CLaC at SMM4H 2020: Birth defect mention detection

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Abstract
For the detection of personal tweets, where a parent speaks of a child’s birth defect, CLaC combines ELMo word embeddings and gazetteer lists from external resources with a GCNN (for encoding dependencies), in a multi layer, transformer inspired architecture. To address the task, we compile several gazetteer lists from resources such as MeSH and GI. The proposed system obtains .69 for $\mu$F1 score in the SMM4H 2020 Task 5 where the competition average is .65.

Introduction Tweets potentially offer a record that is distilled from messages that are written for other purposes. They contain many particular, directly observed experiences, which are of great interest to epidemiologists and health monitors. Situating congenital abnormalities (birth defects) in time and space is important to identify causes of birth defects, find opportunities to prevent them, and improve the health of those living with them. Therefore, identifying tweets mentioning birth defect experiences by a family is helpful, which motivated the SMM4H 2020 Task 5 (Klein et al., 2020).

This paper reports our effort toward building a predictive system to address the task. We try to leverage medical annotations, family relation annotations, as well as dependency relations in our model.

Task description and data The SMM4H 2020 task 5 is a 3-way classification problem. Class 1 tweets refer to the user’s child and indicate that he/she has a birth defect. Class 2 tweets are ambiguous about whether someone is the user’s child or has a birth defect mentioned in the tweet. Class 3 tweets merely mention birth defects. Training and development sets provided by the organizers include 14705 and 3677 tweets respectively and the evaluation set includes 4603 tweets.

Preprocessing and annotations Tweets are tokenized using the ANNIE tweet tokenizer (Cunningham et al., 2002) as well as the hashtag tokenizer (Maynard and Greenwood, 2014). URLs and user mentions are removed. We use the Stanford parser (Klein and Manning, 2003) to encode dependencies and ANNIE Names for named entity recognition.

We compiled gazetteer lists for birth defect detection from MeSH (Lipscomb, 2000), namely BirthDef, a list of congenital, hereditary, and neonatal diseases and abnormalities compiled from MeSH C16 and PregComp, a list of pregnancy complications compiled from MeSH C13.703. Each MeSH sub-tree is traversed depth-first and all entry terms for each heading (both for internal nodes and leaves) are added to the gazetteers. A word list of family terms, FamilyRel, that includes terms like son, daughter, cousin, etc. is also complied. Moreover, a list Acquaintance which contains terms like friend, colleague, neighbor, etc. is extracted from the General Inquirer (Stone et al., 1966).

These four gazetteer lists form the parameter Annotation or $A = \{\text{BirthDef}, \text{PregComp}, \text{FamilyRel}, \text{Acquaintance}\}$ and form the four annotation types.

Deep model Our system consists of four stacked layers. Each layer $l \geq 2$ receives token represenations $h_l^{l-1}$ and passes new represenations $h_l^l$ to the next layer. The layers are:

Layer 1: annotation embedding and token embedding. Annotation types are embedded using a matrix $M \in \mathbb{R}^{4 \times 1024}$ (four rows corresponding to four annotation types). $M$ is initialized randomly.
and learned as a parameter during training for the main classification task. To embed tokens we use ELMo (Peters et al., 2018). The new representations \( h_1^i \) is obtained by summing annotation embeddings to token embeddings (see Figure 1).

**Layer 2:** the encoder part of the Transformer (Vaswani et al., 2017). The encoder gets the representations \( h_1^i \) and outputs representations \( h_2^i \). The number of heads in the multi-head attention is \( n_{heads} = 4 \) and the dimensionality of the feed-forward layer is \( d_{FF} = 1024 \).

**Layer 3:** graph convolutional network (GCNN) (Kipf and Welling, 2017) for dependency relation encoding following (Marcheggiani and Titov, 2017). In GCCN each token is represented based on its adjacent tokens in dependency parse by
\[
 h_l^i = \text{ReLU} \left( \sum_{j \in \mathcal{N}(i)} W_{L(j,i)} h_l^j + b \right)
\]
where \( \mathcal{N}(i) \) is the set of tokens adjacent to token \( i \) and \( L(j,i) \) is the label of the arc from token \( j \) to token \( i \). Note that the network is not tied, i.e. \( W_{L(i,j)} \) depends on the arc labels. GCNN receives \( h_2^i \) and outputs token-wise representations \( h_3^i \).

**Layer 4:** attention (Bahdanau et al., 2015), which calculates importance scores
\[
e_i = w^T_{\text{att}} h_3^i
\]
using a latent context vector \( w_{\text{att}} \) and normalizes the scores using softmax
\[
 \alpha_i = \frac{\exp(e_i)}{\sum_j e_j}
\]
for a weighted sum
\[
 H = \sum_i \alpha_i \times h_3^i.
\]
Attention produces an output vector \( H \in \mathbb{R}^{1024} \) for the tweet, which is fed into three decision neurons for classifying into the three output classes.

Our model is implemented using PyTorch (Paszke et al., 2017) and optimized with the Adam optimizer (Kingma and Ba, 2015) with a learning rate of \( lr = 0.0005 \) for 7 to 10 epochs.

| Annotation Embedding | \( b_1^i \) | \( b_2^i \) | \( b_3^i \) | \( b_4^i \) | \( b_5^i \) | \( b_6^i \) | \( b_7^i \) | \( b_8^i \) |
|---------------------|---------|---------|---------|---------|---------|---------|---------|---------|
| \( M_{Name} \)      | 0       | 0       | 0       | 0       | 0       | 0       | 0       | 0       |
| \( M_{BirthDef} \)  | +       | +       | +       | +       | +       | +       | +       | +       |

Figure 1: Additive annotation embedding. \( M_a \) is the row in \( M \) that corresponds to annotation type \( a \in A \)

**Submitted system** Due to a submission issue, only one of three planned configurations was submitted.

Ablation studies on our validation data showed that all four layers of the architecture add to the overall performance:

| System           | Layer | Validation set F1 | Test set F1 |
|------------------|-------|-------------------|-------------|
| \( \text{TE+Trans} \) | 1,2,4 | .70               | .65         |
| \( \text{TE+GCNN} \)   | 1,3,4 | .72               | .67         |
| \( \text{TE+AE+Trans} \) | 1,2,4 | .75               | .70         |
| \( \text{TE+AE+Trans+GCNN} \) | 1,2,3,4 | .76               | .71         |
| competition mean  | -     | -                 | .62         |

The results on our development set suggest that the best performance is achieved by the full system (indicated in boldface). The official competition results are provided on the right side of Table 1. The micro average scores for our submission is close to its development score, which we consider an important sign of robustness in our system.

**Conclusion** For the SMM4H 2020 Task 5 competition we proposed a multi-layer system to leverage gazetteer list annotations as well as a dependency parse. The reported experiments here suggest that incorporating external knowledge in form of textual annotation has the potential to enhance the performance of models trained on moderate-sized training sets in a robust and efficient manner.
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