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

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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,[1] 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 both 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 Super-GLUE 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. jiant should also 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).

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[1]The name jiant doesn't mean much. The 'j' stands for JSALT, the summer research workshop program at which development of jiant began. That's all the acronym we have.
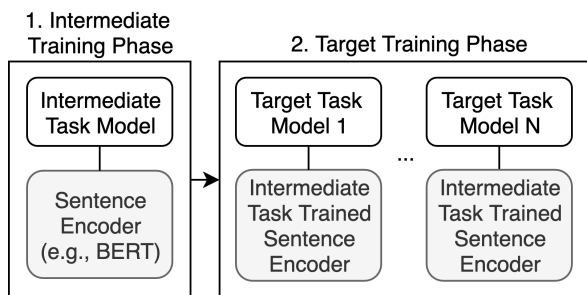
Figure 1: Multi-phase `jiant` experiment configuration used by Wang et al. (2019a): a BERT sentence encoder is trained with an intermediate task model during `jiant`'s intermediate training phase, and fine-tuned with various target task models in `jiant`'s target training phase.

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.

`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 **jiant** System Overview

3.1 Requirements

`jiant` v1.3.0 requires Python 3.5 or later. `jiant` can be installed via pip, or cloned and installed from GitHub. `jiant`'s core dependencies are PyTorch (Paszke et al., 2019), AllenNLP (Gardner et al., 2017), and HuggingFace's Transformers (Wolf et al., 2019). `jiant` is released under the MIT License (Open Source Initiative, 2020).

3.2 **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 metthods, 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[2] format. Configs specify parameters for `jiant` experiments including choices of tasks, sentence encoder, and training routine.[3]

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

3.3 **jiant** Pipeline Overview

`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.

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[2] Human-Optimized Config Object Notation (lightbend, 2011). `jiant` uses HOCON's logic to consolidate multiple config files and command-line overrides into a single run config.

[3] `jiant` configs support multi-phase training routines as described in section 3.3 and illustrated in Figure 2.
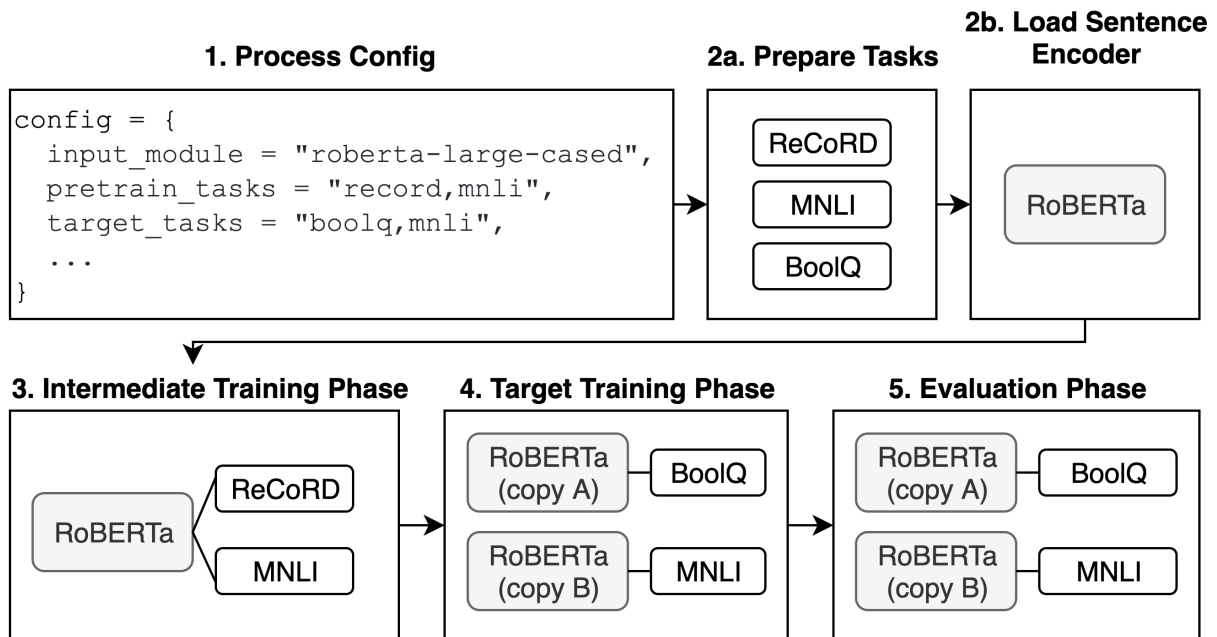
1. Process Config

```
config = {
  input_module = "roberta-large-cased",
  pretrain_tasks = "record,mnli",
  target_tasks = "boolq,mnli",
  ...
}
```

2a. Prepare Tasks

ReCoRD

MNLI

BoolQ

2b. Load Sentence Encoder

RoBERTa

3. Intermediate Training Phase

RoBERTa — ReCoRD / MNLI

4. Target Training Phase

RoBERTa (copy A) — BoolQ

RoBERTa (copy B) — MNLI

5. Evaluation Phase

RoBERTa (copy A) — BoolQ

RoBERTa (copy B) — MNLI

Figure 2: `jiant` pipeline stages using RoBERTa as the sentence encoder, ReCoRD and MNLI tasks as intermediate tasks, and MNLI and BoolQ as tasks for target training and evaluation. The diagram highlights that during target training and evaluation phases, copies are made of the sentence encoder model, and fine tuning and evaluation for each task are conducted on separate copies.

2. The tasks and sentence encoder are prepared:

  (a) The task data is loaded, tokenized, and indexed, and (optionally) 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.[4]

  (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,[5] 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, 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: BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019b), XLNet (Yang et al., 2019), XLM (Conneau and Lample, 2019), GPT (Radford, 2018), GPT-2 (Radford et al., 2019), ALBERT (Lan et al., 2019) and ELMo (Peters et al., 2018). `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 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).

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[4] The sentence encoder's weights can optionally be left frozen, or be included in the training procedure.

[5] Tasks can be sampled using a variety of sample weighting methods, e.g., uniform or proportional to the tasks' number of training batches or examples.

```
// 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
}
```

Figure 3: Example `jiant` experiment config file.

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, \
              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.

`jiant` also implements the option to provide command line overrides with a flag. This option makes it 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 `jiant` Deployment Environments

`jiant` runs on consumer-grade hardware or in cluster environments with or without CUDA GPUs. The `jiant` repository also contains documentation and configuration files demonstrating how to deploy `jiant` in Kubernetes clusters on Google Kubernetes Engine.

3.8 Logging and Metric Tracking

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

`jiant` also 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.

3.9 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.

3.10 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.[6] `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[7] code formatting requirements.

3.11 Limitations

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.[8] Making multi-stage training configurations more flexible is on `jiant`'s development roadmap.

3.12 `jiant` Development Roadmap

`jiant` is actively being developed. The `jiant` project has prioritized continuing to add support for new Transformer models and adding tasks that are commonly used for pretraining and evaluation in NLU, including sequence-to-sequence tasks.

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 $\text{RoBERTa}_{\text{LARGE}}$, `jiant` achieves an accuracy of 0.722, comparable to 0.721 reported

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

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

[8]While 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.

by Liu et al. (2019b). On SocialIQA with BERT-large, `jiant` achieves a dev set accuracy of 0.658, comparable to 0.66 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 0.78 to 0.82 on the dev set, and `jiant` achieves an improvement of 0.78 to 0.80.

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`.

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