Which Sentence Representation is More Informative: An Analysis on Text Classification

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Abstract

Text classification is a popular and well-studied problem in Natural Language Processing. Most previous work on text classification has focused on deep neural networks such as LSTMs and CNNs. However, text classification studies using syntactic and semantic information are very limited in the literature. In this study, we propose a model using Graph Attention Network (GAT) that incorporates semantic and syntactic information as input for the text classification task. The semantic representations of UCCA and AMR are used as semantic information and the dependency tree is used as syntactic information. Extensive experimental results and in-depth analysis show that UCCA-GAT model, which is a semantic-aware model outperforms the AMR-GAT and DEP-GAT, which are semantic and syntax-aware models respectively. We also provide a comprehensive analysis of the proposed model to understand the limitations of the representations for the problem.

1 Introduction

The text classification problem has been widely studied in the literature (Yao et al., 2019; Malekzadeh et al., 2021) in the field of Natural Language Processing (NLP).

The text classification problem has been recently used as a downstream task in SentEval (Conneau and Kiela, 2018), a toolkit for evaluating sentence representations. In the literature, studies on Semantic Textual Similarity (STS) (Reimers et al., 2019; Gao et al., 2021) have used the text classification to evaluate the sentence embeddings learned by their proposed models using the datasets provided by the SentEval toolkit (Conneau and Kiela, 2018).

For text classification, traditional deep learning models such as Long Short-Term Memory (LSTM) Networks (Hochreiter and Schmidhuber, 1997) and Convolutional Neural Networks (CNN) (Kim, 2014) have been adopted. These deep learning models capture the local semantic and syntactic information by using the input as a sequence of words but they ignore the semantic and syntactic information of the input (Peng et al., 2018). Recently, Graph Neural Networks (GNNs) (Battaglia et al., 2018; Cai et al., 2018) have been used for text classification (Yao et al., 2019; Malekzadeh et al., 2021), sequence labeling (Marcheggiani and Titov, 2017; Zhang et al., 2018a), and question answering (Song et al., 2018; De Cao et al., 2019).

In dependency parsing the aim is to find a tree that represents dependencies between words in a sentence. On the contrary, semantic parsing maps a text to its formal representation that provides an abstraction of its meaning. There has been a recent increase in the studies that propose various neural network architectures such as tree-LSTM (Takase et al., 2016), Heterogeneous Graph Transformer (Li et al., 2020), and Transformer (Xie et al., 2021) that integrate semantic and syntactic information. GNN models that integrate external representations into deep learning models referred to as semantic and syntax-aware models, are the well-studied models in the literature for various NLP problems such as Neural Machine Translation (NMT) (Bastings et al., 2017) and text classification (Elbasani and Kim, 2022). These models have gained attention because they are capable of capturing information over long distances, especially between discontinuous constituents (Wang and Li, 2022).

In this study, we analyzed the impact of semantic and syntactic representations within Graph Attention Networks (GAT), particularly for the text classification problem. We used the dataset provided by SentEval toolkit (Conneau and Kiela, 2018). We constructed the GAT model by integrating Abstract Meaning Representation (AMR) (Banarescu et al., 2013) and the Universal Conceptual Cognitive Annotation (UCCA) (Abend and Rappoport, 2013) as graph-based semantic representations and the dependency tree as syntactic representation. Since the size of the datasets in SentEval toolkit (Con-

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neau and Kiela, 2018) is different, we evaluated the results of our proposed model with the studies that use the SentEval toolkit (Conneau and Kiela, 2018). [1]

The rest of the paper is organized as follows. Section 2 reviews similar semantic and syntax-aware models. Section 3 describes our methodology for addressing the text classification problem using semantic and syntactic parser models. Section 4 presents our experimental results along with a detailed analysis of the proposed models. Finally, Section 5 concludes the paper with insights on the impact of the semantic and syntactic information on the classification problem.

2 Related Work

In addition to the traditional neural networks that simply rely on neural language models, semantic and syntax-aware models have been recently used effectively in NLP problems such as text classification (Ahmed et al., 2018; Huang et al., 2020; Liang et al., 2022; Elbasani and Kim, 2022), natural language generation (Guo et al., 2021), question answering (Schlichtkrull et al., 2020), semantic role labeling (SRL) (Schlichtkrull et al., 2020; Mohammadshahi and Henderson, 2021), reading comprehension (Sachan and Xing, 2016; Galitsky, 2020), text summarization (Takase et al., 2016; Dohare and Karnick, 2017), language modelling (Zhang et al., 2020), and machine translation (Qin and Liang, 2020; Slobodkin et al., 2021; Nguyen et al., 2021; Li and Flanigan, 2022).

Dependency trees usually provide sufficient syntactic information in various NLP tasks (Huang et al., 2020; Liang et al., 2022; Guo et al., 2021) and improve the performance of the models considerably. As for the external resource of semantic information, the most popular semantic representation is the AMR (Hardy and Vlachos, 2018; Elbasani and Kim, 2022; Kouris et al., 2022).

In particular, GNNs (Bastings et al., 2017; Marcheggiani and Titov, 2019; Schlichtkrull et al., 2020; Guo et al., 2021; Elbasani and Kim, 2022) have been used as models into which syntactic and semantic information are easily integrated. In addition to GNNs, Transformers have also been used to integrate such external resources such as syntax-aware word representation (SAWR) (Xie et al., 2021), syntax-aware local attention (SLA) (Li et al., 2020), syntax-graph guided self-attention (SGSA) (Gong et al., 2022), Scene-Aware Self-Attention (SASA), and Scene-Aware Cross-Attention (SACrA) head (Slobodkin et al., 2021). Last but not least, the Heterogeneous Graph Transformer (Hu et al., 2020), a customized version of the Transformer (Vaswani et al., 2017), has been recently introduced as a model with semantic AMR information (Yao et al., 2020).

3 Methodology

In this section, we describe the proposed semantic- and syntax-aware GAT models that integrate semantic and syntactic information as external resources into the model. First, we explain the preprocessing step that is performed to convert the text into the required form to be processed by the GAT model.

3.1 Preprocessing

GAT models use adjacency and feature matrices that are extracted from graphs as input. There are several approaches to transform a text into a graph, such as digitizing text (Hamid et al., 2020), statistical methods (PMI, TF-IDF) (Yao et al., 2019), dependency trees (Zhang et al., 2018b) or semantic graphs (AMR) (Elbasani and Kim, 2022).

In this study, we use dependency trees and semantic graphs. Here we explain the preprocessing step along with the parser model that is used to convert datasets into dependency trees and semantic graphs, as well as the details of extracting adjacency and feature matrices from graphs and trees.

Converting datasets into graphs/trees The parser models that are employed to extract the graphs and trees from the datasets are described below:

- **UCCA Semantic Parser** We use the self-attentive semantic parser model by Bölücü and Can (2021) to extract the UCCA-based semantic representations. The model is based on a graph-based approach with an encoder-decoder architecture, where the encoder is a Transformer (Vaswani et al., 2017) with 2 MLP classifiers and the decoder corresponds to the CYK algorithm (Chappelier and Rajman, 1998) that generates a constituency tree with the maximum score using the per-span scores obtained from the transformer encoder.

[1]The code is publicly available at `https://github.com/adalin16/depling-GAT`

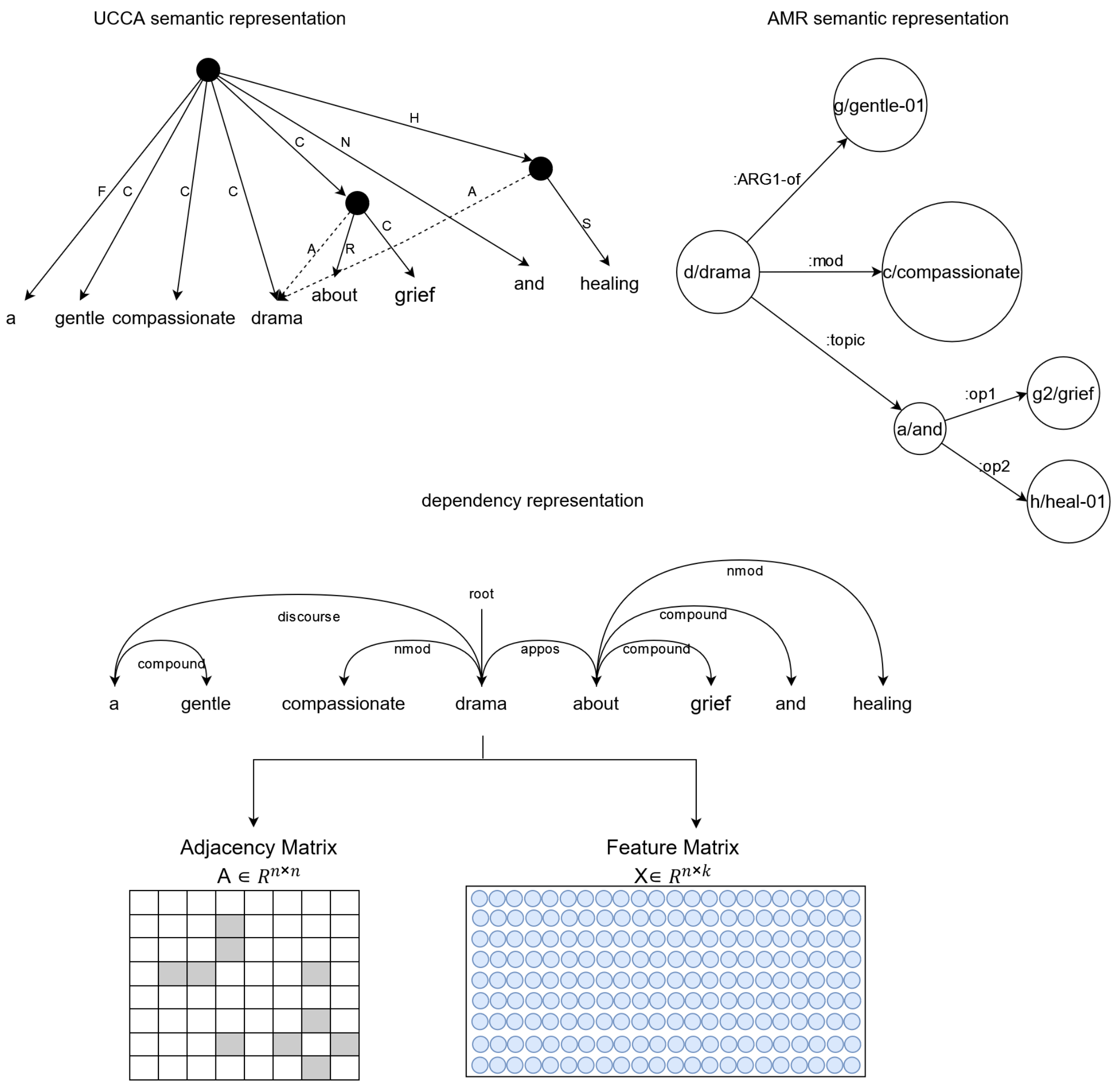


Figure 1: UCCA, AMR semantic graphs, and the dependency trees along with the feature and adjacency matrices that are used as input to the GAT model are illustrated for the example phrase *"a gentle compassionate drama about grief and healing"* from the MR dataset (Pang and Lee, 2005). The gray color in the matrix represents the value of 1 and the white color represents the value of 0. Each row in the feature matrix corresponds to the pre-trained word embedding of a node in the graph/tree.

- **AMR Semantic Parser** As an AMR semantic parser, we use the T5 parser (Roberts et al., 2020). The model is based on a language model that is fine-tuned on English. The model is integrated into the spaCy library (Honnibal and Montani, 2017) and is called AMRLib[2].

- **Dependency Parser** We use the Deep Biaffine dependency parser model Dozat and Manning (2016) to extract the dependency trees. The model is based on a graph-based approach where BiLSTM with biaffine classifiers is used as an encoder and MST is used as a decoder that generates dependency trees from predicted arcs and labels in the encoder. We use the model[3] integrated within the Stanza library (Qi et al., 2020).

Extracting adjacency and feature matrices from graphs/trees Since the inputs of the proposed model are adjacency and feature matrices, we extracted the matrices from graphs and trees. The semantic representations of UCCA and AMR are based on DAG, and the dependency trees are represented by trees. We followed the same proce-

[2]https://spacy.io/universe/project/amrlib

[3]https://stanfordnlp.github.io/stanza/depparse.html

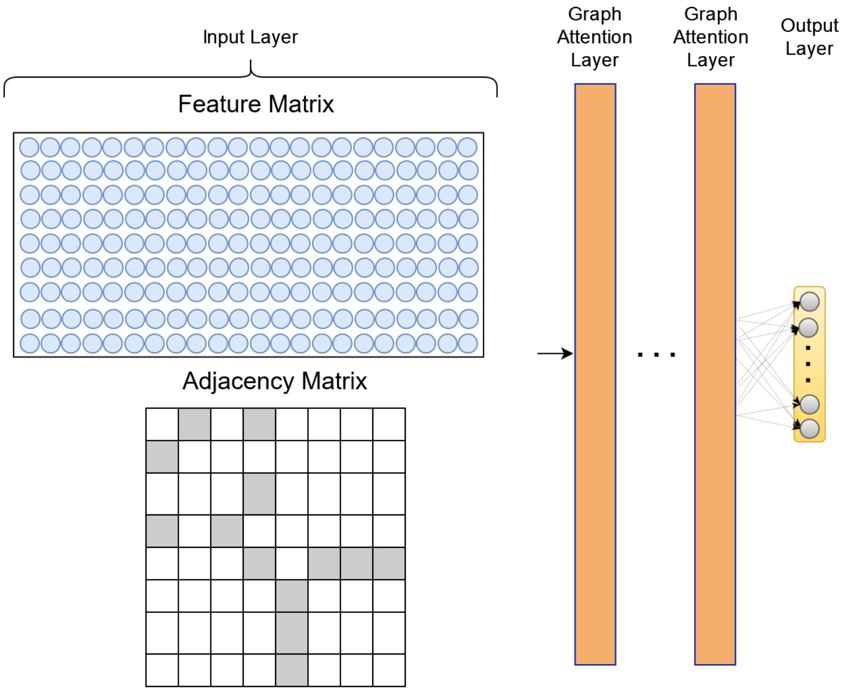


Figure 2: Overview of the GAT model along with its input in the form of a feature and adjacency matrix. The matrices correspond to semantic and syntactic information in the form of a UCCA or an AMR graph, or a dependency tree.

Dataset	Train	Dev	Test
Movie Review (MR) (Pang and Lee, 2005)	10,662	train in k-fold	test in k-fold
Customer Review (CR) (Hu and Liu, 2004)	3,770	train in k-fold	test in k-fold
Subjectivity / Objectivity (SUBJ) (Pang and Lee, 2004)	10,000	train in k-fold	test in k-fold
Multi-Perspective Question and Answering (MPQA) (Wiebe et al., 2005)	10,606	train in k-fold	test in k-fold
Stanford Sentiment Analysis 2 (SST-2) (Socher et al., 2013)	67,349	872	1,821
Text Retrieval Conference (TREC) (Voorhees and Tice, 2000)	5,452	train in k-fold	500
The Microsoft Research Paraphrase Corpus (MRPC) (Dolan et al., 2004)	4,726	train in k-fold	1,725

Table 1: The details of the datasets given in the downstream tasks in SentEval toolkit.

dure for all of the representations considering all as graphs.

For a given graph $G = (V, E)$, V is the set of nodes and E is the set of labeled edges (UCCA - edges, AMR - relations between nodes, dependency tree - dependency relations). We extracted:

- the feature matrix X ($n \times k$, where n is the number of nodes (UCCA - terminal and non-terminal nodes, AMR - words, dependency tree - words except the `ROOT` node) in the graph and k is the embedding dimension),
- the adjacency matrix A ($n \times n$, where n is the number of nodes in the graph), which is not trainable.

For the feature matrix, we used pre-trained word embeddings (BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019), and XLNet (Yang et al., 2019)) for nodes (UCCA - terminal nodes, AMR - words, dependency tree - words) and a randomly generated embedding with the same embedding dimension of the pre-trained word embeddings for non-terminal nodes in UCCA.

UCCA, AMR, and dependency tree representations of the phrase *"a gentle compassionate drama about grief and healing"* from the Movie Review (MR) dataset (Pang and Lee, 2005) with extracted adjacency and feature matrices are given in Figure 1.

3.2 Graph Attention Network

In order to incorporate external semantic information, we adopted Graph Attention Networks (GAT) (Veličković et al., 2017) that are based on self-attention layers. We used GATs for the text classification problem since they provide a straightforward method to utilise semantic information in the form of a semantic graph (UCCA/AMR) or a dependency tree. The overview of the model is given in Figure 2.

GNN models have different types of updating mechanisms for nodes. The basic version of updating, as applied in this study, updates each node i in the l-th layer, H^{l+1} as follows:

$$H^{l+1} = \sigma(AH^l W^l) \tag{1}$$

where $\sigma(\cdot)$ refers to ReLU non-linear activation function, A is the adjacency matrix, W^l is the attention weights in the l-th layer. H^l is the feature matrix of the l-th layer ($H^0 = X$, where X is the feature matrix extracted from a semantic graph or a dependency tree) where l is a hyperparameter that needs to be finetuned for the graph.

We fed the output of the node in the final layer into the output layer that applies the softmax function to generate the output class of a given text either as a binary or a multi-class classification:

$$Z = softmax(H^o) \tag{2}$$

where H^o is the feature matrix of the final GAT layer.

4 Experiments and Results

4.1 Datasets

We evaluated the model on 7 downstream tasks given in the SentEval toolkit (Conneau and Kiela, 2018). The details of the datasets are given in Table 1.

4.2 Experimental Setting

We used PyTorch 3.7 to implement the model. We used cross-entropy loss for both binary and multi-class classification. The Adam (Kingma and Ba, 2014) was used as the optimizer in all models with $\epsilon = 1e - 8$, and the default max grad norm for gradient clipping.

We used the monolingual (BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019), XLNet (Yang et al., 2019)) and multilingual pre-trained language models (M-BERT (Devlin et al., 2019), XLM-R (Conneau and Lample, 2019), XLM-R-large (Conneau et al., 2020)) in order to build the feature matrices as described in Section 3.1. All hyperparameters along with their values are given in Appendix A.

We evaluated the models applied to binary and multi-class classification problems using the SentEval toolkit (Conneau and Kiela, 2018). We used accuracy metric in all downstream tasks and reported Precision, Recall, and F1 for a detailed analysis of the class-wise results for TREC.

4.3 Results

The results obtained from the semantic and syntax-aware GAT models (UCCA-GAT, AMR-GAT, and Dep-GAT) on 7 datasets in SentEval toolkit (Conneau and Kiela, 2018) along with the state-of-the-art results are given in Table 2. The results show that the performance of the GAT models is slightly behind the state-of-the-art results (Cer et al., 2018; Gao et al., 2021; Reimers et al., 2019). The main reason is that these models learn sentence embeddings and then apply the learned sentence embeddings to the downstream tasks (Reimers et al., 2019; Gao et al., 2021). Here, the main aim is to investigate the external usage of semantic and syntactic information without performing separate learning for sentence embeddings but solely relying on the existing semantic and syntactic information. Therefore, we only compare the performance of the semantic- and syntax-aware GAT models with each other for 7 downstream tasks. The results show that the UCCA-GAT model performs better than the AMR-GAT and the Dep-GAT models. The analysis of the adjacency matrices extracted from the AMR semantic parser and the UCCA semantic parser shows that the relations such as “about", “like", “of", etc. are defined as concepts and used as edge labels instead of nodes in the AMR representation. Since our models use the nodes without edge labels, the model misses the concepts that might give a clue about the target class. This also leads to sparse adjacency matrices for AMR graphs compared to other adjacency matrices extracted from UCCA graphs and dependency trees.

We analyse the class-wise results obtained from the three models using the TREC dataset (Voorhees and Tice, 2000) (multi-class classification problem). The results are given in Table 3. It can be clearly seen that UCCA-GAT is particularly good at predicting the classes “num" and “loc", since the number of relations in the UCCA graphs is higher in these classes than in other classes. The performance of AMR-GAT is worse than the other models (UCCA-GAT, Dep-GAT) because we lose the relations represented as labels in the AMR semantic representation and we used only the nodes in the semantic and syntactic representations in the preprocessing step during the extraction of the adjacency matrices for the AMR-GAT model. The Dep-

	Our proposed models							
	MR	CR	SUBJ	MPQA	SST-2	TREC	MRPC	Avg.
UCCA-GAT	82.04	83.37	90.38	87.29	89.35	81.92	73.50	83.98
AMR-GAT	81.55	81.11	88.98	83.94	85.83	79.65	72.87	83.42
Dep-GAT	80.66	81.62	89.10	85.76	88.03	81.06	75.25	83.07
	State-of-the-art							
BERT-CLS embedding ♡	78.68	84.85	94.21	88.23	84.13	**91.40**	71.13	84.66
BiLSTM ♢	81.1	86.3	92.4	90.2	-	-	-	-
Universal Sentence Encoder ♣	80.09	85.19	93.98	86.70	86.38	93.2	70.14	85.10
SimCSE-BERT$_{base}$ ♠	83.64	89.43	94.39	89.86	88.96	89.60	**76.00**	87.41
SBERT-NLI-large ♡	**84.88**	**90.07**	**94.52**	**90.33**	**90.66**	87.4	75.94	**87.69**

Table 2: Accuracy results of the downstream tasks using the proposed models and the other state-of-the-art models. The highest scores are given in bold. (♣ results from (Cer et al., 2018); ♠ results from (Gao et al., 2021); ♡ results from (Reimers et al., 2019); ♢ results from (Conneau et al., 2017))

	UCCA-GAT			AMR-GAT			Dep-GAT		
Class	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
num	0.97	0.89	**0.93**	0.90	0.84	0.87	0.91	0.82	0.87
loc	0.86	0.79	**0.83**	0.86	0.78	0.82	0.82	0.80	0.81
hum	0.80	0.80	0.80	0.74	0.80	0.77	0.77	0.85	**0.81**
desc	0.85	0.83	0.84	0.82	0.83	0.82	0.87	0.87	**0.87**
enty	0.70	0.85	0.77	0.77	0.83	0.80	0.81	0.87	**0.84**
abbr	0.86	0.67	**0.75**	0.64	0.78	0.70	0.67	0.67	0.67
avg.	0.84	0.81	0.82	0.79	0.81	0.80	0.81	0.81	0.81

Table 3: Class-wise results on the TREC dataset (Voorhees and Tice, 2000)

PLM	MR	CR	SUBJ	MPQA	SST-2	TREC	MRPC
	Monolingual Embeddings						
BERT	78.33	79.15	87.80	82.78	85.01	80.40	69.68
RoBERTa	80.16	79.89	89.11	**87.29**	**89.35**	79.11	72.52
XLNet	74.62	75.99	83.15	77.46	80.56	76.82	67.71
	Multilingual Embeddings						
M-BERT	79.27	81.94	88.15	83.11	83.14	81.00	72.35
XLM-R	**82.04**	82.23	89.48	84.76	85.01	**81.92**	72.93
XLM-R-large	78.78	**83.37**	**90.38**	85.82	87.59	81.42	**73.50**

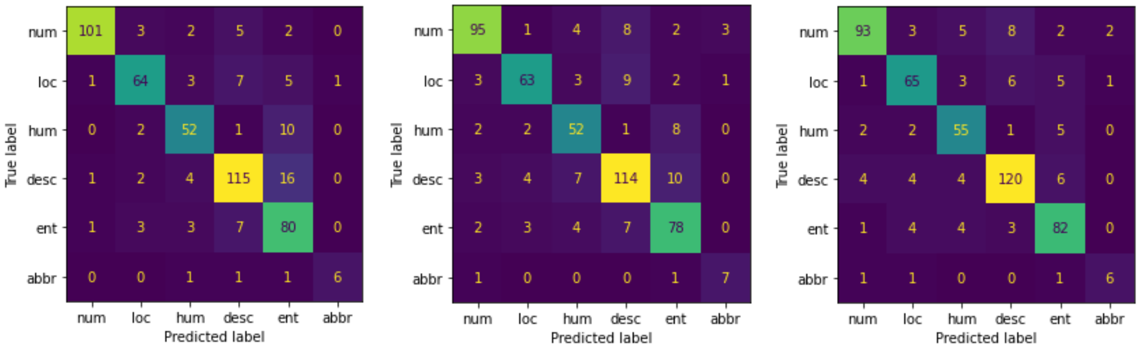
Table 4: Accuracy results obtained with monolingual and multilingual embeddings in UCCA-GAT model. The best values are in bold.

GAT model achieves better overall results since the dependency trees can capture long-distance information. The only class that Dep-GAT cannot capture is “abbr", compared to the success achieved with other classes in the TREC dataset (Voorhees and Tice, 2000).

Figure 3 illustrates the confusion matrices of the semantic and syntax-aware GAT models for the TREC dataset. The results show that the UCCA-GAT model predicts the class “num" better than other models. In addition, the Dep-GAT model is better at predicting the class “desc". For all models, there is a general confusion between the classes “desc" and “ent".

We also analyse the models deeply in terms of the impact of the layers and embeddings.

- **Embeddings** We present an analysis of the pre-trained language models used in the extraction of feature matrix X from UCCA, AMR, and dependency



(a) UCCA-GAT (b) AMR-GAT (c) Dep-GAT

Figure 3: Confusion matrices of the semantic and syntax-aware GAT models on TREC dataset (Voorhees and Tice, 2000)

PLM	MR	CR	SUBJ	MPQA	SST-2	TREC	MRPC
Monolingual Embeddings							
BERT	77.68	**81.11**	83.98	83.11	82.48	75.61	70.43
RoBERTa	**81.55**	79.44	85.44	83.44	**85.83**	**79.65**	70.78
XLNet	72.64	72.12	82.56	78.15	79.68	71.95	68.87
Multilingual Embeddings							
M-BERT	78.77	79.71	87.45	82.17	83.91	76.42	71.19
XLM-R	79.49	79.28	**88.98**	83.56	84.46	78.20	**72.87**
XLM-R-large	80.10	80.08	87.95	**83.94**	85.01	78.62	72.35

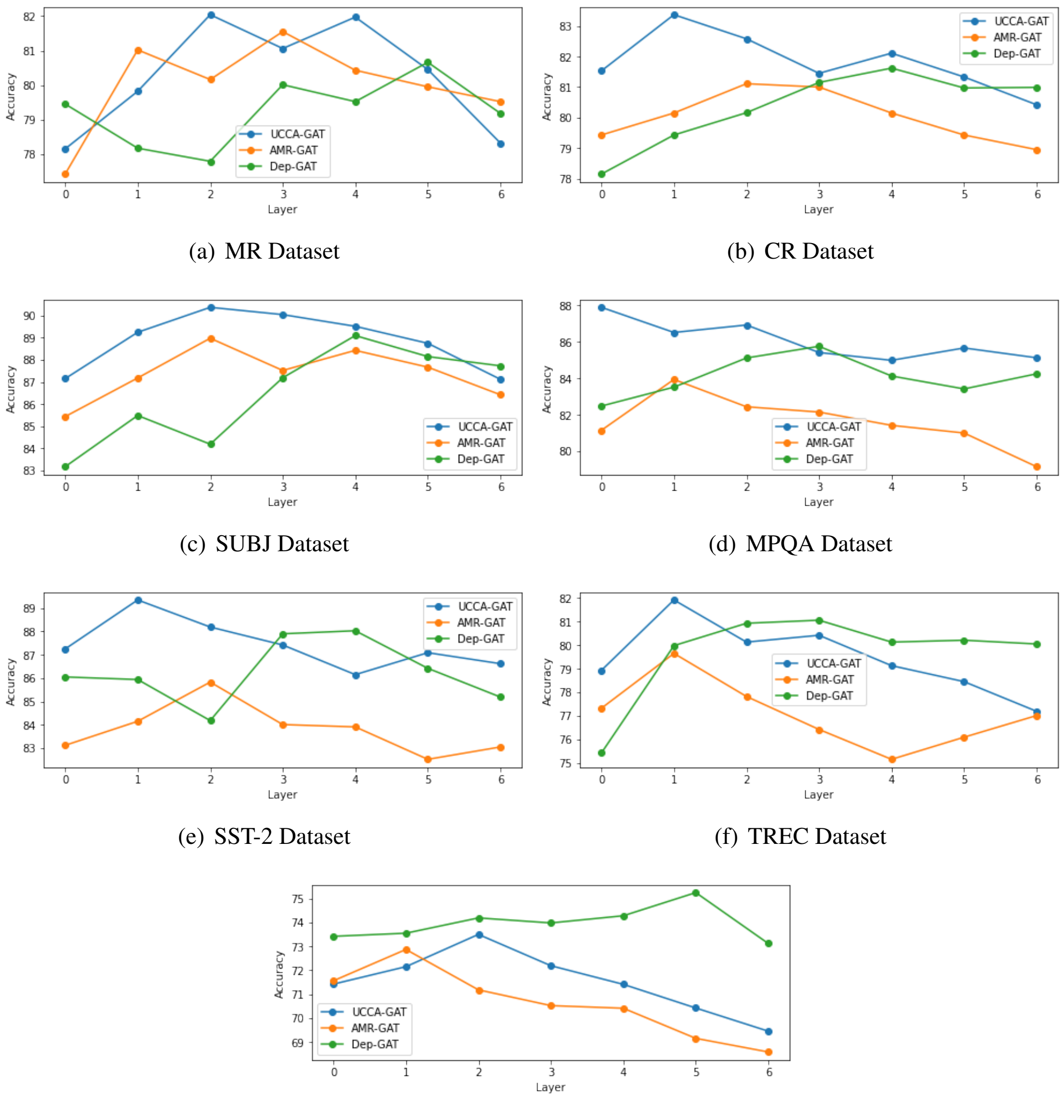
Table 5: Accuracy results obtained with monolingual and multilingual embeddings in AMR-GAT model. The best values are in bold.

PLM	MR	CR	SUBJ	MPQA	SST-2	TREC	MRPC
Monolingual Embeddings							
BERT	77.30	79.50	86.43	82.99	83.64	78.80	70.78
RoBERTa	78.95	**80.11**	89.10	83.14	**88.03**	79.62	71.59
XLNet	72.45	74.40	82.47	78.04	81.38	75.27	69.51
Multilingual Embeddings							
M-BERT	79.39	79.55	84.69	82.64	84.51	79.89	73.51
XLM-R	80.19	81.62	87.59	83.84	85.78	**81.06**	74.09
XLM-R-large	**80.66**	81.14	**88.11**	**85.76**	86.49	79.49	**75.25**

Table 6: Accuracy results obtained with monolingual and multilingual embeddings in Dep-GAT model. The best values are in bold.

tree. We used BERT (Devlin et al., 2019) (`bert-base-cased`), RoBERTa (Liu et al., 2019) (`roberta-base`), and XLNet (Yang et al., 2019) (`xlnet-base-cased`) monolingual embeddings with base variants consisting of 768 hidden dimensions, whereas we used multilingual version of BERT (M-BERT) (Devlin et al., 2019), and RoBERTa (XLM-R) (Conneau and Lample, 2019) and its large version (XLM-R-large) (Conneau and Lample, 2019).

The results obtained using monolingual and multilingual pre-trained embeddings are given in Table 4, 5 and 6 for UCCA-GAT, AMR-GAT, and Dep-GAT respectively. The re-



(a) MR Dataset

(b) CR Dataset

(c) SUBJ Dataset

(d) MPQA Dataset

(e) SST-2 Dataset

(f) TREC Dataset

(g) MRPC Dataset

Figure 4: Accuracy scores based on the number of layers in the proposed models.

sults show that multilingual embeddings are more effective for both proposed semantic and syntax-aware models. In monolingual embeddings, the results obtained from the models RoBERTa pre-trained word embeddings are higher than that of the others (BERT, XLNet).

- **Impact of the layers** We also analyse the impact of the number of layers in the proposed models (UCCA-GAT, AMR-GAT, Dep-GAT) on the performance of the models. We perform the experiments with embeddings with which we obtained the best results. We vary the number of the layers from 1 to 7 and report the results in Figure 4 for all datasets with UCCA-GAT, AMR-GAT, and Dep-GAT models. The results show that the syntax-aware model (Dep-GAT) learns in deeper layers, and semantic-aware models (UCCA-GAT and AMR-GAT) tend to learn in shallow layers or in the middle layers. The previous studies already show that syntactic features are encoded in the shallow layers and semantic features are encoded in the deeper layers of the pre-trained language models (Conneau et al., 2018; Jawahar et al., 2019), and here we also obtained better results with deeper layers in the syntax-aware model and with shallow layers in the semantic-aware models (UCCA-GAT and AMR-GAT).

5 Conclusion

Semantic and syntax-aware models have recently been proposed for various NLP problems, that especially require long-distance information, especially between discontinuous constituents, in addition to the local information captured by sequential models. In this paper, we propose a graph neural network model that incorporates semantic and syntactic information for the text classification task. To the best of our knowledge, this is the first study that compares semantic and syntactic information used in a graph neural network, specifically for the task of text classification. We present a detailed analysis of the results, showing that the UCCA semantic information improves the performance of the classification model compared to syntactic information (i.e. dependency tree). However, we were not able to obtain similar results with the model using the AMR semantic representation. This shows that the preprocessing step to convert the graph into adjacency and feature matrices is a very important step in GNN models.

As future work, we plan to improve the preprocessing step to obtain more informative adjacency and feature matrices.

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A Hyperparameter Values

Table 7, 8, and 9 list the hyperparameter values used in the UCCA-GAT, AMR-GAT and Dep-GAT models, respectively, for downstream tasks.

Parameters	MR	CR	SUBJ	MPQA	SST-2	TREC	MRPC
weight decay	0.2	0.1	0.2	0.2	0.2	0.1	0.1
batch size	1	1	1	1	1	1	1
learning rate	1e-4	1e-4	1e-4	1e-4	1e-4	1e-4	1e-4
dropout rate	0.1	0.1	0.1	0.2	0.1	0.1	0.1
number of hidden	800	800	800	800	400	800	800
number of head	2	1	2	2	4	1	1

Table 7: Hyperparameters used for the UCCA-GAT for downstream tasks in experiments

Parameters	MR	CR	SUBJ	MPQA	SST-2	TREC	MRPC
weight decay	0.1	0.1	0.2	0.1	0.2	0.1	0.1
batch size	1	1	1	1	1	1	1
learning rate	1e-4	1e-4	1e-4	1e-4	1e-4	1e-4	1e-4
dropout rate	0.2	0.1	0.2	0.1	0.2	0.1	0.1
number of hidden	800	400	800	800	800	400	800
number of head	2	1	2	2	4	1	1

Table 8: Hyperparameters used for the AMR-GAT for downstream tasks in experiments

Parameters	MR	CR	SUBJ	MPQA	SST-2	TREC	MRPC
weight decay	0.1	0.1	0.2	0.1	0.2	0.1	0.1
batch size	1	1	1	1	1	1	1
learning rate	2e-5	2e-5	2e-5	2e-5	2e-5	2e-5	2e-5
dropout rate	0.1	0.1	0.2	0.1	0.2	0.1	0.1
number of hidden	800	400	800	800	800	400	800
number of head	2	1	2	2	4	1	1

Table 9: Hyperparameters used for the Dep-GAT for downstream tasks in experiments