Token Sequence Labeling vs. Clause Classification for English Emotion Stimulus Detection

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Abstract

Emotion stimulus detection is the task of finding the cause of an emotion in a textual description, similar to target or aspect detection for sentiment analysis. Previous work approached this in three ways, namely (1) as text classification into an inventory of predefined possible stimuli (“Is the stimulus category A or B?”), (2) as sequence labeling of tokens (“Which tokens describe the stimulus?”), and (3) as clause classification (“Does this clause contain the emotion stimulus?”). So far, setting (3) has been evaluated broadly on Mandarin and (2) on English, but no comparison has been performed. Therefore, we analyze whether clause classification or token sequence labeling is better suited for emotion stimulus detection in English. We propose an integrated framework which enables us to evaluate the two different approaches comparably, implement models inspired by state-of-the-art approaches in Mandarin, and test them on four English data sets from different domains. Our results show that token sequence labeling is superior on three out of four datasets, in both clause-based and token sequence-based evaluation. The only case in which clause classification performs better is one data set with a high density of clause annotations. Our error analysis further confirms quantitatively and qualitatively that clauses are not the appropriate stimulus unit in English.

1 Introduction

Research in emotion analysis from text focuses on classification, i.e., mapping sentences or documents to emotion categories based on psychological theories (e.g., Ekman (1992), Plutchik (2001)). While this task answers the question which emotion is expressed in a text, it does not detect the textual unit, which reveals why the emotion has been developed. For instance, in the example “Paul is angry because he lost his wallet.” it remains hidden that *lost his wallet* is the reason for experiencing the emotion of anger. This stimulus, e.g., an event description, a person, a state of affairs, or an object enables deeper insight, similar to targeted or aspect-based sentiment analysis (Jakob and Gurevych, 2010; Yang and Cardie, 2013; Klinger and Cimiano, 2013; Pontiki et al., 2015, 2016, i.a.). This situation is dissatisfying for (at least) two reasons. First, detecting the emotions expressed in social media and their stimuli might play a role in understanding why different social groups change their attitude towards specific events and could help recognize specific issues in society. Second, understanding the relationship between stimuli and emotions is also compelling from a psychological point of view, given that emotions are commonly considered responses to relevant situations (Scherer, 2005).

Models which tackle the task of detecting the stimulus in a text have seen three different problem formulations in the past: (1) Classification into a predefined inventory of possible stimuli (Mohammad et al., 2014), similarly to previous work in sentiment analysis (Ganu et al., 2009), (2) classification of precalculated or annotated clauses as containing a stimulus or not (Gui et al., 2016, i.a.), and (3) detecting the tokens that describe the stimulus, e.g., with IOB labels (Ghazi et al., 2015, i.a.). We follow the two settings in which the stimuli are not predefined categories (2+3, cf. Figure 1).

These two settings have their advantages and disadvantages. The clause classification setting is more coarse-grained and, therefore, more likely to perform well than the token sequence labeling setting, but it might miss the exact starting and endpoints of a stimulus span and needs clause annotations or a syntactic parse with the risk of error.
The remainder of the paper is organized as follows. We first introduce our integrated framework of stimulus detection which enables us to evaluate clause classification and token sequence labeling in a comparable manner (Section 2). We then turn to the experiments (Section 3) in which we analyze results on four different English data sets. Section 4 discusses typical errors in detail, which leads to a better understanding of how stimuli are formulated in English. We conclude in Section 6.

2 An Integrated Framework for Stimulus Detection

The two approaches for open-domain stimulus detection, namely, clause classification and token sequence labeling, have not been compared on English. We propose an integrated framework (Figure 2) which takes tokens \( \mathbf{t} \) as input, splits this sequence into clauses and classifies them (clause detection can be bypassed if manual annotations of clauses are available). The token sequence labeling does not rely on clause annotations. The output, either clauses \( \mathbf{c} \) with classifications \( \mathbf{y} \) (\( y \in \{ \text{yes}, \text{no} \} \)) or tokens \( \mathbf{t} \) with labels \( \mathbf{l} \) are then mapped to each other to enable a comparative evaluation. We explain these steps in the following subsections.

2.1 Clause Extraction

The clause classification methods rely on representing an instance as a sequence of clauses. Clauses in English grammar are defined as the smallest grammatical structures that contain a subject and a predicate, and can express a complete proposition (Kroeger, 2005). We show our algorithm to detect clauses in Algorithm 1.

To mark the segments that would potentially approximate clauses, we rely on the constituency parse tree of the token sequence (Line 2). For that reason, we use the Berkeley Neural Parser (Kitaev and Klein, 2018). As illustrated by Feng et al. (2012) and Tafreshi and Diab (2018) we also do that by segmenting the constituency parse tree of the instance (Line 9) at the borders of constituents sequence labeling is indeed the preferred approach for stimulus detection in most available English datasets; (4) show in an error analysis that this is mostly because clauses are not the appropriate unit for stimuli in English. Finally, (5), we make our implementation and annotations for both clauses and tokens available at http://www.ims.uni-stuttgart.de/data/emotion-stimulus-detection.

Figure 1: Different formulations for emotion stimulus detection.

```plaintext
| Clause-based Classification: |
|-----------------------------|
| No Stimulus | Stimulus |
| [ She’s pleased at ] | [ how things have turned out ] |

Figure 2: Framework for emotion stimulus detection.

| Token Sequence Labeling: |
|--------------------------|
| 0 0 0 1 1 1 1 1 0 |
| She ‘s pleased at how things have turned out |

Our contributions are as follows: (1) we develop an integrated framework that represents different formulations for the emotion stimulus detection task and evaluate these on four available English datasets; (2) as part of this framework, we propose a clause detector for English which is required to perform stimulus detection via clause classification in a real-world setting; (3) show that token

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labeled as clause-type (Bies et al., 1995). We then join the segments until convergence heuristically based on punctuation (Line 12). We illustrate the algorithm in the example in Figure 3.

2.2 Stimulus Detection

Our goal is to compare sequence labeling and clause classification. To attribute the performance of the model to the formulation of the task, we keep the differences between the models at a minimum. We therefore first discuss the model components and then how we put them together.

Our models are composed of four layers. As Embedding Layer, we use pretrained embeddings to embed each token in the instance \( s = t_1 \ldots t_n \) to obtain \( \tilde{e}_1, \ldots, \tilde{e}_n \). For the Encoding Layer, we use a bidirectional LSTM which outputs a sequence of hidden states \( \tilde{h}_1, \ldots, \tilde{h}_n \). In an additional Attention Layer, each word or clause is represented as the concatenation of its embedding and a weighted average over other words or clauses in the instance: \( \tilde{u}_i = \left[ \tilde{h}_i; \sum_{j=1}^{n} a_{i,j} \cdot \tilde{h}_j \right] \). The weights \( a_{i,j} \) are calculated as the dot-product between \( \tilde{h}_i \) and every other word, and by normalizing the scores using softmax \( \tilde{u}_i = \text{softmax}(\tilde{h}_i; \tilde{h}_j) \). We concatenate all representations to obtain the final representation vector \( \tilde{s} \). The Output Layer is different for the two different task formulations (sequence labeling vs. single softmax). For the case of the single softmax, the input to the classifier is the representation of the clause obtained on the previous layer and the classifier output is defined as \( \tilde{o}_i = \text{softmax}(W \cdot \text{ReLU(Dropout}(h(s)))) \). When labels are not predicted independently from each other but rather in a sequential manner, we use a linear-chain conditional random field (Lafferty et al., 2001). It takes the sequence of probability vectors from the previous layer \( \tilde{u}_1, \tilde{u}_2, \ldots \) and outputs a sequence of labels \( \tilde{y}_1, \tilde{y}_2, \ldots \). The score of the labeled sequence is defined as the sum of the probabilities of individual labels and the transition probabilities:

\[
\tilde{s}(y_{1:n}) = \sum_{i=1}^{n} \tilde{u}_i(y_i) + \sum_{i=2}^{n} T[y_{i-1}, y_i],
\]

where the matrix \( T \) that contains the transition probabilities between one label and another (i.e., \( T[i, j] \) represents the probability that a token labeled \( i \) is followed by a token labeled \( j \)). At prediction time, the most likely sequence is chosen with the Viterbi algorithm (Viterbi, 1967).

With these components, we can now put together the actual models which we use for stimulus detection. We compare three different models, one for token sequence labeling (SL) and two for clause classification (CC). The model architectures are illustrated in Figure 4.

Token Sequence Labeling (SL). In this model, we formulate emotion stimulus detection as token sequence labeling with the IOB alphabet (Ramshaw and Marcus, 1995). As embeddings, we use word-level GloVe embeddings (Pennington et al., 2014). The sequence-to-sequence architecture comprises a bidirectional LSTM, an attention layer and the CRF output layer.

Independent Clause Classification (ICC). This

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**Algorithm 1: Clause Extraction**

Input: \( \text{text} \)  
Output: \( \text{Clauses} \)

1. \( t \leftarrow \text{tokenize(} \text{text} \text{)} \)  
2. \( \text{tree} \leftarrow \text{parse(} t \text{)} \)  
3. \( \text{gaps} \leftarrow \{0, |t|\} \)  
4. \( \text{segments} \leftarrow \emptyset \)  
5. **foreach** node \( n \) in tree do
   
6.   if \( \text{label}(n) \in \{\text{SBAR}, \text{SBARQ}, \text{INV}, \text{SQ}\} \)
   
7.     \( r \leftarrow \text{first token leaf that } n \text{ governs} \)
   
8.     \( g \leftarrow \text{last token leaf that } n \text{ governs} \)

9.     gaps \( = \) gaps \( \cup \{\text{idx}_r, \text{idx}_g + 1\} \)

10. **foreach** adjacent pair \((i,j)\) in sort(gaps) do

11.     segments \( = \) segments \( \cup \{t[i:j]\} \)

12. **repeat**

13.     **foreach** \( s_i \) in segments do

14.         if \( |s_i| \leq 3 \)

15.             \( s_{i+1} = s_i \parallel s_{i+1} \)

16.             segments \( = \) segments \( \setminus s_i \)

17.         \( s_{i+1} = s_i \parallel s_{i+1} \)

18.         segments \( = \) segments \( \setminus s_i \)

19. **until convergence**

20. return segments

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Figure 3: Example for the application of Algorithm 1.
model, similarly proposed by Cheng et al. (2017), takes the clauses from the clause detector (or from annotated data) and classifies them as containing the stimulus or not. The model has a similar architecture to the one before, with the exception of the final classifier, which is a single softmax to output a single label. The training objective is to minimize the cross-entropy loss. This model does not have access to clauses other than the one it predicts for.

**Joint Clause Classification (JCC).** In this model, the neural architecture we employ is slightly different from before to enable it to make a prediction for clauses in the context of all clauses. It comprises multiple LSTM modules as word-level encoders, one for each clause. The LSTM at the word-level encodes the tokens of one clause into one representation. The next layer is a clause-level encoder based on two bidirectional LSTMs, where the clause representations are learned and updated by integrating the relations between multiple clauses. After we obtain the final clause representation for each clause, we perform sequence labeling with a **CRF on the clause level.** The training objective is to minimize the negative log-likelihood loss across all clauses. This implementation follows the architecture by Xia et al. (2019), with the change of the upper layer, which is, in our case, an LSTM clause encoder and not a transformer, to keep the architecture comparable across our different formulations. Therefore, this is comparable to all other hierarchical models proposed for the task (Ding et al., 2019; Xu et al., 2019; Xia and Ding, 2019).

### 3.1 Data Sets

We base our experiments on four data sets. For each data set, we report the size, the number of stimulus annotations and statistics for tokens and clauses in Table 1.

- **EmotionStimulus.** This data set proposed by Ghazi et al. (2015) is constructed based on FrameNet’s emotion-directed frame. The authors used FrameNet’s annotated data for 173 emotion lexical units, grouped the lexical units into seven basic emotions using their synonyms and built a dataset manually annotated with both the emotion stimulus and the emotion. The corpus consists of 820 sentences with annotations of emotion categories and stimuli. The rest of 1,594 sentences only contain an emotion label. For this dataset, we see the lowest average number of clauses for which all tokens correspond to a stimulus (μ w. all S/I in Table 1). This result shows that the stimuli annotations rarely align with the clause boundaries.

- **ElectoralTweets.** Frame Semantics also inspires a dataset of social media posts (Mohammad et al., 2014). The corpus consists of 4,056 tweets of which 2,427 contain emotion stimulus annotations on the token level. The annotation was performed via crowdsourcing. The tweets are the shortest in length and have a higher average of clauses per instance than the GoodNewsEveryone or the EmotionStimulus datasets. They also show

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1. Corpora which we do not consider for our experiments are discussed in the related work section.
2. https://framenet2.icsi.berkeley.edu/fnReports/data/frameIndex.xml?frame=Emotion_directed
Good News Everyone Emotion Cause Analysis (Gao et al., 2017) consists of news headlines. From a total of 5000 instances, 4,798 contain a stimulus. The headlines have the shortest stimuli in token count. Similar to the Electoral Tweets, they also have a high average stimulus token density in clauses. This set has the lowest mean number of clauses per instance ($\mu$ I in Table 1).

**Electoral Tweets**. The data set by Bostan et al. (2020) consists of news headlines. From a total of 5000 instances, 4,798 contain a stimulus. The headlines have the shortest stimuli in token count. Similar to the Electoral Tweets, they also have a high average stimulus token density in clauses. This set has the lowest mean number of clauses per instance ($\mu$ I in Table 1).

**Emotion Cause Analysis** (Gao et al., 2017) comparably annotate English and Mandarin texts on the clause level and the token level. In our work, we use the English subset, which is the only English corpus annotated for stimuli both at the clause level and at the token level. This dataset has the fewest instances without stimuli among all the others. It also has the longest instances and stimuli. The mean of stimuli tokens annotated per clause is comparable to Emotion Stimulus despite having a higher mean of stimuli tokens per instance. In the upcoming experiments, we use the clause annotations and not automatically recognized clauses with Algorithm 1 as input to our framework.

### 3.2 Clause Identification Evaluation

Before turning to the actual evaluation of the emotion stimulus detection methods, we evaluate the quality of the automatic clause detection. For an intrinsic evaluation, we annotate 50 instances from each test corpus in each data set with two annotators trained on the clause extraction task in two iterations. The two annotators are graduate students and have different scientific backgrounds: computational linguistics (A1) and computer science with a specialization in computer vision (A2). Each student annotated 50 instances of each dataset from the datasets we use in the same order. As an environment for the annotation process, we used a simple spreadsheet application. We did this small annotation experiment as an inner check for our understanding of the clause extraction task. None of the annotators is a native English speaker; A1 is a native speaker of a Romance language, and A2 a German speaker. The inter-annotator agreement is shown in Table 2. We achieve an acceptable average agreement of $\kappa=0.65$.

We now turn to the question if annotated clauses (as an upper bound to an automatic system) align well with annotated stimuli (Stimuli vs. Anno. Clauses in Table 2). The evaluation is based on recall (i.e., measuring for how many stimuli a clause exists), either for the whole stimulus (exact), or for the left or the right boundary. We see that except for the corpus Emotion Stimulus, the right boundaries match better than the left.

Turning to extracted clauses instead of annotated ones (Extra. vs. Anno. Clauses) we first evaluate the automatic extraction algorithm. We obtain $F_1$ values between 0.76% and 0.80%, which we consider acceptable though they also show that error propagation could occur.

For the actual extrinsic evaluation, if clause boundaries are correctly found for annotated stimuli (Stimuli vs. Extra. Clauses), we see that the results are only slightly lower than for the gold annotations, except for Emotion Stimulus. Therefore, we do not expect to see error propagation due to an imperfect extraction algorithm for most data sets.

These results suggest that clauses are not an appropriate unit for stimuli in English. Still, we do not know yet if the clause detection task’s simplicity outweighs these disadvantages in contrast to token sequence labeling. We turn to answer this in the following.

| Data set       | Size | Stimuli | Tokens | Clauses |
|----------------|------|---------|--------|---------|
|                |      |         | $\mu$  | $\sigma$| $\mu S/I$| $\mu S/C$| $\mu$ | $\mu$ |
| Emotion Stimulus | 2,414 | 820     | 7.29   | 5.20   | 0.12   | 0.11   | 5.818 | 1.117|
| Electoral Tweets | 4,056 | 2,427   | 6.22   | 4.00   | 0.20   | 0.17   | 13,012| 3,295|
| GoodNewsEveryone | 5,000 | 4,798   | 7.27   | 3.67   | 0.55   | 0.50   | 9,190 | 6,301|
| Emotion Cause Ana. | 2,655 | 2,580   | 8.48   | 5.20   | 0.20   | 0.10   | 19,473| 2,897|

Table 1: Data sets available for the Emotion Stimulus Detection task in English. Size: number of annotated instances, Stimuli: number of instances with stimuli annotated; $\mu$, $\sigma$: mean/standard deviation of length of stimuli in tokens; $\mu S/I$: mean number of stimulus tokens per instance; $\mu S/C$: mean number of stimulus tokens per clause; Total: total number of clauses, w. S: number of clauses that contain a stimulus; $\mu$ I: average number of clauses per instance; $\mu$ w. all S/I: average number of clauses in which all tokens correspond to annotated stimuli.
### Table 2: Evaluation of Clause Detection

Note that for **EmotionCauseAnalysis**, the clauses stem from the annotation provided in the original data and not from our automatic detection method.

| Dataset                 | IAA   | Stimuli vs. Anno. Clauses | Extra. vs. Anno. Clauses | Stimuli vs. Extra. Clauses |
|-------------------------|-------|---------------------------|--------------------------|---------------------------|
|                         | $\kappa$ | Exact | Left | Right | Precision | Recall | F1    | Exact | Left | Right |
| **EmotionCauseAnalysis**| 0.60  | 0.60 | 0.35 | 0.86 | 0.77      | 0.75   | 0.76  | 0.59  | 0.36 | 0.84  |
| **GoodNewsEveryone**    | 0.77  | 0.62 | 0.29 | 0.90 | 0.87      | 0.76   | 0.80  | 0.61  | 0.27 | 0.89  |
| **EmotionStimulus**     | 0.59  | 0.47 | 0.83 | 0.11 | 0.86      | 0.72   | 0.76  | 0.17  | 0.26 | 0.07  |
| **ElectoralTweets**     | 0.63  | 0.56 | 0.39 | 0.63 | 0.82      | 0.78   | 0.80  | 0.54  | 0.43 | 0.60  |

### Figure 5: Results of the three different models across four different datasets

#### 3.3 Stimulus Detection Evaluation

##### 3.3.1 Evaluation Procedure

We evaluate the quality of all models with five different measures. Motivated by the formulation of clause classification, we (1) evaluate the prediction on the clause level with precision, recall, and F1. For the sequence labeling evaluation, we use four variations. (2) **Exact**, where we consider a consecutive token sequence to be correct if a gold annotation exists that exactly matches, (3) **Relaxed**, where an overlap of one token with a gold annotation is sufficient, (4) **Left-Exact** and (5) **Right-Exact**, where at least the most left/right token in the prediction needs to have a gold-annotated counterpart.

One might argue that sequence labeling evaluation is unfair for the clause classification, as it is more fine-grained than the actual prediction method. However, for transparency across methods and analysis of advantages and disadvantages of the different methods, we use this approach in addition to clause classification evaluation.

We split the data for each set randomly into three sets: 80% train, 10% dev, and 10% test. We use dropout with a probability of 0.5, train with Adam (Kingma and Ba, 2015) with a base learning rate of 0.003, and a batch size of 10. At test time, we select the model with the best validation accuracy after 50 epochs with a patience of 10 epochs. All models use embedding sizes of 300 and hidden state sizes of 100 (Pennington et al., 2014). We do not tune hyperparameters for any of the architectures and implement all models with the AllenNLP library (Gardner et al., 2018).

##### 3.3.2 Results

We now study the performance of the different models on the English data sets. Figure 5 summarizes the results. (Precision and recall values are available in Table 7 in Appendices.)

Which of the modeling approaches performs best on English data? If we only compare the absolute numbers in F1, we see that the clause classification evaluation (Class) shows the highest result across all models and data set. The only exception is the **EmotionStimulus** data, in which the Left-Exact evaluation is slightly higher. When we rely on this evaluation score, we see that the token sequence labeling method shows a superior result to the classification methods in two data sets, namely **GoodNewsEveryone** and **EmotionCauseAnalysis**. On **ElectoralTweets** and **EmotionStimulus**, the re-
Table 3: Counts for each error type for each model across all data sets.

| Error types              | SL          | ICC         | JCC         | Sum     |
|--------------------------|-------------|-------------|-------------|---------|
| Early stop               | 0           | 4           | 1           | 3       |
| Late stop                | 11          | 9           | 10          | 8       |
| Early start & stop       | 0           | 3           | 0           | 1       |
| Early start              | 152         | 16          | 0           | 6       |
| Late start               | 28          | 3           | 0           | 1       |
| Late start & stop        | 2           | 1           | 0           | 0       |
| Contained                | 0           | 0           | 0           | 0       |
| Multiple                 | 143         | 189         | 11          | 260     |
| Surrounded               | 9           | 10          | 0           | 5       |
| False Negative           | 231         | 160         | 59          | 228     |
| False Positives          | 10          | 18          | 2           | 14      |
| All                      | 586         | 413         | 83          | 526     |
| 493                      | 389         | 82          | 388         | 449     |
| 302                      | 56          | 325         | 4092        |         |

4 Error Analysis

In the following, we analyze the error types made by the different models on all data sets and investigate in which ways SL improves over the ICC and JCC models. We hypothesize that the higher flexibility of token-based sequence labeling leads to different types of errors than the clause-based classification models.

For quantitative analysis, we define different error types, illustrated in Table 3 with different symbols as abbreviations. The top bar illustrates the gold span, while the bottom corresponds to the predicted span. The error types illustrated with symbols $\square$ and $\square$ correspond to false positives; $\square$ are false negatives. All other error types correspond to either both false positive and false negative in a strict evaluation setting or true positives in one of
the relaxed evaluation settings.

Do ICC and JCC particularly miss starting or end points of the stimulus annotation? We see in Table 3 that for Late stop, CC models make considerably more mistakes across all datasets. ICC does so on ET and ECA, while JCC makes more mistakes on GNE and ES. For data sets in which stimulus annotations end with a clause, errors of this type are less likely. These results are more prominent for Early start & stop.

Do all methods have similar issues with finding the whole consecutive stimulus? We see this in the error type Multiple. When the CC models make this mistake, it can be attributed to the automatic fine-grained clause extraction, which can cause a small clause within a gold span to become a false negative. However, we see that SL shows higher numbers of this issue than CC. This result is also reflected in the surprisingly low number of Contained ( – if the prediction is completely inside a gold annotation, the gold annotation tends to be long, and this increases the chance that it is (wrongly) split into multiple predictions.

How do the error types differ across models? The Early Start (& Stop) and Surrounded counts show differences across the different types of models. Presumably, the clause classification models do have difficulties in finding the left boundary, and they are more prone to “start early” than the token sequence labeling models. This might be due to gold spans starting in the middle of a clause which is predicted to contain the stimulus.

How do the error types differ across data sets? The results and error types differ across data sets (see particularly & ). This points out what we have seen in the evaluation already: The structure of a stimulus depends on the domain and annotation. The least challenging data set is EmotionStimulus with the lowest numbers of errors across all models. This result is caused by most sentences having similar syntactic trees, all stimuli are explicit and mostly introduced in a similar way.

For qualitative analyses, Figure 6 shows one example of each type of error described above. In the first example, the JCC model does not learn to include the second part of the coordination – “and the pain”. In the second example, similarly, the SL model misses the right part of the coordination. For most cases of independent clauses that we inspect, we see a common pattern for both types of models, which is that the prediction stops while encountering coordinating conjunctions. In the sixth example, the prediction span includes the emotion cue. This issue could be solved by doing sequence labeling instead or by informing the model of the presence of other semantic roles. These examples raise the following question: would improved clause segmentation lead to improvements for the clause-classification models across all data sets?

5 Related Work

The task of detecting the stimulus of an expressed emotion in text received relatively little attention.

Next to the corpora we mentioned so far, the REMAN corpus (Kim and Klinger, 2018) consists of English excerpts from literature, sampled from Project Gutenberg. The authors consider triples of sentences as a trade-off between longer passages and sentences. Further, Neviarouskaya and Aono (2013) annotated English sentences on the token level.
Besides English and Mandarin, Russo et al. (2011) developed a method for the identification of Italian sentences that contain an emotion cause phrase. Yada et al. (2017) annotate Japanese sentences on newspaper articles, web news articles, and Q&A sites. Table 8 in Appendices shows which corpora and methods have been used and compared in previous work for the available English and Chinese sets. We see that the methods applied on the Chinese sets are not evaluated on the English sets.

Lee et al. (2010) firstly investigated the interactions between emotions and the corresponding stimuli from a linguistic perspective. They publish a list of linguistic cues that help in identifying emotion stimuli and develop a rule-based approach. Chen et al. (2010) build on top of their work to develop a machine learning method. Li and Xu (2014) implement a rule-based system to detect the stimuli in Weibo posts and further inform an emotion classifier with the output of this system. Other approaches to develop rules include manual strategies (Gao et al., 2015), bootstrapping (Yada et al., 2017) and the use of constituency and dependency parsing (Neviarouskaya and Aono, 2013).

All recently published state-of-the-art methods for the task of emotion stimulus detection via clause classification are evaluated on the Mandarin data by Gui et al. (2016). They include multi-kernel learning (Gui et al., 2016) and long short-term memory networks (LSTM) (Cheng et al., 2017). Gui et al. (2017) propose a convolutional multiple-slot deep memory network (ConvMS-Memnet), and Li et al. (2018) a co-attention neural network model, which encodes the clauses with a co-attention based bi-directional long short-term memory into high-level input representations, which are further passed into a convolutional layer. Ding et al. (2019) proposed an architecture with components for “position augmented embedding” and “dynamic global label” which takes the relative position of the stimuli to the emotion keywords and use the predictions of previous clauses as features for predicting subsequent clauses. Xia et al. (2019) integrate the relative position of stimuli and evaluate a transformer-based model that classifies all clauses jointly within a text. Similarly, Yu et al. (2019) propose a word-phrase-clause hierarchical network. The transformer-based model achieves state of the art, however, it is shown that the RNN based encoders are very close in performance (Xia et al., 2019). Therefore, we use a comparable model that is grounded on the same concept of a hierarchical setup with LSTMs as encoders. Further, there is a strand of research which jointly predicts the clause that contains the emotion stimulus together with its emotion cue (Wei et al., 2020; Fan et al., 2020). However, the comparability of methods across data sets has been limited in previous work, as Table 8 in the appendices shows.

6 Conclusion

We contributed to emotion stimulus detection in two ways. Firstly, we evaluated emotion stimulus detection across several English annotated data sets. Secondly, we analyzed if the current standard formulation for stimulus detection on Mandarin Chinese is also a good choice for English.

We find that the domain and annotation of the data sets have a large impact on the performance. The worst performance of the token sequence labeling approach is obtained on the crowdsourced data set ElectoralTweets. The well-formed sentences of EmotionStimulus pose fewer difficulties to our models than tweets and headlines. We see that the sequence labeling approaches are more appropriate for the phenomenon of stimulus mentions in English. This shows in the evaluation of the comparably coarse-grained clause level and is also backed by our error analysis.

For future work, we propose closer investigation of whether other smaller constituents might represent the stimulus better for English and a check of whether the strong results for the sequence labeling hold for other languages. Notably, the clause classification setup has its benefits, and this might lead to a promising setting as joint modeling or as a filtering step to finding parts of the text which might contain a stimulus mention. Another step is to investigate if the emotion stimulus and the emotion category classification benefit from joint modeling in English as it has been shown for Mandarin (Chen et al., 2018).

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A Appendix

| Data                      | SL Evaluation | CC Evaluation |
|---------------------------|---------------|---------------|
|                           | Exact | Relaxed | Left-Exact | Right-Exact | Clause |
|                           | P   | R     | F₁   | P   | R     | F₁   | P   | R     | F₁   | P   | R     | F₁   |
| EmotionStimulus           |      |       |      |      |       |      |      |       |      |      |       |      |
| SL                        | 69   | 73    | 71   | 69   | 74    | 72   | 100  | 74    | 85   | 100  | 59    | 74   |
| ICC                       | 03   | 26    | 05   | 10   | 100   | 18   | 03   | 26    | 05   | 05   | 44    | 09   |
| JCC                       | 05   | 12    | 07   | 21   | 42    | 30   | 12   | 10    | 12   | 17   | 46    | 24   |
| ElectoralTweets           |      |       |      |      |       |      |      |       |      |      |       |      |
| SL                        | 15   | 07    | 10   | 41   | 30    | 35   | 52   | 09    | 15   | 42   | 11    | 17   |
| ICC                       | 12   | 47    | 19   | 22   | 100   | 37   | 13   | 47    | 21   | 21   | 74    | 32   |
| JCC                       | 14   | 30    | 19   | 25   | 54    | 34   | 15   | 48    | 23   | 28   | 47    | 35   |
| EmotionCauseAnalysis      |      |       |      |      |       |      |      |       |      |      |       |      |
| SL                        | 16   | 20    | 18   | 42   | 60    | 49   | 76   | 29    | 41   | 83   | 23    | 36   |
| ICC                       | 05   | 35    | 09   | 14   | 100   | 24   | 05   | 35    | 09   | 13   | 82    | 22   |
| JCC                       | 06   | 29    | 10   | 18   | 40    | 25   | 11   | 15    | 12   | 35   | 29    | 31   |
| GoodNewsEveryone          |      |       |      |      |       |      |      |       |      |      |       |      |
| SL                        | 39   | 30    | 34   | 66   | 92    | 77   | 79   | 30    | 44   | 86   | 86    | 86   |
| ICC                       | 15   | 29    | 19   | 37   | 100   | 54   | 15   | 29    | 20   | 48   | 92    | 63   |
| JCC                       | 16   | 25    | 19   | 40   | 90    | 55   | 17   | 25    | 20   | 54   | 82    | 65   |

Figure 7: Results of the three different models across the five different datasets

| Data sets and Annotation Approach | Categorical Class. & Sequence Lab. | Sequence Labeling | Clause Class. |
|-----------------------------------|------------------------------------|-------------------|---------------|
| Models                            | ET (en) | ES (en) | REMAN (en) | GNE (en) | ECA (en) | EDCE (zh) |
| CRF                               |         |         | +           |          |          |          |
| BiLSTM-CRF                        |         |         | +           |          |          |          |
| BiLSTM-CRF                        |         |         | +           |          |          |          |
| SVM                               |         |         | +           |          |          |          |
| CRF                               |         |         | +           |          |          |          |
| LSTM                              |         |         | +           |          |          |          |
| JMECause                          |         |         | +           |          |          |          |
| multi-kernel SVM                  |         |         | +           |          |          |          |
| Multi-Kernel                      |         |         | +           |          |          |          |
| ConvMS-Memnet                     |         |         | +           |          |          |          |
| CANN                              |         |         | +           |          |          |          |
| PAE-DGL                           |         |         | +           |          |          |          |
| HCS                               |         |         | +           |          |          |          |
| Ranking                           |         |         | +           |          |          |          |
| Our work                          |         |         | +           |          |          |          |

Figure 8: Mapping of previous state-of-the-art methods to data sets. + indicates that we are aware of a publication which reports on the method being evaluated on the respective data set and a − indicates our assumption that no reported results exist with the respective method being evaluated on the respective data set. ET corresponds to ElectoralTweets, ES to EmotionStimulus, GNE to GoodNewsEveryone, whereas the other data set are as being introduced above.