CARER: Contextualized Affect Representations for Emotion Recognition

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Emotion Analysis

Task: To detect the fine-grained emotions expressed in textual information.

Challenge: Emotions are communicated using a variety of linguistic phenomena due to social and cultural differences: slang, emoticons, abbreviations, etc.

Thanks God for everything #safe

Tnx mom for waaaaking me two hours early. Can’t fall asleep now #angry
Discovering Emotional Language

Due to linguistic variability, we need a robust method that properly models and captures both contextual and implicit emotional information.

"Thanks God for everything"

"thanks goodness for a great team .. ”

"thanks fro all the continued support and prayers gotta keep working hard!!”

"Thanks for all the tweets… onto the next path now.”

"Thanks mom for waaaking me two hours early. Can’t get asleep now.”

"thanks dad i can always count on u to mess up my day”
Graph-Based Pattern Extraction

Subjective tweets

Objective tweets

Graph Aggregation

Graph Analysis

Subject Words (SW)

Connector Words (CW)

Pattern Extraction

Saravia et al., 2016
Are Graph-Based Emotion Patterns Enough?

Joy Pattern: “thanks *”

“Thanks God for everything”
“thanks goodness for a great team .. ”

“thanks fro all the continued support and prayers gotta keep working hard!!”
“Thanks for all the tweets… onto the next path now.”

“Thanks mom for waaaaking me two hours early. Can’t get asleep now.”
“thanks dad i can always count on u to mess up my day”

Wildcards (i.e., *) are helpful for preserving structure and generalizing but cannot preserve semantic relationships
Objectives

- Build an automatic graph-based algorithm for **emotion-relevant feature extraction**
- Construct **contextualized representations that preserve semantic relationships**
- Analyse model for **robustness and explainability** given the proposed representations
Methodology

➔ Building Syntactic Patterns
➔ Contextualizing Patterns
➔ Representation Learning
Step 1: Cluster Word Embeddings

**Goal:**
- Model words using Word2Vec
- Cluster words based on similarity measure
- Antonyms are close due to similar context

So its **badness** would be …
would its **goodness** be revealed…
… about the **badness** of human.
**Goodness** of a human …

Mikolov et al., 2013
Step 2: Update Word Embeddings

Pretrained Word2Vec Embeddings

- god
- goodness
- lord
- heavens
- anyone
- your
- ur
- you
- dad
- mom
- mum
- daddy

Sentiment Updated Word2Vec

- bad
- badness
- goodness
- heaven
- lord
- gooodness
- heavens
- you
- ur
- your
- anyone
- dad
- mom
- mum

Sentiment Task

Deriu et al., 2016

Sentiment-labelled Tweets

Pretrained Word2Vec Embeddings

Update trainable embedding vectors

Positive / Negative

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### Step 3: Preserving semantic relationship

| Pattern  | Text              | Contextualized Pattern |
|----------|-------------------|------------------------|
| thanks * | “thanks god”      | thanks C#58            |
|          | “Thanks goodness” | thanks C#58            |
|          | “Thanks goooodness” | thanks C#58            |
|          | “thanks your”     | thanks C#90            |
|          | “thanks mom”      | thanks C#28            |
|          | “thanks mum”      | thanks C#28            |

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### Input: Contextualized Patterns

“Thanks mom for waaaaking me two hours early. Can’t…”

| Input Matrix | anger | anticipation | disgust | fear | joy | sadness | surprise | trust |
|--------------|-------|---------------|---------|------|-----|---------|----------|-------|
| thanks C#28  |       |               |         |      |     |         |          |       |
| C#28 for     |       |               |         |      |     |         |          |       |
| for C#775    |       |               |         |      |     |         |          |       |
| me C#1201    |       |               |         |      |     |         |          |       |
| C#1201 hours |       |               |         |      |     |         |          |       |
| ...          |       |               |         |      |     |         |          |       |
| <empty>      |       |               |         |      |     |         |          |       |

**Zero padding**

Assume a convolution layer with window size of 3

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CNN-Based Emotion Recognition Model

- CNN-based (multilayer)
- Zero padding
- Pattern scores as embedding vectors
- Two filter sizes for features with different length

Emotion Dataset

Contextualized Patterns

Embedding

Filter Size = 3

Conv

Conv

Filter Size = 16

Conv

Conv

Flatten

Dense_512

Dense_128

Softmax

8 Emotions

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Experiments

Emotion Recognition for English Short Texts
Experimental Setup: Dataset

- Crawl English tweets
  - Annotated via distant supervision
  - Total 339 hashtags corresponding to the eight emotions

- Refining process (Abdul et al., 2017)
  - 0.66M tweets in total

| Emotion    | Amount  | Hashtags               |
|------------|---------|------------------------|
| sadness    | 214,454 | #depressed, #grief     |
| joy        | 167,027 | #fun, #joy             |
| fear       | 102,460 | #fear, #worried        |
| anger      | 102,289 | #mad, #pissed          |
| surprise   | 46,101  | #strange, #surprise    |
| trust      | 19,222  | #hope, #secure         |
| disgust    | 8,934   | #awful, #eww           |
| anticipation | 3,975 | #pumped, #ready        |
### Experimental Results: 8 Emotions Task

| Model             | Feature          | anger  | anticipation | disgust | fear   | joy    | sadness | surprise | trust   | F1-avg |
|-------------------|------------------|--------|--------------|---------|--------|--------|---------|----------|---------|--------|
| **Traditional Methods** |                  |        |              |         |        |        |         |          |         |        |
| BoW               | word freq.       | 0.53   | 0.08         | 0.17    | 0.53   | 0.71   | 0.60    | 0.36     | 0.33    | 0.57   |
| N-gram            | word freq.       | 0.56   | 0.09         | 0.17    | 0.57   | 0.73   | 0.64    | 0.42     | 0.39    | 0.61   |
| char              | char. freq.      | 0.35   | 0.03         | 0.04    | 0.20   | 0.51   | 0.46    | 0.10     | 0.12    | 0.37   |
| **Lexica-based**  |                  |        |              |         |        |        |         |          |         |        |
| LIWC              | affect lexicons  | 0.35   | 0.03         | 0.11    | 0.30   | 0.49   | 0.35    | 0.18     | 0.19    | 0.35   |
| **State-of-the-Art Methods** |                |        |              |         |        |        |         |          |         |        |
| CNN<sub>sw2v</sub> | s-word embed.    | 0.57   | 0.10         | 0.15    | 0.63   | 0.75   | 0.64    | 0.61     | 0.70    | 0.65   |
| EmoNet            | word embed.      | 0.36   | 0.00         | 0.00    | 0.46   | 0.69   | 0.61    | 0.13     | 0.25    | 0.52   |
| FastText          | word embed.      | 0.57   | 0.01         | 0.01    | 0.65   | 0.77   | 0.71    | 0.50     | 0.54    | 0.66   |
| DeepMoji          | word embed.      | 0.60   | 0.00         | 0.03    | 0.49   | 0.75   | 0.67    | 0.20     | 0.27    | 0.59   |
| **Baseline and our work** |                |        |              |         |        |        |         |          |         |        |
| CNN<sub>EP</sub>  | EmoPattern‡      | 0.65   | 0.10         | 0.22    | 0.64   | 0.73   | 0.56    | 0.15     | 0.08    | 0.52   |
| CARER<sub>8</sub> | cont. patt.‡     | 0.61   | 0.31         | 0.34    | 0.67   | 0.75   | 0.68    | 0.60     | 0.55    | 0.67   |
| CARER             | cont. patt.      | 0.74   | 0.41         | 0.43    | 0.79   | 0.83   | 0.82    | 0.76     | 0.75    | 0.79   |

Note: CARER uses a recent dataset and fewer pattern templates (details in paper)
Emotion Recognition (8 emotions)

| Method                      | F1-score |
|-----------------------------|----------|
| CARER $\beta$              | 67%      |
| CARER                       | 79%      |
| DeepMoji                    | 59%      |
| ELMo                        | 62%      |
| FastText                    | 66%      |
| ELMo + DeepMoji             | 76%      |
What’s Captured by CARER?

Our proposed method can grasp emotional cues in cases of *short text*, *rare words* and *mixed emotions*

| Case             | Document                                    | Label | DeepMoji | EmoNet | CARER | Contextualized Pattern |
|------------------|---------------------------------------------|-------|----------|--------|-------|------------------------|
| Short text       | damn what a **night**                       | joy   | surprise | sadness| joy   | what a **{night, day, rush, pass}** |
| Rare words       | got **thee** worst sleep ever              | anger | sadness | sadness| anger | got **{thee, madd, thatt, bacc}** |
| Mixed emotions   | what the h**k** is **going** on !?          | fear  | anger    | sadness| fear  | is **{going, ends, finishes}**    |
Conclusion

- We proposed **contextualized affect representations** for improving emotion recognition.
- In the future, we anticipate a comprehensive study of how contextualized patterns can be adapted to other **emotion-related tasks**.
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