Evidence > Intuition: Transferability Estimation for Encoder Selection

Elisa Bassignana, Max Müller-Eberstein, Mike Zhang, Barbara Plank

Department of Computer Science, IT University of Copenhagen, Denmark
Center for Information and Language Processing (CIS), LMU Munich, Germany
Munich Center for Machine Learning (MCML), Munich, Germany
{elba, mamy, mikz}@itu.dk b.plank@lmu.de

Abstract

With the increase in availability of large pre-trained language models (LMs) in Natural Language Processing (NLP), it becomes critical to assess their fit for a specific target task a priori—as fine-tuning the entire space of available LMs is computationally prohibitive and unsustainable. However, encoder transferability estimation has received little to no attention in NLP. In this paper, we propose to generate quantitative evidence to predict which LM, out of a pool of models, will perform best on a target task without having to fine-tune all candidates. We provide a comprehensive study on LM ranking for 10 NLP tasks spanning the two fundamental problem types of classification and structured prediction. We adopt the state-of-the-art Logarithm of Maximum Evidence (LogME) measure from Computer Vision (CV) and find that it positively correlates with final LM performance in 94% of the setups. In the first study of its kind, we further compare transferability measures with the de facto standard of human practitioner ranking, finding that evidence from quantitative metrics is more robust than pure intuition and can help identify unexpected LM candidates.

1 Introduction

Advances in Deep Learning-based NLP and CV build on expressive representations from encoder models pre-trained on massive corpora. Downstream models make use of latent information in these representations to extract relevant features for the task at hand. Within this paradigm, deciding which pre-trained encoder to use in any task-specific architecture is crucial, however training a model using each encoder candidate is infeasible. In absence of prior heuristics (e.g., via related work), the choice of encoder has therefore prevalently been based on practitioner intuition rather than quantitative evidence.

In NLP, prior work has examined the different yet related task of performance prediction (Xia et al., 2020a; Ye et al., 2021), surveyed and categorized LMs (Xia et al., 2020b), and used probing to predict LM performance specifically for dependency parsing (Müller-Eberstein et al., 2022b), but has yet to extensively investigate how to rank the increasingly large number of pre-trained LM encoders across various tasks and domains. Preliminary work by You et al. (2021) shows that the LogME estimator holds promise, including the first steps for encoder selection in NLP. With their main focus being on CV, however, they evaluate only a limited set of tasks and models for NLP and use self-reported benchmark scores instead of running controlled experiments which should include, e.g., the variance across initializations, domains, and fine-tuning strategies (Section 2). As such, we seek to answer: How well can we estimate the transferability of pre-trained LMs to specific NLP tasks? To do so, we contribute:

• The broadest encoder selection study in NLP to date, on 10 domain-diverse classification and structured prediction tasks (Section 3);

• An extensive evaluation and analysis across multiple dimensions of variation, including seven general vs. domain-specific LMs, [CLS] vs. mean representations, and head vs. full model fine-tuning (Section 4);

• A study with NLP experts, comparing the prevailing ranking of LMs by human intuition with LogME’s empirical evidence (Section 5);

• Guidelines for applying and interpreting transferability measures to NLP (Section 6), and an open-source toolkit for efficient, task-adaptive LM pre-selection.¹

¹https://github.com/mainlp/logme-nlp
2 Transferability Estimation

Transferability estimation aims to quantify the ability of a model to transfer knowledge learned from one task to another (Eaton et al., 2008; Sinapov et al., 2015). Formally, given a pool of $L$ pre-trained LMs $\{\phi_l\}_{l=1}^L$ and a dataset $D$, we calculate a predictive score $S_l(D)$ for each $\phi_l$ which ideally correlates with the model’s final performance $P_l(D)$. $S_l(D)$ is computed without fine-tuning $\phi_l$ on $D$ such that the optimal $\phi_l^*$ can be chosen from a large model pool at a low computational cost.

The CV community has begun to explore methods for encoder pre-selection and ranking through metrics such as LogME and the Log Expected Empirical Prediction (LEEP; Nguyen et al., 2020). These are widely-used state-of-the-art methods in CV. Recent work introduced the Gaussian Bhat-charyya Coefficient (GBC; Pándy et al., 2021) and Optimal Transport based Conditional Entropy (OTCE; Tan et al., 2021), the exploration of which is intractable, it is estimated by mapping $F \rightarrow y$ using a linear transformation $w$; this is akin to training a linear probe with optimal parameters $w^*$ and using the likelihood $p(y|F, w^*)$ as a proxy for feature suitability. Because a simple linear model will overfit on the training data, it would be beneficial to obtain the marginal likelihood, or evidence, by integrating over all possible values of $w$: $p(y|F) = \int p(y|F, w)p(w)dw$. To once again make this computation tractable, You et al. (2021) reformulate it as an efficient, iterative evidence maximization problem where both $w$ as well as $y$ are drawn from lightly parametrized, isotropic Gaussian distributions. The normalized logarithm of the maximized evidence (LogME) can then be used as $S_l(D)$ to rank encoder models directly.

**NLP Setting** LogME has shown promise for CV, and an initial study on the GLUE benchmark (Wang et al., 2018) indicate the same for NLP (You et al., 2021). However, for NLP, there are notable differences in setups across tasks. We adapt and apply LogME extensively to a wide range of NLP settings to identify empirically grounded guidelines.

In particular, we investigate variations concerning the task, instance granularity, domain, and tuning strategy. First, compared to most image classification tasks, NLP tasks are subject to differences in granularity, i.e., classification (C) and structured prediction (SP). Furthermore, there is less clarity than for individual images as to which representation best captures the full language input (Mosbach et al., 2020). Therefore, for C setups we experiment with two representations: i.e., using [CLS]/<s> versus mean over sequence/subwords.

Second, depending on differences in the data

---

Table 1: Datasets. Indicated are the 10 datasets used in this study, distinguished between the two NLP problem types C and SP for a wide variety of tasks and domains. C tasks cover AGNews (news articles), Twitter Airline Sentiment (Airline; Twitter feedback), SciERC (AI proceedings), MNLI (speech, (non-)fiction, government), QNLI (Wikipedia) and RTE (Wikipedia, news). Within the SP tasks, we experiment on the English Web Treebank (EWT; social media, reviews, emails), CrossNER (news, scientific Wikipedia) and JobStack (Stack Overflow job ads). For each task, we report their TRAIN/DEV split, label space, and task-specific performance metric.

| Dataset                  | Task                                | Train / Dev  | | | Metric |
|--------------------------|-------------------------------------|--------------|---|---|---|
| AGNews (Zhang et al., 2015) | Topic Classification                | 84K / 12K    | 4 | micro-F1 |
| Airline (Crowdflower, 2020)   | Sentiment Analysis                  | 10K / 1.5K   | 3 | micro-F1 |
| SciERC (Luan et al., 2018)    | Relation Classification             | 1.9K / 275   | 7 | macro-F1 |
| MNLI (Williams et al., 2018)  | Natural Language Inference          | 393K / 20K   | 3 | micro-F1 |
| QNLI (Rajpurkar et al., 2016) | Q&A/Natural Language Inference      | 105K / 5.4K  | 2 | micro-F1 |
| RTE (Giampiccolo et al., 2007) | Natural Language Inference          | 2.5K / 2K    | 3 | micro-F1 |
| EWT (Silveira et al., 2014)   | Dependency Labeling                 | 12.5K / 2k   | 36| span-F1  |
| CrossNER (Liu et al., 2021)   | Named Entity Recognition            | 15K / 3.5K   | 4 | span-F1  |
| CrossNER (Liu et al., 2021)   | Named Entity Recognition            | 200 / 450    | 17| span-F1  |
| JobStack (Jensen et al., 2021)| De-identification                  | 18K / 2K     | 11| span-F1  |
domain, NLP practitioners are often faced with a pool of domain-adapted LMs in addition to more general-purpose encoders—the correct choice of which may not be immediately apparent.

Finally, the best performance in NLP is often achieved using full fine-tuning, while CV models usually do not fine-tune the encoder (Peters et al., 2019). It will therefore be crucial to investigate whether the predictive performance of $S_l(D)$ holds when it is computed based on untuned $F$ while $P_l(D)$ is based on fully fine-tuned representations.

3 Experimental Setup

Applying seven architecturally and domain-diverse pre-trained LMs with up to four configurations each to 10 datasets and a wide variety of tasks, we investigate LogME’s predictive power for transferability estimation in NLP—for a total of 280 setups. We refer to Table 1 for our detailed set of tasks.

Language Models We pick seven pre-trained LMs with a wide domain and architectural variety from the Transformers library’s model hub (Wolf et al., 2020). Three are “general-purpose” models, namely BERT$_{\text{base}}$ (Devlin et al., 2018), RoBERTa$_{\text{base}}$ (Liu et al., 2019), and DistilBERT$_{\text{base}}$ (Sanh et al., 2019). Four models are pre-trained on domain-specific corpora, namely Clinical-BioBERT (Alsentzer et al., 2019), BioBERT (Lee et al., 2020), Twitter-RoBERTa$_{\text{base}}$ (Barbieri et al., 2020), and SciBERT$_{\text{base}}$ (Beltagy et al., 2019). Note that for BioBERT variants domain-adaptive pre-training has been applied (Gururangan et al., 2020).

Model Setups The model setup follows the same structure for each task: A pre-trained LM encoder and a 3-layer perceptron head, following Tenney et al. (2019). The input to the latter is either the [CLS] token or mean over sequence subwords for C tasks or mean over token subwords for SP tasks. While it is common in CV to keep the encoder frozen and only fine-tune the task-specific head, we also evaluate the practice of full model fine-tuning, as is more common in NLP (Peters et al., 2019). Considering these variations (frozen vs. fine-tuning, and [CLS] vs. mean), we obtain up to four setups per C task and two setups per SP task. Each experiment is run with five random seeds. Details for reproducibility can be found in Appendix A.

Evaluation Following You et al. (2021), we evaluate LogME’s predictive power for ranking LMs according to their final performance by using the two correlation coefficients Pearson’s $\rho$ and weighted Kendall’s $\tau_w$ (Vigna, 2015), both in $[-1, 1]$. Kendall’s $\tau_w$ further allows us to estimate the probability of a higher-ranked LM actually performing better by computing $\tau_w^{1 + \frac{1}{2}}$.

4 Analysis of Results

Our results across all setups are consolidated in Figure 1 and Figure 2 (C: blue, SP: beige). The left of each figure plots the performance using frozen LM embeddings (hawks) against LogME scores, while on the right, full LM fine-tuning is applied (fi). Figure 1 shows the results of using mean-pooled embeddings in both C/SP settings. For hawks, we obtain $\rho > 0.8$ on 8/10 tasks and $\tau_w > 0.7$ on 6/10 tasks, indicating a strong relationship between model performance and LogME. After fine-tuning (fi), we observe a general reduction in $\rho$ and $\tau_w$ (most on CrossNER, EN-EWT), however overall correlations remain positive to a significant degree.

For C setups using the alternative [CLS]/<s> representations (Figure 2), LogME correlates highly at $\rho > 0.95$ on 5/6 tasks and $\tau_w > 0.7$ on 4/6 tasks when using head-only tuning (hawks). After full fine-tuning (fi), SciERC, RTE and AGNews have lower correlations, particularly with the high-variance RoBERTa model. However, the remaining tasks maintain a stable correlation, with $\rho > 0.6$ and $\tau_w > 0.3$ across 5/6 tasks.

Overall, LogME has a positive correlation with final performance in 30/32 cases. In more detail, LogME has a $\tau_w > 0.41$ in 20/32 setups, meaning that selecting a higher ranked model is the better choice. However, LogME both identifies intuitive, domain-specific scenarios (e.g., Twitter-RoBERTa performing well on Airline Twitter), but also finds cases that may be unintuitive, such as DistilBERT’s occasionally high performance for CrossNER and JobStack. This finding holds across C, SP, domains as well as different input representations. For the latter, we note that, surprisingly, even the untuned representation of [CLS]/<s> seems to contain useful information with comparable performance to mean pooling.

Comparing hawks versus fi, we notice that, as expected, model performance improves, but in

---

2Exact results can be found in Appendix B.

3We successfully reproduce the results reported in You et al. (2021) for MNLI, QNLI and RTE.

4Note that LogME is only computed on frozen embeddings and does not differ between hawks and fi.
general, LogME’s predictive power decreases. The fully fine-tuned model makes predictions on updated representations such that decreases in predictive performance are inevitable unless the initial LM already represents a local optimum for the task at hand. This fact is crucial for NLP practitioners where full fine-tuning is the standard practice. Taking these factors into account, LogME’s efficiency is especially beneficial, as it offers an 86× speedup over full model fine-tuning (You et al., 2021), and its positive correlation in 94% of our evaluated setups indicates that it is an effective score for transferability estimation in NLP.

5 Human Performance

Given the lack of prior work examining transferability estimation of pre-trained LM encoders, the most common method for encoder selection employed today is practitioner intuition. As such, we conduct a small-scale study with 12 NLP practitioners and ask them to perform the same ranking as in Section 3. Despite having access to model details and associated papers, this task is difficult even for experts. While for LogME, the range of $\tau_w$ is in $[-0.20; 1.00]$, human rankings fall into a wider range of $[-0.54; 1.00]$, indicating higher uncertainty. Similarly, we observe that human correlations are negative thrice as often as for LogME. Additionally, LogME provides a continuous scale for comparing models, while human rankings offer no indication of relative performance differences. At the same time, they are more inaccurate for tasks without an associated domain-specific model (e.g., news, mixture of genres in EWT). Moreover, even when domains are clear (e.g., Twitter, science), LogME tends to be more accurate than the predictions of most human participants. Finally, the high variance between practitioners and the fact that no single person was an expert in all setups further reinforces the necessity of quantitative transferability scores.
6 Conclusion

We show the value of transferability estimation for selecting high-performing LMs before full model fine-tuning in experiments, covering the two fundamental NLP settings of classification and structured prediction. By adopting the state-of-the-art LogME scoring method, we are able to rank LMs on a continuous scale which correlates with final performance—with the better encoder being chosen in 71% of cases. Additionally, we identify NLP-specific guidelines for transferability estimation: In particular, predicting the best LM for tasks/domains which greatly deviate from an encoder’s pre-training setup and require large amounts of full fine-tuning may require larger pre-selections of LMs due to the higher uncertainty of the scoring methods. Finally, our human study showed that practitioners frequently misconstrue the performance of LMs even on domain-specific tasks. As such transferability quantification methods provide valuable evidence over intuition.

Limitations

A key limitation that practitioners should consider is that, while LogME is viable for the quantitative transferability estimation of LM encoders, there is a noticeable drop in predictive accuracy after full model fine-tuning. We attribute this to the misalignment between the frozen representations of the encoder, which LogME is applied to, and the representations after fine tuning. As stated in Section 4, unless the untuned LM already constitutes a local optimum for the task at hand, task-specific shifts in its parameters and representations are inevitable.

This similarly applies to cases where the untuned representations differ substantially from what a fully fine-tuned model uses during training. Specifically, for the relation classification task of SciERC, it is important to note that the input given to the model is augmented with special tokens delimiting the entities involved in the relation (Baldini Soares et al., 2019) which are unknown to the untuned model and thus the representations that LogME is computed on. Furthermore, for EN-EWT we suspect that dependency labeling is a more fundamental task solvable with high accuracy by most LMs, especially after fine-tuning as reflected in micro-F1 scores between 93–95. This is mirrored by work on probing untuned LMs which identifies high levels of inherent dependency information (Tenney et al., 2019; Müller-Eberstein et al., 2022a).

Such sensitivity to representational shifts is not exclusive to LogME: In preliminary experiments, we examined LEEP (Nguyen et al., 2020) as an alternative predictive score $S_l(D)$. Its original use was to rank the transferability of a classifier trained on one dataset, to a new task—leaving the ranking of pre-trained LMs for future work. LEEP has so far only been applied to CV tasks, but we apply it to LM ranking on the collection of NLP tasks above. Our initial experiments achieved low and unintuitive correlations between LEEP’s $S_l(D)$ and $P_l(D)$. We speculate that this is due to the absence of a normalizing factor over the number of source classes, i.e., the high number of embedding dimensions in our case (see Equation 2 in Nguyen et al., 2020). While it would further be valuable to investigate methods beyond LEEP and LogME, as mentioned in Section 2, we leave their evaluation on NLP to future work. At the time of writing, the former two were the most extensively explored in CV, in addition to the original LogME work containing an initial study showing promise for NLP.

Finally, our human ranking study in Section 5 was limited by the number of practitioners with a publication record which we could contact confidentially. However, the group still constituted a diverse set over seniority, gender, and cultural background. A larger group would cover a broader range of backgrounds and may produce different rankings. However, as the surveyed group already displayed high variance, overall predictive performance is unlikely to be significantly higher.

Keeping these limitations in mind, correlations do remain mostly positive for LogME and scores are well suited to be applied to high-dimensional embedding spaces, such that it offers a predictive and efficient measure for quantifying transferability compared to human practitioner intuition.

Ethics Statement

It is difficult to foresee ethical issues for this work due to the broad applicability of LM encoder pre-selection. To the best of our knowledge, in the CV community from which our evaluated scoring methods originate, there have been no harmful applications thus far. In fact, as fine-tuning the entire space of available language models is unsustainable and unethical in terms of climate sustainability, efficient encoder pre-selection methods such as LogME provide a positive first step towards tackling this problem.
Acknowledgements

We would like to wholeheartedly thank the members NLPnorth group at the IT University of Copenhagen, The Center for Information and Language Processing at the Ludwig Maximilian University of Munich, and the Dialogue Modeling Group at the University of Amsterdam for comments on earlier versions of this work and participating in the human practitioner ranking study.

MZ and BP are supported by the Independent Research Fund Denmark (DFF) grant 9131-00019B, EB, MME, and BP are supported by the Independent Research Fund Denmark (DFF) Sapere Aude grant 9063-00077B. BP is supported by the ERC Consolidator Grant DIALECT 101043235.

References

Emily Alsentzer, John Murphy, William Boag, Weihung Weng, Di Jindi, Tristan Naumann, and Matthew McDermott. 2019. Publicly available clinical BERT embeddings. In Proceedings of the 2nd Clinical Natural Language Processing Workshop, pages 72–78, Minneapolis, Minnesota, USA. Association for Computational Linguistics.

Livio Baldini Soares, Nicholas FitzGerald, Jeffrey Ling, and Tom Kwiatkowski. 2019. Matching the blanks: Distributional similarity for relation learning. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 2895–2905, Florence, Italy. Association for Computational Linguistics.

Francesco Barbieri, Jose Camacho-Collados, Luis Espinosa Anke, and Leonardo Neves. 2020. TweetEval: Unified benchmark and comparative evaluation for tweet classification. In Findings of the Association for Computational Linguistics: EMNLP 2020, pages 1644–1650, Online. Association for Computational Linguistics.

Iz Beltagy, Kyle Lo, and Arman Cohan. 2019. SciBERT: A pretrained language model for scientific text. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3615–3620, Hong Kong, China. Association for Computational Linguistics.

Crowdflower. 2020. Twitter us airline sentiment. https://www.kaggle.com/crowdflower/twitter-airline-sentiment. Accessed: 2022-02-20.

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.

Eric Eaton, Marie Desjardins, and Terran Lane. 2008. Modeling transfer relationships between learning tasks for improved inductive transfer. In Joint european conference on machine learning and knowledge discovery in databases, pages 317–332. Springer.

Danilo Giampiccolo, Bernardo Magnini, Ido Dagan, and Bill Dolan. 2007. The third PASCAL recognizing textual entailment challenge. In Proceedings of the ACL-PASCAL Workshop on Textual Entailment and Paraphrasing, pages 1–9, Prague. Association for Computational Linguistics.

Suchin Gururangan, Ana Marasović, Swabha Swayamdipta, Kyle Lo, Iz Beltagy, Doug Downey, and Noah A Smith. 2020. Don’t stop pretraining: Adapt language models to domains and tasks. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 8342–8360.

Kristian Nørgaard Jensen, Mike Zhang, and Barbara Plank. 2021. De-identification of privacy-related entities in job postings. In Proceedings of the 23rd Nordic Conference on Computational Linguistics (NoDaLiDa), pages 210–221, Reykjavik, Iceland (Online). Linköping University Electronic Press, Sweden.

Jinhyuk Lee, Wonjin Yoon, Sungdong Kim, Donghyeon Kim, Sunkyu Kim, Chan Ho So, and Jaewoo Kang. 2020. Biobert: a pre-trained biomedical language representation model for biomedical text mining. Bioinformatics, 36(4):1234–1240.

Yinhua Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandarin Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized BERT pretraining approach. CoRR, abs/1907.11692.

Zihan Liu, Yan Xu, Tiezeng Yu, Wenliang Dai, Ziwei Ji, Samuel Cahyawijaya, Andrea Madotto, and Pascale Fung. 2021. Crossner: Evaluating cross-domain named entity recognition. In AAAI.

Yi Luan, Luheng He, Mari Ostendorf, and Hannaneh Hajishirzi. 2018. Multi-task identification of entities, relations, and coreference for scientific knowledge graph construction. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 3219–3232, Brussels, Belgium. Association for Computational Linguistics.

Marius Mosbach, Anna Khokhlova, Michael A. Hedderich, and Dietrich Klakow. 2020. On the Interplay Between Fine-tuning and Sentence-level Probing for Linguistic Knowledge in Pre-trained Transformers. In Findings of the Association for Computational Linguistics: EMNLP 2020, pages 2502–2516, Online. Association for Computational Linguistics.

Max Müller-Eberstein, Rob van der Goot, and Barbara Plank. 2022a. Probing for labeled dependency trees. In Proceedings of the 60th Annual Meeting of the
Appendix

A Reproducibility

Each model is trained on an NVIDIA A100 GPU with 40GBs of VRAM and an AMD Epyc 7662 CPU. The seed numbers the models are initialized with are 4012, 5060, 9908, 8857, 8823. We run the models for 30 epochs with a patience of 3 on each respective dev. data. We use a batch size of 16, 32, or 64 depending on the size of the dataset. When keeping the language model weights frozen, we use a learning rate of $1e^{-3}$. For full model fine-tuning, the learning rate is set at $5e^{-5}$. On GLUE, JobStack, and CrossNER (News), we observed training instability and set the learning rate to $5e^{-7}$. The evaluated LMs have between 66M parameters (DistilBERT$_{\text{base}}$) and 125M parameters (RoBERTa$_{\text{base}}$), taking between 10 minutes (SciERC) and 3 days (e.g., AGNews, MNLI) to fully fine-tune. Keeping the LM frozen and only fine-tuning the task-specific head is around 70% more time-efficient. Computing LogME requires one forward pass to embed the dataset instances, before completing the score calculation in under 1 minute.

B Exact Results

In Table 2 and Table 3, we present the exact performance numbers shown in Figure 1 and Figure 2. The results here are separated by task.
| Dataset | Language Model | LogME | Frozen | Tuned | LogME | Frozen | Tuned |
|---------|----------------|-------|--------|-------|-------|--------|-------|
| AGNews | bert-base-uncased | 0.0822 | 92.62±0.13 | 93.51±0.23 | 0.1555 | 91.52±0.10 | 93.51±0.46 |
|         | roberta-base | 0.1628 | 93.30±0.17 | 91.70±0.18 | 0.1689 | 92.71±0.42 | 92.57±0.28 |
|         | distilbert-base-uncased | 0.1786 | 92.26±0.37 | 93.85±0.11 | 0.1716 | 91.65±0.22 | 93.77±0.24 |
|         | emilyalsentzer/Bio_ClinicalBERT | -0.1801 | 87.52±0.29 | 92.62±0.62 | -0.1384 | 84.50±0.34 | 93.05±0.52 |
|         | dmis-lab/biobert-v1.1 | -0.0548 | 90.05±0.29 | 93.16±0.23 | -0.0300 | 88.84±0.25 | 93.19±0.26 |
|         | cardiffnlp/twitter-roberta-base | 0.1768 | 92.55±0.21 | 93.34±0.55 | 0.2070 | 93.16±0.25 | 93.15±0.58 |
|         | allenai/scibert_scivocab_uncased | -0.0527 | 90.06±0.17 | 92.40±0.47 | -0.0348 | 89.25±0.20 | 92.32±0.40 |
| MNLI   | bert-base-uncased | -0.2484 | 82.58±0.19 | 84.03±1.10 | -0.2789 | 80.88±0.83 | 82.27±0.45 |
|         | roberta-base | -0.2407 | 87.83±0.52 | 85.43±0.05 | -0.2460 | 85.19±0.52 | 85.19±0.52 |
|         | distilbert-base-uncased | -0.2612 | 81.71±0.39 | 83.89±1.21 | -0.2691 | 79.95±0.45 | 83.99±0.95 |
|         | emilyalsentzer/Bio_ClinicalBERT | -0.3205 | 78.46±0.57 | 83.17±0.62 | -0.3402 | 75.98±1.14 | 82.70±0.81 |
|         | dmis-lab/biobert-v1.1 | -0.3295 | 76.67±0.93 | 82.55±0.06 | -0.3376 | 75.50±0.71 | 81.62±0.57 |
|         | cardiffnlp/twitter-roberta-base | -0.2094 | 84.89±0.21 | 86.05±0.09 | -0.2074 | 84.57±0.62 | 85.51±0.61 |
|         | allenai/scibert_scivocab_uncased | -0.3122 | 77.58±0.51 | 82.05±0.58 | -0.3275 | 76.01±0.51 | 82.27±0.81 |
| QNLI   | bert-base-uncased | -0.5818 | 59.18±0.39 | 81.85±0.31 | -0.5786 | 59.64±0.45 | 82.23±0.19 |
|         | roberta-base | -0.5815 | 64.18±0.34 | 86.57±0.24 | -0.5539 | 61.48±0.68 | 86.71±0.19 |
|         | distilbert-base-uncased | -0.5938 | 58.13±0.58 | 79.64±0.39 | -0.5940 | 57.13±0.73 | 80.54±0.09 |
|         | emilyalsentzer/Bio_ClinicalBERT | -0.6154 | 56.53±0.35 | 79.21±0.24 | -0.5942 | 57.52±0.45 | 79.54±0.11 |
|         | dmis-lab/biobert-v1.1 | -0.5841 | 60.12±0.33 | 80.89±0.43 | -0.5569 | 62.40±0.51 | 80.84±0.41 |
|         | cardiffnlp/twitter-roberta-base | -0.5826 | 67.17±0.36 | 85.41±0.58 | -0.5765 | 59.23±0.13 | 83.52±0.25 |
|         | allenai/scibert_scivocab_uncased | -0.5787 | 59.57±0.44 | 80.41±0.69 | -0.5672 | 61.29±0.28 | 80.40±0.31 |
| RE     | bert-base-uncased | -0.5823 | 75.75±0.11 | 88.17±0.19 | -0.6008 | 72.23±0.48 | 88.46±0.74 |
|         | roberta-base | -0.5557 | 78.09±0.39 | 92.17±0.26 | -0.5749 | 74.42±0.64 | 92.23±0.22 |
|         | distilbert-base-uncased | -0.5881 | 74.25±0.44 | 86.26±0.33 | -0.6079 | 71.55±0.36 | 86.68±0.38 |
|         | emilyalsentzer/Bio_ClinicalBERT | -0.5908 | 74.69±0.38 | 84.13±0.27 | -0.5957 | 73.67±0.33 | 84.31±0.46 |
|         | dmis-lab/biobert-v1.1 | -0.5502 | 71.28±0.26 | 88.19±0.42 | -0.5432 | 77.25±0.29 | 88.57±0.07 |
|         | cardiffnlp/twitter-roberta-base | -0.5728 | 77.49±0.20 | 91.22±0.41 | -0.5826 | 73.99±0.69 | 91.03±0.39 |
|         | allenai/scibert_scivocab_uncased | -0.5737 | 76.84±0.30 | 87.24±0.26 | -0.5577 | 76.31±0.32 | 86.77±0.90 |

Table 2: Exact Results of Classification Tasks. We indicate the LogME score of each model (LANGUAGE MODEL) and its performance on a wide variety of datasets (DATASET) in different settings (FROZEN, TUNED) by either taking the representations of the tokens and apply mean pooling (μ) or the representation of the [CLS] token. Given the LogME scores and the performance metrics, we can calculate the Pearson correlation coefficient (ρ) and the weighted Kendall’s tau (τ_w).
Table 3: Exact Results of Structured Prediction Tasks. We indicate the LOGME score of each model (LANGUAGE MODEL) and its performance on a wide variety of datasets (DATASET) in different settings (FROZEN, TUNED) by taking the representations of the tokens and apply mean pooling ($\mu$). Here we do not take the representation of the [CLS] token as this has no meaning for the structured prediction task. Given the LogME scores and the performance metrics, we can calculate the Pearson correlation coefficient ($\rho$) and the weighted Kendall’s tau ($\tau_w$).