EXPATS: A Toolkit for Explainable Automated Text Scoring

Hitoshi Manabe
LegalForce, Inc.
Tokyo, Japan
hitoshi.manabe@legalforce.co.jp

Masato Hagiwara
Octanove Labs
Seattle, WA, USA
masato@octanove.com

Abstract
Automated text scoring (ATS) tasks, such as automated essay scoring and readability assessment, are important educational applications of natural language processing. Due to their interpretability of models and predictions, traditional machine learning (ML) algorithms based on handcrafted features are still in wide use for ATS tasks. Practitioners often need to experiment with a variety of models (including deep and traditional ML ones), features, and training objectives (regression and classification), although modern deep learning frameworks such as PyTorch require deep ML expertise to fully utilize. In this paper, we present EXPATS, an open-source framework to allow its users to develop and experiment with different ATS models quickly by offering flexible components, an easy-to-use configuration system, and the command-line interface. The toolkit also provides seamless integration with the Language Interpretability Tool (LIT) so that one can interpret and visualize models and their predictions. We also describe two case studies where we build ATS models quickly with minimal engineering efforts.

1 Introduction
Automated essay scoring (AES) (Alikaniotis et al., 2016; Taghipour and Ng, 2016; Ke and Ng, 2019), text readability/difficulty assessment (Vajjala and Meurers, 2012; Xia et al., 2016; Vajjala and Rama, 2018), and grammatical acceptability judgment (Heilman et al., 2014; Warstadt et al., 2019) are all important NLP tasks for a wide range of applications including assessment, text simplification, and language education.

All these tasks can be generalized as a task where, given an input text $x$ and an optional context $c$, the model predicts some quality about $x$ as $y = f(x, c)$ where $y$ is a continuous value ($y \in \mathbb{R}$) or a class on an ordinal scale, such as $y \in \mathbb{N}$ or discrete classes (e.g., $y \in \{\text{low}, \text{mid}, \text{high}\}$). For example, in automated essay scoring (AES), $c$ is a prompt (question), $x$ is an input essay, and $y$ is its score. Throughout this paper, we use automated text scoring (ATS) as an umbrella term to subsume all such tasks.

Deep neural methods have been used in many NLP tasks including ATS. However, only recently have deep contextualized methods started to be applied to ATS tasks, and their results are still mixed (Nadeem et al., 2019; Yang et al., 2020; Mayfield and Black, 2020). In some applications,
especially in settings (such as high-stakes AES systems) where fairness and interpretability are important considerations, traditional, machine learning models with handcrafted, well-studied linguistic features are still in use and are preferred\(^2\). Due to these reasons, practitioners often need to experiment with a wide variety of models, features, and/or training objectives, including regression, (ordinal) classification, and ranking objectives.

Generic deep NLP frameworks such as AllenNLP (Gardner et al., 2018) and Transformers (Wolf et al., 2020) have been proposed and in wide use, but these require deep understanding of machine learning concepts to fully utilize. There are also many application-specific NLP toolkits such as OpenKiwi (Kepler et al., 2019) for quality estimation, OpenNMT (Klein et al., 2017) and fairseq (Ott et al., 2019) for machine translation, and NeuralClassifier (Liu et al., 2019) for text classification. However, no general-purpose toolkits exist for automated text scoring, except for EASE\(^3\), a library for text scoring based on traditional ML, whose scope and usability is quite limited.

In this paper, we present EXPATS (EXPlainable Automated Text Scoring), an open-source toolkit which allows its users to develop and experiment with different automated text scoring models quickly and easily. Its notable features include:

- It provides a simple configuration system via human-readable YAML files and an easy-to-use command line interface.
- It implements composable and extendable components for both traditional and deep neural models, along with features, training objectives, and metrics commonly used in ATS tasks.
- It seamlessly integrates with LIT (Tenney et al., 2020) for providing comprehensive interpretation and visualization of the models and their predictions

In this paper, we also describe two case studies—one for automated essay scoring with the ASAP-AES dataset and the other for Chinese reading assessment—where we used EXPATS to build competitive ATS models quickly with minimal engineering efforts.

2 EXPATS

EXPATS consists of composable and extendable components, a configuration system, and the command line interface (CLI), which all make it easy for practitioners to design and build a wide variety of ATS models and to interpret them. In this section, we’ll cover some of the toolkit’s technical details.

2.1 System Design

Figure 2 shows the overall system design of EXPATS, along with its main components.

**Profiler** The profiler is the core component of EXPATS. By wrapping around an ML model, it produces predictions (e.g., scores for AES) given the input text (e.g., an essay). The design of the
profiler is agnostic of the underlying ML frameworks, which means that toolkit users can define and implement their own profiler with a framework of choice, such as PyTorch (Paszke et al., 2019) or Scikit-learn (Pedregosa et al., 2011).

EXPATS defines two implementations of the profiler out-of-the-box—feature-based and deep learning profilers. The former produces predictions based on hand-crafted features and traditional ML algorithms implemented in Scikit-learn such as support vector machines (SVMs). The features given to the model are abstracted as features objects, as detailed below. The latter implements neural network-based contextualizers such as BERT (Devlin et al., 2019) and any other pretrained language models implemented in Transformers (Wolf et al., 2020).

Pretrained profilers and model weights are packaged into files called artifacts with their configuration, which can be deserialized and used at the test time to make predictions for the given data.

Datasets A dataset is a collection of instances used for training and evaluating the model, whose design is heavily influenced by how datasets are handled in other ML frameworks such as AllenNLP and PyTorch. Each instance is implemented as a Python dataclass and groups the text input, the label, along with any other extra fields required by the profiler. The toolkit is shipped with dataset readers for common data formats, such as TSV (tab-separated values), as well as a dataset reader for The Automated Student Assessment Prize (or ASAP, a standard corpus for AES).

Features Choice of appropriate features is an important factor for ATS tasks. For example, Xia et al. (2016) discuss various types of features for readability assessment extracted from raw text or syntactic trees. EXPATS abstracts features as functions that extract some useful statistics from the input text and passes them to the profiler. These feature extractors are defined on the top of the analysis results from spaCy, a widely used toolkit for language analysis.

EXPATS implements a set of basic features by default, as shown below. It is trivial for users to implement their own features by inheriting from the feature class.

- Total number of tokens
- Average length of tokens (in characters)
- Document embeddings
- Unigram likelihood (provided by an external dictionary)

Objectives Different automated text scoring tasks use different training objectives, such as regression (Taghipour and Ng, 2016), classification (Vajjala and Rama, 2018), and ranking (Yang et al., 2020), and model developers often need to experiment with more than one. With EXPATS, users can switch between regression (e.g., mean squared errors) and classification objectives (e.g., cross entropy) easily. Their predictions are converted to one another for easier evaluation, as we describe below.

Metrics The predictive performance of trained models is usually evaluated using many quantitative measures. EXPATS supports a variety of metrics (abstracted by a Metrics class) widely used in classification or regression settings for ATS, including:

- Classification accuracy
- Precision, recall, and $F_1$ measure (micro and micro averaged)
- Pearson’s correlation coefficient
- Quadratic weighted kappa (QWK)

A variety of evaluation metrics and training objectives are used for text scoring tasks, including regression-based ones such as correlation coefficients and classification-based ones such as accuracy and quadratic weighted Kappa, or QWK. For example, Taghipour and Ng (2016) trained the model with a mean squared error (MSE) loss and evaluated with QWK. Alkaniotis et al. (2016) also used MSE but evaluated with Pearson’s and Spearman’s correlation coefficients.

EXPATS provides an abstract component (“Converter” in Figure 2) in charge of converting regression-based continuous predictions into classification-based ordinal labels (for example, by binning continuous values into discrete labels) and vice versa, enabling it to evaluate the model with the same set of evaluation metrics regardless of the training scheme (regression or classification).
2.2 Command Line Interface

EXPATS is equipped with a command line interface (CLI) for running various jobs in an experiment workflow so that its users can develop and experiment with ATS models quickly and easily. The CLI of EXPATS consists of the following four sub-commands:

- **train**: trains the model based on the configuration file and saves the result as artifacts
- **evaluate**: runs evaluation of a pretrained model with specified evaluation metrics and conversion (e.g., regression to discrete classes)
- **predict**: make predictions for given input with a pretrained model
- **interpret**: runs the LIT server so that users can visualize and interpret model predictions

2.3 Configuration System

Users often need to experiment with a wide range of models with different model architectures and hyperparameters, and optimal settings differ vastly from tasks to tasks. In EXPATS, users configure these settings by writing human-readable YAML files, which enables them to run a number of experiments easily without writing Python code. It also encourages model reproducibility and easy tracking of experiments.

The following is an example of a configuration file used for training a transformer-based regression model for the ASAP-AES dataset:

```yaml
task: regression
profiler:
  type: TransformerRegressor
params:
  trainer:
    gpus: 1
    max_epochs: 30
  network:
    output_normalized: true
    pretrained_model_name_or_path: bert-base-uncased
    lr: 1e-5
  data_loader:
    batch_size: 8

dataset:
  type: asap-aes
params:
  path: /path/to/training_tsv_file
```

There are three main sections in EXPATS configuration files. The task section specifies the task setting to use (e.g., classification or regression). The profiler section defines the type of model or hyperparameters used to train the model, such as the number of training epochs and the learning rate. Finally, the dataset section defines the type of dataset and its parameters to load the data. The params sections are interpreted and passed to corresponding Python object constructors.

2.4 Visualization

Traditional, feature-based methods such as linear regressions and decision trees are, almost by definition, interpretable, making it easier for developers to see which elements contributed to the model predictions and how. On the other hand, deep neural network-based methods, which are inherently black boxes, have been gaining popularity for automated text scoring tasks. Interpretability is an important factor for text scoring, especially for high-stakes settings such as AES for admission tests and for situations where students wish to receive feedback from the system. To make models and their predictions more interpretable, EXPATS support integration with Language Interpretability Tool (LIT; Tenney et al. 2020) by default. LIT offers a web-based graphical interface where users can visualize, e.g., saliency maps for tokens that contributed to the prediction. The models built with EXPATS are automatically connected with LIT abstractions and can be visualized and interpreted on a web browser. Figure 1 shows a screenshot of visualization via LIT.

3 Case Studies

In the remainder of this paper, we’ll describe two case studies where we used EXPATS to build ATS models. Since EXPATS is designed so that practitioners who are not necessarily familiar with NLP research or software engineering can also use, all users need to prepare is the datasets for training and validating the model on, and configuration files. After preparing a YAML file shown in the previous section, one can train a model by running the expats train command. The resulting model is stored in an artifact package along with its configuration, and one can evaluate, make prediction from, and/or interpret the model by running evaluate, predict, and interpret commands, respectively.
### Table 1: Evaluation results of QWK scores on test set for ASAP dataset

| Model       | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    |
|-------------|------|------|------|------|------|------|------|------|
| Random forest | 0.552 | 0.608 | 0.723 | 0.665 | 0.799 | 0.614 | 0.242 | 0.303 |
| BERT        | 0.523 | 0.598 | 0.680 | 0.787 | 0.805 | 0.790 | 0.432 | 0.516 |

#### 3.1 ASAP-AES Scorer

In this first case study, we build an AES system based on ASAP-AES, a de-facto standard dataset published at Kaggle\(^6\). We build two regression models based on a feature-based algorithm and a deep learning-based algorithm.

- **Random forest**: This model is based on random forest regressor with hand-crafted features. The number of estimators and the maximum tree depth are 100 and 5, respectively. We extracted three linguistic features from a tokenized text: number of tokens, average token length, and average unigram likelihood. The unigram likelihood of each token is computed from unigram counts obtained from the Tatoeba dataset\(^7\).

- **BERT**: This model is based on the pretrained BERT (Devlin et al., 2019) model and fine-tuned on the training corpus for automated essay scoring without any hand-crafted features. We tokenized input texts and prepended with the special token `[CLS]`. The hidden representation aligned at the position of `[CLS]` token is projected into one-dimensional scalar with a linear layer. We used the mean squared error as the objective function.

We used 80% of the published ASAP-AES dataset (which contains 12,978 essays in total) as the training set and 20% as the test set to evaluate all models. One model is trained for each prompt (question). We followed (Taghipour and Ng, 2016) for all other experimental settings. We describe the results of experiments in Table 1. Overall, the BERT-based method outperforms Random Forest regressor with hand-crafted features.

Next, we qualitatively analyzed the behavior of the trained BERT-based model on the test set using the LIT integration. We inspected saliency maps based on the input gradients, which highlight the importance of input tokens with respect to the model predictions.

In a case where the model predicted lower scores, we find that the tokens containing typos (e.g., `ting` in Figure 3) show more importance than others. On the other hand, infrequent tokens (e.g., `predators`) tend to be highly important for the essays with higher scores. This demonstrates that the BERT-based model is making reasonable decisions and the EXPATS-LIT integration is effective for inspecting such relationship.

#### Figure 3: Gradient-based saliency map visualized via LIT. Typos (e.g., `ting`) receive higher importance in this low-score essay.

#### 3.2 Chinese Readability Assessment

Readability assessment in other languages has not been explored as much compared to English (Chen et al., 2013). In this case study, we will show a case study where we build Chinese readability assessment models based on traditional ML and neural networks (BERT), where the ML models classify a given Chinese passage into six different HSK levels (1-6), which roughly correspond to six levels of CEFR (the Common European Framework of Reference) (Council of Europe, 2001). As you’ll see below, one can easily build models in different languages using EXPATS with minimal modification.

The Chinese dataset for readability assessment...
Table 2: Chinese readability assessment results

| Model        | Acc. | $F_1$  | QWK  | Corr. |
|--------------|------|--------|------|-------|
| Random forest| 0.398| 0.251  | 0.463| 0.482 |
| BERT         | 0.584| 0.468  | 0.755| 0.762 |

we used consists of level-balanced reading passages taken from HSK (a standard Chinese proficiency test) sample questions. The toolkit supports tab-delimited format of level[tab]text out of the box, which means that all we needed to do was prepare their datasets in the same format.

We compared a random forest classifier as well as a BERT-based classifier. All the other experimental settings are essentially the same as the previous case study. There were only three changes we needed to make to support the Chinese readability assessment:

- **Tokenizer**: we replaced the spaCy tokenizer model from English to the one for Chinese (zh_core_web_sm)
- **Unigram likelihood**: we used a unigram likelihood table computed from a dataset of sentences (approximately 2 million characters) sampled from Wikipedia and Tatoeba.
- **Contextualizer**: we switched from an English pretrained BERT model to a Chinese one (bert-base-chinese)

We ran some light hyperparameter tuning on the validation set, and evaluated the performance on the test portion of the dataset. Table 2 shows the experimental results. We again see that the BERT-based neural model achieves better readability assessment performance compared to the random forest, although adding and improving the features used for the traditional ML algorithm will certainly improve its performance. This case study demonstrates that, despite that fact that we dealt with another task in a very different language, we were able to quickly build new models thanks to the EXPATS toolkit’s flexibility.

4 Conclusion

We presented an open-source framework called EXPATS for automated text scoring (ATS) tasks.

EXPATS allows practitioners to develop and experiment with different ATS models quickly and easily, by offering easy-to-use components, the configuration system, and the command-line interface, as well as the integration with LIT for model interpretability and visualization.

We are planning to cover more features and methods (including non-BERT neural networks) with EXPATS as future work. In addition, giving feedback is an important aspect for automated text scoring (see (Beigman Klebanov and Madnani, 2020) for a recent review) and providing more comprehensive visualization not only for model developers but also for language learners is an important venue for future research.

**Broader Impact**

As with other machine learning fields and tasks, fairness and algorithmic biases are an important consideration for ATS tasks and have been discussed intensively in the literature (Beigman Klebanov and Madnani, 2020). A scoring system is said to be fair if the score differences are due only to the differences in the constructs (the skills/abilities the system is intended to measure), not due to other indirect factors such as genders or native languages. Common analyses methods for fairness include mean score differences and the model performance for different subgroups (Loukina et al., 2019), and some open-source toolkits exist for assisting fairness-related analyses (Madnani and Loukina, 2016).

The design of EXPATS can contribute to validation and fairness analysis of ATS systems. Its framework (components, the configuration system, and the CLI) enables quick experimentation and validation of various settings, which potentially helps find feature/model biases. It is also straightforward to implement such fairness analysis techniques either directly or via LIT integration. Finally, the EXPATS-LIT integration offers ways for visualizing and identifying sources of potential algorithmic biases. Although little attention has been paid to explainable neural methods for ATS tasks (Kumar and Boulanger, 2020), EXPATS can open up a new, important line of research on this front.
References

Dimitrios Alikaniotis, Helen Yannakoudakis, and Marek Rei. 2016. Automatic text scoring using neural networks. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 715–725, Berlin, Germany. Association for Computational Linguistics.

Beata Beigman Klebanov and Nitin Madnani. 2020. Automated evaluation of writing – 50 years and counting. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7796–7810, Online. Association for Computational Linguistics.

Yu-Ta Chen, Yaw-Huei Chen, and Yu-Chih Cheng. 2013. Assessing Chinese readability using term frequency and lexical chain. In International Journal of Computational Linguistics & Chinese Language Processing, Volume 18, Number 2, June 2013-Special Issue on Chinese Lexical Resources: Theories and Applications.

Council of Europe. 2001. Common European Framework of Reference for Languages: Learning, Teaching, Assessment. Press Syndicate of the University of Cambridge.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. 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, Minneapolis, Minnesota. Association for Computational Linguistics.

Matt Gardner, Joel Grus, Mark Neumann, Oyvind Tafjord, Pradeep Dasigi, Nelson F. Liu, Matthew Peters, Michael Schmitz, and Luke Zettlemoyer. 2018. AllenNLP: A deep semantic natural language processing platform. In Proceedings of Workshop for NLP Open Source Software (NLP-OSP), pages 1–6, Melbourne, Australia. Association for Computational Linguistics.

Michael Heilman, Aoife Cahill, Nitin Madnani, Melissa Lopez, Matthew Mulholland, and Joel Tetreault. 2014. Predicting grammaticality on an ordinal scale. In Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers), pages 174–180, Baltimore, Maryland. Association for Computational Linguistics.

Zixuan Ke and Vincent Ng. 2019. Automated essay scoring: A survey of the state of the art. In Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI-19, pages 6300–6308. International Joint Conferences on Artificial Intelligence Organization.

Fabio Kepler, Jonay Trénous, Marcos Treviso, Miguel Vera, and André F. T. Martins. 2019. OpenKiwi: An open source framework for quality estimation. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics: System Demonstrations, pages 117–122, Florence, Italy. Association for Computational Linguistics.

Guillaume Klein, Yoon Kim, Yuntian Deng, Jean Senellart, and Alexander Rush. 2017. OpenNMT: Open-source toolkit for neural machine translation. In Proceedings of ACL 2017. System Demonstrations, pages 67–72, Vancouver, Canada. Association for Computational Linguistics.

Vivekanandan Kumar and David Boulanger. 2020. Explainable automated essay scoring: Deep learning really has pedagogical value. Frontiers in Education, 5:186.

Liqun Liu, Funan Mu, Pengyu Li, Xin Mu, Jing Tang, Xingsheng Ai, Ran Fu, Lifeng Wang, and Xing Zhou. 2019. NeuralClassifier: An open-source neural hierarchical multi-label text classification toolkit. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics: System Demonstrations, pages 87–92, Florence, Italy. Association for Computational Linguistics.

Anastassia Loukina, Nitin Madnani, and Klaus Zechner. 2019. The many dimensions of algorithmic fairness in educational applications. In Proceedings of the Fourteenth Workshop on Innovative Use of NLP for Building Educational Applications, pages 1–10, Florence, Italy. Association for Computational Linguistics.

Nitin Madnani and Anastassia Loukina. 2016. RSM-Tool: A collection of tools for building and evaluating automated scoring models. Journal of Open Source Software, 1(3).

Elijah Mayfield and Alan W Black. 2020. Should you fine-tune BERT for automated essay scoring? In Proceedings of the Fifteenth Workshop on Innovative Use of NLP for Building Educational Applications, pages 151–162, Seattle, WA, USA → Online. Association for Computational Linguistics.

Farah Nadeem, Huy Nguyen, Yang Liu, and Mari Ostendorf. 2019. Automated essay scoring with discourse-aware neural models. In Proceedings of the Fourteenth Workshop on Innovative Use of NLP for Building Educational Applications, pages 484–493, Florence, Italy. Association for Computational Linguistics.

Myle Ott, Sergey Edunov, Alexei Baevski, Angela Fan, Sam Gross, Nathan Ng, David Grangier, and Michael Auli. 2019. fairseq: A fast, extensible toolkit for sequence modeling. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics (Demonstrations), pages 48–53, Minneapolis, Minnesota. Association for Computational Linguistics.
Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary 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. In Advances in Neural Information Processing Systems, volume 32. Curran Associates, Inc.

Fabian Pedregosa, Gaël Varoquaux, Alexandre Gramfort, Vincent Michel, Bertrand Thirion, Olivier Grisel, Mathieu Blondel, Peter Prettenhofer, Ron Weiss, Vincent Dubourg, Jake Vanderplas, Alexandre Passos, David Cournapeau, Matthieu Brucher, Matthieu Perrot, and Édouard Duchesnay. 2011. Scikit-learn: Machine learning in python. Journal of Machine Learning Research, 12(85):2825–2830.

Kaveh Taghipour and Hwee Tou Ng. 2016. A neural approach to automated essay scoring. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing, pages 1882–1891, Austin, Texas. Association for Computational Linguistics.

Ian Tenney, James Wexler, Jasmijn Bastings, Tolga Bolukbasi, Andy Coenen, Sebastian Gehrmann, Ellen Jiang, Mahima Pushkarna, Carey Radebaugh, Emily Reif, and Ann Yuan. 2020. The language interpretability tool: Extensible, interactive visualizations and analysis for NLP models. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 107–118, Online. Association for Computational Linguistics.

Sowmya Vajjala and Detmar Meurers. 2012. On improving the accuracy of readability classification using insights from second language acquisition. In Proceedings of the Seventh Workshop on Building Educational Applications Using NLP, pages 163–173, Montréal, Canada. Association for Computational Linguistics.

Sowmya Vajjala and Taraka Rama. 2018. Experiments with universal CEFR classification. In Proceedings of the Thirteenth Workshop on Innovative Use of NLP for Building Educational Applications, pages 147–153, New Orleans, Louisiana. Association for Computational Linguistics.

Alex Warstadt, Amanpreet Singh, and Samuel Bowman. 2019. Neural network acceptability judgments. Transactions of the Association for Computational Linguistics, 7(0):625–641.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. 2020. Transformers: State-of-the-art natural language processing. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 38–45, Online. Association for Computational Linguistics.

Menglin Xia, Ekaterina Kochmar, and Ted Briscoe. 2016. Text readability assessment for second language learners. In Proceedings of the 11th Workshop on Innovative Use of NLP for Building Educational Applications, pages 12–22, San Diego, CA. Association for Computational Linguistics.

Ruosong Yang, Jiannong Cao, Zhiyuan Wen, Youzheng Wu, and Xiaodong He. 2020. Enhancing automated essay scoring performance via fine-tuning pre-trained language models with combination of regression and ranking. In Findings of the Association for Computational Linguistics: EMNLP 2020, pages 1560–1569, Online. Association for Computational Linguistics.