Aspect-level Sentiment Analysis Based on Semantic Heterogeneous Graph Convolutional Network

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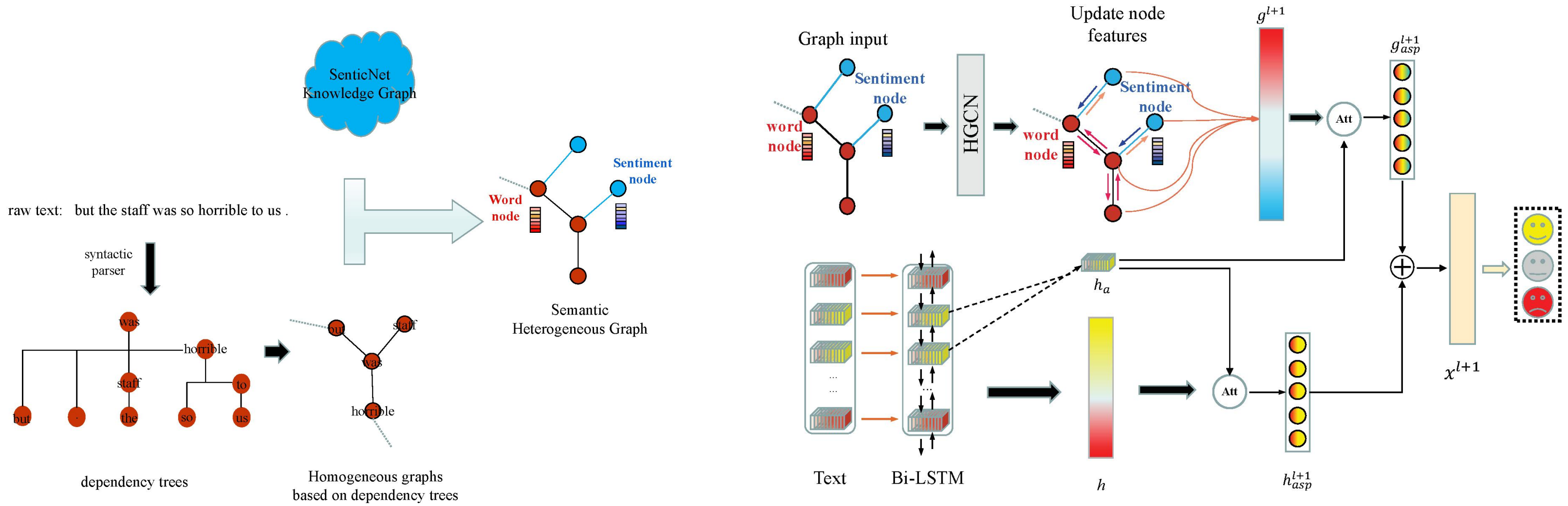
Problems & Ideas

- Problems of conventional stereo matching approaches:
  - The accuracy of the dependency parser cannot be determined, which may keep aspect words away from its related opinion words in a depen dency tree.
  - Existing research does not effectively integrate the affective nowledge into the graph convolution network.
- Ideas: A heterogeneous model that takes into account the emotional information of the words themselves.

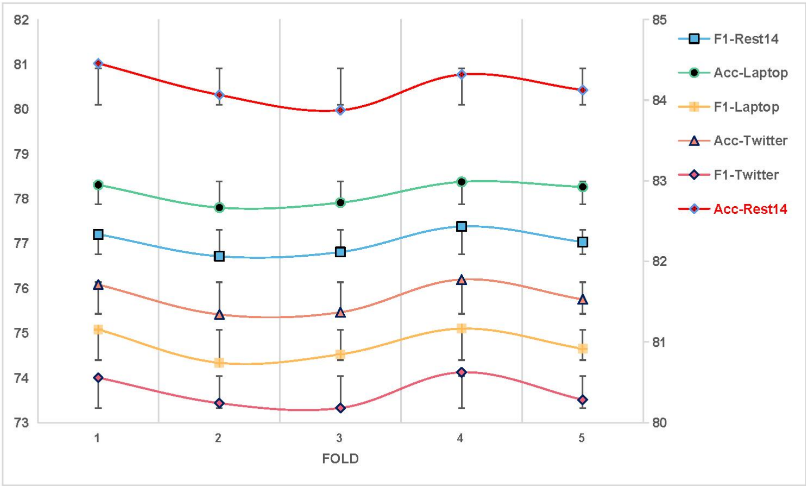


Left: Heterogeneous graphs formed by introducing the sentiment information of words; Right: The training framework of the whole model (Semantic-HGCN).

Main Conclusions

- Conclusions:
  - We introduce sentiment information of words to construct heterogeneous graphs for aspect-level sentiment analysis.
  - Our method consistently outperforms all compared models in both of accuracy and macro-F1 scores on datasets Rest14, Laptop and Rest16. It is worth noting that our method outperforms all other methods for Accuracy on all data sets.

Model	Rest14		Laptop		Twitter		Rest15		Rest16	
	Acc	Mac-F1	Acc	Mac-F	Acc	Mac-F1	Acc	Mac-F1	Acc	Mac-F1
LSTM+SynATT [50]	80.45	71.26	72.57	69.13	-	-	-	-	-	-
ASGCN [7]	80.77	72.02	75.55	71.05	72.15	70.40	79.89	61.89	86.24	67.62
CDT [23]	82.30	74.02	77.19	72.99	74.66	73.66	70.92	61.68	86.24	67.62
GAT [24]	78.21	67.17	73.04	68.11	71.67	70.13	-	-	-	-
TD-GAT [25]	80.35	76.13	74.13	72.01	72.68	71.15	80.38	60.50	87.71	67.87
BiGCN [10]	81.97	73.48	74.59	71.84	74.16	73.35	81.16	64.79	88.96	70.84
KGCapsAN [35]	82.05	74.04	76.96	72.89	74.13	72.52	81.86	65.60	88.47	70.72
ATAE-LSTM [3]	77.20	-	68.70	-	-	-	75.2	64.1	82.1	64.4
IAN [12]	78.60	-	72.10	-	-	-	75.5	63.9	83.6	65.2
RAM [5]	80.23	70.80	74.49	71.35	69.36	67.30	76.7	64.5	83.9	66.1
MGAN [13]	81.25	71.94	75.39	72.47	72.54	70.81	-	-	-	-
LSTM [51]	79.10	69.00	71.22	65.75	69.51	67.98	77.37	55.17	86.80	63.88
SIOT-Bi-GRU [52]	82.05	72.53	77.11	73.28	74.56	73.52	-	-	-	-
R-GAT [26]	83.30	76.08	77.42	73.76	75.57	73.82	-	-	-	-
TM [53]	78.02	67.85	73.51	70.80	-	-	-	-	-	-
MCRF-SA [19]	82.86	73.78	77.64	74.23	-	-	80.82	61.59	89.51	**75.72**
TNET [54]	80.69	71.27	76.54	71.75	74.90	73.60	-	-	-	-
PWCN [17]	80.89	72.16	75.86	71.94	72.10	70.75	-	-	-	-
RGAT-FT-RoBERTa [55]	82.76	75.25	77.43	74.21	75.43	**74.04**	-	-	-	-
Semantic-HGCN	**84.27**	**77.16**	**78.29**	**74.78**	**75.78**	73.68	**82.31**	**66.46**	**90.12**	72.6



Left: Comparision results for all methods on the five datasets, where Acc means Accuracy, Mac-F1 means Macro-F1.Right: Visualization of robustness evaluation of Semantic-HGCN.