

Team Phoenix at WASSA 2021: Emotion Analysis on News Stories with Pre-Trained Language Models

Yash Butala*, Kanishk Singh*, Adarsh Kumar* and Shrey Shrivastava

Indian Institute of Technology Kharagpur, India
{yashbutala, kanishksingh, adarshkumar712}@iitkgp.ac.in
shrivastava.shrey@iitkgp.ac.in

Abstract

Emotion is fundamental to humanity. The ability to perceive, understand and respond to social interactions in a human-like manner is one of the most desired capabilities in artificial agents, particularly in social-media bots. Over the past few years, computational understanding and detection of emotional aspects in language have been vital in advancing human-computer interaction. The WASSA Shared Task 2021 released a dataset of news-stories across two tracks, Track-1 for Empathy and Distress Prediction and Track-2 for Multi-Dimension Emotion prediction at the essay-level. We describe our system entry for the WASSA 2021 Shared Task (for both Track-1 and Track-2), where we leveraged the information from Pre-trained language models for Track specific Tasks. Our proposed models achieved an Average Pearson Score of **0.417**, and a Macro-F1 Score of **0.502** in Track 1 and Track 2, respectively. In the Shared Task leaderboard, we secured **4th** rank in Track 1 and **2nd** rank in Track 2.

1 Introduction

Sentiment analysis over texts has been a widely researched area in NLP. The number of papers published in sentiment analysis related domains has increased from 37 papers in 2000 to 6996 in 2016 (Mäntylä et al., 2016). Sentiment analysis is a trending research topic, possibly due to its applications that automatically collect and analyze a large corpus of opinions with text mining tools. From the conventional task of predicting polarity as positive, negative or neutral, the researchers are now increasingly focused on sophisticated tasks such as emotion recognition, aspect level sentiment analysis, intensity prediction, etc.

Recently, the researchers started exploring more sophisticated models of human emotion on a larger

scale. Several datasets and corpora have been curated in this domain, such as (Mohammad et al., 2018), (Alm and Sproat, 2005), and larger datasets like (Demszky et al., 2020). (Buechel et al., 2018) presented an interesting computational work distinguishing between multiple forms of empathy, empathic concern, and personal distress. This data of empathic concern and personal distress along with Multi-dimension Emotions Labelling on news-stories across seven classes, namely: sadness, fear, neutral, anger, disgust, joy, surprise, has been released a Shared Task (Tafreshi et al., 2021) in WASSA-2021 Workshop as Two Tracks¹.

In this paper, we describe our system entry for both the tracks of WASSA 2021 Shared Task. The primary contributions of the paper are as follows:

Track 1:

- We demonstrate the efficacy of multi-tasking through parameter sharing which further strengthens the belief that empathic concern and personal distress are co-related.
- We amalgamate the information from sentence embeddings with normalized additional information to finally predict the empathic concern and personal distress using regression.

Track 2:

- We provide a comparative analysis of generation modelling against classification modelling for the task of Emotion Prediction.
- We illustrate the efficiency of Task Specific Incremental Fine-Tuning approach 4.2 on Pre-Trained Models for a small sized dataset.

2 Related Works

Pre-trained language models have proved to be a breakthrough in analyzing a person’s emotional state. We now describe briefly some of these highly influential works.

* Equal Contribution

¹refer Section 3 for more details

2.1 Pre-trained Language Models

Over the past few years, pre-trained language models have progressed greatly in learning contextualized representations. Transformer (Vaswani et al., 2017), first proposed for machine translation, has enabled faster learning of complex representations of text. GPT (Radford et al., 2018), BERT (Devlin et al., 2018), RoBERTa (Liu et al., 2019), XLNet (Yang et al., 2019) all leverage transformer architecture along with statistical tokenizers. ELECTRA (Clark et al., 2020) a recent generator-discriminator-based pre-training approach offers a competitive performance despite requiring lesser compute. Domain specific language models also leads to a significant performance gain (Vaidhya and Kaushal, 2020; Lee et al., 2019; Beltagy et al., 2019).

2.2 Emotion Recognition

Emotion recognition through facial expressions and speech data has been the subject of extensive study in the past. (Tarnowski et al., 2017) presents an approach for recognition of seven emotional states based on facial expressions. (Yoon et al., 2018) utilizes a novel deep dual recurrent encoder model to obtain a better understanding of speech data using text data and audio signals simultaneously.

For text, various approaches have been proposed for emotion recognition. Deshmukh and Kirange (2012) proposed an SVM-based approach for predicting opinions on news headlines. Acheampong et al. (2020) paper analyses the efficacy of utilizing transformer encoders for detecting emotions. Kant et al. (2018) demonstrates the practical efficiency of large pre-trained language models for Multi-Emotion sentiment classification.

2.3 Computation of Empathy

Empathy and distress are core components of a person’s emotional state, and there has been a growing interest in computational approaches to model them. Considering language variations across different regions, empathy and distress can also vary with demographics (Lin et al., 2018; Loveys et al., 2018), and recently (Guda et al., 2021) proposed a demographic-aware empathy modelling framework using BERT and demographics features.

Understanding empathy and distress are crucial for analyzing mental health and providing aid. Recently (Sharma et al., 2020) explored language models for identifying empathetic conversations in the mental health support system.

3 Task and Dataset Description

Our experiments’ data consists of the emotion-labels to news stories released as part of the WASSA 2021 shared task. The dataset provided (Buechel et al., 2018) contained essays of 300-800 characters length, Batson empathetic concern, and personal distress scores along with other additional demographic and personality information.

The training corpus of WASSA-2021 shared task consists of 1860 training pairs containing seven emotion labels, namely: sadness, fear, neutral, anger, disgust, joy, surprise. The dataset also includes person-level demographic information (age, gender, ethnicity, income, education level) and personality information. We normalized these information before using in our model for Track 1. We excluded this information in Track 2 model.

Emotion	Train	Dev
sadness	647	96
anger	349	76
neutral	275	31
fear	194	25
surprise	164	14
disgust	149	14
joy	82	12
Total	1860	270

Table 1: Composition of Training and Development dataset

The objective of the Track-1 is to predict the Batson empathetic concern and personal distress using the essay and any of the additional information to improve Pearson correlation between the predicted labels and gold standard labels. The task can formally be described as following:

Empathetic concern and personal distress prediction: Given a paragraph t , additional information i , learn a model:

$$g(t, I) \rightarrow (x, y) \text{ where } x \in R^+ \text{ and } y \in R^+.$$

The Track 2 is formulated as essay-level Multi-Dimension emotion prediction task. It is defined formally as:

Emotion Prediction: Given a paragraph t , the classification task aims to learn a model $g(t) \rightarrow \{l_1, l_2, \dots, l_k\}$ where l_i is a label $\in \{sadness, anger, \dots, etc\}$.

4 Approach

4.1 Empathy and Distress Prediction Model

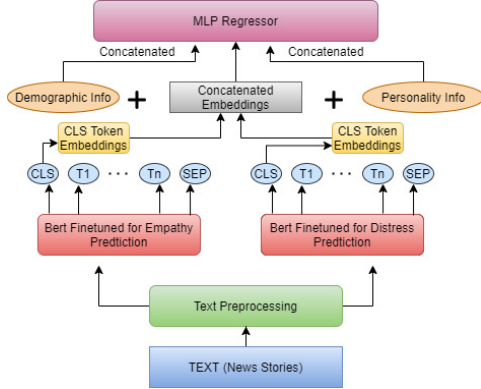


Figure 1

The system architecture for Empathy and Distress Prediction is shown in Figure 1. The approach is primarily based on fine-tuning pre-trained language models for down-stream tasks. We enforce the technique of hard-parameter sharing through concatenation of BERT-fine-tuned embeddings trained separately for Empathy and Distress Prediction. The final shared parameters are then concatenated with the scaled demographic and personality features given in the dataset. These separately fine-tuned BERT-embeddings for distress and empathy prediction are then concatenated with rest of the features before feeding them to the regression models. This parameter shared multi-task framework (Kaushal and Vaidhya, 2020) allows for the use of the same model, loss function, and hyper-parameters for the task of empathy prediction as well as Distress Prediction.

$$MSE(y_{true}, y_{pred}) = \sqrt{\left(\frac{1}{n}\right) \sum_{i=1}^n (y_{true_i} - y_{pred_i})^2}$$

$$r = \frac{\sum_{i=1}^n (y_{true_i} - \bar{y}_{true})(y_{pred_i} - \bar{y}_{pred})}{\sqrt{\sum_{i=1}^n (y_{true_i} - \bar{y}_{true})^2} \sqrt{\sum_{i=1}^n (y_{pred_i} - \bar{y}_{pred})^2}}$$

where y_{true} are the gold-standard and y_{pred} being the predicted scores for empathy and distress. The final Pearson correlation score used for final evaluation was:

$$r_{avg} = \frac{r_{empathy} + r_{distress}}{2}$$

4.2 Emotion Label Generation Model

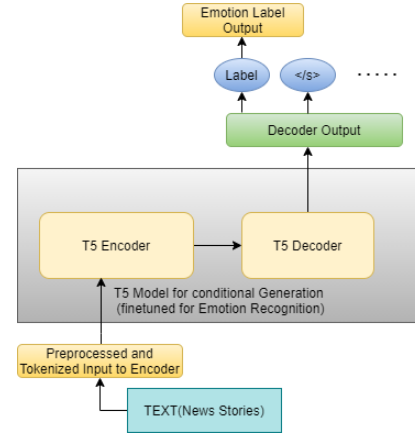


Figure 2

Our proposed approach for Emotion Prediction is shown in Figure 2. The approach is primarily based on T5 Model (Raffel et al., 2019) for conditional generation of emotion labels. Hence before feeding into the network, the emotion prediction task is cast as feeding the essay text as input and training it to generate target emotion labels as text. This allows for the use of the same model, loss function, and hyper-parameters for the task of emotion prediction as is done in other Text Generation tasks. More formally, the modeling of the task can be described as:

$$p(x|c) = \prod_{i=1}^2 p(x_i|x_{<i}, c)$$

where c is the encoder input obtained after text tokenization and x is the target decoder output which is of length 2, with x_1 and x_2 as *label_token* and *eos_token* respectively.

Here, the transformer network parameters θ are trained with negative log-likelihood over a dataset $D = \{(c^1, x^1), (c^2, x^2), \dots, (c^D, x^D)\}$:

$$\mathcal{L}(D) = - \sum_{k=1}^{|\mathcal{D}|} \log p_{\theta}(x_i^k | x_{<i}^k, c^k)$$

Task Specific Incremental Finetuning: Along with the architecture proposed, instead of the T5 base model, we propose to use the T5 model finetuned on emotion recognition dataset (Saravia et al., 2018) for Emotion Recognition downstream task (Romero). This is done to leverage the task-specific knowledge beyond the available dataset of 1860 samples and to analyze the effect of task specific-incremental finetuning.

5 Experiments

The experiments were conducted using Pytorch (Paszke et al., 2019) and Hugging Face’s transformers (Wolf et al., 2019). The experiments were performed on the Google Colab Laboratory tool, which provides a Tesla T4 GPU and 16 GB RAM. Adam’s Optimizer (Kingma and Ba, 2017) with a learning rate of $2e-5$ was used for optimization. The training batch provided in the WASSA-2021 Shared task consisted of 1860 examples. An 80-20 split on the training set was performed for the train-valid split. The development set consisted of 210 examples was used as a test set. As suggested in the WASSA-2021 Shared Task, the average value of the Pearson correlation score of distress and empathy was used for evaluation in Track 1 and Macro F1 score was used in Track 2. The code and trained models are available at <https://github.com/yashbutala/WASSA>²

Models used in Experiment for Track 1: For Empathy and Distress Prediction from the finally obtained parameter-rich concatenated vector, we experimented on a variety of Supervised Machine-Learning architectures along with our final system. Brief details on these architectures are given below:

- **SVR** is a Support vector machine that supports linear and non-linear regression. It tries to fit as many instances as possible between the lines while limiting the margin violations.
- **Ada-Boost** is a meta-estimator that begins by fitting a regressor on the original dataset and then fits additional copies of the regressor on the same dataset but where the weights of instances are adjusted according to the error of the current prediction.
- **XG-Boost** is an applied machine learning algorithm, decision-tree-based ensemble that uses a framework for gradient boosting. It is an implementation of gradient boosted decision trees designed for speed and performance.
- **MLP** is a class of feedforward artificial neural network (ANN). MLP utilizes a supervised learning technique called backpropagation for training.³ Used the architecture described in the Section 4.1 for final prediction.

²<https://github.com/yashbutala/WASSA>

³Our final approach used for submission in WASSA-2021 Shared Task Track 1

Models used in Experiment for Track 2: For Emotion Classification, we experimented on a variety of architectures along with our final system. Brief details on these architectures are given below:

- **BERT-base** (Devlin et al., 2018) and **ALBERT-base-v2** (Lan et al., 2019) are the text classification models, in which pooled output, (i.e. output from the first token or *[CLS]* token of last layer of the model) is used as the contextualized embeddings for the text which was then fed into a single feed-forward linear layer for Binary Classification (Kamal et al., 2021), trained with Binary Cross-Entropy Loss.
- **T5-base** (Raffel et al., 2019) and **T5-Finetuned (Romero)**⁴ models use the architecture described in the Section 4.2 for conditional generation, the only difference being the pre-trained versions of T5 model used.
- **Pegasus-xsum** (Zhang et al., 2019) model also uses the same approach as used in T5 model for conditional generation, and performs better in several downstream tasks.

Links to pre-trained models used for experiment can be found in the Supplemental Section A.

6 Result

This section discusses the results from different approaches and architectures used in our experiments. While the train and development dataset were already available, the gold standard annotations of the test are withheld in the Shared Task of WASSA-2021. The experiments were performed considering Development set as our test dataset. Performance of only the final submissions are provided on the held-out test dataset.

6.1 Results for Track 1

Table 2 shows the model performance discussed in the development dataset section (used as validation set) for Track 1. Our final approach, which is described in Section 4.1 outperforms other approaches by an appreciable margin on development set but it failed on empathy prediction on the latest test set submission in the Codalab. It was due to an erroneous submission from us. Though during the post-evaluation phase, the model performed better

⁴Our final approach used for submission in WASSA-2021 Shared Task Track 2

Predictor	Distress	Empathy	Average
SVR	0.400	0.406	0.403
XG-Boost	0.431	0.394	0.413
Ada-Boost	0.418	0.374	0.396
MLP*	0.462	0.473	0.468

Table 2: Performance of our system on the development dataset of Track 1. Our final submission approach for Track 1 is marked with *.

Predictor	Distress	Empathy	Average
MLP	0.476	0.358	0.417

Table 3: Performance of our final submission on the held-out Test dataset of Track 1. Our final submission secured 4th rank on the Shared Task Leaderboard

on test set than the (Buechel et al., 2018). Table 3 shows the performance of our final submission for WASSA-2021 on the held-out test dataset

6.2 Results for Track 2

Table 4 shows the performance of the models discussed in section on the Development dataset (used as validation set) for Track 2. While its clear that our final approach described in Section 4.2 outperforms other approaches by an appreciable margin, there are two other important aspects to note from the table. First, the performance of Conditional Generation models, i.e. Pegasus-xsum and T5 models over Pre-trained Contextual Embedding based Classification model used for BERT and ALBERT models. Second, the improvement obtained by using already finetuned model⁵ over T5-base model. As can be seen in Table 4, our approach of generation of emotion labels performs way better than Contextual Embeddings-based classification. Furthermore, the improvement obtained by using task-specific finetuned model over the base T5 model suggests that the model is able to exploit the benefit of task specific incremental finetuning and was able to extrapolate the knowledge features learned from previous finetuning on Emotion recognition onto the newly finetuned model. Table 5 shows the performance of our final submission for WASSA-2021 on the held-out test dataset.

7 Conclusion and Future Work

In this paper, we presented an approach for predicting empathic concern and personal distress by fine-

⁵<https://huggingface.co/mrm8488/t5-base-finetuned-emotion>

Model	Macro-F1 score
BERT-base	0.38
ALBERT-base-v2	0.4739
Pegasus-xsum	0.502
T5-base	0.5259
T5-Finetuned*	0.572

Table 4: Macro F1 score for Emotion Prediction on Development set. Model descriptions are provided in Section 6. Our final submission approach for Track 2 is marked with *.

Metric	Result
Macro F1 Score	0.502
Micro F1 Score	0.594
Accuracy	0.594
Macro Precision	0.550
Micro Precision	0.594
Macro Recall	0.483
Micro Recall	0.594

Table 5: Performance of our system on the held-out test dataset, for track 2. Our final submission secured 2nd rank on the Shared Task Leaderboard

tuning a pre-trained language model using parameter sharing. As empathy and distress are correlated, we observe that parameter sharing improves the performance on this task. We amalgamated the sentence embeddings and other additional data, which further used the regression model for prediction. The ablation studies show that on the validation set, the MLP works best.

Also, opposite to most text classification approaches, which use embeddings from the final layer of pre-trained language models, we illustrated the efficiency of formulating finetuning of language models as a label generation task for emotion prediction. Our ablation studies demonstrated usefulness of using task-specific incremental finetuning.

In the future, we plan to extend our multi-tasking based model to incorporate soft parameter sharing. Inclusion of personality related traits provided in the dataset used in this paper, while predicting emotion labels might also be a promising direction to work on.

References

- Francisca Acheampong, Henry Nunoo-Mensah, Chen Wenyu, and Rubungo Andre Niyongabo. 2020. Recognizing emotions from texts using a bert-based approach.
- Cecilia Alm and Richard Sproat. 2005. Emotional sequencing and development in fairy tales. pages 668–674.
- Iz Beltagy, Kyle Lo, and Arman Cohan. 2019. Scibert: A pretrained language model for scientific text.
- Sven Buechel, Anneke Buffone, Barry Slaff, Lyle Ungar, and João Sedoc. 2018. Modeling empathy and distress in reaction to news stories. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 4758–4765, Brussels, Belgium. Association for Computational Linguistics.
- Kevin Clark, Minh-Thang Luong, Quoc V. Le, and Christopher D. Manning. 2020. Electra: Pre-training text encoders as discriminators rather than generators.
- Dorottya Demszky, Dana Movshovitz-Attias, Jeongwoo Ko, Alan Cowen, Gaurav Nemade, and Sujith Ravi. 2020. GoEmotions: A dataset of fine-grained emotions. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4040–4054, Online. Association for Computational Linguistics.
- Ratnadeep Deshmukh and D. Kirange. 2012. Emotion classification of news headlines using svm.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. BERT: pre-training of deep bidirectional transformers for language understanding. *CoRR*, abs/1810.04805.
- Bhanu Prakash Reddy Guda, Aparna Garimella, and Niyati Chhaya. 2021. Empathbert: A bert-based framework for demographic-aware empathy prediction.
- Ojasv Kamal, Adarsh Kumar, and Tejas Vaidhya. 2021. Hostility detection in hindi leveraging pre-trained language models.
- Neel Kant, Raul Puri, Nikolai Yakovenko, and Bryan Catanzaro. 2018. Practical text classification with large pre-trained language models. *CoRR*, abs/1812.01207.
- Ayush Kaushal and Tejas Vaidhya. 2020. Winners at W-NUT 2020 shared task-3: Leveraging event specific and chunk span information for extracting COVID entities from tweets. In *Proceedings of the Sixth Workshop on Noisy User-generated Text (W-NUT 2020)*, pages 522–529, Online. Association for Computational Linguistics.
- Diederik P. Kingma and Jimmy Ba. 2017. Adam: A method for stochastic optimization.
- Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. 2019. ALBERT: A lite BERT for self-supervised learning of language representations. *CoRR*, abs/1909.11942.
- Jinhyuk Lee, Wonjin Yoon, Sungdong Kim, Donghyeon Kim, Sunkyu Kim, Chan Ho So, and Jaewoo Kang. 2019. Biobert: a pre-trained biomedical language representation model for biomedical text mining.
- Bill Yuchen Lin, Frank F. Xu, Kenny Zhu, and Seungwon Hwang. 2018. Mining cross-cultural differences and similarities in social media. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 709–719, Melbourne, Australia. Association for Computational Linguistics.
- Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized BERT pretraining approach. *CoRR*, abs/1907.11692.
- Kate Loveys, Jonathan Torrez, Alex Fine, Glen Moriarty, and Glen Coppersmith. 2018. Cross-cultural differences in language markers of depression online. In *Proceedings of the Fifth Workshop on Computational Linguistics and Clinical Psychology: From Keyboard to Clinic*, pages 78–87, New Orleans, LA. Association for Computational Linguistics.
- Mika Viking Mäntylä, Daniel Graziotin, and Miikka Kuutila. 2016. The evolution of sentiment analysis - A review of research topics, venues, and top cited papers. *CoRR*, abs/1612.01556.
- Saif M. Mohammad, Felipe Bravo-Marquez, Mohammad Salameh, and Svetlana Kiritchenko. 2018. Semeval-2018 Task 1: Affect in tweets. In *Proceedings of International Workshop on Semantic Evaluation (SemEval-2018)*, New Orleans, LA, USA.
- Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Köpf, Edward Yang, Zach DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. 2019. Pytorch: An imperative style, high-performance deep learning library. *CoRR*, abs/1912.01703.
- Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2018. Language models are unsupervised multitask learners.
- Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2019. Exploring the limits of transfer learning with a unified text-to-text transformer. *CoRR*, abs/1910.10683.

- Manuel Romero. [T5 finetuned model for emotion recognition](#).
- Elvis Saravia, Hsien-Chi Toby Liu, Yen-Hao Huang, Junlin Wu, and Yi-Shin Chen. 2018. [CARER: Contextualized affect representations for emotion recognition](#). In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 3687–3697, Brussels, Belgium. Association for Computational Linguistics.
- Ashish Sharma, Adam Miner, David Atkins, and Tim Althoff. 2020. [A computational approach to understanding empathy expressed in text-based mental health support](#). In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 5263–5276, Online. Association for Computational Linguistics.
- Shabnam Tafreshi, Orphée De Clercq, Valentin Barriere, Sven Buechel, João Sedoc, and Alexandra Balahur. 2021. [WASSA2021 Shared Task: Predicting Empathy and Emotion in Reaction to News Stories](#). In *Proceedings of the Eleventh Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis*. Association for Computational Linguistics.
- Paweł Tarnowski, Marcin Kołodziej, Andrzej Majkowski, and Remigiusz J. Rak. 2017. [Emotion recognition using facial expressions](#). *Procedia Computer Science*, 108:1175–1184. International Conference on Computational Science, ICCS 2017, 12-14 June 2017, Zurich, Switzerland.
- Tejas Vaidhya and Ayush Kaushal. 2020. [IITKGP at W-NUT 2020 shared task-1: Domain specific BERT representation for named entity recognition of lab protocol](#). In *Proceedings of the Sixth Workshop on Noisy User-generated Text (W-NUT 2020)*, pages 268–272, Online. Association for Computational Linguistics.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. [Attention is all you need](#). *CoRR*, abs/1706.03762.
- Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, and Jamie Brew. 2019. [Huggingface’s transformers: State-of-the-art natural language processing](#). *CoRR*, abs/1910.03771.
- Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Russ R Salakhutdinov, and Quoc V Le. 2019. [Xlnet: Generalized autoregressive pretraining for language understanding](#). In *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc.
- Seunghyun Yoon, Seokhyun Byun, and Kyomin Jung. 2018. [Multimodal speech emotion recognition using audio and text](#). *CoRR*, abs/1810.04635.
- Jingqing Zhang, Yao Zhao, Mohammad Saleh, and Peter J. Liu. 2019. [PEGASUS: pre-training with extracted gap-sentences for abstractive summarization](#). *CoRR*, abs/1912.08777.

A Supplemental Material

Links to the huggingface models used in the experiment:

- Bert-base: <https://huggingface.co/bert-base-uncased>
- Albert-base-v2: <https://huggingface.co/albert-base-v2>
- Pegasus-xsum: <https://huggingface.co/google/pegasus-xsum>
- T5-base: <https://huggingface.co/t5-base>
- T5-Finetuned: <https://huggingface.co/mrm8488/t5-base-finetuned-emotion>