Emotion Recognition in Text

Using Graph Similarity Criteria

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AIM

1. Developing the approach to **emotion recognition** employing $\boldsymbol{n}$**-grams** to obtain **graph** representation of text
2. Text represented as a sequence of characters divided into n-grams
3. Constructing the graphs of n-grams

Capturing the relations between words in the text that occur close together using graph representation

RELATED WORK

- Employing word embedding vectors
- **GNN** enhanced by utilizing BERT to obtain semantic features
- Probabilistic classifiers, e.g., Bayes Classification, Support Vector Machine
- Similarity criteria: subgraph matching, edit distance, belief propagation

METHODOLOGY

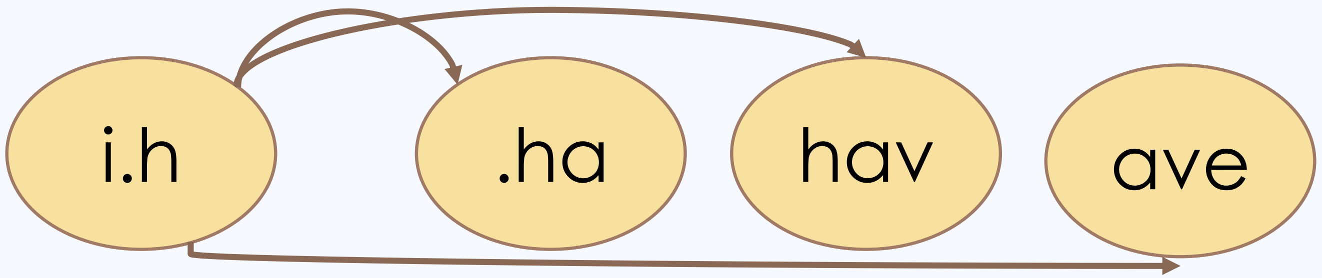
GRAPH REPRESENTATION OF THE TEXT

Using $\boldsymbol{n}$**-grams**; testing different values of $\boldsymbol{n}$

Text example: "i have a good feeling about this so i am excited"

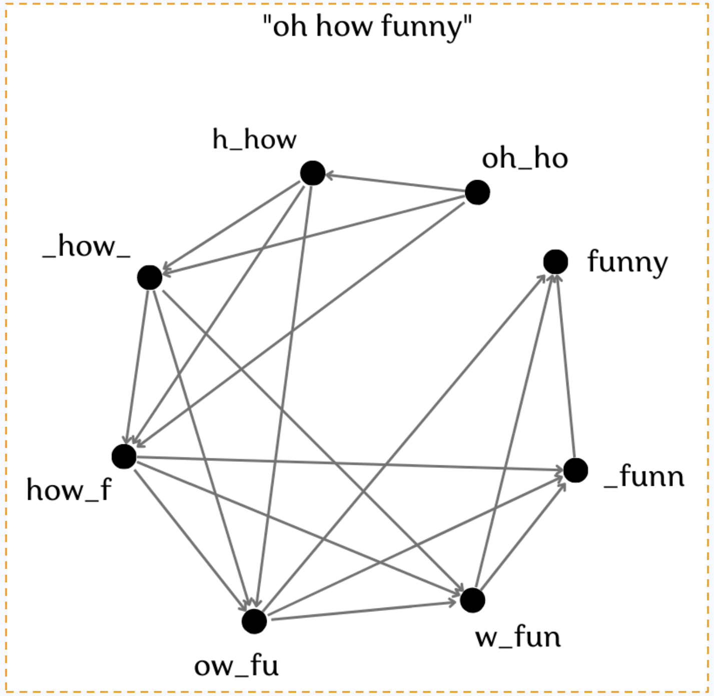
Vertices: n-grams of characters

Edges: the connections between the adjacent n-grams; directed and undirected graphs



CLASSIFICATION USING GRAPH COMPARISON

- Given the data set of texts **labeled** with emotions
- Construct the graphs corresponding to emotions using all the labeled texts



Given an **unlabeled** text:

1) construct the graph of the text

2) compare with the category graphs

3) the highest score of similarity → an emotion predicted

EXAMPLES OF CLASSIFICATION

happy	"joy was in every face and every heart"
fearful	"peter sat down to rest he was out of breath and trembling with fright and he had not the least idea which way to go"
surprised	"the duck stared at it and exclaimed it is very large and not at all like the others"

VARIABLES

Testing different similarity criteria between the two graphs

- Number of common **vertices** in the graphs
- Number of common **edges** in the graphs
- Number of edges in the **maximum common subgraph** (MCS)
- Number of vertices in the MCS (***m***)
- The difference between the number of edges in the complete graph with ***m*** vertices and the number of edges in the MCS (**z**)

EXPERIMENTAL RESULTS

- TABLE 1: Results of text classification using directed graphs

Similarity criterion	Accuracy	Precision	Recall	F1
Common vertices	0.488	0.506	0.332	0.323
Common edges	0.537	**0.683**	0.408	0.432
z	0.372	0.074	0.200	0.108
Vertices in the MCS	0.570	0.622	0.426	0.446
Edges in the MCS	**0.579**	0.625	**0.454**	**0.478**

EXPERIMENTAL RESULTS

- TABLE 2: Results of text classification using undirected graphs

Similarity criterion	Accuracy	Precision	Recall	F1
Common vertices	0.488	0.506	0.332	0.323
Common edges	0.554	**0.669**	0.429	**0.460**
z	0.372	0.074	0.200	0.108
Vertices in the MCS	0.545	0.527	0.399	0.406
Edges in the MCS	**0.570**	0.581	**0.439**	0.453

EXPERIMENTAL RESULTS

Confusion matrix for the setup utilizing the similarity criteria based on the construction of the MCS

The prediction / **The actual label**	**Happy**	**Fearful**	**Surprised**	**Sad**	**Angry-Disgusted**
Happy	**0.98**	0	0	0	0.02
Fearful	0.65	**0.24**	0.06	0.06	0
Surprised	0.55	0.18	**0.09**	0	0.18
Sad	0.54	0	0	**0.46**	0
Angry-Disgusted	0.50	0.05	0	0.09	**0.36**

DISCUSSION

Strengths

- Ability to capture the context of the given words on different levels
- Breadth of the contextual frame varied by altering the number of n-grams with which a certain n-gram is connected

Limitations

- Imbalanced data set
- Large graphs when training on bigger data sets: complex to compute

CONCLUSION

Constructing a graph of n-grams for a given text; comparing this graph to each of the emotion category graphs

Future work

- Employing alternative graph similarity measures
- Using clustering algorithms to obtain patterns characteristic to emotion categories
- Utilizing graph neural network architecture