

A Frequency-Channel Enhanced Dynamic GCN for Aspect-Based Sentiment Analysis

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- **Aspect-Based Sentiment Analysis (ABSA)**
 - Task: Identify the sentiment polarity of different aspects within a sentence.

- **Example:**
 - 'The ambiance is excellent, but the service is disappointing'
 - Aspect:"ambiance",Sentiment:Positive
 - Aspect:"service",Sentiment:Negative

- **Sequence-based Neural Models**
 - Early approaches focused on linear sequence modeling (e.g., LSTMs, attention mechanisms) to capture semantic correlations.
 - Limitation: Treating sentences as linear sequences restricts the ability to capture long-range dependencies.
- **Syntax-aware Static Graph Models**
 - Pioneered the use of Graph Convolutional Networks (GCNs) over dependency trees to bridge distant aspect-opinion pairs.
 - Limitation: Relying solely on static dependency trees inevitably introduces noise from parsing errors.
- **Dynamic Graph & Multi-view Learning**
 - Recent research shifted to dynamically updating graph structures during training to capture evolving dependencies and mitigate noise.
 - Limitation: These dynamic graph approaches still suffer from the inherent over-smoothing problem in deep GCNs.

- **Motivation:**
 - Heavy reliance on static dependency trees inevitably propagates parsing noise and erroneous connections.
 - Deep GCNs suffer from the over-smoothing problem, washing out critical high-frequency sentiment signals.
- **Our Contributions**
 - We propose FCD-GCN, a dynamic architecture that reduces reliance on static parsing tools by learning to refine the graph structure adaptively.
 - We introduce a novel Frequency Attention mechanism to capture global semantic patterns in the spectral domain, offering a new perspective to mitigate over-smoothing.
 - We validate our model through extensive experiments on three benchmark datasets, demonstrating that FCD-GCN consistently outperforms state-of-the-art baselines.

Model Overview

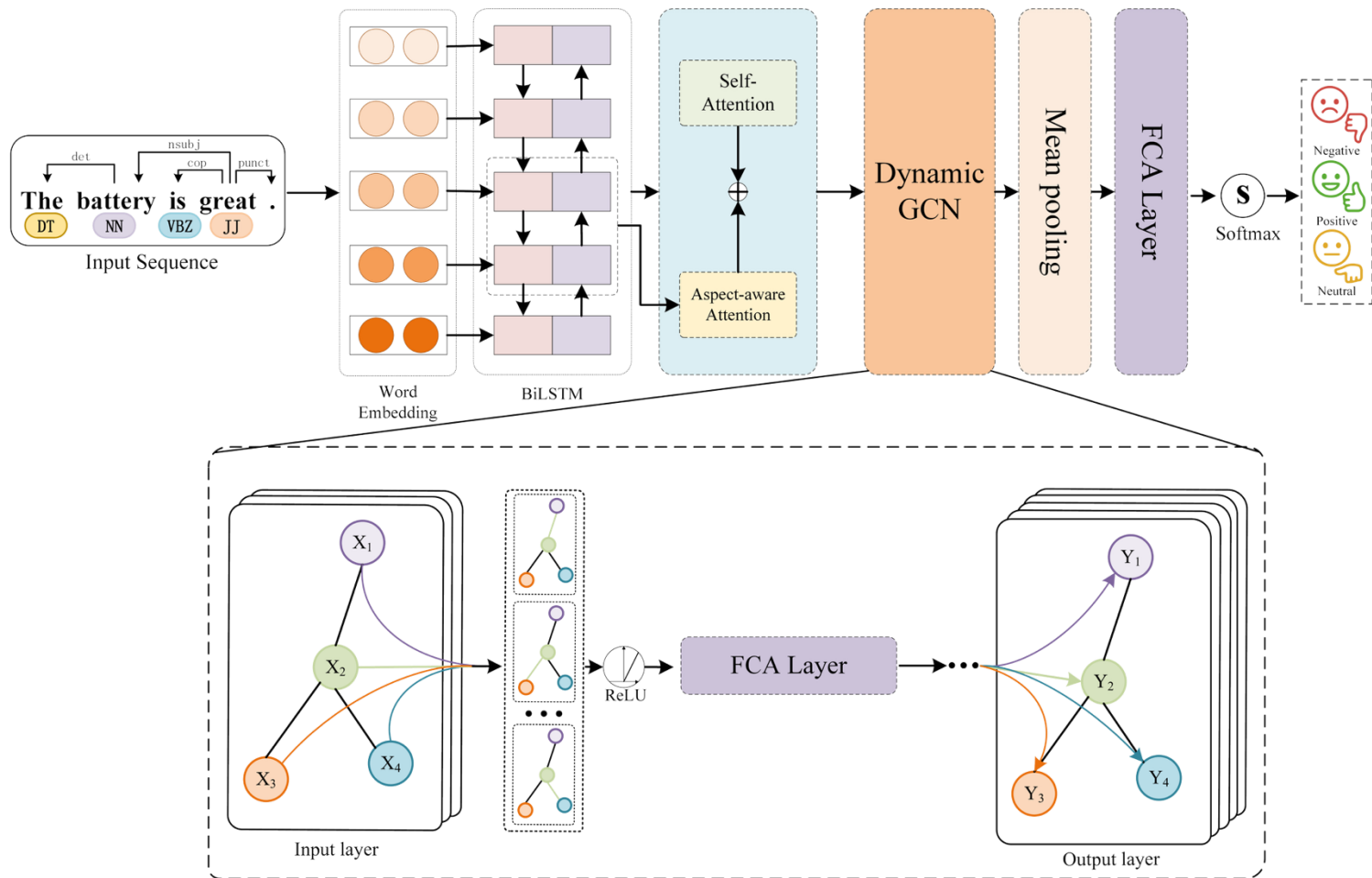
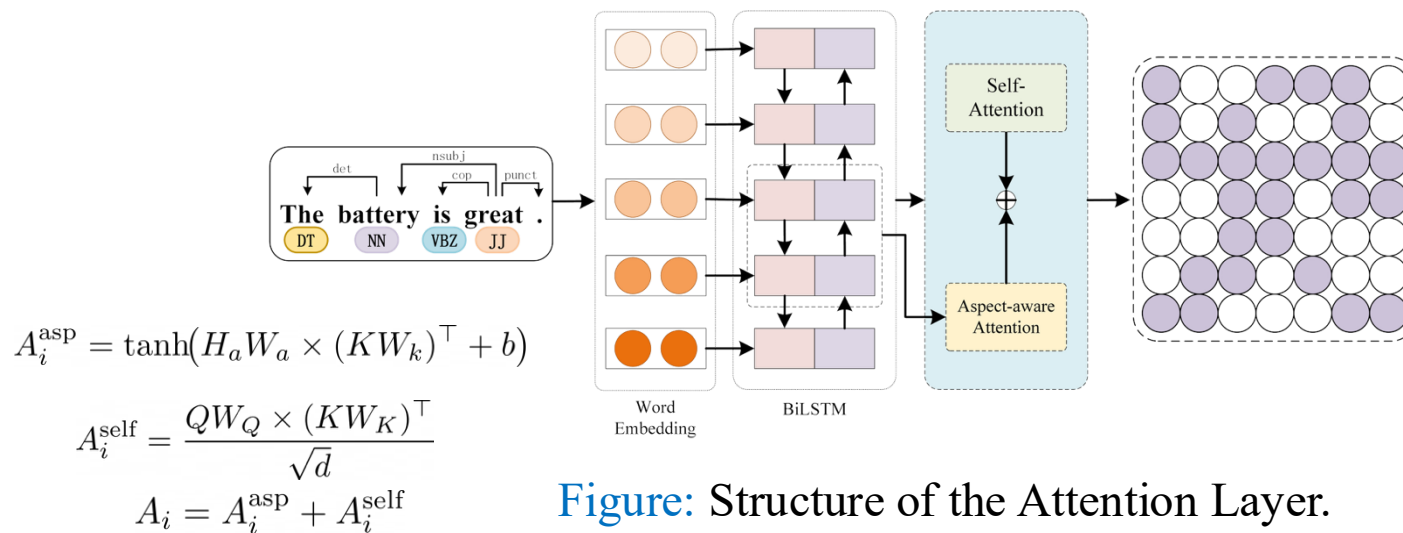


Figure: Overall architecture of the proposed network

Attention Layer



Aspect-aware Branch: Models dependencies conditioned on the specific aspect target.

Self-Attention Branch: Captures global contextual interactions among all tokens.

Head-wise Fusion: Aggregates scores into a unified initial adjacency matrix for the subsequent GCN.

Frequency–Channel Attention Layer

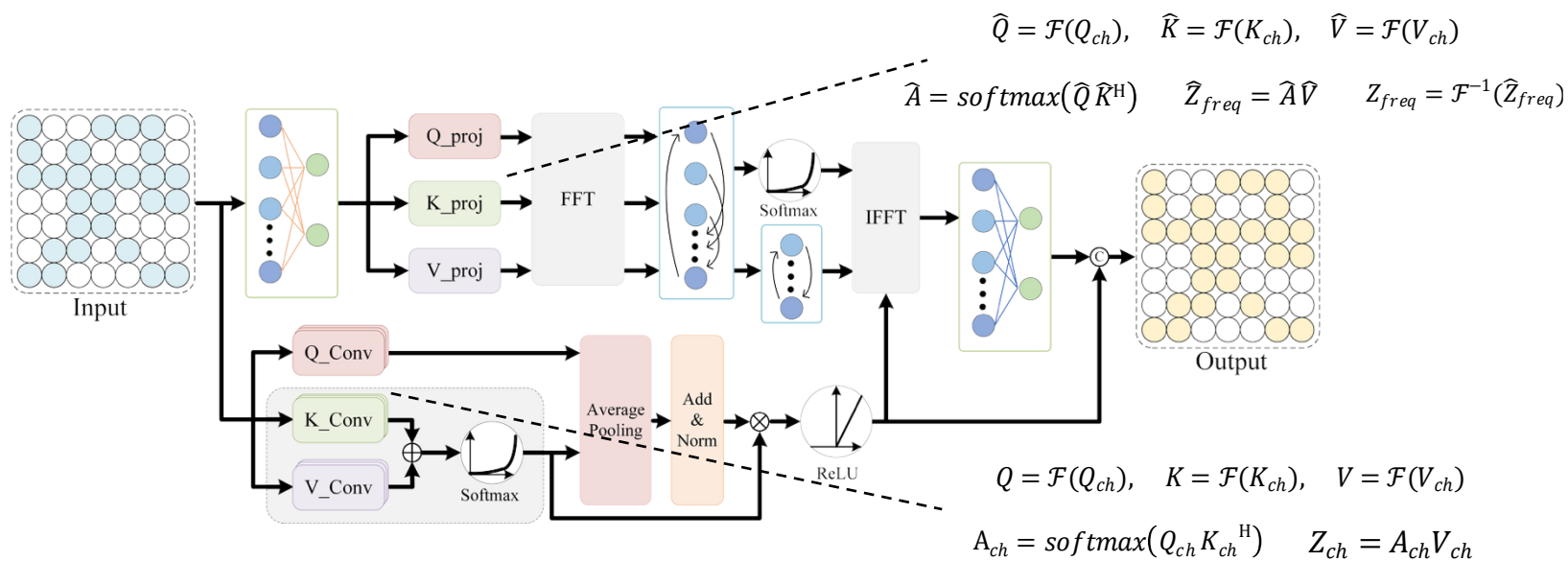


Figure: Structure of the Frequency-Channel Attention (FCA) module.

Frequency Branch: Utilizes Fast Fourier Transform (FFT) to capture long-range patterns in the spectral domain.

Channel Branch: Models inter-dependencies to adaptively reweight informative feature subspaces.

Gated Fusion: Combines dual-branch outputs via a gated residual mechanism to mitigate over-smoothing.

Dynamic GCN Layer

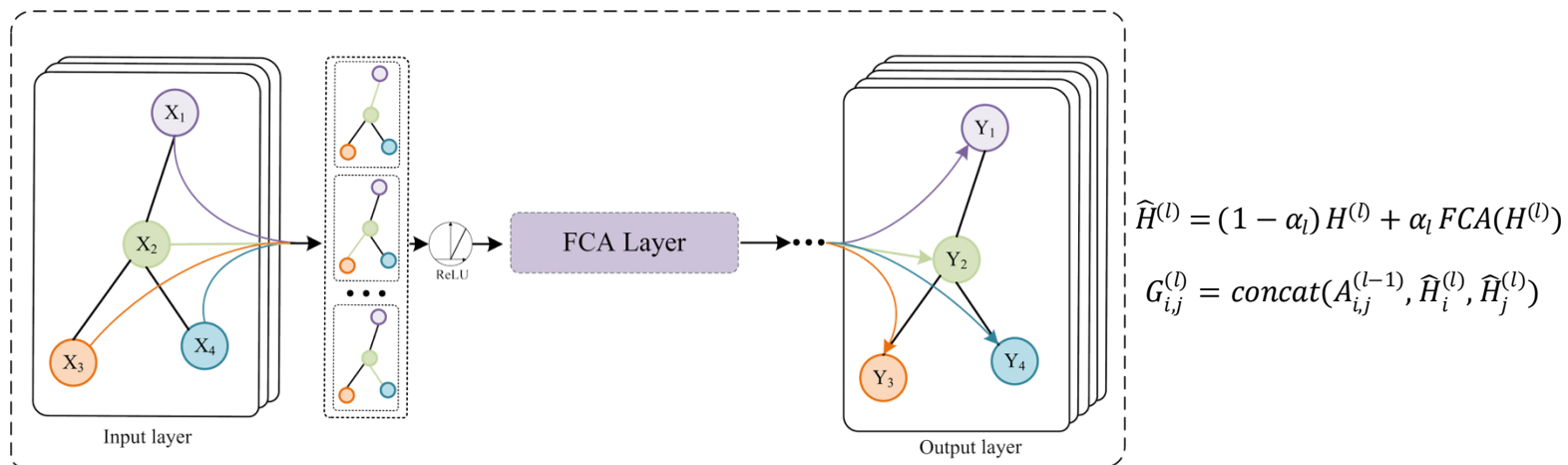


Figure: Structure of the Dynamic GCN Layer.

• Datasets

Dataset	Division	Positive	Negative	Neutral
Laptop	Train	976	851	455
	Test	337	128	167
Restaurant	Train	2164	807	637
	Test	727	196	196
Twitter	Train	1507	1528	3016
	Test	172	169	336

Table: Statistics information of datasets.

- SemEval-2014 Task 4 Restaurant and Laptop (Pontiki et al., 2014)
- Twitter (Dong et al., 2014)

• Evaluation Metric

- Accuracy and Macro F1

We compare our model with the following baselines:

- **ASGCN**
 - Utilizes GCNs on dependency trees to capture syntactic structures and long-range dependencies.
- **DualGCN**
 - Combines syntax-based and semantic-based GCNs with regularizers to capture complementary features.
- **SPGCN**
 - Integrates semantic dependencies and sentiment interactions via multi-graph perception.
- **SSEGCN**
 - Combines syntactic mask matrices with attention to integrate syntax and semantics.
- **SEGCN**
 - Introduces sentiment knowledge nodes with dynamic storage, update, and sharing mechanism.
- **TextGT**
 - Integrates GCN and Transformer layers in a double-view architecture to alleviate over-smoothing.

Main Results

Model	Restaurant		Laptop		Twitter	
	Acc	F1	Acc	F1	Acc	F1
ATAE-LSTM (2016)	77.20	67.02	68.70	63.93	-	-
IAN (2017)	79.26	70.09	72.05	67.38	72.50	70.81
AOA (2018)	79.97	70.42	72.62	67.52	72.30	70.20
Sentic LSTM (2018)	79.43	70.38	70.88	67.19	70.66	67.87
TNet (2018)	80.69	71.27	76.54	71.75	74.90	73.60
ASGCN (2019)	80.77	72.02	75.55	71.05	72.15	70.40
R-GAT (2020)	83.30	76.08	77.42	73.76	75.57	73.82
DGEDT (2020)	83.90	75.10	76.80	72.30	74.80	73.40
DualGCN (2021)	84.27	78.08	78.48	74.74	75.92	74.29
AGCN (2022)	80.02	71.02	75.07	70.96	73.98	72.48
SPGCN (2022)	83.16	74.91	77.90	73.86	74.86	72.95
SSEGCN [†] (2022)	84.32	77.43	<u>79.11</u>	<u>75.97</u>	76.03	74.78
SEGCN (2023)	84.38	77.88	<u>78.21</u>	<u>74.82</u>	76.16	74.68
TextGT [†] (2024)	<u>84.65</u>	<u>78.42</u>	78.52	74.78	<u>76.43</u>	<u>75.15</u>
IDGNN (2024)	<u>83.40</u>	<u>76.37</u>	78.07	74.17	<u>75.94</u>	<u>74.37</u>
FCD-GCN (Ours)	84.87	78.59	79.17	75.98	76.89	75.34
AGCN+BERT (2022)	82.77	73.29	79.94	76.52	75.43	74.11
R-GAT+BERT (2020)	86.68	80.92	80.94	78.20	76.28	75.25
DualGCN+BERT (2022)	87.13	81.16	81.80	78.10	77.40	76.02
SSEGCN+BERT [†] (2022)	86.68	80.50	80.85	77.93	77.56	76.20
SEGCN+BERT (2023)	86.94	81.34	82.76	<u>79.03</u>	77.17	75.26
TextGT+BERT [†] (2024)	87.02	<u>81.87</u>	80.93	<u>77.98</u>	<u>77.63</u>	<u>76.43</u>
IDGNN+BERT (2024)	87.25	81.16	81.12	77.73	<u>76.72</u>	<u>75.92</u>
FCD-GCN+BERT (Ours)	<u>87.20</u>	82.21	<u>81.78</u>	79.14	77.59	76.52

Table: Results comparisons on different datasets.

Model	Restaurant		Laptop		Twitter	
	Acc	F1	Acc	F1	Acc	F1
w/o Frequency Attn	84.02	77.45	78.35	74.90	76.15	74.55
w/o Channel Attn	84.45	77.95	78.70	75.40	76.40	74.90
w/o Dynamic Graph	82.90	75.80	77.50	73.80	75.50	73.40
w/o FCA Module	83.25	76.50	77.90	74.50	75.80	74.10
FCD-GCN (Full)	84.87	78.59	79.17	75.98	76.89	75.34

Table: Experimental results of ablation study.

Review Sentences with Targets	R-GAT	DualGCN	SSEGCN	TextGT	Ours
1. If you are a Tequila fan you will not be disappointed.	😞✗	😞✗	😊✓	😞✗	😊✓
2. The falafal was rather over cooked..., but the chicken was fine.	😞✓, 😞✗	😞✓, 😞✗	😞✓, 😞✗	😞✓, 😊✓	😞✓, 😊✓
3. Windows 8 was not to my liking but the touch screen ... were cool.	😞✓, 😞✗	😞✓, 😊✓	😞✓, 😊✓	😞✓, 😊✓	😞✓, 😊✓
4. I love my iPhone but hate the AT&T service and battery .	😊✓, 😞✗, 😞✓	😊✓, 😞✓, 😞✗	😊✓, 😞✓, 😞✓	😊✓, 😞✓, 😞✓	😊✓, 😞✓, 😞✓

Table: Comparison of our model with state-of-the-art methods in a case study.

Effect of Activation Functions

Function	Restaurant		Laptop		Twitter	
	Acc	F1	Acc	F1	Acc	F1
Tanh	84.07	77.52	78.21	75.07	75.96	74.58
PReLU	84.36	77.93	78.52	75.34	76.13	74.85
SELU	83.94	77.41	78.04	74.92	75.77	74.36
Sigmoid	83.76	76.80	77.95	74.85	75.32	73.96
ReLU	84.87	78.59	79.17	75.98	76.89	75.34

Table: Effect of Activation Functions in the FCA Module.

Impact of GCN Layers

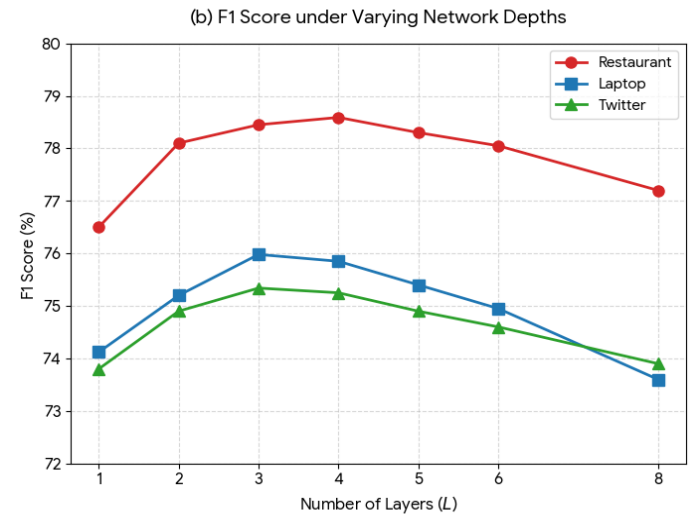
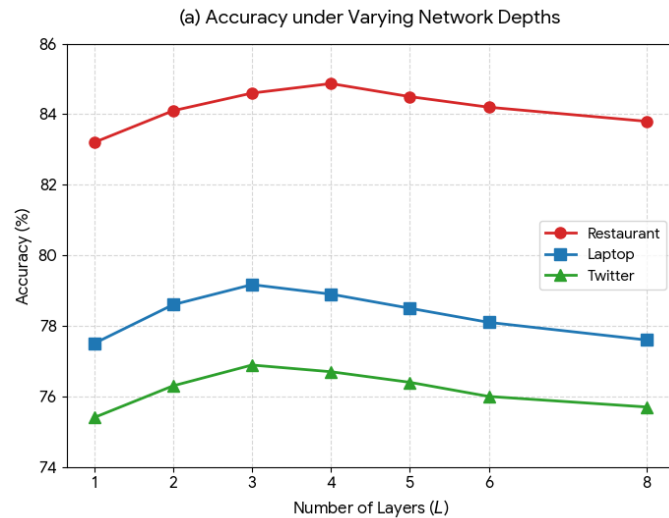


Figure: Effect of the number of GCN layers.

- We proposed FCD-GCN, a frequency-channel enhanced dynamic graph convolutional network for ABSA.
- Introduced dynamic graph refinement and frequency-channel attention to better capture aspect-context associations.
- Achieved state-of-the-art performance on multiple benchmark datasets.

Thank you!

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