jiant: A Software Toolkit for Research on General-Purpose Text Understanding Models

Yada Pruksachatkun, Phil Yeres, Haokun Liu, Jason Phang, Phu Mon Htut, Alex Wang, Ian Tenney, Samuel R. Bowman

1New York University, 2Google Research
{yp913,bowman}@nyu.edu

Abstract

We introduce jiant, an open source toolkit for conducting multitask and transfer learning experiments on English NLU tasks. jiant enables modular and configuration-driven experimentation with state-of-the-art models and implements a broad set of tasks for probing, transfer learning, and multitask training experiments. jiant implements over 50 NLU tasks, including all GLUE and SuperGLUE benchmark tasks. We demonstrate that jiant reproduces published performance on a variety of tasks and models, including BERT and RoBERTa. jiant is available at https://jiant.info.

1 Introduction

This paper introduces jiant, an open source toolkit that allows researchers to quickly experiment on a wide array of NLU tasks, using state-of-the-art NLP models, and conduct experiments on probing, transfer learning, and multitask training. jiant supports many state-of-the-art Transformer-based models implemented by Huggingface’s Transformers package, as well as non-Transformer models such as BiLSTMs.

Packages and libraries like HuggingFace’s Transformers (Wolf et al., 2019) and AllenNLP (Gardner et al., 2017) have accelerated the process of experimenting and iterating on NLP models by abstracting out implementation details, and simplifying the model training pipeline. jiant extends the capabilities of both toolkits by presenting a wrapper that implements a variety of complex experimental pipelines in a scalable and easily controllable setting. jiant contains a task bank of over 50 tasks, including all the tasks presented in GLUE (Wang et al., 2018), SuperGLUE (Wang et al., 2019b), the edge-probing suite (Tenney et al., 2019b), and the SentEval probing suite (Conneau and Kiela, 2018), as well as other individual tasks including CCG supertagging (Hockenmaier and Steedman, 2007), SocialIQA (Sap et al., 2019), and CommonsenseQA (Talmor et al., 2019). jiant is also the official baseline codebase for the SuperGLUE benchmark.

jiant’s core design principles are:

- Ease of use: jiant should allow users to run a variety of experiments using state-of-the-art models via an easy to use configuration-driven interface.
- Reproducibility: jiant should provide features that support correct and reproducible experiments, including logging and saving and restoring model state.
- Availability of NLU tasks: jiant should maintain and continue to grow a collection of tasks useful for NLU research, especially popular evaluation tasks and tasks commonly used in pretraining and transfer learning.
- Availability of cutting-edge models: jiant should make implementations of state-of-the-art models available for experimentation.
- Open source: jiant should be free to use, and easy to contribute to.

Early versions of jiant have already been used in multiple works, including probing analyses (Tenney et al., 2019b,a; Warstadt et al., 2019; Lin et al., 2019; Hewitt and Manning, 2019; Jawahar et al., 2019), transfer learning experiments (Wang et al., 2019a; Phang et al., 2018), and dataset and benchmark construction (Wang et al., 2019b, 2018; Kim et al., 2019).

*Equal contribution.

1The name jiant stands for “jiant is an NLP toolkit”.
Figure 1: Multi-phase \textit{jiant} experiment configuration used by Wang et al. (2019a): a BERT sentence encoder is trained with an intermediate task model during \textit{jiant}'s intermediate training phase, and fine-tuned with various target task models in \textit{jiant}'s target training phase.

2 Background

Transfer learning is an area of research that uses knowledge from pretrained models to transfer to new tasks. In recent years, Transformer-based models like BERT (Devlin et al., 2019) and T5 (Raffel et al., 2019) have yielded state-of-the-art results on the lion’s share of benchmark tasks for language understanding through pretraining and transfer, often paired with some form of multitask learning.

\textit{jiant} enables a variety of complex training pipelines through simple configuration changes, including multi-task training (Caruana, 1993; Liu et al., 2019a) and pretraining, as well as the sequential fine-tuning approach from STILTs (Phang et al., 2018). In STILTs, intermediate task training takes a pretrained model like ELMo or BERT, and applies supplementary training on a set of intermediate tasks, before finally performing single-task training on additional downstream tasks.

3 \textit{jiant} System Overview

3.1 Requirements and Deployment

\textit{jiant} can be cloned and installed from GitHub: https://github.com/nyu-mll/jiant. \textit{jiant} v1.3.0 requires Python 3.5 or later, and \textit{jiant}'s core dependencies are PyTorch (Paszke et al., 2019), AllenNLP (Gardner et al., 2017), and HuggingFace’s Transformers (Wolf et al., 2019). \textit{jiant} is released under the MIT License (Open Source Initiative, 2020). \textit{jiant} runs on consumer-grade hardware or in cluster environments with or without CUDA GPUs. The \textit{jiant} repository also contains documentation and configuration files demonstrating how to deploy \textit{jiant} in Kubernetes clusters on Google Kubernetes Engine.

3.2 \textit{jiant} Components

- Tasks: Tasks have references to task data, methods for processing data, references to classifier heads, and methods for calculating performance metrics, and making predictions.
- Sentence Encoder: Sentence encoders map from the indexed examples to a sentence-level representation. Sentence encoders can include an input module (e.g., Transformer models, ELMo, or word embeddings), followed by an optional second layer of encoding (usually a BiLSTM). Examples of possible sentence encoder configurations include BERT, ELMo followed by a BiLSTM, BERT with a variety of pooling and aggregation methods, or a bag of words model.
- Task-Specific Output Heads: Task-specific output modules map representations from sentence encoders to outputs specific to a task, e.g. entailment/neutral/contradiction for NLI tasks, or tags for part-of-speech tagging. They also include logic for computing the corresponding loss for training (e.g. cross-entropy).
- Trainer: Trainers manage the control flow for the training and validation loop for experiments. They sample batches from one or more tasks, perform forward and backward passes, calculate training metrics, evaluate on a validation set, and save checkpoints. Users can specify experiment-specific parameters such as learning rate, batch size, and more.
- Config: Config files or flags are defined in HOCON\footnote{Human-Optimized Config Object Notation (lightbend, 2011).} format.Configs specify parameters for \textit{jiant} experiments including choices of tasks, sentence encoder, and training routine.\footnote{\textit{jiant} configs support multi-phase training routines as described in section 3.3 and illustrated in Figure 2.}

Configs are \textit{jiant}'s primary user interface. Tasks and modeling components are designed to be modular, while \textit{jiant}'s pipeline is a monolithic, configuration-driven design intended to facilitate a number of common workflows outlined in 3.3.

3.3 \textit{jiant} Pipeline Overview

\textit{jiant}'s core pipeline consists of the five stages described below and illustrated in Figure 2:
1. A config or multiple configs defining an experiment are interpreted. Users can choose and configure models, tasks, and stages of training and evaluation.

2. The tasks and sentence encoder are prepared:
   (a) The task data is loaded, tokenized, and indexed, and the preprocessed task objects are serialized and cached. In this process, AllenNLP is used to create the vocabulary and index the tokenized data.
   (b) The sentence encoder is constructed and (optionally) pretrained weights are loaded.
   (c) The task-specific output heads are created for each task, and task heads are attached to a common sentence encoder. Optionally, different tasks can share the same output head, as in Liu et al. (2019a).

3. Optionally, in the intermediate phase the trainer samples batches randomly from one or more tasks, and trains the shared model.

4. Optionally, in the target training phase, a copy of the model is configured and trained or fine-tuned for each target task separately.

5. Optionally, the model is evaluated on the validation and/or test sets of the target tasks.

3.4 Task and Model resources in jiant

jiant supports over 50 tasks. Task types include classification, regression, sequence generation, tagging, masked language modeling, and span prediction. jiant focuses on NLU tasks like MNLI (Williams et al., 2018), CommonsenseQA (Talmor et al., 2019), the Winograd Schema Challenge (Levesque et al., 2012), and SQuAD (Rajpurkar et al., 2016). A full inventory of tasks and task variants is available in the jiant/tasks module.

jiant provides support for cutting-edge sentence encoder models, including support for Huggingface’s Transformers. Supported models include: ELMo (Peters et al., 2018), GPT (Radford, 2018), BERT (Devlin et al., 2019), XLM (Conneau and Lample, 2019), GPT-2 (Radford et al., 2019), XLNet (Yang et al., 2019), RoBERTa (Liu et al., 2019b), and ALBERT (Lan et al., 2019). jiant also supports the from-scratch training of (bidirectional) LSTMs (Hochreiter and Schmidhuber, 1997) and deep bag of words models (Iyyer et al., 2015), as well as syntax-aware models such
Figure 3: Example jiant experiment config file.

```bash
// Config for BERT experiments.
// Get default configs from a file:
include "defaults.conf"
exp_name = "bert-large-cased"

// Data and preprocessing settings
max_seq_len = 256

// Model settings
input_module = "bert-large-cased"
transformers_output_mode = "top"
s2s = {
    attention = none
}
sent_enc = "none"
sep_embs_for_skip = 1
classifier = log_reg
// fine-tune entire BERT model
transfer_paradigm = finetune

// Training settings
dropout = 0.1
optimizer = bert_adam
batch_size = 4
max_epochs = 10
lr = .00001
min_lr = .0000001
lr_patience = 4
patience = 20
max_vals = 10000

// Phase configuration
do_pretrain = 1
do_target_task_training = 1
do_full_eval = 1
write_preds = "val,test"
write_strict_glue_format = 1

// Task specific configuration
commitbank = {
    val_interval = 60
    max_epochs = 40
}
```

as PRPN (Shen et al., 2018) and ON-LSTM (Shen et al., 2019). jiant also supports word embeddings such as GloVe (Pennington et al., 2014).

### 3.5 User Interface

jiant experiments can be run with a simple CLI:

```
python -m jiant \
    --config_file roberta_with_mnli.conf \
    --overrides "target_tasks = swag,\n    run_name = swag_01"
```

jiant provides default config files that allow running many experiments without modifying source code.

jiant also provides baseline config files that can serve as a starting point for model development and evaluation against GLUE (Wang et al., 2018) and SuperGLUE (Wang et al., 2019b) benchmarks.

More advanced configurations can be developed by composing multiple configurations files and overrides. Figure 3 shows a config file that overrides a default config, defining an experiment that uses BERT as the sentence encoder. This config includes an example of a task-specific configuration, which can be overridden in another config file or via a command line override.

Because jiant implements the option to provide command line overrides with a flag, it is easy to write scripts that launch jiant experiments over a range of parameters, for example while performing grid search across hyperparameters. jiant users have successfully run large-scale experiments launching hundreds of runs on both Kubernetes and Slurm.

### 3.6 Example jiant Use Cases and Options

Here we highlight some example use cases and key corresponding jiant config options required in these experiments:

- Fine-tune BERT on SWAG (Zellers et al., 2018) and SQUAD (Rajpurkar et al., 2016), then fine-tune on HellaSwag (Zellers et al., 2019):

  ```
  input_module = bert-base-cased
  pretrain_tasks = "swag,squad"
  target_tasks = hellaswag
  ```

- Train a probing classifier over a frozen BERT model, as in Tenney et al. (2019a):

  ```
  input_module = bert-base-cased
  target_tasks = edges-dpr
  transfer_paradigm = frozen
  ```

- Compare performance of GloVe (Pennington et al., 2014) embeddings using a BiLSTM:

  ```
  input_module = glove
  sent_enc = rnn
  ```

- Evaluate ALBERT (Lan et al., 2019) on the MNLI (Williams et al., 2018) task:

  ```
  input_module = albert-large-v2
  target_task = mnli
  ```

### 3.7 Optimizations and Other Features

jiant implements features that improve run stability and efficiency:

- jiant implements checkpointing options designed to offer efficient early stopping and to show consistent behavior when restarting after an interruption.
• **jiant** caches preprocessed task data to speed up reuse across experiments which share common data resources and artifacts.

• **jiant** implements gradient accumulation and multi-GPU, which enables training on larger batches than can fit in memory for a single GPU.

• **jiant** supports outputting predictions in a format ready for GLUE and SuperGLUE benchmark submission.

• **jiant** generates custom log files that capture experimental configurations, training and evaluation metrics, and relevant run-time information.

• **jiant** generates TensorBoard event files (Abadi et al., 2015) for training and evaluation metric tracking. TensorBoard event files can be visualized using the TensorBoard Scalars Dashboard.

### 3.8 Extensibility

**jiant**’s design offers conveniences that reduce the need to modify code when making changes:

• **jiant**’s task registry makes it easy to define a new version of an existing task using different data. Once the new task is defined in the task registry, the task is available as an option in **jiant**’s config.

• **jiant**’s sentence encoder and task output head abstractions allow for easy support of new sentence encoders.

In use cases requiring the introduction of a new task, users can use class inheritance to build on a number of available parent task types including classification, tagging, span prediction, span classification, sequence generation, regression, ranking, and multiple choice task classes. For these task types, corresponding task-specific output heads are already implemented.

More than 30 researchers and developers from more than 5 institutions have contributed code to the **jiant** project.**jiant**’s maintainers welcome pull requests that introduce new tasks or sentence encoder components, and pull request are actively reviewed. The **jiant** repository’s continuous integration system requires that all pull requests pass unit and integration tests and meet Black™ code formatting requirements.

### 3.9 Limitations and Development Roadmap

While **jiant** is quite flexible in the pipelines that can be specified through configs, and some components are highly modular (e.g., tasks, sentence encoders, and output heads), modification of the pipeline code can be difficult. For example, training in more than two phases would require modifying the trainer code. Making multi-stage training configurations more flexible is on **jiant**’s development roadmap.

**jiant**’s development roadmap prioritizes adding support for new Transformer models, and adding tasks that are commonly used for pretraining and evaluation in NLU. Additionally, there are plans to make **jiant**’s training phase configuration options more flexible to allow training in more than two phases, and to continue to refactor **jiant**’s code to keep **jiant** flexible to track developments in NLU research.

### 4 Benchmark Experiments

To benchmark **jiant**, we perform a set of experiments that reproduce external results for single fine-tuning and transfer learning experiments. **jiant** has been benchmarked extensively in both published and ongoing work on a majority of the implemented tasks.

We benchmark single-task fine-tuning configurations using CommonsenseQA (Talmor et al., 2019) and SocialIQA (Sap et al., 2019). On CommonsenseQA with RoBERTa™LARGE, **jiant** achieves an accuracy of 72.2, comparable to 72.1 reported by Liu et al. (2019b). On SocialIQA with BERT-large, **jiant** achieves a dev set accuracy of 65.8, comparable to 66.0 reported in Sap et al. (2019).

Next, we benchmark **jiant**’s transfer learning regime. We perform transfer experiments from MNLI to BoolQ with BERT-large. In this configuration Clark et al. (2019) demonstrated an accuracy improvement of 78.1 to 82.2 on the dev set, and **jiant** achieves an improvement of 78.1 to 80.3.

---

6https://github.com/nyu-mll/jiant/graphs/contributors

7https://github.com/psf/black

8While not supported by config options, training in more than two phases is possible by using **jiant**’s checkpointing features to reload models for additional rounds of training.
5 Conclusion

jiant provides a configuration-driven interface for defining transfer learning and representation learning experiments using a bank of over 50 NLU tasks, cutting-edge sentence encoder models, and multi-task and multi-stage training procedures. Further, jiant is shown to be able to replicate published performance on various NLU tasks.

jiant’s modular design of task and sentence encoder components make it possible for users to quickly and easily experiment with a large number of tasks, models, and parameter configurations, without editing source code. jiant’s design also makes it easy to add new tasks, and jiant’s architecture makes it convenient to extend jiant to support new sentence encoders.

jiant code is open source, and jiant invites contributors to open issues or submit pull request to the jiant project repository: https://github.com/nyu-mll/jiant.

Acknowledgments

Katherin Yu, Jan Hula, Patrick Xia, Raghu Pappagari, Shuning Jin, R. Thomas McCoy, Roma Patel, Yinhui Huang, Edouard Grave, Najoung Kim, Thibault Févry, Berlin Chen, Nikita Nangia, Anhad Mohananey, Katharina Kann, Shikha Bordia, Nicolas Patry, David Benton, and Ellie Pavlick have contributed substantial engineering assistance to the project.

The early development of jiant took at the 2018 Frederick Jelinek Memorial Summer Workshop on Speech and Language Technologies, and was supported by Johns Hopkins University with unrestricted gifts from Amazon, Facebook, Google, Microsoft and Mitsubishi Electric Research Laboratories.

Subsequent development was possible in part by a donation to NYU from Eric and Wendy Schmidt made by recommendation of the Schmidt Futures program, by support from Intuit Inc., and by support from Samsung Research under the project Improving Deep Learning using Latent Structure. We gratefully acknowledge the support of NVIDIA Corporation with the donation of a Titan V GPU used at NYU in this work. Alex Wang’s work on the project is supported by the National Science Foundation Graduate Research Fellowship Program under Grant No. DGE 1342536. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation. Yada Pruksachatkun’s work on the project is supported in part by the Moore-Sloan Data Science Environment as part of the NYU Data Science Services initiative. Sam Bowman’s work on jiant during Summer 2019 took place in his capacity as a visiting researcher at Google.

References

Martín Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Ian Goodfellow, Andrew Harp, Geoffrey Irving, Michael Isard, Yangqing Jia, Rafal Jozefowicz, Lukasz Kaiser, Manjunath Kudlur, Josh Levenberg, Dandelion Mané, Rajat Monga, Sherry Moore, Derek Murray, Chris Olah, Mike Schuster, Jonathon Shlens, Benoit Steiner, Ilya Sutskever, Kunal Talwar, Paul Tucker, Vincent Vanhoucke, Vijay Vasudevan, Fernanda Viégas, Oriol Vinyals, Pete Warden, Martin Wattenberg, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng. 2015. TensorFlow: Large-scale machine learning on heterogeneous systems. Software available from tensorflow.org.

Rich Caruana. 1993. Multitask learning: A knowledge-based source of inductive bias. In ICML.

Christopher Clark, Kenton Lee, Ming-Wei Chang, Tom Kwiatkowski, Michael Collins, and Kristina Toutanova. 2019. BooQL: Exploring the surprising difficulty of natural yes/no questions. 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 2924–2936, Minneapolis, Minnesota. Association for Computational Linguistics.

Alexis Conneau and Douwe Kiela. 2018. SentEval: An evaluation toolkit for universal sentence representations. In Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC-2018), Miyazaki, Japan. European Languages Resources Association (ELRA).

Alexis Conneau and Guillaume Lample. 2019. Cross-lingual language model pretraining. In Advances in Neural Information Processing Systems 32, pages 7057–7067.

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 S. Zettlemoyer. 2017. AllenNLP: A deep semantic natural language processing platform. Unpublished manuscript available on arXiv.

John Hewitt and Christopher D. Manning. 2019. A structural probe for finding syntax in word representations. 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 4129–4138, Minneapolis, Minnesota. Association for Computational Linguistics.

Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long short-term memory. Neural computation, 9(8):1735–1780.

Julia Hockenmaier and Mark Steedman. 2007. CCG-bank: A corpus of CCG derivations and dependency structures extracted from the Penn treebank. Computational Linguistics, 33(3):355–396.

Mohit Iyyer, Varun Manjunatha, Jordan Boyd-Graber, and Hal Daumé III. 2015. Deep unordered composition rivals syntactic methods for text classification. In Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 1681–1691, Beijing, China. Association for Computational Linguistics.

Ganesh Jawahar, Benoît Sagot, and Djamé Seddah. 2019. 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, Florence, Italy. Association for Computational Linguistics.

Najoung Kim, Roma Patel, Adam Poliak, Patrick Xia, Alex Wang, Tom McCoy, Ian Tenney, Alexis Ross, Tal Linzen, Benjamin Van Durme, Samuel R. Bowman, and Ellie Pavlick. 2019. Probing what different NLP tasks teach machines about function word comprehension. In Proceedings of the Eighth Joint Conference on Lexical and Computational Semantics (*SEM 2019), pages 235–249, Minneapolis, Minnesota. Association for Computational Linguistics.

Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. 2019. ALBERT: A lite BERT for self-supervised learning of language representations.

Hector J. Levesque, Ernest Davis, and Leora Morgenstern. 2012. The Winograd schema challenge. In Proceedings of the Thirteenth International Conference on Principles of Knowledge Representation and Reasoning, KR’12, pages 552–561. AAAI Press.

Yongjie Lin, Yi Chen, Tan, and Robert Frank. 2019. Open sesame: Getting inside BERT’s linguistic knowledge. In Proceedings of the 2019 ACL Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP, pages 241–253, Florence, Italy. Association for Computational Linguistics.

Xiaodong Liu, Pengcheng He, Weizhu Chen, and Jianfeng Gao. 2019a. Multi-task deep neural networks for natural language understanding. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4487–4496, Florence, Italy. Association for Computational Linguistics.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019b. RoBERTa: A robustly optimized BERT pretraining approach.

Open Source Initiative. 2020. The MIT License.

Jeffrey Pennington, Richard Socher, and Christopher Manning. 2014. Glove: Global vectors for word representation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1532–1543, Doha, Qatar. Association for Computational Linguistics.

Matthew Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. Deep contextualized word representations. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 2227–2237, New Orleans, Louisiana. Association for Computational Linguistics.

Jason Phang, Thibault Févery, and Samuel R. Bowman. 2018. Sentence Encoders on STILTs: Supplementary Training on Intermediate Labeled-data Tasks. Unpublished manuscript available on arXiv.

Alec Radford. 2018. Improving language understanding by generative pre-training.
Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 93–104, Brussels, Belgium. Association for Computational Linguistics.

Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. 2019. HellaSwag: Can a machine really finish your sentence? In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 4791–4800, Florence, Italy. Association for Computational Linguistics.