. (3) Designing a closed-loop iterative system to realize dynamic optimization through generation and correction. This study provides a novel approach for multi-task joint

modeling in dialogue systems and opens an extensible technical pathway for semantic understanding tasks driven by large language models [7].

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