Augmenting BERT Carefully with Underrepresented Linguistic Features

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Abstract
Fine-tuned Bidirectional Encoder Representations from Transformers (BERT)-based sequence classification models have proven to be effective for detecting Alzheimer’s Disease (AD) from transcripts of human speech. However, previous research shows it is possible to improve BERT’s performance on various tasks by augmenting the model with additional information. In this work, we use probing tasks as introspection techniques to identify linguistic information not well-represented in various layers of BERT, but important for the AD detection task. We supplement these linguistic features in which representations from BERT are found to be insufficient with hand-crafted features externally, and show that jointly fine-tuning BERT in combination with these features improves the performance of AD classification by up to 5% over fine-tuned BERT alone.

Keywords: Alzheimer’s disease, dementia detection, BERT, feature engineering, transfer learning

1. Introduction
BERT (Bidirectional Encoder Representations from Transformers) (Devlin et al., 2019) builds on Transformer networks to pre-train bidirectional representations of text by conditioning on both left and right contexts jointly in all layers. These models have achieved state-of-the-art on a variety of tasks in NLP, when fine-tuned. Previous research (Jawahar et al., 2019) has hence suggested that it encodes language information (lexics, syntax etc.) that is known to be important for performing complex natural language tasks.

The task we focus on in this work is Alzheimer’s disease (AD) detection from transcripts of speech. AD is a neurodegenerative disease affecting over 40 million people worldwide (Prince et al., 2016). Previous research has indicated that spontaneous speech elicited using pictures can be used to detect AD and serve as a quick, objective AD assessment (Fraser et al., 2016). Several studies have used ML-based speech analysis to distinguish between healthy and cognitively impaired speech of participants in picture description datasets (Balagopalan et al., 2018; Zhu et al., 2019). Clinical literature in the space of AD has identified specific linguistic features, such as part-of-speech (POS) tag frequencies and measures of lexical diversity (Bucks et al., 2000) particularly indicative of AD. Past research has also shown that fine-tuned BERT can be used for AD detection (Balagopalan et al., 2020).

Diagnostic probing tasks (Adi et al., 2016; Conneau et al., 2018) are useful in trying to understand language phenomena encoded by high dimensional embeddings, and have
become standard in studying properties of high-level representations. The probing setup consists of using representations to predict a linguistic property of interest. As such, probing tasks are a useful tool to understand what linguistic features are under-represented in BERT.

Jawahar et al. (2019) used probing tasks to show that the intermediate layers in BERT encode a rich hierarchy of linguistic information, and showed that pre-training BERT on a variety of auxiliary tasks, as proposed in Devlin et al. (2019), improves the predictive performance and hence the language information encoded. We attempt to extend this work by using diagnostic tasks proposed by Conneau et al. (2018) to probe representations from a BERT model fine-tuned for AD detection.

Prior research has also shown that neural language representation models can be supplemented with domain-specific knowledge either while training (Cai and Wan, 2019), or fine-tuning (Wang et al., 2020). Motivated by this, we study if BERT can be augmented with additional linguistic features relevant to the AD detection task. Probing tasks are used as introspection techniques to study the linguistic information encoded in BERT, and identify the list of linguistic features to supplement BERT externally with.

The main contributions of our paper are: (1) We benchmark fine-tuned BERT models at utterance-level on a standard dataset for AD detection from picture descriptions, (2) We probe linguistic information encoded in BERT models fine-tuned for AD detection using diagnostic tasks proposed by Conneau et al. (2018), (3) We augment BERT by combining representations from pre-trained BERT and manually extracted linguistic features, where the additional features represent the linguistic information only present to a small degree in BERT representations. We show that performance of the augmented model increases by 5% comparing to a non-augmented fine-tuned BERT model.

2. Related Work

BERT for AD Detection: Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2019) is a deep neural language representation model. Past research has shown that BERT can be used for AD detection (Balagopalan et al., 2020). Prior work has shown that pre-trained BERT models do not encode several phenomena related to lexics, syntax, and semantics (Jawahar et al., 2019). Since clinical literature shows that AD detection from transcribed speech highly depends on a specific set of linguistic features, it is important to study, and potentially enhance the linguistic properties that a BERT-model fine-tuned for an AD detection task encompasses.

Augmenting Neural Language Representation Models: Incorporating domain-specific external knowledge in neural language representations is a field of research that has been actively explored (Cai and Wan, 2019). Wang et al. (2020) combined fine-tuning with a feature-based approach for aspect extraction. Similarly, Cai and Wan (2019) combined domain specific word-embeddings with general word embeddings for performance boosts in a sentiment classification task. Kiela et al. (2018) developed methods to dynamically combine neural embeddings from different sources and obtain robust sentence embeddings.

Probing tasks: Diagnostic tasks (Hupkes et al., 2018; Conneau et al., 2018) reate auxiliary classification tasks for representations, by using the embedded representations to predict a specific linguistic feature, such as predicting the
length of a sentence from its sentence-level representation. The intuition is that if the classifier trained using these representations are capable of predicting the linguistic feature well, then it likely encodes information about the linguistic phenomenon. In this work, we use probing tasks following (Jawahar et al., 2019) and (Conneau et al., 2018) to assess linguistic features captured in various layers of a BERT model fine-tuned for an AD detection downstream task. We use 5 probing tasks (see Table 1), focusing on surface and syntactic phenomenon.

4. Probing Intermediate Representations of Fine-tuned BERT

We fine-tune BERT on DementiaBank for the AD detection task, and probe representations of the first classification token (‘[CLS]’) from each layer (Jawahar et al., 2019). We train Multi-layer Perceptrons (MLPs) using embedded representations from various layers of BERT as input to predict the following 5 properties:

- **WordContent**: Given a (word, sentence) pair, predict if the word is present in the sentence or not.
- **SentenceLength**: Given a sentence, predict its length in number of word tokens.
- **TopConstituents**: Given a sentence, predict the sequence of top-level constituents in its syntax tree.
- **TreeDepth**: Given a sentence, predict the length of its syntactic parse-tree.
- **BiGramShift**: Given a sentence, predict whether adjust words are inverted or word order is preserved (For example, inversion is seen “This an is example sentence.”). Grid-search hyperparameter optimization is performed to arrive at the optimal parameter setting using the validation set. We observe that performance on the syntactic task of tree-depth prediction is low, as is the performance on the word content prediction task (see Table 1).

Prior work has shown that features relying on both of the above underrepresented properties are important for AD detection from picture descriptions (Fraser et al., 2016; Yancheva et al., 2015). Particularly, variations in proportions of various production rules from the constituency parse representation, depth of the constituency parse tree, etc., which are features of syntactic type, were mentioned to be an important characteristic of impaired speech in Yancheva et al. (2015). Presence of in-

3. Dataset

For all our experiments, we use DementiaBank (Becker et al., 1994), which is a longitudinal dataset of speech for assessing cognitive impairment. It contains 473 narrative picture descriptions (Becker et al., 1994) where each participant describes a picture shown to them. We divided each transcript into individual utterances. We treat each utterance as a sample similar to methodology followed by Karlekar et al. (2018). In contrast to Karlekar et al. (2018) we only utilize data from these picture description task. This is done because other speech tasks are exclusively performed by participants with AD. Hence, the aim of our classification setup is of AD detection at utterance level from transcripts of speech elicited via pictures. We benchmark all classification models at utterance level, i.e, each sentence spoken by the participant is associated with the diagnosis label of the participant. On performing this, our sample size increases to 5103 utterances, out of which we use about 82%/9%/9% for train/development/testing respectively, similar to Karlekar et al. (2018). See Table 3 in Appendix for the exact split details.
formative content words such as “cookie” or “boy” while describing the picture, was mentioned as an important characteristic in Fraser et al. (2016) and it is associated with the features emphasized by the word content prediction probing task. Note that these important content words for the picture stimulus have been identified by clinicians, and not arbitrarily defined (see Appendix D).

5. Classification Results

Based on our observations in Section 4, we identify that externally hand-engineered features capturing: (1) presence of informative content words in utterances, and (2) syntactic tree depths, might help in improving the AD detection performance when combined with BERT. We extract 119 – 117 syntactic and 2 word-content based – features at utterance-level. The two word-content features we extract are: (1) a boolean indicating the presence of informative content units (see Appendix B for list), (2) total number of information content units in each utterance. The 117 syntactic features include depth-related features of the constituency parse representations, the height of the constituency parse-tree, proportion of verb-phrases, proportion of production rules of type “adjective phrase followed by adjective”, etc.

We compare several input settings to see the effect of these features:

| Linguistic Feature   | Highest Accuracy | Layer | Feature Type |
|----------------------|------------------|-------|--------------|
| WordContent          | 22.47            | 4     | Surface      |
| SentenceLength       | 92.81            | 3     | Surface      |
| TopConstituents      | 80.86            | 7     | Syntactic    |
| TreeDepth            | 36.14            | 6     | Syntactic    |
| BiGramShift          | 85.42            | 12    | Syntactic    |

Table 1: Probing results on BERT fine-tuned on AD classification task. Bold indicates the worst performance in each feature type.

| Model                | Accuracy | Sensitivity | Specificity |
|----------------------|----------|-------------|-------------|
| NN + FS1             | 0.63     | 0.64        | 0.62        |
| Fine-tuned BERT      | 0.71     | 0.62        | 0.79        |
| BERT + FS1           | 0.76     | 0.63        | 0.86        |

Table 2: Results on the AD detection task with (1) NN using FS1, (2) Fine-tuned BERT using text, (3) Augmented BERT using text and FS1. FS1 is the feature set identified via linguistic probing in Table 1. Bold indicates highest performance.

**NN with FS1:** A Neural Network (NN) classifier using the set of all 119 features

**Fine-tuned BERT:** Fine-tuning a BERT sequence classification model, where a linear layer maps the concatenation of the final hidden layer representation from BERT to binary class labels (Wolf et al., 2019).

**BERT+FS1:** Fine-tuning a BERT sequence classification model, where a linear layer maps the concatenation of the final hidden layer representation from BERT and the feature vector to binary class labels.

All classification models are optimized to the best possible parameter setting with 5-fold grid-search cross-validation (see Appendix C).

We find that fine-tuned BERT models are able to perform well above chance for the AD detection task, similarly to previous findings by Pompili et al. (2020); Balagopalan et al. (2020). We observe that the third setting (BERT+FS1) attains the highest accuracy, which is about 13% accuracy points higher than using classification models using features alone, and about 5% higher than fine-tuning BERT alone (see Table 2).

6. Discussion

In this work, we probe intermediate representations of fine-tuned BERT models for an Alzheimer’s Disease task to understand its deficiencies. We identify that there is
scope for better representation of two categories of features important for the downstream task — (1) constituency tree-based features, (2) presence of specific informative words in the text. On supplementing these features by engineering them separately, and jointly fine-tuning them with BERT, we achieve a 5% increase in predictive performance. This is promising for reliably detecting AD early. Though we use probing tasks (Pimentel et al., 2020; Conneau et al., 2018) exclusively to identify scope of improvement in BERT models, this can be replaced with other methods, such as generating explanations (Mothilal et al., 2020). Ongoing work is on performing similar analyses with other neural language representation models.

References

Yossi Adi, Einat Kermany, Yonatan Belinkov, Ofer Lavi, and Yoav Goldberg. Fine-grained analysis of sentence embeddings using auxiliary prediction tasks. International Conference on Learning Representations, 2016.

Aparna Balagopalan, Jekaterina Novikova, Frank Rudzicz, and Marzeyh Ghassemi. The effect of heterogeneous data for alzheimer’s disease detection from speech. NeurIPS Workshop on Machine Learning for Health ML4H, 2018. URL https://arxiv.org/abs/1811.12254.

Aparna Balagopalan, Benjamin Eyre, Frank Rudzicz, and Jekaterina Novikova. To BERT or Not To BERT: Comparing Speech and Language-based Approaches for Alzheimer’s Disease Detection. Proceedings of 21st Annual Conference of the International Speech Communication Association, INTERSPEECH, 2020. URL https://arxiv.org/abs/2008.01551.

James T Becker, François Boiler, Oscar L Lopez, Judith Saxton, and Karen L McGonigle. The natural history of alzheimer’s disease: description of study cohort and accuracy of diagnosis. Archives of Neurology, 51(6):585–594, 1994.

Romola S Bucks, Sameer Singh, Joanne M Cuerden, and Gordon K Wilcock. Analysis of spontaneous, conversational speech in dementia of alzheimer type: Evaluation of an objective technique for analysing lexical performance. Aphasiology, 14(1):71–91, 2000.

Yitao Cai and Xiaojun Wan. Multi-domain sentiment classification based on domain-aware embedding and attention. In IJCAI, pages 4904–4910, 2019.

Alexis Conneau, Germán Kruszewski, Guillaume Lample, Loïc Barrault, and Marco Baroni. What you can cram into a single $&!#* vector: Probing sentence embeddings for linguistic properties. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 2126–2136, 2018.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, 2019.

Kathleen C Fraser, Jed A Meltzer, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proc.

Dieuwke Hupkes, Sara Veldhoen, and Willem Zuidema. Visualisation and diagnostic
classifiers’ reveal how recurrent and recursive neural networks process hierarchical structure. *Journal of Artificial Intelligence Research*, 61:907–926, 2018.

Ganesh Jawahar, Bénôït Sagot, and Djamé Seddah. What does bert learn about the structure of language? In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 3651–3657, 2019.

Sweta Karlekar, Tong Niu, and Mohit Bansal. Detecting linguistic characteristics of alzheimer’s dementia by interpreting neural models. *arXiv preprint arXiv:1804.06440*, 2018.

Douwe Kiela, Changhan Wang, and Kyunghyun Cho. Dynamic meta-embeddings for improved sentence representations. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1466–1477, 2018.

Ramaravind K Mothilal, Amit Sharma, and Chenhao Tan. Explaining machine learning classifiers through diverse counterfactual explanations. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency*, pages 607–617, 2020.

Tiago Pimentel, Josef Valvoda, Rowan Hall Maudslay, Ran Zmigrod, Adina Williams, and Ryan Cotterell. Information-theoretic probing for linguistic structure. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4609–4622, Online, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.420. URL https://www.aclweb.org/anthology/2020.acl-main.420.

Anna Pompili, Thomas Rolland, and Alberto Abad. The inesc-id multi-modal system for the adress 2020 challenge. *arXiv preprint arXiv:2005.14646*, 2020.

Martin Prince, Adelina Comas-Herrera, Martin Knapp, Maëllenn Guerchet, and Maria Karagiannidou. World alzheimer report 2016: improving healthcare for people living with dementia: coverage, quality and costs now and in the future. 2016.

Xili Wang, Hua Xu, Xiaomin Sun, and Guangcan Tao. Combining fine-tuning with a feature-based approach for aspect extraction on reviews (student abstract). In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 13951–13952, 2020.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, et al. Huggingface’s transformers: State-of-the-art natural language processing. *ArXiv*, pages arXiv–1910, 2019.

Maria Yancheva, Kathleen C Fraser, and Frank Rudzicz. Using linguistic features longitudinally to predict clinical scores for alzheimer’s disease and related dementias. In *Proceedings of SLPAT 2015: 6th Workshop on Speech and Language Processing for Assistive Technologies*, pages 134–139, 2015.

Zining Zhu, Jekaterina Novikova, and Frank Rudzicz. Detecting cognitive impairments by agreeing on interpretations of linguistic features. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, Volume 1 (Long and Short Papers), pages 1431–1441, 2019.
Appendix A. DementiaBank

The table below shows the train/val/test splits of DementiaBank we benchmark all models settings on.

| Data subset | # utterances |
|-------------|--------------|
| Train       | 4269         |
| Validation  | 429          |
| Test        | 409          |

Table 3: DementiaBank statistics

Appendix B. Feature list

Table 4 contains a summary of all the engineered linguistic features we extract.

Appendix C. Hyperparameter Tuning

We search for the optimal set of parameters by grid-search based on the validation performance.

C.1. Finetuning BERT

The search space for finetuning BERT was:

- number of epochs ∈ \{2, 3, 4, 5, 6\}, and
- Adam initial learning rate ∈ \{2 × 10^{-5}, 2 × 10^{-4}\}.

C.2. NN + FS1

The search space for the parameters of the NN model was:

- layers ∈ \{1, 2, 3\}
- number of units per layer ∈ \{10, 100\}.

Appendix D. Information Content Units

The list is: “boy”, “son”, “brother”, “girl”, “daughter”, “sister”, “female”, “woman”, “adult”, “grownup”, “mother”, “lady”, “cookie”, “biscuit”, “treat”, “cupboard”, “closet”, “shelf”, “curtain”, “draper”, “drapery”, “dish”, “cup”, “counter”, “apron”, “dishcloth”, “dishrag”, “towel”, “rag”, “cloth”, “jar”, “container”, “plate”, “sink”, “basin”, “washbasin”, “washbowl”, “washstand”, “tap”, “faucet”, “stool”, “seat”, “chair”, “water”, “dishwater”, “liquid”, “window”, “frame”, “glass”, “floor”, “outside”, “yard”, “outdoors”, “backyard”, “garden”, “driveway”, “path”, “tree”, “bush”, “exterior”, “kitchen”, “room”, “take”, “steal”, “fall”, “ignore”, “notice”, “daydream”, “pay”, “overflow”, “spill”, “wash”, “dry”, “sit”, “stand”
Table 4: Summary of all underrepresented features extracted. The number of features in each subtype is shown in the second column (titled "#features").

| Feature type                  | #Features | Brief Description                                                                 |
|-------------------------------|-----------|-----------------------------------------------------------------------------------|
| Production Rules and parse tree depth | 104       | Number of times a production type occurs divided by total number of productions    |
| Phrasal type ratios           | 13        | Proportion, average length and rate of phrase types                                |
| Word Content                  | 2         | Presence of information content units in utterance                                 |