AMR-DA: Data Augmentation by Abstract Meaning Representation

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Abstract

Abstract Meaning Representation (AMR) is a semantic representation for NLP/NLU. In this paper, we propose to use it for data augmentation in NLP. Our proposed data augmentation technique, called AMR-DA, converts a sample sentence to an AMR graph, modifies the graph according to various data augmentation policies, and then generates augmentations from graphs. Our method combines both sentence-level techniques like back translation and token-level techniques like EDA (Easy Data Augmentation). To evaluate the effectiveness of our method, we apply it to the English tasks of semantic textual similarity (STS) and text classification. For STS, our experiments show that AMR-DA boosts the performance of the state-of-the-art models on several STS benchmarks. For text classification, AMR-DA outperforms EDA and AEDA and leads to more robust improvements.1

1Introduction

Data augmentation (DA) techniques automatically generate additional data from existing data set for training machine learning models. They are widely used in computer vision (see, e.g. Perez and Wang, 2017) and can boost the performance of the trained models.

In NLP, DA methods can be roughly classified into token-level ones and sentence-level ones (Chen et al., 2021). Token-level DA methods generate new sample sentences from the original ones by changing some of their tokens (words). They include the method in Zhang et al. (2015) that replaces some random tokens by their synonyms using a thesaurus, the now widely used Easy Data Augmentation (EDA) methods in Wei and Zou (2019) that allow some random token insertion, deletion and swaps, and the more recent one in Liu et al. (2020) that performs token replacement using their embeddings. One advantage of these token-level DA methods is that they are easy to implement. However, they can sometimes generate ill-formed or incoherent sentences as they do not take the sentence structures into account. In contrast, sentence-level methods generate new sample sentences by modifying the whole original sentences. They typically work by having an encoder that converts the input sentence to an intermediate representation and a decoder that generates new sentences from the intermediate representations. For example, in back translation (Sennrich et al., 2016), the intermediate representation is a sentence in another natural language. In generation methods (Kumar et al., 2020; Yang et al., 2020), the intermediate representation is a hidden state. One advantage of sentence-level DA methods is that they can preserve the semantics of the sentences. A major limitation of current sentence-level DA methods is that there is not much variation in the generated sentences as the intermediate representations used are not easily controllable (Li et al., 2021). For example, modifying the sentences in back translation requires knowledge of other languages, and minor changes of hidden states severely increase training difficulty.

In this paper, we propose a new DA method called AMR-DA that uses the Abstract Meaning Representation (AMR, Banerescu et al., 2013) as the intermediate language. AMR is a well-known semantic meaning representation. It aims to remove syntactic idiosyncrasies and to represent the semantic structure of a sentence as a rooted, directed graph. It works well as an intermediate language for data augmentation as it allows us to combine the token-level and sentence-level methods in a single framework. Like the sentence-level method, our method encodes the entire sentence as an AMR graph. Like the token-level methods, our method manipulates AMR graphs at the node
I was a little skeptical because of how cheap it was.

Figure 1: Overview of AMR-DA pipeline: (1) Text to AMR: the AMR parser captures the meaning of the input sentence and transduces it to an AMR graph. (2) Graph Modification: the fundamental choice is not to modify the AMR graph to preserve the entire semantics. Inspired by EDA (Wei and Zou, 2019), we apply four strategies to diversify the graph. RS: random swap; RD: random deletion; RI: random insertion; SR: synonym replacement. (3) AMR to Text: the AMR generator synthesizes sentences from AMR graphs.

(AMR graph)
1. Text to AMR
2. Graph Modification
3. AMR to Text

Figure 2: Three sentences with varied surface syntax share the same AMR. Textual and graphical representations are equal.
2.2 AMR Parsing

AMR parser is the first component of AMR-DA (Figure 1). AMR parsing is the task of understanding the sentence and then transducing it to AMR graphs. Lack of explicit alignments between AMR nodes and tokens brings obstacles to AMR parsing. Previous AMR parsers always include complex and fine-grained pre- and post-processing processes. It is very brittle to extend and apply in other tasks. With the help of pretrained language models, sequence-to-sequence (seq2seq) methods win a continual growth of interests. This paper adopts SPRING\(^2\) (Bevilacqua et al., 2021), which achieves state-of-the-art performance on AMR parsing, as our AMR parser. SPRING also implemented the generator in their work, however, we adopt another generator with better performance alternatively introduced in section 2.4.

SPRING first linearized AMR graphs to sequences through DFS-based PENMAN annotation. Nevertheless, when using seq2seq models, a lack of a clear distinction between variables and concepts may cause confusion. Considering that AMR variables have no semantics, SPRING proposed to use special tokens \(<\text{R}0>, \text{<R}1>, \ldots, \text{<R}n>\) to represent variables in the linearization graph and to handle co-referring nodes. They also abandoned the redundant slash token "/". Under this setting, AMR graph in Figure 2 became: \(<\text{R}0>\text{describe-01} :\text{ARG}0 (<\text{R}1> \text{woman}) :\text{ARG}1 (<\text{R}2> \text{mission}) :\text{ARG}2 (<\text{R}3> \text{disaster})\). Adjacency information was still preserved in the linearization process.

After linearizing AMR graphs, SPRING extended a pretrained model, BART (Lewis et al., 2020) which is a transformer-based encoder-decoder model. In order to make BART vocabularies suitable for AMR, they added relations and frames frequently occurring in the training data and initialized the vectors as the average of words embeddings. The results from the seq2seq model need only slight post-processing to transfer sequences to standard PENMAN notations. Details can be found in SPRING paper (Bevilacqua et al., 2021). AMR-DA adopts the model which achieves state-of-the- art performance on AMR 2.0 as AMR parser.

2.3 AMR Graph Modification

Discreteness in languages is the obstacle to transferring data augmentation methods from vision to NLP. Token-level methods attempt to apply modifications on tokens but ignore the entire structure of sentences. However, modifications in sentence-level methods always increase the difficulty of training. The benefit of AMR-DA is that intermediate AMR graphs can be modified through low-cost operations to obtain diverse augmentations; meanwhile, AMR generator will adjust the entire structure of sentences. We shift operations in EDA to AMR graphs. Following EDA, we introduce \(\alpha\) to control the percentage of data that operations in AMR-DA will modify.

Keep Original (Ori) The fundamental choice is to preserve the entire intermediate AMR graph. In this way, AMR-DA will generate paraphrased text for the input sentence.

Random Swap (RS) Traditionally, RS operation randomly chooses words and swaps their positions. However, randomly swapping concepts may impact the performance of AMR generator. In Figure 1, if we want to swap positions of "I" and "so" in the original AMR graph, the final graph becomes ":domain (so)" and ":degree (I)" which are not expected to appear in a regular AMR graph. Therefore, we swap concepts and their immediately adjacent edges at the same time. More specifically, we swap edge-node pairs ":degree (so)" and ":domain (I)" instead of tokens. There are two types of effect: if swapping nodes are not siblings, RS operation would change the graph structure, while sibling nodes swapping changes the linearization sequence instead of the graph structure. For one augmentation, RS repeats \(n\) times the operation of randomly selecting two edge-node pairs and swapping their positions where \(n = \max(1, \alpha \times |\text{edge-node pairs}|)\). |edge-node pairs| means the number of edge-node pairs.

Random Deletion (RD) Instead of removing concepts, we randomly delete concepts with their adjacent edges to guarantee that the rest of graph has necessary components. To control the effects on the AMR graph, RD only applies to leaf nodes. Non-leaf nodes with descendants will possibly have a severe impact on original AMR graphs. For one augmentation, RD repeats random leaf deletion \(n\) times where \(n = \max(1, \alpha \times |\text{edges-node pairs}|)\).

Random Insertion (RI) RI inserts edge-node pairs instead of concepts to preserve the rationality of AMR graph. We collect edge-node pairs (leaves) from AMR 2.0 training data and filter un-
suitable pairs based on their edges. For example, ":polarity -" which converts the polarity of semantics, is discarded in RI operation. More examples are listed in Appendix A. For one augmentation, RI randomly inserts \( n = \max(1, \alpha \times |\text{edge-node pairs}|) \).

**Synonym Replacement (SR)** SR only cares about concepts for that AMR edges are well-designed in AMR. In the linearized graph, we filter tokens that begin with "," and parentheses, randomly select other tokens, and replace them with one of their synonyms correspondingly. SR randomly replace \( n \) concepts where \( n = \max(1, \alpha \times |\text{concepts}|) \). We substitute similar words according to PPDB synonym (Pavlick et al., 2015). The substitution function is included in nlpaug\(^3\).

### 2.4 AMR Generation

AMR generation generates sentences from the AMR graph, which is the inverse task of AMR parsing. Pretrained transformer-based architectures gradually dominate the development trend of generators (Mager et al., 2020; Bevilacqua et al., 2021). Ribeiro et al.\(^4\) proposed a generator based on pretrained language models (PLMs-generator) and added extra task-adaptive pretraining. Compared with SPRING, PLMs-generator simplifies PENMAN annotations without adding special tokens as pointers. They examined and compared two PLMs, BART and T5 (Raffel et al., 2019). PLMs-generator continued task-specific pretraining using language model adaptation (LMA) or supervised task adaptation (STA) training with silver data they collected. Details can be found in the paper (Ribeiro et al., 2021). The default AMR generator in our experiments is based on T5-base.

3 Experiments

We conduct experiments on two NLP tasks, semantic textual similarity tasks and text classification tasks, to evaluate our augmentation method.

### 3.1 Semantic Textual Similarity Tasks

Semantic textual similarity deals with determining how similar two pieces of sentences are. Recently, contrastive learning has become an influential formalism for unsupervised sentence representation, based on the idea of concentrating similar samples and pushing apart dissimilar samples in the vector space (Chen et al., 2020). That is, given a set of paired sentences \( D = \{(x_i, x_i^+)\}_{i=1}^m \) where \( x_i \) and \( x_i^+ \) are semantically related, we regard \( x_i^+ \) as "positive" of \( x_i \) and other sentences in the same mini-batch as "negatives". Let \( h_i \) and \( h_i^+ \) denote the representations of \( x_i \) and \( x_i^+ \), then the training objective for a mini-batch of size \( N \) is:

\[
\ell_i = -\log \frac{\exp^{\text{sim}(h_i, h_i^+)}/\tau}{\sum_{j=1}^N \exp^{\text{sim}(h_i, h_j^+)/\tau}}
\]

where \( \tau \) is a temperature hyperparameter and \( \text{sim}(h_1, h_2) \) is the cosine similarity function.

Data augmentation, as the central issue in unsupervised contrastive learning, is utilized to construct "positive pairs". SimCSE (Gao et al., 2021) puts one sentence through pretrained model twice with varied standard dropout masks inside transformers as a minimal form of data augmentation. Although it performs quite well, there still exists a large margin between unsupervised and supervised models. Here we propose a hypothesis that an effective data augmentation in this task requires distinct syntax but related semantics. For this reason, we use AMR-DA as data augmentation to construct positive instances.

### 3.1.1 Experimental Settings

To verify the effectiveness of AMR-DA, we choose recently proposed models unsup-ConSERT (Yan et al., 2021) and unsup-SimCSE (Gao et al., 2021), which are referred as ConSERT and SimCSE for simplification, as our baseline models. We only replace the original data augmentation methods inside the two models with AMR-DA.

We evaluate on seven STS datasets including STS 2012–2016 (Agirre et al., 2012, 2013, 2014, 2015, 2016), STS Benchmark (Cer et al., 2017) and SICK-Relatedness (Marelli et al., 2014) and report Spearman’s correlation.

Following ConSERT, we use a mixture of unlabeled texts from seven STS datasets as training data and average the token embeddings at the last two layers as the sentence embedding. Following SimCSE, we use 1-million sentences randomly sampled from English Wikipedia as training data and adopt the [CLS] representation with an MLP layer on top of it as the sentence embedding. More training details could be found in Appendix B.
Table 1: Performance comparison of models with different AMR-DA operations. †: results from Yan et al., 2021.

| AMR Operation                  | Model Avg. |
|-------------------------------|------------|
| BERT<sub>base</sub>†          | 63.84      |
| +token augmentations (ConSERT)<sup>†</sup> | 72.74      |
| +AMR-RS augmentation          | 76.11      |
| +AMR-RD augmentation          | 74.34      |
| +AMR-RI augmentation          | 75.31      |
| +AMR-SR augmentation          | 75.68      |
| +AMR-Ori augmentation         | 76.14      |

Table 2: Overlap F1 score of AMR-DA operations.

| AMR Operation | Ori | RS | RD | RI | SR |
|---------------|-----|----|----|----|----|
| Overlap F1    | 0.554 | 0.531 | 0.476 | 0.510 | 0.449 |

Table 3: The average sentence embedding performance on seven STS test sets, in terms of Spearman’s correlation. †: results from Yan et al., 2021. ‡: results from Gao et al., 2021; §: results from Wu et al., 2021. Models begin with "AMR" are the models with AMR-DA.

| Model                  | Avg. |
|------------------------|------|
| unsup-ConSERT Setups   |      |
| ConSERT-BERT<sub>base</sub>† | 72.74 |
| AMR-ConSERT-BERT<sub>base</sub> | 76.14 (+3.40) |
| ConSERT-BERT<sub>large</sub>† | 76.45 |
| AMR-ConSERT-BERT<sub>large</sub> | 78.19 (+1.74) |
| unsup-SimCSE Setups    |      |
| SimCSE-BERT<sub>base</sub>† | 76.25 |
| + back translation     | 71.71 |
| ESimCSE-BERT<sub>base</sub>§ | 78.27 |
| - momentum contrast    | 77.45 |
| AMR-SimCSE-BERT<sub>base</sub> | 77.95 (+1.70) |
| SimCSE-RoBERTa<sub>base</sub>† | 76.57 |
| ESimCSE-RoBERTa<sub>base</sub>§ | 77.44 |
| AMR-SimCSE-RoBERTa<sub>base</sub> | 78.43 (+1.86) |
| SimCSE-RoBERTa<sub>large</sub>† | 78.90 |
| ESimCSE-RoBERTa<sub>large</sub>§ | 79.45 |
| AMR-SimCSE-RoBERTa<sub>large</sub> | 79.70 (+0.80) |

3.1.2 Main Results

The first question is which operation we should choose for contrastive learning in the STS task. Table 1 shows the comparison on different augmentation strategies. ConSERT considered cutoff and shuffle token augmentations while we replaced their DA with AMR-DA. The results show that all operations in AMR-DA outperform ConSERT with token augmentations. Since we use AMR-DA to construct positive pairs for STS model training, Table 1 presents that AMR-Ori generates augmentations more similar to the original sentences than other operations. To access the diversity of augmented data, we adopt F1 measured between two bags of words as lexical overlap score. A higher lexical overlap F1 indicates more overlap between augmented data and original sentences and less diversity. Table 2 provides the summary statistics for various operations of AMR-DA.

Table 3 shows the main results, where the highest numbers among models with the same pretrained encoder are highlighted in bold. Only changing the data augmentation module in ConSERT and SimCSE to AMR-DA, the performance could be boosted substantially to the state-of-the-art. AMR-ConSERT obtains absolute improvements of 3.40 and 1.74 on BERT<sub>base</sub> and BERT<sub>large</sub> respectively compared with the original ConSERT that utilizes feature cutoff and shuffle on tokens as DA methods. While AMR-SimCSE outperforms SimCSE significantly on BERT<sub>base</sub> (1.70 †), BERT<sub>large</sub> (1.22 †), RoBERTa<sub>base</sub> (1.86 †) and RoBERTa<sub>large</sub> (0.80 †). We also make a comparison between our models and current state-of-the-art model ESimCSE (Wu et al., 2021), which uses word repetition to construct positive pairs and momentum contrast to expand negative pairs. Experimental results indicate that AMR-SimCSE surpasses ESimCSE on BERT<sub>large</sub> (0.33 †), RoBERTa<sub>base</sub> (0.99 †) and RoBERTa<sub>large</sub> (0.25 †). If we discard momentum contrast in ESimCSE and only compare the effectiveness of DA methods, AMR-SimCSE (77.95) outperforms ESimCSE (77.43) on BERT<sub>base</sub>.

In addition, we implemented SimCSE with back translation based on WMT’19 English-German translation models (Ng et al., 2019) as the DA method. We use random sampling for decoding as recommended by (Edunov et al., 2018a), and set the temperature to 0.8. Other training settings are the same as those of SimCSE. As shown in Table 3, back translation is inferior to AMR-DA in STS tasks. The possible reason is that augmentations with limited diversity are hard to improve
3.2 Text Classification Tasks

Text classification tasks are widely studied in many real applications, such as document categorization, email spam filtering, etc. The performance of machine learning methods in this task always depends on the quality of training data. How to use DA techniques to improve machine learning systems attracts a number of studies (Wang and Yang, 2015; Wei and Zou, 2019; Liu et al., 2020; Karimi et al., 2021). AMR-DA is partly inspired by EDA, which explores text editing techniques for data augmentation. EDA performs SR, RI, RS, or RD operations on tokens, whereas AMR-DA performs these DA strategies on AMR graphs. In order to answer whether DA strategies on AMR graphs perform better than on tokens, we conduct a fair assessment on EDA and AMR-DA. In addition, to show the effectiveness of AMR-DA, we take AEDA (Karimi et al., 2021), another strong DA, into comparison.

3.2.1 Experimental Settings

We conduct experiments on four benchmark datasets: Stanford Sentiment Treebank (SST-2, Socher et al., 2013); Customer Reviews Dataset (CR, Hu and Liu, 2004; Liu et al., 2015b), Subjectivity/Objectivity Dataset (SUBJ, Pang and Lee, 2004); Pros and Cons Dataset (PC, Ganapathihotla and Liu, 2008). The detailed statistics are listed in Table F.5.

We chose Recurrent Neural Network (RNN, Liu et al., 2016), Convolutional Neural Network (CNN, Kim, 2014) and BERT (Devlin et al., 2019) as backbone models.

Data selection module has been modified to be close to application scenarios in real life. We select proportions of original training data and then add the corresponding augmentations for that only visible data can be extended. Experimental setups are identical to all DA methods. All experiments are run with five different random seeds and reported as average performance. Training details are in Appendix C.

3.2.2 Main Results

We ran CNN, RNN and BERT across all four datasets using three DA methods. First, we added one augmented sentence for each instance to assess the effectiveness of single augmentation. We reported the average performance of all different operations in EDA and AMR-DA as final one augmentation performance. As the top part of Table 4 shows, the average improvement of AMR-DA on three models is 0.55%, which is 0.91% better than EDA and 0.14% better than AEDA, respectively.

How about using all operations to augment data in the training process? To answer this question, we added each operation augmentations together in AMR-DA and trained models with all five augmentations. Correspondingly, we randomly selected five augmentations using AEDA and EDA operations. We reported the average performance in the bottom part of Table 4. AMR-DA achieved 0.83% performance gain with five augmentations better than one augmentation, which means our operations brought diversified information to improve models. Regarding the effectiveness of operations (SR, RI, RS and RD), we made a detailed comparison on EDA and AMR-DA. Figure 3 shows that AMR-DA outperforms EDA remarkably on various fractions of the training set.

| Model    | CNN   | RNN   | BERT  | Avg. |
|----------|-------|-------|-------|------|
| Original | 88.15 | 86.49 | 93.19 | 89.28|
| +EDA     | 87.29 | 86.16 | 93.39 | 88.92|
| +AEDA    | 88.30 | 87.59 | 93.19 | 89.69|
| +AMR-DA  | **88.40** | **87.63** | **93.47** | **89.83**|

| Model    | CNN   | RNN   | BERT  | Avg. |
|----------|-------|-------|-------|------|
| +EDA     | 87.75 | 86.37 | 93.29 | 89.14|
| +AEDA    | 88.78 | 87.21 | 93.53 | 89.84|
| +AMR-DA  | **88.80** | **88.00** | **93.54** | **90.11**|

Table 4: Average performance of CNN, RNN and BERT trained on original, EDA, AEDA and AMR-DA (with 1 or 5 augmentations for each instance) data across all datasets.

![Figure 3: Average performance of RNN model trained on different proportions of original, EDA and AMR-DA training data for four datasets.](image-url)
4 Analysis

Effect of AMR Generators From the introduction in Section 2.1, paraphrased sentences correspond to the identical AMR graph. In other words, AMR graph to sentences is a one-to-many relationship. Since there is no uniform evaluation of AMR generators, it is necessary to study the impact of AMR generators on the performance of AMR-DA. We compared AMR-Ori with various generators based on BART\textsubscript{base}, T5\textsubscript{small} and T5\textsubscript{base}. Table 5 shows comparison on PLMs-generators. We found that pretrained models with larger sizes are capable of generating better quality augments. So we choose AMR generator with T5\textsubscript{base} as final generator in AMR-DA.

| Model                                                | Avg.  |
|------------------------------------------------------|-------|
| BERT\textsubscript{base}-flow\ddagger               | 66.55 |
| SimCSE-BERT\textsubscript{base} \ddagger            | 76.25 |
| AMR(BART\textsubscript{base} generator)-SimCSE       | 77.81 |
| AMR(T5\textsubscript{small} generator)-SimCSE       | 77.65 |
| AMR(T5\textsubscript{base} generator)-SimCSE        | 77.95 |

Table 5: Performance of AMR-DA (Ori) in STS tasks with various generators.\ddagger: results from Gao et al., 2021;\ddagger\ddagger: results from Wu et al., 2021.

Why does AMR-DA work in STS task? To answer this question, we use alignment and uniformity, which are proposed by (Wang and Isola, 2020) to measure the quality of representations. Alignment calculates how close the positive instances stay, while uniformity evaluates how uniformly the random instances are scattered on the hypersphere. For both metrics, lower numbers are better. We take the checkpoint of SimCSE and AMR-SimCSE every 10 steps during training (100 steps in total) and visualize the alignment and uniformity computed on STSB dataset. Figure 4 demonstrates that both SimCSE and AMR-SimCSE improve the uniformity steadily. Additionally, AMR-SimCSE provides a continuously decreasing alignment. It verifies our hypothesis that data augmentation with different syntax but highly related semantics results in better sentence embeddings.

Analysis of Generated Outputs To analyze generated outputs by back-translation and AMR-Ori, we use supervised SimCSE-RoBERTa\textsubscript{large}, which achieves the state-of-the-art performance on various semantic textual similarity benchmarks, to compute the sentence embedding cosine similarity between the generated sentences and the original ones. Figure 5 summarizes the results. First we can see that for both AMR-Ori and back-translation, their generated sentences have high similarity scores with the original sentences. However, AMR-Ori generates much more diversified outputs. For back-translation, more than 30% of the generated sentences have the similarity score of 1.0 (highest) with their original sentences, and more than 50% of them have the similarity score of 0.99 or above. While AMR-Ori is more uniform. The highest frequency rate, about 10%, is at the similarity score of 0.97.

We also computed the F1 scores measured between two bags of words. We find that the overlap score of back-translation method is 0.760, compared to 0.566 for AMR-Ori (evaluated using unsupervised SimCSE experiment data in Table 3).

For illustration, we list some examples of back-translation and AMR-Ori in Table 6 and more in Table D.3 in the appendix. One could see that back-translation paraphrases source sentences with little...
amendment. On the other hand, AMR-Ori can produce quite different sentences even though it does not modify the intermediate representations. A key factor is that AMR graphs abstract away from syntactic idiosyncrasies while retain semantic frame arguments.

Finally, Table D.4 in the appendix lists some example outputs from EDA and AMR-DA. The original sentence is the same as EDA-None. Except for between EDA-None and AMR-Ori, AMR-DA generated outputs are more fluent than their corresponding outputs by EDA.

5 Related Work

Our proposed data augmentation method is based on manipulating AMR graphs. Similar tree-edit techniques on syntax trees have been found to be useful in paraphrases generation (Heilman and Smith, 2010; Vila and Dras, 2012). Other applications of AMR have also been based on graph manipulation. For example, Liu et al. (2015a) used AMR in summarization task by first parsing the source text to a set of graphs, transforming it to a summary graph, and then generating a summary using the summary graph. Sachan and Xing (2016) represented text and questions as AMR graphs and reduced the machine comprehension problem to a graph containment problem. We have seen a growing body of work that makes use of AMR in other applications such as dialogue modeling, information extraction and commonsense reasoning (Bai et al., 2021; Zhang et al., 2021; Lim et al., 2020).

Based on the influence scope of augmentation, related data augmentation methods can be roughly classified into token-level and sentence-level methods (Chen et al., 2021).

In token-level, synonyms replacement, random swap, random insertion, random deletion (Zhang et al., 2015; Wei and Zou, 2019) have been proven to improve the performance in classification tasks. In STS task, plenty of data augmentation techniques have been utilized such as shuffling, cut-off (Yan et al., 2021), synonyms replace (Wang et al., 2021), word repetition (Wu et al., 2021), etc. However, these methods all risk impairing structure information, resulting in incoherent augmentations.

In contrast, sentence-level take the whole sentence into consideration. Widely used back translation (Sennrich et al., 2016; Edunov et al., 2018b; Qu et al., 2021) translates sentences into intermediate languages and then translates back. Some studies attempt to incorporate syntactic information (Chen et al., 2019) or latent variables (Gupta et al., 2018) to guide generators synthesize various augmentations. But these methods significantly increase the training difficulty. AMR-DA uses AMR as an intermediate language, which can modify graphs as easily as in token-level methods, and synthesizes high-quality and diversified augmentations without grinding in training.

6 Conclusion and Future Work

We propose a novel data augmentation method called AMR-DA. AMR-DA transduces sentences to AMR graphs, applies multiple strategies to modify graphs, and then generates diversified augmentations. To the best of our knowledge, this paper is the first work that utilizes AMR for data augmentation. AMR-DA overcomes the deficiency of previous sentence-level generation methods and diversifies augmentations without retraining decoders. Our experiments show that AMR-DA boosts the performance of models to achieve state-of-the-art results in several STS benchmarks and outperforms...
EDA and AEDA in text classification tasks. In this paper, we mainly use AMR-DA to generate positive augmentations. Further research could use AMR-DA to carefully construct adversarial samples for specific tasks and.

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A Discarding pairs in RI operation

We filter pairs based on edge properties. The discarding edges are listed in the following table.

| Edge  | Reasons                                          |
|-------|--------------------------------------------------|
| :ARGn| potential ambiguity of arguments                |
| :polarity | convert the polarity of semantics               |
| :wiki | Unsuitable for most graphs                      |
| :opn | Unsuitable for most graphs                       |
| :sntn | Unsuitable for most graphs                       |
| :value | Unsuitable for most graphs                       |

B STS tasks Training Details

For AMR-SimCSE, grid-search of batch size ∈ {64, 96, 128, 160} and learning rate ∈ {5e-6, 1e-5, 3e-5, 5e-5} is carried out on STS-B development set, and the hyperparameter settings are listed in Table B.1. The dropout rate is set to 0.1 for base models and 0.15 for large models. We use the temperature \( \tau = 0.05 \) for all the experiments. During training, we found that a larger maximum sequence length equal to 96 benefits our AMR-SimCSE, while in SimCSE the value is 32. So we also enlarge the maximum sequence length to 96 in SimCSE but do not observe any improvement.

|              | BERT | RoBERTa |
|--------------|------|---------|
| Batch size   | 96   | 128     |
| Learning rate| 5e-5 | 5e-5    |

Table B.1: Hyperparameters for AMR-SimCSE.

For AMR-ConSERT, we use hyperparameter settings that are the same as the original paper.

C Text Classification Training Details

For CNN models, we followed the architecture in EDA and modified filters. The entire architecture of our CNN: input layer; the concatenation of 1D convolutional layer of 128 filters of size 3, 4 and 5 with global 1D max pool layer for each convolutional layer; dropout layer with \( \rho = 0.2 \); dense layer of 20 hidden units with ReLU activation function, softmax output layer. Other CNN settings and RNN settings are identical to EDA. As for BERT experiments, we adopt base, uncased version BERT as backbone and the Adam optimizer (Kingma and Ba, 2015) with an initial learning rate of 2e-5. We pick the best checkpoint according to the validation loss. Random seeds are from 0 to 4. The default alpha setting for 4 operations are listed in the following table:

| RS | RD | RI | SR |
|----|----|----|----|
| 0.05 | 0.1 | 0.05 | 0.1 |

Table C.2: Setting of \( \alpha \) for four different operations.

D Comparison on Data Augmentation Outputs

More examples on generated outputs from back-translation and AMR-Ori are presented in Table D.3. Augmented examples using EDA and AMR-DA are presented in Table D.4.

E Effect of alpha in Augmentation Operations

We test each of operations individually for different training set sizes to determine their ability with \( \alpha = 0.05, 0.1, 0.2, 0.3, 0.4, 0.5 \). For each value, we randomly synthesized two augmentations and ran CNN models in this experiment. In Figure 6, all operations in AMR-DA contribute to performance gain. On average, operations achieve more significant gains in smaller datasets.

F Detailed Experimental Results

Table F.6 and F.7 are detailed versions of Table 3. Table F.8 is the detailed version of Table 5. Table F.9 is the detailed version of Table 1. Table F.10 is the detailed version of Table 4.
| Source | IDS Tirana is a football club based in Tirana, Albania. |
|--------|-------------------------------------------------------|
| BT     | IDS Tirana is a football club from Tirana, Albania.   |
| AMR-Ori| The football club IDS Tirana is based in Tirana, Albania. |

| Source | The library was established through the philanthropy of Martha Bayard Stevens. |
|--------|----------------------------------------------------------------------------|
| BT     | The library was founded through the philanthropy of Martha Bayard Stevens.  |
| AMR-Ori| Martha Bayard Stevens philanthropy has established a library.               |

| Source | A meeting of promoters was also held at Presbyterian Church. |
|--------|------------------------------------------------------------|
| BT     | A meeting of the project promoters was also held in the Presbyterian Church. |
| AMR-Ori| The promoters also held a meeting at the Presbyterian Church. |

| Source | He died suddenly on his way home from work on 23 December 1970. |
|--------|----------------------------------------------------------------|
| BT     | On December 23, 1970, he died suddenly on his way home from work. |
| AMR-Ori| On 23 December 1970, when he went home from work, he suddenly died. |

| Source | Supported by a senior leadership team he assembled he took the organization from near insolvency to financial security and a higher level of service delivery. |
|--------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| BT     | Supported by a management team he assembled, he led the organization from near bankruptcy to financial security and improved service delivery.                                                               |
| AMR-Ori| With the support of his assembled senior leadership team, he took the organization from near non-financial security to higher levels of service delivery.                                                                                            |

| Source | Malika Arora, Geeta Kapoor, and Terence Lewis is going to Judge of Sony TV’s dance reality show India’s Best Dancer. |
|--------|------------------------------------------------------------------------------------------------------------------|
| BT     | Malika Arora, Geeta Kapoor and Terence Lewis will be the judges of Sony TV’s dance reality show India’s Best Dancer. |
| AMR-Ori| Malika Arora, Geeta Kapoor and Terence Lewis are judges for Sony TV ’ s dance reality show Best Dancer.            |

| Source | The Yurts lay the foundation for the whole philosophy of family relationships to which nomadic societies have always attached significant importance. |
|--------|----------------------------------------------------------------------------------------------------------------------------------------|
| BT     | The yurts form the basis of the whole philosophy of family relations, to which nomadic societies have always attached great importance.       |
| AMR-Ori| The whole philosophy of family relationships, which nomad societies always attach significant importance, was laid by the Yurts.           |

| Source | From then on, I went through different adventures and endangered my life many times. |
|--------|-----------------------------------------------------------------------------------|
| BT     | From then on, I experienced various adventures and was in danger of my life many times. |
| AMR-Ori| From then on, I have gone through different adventures, and have put my life in danger many times. |

| Source | Comedian Bharti Singh will Host this show along with her husband writer Haarsh Limbachiyaa. |
|--------|------------------------------------------------------------------------------------------|
| BT     | Comedian Bharti Singh will host the show with her husband, writer Haarsh Limbachiyaa.    |
| AMR-Ori| This show will be hosted by comedian Bharti Singh’s husband, writer Haarsh limbachiyaa. |

| Source | Table D.3: Sentences generated using back-translation and using AMR-Ori. BT: back-translation |
|--------|---------------------------------------------------------------------------------------------|
| BT     |                                                                                             |
| AMR-Ori|                                                                                             |
| Operation | EDA | AMR-DA |
|-----------|-----|--------|
| None      | A sad, superior human comedy played out on the back roads of life. | The superior human sad comedy plays out on the back road of life. |
| SR        | A lamentable, superior human comedy played out on the backward road of life. | A top human regrettable comedy plays out on the backroads of life. |
| RI        | A sad, superior human comedy played out on funniness the back roads of life. | The superior human sad comedy of warmth plays out on the backroad of life. |
| RS        | A sad, superior human comedy played out on roads back the of life. | The superior human back comedy plays out on the sad road of life. |
| RD        | A sad, superior human comedy played out on the back roads of life. | The sad superior human comedy plays out on the back road of life. |

| None      | the solid filmmaking and convincing characters makes this a high water mark for this genre. | Solid filmmaking and convincing characters make this a high - watermark for these genera. |
| SR        | the solid filmmaking and convert characters makes this a high water mark for this genre | Solid motion pictures and convincing characters make these high - watermarks for this genre. |
| RI        | in high spirits the solid filmmaking and convincing characters makes this a high water mark for this genre. | This solid, entertaining filmmaking, and convincing character, makes a high water mark for this genre. |
| RS        | the solid filmmaking and convincing characters makes this a high water mark this genre for | This is a high water mark for this genre, with convincing characters and solid films. |
| RD        | the solid filmmaking and convincing characters makes this a high water mark for this genre | Solid filmmaking and convincing characters make a high water mark for this genre. |

| None      | in addition, his album bat out of hell stayed nine years on the english charts, and sold more than 40 million copies worldwide. | And his album, Bat Out of Hell, has stayed on the English charts for 9 years, and sold more than 40 million copies worldwide. |
| SR        | in addition, his album lick out of hell stayed nine years on the english charts and sold more than 40 million replicate worldwide. | And his album "Bat Out of Hell" has stayed on the charts in England for 9 years and sold more than 40 million copies worldwide. |
| RI        | holdup delay in addition, his more than album bat out of hell stayed nine years on the english charts, and sold more than 40 million copies worldwide. | And his album, Bat Out of Hell, has stayed on the charts in England correctly for 9 years, and sold more than 40 million copies worldwide. |
| RS        | the addition, his album bat out of hell stayed nine years on in english charts and sold copies than million more worldwide. | And his album, Bat out of Hell, stayed at more than 40 million copies for 9 years, and sold worldwide on the chart in England. |
| RD        | in addition, his album bat out of hell stayed nine years on the english charts, and sold more than 40 million copies worldwide. | And his album, Bat Out of Hell, has stayed on the English charts for a long time, selling more than 40 million copies worldwide. |

Table D.4: Sentences generated using EDA and using our data augmentation method AMR-DA. EDA returns the input sentence with "None" operation, while AMR-DA returns a paraphrased sentence. SR: synonym replacement. RI: random insertion. RS: random swap. RD: random deletion.
Figure 6: Average performance gain of individual AMR-DA operations over four text classification datasets for different training set sizes. $\alpha$ roughly controls the range that the operation can impact in each augmentation.

| Dataset | # Classes | # Train samples | # Test samples | Average length | Vocabulary size |
|---------|-----------|-----------------|---------------|----------------|----------------|
| SST-2   | 2         | 7,791           | 1,821         | 19             | 15,771         |
| CR      | 2         | 4,068           | 451           | 19             | 9,048          |
| SUBJ    | 2         | 9,000           | 1,000         | 25             | 22,715         |
| PC      | 2         | 40,000          | 26,090        | 7              | 26,090         |

Table F.5: Statistics of four text classification datasets.

| Model               | STS12 | STS13 | STS14 | STS15 | STS16 | STS-B | SICK-R | Avg.  |
|---------------------|-------|-------|-------|-------|-------|-------|--------|-------|
| ConSERT-BERT$_{\text{base}}$ | 64.64 | 78.49 | 69.07 | 79.72 | 75.95 | 73.97 | 67.31  | 72.74 |
| AMR-ConSERT-BERT$_{\text{base}}$ | 71.98 | 81.96 | 72.91 | 82.00 | 76.31 | 77.00 | 70.85  | 76.14 |
| ConSERT-BERT$_{\text{large}}$ | 70.69 | 82.96 | 74.13 | 82.78 | 76.66 | 77.53 | 70.37  | 76.45 |
| AMR-ConSERT-BERT$_{\text{large}}$ | 73.93 | 85.45 | 76.27 | 82.86 | 77.87 | 79.28 | 71.65  | 78.19 |

Table F.6: The performance comparison of ConSERT with AMR-ConSERT in the unsupervised setting. We report Spearman correlation magnified by a factor of 100 on all splits of seven STS datasets. †: results from Yan et al., 2021.
| Model | STS12 | STS13 | STS14 | STS15 | STS16 | STS-B | SICK-R | Avg. |
|-------|-------|-------|-------|-------|-------|-------|--------|------|
| SimCSE-BERT<sub>base</sub> † | 68.40 | 82.41 | 74.38 | 80.91 | 78.56 | 76.85 | 72.23 | 76.25 |
| ESimCSE-BERT<sub>base</sub> § | 73.40 | 83.27 | 73.83 | 82.66 | 78.81 | 80.17 | 72.30 | 78.27 |
| AMR-SimCSE-BERT<sub>base</sub> | 72.5 | 83.40 | 75.91 | 83.35 | 79.70 | 78.94 | 71.86 | 77.95 |
| SimCSE-BERT<sub>large</sub> † | 70.88 | 84.16 | 76.43 | 84.50 | 79.76 | 79.26 | 73.88 | 78.41 |
| ESimCSE-BERT<sub>large</sub> § | 73.21 | 85.37 | 77.33 | 83.19 | 80.30 | 80.99 | 70.54 | 77.44 |
| AMR-SimCSE-BERT<sub>large</sub> | 75.47 | 84.77 | 77.56 | 85.4 | 80.06 | 80.28 | 73.81 | 79.63 |
| SimCSE-RoBERTa<sub>base</sub> † | 70.16 | 81.77 | 73.24 | 81.36 | 80.65 | 80.22 | 68.56 | 76.57 |
| ESimCSE-RoBERTa<sub>base</sub> § | 69.90 | 82.50 | 74.68 | 83.19 | 80.30 | 80.30 | 70.54 | 79.44 |
| AMR-SimCSE-RoBERTa<sub>base</sub> | 74.80 | 82.67 | 75.42 | 82.57 | 80.49 | 80.36 | 72.70 | 78.43 |
| SimCSE-RoBERTa<sub>large</sub> † | 72.86 | 83.99 | 75.62 | 84.77 | 81.80 | 81.98 | 71.26 | 78.90 |
| ESimCSE-RoBERTa<sub>large</sub> § | 73.20 | 84.93 | 76.88 | 84.86 | 81.21 | 82.97 | 72.27 | 79.45 |
| AMR-SimCSE-RoBERTa<sub>large</sub> | 74.35 | 84.72 | 77.32 | 85.90 | 81.77 | 81.07 | 72.76 | 79.70 |

Table F.7: The performance comparison of unsupervised SimCSE and its variants on seven STS test splits. The reported score is Spearman correlation magnified by a factor of 100. †: results from Gao et al., 2021; §: results from Wu et al., 2021.

| Model | STS12 | STS13 | STS14 | STS15 | STS16 | STS-B | SICK-R | Avg. |
|-------|-------|-------|-------|-------|-------|-------|--------|------|
| BERT<sub>base</sub>-flow† | 63.48 | 72.14 | 68.42 | 73.77 | 75.37 | 70.72 | 63.11 | 69.57 |
| ConSERT-BERT<sub>base</sub> † | 64.64 | 78.49 | 69.07 | 79.72 | 75.95 | 73.97 | 67.31 | 72.74 |
| +AMR-SR augmentation | 71.33 | 78.37 | 71.99 | 83.34 | 75.24 | 76.89 | 72.62 | 75.68 |
| +AMR-RD augmentation | 64.31 | 80.69 | 71.87 | 81.73 | 76.76 | 75.78 | 69.28 | 74.34 |
| +AMR-RI augmentation | 71.4 | 79.24 | 71.35 | 82.56 | 76.07 | 77.31 | 73.22 | 75.31 |
| +AMR-RS augmentation | 72.01 | 82.19 | 72.94 | 81.93 | 76.15 | 77.24 | 70.31 | 76.11 |
| +AMR-Ori augmentation | 71.98 | 81.96 | 72.91 | 82.00 | 76.31 | 77.00 | 70.85 | 76.14 |

Table F.8: Performance comparison of models with different DA methods. †: results from Yan et al., 2021.

| Model | STS12 | STS13 | STS14 | STS15 | STS16 | STS-B | SICK-R | Avg. |
|-------|-------|-------|-------|-------|-------|-------|--------|------|
| BERT<sub>base</sub>-flow† | 58.40 | 67.10 | 60.85 | 75.16 | 71.22 | 68.66 | 64.47 | 66.55 |
| SimCSE-BERT<sub>base</sub> † | 68.40 | 82.41 | 74.38 | 80.91 | 78.56 | 76.85 | 72.23 | 76.25 |
| +word repetition† | 69.79 | 83.43 | 75.65 | 82.44 | 79.43 | 79.44 | 71.86 | 77.43 |
| +back translation | 66.50 | 74.53 | 66.34 | 76.61 | 77.33 | 72.15 | 68.54 | 71.71 |
| +AMR(BART<sub>base generator</sub>)-SimCSE | 72.30 | 83.15 | 75.53 | 83.17 | 79.23 | 78.15 | 73.16 | 77.81 |
| +AMR(T5<sub>small generator</sub>)-SimCSE | 72.26 | 81.77 | 75.93 | 83.44 | 79.78 | 77.93 | 72.44 | 77.65 |
| +AMR(T5<sub>base generator</sub>)-SimCSE | 72.51 | 83.40 | 75.91 | 83.35 | 79.70 | 78.94 | 71.86 | 77.95 |

Table F.9: Performance comparison of AMR-DA (Ori) with different generators. †: results from Gao et al., 2021; §: results from Wu et al., 2021.
Table F.10: Average performance of CNN, RNN and BERT on four classification datasets.

|         | CR   | SST2 | SUBJ | PC   | Avg.  |
|---------|------|------|------|------|-------|
| RNN     | 79.38| 82.32| 91.96| 92.31| 86.49 |
| +EDA (num_aug=1) | 80.95| 82.04| 91.43| 90.22| 86.16 |
| +AEDA (num_aug=1) | 82.22| 82.86| 92.56| 92.70| 87.59 |
| +AMR-DA (num_aug=1) | 81.70| **83.37**| **92.68**| **92.76**| **87.63** |
| +EDA (num_aug=5) | 80.93| 82.99| 91.14| 90.42| 86.37 |
| +AEDA (num_aug=5) | 80.53| 83.10| 92.62| 92.59| 87.21 |
| +AMR-DA (num_aug=5) | **82.93**| **83.74**| **92.72**| **92.60**| **88.00** |
| CNN     | 83.68| 84.28| 91.84| 92.79| 88.15 |
| +EDA (num_aug=1) | 82.90| 83.62| 91.51| 90.79| 87.20 |
| +AEDA (num_aug=1) | 83.55| 84.50| **92.48**| 92.65| 88.30 |
| +AMR-DA (num_aug=1) | **83.85**| **84.68**| 92.38| **92.70**| **88.40** |
| +EDA (num_aug=5) | 83.59| 84.12| 91.90| 91.40| 87.75 |
| +AEDA (num_aug=5) | 84.75| **85.11**| **92.68**| 92.59| 88.78 |
| +AMR-DA (num_aug=5) | **85.05**| 84.94| 92.54| **92.67**| **88.80** |
| BERT    | 89.67| 90.72| 96.38| **95.98**| 93.19 |
| +EDA (num_aug=1) | **90.73**| **91.22**| 95.88| 95.74| 93.39 |
| +AEDA (num_aug=1) | 90.15| 90.42| 96.26| **95.94**| 93.19 |
| +AMR-DA (num_aug=1) | 90.53| 90.90| **96.52**| 95.92| **93.47** |
| +EDA (num_aug=5) | 89.80| **91.76**| 95.70| 95.88| 93.29 |
| +AEDA (num_aug=5) | 90.01| 91.71| 96.50| 95.89| 93.53 |
| +AMR-DA (num_aug=5) | **90.47**| 91.02| **96.70**| **95.97**| **93.54** |