Text Based Cross-Lingual Emotion Detection

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1. Introduction

Emotion Detection (ED) task:

- for a given text sample (sentence, paragraph, sequence of messages), determine which emotions is the author experiencing or conveying
- the set of possible emotions is predefined

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- Largest gains in performance are thanks to the rise of pre-trained Large Language Models (LLMs)

2. Task and Data

Cross-Lingual Emotion Detection:

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Cross-Lingual Emotion Detection:

- texts from a set of **source languages** are annotated for ED
- the goal is to obtain an emotion detector for a new **target language** which has no annotated data for this task

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The data used in this project comes from Task 11 of SemEval 2025.

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The set of emotions to be recognised are: anger, disgust, fear, joy, sadness and surprise

Designed setup:

- Use English (eng)*, German (deu) and Spanish (esp) as **source languages**
- Test on Romanian (ron), Ukrainian (ukr) and Hindi (hin) as **target languages**

*English texts are not labeled for **disgust**

3. Approach & Results

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- the centerpiece of the approach is a Cross-Lingual LLM capable of processing all the source and target languages
- assuming that the LLM provides language-agnostic representations for the input texts, then a detector trained on the source languages should generalize to the target languages as well

3. Approach & Results

a. LEALLA-large: linear probing (lp)

Source languages	Val acc.	Target language		
		ron	ukr	hin
eng	53.49	41.87	18.12	27.16
deu	46.37	45.89	20.89	26.56
esp	59.23	42.89	**26.50**	**44.43**
eng, deu, esp	52.94	**46.97**	23.58	32.68

Table 1: Results on the dev set of target languages for the linear classifiers trained on embeddings from the LEALLA-large model.

3. Approach & Results

b. LEALLA-large: linear probing and fine-tuning (LP-FT)

Source languages	Val acc.	Target language		
		ron	ukr	hin
eng, deu, esp	70.93	53.72	36.32	53.17

Table 2: Results of the finetuned LEALLA-large model on the dev set of target languages. The model checkpoint is selected based on the validation macro F_1 score.

3. Approach & Results

c. QWEN2.5 7B: linear probing

Source languages	Val acc.	Target language		
		ron	ukr	hin
eng	46.01	36.69	14.53	19.35
deu	40.44	43.94	15.82	22.60
esp	55.58	44.10	**16.79**	21.39
eng, deu, esp	52.03	**45.21**	16.67	**23.46**
eng*	41.04	37.26	**16.85**	16.78
deu*	37.85	31.48	11.69	19.08
esp*	52.66	28.81	15.52	18.90
eng, deu, esp*	50.80	**37.35**	15.16	**21.43**

Table 3: Results on the dev set of target languages for the linear classifiers trained on embeddings from the QWEN2.5 model. The mark * indicates results for the sklearn implementation of logistic regression.

3. Approach & Results

c. QWEN2.5 7B: PCA & linear probing

#Principal components	Val acc.	Target language		
		ron	ukr	hin
64	44.05	27.38	15.53	**23.93**
128	45.17	29.09	16.17	20.96
256	45.97	34.15	**17.64**	19.94
3584	52.03	**45.21**	16.67	23.46

Table 4: Results on the dev set of target languages for the linear classifiers trained on embeddings from the QWEN2.5 model (from all source languages) after dimensionality reduction with PCA.

4. Discussion - Distribution Shift

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Model selection

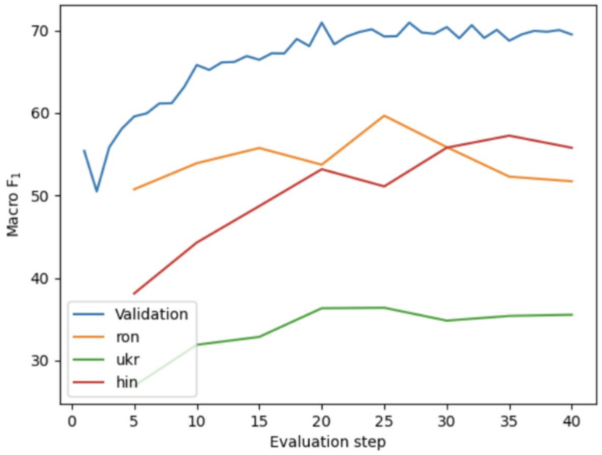
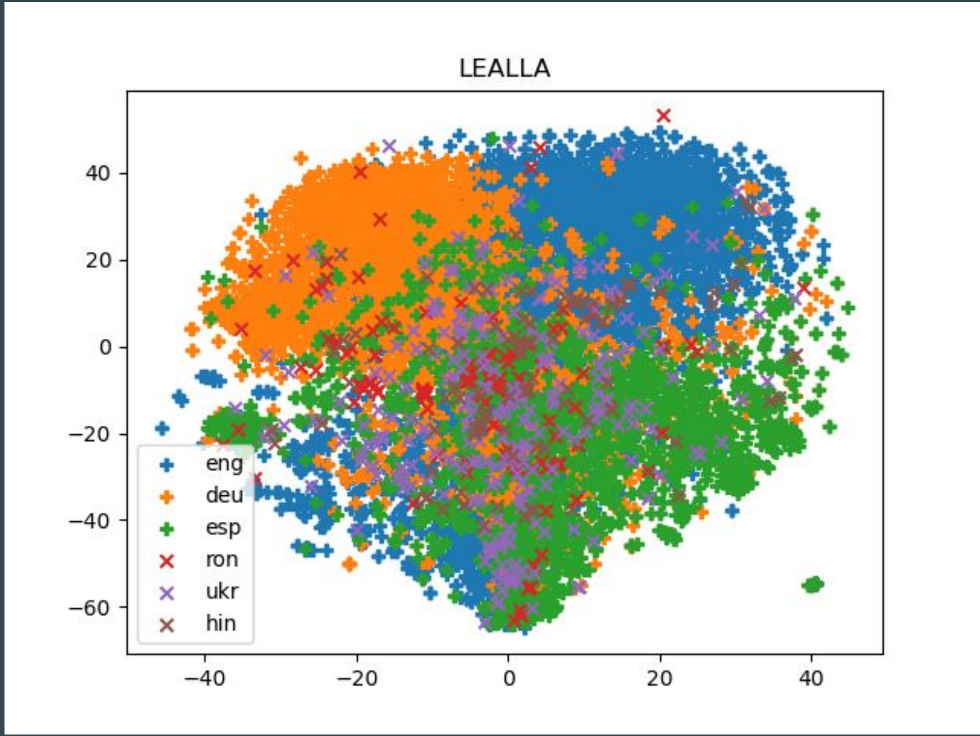


Figure 1: Macro F_1 scores on the validation set of source languages and the dev set of target languages when fine-tuning the LEALLA-large model on all the source languages.

4. Discussion - Distribution Shift

Embedding space

t-SNE visualization



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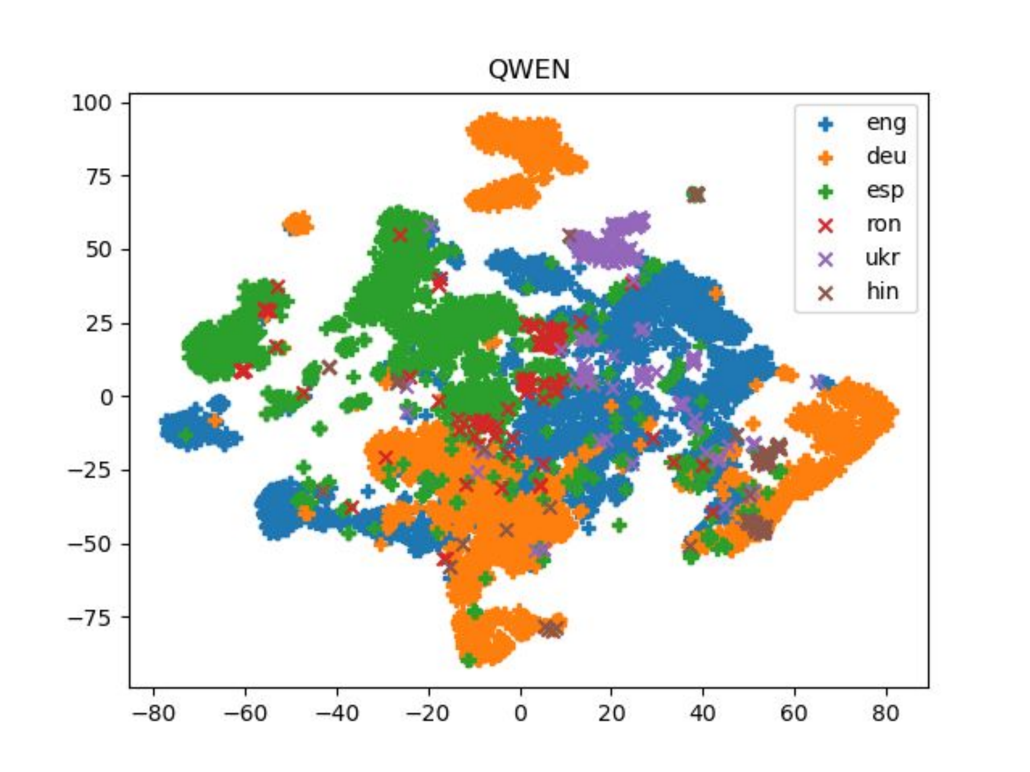
Embedding space

t-SNE visualization



4. Discussion - Distribution Shift

Topics covered in the data

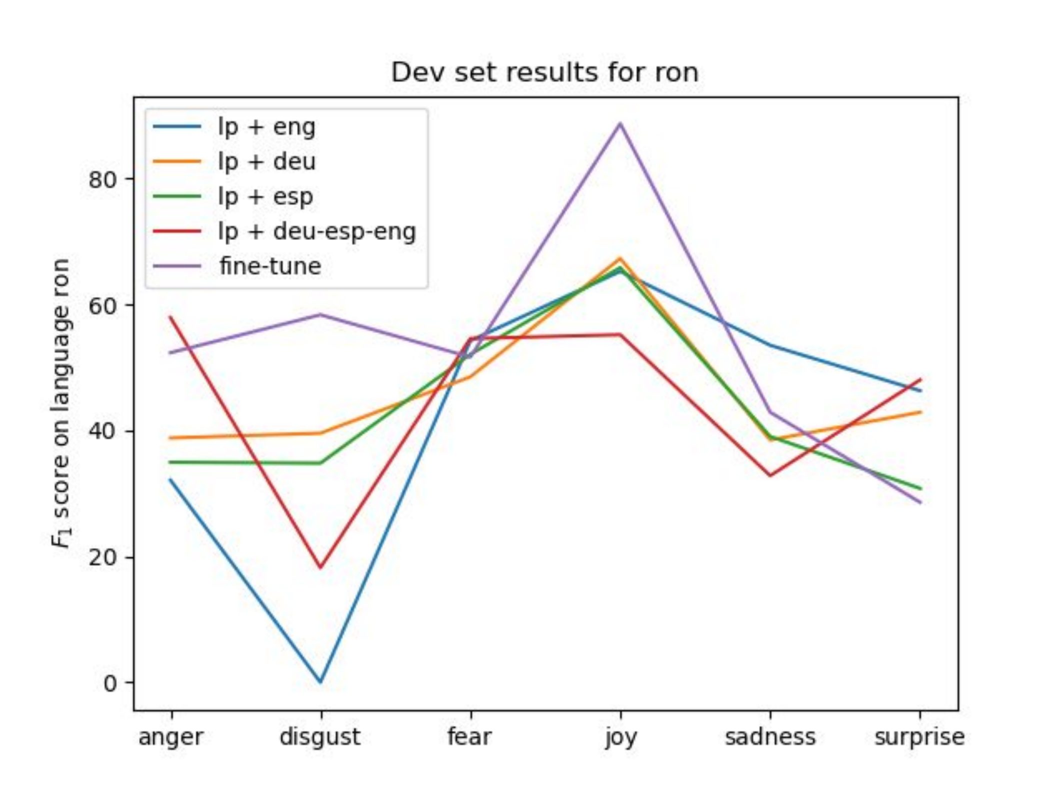
- I manually looked at the samples from the Romanian and English datasets and concluded that the texts were most likely retrieved from news websites and social media
- Romanian texts were mostly about political debates or the recent COVID-19 pandemic
- the English ones where a lot more diverse, covering stories and experiences of people

4. Discussion - Per emotion performance

For each language I observed a trend where certain emotions are better recognized than the others, irrespective of the source languages used for training.

4. Discussion - Per emotion performance

LEALLA encoder



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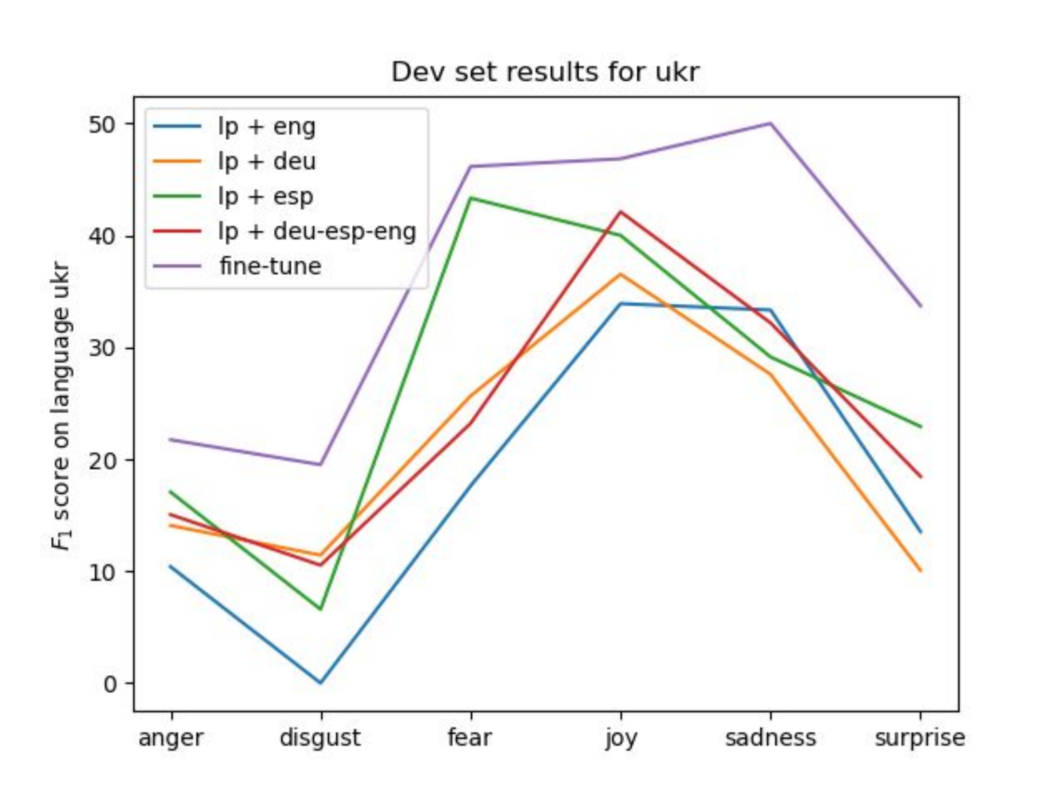
LEALLA encoder



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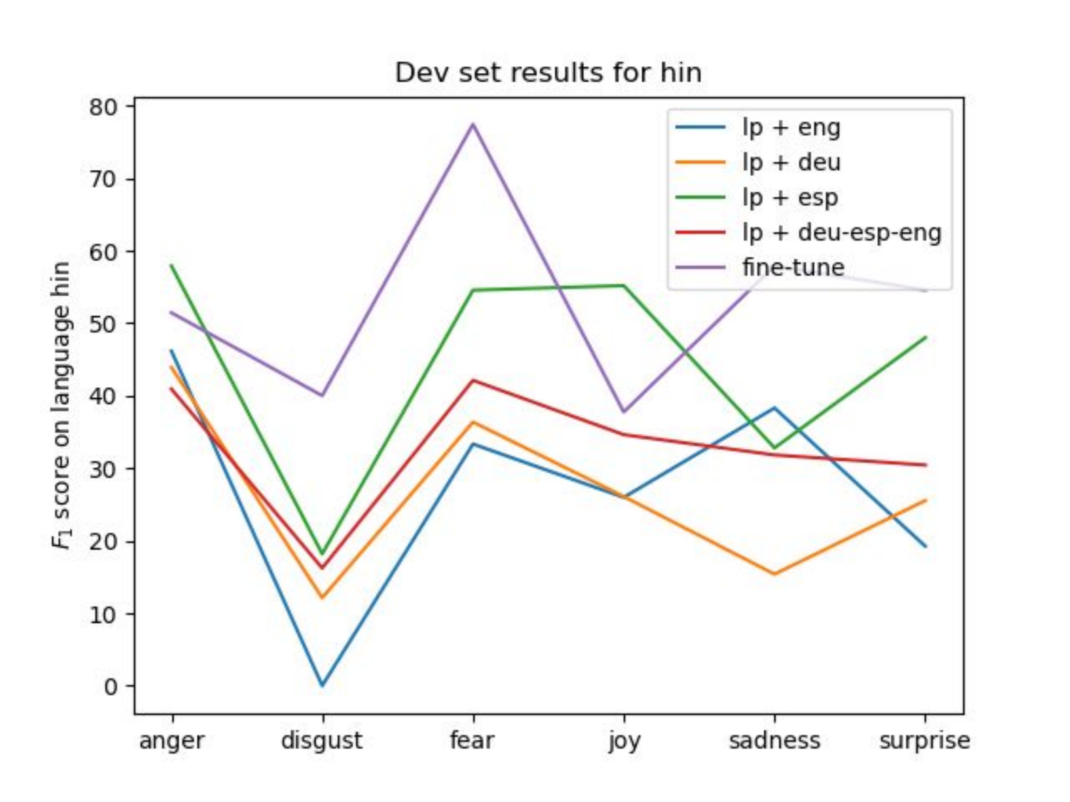
LEALLA encoder



5. Discussion - More data is not always better

5. Limitations

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- resources (data & GPU)

6. Conclusions

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- the generalization capabilities of the approach is heavily impacted by the similarity of the source and target language
- model selection based on source language validation data is not always optimal

7. Future work

- cover a larger number of target languages and looking for trends based on the studied language families and architectures

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- translating the annotated texts from the source languages into the target one to escape the requirement of having a good Cross-Lingual LLM
- using cross-lingual data augmentations and specialized algorithms to train detectors which are invariant to changes in the language of texts