### **Text Based Emotion Detection**

SemEval2025-Task 11 [1]

### CS779 Group-3

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- ► Future Directions

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  - Track A: Multi-label Emotion Detection
  - Track B: Emotion Intensity
  - Track C: Cross-lingual Emotion Detection

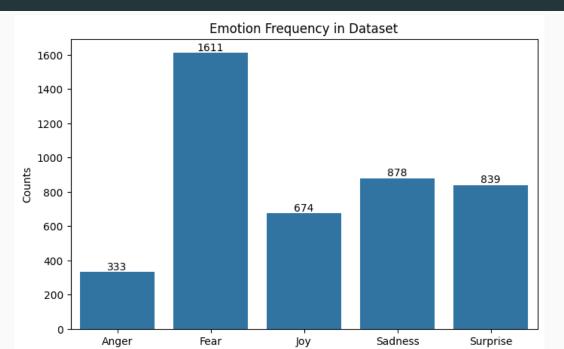
## Dataset for Track A

	Α	В	С	D	Е	F	G
1	id	text	Anger	Fear	Joy	Sadness	Surprise
2	eng_train_track_a_00001	But not very happy.	0	0	1	1	0
3	eng_train_track_a_00002	Well she's not gon na last the whole song like that, so since I'm ▶	0	0	1	0	0
4	eng_train_track_a_00003	She sat at her Papa's recliner sofa only to move next to me and	0	0	0	0	0
5	eng_train_track_a_00004	Yes, the Oklahoma city bombing.	1	1	. 0	1	1
6	eng_train_track_a_00005	They were dancing to Bolero.	0	0	1	0	0
7	eng_train_track_a_00006	Still had sex with her, though.	0	0	1	0	0
8	eng_train_track_a_00007	But I am exhausted-my eyes feel like they are about to pop out &	0	1	. 0	1	0
9	eng_train_track_a_00008	We ordered some food at Mcdonalds instead of buying food at the	1	0	0	0	0
10	eng_train_track_a_00009	Now my parents live in the foothills, and the college is in a large	0	0	0	0	0
11	eng_train_track_a_00010	We get to the porch and my dog starts *growling*, like a big boy	0	1	. 0	0	1
12	eng_train_track_a_00011	I moved my arms, stretching the muscles, watching ribbons of fl	0	0	1	0	0
13	eng_train_track_a_00012	The room was small but brightly lit and I sat on a two-seater could	0	0	0	0	0
14	eng_train_track_a_00013	The top of the mattress comes up a little above my waist!	0	0	1	0	0
15	eng_train_track_a_00014	I have plenty more.	0	0	1	0	0
16	eng_train_track_a_00015	it took a little longer for my feet to hurt which was nice.	0	0	1	0	0
17	eng_train_track_a_00016	About 2 weeks ago I thought I pulled a muscle in my calf.	0	1	. 0	1	0
18	eng_train_track_a_00017	I still cannot explain this.	0	1	. 0	0	1
19	eng_train_track_a_00018	more funny than creepy being on this side of the story:	0	1	. 1	0	1
20	eng_train_track_a_00019	5 year old me was scarred for life.	0	1	. 0	1	0
21	eng_train_track_a_00020	The waitress had physical therapy experience and prepared a nib	0	0	1	0	0
22	eng_train_track_a_00021	Then I decided to try and get up to go to the restroom, but I could	0	1	. 0	0	1
23	eng_train_track_a_00022	" The cop tells him to have a nice day and walks away.	1	0	1	0	1
24	eng_train_track_a_00023	The following two days, I was in a moderate amount of pain and	0	1	. 0	1	0
25	eng_train_track_a_00024	He saw blood and said, "Mommy!	0	1	. 0	1	1
26	eng_train_track_a_00025	Not the most unnerving feeling, but the most prominent event in	0	1	. 0	0	1
27	eng_train_track_a_00026	When the dust settled I looked over at my wife and saw she was	0	0	1	0	0
28	eng_train_track_a_00027	I love you boy.	0	0	1	0	0
29	eng_train_track_a_00028	i brush my teeth at least twice a day.	0	0	0	0	0
30	eng_train_track_a_00029	Needless to say, I turned her down.	0	0	0	0	0

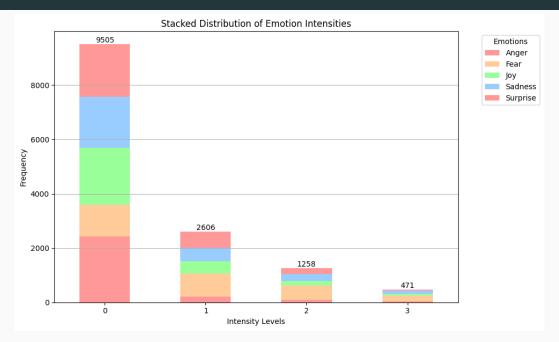
## Dataset for Track B

	В	С	D	Е	F	G
1	text	Anger	Fear	Joy	Sadness	Surprise
2	My Spanish language skills were fairly basic.	0	1	0	0	0
3	Don't mess with my orange juice.	2	0	0	0	0
4	So, I am from a science background and analyze everything skeptically.	0	0	0	0	0
5	I was writing away.	0	0	1	0	0
6	Apparently it wasn't as life threatening as I believed at the time because the doctor of	0	1	. 0	1	0
7	I could not believe how fast it went considering I had to stay on my back the whole I	0	1	. 0	0	1
8	The room really isn't a room, it is as though she is kneeling on the floor but I don't set	0	2	0	0	2
9	It looks like dark smelly applesauce.	0	1	0	0	1
10	like seriously, alot can not understand and im slow at registering words in my brain of	0	2	0	1	0
11	Life readings obviously defective.	1	1	0	0	0
12	months before that, i just prayed to God that i wanted to meet someone right for me,	0	0	0	2	0
13	My grandmother fell very ill this past summer, and ended up suffering from encephab	0	1	0	3	0
14	A highly intoxicated roommate and a black girl going at it.	1	2	0	0	2
15	You are the demon.	2	1	0	0	1
16	I had an ant crawling on my elbow just now, and I flicked him off.	0	1	0	0	0
17	Immediately my throat tightens.	0	3	0	0	0
18	Kick my heels up and shout.	0	0	2	0	0
19	I closed my eyes as I took in a deep breath.	0	0	1	0	0
20	he got pretty fucking scared and started sprinting away from me.	0	3	0	0	1
21	Nothing was touching it.	0	1	0	0	1
22	Met a lot of random canadians that night.	0	0	1	0	1
23	I saw that, too.	0	0	0	0	1
24	just the thought of having to get up and speak in front of 30 people makes my heart	0	3	0	0	0
25	Moral of the story?	0	0	0	0	1
26	I got my first raspberry from a crowd surfer falling and my face hitting the monitor, b	0	1	0	1	1
27	At this point he decided to consult the woman at the front desk for more information.	0	1	0	0	0
28	When she decided it was time to go back to my stall, I didn't want to leave and I pre	0	1	0	1	0
29	Finding them, I whipped one out and put it in my ear, swabbing.	0	0	0	0	0
30	I looked down only to see a flashing red light buried in the dirt under my feet.	0	1	0	0	1

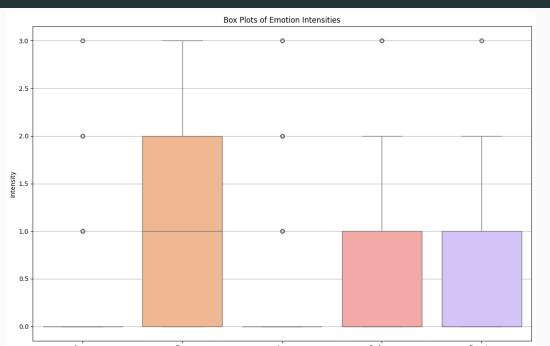
### How are the emotions distributed?



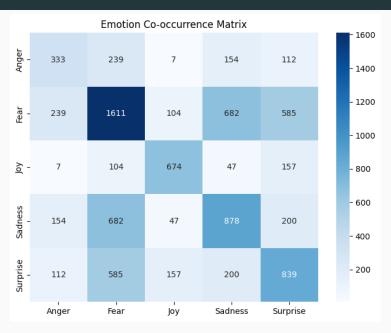
## How are the intensity levels distributed?



# How are the intensity levels distributed?



## How frequently are the emotions co-occurring?



## Datasets available for TBED

Dataset	Source	Size	Emotion Model	
GoEmotions [8]	Blogs (Reddit) ; labeled between 27 emotional classes.	58 K	Discrete, Componential	
ISEAR (2017) [19]	Worldwide survey on causes and consequences. Emotional state reported as happiness, fear, anger, sorrow, disgust, humiliation, and guilt.	7.6K	Dimensional	
SemEval (2018) [16]	SemEval (2018) [16] Blogs, Tweets		Discrete	
SemEval (2019) [6]	Text conversation between two people. Dialogue classified as either happy, angry, unhappy, or other	39 K	Discrete	
EMOBANK [5]	EMOBANK [5] Blogs, newspaper headlines, letters, and travel guides		Dimensional	
SuperTweetEval [4]	Benchmark for evaluating tweet-level sentiment and language. It contains a diverse collection of tweets, annotated for 12 heterogeneous NLP tasks.		Discrete; Dimensional	
Valence and arousal [17]	Facebook posts. Contains labels for two different grades, which are not related to each other:	3.2K	Dimensional	
CBET [10]	Tweets	77k	Componential	
ISEAR (2018)	Cross-cultural studies	40 K	Discrete	

#### **Dataset Overview**

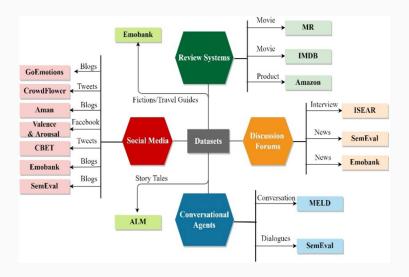


Figure 1: Dataset with topic and domains

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- Experiments on **SemEval2018 multi-label emotion data** [16].
- Performed over three languages: English, Arabic, Spanish.

### Contextual emotion detection using ensemble deep learning

- Proposed an ensemble deep learning approach for TBED by Bi-LSTM, Bi-GRU, CNN along with BERT, RoBERTa, and XLNet. [20]
- Uses weighted hard voting ensemble, the class with the highest number of votes is selected as the final prediction.

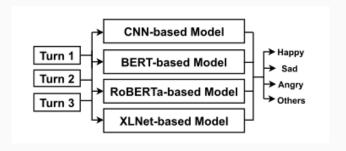


Figure 2: Ensemble Approach

## Contextual emotion detection using ensemble deep learning

#### Results

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#### Results

- The best results were achieved when BERT and RoBERTa were given double the weight (0.333) compared to CNN and XLNet (0.167)
- Evaluated using the **SemEval-2019 Task 3: EmoContext** [6] dataset that contains 3-turn conversations classified as Happy, Angry, Sad, and Others.

## **Emotion Detection in Low-Resource Languages**

 Multilingual models trained on diverse datasets for language-agnostic emotion recognition.

### **Emotion Detection in Low-Resource Languages**

- Multilingual models trained on diverse datasets for language-agnostic emotion recognition.
- Takes a specific focus on the domain of depression detection within the Thai context. It proposes knowledge transfer from English to Thai as a viable strategy.
   [2]

#### **Shortlisted Models**

- ► Small Models:
  - ► SamLowe/roberta-base-go\_emotions [15]
  - ► cardiffnlp/twitter-roberta-large-emotion-latest [4]
  - ► Emanuel/twitter-emotion-deberta-v3-base [12]
- ► Large Models:
  - ► meta-llama/Meta-Llama-3-8B-Instruct [9]

## SamLowe/roberta-base-go-emotions

- ► Pretrained Model: FacebookAl/roberta-base[14]
- ► Linear classifier trained on top of Roberta base model
- ▶ Dataset trained on: google-research-datasets/go-emotions [8]
- ► Results[15] on Goemotions dataset:
  - ► Accuracy: 0.474
  - ► F1: 0.450
- ▶ 28 classes for classification (multi-emotion labels)

### cardiffnlp/twitter-roberta-large-emotion-latest

- ► Pretrained model: FacebookAl/roberta-large[14]
- ► Linear classifier finetuned on: 154M tweets
- ► Finetuned on: cardiffnlp/super\_tweeteval[4]
- Results[4] on super\_tweeteval dataset:
  - ► Avg Macro F1: 0.58
- ▶ Results[18] on further finetuned on Goeomotions dataset:
  - ► F1: 0.92
- ▶ 11 classes for classification (multi-emotion labels)

## Emanuel/twitter-emotion-deberta-v3-base

- ► Pretrained model: microsoft/deberta-v3-base[11]
- ► Pretrained on: 160GB Data
- ► Linear classifier finetuned on: dair-ai/emotion[7]
- ► Results[12] on dair-ai/emotion dataset:
  - ► Accuracy: 0.937
- ► 6 classes for classification (single-emotion labels)

## meta-llama/Meta-Llama-3-8B-Instruct

- ► Pretrained Model: LLama3-8B[9]
- ► Trained on: 15T+ web tokens
- ▶ instruction tuned

### **Experiments**

- ► The training data was released on 10/09/24
- ► The models were evaluated on the training data for english language without any fine-tuning
- Accuracy, Micro, Macro and Weighted F-1 Scores were calculated for the predictions of these models for Track A dataset
- ► Accuracy calculated for Track B dataset on the same models

#### Results

Model Name	A	Micro	Macro	Weighted
woder warne	Accuracy	F1	F1	F1
SamLowe/roberta-base-go_emotions	0.21	0.45	0.44	0.42
cardiffnlp/twitter-roberta-large-emotion-latest	0.29	0.54	0.53	0.50
Emanuel/twitter-emotion-deberta-v3-base	0.16	0.45	0.40	0.45
meta-Ilama/Meta-Llama-3-8B-Instruct	0.24	0.58	0.59	0.58

 Table 1: Results for Track A dataset without fine-tuning on the shortlisted transformer models

Model Name	Accuracy
SamLowe/roberta-base-go_emotions	0.11
cardiffnlp/twitter-roberta-large-emotion-latest	0.10
meta-Ilama/Meta-Llama-3-8B-Instruct	0.18

Table 2: Results for Track B dataset without fine-tuning on the shortlisted transformer models

#### **Future Directions**

- ► Fine-tuning with released data to be done on all the models.
- ► Fine-tuning with an extra classifier on top of some models with fine-grained emotion labels to be done with all weights freezed.
- Ensemble modelling to be explored
- ▶ Building and finetuning novel architectures for all the tracks

## Timeline

Future Task	Member Responsible and Timeline
Selection of some more models for track A and B	Every member- till 05/10/24
Selection of multi-lingual models for track C	Every member- till 05/10/24
Fine-tuning on all the shortlisted models	Every member- till 13/10/24
Exploring different combination of ensemble models	Every member- till 20/10/24
Building our own models for all the tracks	Every member- till 10/11/24
Fine-tuning our models	Every member- till 20/11/24
Improving and finalizing our models	Every member- till 05/01/25
Final submission on the competition webpage	Every member- till 15/01/25

Table 3: Timeline of planned future tasks

## Contribution

Task Done	Members Contribution		
Literature survey for Text Based	Equal contribution by all		
Emotion Detection	Equal contribution by all		
Group discussions on literature survey	Equal contribution by all		
Shortlisting the models based on	Equal contribution by all		
literature survey	Equal contribution by all		
Initial experimentation with the	Equal contribution by all		
pretrained models	Equal contribution by all		
Creation of presentation slides, Project	Equal contribution by all		
Document and Mid-Term Project Report	Equal contribution by all		

Table 4: Member Contribution

#### References

- [1] Idris Abdulmumin. Semeval2025-task11, 2024. URL https://github.com/emotion-analysis-project/SemEval2025-Task11.
- [2] Vachirapong Ajrobol, Nidhi Aggarwal, Utkarsh Shukla, et al. Explainable cross-lingual depression identification based on multi-head attention networks in thai context. *International Journal of Information Technology*, 2023. doi: 10.1007/s41870-023-01512-3.
- [3] Hassan Alhuzali and Sophia Ananiadou. Spanemo: Casting multi-label emotion classification as span-prediction. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing (EMNLP)*, Online and Punta Cana, Dominican Republic, 2021. Association for Computational Linguistics.
- [4] Dimosthenis Antypas, Asahi Ushio, Francesco Barbieri, Leonardo Neves, Kiamehr Rezaee, Luis Espinosa-Anke, Jiaxin Pei, and Jose Camacho-Collados. Supertweeteval: A challenging, unified and heterogeneous benchmark for social media nlp research, 2023. URL https://arxiv.org/abs/2310.14757.
- [5] Sven Buechel and Udo Hahn. Emobank: Studying the impact of annotation perspective and representation format on dimensional emotion analysis. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers, pages 578–585, 2017.
- [6] Ankush Chatterjee, Khyathi Raghavi Narahari, Meghana Joshi, and Puneet Agrawal. Semeval-2019 task 3: Emocontext contextual emotion detection in text. In Proceedings of the 13th International Workshop on Semantic Evaluation, pages 39–48, 2019.
- [7] DAIR.Al. dair-ai/emotion, 2024. URL https://huggingface.co/datasets/dair-ai/emotion/tree/main.
- [8] Dorottya Demszky, Dana Movshovitz-Attias, Jeongwoo Ko, Alan Cowen, Gaurav Nemade, and Sujith Ravi. Goemotions: A dataset of fine-grained emotions, 2020. URL https://arxiv.org/abs/2005.00547.
- [9] Abhimanyu Dubey and et al. The llama 3 herd of models, 2024. URL https://arxiv.org/abs/2407.21783.

#### References ii

- [10] Amir Gholipour Shahraki. Emotion mining from text, 2015. Available at: https://example.com.
- [11] Pengcheng He, Jianfeng Gao, and Weizhu Chen. Debertav3: Improving deberta using electra-style pre-training with gradient-disentangled embedding sharing, 2023. URL https://arxiv.org/abs/2111.09543.
- [12] Emanuel Huber. Emanuel/twitter-emotion-deberta-v3-base, 2021. URL https://huggingface.co/Emanuel/twitter-emotion-deberta-v3-base.
- [13] Sheetal Kusal, Shruti Patil, Jyoti Choudrie, Ketan Kotecha, Deepali Vora, and Ilias Pappas. A systematic review of applications of natural language processing and future challenges with special emphasis in text-based emotion detection. Artificial Intelligence Review, 56: 15129–15215, 2023. doi: 10.1007/s10462-023-10509-0.
- [14] Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized bert pretraining approach, 2019. URL https://arxiv.org/abs/1907.11692.
- [15] Sam Lowe. Samlowe/roberta-base-go\_emotions, 2022. URL https://huggingface.co/SamLowe/roberta-base-go\_emotions.
- [16] Saif Mohammad, Felipe Bravo-Marquez, Mohammad Salameh, and Svetlana Kiritchenko. Semeval-2018 task 1: Affect in tweets. In Proceedings of the 12th International Workshop on Semantic Evaluation, pages 1–17, 2018.
- [17] Daniel Preoţiuc-Pietro, H. Andrew Schwartz, Gregory Park, Johannes Eichstaedt, Margaret Kern, Lyle Ungar, and Elizabeth Shulman. Modelling valence and arousal in facebook posts. In Proceedings of the 7th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis, pages 9–15, 2016.
- [18] Mahdi Rezapour. Emotion detection with transformers: A comparative study, 2024. URL https://arxiv.org/abs/2403.15454.
- [19] Klaus R Scherer and Harald G Wallbott. Evidence for universality and cultural variation of differential emotion response patterning. Journal of Personality and Social Psychology, 66(2):310–328, 1994.
- [20] Asalah Thiab, Luay Alawneh, and Mohammad AL-Smadi. Contextual emotion detection using ensemble deep learning. Computer Speech Language, 86:101604, 2024. ISSN 0885-2308. doi: https://doi.org/10.1016/j.csl.2023.101604. URL https://www.sciencedirect.com/science/article/pii/S0885230823001237.