GradAscent at EmoInt-2017: Character- and Word-Level Recurrent Neural Network Models for Tweet Emotion Intensity Detection

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Abstract
The WASSA 2017 EmoInt shared task has the goal to predict emotion intensity values of tweet messages. Given the text of a tweet and its emotion category (anger, joy, fear, and sadness), the participants were asked to build a system that assigns emotion intensity values. Emotion intensity estimation is a challenging problem given the short length of the tweets, the noisy structure of the text and the lack of annotated data. To solve this problem, we developed an ensemble of two neural models, processing input on the character- and word-level with a lexicon-driven system. The correlation scores across all four emotions are averaged to determine the bottom-line competition metric, and our system ranks place forth in full intensity range and third in 0.5-1 range of intensity among 23 systems at the time of writing (June 2017).

1 Introduction
Sentiment analysis of a text reveals information on the degree of positiveness or negativeness of the opinion expressed by the writer. Such information can be useful for providing better services for users (Kang and Park, 2014) or preventing potentially dangerous situations (O’Dea et al., 2015). Traditionally the most popular way of sentiment representation is either binary (positive, negative) or multi-class (for example 5 classes: very negative, negative, neutral, positive, very positive). While being simple, such a scheme looses interpretability and a continuous intensity scale might be preferred. Twitter sentiment and emotion intensity detection are still challenging tasks and remain active areas of research. These difficulties have several reasons: extensive usage of hashtags, slang, abbreviations, and emoticons. Also, tweets are usually typed on mobile devices which can lead to a substantial amount of typos. As traditional NLP tools are usually trained on datasets containing clean text, which makes it difficult to use them for tweet analysis.

Existing approaches for modeling emotion intensity rely heavily on manually constructed lexicons, which contain information about intensity weights for each available word (Mohammad and Bravo-Marquez, 2017a; Neviarouskaya et al., 2007). The intensity for the whole sentence can be inferred by combining individual scores of words. While being easily interpretable, such models have several limitations. Ignoring word order and compositionality of the language is the first issue, which is critical for modeling sequences. Constructing such lexicons is a labour-intensive process, which needs to be carried out continuously due to the constant development of language. Data-driven approaches like deep neural networks can overcome such limitations, and they have been behind many recent advances in text processing tasks, such as language modeling, machine translation, POS tagging, and classification (Irsoy and Cardie, 2014; Socher et al., 2013). The appealing property of such models is their ability to combine feature extraction and classification stages given a sufficient amount of training data.

In this paper, we augment traditional lexicon-based models with two neural network-based models: one with character and one with word input. Character-level deep neural networks recently showed outstanding results on text understanding tasks such as machine translation (Kalchbrenner et al., 2016) and text classification (Zhang et al., 2015). In a domain-specific task such as predict-
ing the emotion intensity of tweets, a character-level model can theoretically capture the notion of hashtags, emoticons, or character repetitions, which are all unique to social media. The intuition is that a character-level model captures common writing patterns such as punctuations and signaling characters. A word-level recurrent neural model can incorporate the order of information using distributed representations of words trained on a large amount of text.

Our final model is a weighted average of the scores provided by the baseline, our character- and word-level model. Our ensemble model achieved forth position in the 0-1 emotion intensity range task and third position in the 0.5-1.0 range task on the public leaderboard (GradAscent team) on CodaLab\(^1\) at the time of writing this paper (June 2017).

2 Approach

Our system is an ensemble of the provided baseline system and two neural network-based models; processing character and word input respectively. Combining the word and character representations we can deal with noisiness of the tweet messages as well as capturing the semantics of the text by using distributed word representations.

2.1 Data pre-processing

We perform only a few preprocessing steps, like stripping URLs, user mentions (@username) and leave only the following characters: a-zA-Z@!:(),;?.‘0-9*. We always convert a message to lowercase before feeding it to the models.

| Split   | Joy | Anger | Fear | Sadness | Sum  |
|---------|-----|-------|------|---------|------|
| Train   | 823 | 856   | 1147 | 786     | 3612 |
| Dev     | 78  | 83    | 109  | 73      | 343  |
| Test    | 714 | 760   | 995  | 673     | 3142 |

2.2 Baseline model

The baseline system is a WEKA-based model called AffectiveTweets (Mohammad and Bravo-Marquez, 2017a). This system combines features derived from several lexicons like MPQA (Wilson et al., 2005), Bing Liu (Hu and Liu, 2004), AFINN (Nielsen, 2011), Sentiment 140 (Kiritchenko et al.), NRC Hashtag sentiment lexicon, NRC Word-Emotion Association Lexicon (Mohammad and Turney, 2013), NRC-10 Expanded (Bravo-Marquez et al., 2016), NRC Hashtag Emotion Association (Saif and Kiritchenko, 2015), and SentiWordNet (Baccianella et al., 2010) with traditional NLP features like word- and character n-grams, POS tags (Gimpel et al., 2011), and processing of negations. In addition to those features, AffectiveTweets incorporates SentiStrength values (Thelwall et al., 2012), Brown clusters (Brown et al., 1992) trained on \(\sim\)53 million tweets\(^2\), combining them with averaged and concatenated first

\(^1\)https://competitions.codalab.org/competitions/16380
\(^2\)http://www.cs.cmu.edu/~ark/TweetNLP/
2.3 Character-level RNN model

We extracted character-level sentence representations by encoding the whole tweet text with the pre-trained recurrent neural network model\(^3\). This model contains a single multiplicative LSTM (Krause et al., 2016) layer with 4,096 hidden units, trained on ~80 million Amazon product reviews as a character-based language model (Radford et al., 2017). We extracted the hidden vector corresponding to the last character of a tweet and also averaged the representations of all hidden vectors. Concatenation of the two vectors is used as a tweet representation. In our experiments, we observed that adding averaged character representations improves the overall performance, especially when evaluating high-intensity tweets.

In addition to the pre-trained character-level language model, we investigate a model trained specifically for tweets. Our observation was that the tweets have a different language structure than product reviews, which might affect the transferability of features between domains. For instance, the extensive use of emoticons, character repetition, and hashtags, which are common for tweet messages, however, significantly different from product reviews which are often longer and grammatically correct.

We trained the character-based language model on the Sentiment 140 corpus comprised of 1.6 million tweets (Go et al., 2009). A single-layer LSTM (Hochreiter and Schmidhuber, 1997) with 1024 hidden units was trained with Adam optimizer (Kingma and Ba, 2014) with 0.0005 learning rate and clipping gradients at norm 1. We used the Support Vector Regressor (SVR) algorithm to classify tweets represented as a fixed-length vector with a character-based recurrent neural network. Results of different setups are reported in Table 2.

2.4 Word-level model

We used distributed representations to model the words in a tweet. We carried out several experiments where we used random initialization for word embeddings and two pre-trained versions of GloVe embeddings (Pennington et al., 2014)\(^4\), to test if Twitter specific word representations are more suitable to solve the problem. Out-of-vocabulary words were replaced with a special word 'OOV' and initialized as a random vector, which was tuned during the training. We used a 50-dimensional embedding representation in all our experiments.

A bidirectional gated recurrent unit (GRU) network (Chung et al., 2014) with a 32-dimension cell size was used for modeling the tweet as a hidden memory vector. The vector corresponding to the last word was fed to a dense layer with 1 neuron predicting emotion intensity. We used GRUs as they tackle the common vanishing gradient problem of RNNs during the training and they contain fewer parameters than LSTM units. The word-level model is trained on the given EmoInt corpus with Adam optimizer using different embedding setups, the results are presented in Table 3.

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\(^3\)https://github.com/openai/generating-reviews-discovering-sentiment

\(^4\)https://nlp.stanford.edu/projects/glove/
Table 4: Pearson and Spearman correlation coefficients of baseline, character and word-level models and its ensemble for fear, anger, joy and sadness emotions and also average values. Results are calculated on the provided test set labels.

| Model | avg_p | avg_s | anger_p | anger_s | fear_p | fear_s | joy_p | joy_s | sad_p | sad_s |
|-------|-------|-------|---------|---------|--------|--------|-------|-------|-------|-------|
| Test set results (Intensity range: 0-1) |       |       |         |         |        |        |       |       |       |       |
| Baseline | 0.655 | 0.652 | 0.631   | 0.623   | 0.631  | 0.622  | 0.645 | 0.654 | 0.712 | 0.711 |
| Char_LM | 0.474 | 0.472 | 0.415   | 0.400   | 0.575  | 0.551  | 0.278 | 0.299 | 0.629 | 0.638 |
| Word_Level | 0.326 | 0.323 | 0.253   | 0.258   | 0.337  | 0.332  | 0.201 | 0.194 | 0.435 | 0.395 |
| Char_LM + Word_Level | 0.659 | 0.656 | 0.580   | 0.572   | 0.658  | 0.638  | 0.708 | 0.714 | 0.688 | 0.701 |
| Baseline + Char_LM + Word_Level | 0.721 | 0.717 | 0.678   | 0.665   | 0.698  | 0.686  | 0.744 | 0.750 | 0.763 | 0.767 |
| Test set results (Intensity range: 0.5-1) |       |       |         |         |        |        |       |       |       |       |
| Baseline | 0.475 | 0.449 | 0.495   | 0.464   | 0.476  | 0.432  | 0.370 | 0.363 | 0.558 | 0.537 |
| Char_LM | 0.419 | 0.413 | 0.316   | 0.327   | 0.488  | 0.435  | 0.416 | 0.423 | 0.457 | 0.467 |
| Word_Level | 0.259 | 0.252 | 0.237   | 0.257   | 0.220  | 0.226  | 0.211 | 0.201 | 0.451 | 0.408 |
| Char_LM + Word_Level | 0.471 | 0.467 | 0.389   | 0.406   | 0.488  | 0.435  | 0.536 | 0.547 | 0.470 | 0.481 |
| Baseline + Char_LM + Word_Level | 0.562 | 0.543 | 0.565   | 0.545   | 0.531  | 0.494  | 0.528 | 0.531 | 0.624 | 0.601 |

3 Experiment

The dataset for the WASSA-2017 competition (Mohammad and Bravo-Marquez, 2017b) is comprised of 7097 annotated tweets, classified into 4 categories: joy, anger, fear, and sadness (dataset statistics are presented in Table 1). For each annotated tweet there is an ID, full text, emotion category, and emotion intensity value. Emotion intensity is a real value in the range from 0 to 1, where higher value correspond to a higher intensity of the emotion conveyed. A sample from the EmoInt corpus:

30112 LOVE LOVE LOVE #smile #fun #relaxationiskey joy 0.740, where 30112 is the ID of a tweet, which is labeled as "joy" with an intensity of 0.740.

3.1 Ensembling of the models

Ensembling of several models is a widely used method to improve the performance of the overall system by combining predictions of several classifiers. Several ensembling techniques have been proposed recently: mixing experts (Jacobs et al., 1991), model stacking, bagging and boosting (Breiman, 1996) and a simple weighted average of the scores of individual models, which we used in this work. The main reason for our choice was the limited size of the training data, and using more complex approach like stacking could lead to overfitting. In this work, we output emotion intensity values as a linear combination of individual predictions of three systems: baseline, character and word-level models.

\[
\text{emotion intensity} = w_b \times \text{baseline}_\text{emotion} + w_w \times \text{w}_\text{rnn}_\text{emotion} + w_c \times \text{c}_\text{rnn}_\text{emotion},
\]

where \(w_b\), \(w_w\) and \(w_c\) are intensities of the baseline, character and word-level models correspondingly for the emotion (joy, anger, fear or sadness). Ensembling coefficients \(w_b\), \(w_c\) and \(w_w\) were tuned on the development set to maximize the average Pearson correlation coefficient using grid-search.

4 Results & Conclusion

We report Pearson and Spearman correlation for each emotion class on the provided test data, shown in Table 4. The correlation rank coefficients assess how relevant and similar the two sets of ranking are. The character and word-level neural models achieve lower correlation values than
the baseline, which is an indicator that models containing much of external knowledge perform better than end-to-end models on the tasks with a handful amount of samples; however, they bring additional value to the ensemble. Pearson and Spearman correlation coefficients are improved by 0.066 and 0.065 for the intensities in the full range of 0-1, achieving #4 position on the leaderboard. Additionally, the systems were evaluated on the sample with moderate or high emotional intensities with values from 0.5 to 1. Our ensemble model places rank #4 and shows 0.087 (∼18.5% relative) improvement on both correlation coefficients.

Surprisingly, tweet representations obtained with the character-level model show competitive or even better results for fear and joy emotion categories for samples with high-intensity emotions, and overall the CharLM model shows similar results to the AffectiveTweet baseline model. Given the fact that the CharLM model did not have any external knowledge or supervision other than the provided data, this demonstrates the effectiveness of the character-level modeling of noisy and short texts.

Acknowledgments

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement No 642667 (SECURE). We would like to thank Dr. Cornelius Weber and Dr. Sven Magg for their helpful comments and suggestions.

References

Stefano Baccianella, Andrea Esuli, and Fabrizio Sebastiani. 2010. Sentiwordnet 3.0: An enhanced lexical resource for sentiment analysis and opinion mining. In Nicoletta Calzolari, Khalid Choukri, Bente Maegaard, Joseph Mariani, Jan Odijk, Stelios Piperidis, Mike Rosner, and Daniel Tapias, editors, Proceedings of the International Conference on Language Resources and Evaluation, LREC 2010, 17-23 May 2010, Valletta, Malta. European Language Resources Association.

Felipe Bravo-Marquez, Eibe Frank, Saif M. Mohammad, and Bernhard Pfahringer. 2016. Determining word-emotion associations from tweets by multi-label classification. In 2016 IEEE/WIC/ACM International Conference on Web Intelligence, WI 2016, Omaha, NE, USA, October 13-16, 2016. IEEE Computer Society, pages 536–539. https://doi.org/10.1109/WI.2016.0091.

Leo Breiman. 1996. Bagging predictors. Machine learning 24(2):123–140.

Peter F Brown, Peter V Desouza, Robert L Mercer, Vincent J Della Pietra, and Jenifer C Lai. 1992. Class-based n-gram models of natural language. Computational linguistics 18(4):467–479.

Junyoung Chung, Caglar Gulcehre, Kyunghyun Cho, and Yoshua Bengio. 2014. Empirical evaluation of gated recurrent neural networks on sequence modeling. arXiv: 1412.3555v1 pages 1–9.

Kevin Gimpel, Nathan Schneider, Brendan O’Connor, Dipanjan Das, Daniel Mills, Jacob Eisenstein, Michael Heilman, Dani Yogatama, Jeffrey Flanigan, and Noah A. Smith. 2011. Part-of-speech tagging for twitter: Annotation, features, and experiments. In The 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, Proceedings of the Conference, 19-24 June, 2011, Portland, Oregon, USA - Short Papers. The Association for Computer Linguistics, pages 42–47.

Alec Go, Richa Bhayani, and Lei Huang. 2009. Twitter sentiment classification using distant supervision. CS224N Project Report, Stanford 1(12).

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural computation 9(8):1735–1780.

Minqing Hu and Bing Liu. 2004. Mining and summarizing customer reviews. In Won Kim, Ron Kohavi, Johannes Gehrke, and William DuMouchel, editors, Proceedings of the Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Seattle, Washington, USA, August 22-25, 2004. ACM, pages 168–177. https://doi.org/10.1145/1014052.1014073.

Ozan Irsoy and Claire Cardie. 2014. Opinion mining with deep recurrent neural networks. In the Proceedings of the Conference on EMNLP, pages 720–728.

Robert A Jacobs, Michael I Jordan, Steven J Nowlan, and Geoffrey E Hinton. 1991. Adaptive mixtures of local experts. Neural Computation 3(1):79–87.

Nal Kalchbrenner, Lasse Espeholt, Karen Simonyan, Aaron van den Oord, Alex Graves, and Koray Kavukcuoglu. 2016. Neural machine translation in linear time. arXiv:1610.10099.

Daekook Kang and Yongtae Park. 2014. Review-based measurement of customer satisfaction in mobile service: Sentiment analysis and vikor approach. Expert Systems with Applications 41(4):1041–1050.

Diederik Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.
Svetlana Kiritchenko, Xiaodan Zhu, and Saif M. Mohammad. 2017. Sentiment analysis of short informal texts 50:723–762.

Ben Krause, Liang Lu, Iain Murray, and Steve Renals. 2016. Multiplicative lstm for sequence modelling. arXiv:1609.07959.

Saif M. Mohammad and Felipe Bravo-Marquez. 2017a. Emotion intensities in tweets. In Proceedings of the Sixth Joint Conference on Lexical and Computational Semantics (*Sem). Vancouver, Canada.

Saif M. Mohammad and Felipe Bravo-Marquez. 2017b. Emotion intensities in tweets. In Proceedings of the Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis (WASSA). Copenhagen, Denmark.

Saif M. Mohammad and Peter D. Turney. 2013. Crowdsourcing a word-emotion association lexicon 29(3):436–465.

Alena Neviarouskaya, Helmut Prendinger, and Mitsuru Ishizuka. 2007. Textual affect sensing for social and expressive online communication. Affective Computing and Intelligent Interaction pages 218–229.

Finn Årup Nielsen. 2011. A new ANEW: evaluation of a word list for sentiment analysis in microblogs. In Matthew Rowe, Milan Stankovic, Aba-Sah Dadzie, and Mariann Hardey, editors, Proceedings of the ESWC2011 Workshop on 'Making Sense of Microposts': Big things come in small packages, Heraklion, Crete, Greece, May 30, 2011. CEUR-WS.org, volume 718 of CEUR Workshop Proceedings, pages 93–98.

Bridianne O’Dea, Stephen Wan, Philip J Batterham, Alison L Clear, Cecile Paris, and Helen Christensen. 2015. Detecting suicidality on twitter. Internet Interventions 2(2):183–188.

Jeffrey Pennington, Richard Socher, and Christopher D Manning. 2014. GloVe: Global vectors for word representation. In the Proceedings of the Conference on EMNLP, pages 1532–1543.

Alec Radford, Rafal Jozefowicz, and Ilya Sutskever. 2017. Learning to generate reviews and discovering sentiment. arXiv: 1704.01444.

Mohammad Saif and Svetlana Kiritchenko. 2015. Using hashtags to capture fine emotion categories from tweets. Computational Intelligence 31(2):301–326. https://doi.org/10.1111/coin.12024.

Richard Socher, Alex Perelygin, Jean Y Wu, Jason Chuang, Christopher D Manning, Andrew Y Ng, and Christopher Potts. 2013. Recursive deep models for semantic compositionality over a sentiment treebank. In the Proceedings of the Conference on EMNLP. volume 1631, pages 1631–1642.

Mike Thelwall, Kevan Buckley, and Georgios Palattoglu. 2012. Sentiment strength detection for the social web. JASIST 63(1):163–173. https://doi.org/10.1002/asi.21662.

Theresa Wilson, Janyce Wiebe, and Paul Hoffmann. 2005. Recognizing contextual polarity in phrase-level sentiment analysis. In HLT/EMNLP 2005, Human Language Technology Conference and Conference on Empirical Methods in Natural Language Processing, Proceedings of the Conference, 6–8 October 2005, Vancouver, British Columbia, Canada. The Association for Computational Linguistics, pages 347–354.

Xiang Zhang, Junbo Zhao, and Yann LeCun. 2015. Character-level convolutional networks for text classification. arXiv: 1509.01626.