A Gentle Introduction to Deep Nets and Opportunities for the Future

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Abstract

The first half of this tutorial will make deep nets more accessible to a broader audience, following “Deep Nets for Poets” and “A Gentle Introduction to Fine-Tuning.” We will also introduce, \textit{gft} (general fine tuning), a little language for fine tuning deep nets with short (one line) programs that are as easy to code as regression in statistics packages such as R using \textit{glm} (general linear models). Based on the success of these methods on a number of benchmarks, one might come away with the impression that deep nets are all we need. However, we believe the glass is half-full: while there is much that can be done with deep nets, there is always more to do. The second half of this tutorial will discuss some of these opportunities.

1 Introduction

This tutorial is split into two parts:

A Glass is half-full: deep nets can do much

B Glass is half-empty: there is always more to do

Part A will make deep nets more accessible to a broader audience (Church et al., 2021b,a) by introducing \textit{gft} (General Fine-Tuning), a new “little language”\footnote{Little languages were advocated by Bentley (1986) and the Unix group. Little languages such as AWK (Aho et al., 1987) make it easy to solve remarkably powerful tasks with short (often one-line) programs.} for deep nets that is similar to \textit{glm} (general linear models) in the statistics package R.\footnote{https://www.r-project.org/} \textit{gft} code will be posted on the tutorial website.\footnote{https://github.com/kwchurch/ACL2022_deeppnets_tutorial}

2 Part A: Glass is Half-Full

2.1 The Standard Recipe

Following (Devlin et al., 2019; Howard and Ruder, 2018), it has become standard practice to use the 3-step recipe in Table 1, with an emphasis on pre-trained (foundation/base) models (Bommasani et al., 2021). \textit{gft} prefers the terms, \textit{fit} and \textit{predict}, which have a long tradition in statistics, and pre-date relatively recent work on deep nets.

\textit{gft} makes it easy to use models and datasets on hubs: HuggingFace\footnote{https://huggingface.co/} and PaddleHub/PaddleNLP.\footnote{https://github.com/PaddlePaddle} The hubs are large (30k models and 3k datasets), and growing quickly (3x/year). The challenge is to make these amazing resources more accessible to a diverse user-base. One does not need to know python and machine learning to use an off-the-shelf regression package. So too, deep nets should not require much (if any) programming skills.

2.2 Examples of Fit (aka Fine-Tuning)

Fit takes a pre-trained model, $f_{\text{pre}}$ (BERT), and uses a dataset (emotion) to output a post-trained model, $f_{\text{post}}$ (to $\text{outdir}$):

```
gft_fit --data "H:emotion"  
--model "H:bert-base-cased"  
--eqn "classify:label~text"  
--output_dir "$outdir"
```

Listing 1: Example of \textit{gft_fit}

The next example is similar but uses a model and a dataset from PaddleNLP. \textit{gft} supports mixing and matching models and datasets from different hubs.

```
gft_fit --data "P:chnsenticorp"  
--model "P:ernie-tiny"  
--eqn "classify:label~text"  
--output_dir "$outdir"
```

Listing 2: H and P refer to HuggingFace and PaddleNLP

Table 1: 3-Step recipe has become standard practice
Table 2: gft solutions for GLUE (Wang et al., 2018)

| –data arg | –eqn arg |
|------------|-----------|
| H:glue,cola | classify: label ∼ sentence |
| H:glue,sst2 | classify: label ∼ sentence |
| H:glue,wnli | classify: label ∼ sentence |
| H:glue,mrpc | classify: label ∼ sentence + sentence |
| H:glue,qnli | classify: label ∼ sentence + sentence |
| H:glue,rte | classify: label ∼ question + sentence |
| H:glue,qqp | classify: label ∼ question1 + question2 |
| H:glue,stsb | regress: label ∼ sentence + sentence |
| H:glue,mnli | classify: label ∼ premise + hypothesis |

Table 3: gft solutions for more benchmarks

| –data arg | –eqn arg |
|------------|-----------|
| squad | classify_spans: answers ∼ question + context |
| tweet_eval,hate | classify: label ∼ text |
| conll2003 | classify_tokens: pos_tags ∼ tokens |
| conll2003 | classify_tokens: ner_tags ∼ tokens |
| conll2003 | classify_tokens: chunk_tags ∼ tokens |
| timit_asr | ctc: text ∼ audio |

2.4 Some Simple Examples

2.4.1 Search

As mentioned above, users are overwhelmed with an embarrassment of riches. How do we find the good stuff on the hubs? The following outputs snippets for datasets, models and tasks:

```bash
m=bhadresh-savani/roberta-base-emotion
gft_summary --data "H:emotion"
gft_summary --model "H:$m"
gft_summary --task "H:classify"
```

Listing 3: Models/datasets/tasks → snippets

Search for datasets and models that contain the substring: emotion, sorted by downloads:

```bash
query=H:__contains__emotion
gft_summary --data "$query" --topn 5
gft_summary --model "$query" --topn 5
```

Listing 4: Searching for best emotion models/datasets

To find the most downloaded datasets and models, set the query to the empty string:

```bash
query=H:__contains__
gft_summary --data "$query" --topn 5
gft_summary --model "$query" --topn 5
```

Listing 5: Searching for best of everything

2.4.2 Predict (aka Inference)

After having found the good stuff, how do we use it? gft_predict takes input, \( x \), from stdin and outputs predictions, \( \hat{y} \).

```bash
echo "I love you" | gft_predict --task $tc
```

There are four major arguments:

1. –data: a dataset on a hub, or a local file
2. –model: a model on a hub, or a local file
3. –task: e.g., classify, regress
4. –eqn (e.g., classify: \( y \sim x_1 + x_2 \)), where a task appears before the colon, and variables refer to columns in the dataset.

The gft interpreter is based on examples from

1. fit (aka fine-tuning): \( f_{\text{pre}} + \text{data} \rightarrow f_{\text{post}} \)
2. predict (aka inference): \( f(x) = \hat{y} \), where \( x \) is an input from a dataset or from stdin
3. eval: \( f + \text{data} \rightarrow \text{score} \)
4. summary: search hubs for popular datasets, models, and tasks, and provide snippets.
5. cat_data: output dataset on stdout

There are four major tasks:

1. –data: a dataset on a hub, or a local file
2. –model: a model on a hub, or a local file
3. –task: e.g., classify, regress
4. –eqn (e.g., classify: \( y \sim x_1 + x_2 \)), where a task appears before the colon, and variables refer to columns in the dataset.

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- eval: \( f + \text{data} \rightarrow \text{score} \)
- summary: search hubs for popular datasets, models, and tasks, and provide snippets.
- cat_data: output dataset on stdout

Currently supported tasks are: classify (aka text-classification), classify_tokens (aka token-classification), classify_spans (aka QA, question-answering), classify_images (aka image-classification), classify_audio (aka audio-classification), regress, text-generation, MT (aka translation), ASR (aka etc, automatic-speech-recognition), fill-mask. Tasks in parentheses are aliases.

Hubs encourage users to modify 500+ lines of pytorch as necessary if they want to change models, datasets and/or tasks. gft generalizes the examples so users can do much of that in a single line of gft code (with comparable performance).
Listing 6: Examples of \texttt{gft\_predict}

\texttt{gft\_predict} can also input from a dataset split, and outputs a prediction, $\hat{y}$, for each $x$ in the split:

\begin{verbatim}
$\texttt{eqn=\textit{\texttt{classify:label-text}}}$
$\texttt{gft\_predict --eqn $\texttt{\$eqn$} --model $\texttt{\$m$} \ --data H:emotion --split test}$
\end{verbatim}

Listing 7: Input from a dataset (instead of stdin)

2.4.3 Evaluation

If we replace \texttt{gft\_predict} (above) with \texttt{gft\_eval} (below), then we obtain a single score (instead of a $\hat{y}$ for each $x$):

\begin{verbatim}
$\texttt{gft\_eval --eqn $\texttt{\$eqn$} --model $\texttt{\$m$} \ --data H:emotion --split test}$
\end{verbatim}

Listing 8: Evaluating a model on a dataset

2.4.4 Ease of Use, Popularity & SOTA

Given an embarrassment of riches, how do we choose the best model? The literature emphasizes SOTA (state-of-the-art), hubs reward downloads, and \texttt{gft} advocates ease-of-use.

Table 4 reports accuracy for a few models containing “MRPC,”\footnote{We tested 22 models from HuggingFace and 135 models from Yuchen Bian (personal communication). To save space, results are reported for the best of Bian’s models, the top 3 HuggingFace models, and models with 100+ downloads.} as well as two custom models. \texttt{gft} makes it easy to achieve competitive results, close to distilbert (compressed) models. One can outperform models on the hubs, by tuning hyper-parameters as Yuchen Bian did. Tuning is possible in \texttt{gft} (but not recommended), as discussed in footnote 9. The validation accuracy in Table 4 are well below test accuracy in Table 5\footnote{https://paperswithcode.com/sota/semantic-textual-similarity-on-mrpc} \footnote{https://gluebenchmark.com/leaderboard}, suggesting that popular/easy-to-use/compressed models are well below SOTA (though we should not compare validation accuracy with test accuracy).

Table 4: \texttt{gft} achieves VAcc (accuracy on validation split) close to distilbert (compressed) models. HuggingFace models were selected using \texttt{gft\_summary} to find popular models by downloads (D).

| Model                                      | VAcc   | D   |
|--------------------------------------------|--------|-----|
| C:RoBERTa large, tuned by Yuchen Bian     | 0.924  |     |
| H:textattack/roberta-base-MRPC             | 0.912  | 1623|
| H:textattack/albert-base-v2-MRPC           | 0.897  | 175 |
| H:mrm8488/deberta-v3-small-finetuned-mrpc  | 0.892  | 30  |
| H:textattack/bert-base-uncased-MRPC        | 0.877  | 10,133|
| H:textattack/distilbert-base-uncased-MRPC  | 0.858  | 108 |
| H:ajrae/bert-base-uncased-finetuned-mrpc   | 0.858  | 115 |
| C:gft\_fit example (BERT with no tuning)   | 0.853  |     |
| H:textattack/distilbert-base-cased-MRPC    | 0.784  | 122 |

Table 5: SOTA (state-of-the-art) for MRPC (GLUE). See footnote 11 for PWC, and 12 for L & HB.

The point of Part A is to demystify deep nets. No one would suggest that regression-like methods are magical, or even artificially intelligent.

The point of Part B is to set appropriate expectations. There are many classic problems in knowledge representation, cognitive science and linguistics that go beyond regression-like methods discussed in Part A.

3 Part B: Opportunities for Improvement

Language models (LMs) are based on (Firth, 1957): “You shall know a word by the company it keeps” and Zellig Harris’s (1954) “distributional hypothesis.” By construction, this approach learns many aspects of language, some more desirable (fluency, collocations, word patterns) and some less desirable (biases (Bender et al., 2021)). However, there are many aspects that are not learned: truth (logical form, temporal/spatial logic and possible worlds), meaning, purpose (planning (Kautz et al., 1986; Litman and Allen, 1987), discourse structure) and commonsense knowledge (time and space). These topics have been studied for decades in AI and knowledge representation and for centuries in linguistics and philosophy.
3.1 Truth
To the extent that a use case places importance on the truth of the outputs provided, it is not a good fit for GPT-3 (Dale, 2021). LMs have a tendency to “hallucinate” when summarizing documents. The output sounds plausible, but may add embellishments to the input. More generally, LMs tend to make up “alternative facts” faster than they can be fact-checked. This may well be their most dangerous failing; people might believe some of these conspiracy theories.

3.2 Meaning
A vivid example of challenges with meaning is Ettinger’s (2020) study of negation. If you ask BERT to fill in the blank in:

• A robin is a ____.
• A robin is not a ____.

the top answer is: “bird,” in both cases. There are few wrong answers in the second case, but “bird” is one of them.

3.3 Purpose, Planning & Document Structure
LMs generate text word-by-word without looking ahead and thinking about the larger picture. Short outputs are remarkably fluent, but longer outputs tend to meander aimlessly. Dialogue systems optimize for smoothness from the most recent turn. Such short-term thinking may not be helpful to the user (Grice, 1975). In one notorious case, a GPT-3 chatbot in the medical domain advised a patient to commit suicide (Rousseau and Baudelaire, 2020). More generally, LMs produce non-sequiturs, contradictions, tautologies, echolalia (Metz, 2020).

3.4 Commonsense knowledge
Commonsense knowledge is basic knowledge of how the world works (Davis and Marcus, 2015). We tested GPT-3’s command of spatial and temporal knowledge with questions such as:

Time: Who came first, Thomas Jefferson or John F. Kennedy?
Space: Which is further from Liverpool, England: Brussels, Belgium or Portland, Oregon?

GPT-3 performed at chance on space, and only slightly better on time. LMs can output dates for historical figures and coordinates of cities, if asked directly, but LMs struggle to use this knowledge for questions such as the ones above.

The questions in our experiment involve particularly simple forms of temporal and spatial reasoning. Many texts make use of complex temporal relations such as possible worlds and hypothetical events (Gordon and Hobbs, 2017). Text often make use of complex features involving shapes and spatial relations (Davis, 2013).

Time and space (Bloom, 1999) have been extensively studied in linguistics and philosophy. It is natural to model time based on tense. One approach starts with speech time, S, reference time, R, and event time, E.

past perfect (had slept) $E < R < S$
simple past (slept) $E \approx R, E < S, R < S$

There are also natural connections between linguistic constructions such as subjunctive (would, could, should) and possible worlds. More generally, much of the work in linguistics assumes a rich set of connections between surface representations (syntax) and deeper structures (semantics/pragmatics).

4 Conclusions: Some Paths Forward
Some of these opportunities can be addressed by relatively easy patches to Firth-based methods. For example, biases can be mitigated in the short term by vetting the training corpus (Hovy and Prabhumoye, 2021). Similarly, penalty terms can be added to the objective function to discourage hallucinations (Durmus et al., 2020). Fine-tuning on a corpus of commonsense knowledge can help with violations of commonsense (Zhang et al., 2021).

In the long term, it may be helpful to consider more radical alternatives (Marcus and Davis, 2019). Part A described some recent advances that have been remarkably successful, though to make long term advances beyond that, it may be necessary to take advantage of more diverse interdisciplinary approaches that include Firth-based methods, as well as decades of work on Knowledge Representation in AI, and centuries of work in linguistics and philosophy.

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13 https://plato.stanford.edu/entries/possible-worlds/
14 https://plato.stanford.edu/entries/logic-temporal/
15 https://plato.stanford.edu/entries/reichenbach/#axi.TheRel192
16 In the past perfect, event time precedes reference time, which precedes speech time. In contrast, in the simple past, event time coincides with reference time, while both precede speech time.
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