Understanding RoBERTa’s Mood: The Role of Contextual-Embeddings as User-Representations for Depression Prediction

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Abstract

Many works in natural language processing have shown connections between a person’s personal discourse and their personality, demographics, and mental health states. However, many of the machine learning models that predict such human traits have yet to fully consider the role of pre-trained language models and contextual embeddings. Using a person’s degree of depression as a case study, we do an empirical analysis on which off-the-shelf language model, individual layers, and combinations of layers seem most promising when applied to human-level NLP tasks. Notably, despite the standard in past work of suggesting use of either the second-to-last or the last 4 layers, we find layer 19 (sixth-to last) is the most ideal by itself, while when using multiple layers, distributing them across the second half (i.e. Layers 12+) of the 24 layers is best.

1 Introduction

Over the past decade natural language processing (NLP) has increasingly set its sights on interdisciplinary tasks, notably those within the computational social sciences (Sap et al., 2014; Preotu-Pietro et al., 2016; Zamani et al., 2018). As more and more language has been generated on social media sites such as Facebook, Twitter, and Reddit researchers have had a wealth of personal discourse available to them that spans across thousands of users.

Many researchers focus on applying these social media datasets to predict user demographics, personality, or mental health (Matero et al., 2019; Iyyer et al., 2014; Lynn et al., 2020). Predicting facets of mental health, such as depression and suicide risk, can help an over-burdened mental health industry by using automated screening (Coppersmith et al., 2018). Often these automated tools can be applied to forums where a user is an active member and their account could be flagged to be brought to the attention of a moderator. Thus a personalized and potentially early intervention could be provided to the user in question.

Here, we investigate one prominent aspect of mental health and life satisfaction: degree of depression (DDep). Predicting depression of social media users is of interest for the following reasons: (1) Depression is often highly correlated with suicidal tendencies (Leonard, 1974) with deaths by suicide on the rise (Curtin et al., 2016) and (2) Predicting depression is of high importance as it is often an under-diagnosed ailment, where such predictions could be useful to screen individuals who are at risk (Eichstaedt et al., 2018).

While many recent NLP pipelines have moved onto leveraging large pre-trained language models based on the transformer architecture (Vaswani et al., 2017), applying these models to human-level analysis has received little attention. Even the use of extracted embeddings, often called contextual embeddings, has yet to be fully explored in this level of analysis (V Ganesan et al., 2021). Our contributions include: (1) A degree of depression predictive model that out-performs the current state-of-the-art, (2) Evaluation of standard extraction techniques on contextual embeddings and their application to depression prediction and (3) Analysis on the effectiveness of layer selection to generate large contextual embedding representations of users.

2 Related Works

One of the downsides when modeling mental health data is often that it is very small, with only a few hundred participants per study (Guntuku et al., 2017). However, it is sometimes possible to get around this by using data from Social Media websites where participants can choose to opt in to share past language data and take a small survey or questionnaire (Coppersmith et al., 2014). Schwartz et al. (2014), which is the current...
state-of-the-art depression prediction model, applies this technique to Facebook users. This model predicts depression on a continuous scale (1-5) rather than bucketing users into classes such as mild/moderate/severe.

While previous models in NLP applied to human-level predictions have used bag-of-words style approaches (Lynn et al., 2019) other areas such as word or document-level tasks, have adopted contextual embedding representations (Bao and Qiao, 2019; Si et al., 2019). As these are often output from very large models, with hundreds of millions or more parameters, they are able to encode syntactic and semantic information that transfer to downstream tasks either through word or sentence embeddings (Devlin et al., 2019).

While there has been some work applying contextual embeddings and transformer language models to human-level predictions, the most in depth has been V Ganesan et al. (2021) who investigated the use of contextual embeddings in low-data scenarios across various areas including mental health, demographics, and personality prediction. However, they only focus on using the base-size variants with an emphasis on dimensionality reduction techniques to apply contextual embeddings to small datasets (N <= 1000). Here, we work with a medium size dataset of 3 million Facebook posts across 25 thousand users and apply both base and large sized language models. As well as investigate layer selection beyond using just the second to last layer of the model.

## 3 Methods

### Task:
A person’s degree of depression score is estimated by their response to a subset of neuroticism questions on a personality assessment through Facebook’s MyPersonality app (Schwartz et al., 2013). The responses were on a scale of 1 to 5 and averaged together to represent a person’s overall degree of depression. Here, we formulate the task of depression prediction as building an average vector, across all words of a user, to generate a single user representation that is then passed into a regression model which predicts their degree of depression.

### Transformer Language Models:
There is a wide selection of general purpose language models and we select the following: XLNet, RoBERTa, ALBERT and BERT (Yang et al., 2019; Liu et al., 2019; Lan et al., 2019; Devlin et al., 2019).

Table 1: Performance of extracting embeddings from second to last layer (11) from base sized variants of each language model on the held-out test set. Each model outputs a 768 dimensional vector for each word that is then averaged for a user representation. Bold indicates best in column and * indicates statistical significance p < .05 w.r.t BERT via paired t-test.

| Model     | r   | mse        |
|-----------|-----|------------|
| Baselines |     |            |
| Open-Ridge| .372| .7696      |
| Schwartz et al. | .386| N/A        |
| XLNet     | .366| .7728      |
| BERT      | .388| .7575      |
| ALBERT    | .373| .7675      |
| RoBERTa   | .398*| .7497*     |

When comparing which language model to perform our layer analysis on, we first evaluate performance using only the second to last layer on our held-out test set. This allows us to deduce which type of model (e.g. autoencoder or autoregressor) may lead to better application to aggregate human-level predictions.

### Layer Selection:
To decide on which layers to extract for our final model, we perform cross-fold validation, using 10 folds, for each individual layer or combination of layers. We first select the best performing layer, once found, we then concatenate all other layers to find the best 2-layer combination. This process is iterated on until we reach a number of layers where we cease to see a performance increase via the cross-folds. Once we settle on the layers that performed best via cross-folds,

Figure 1: Layer-wise mean squared error performance across the 10-fold validation set with standard error shown by the shaded region for both RoBERTa-base and large. At lower layers, RoBERTa-base has a clear advantage in performance. However at layer 13 and beyond of RoBERTa-large there is lower mean squared error beyond any available base layer.
| Model          | Hid. Size | r    | mse  |
|----------------|-----------|------|------|
| RoBERTa-B L11  | 768       | .398 | .7497|
| RoBERTa-L L23  | 1024      | .399 | .7476|
| DistilRoBERTa L5 | 768       | .391 | .7545|

Table 2: Performance of extracting embeddings from second to last layer for different variants of RoBERTa, which was found to be the best performing among base models, on the held-out test set. DistilRoBERTa is also considered as a small sized alternative for the computation cycle minded. The smaller models use hidden size of 768 while large uses 1,024 dimensions. **Bold** indicates best in column.

we extract a final test set representation and run the final selected model on our held-out test set. When comparing within cross-folds we only compare the mean squared error, rather than Pearson-r correlation, as that is the metric being optimized as well as being a less noisy evaluation of each model compared to Pearson-r.

As well as our best performing layer combinations, for a final comparison on the test set, we also evaluate performance of standard layer extraction techniques. This includes the second-to-last layer and the concatenation of the top-4 layers. This enables us to validate that our layer selection method and suggested layers are worthwhile.

**Regression:** Our model of choice is a regularized linear regression (ridge) with input being the aggregate of extracted contextual embeddings. A simple predictive model is chosen to highlight the improvements from the features themselves rather than any specific network architecture.

## 4 Dataset & Baseline

**Dataset:** We use the same dataset used in Schwartz et al. (2014). The data was collected from Facebook users who opted in to share their status updates between 2009 and 2011 and completed a personality questionnaire. The dataset consists of roughly 25,000 train users and 1,000 test users. Users are then filtered down to those who wrote at least 1,000 words across all of their status updates. The final result is a training set of 17,599 and test set of 986 users.

**Baseline:** We compare to the previously introduced work of Schwartz et al which leverages both open-vocab and count based lexicons. Notably, the model is trained on 1 - 3 grams, a 2000 dimensional social media topic vector, Lexical Inquiry and Word Count (LIWC) lexicon, and NRC sentiment lexicon (Pennebaker et al., 2001; Mohammad et al., 2013). We compare our models both to the reported scores in the original publication and to a version we recreated, referred to as Open-Ridge.

**Ethics Statement:** This research has been approved (deemed exempt status) by an academic institutional review board. Our work is part of a growing body of interdisciplinary research that aims to improve the automatic assessment of a person’s mental health. However, at this time we do not suggest our model(s) be used in practice to label mental health states and instead this should be viewed as a step toward a clinical tool that would be used with professional oversight.

## 5 Evaluation

We first recreate the model from Schwartz et al. (2014). Although we did not match the results claimed in the original work. We did see results within .014 Pearson correlation. However, both the recreated and original model are outperformed by both BERT and RoBERTa base variants, as shown in table 1. An interesting result here is that ALBERT, while being 10x smaller than the other language models, performs quite well; outperforming both XLNET and the Open-Ridge models. Notably, we also see that models based on the autoencoder style architecture (BERT variant) perform better than autoregressors (XLNet).

After establishing that RoBERTa-base is the best performing model, we compare against it’s possible variants, which offer a computation versus performance trade-off, we compare against RoBERTa-large (24 total layers) and DistilRoBERTa (6 total layers) in table 2. Ultimately, RoBERTa-large performs only slightly better than the base model but this small difference is found to not be statistically significant. However, due to the number of available layers of RoBERTa-large this gives more options for layer selection without a loss in performance, thus we move forward with RoBERTa-large for depression prediction.

As mentioned in section 3, for investigating layer selection we only evaluate on cross-fold validation results to avoid any overfitting to the test set. First, we look at all individual layers of RoBERTa-large, as shown in in figure 1, and the standard errors associated with each layer’s performance across the 10 cross-folds. We find that performance slowly improves as you move up the model but begins to
Table 3: Comparison of performance between the top 10 best individual layers and additional layers on the 10-fold cross validation data, ordered by mean squared error. **Bold** indicates best in column and ↓ indicates significantly lower performing models $p < .05$ via paired t-test compared to best in column (rank 1). The best performing of the previous column is used to find the next best layer to add on (via concatenation indicated by ;).

| Layer Combo | $r$ | mse  |
|-------------|-----|------|
| **Standard** |     |      |
| L23         | .399| .7476|
| L21+22+23+24| .401| .7479|
| **Optimized** |     |      |
| L19         | .406| .7439|
| L16+19+22+24| .405*| .7208*|
| **Other Sizes** |     |      |
| L16+18+19+22+24 | .407* | .7206* |
| L14+16+18+19+22+24 | .406* | .7433* |

Table 4: Performance of extracting embeddings using standard techniques and from the optimized layers we find to be most promising via cross-fold selection. **Bold** indicates best in column and * indicates statistical significance $p < .05$ w.r.t standard top-4 (21-24) layer extraction via paired t-test.

Next, we explore the important question of how many layers should be used as well as which layers to extract in order to build a user representation. For this we apply our layer selection technique based on empirical results of the cross-folds. We show results for the top 10 best combinations per layer amount in table 3. We find 3 interesting outcomes from our experiments: (1) When using only a single layer the second-to-last is not the best and is not even in the top 5, (2) We do not see a drop in performance from using more than 4 layers, in fact, we do not see a plateau until we try 6 total layers thus suggesting that for user-level predictions large representations are ideal and (3) The layers that boost performance all come from the top half of RoBERTa-large likely due to them including more semantic information than syntactic, which could be more of a necessity for modeling at the human-level.

Additionally, to validate our findings, we compare our single layer and 4-layer models to the standard approaches on the held-out test set; shown in table 4. There are 2 major takeaways: first that our layer 19 model performs quite well but is not a statistically significant finding ($p=.08$) when compared against layer 23 and second that our 4-layer model continues to give a modest boost in performance and is found to be statistically significant compared to standard top-4 extraction.

Lastly, we also evaluate our 5-layer and 6-layer models on the test set. The 5-layer version has a small reduction in both metrics and is found to be significant ($p=.02$) compared to our optimized 4-layer model. For the 6-layer model we see an expected drop in performance, based on cross-fold analysis, resulting in error on par with using just layer 19 suggesting that the additional layer has hurt the model’s ability to generalize.

6 Conclusion

With many tasks in NLP focused around human-level prediction, methods that can use state-of-the-art off-the-shelf models in the best way are of interest to the community at large. In this work, we found that applying pre-trained transformer language models to degree of depression prediction benefited from non-standard extraction techniques and applying a straightforward empirical analysis of layer performance could lead to noticeable boosts in downstream applications. Ultimately, we achieved state-of-the-art performance with $r = .407$ using RoBERTa-large and a 5-layer user representation.
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