Libraries and Tools

🤗 Transformers, AllenNLP

LING575 Analyzing Neural Language Models
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Apr 27 2022

Outline

- Very helpful tools
  - 🤗 Transformers
  - AllenNLP
    - Walk-through of a classifier and a tagger
- Second half: tips/tricks for experiment running and paper writing

🤗 Transformers

https://huggingface.co/transformers

Where to get LMs to analyze?

- RNNs: see week 3 slides
  - Josefewicz et al “Exploring the limits…”
  - Gulordava et al “Colorless green ideas…”
  - ELMo via AllenNLP (about which more later)
- Effectively a unique API for each model
- All (essentially) Transformer-based models: HuggingFace!

Overview of the Library

- Access to many variants of many very large LMs (BERT, RoBERTa, XLNET, ALBERT, T5, language-specific models, …) with fairly consistent API
  - Build tokenizer + model from string for name or config
  - Then use just like any PyTorch nn.Module
- Emphasis on ease-of-use
  - E.g. low barrier-to-entry to *using* the models, including for analysis
  - [new `pipeline` abstraction too, but I think this is *too easy* for most analysis / probing purposes, but can work if all you need are model judgments on data]
- Interoperable with PyTorch or TensorFlow 2.0

Example: Tokenization

```
>>> from transformers import AutoTokenizer

>>> tokenizer = AutoTokenizer.from_pretrained("bert-base-cased")
```

```
>>> encoded_input = tokenizer("Do not meddle in the affairs of wizards, for they are subtle and quick to
>>> print(encoded_input)
{'input_ids': [101, 2079, 2025, 19960, 10362, 1999, 1996, 3821, 1997, 16657, 1010, 2005, 2027, 2024, 112
 'token_type_ids': [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
 'attention_mask': [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1]}
```

See http://juditacs.github.io/2019/02/19/bert-tokenization-stats.html (h/t Naomi Shapiro)

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```

```
>>> tokenizer.decode(encoded_input["input_ids"])
'[CLS] Do not meddle in the affairs of wizards, for they are subtle and quick to anger. [SEP]'
```

See http://juditacs.github.io/2019/02/19/bert-tokenization-stats.html (h/t Naomi Shapiro)

Example: Tokenizing a Batch

```
>>> batch_sentences = [
...     "But what about second breakfast?",
...     "Don't think he knows about second breakfast, Pip.",
...     "What about elevensies?",
... ]
>>> encoded_input = tokenizer(batch_sentences, padding=True)
>>> print(encoded_input)
{'input_ids': [[101, 1252, 1184, 1164, 1248, 6462, 136, 102, 0, 0, 0, 0, 0, 0, 0],
               [101, 1790, 112, 189, 1341, 1119, 3520, 1164, 1248, 6462, 117, 21902, 1643, 119, 102],
               [101, 1327, 1164, 5450, 23434, 136, 102, 0, 0, 0, 0, 0, 0, 0, 0]],
 'token_type_ids': [[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
                    [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
                    [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]],
 'attention_mask': [[1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0],
                    [1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1],
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 'token_type_ids': [[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
                    [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0],
                    [0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]],
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```

Add \`return_tensors="pt"\` to get these outputs as PyTorch Tensors

Example: Forward Pass

```
>>> from transformers import BertTokenizer, BertModel
>>> import torch

>>> tokenizer = BertTokenizer.from_pretrained("bert-base-uncased")
>>> model = BertModel.from_pretrained("bert-base-uncased")

>>> inputs = tokenizer("Hello, my dog is cute", return_tensors="pt")
>>> outputs = model(**inputs)

>>> last_hidden_states = outputs.last_hidden_state
```

Outputs from the forward pass

- Outputs are *usually* Python objects with various attributes corresponding to different model outputs (NB: can be *tuples of Tensors* if specified, but I recommend against that)
  - BERT, by default, gives two things:
    - **`last_hidden_state`**: sequence of hidden states at the last layer of the model.
      Shape: (batch_size, max_length, embedding_dimension)
    - **`pooler_output`**: embedding of '[CLS]' token, passed through one tanh layer (more on this later)
      Shape: (batch_size, embedding_dimension)

Getting more out of a model

```
from transformers import BertModel
model = BertModel.from_pretrained(“bert-base-uncased”)

outputs = model(inputs, output_hidden_states=True,
output_attentions=True)
```

Getting more out of a model

```
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model = BertModel.from_pretrained("bert-base-uncased")

outputs = model(inputs, output_hidden_states=True,
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```

- Now, the output object has additional attributes:
  - **`hidden_states`**: A tuple of tensors, one for each layer. Length: # layers
    Shape of each: `(batch_size, max_length, embedding_dimension)`
  - **`attentions:`** tuple of tensors, one for each layer. Length: # layers
    Shape of each: `(batch_size, num_heads, max_length, max_length)`
- [Can also be done with BertConfig object]

What the library does well

- Very easy tokenization
- Forward pass of models
  - Exposing as many internals as possible
    - All layers, attention heads, etc
- As unified an interface as possible
  - But: different models have different properties, controlled by Configs or by arguments
  - Read the docs carefully!
    - e.g. https://huggingface.co/docs/transformers/model_doc/bert#transformers.BertModel
    - The docs for `forward` just below explain the inputs/outputs

More Info

- Model search: https://huggingface.co/models
- Dataset search: https://huggingface.co/datasets
- Relatively new portions of the library (Trainer) may be useful for probing, but we'll look at another route for that now.

AllenNLP

https://allenai.org/allennlp/software/allennlp-library

Overview of AllenNLP

- Built on top of PyTorch
- Flexible data API
- Abstractions for common use cases in NLP
  - e.g. take a sequence of representations and give me a single one
- Modular:
  - Because of that, can swap in and out different options, for good experiments
- Declarative model-building / training via config files
- See https://github.com/allenai/writing-code-for-nlp-research-emnlp2018
- Guide: https://guide.allennlp.org/ <— very helpful for explaining some of the abstractions

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for each epoch:
  for each batch:
    get model outputs on batch
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  - ….

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- Not *that* complicated, but:
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  - Check-pointing (saving best model(s))
  - Generating and padding the batches
  - Logging results
  - …. `allennlp train myexperiment.jsonnet`

Example Abstractions

- TextFieldEmbedder
- Seq2SeqEncoder
- Seq2VecEncoder
- Attention
- …

- Allows for easy swapping of different choices at every level in your model.

AllenNLP Bert Example

- See https://github.com/shanest/allennlp-bert-example [linked on course webpage as well]
- Using AllenNLP to probe BERT for two tasks:
  - Classification [Stanford Sentiment Treebank]
  - Tagging [Semantic Tagging]

Classifying

Overall Structure (Classification)

```
model_string = "bert-base-uncased"

tokenizer = PretrainedTransformerTokenizer(model_string)
token_indexer = PretrainedTransformerIndexer(model_string)

reader = SSTDatasetReader(tokenizer, {"tokens": token_indexer})
train_path = "sst/trees/train.txt"
dev_path = "sst/trees/dev.txt"

train_dataset = reader.read(train_path)
val_dataset = reader.read(dev_path)

print(list(train_dataset)[0])

vocab = Vocabulary.from_instances(chain(train_dataset, val_dataset))

bert_token_embedder = PretrainedTransformerEmbedder(model_string)
bert_textfield_embedder = BasicTextFieldEmbedder({"tokens": bert_token_embedder})
cls_pooler = ClsPooler(bert_token_embedder.get_output_dim())

model = BertClassifier(
    vocab, bert_textfield_embedder, cls_pooler, freeze_encoder=False
)

data_loader = MultiProcessDataLoader(reader, train_path, batch_size=32)
data_loader.index_with(vocab)

trainer = GradientDescentTrainer(
    model=model,
    optimizer=optim.Adam(model.parameters()),
    serialization_dir="/tmp/test",
    data_loader=data_loader,
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DatasetReader

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DatasetReader

Model

Data Loader/Iterator

Trainer

Basic Components: Dataset Reader

- Datasets are collections of *Instances*, which are collections of *Fields*
  - For text classification, e.g.: one TextField, one LabelField
  - Many more: https://guide.allennlp.org/reading-data
- DatasetReaders….. read data sets. Two primary methods:
  - _read(file): reads data from disk, yields Instances. By calling:
  - text_to_instance (variable signature)
    - Processing of the "raw" data from disk into final form
    - Produces one Instance at a time

DatasetReader: Stanford Sentiment Treebank

- One line from train.txt:

(**3** (2 (2 The) (2 Rock)) (4 (3 (2 is) (4 (2 destined) (2 (2 (2 (2 (2 to) (2 (2 be) (2 (2 the) (2 (2 21st) (2 (2 (2 Century) (2 's)) (2 (3 new) (2 (2 ``) (2 Conan))))))))) (2 '')) (2 and)) (3 (2 that) (3 (2 he) (3 (2 's) (3 (2 going) (3 (2 to) (4 (3 (2 make) (3 (3 (2 a) (3 splash)) (2 (2 even) (3 greater)))) (2 (2 than) (2 (2 (2 (2 (1 (2 Arnold) (2 Schwarzenegger)) (2 ,)) (2 (2 Jean-Claud) (2 (2 Van) (2 Damme)))) (2 or)) (2 (2 Steven) (2 Segal))))))))))))) (2 .)))

- Core of _read:

```
parsed_line = Tree.fromstring(line)
instance = self.text_to_instance(parsed_line.leaves(), parsed_line.label())
if instance is not None:
    yield instance
```

- Core of text_to_instance:

```
if self._tokenizer:
    new_tokens = self._tokenizer.tokenize(' '.join(tokens))
else:
    new_tokens = [Token(token) for token in tokens]
text_field = TextField(new_tokens, token_indexers=self._token_indexers)
fields: Dict[str, Field] = {"tokens": text_field}
```

…

```
    fields["label"] = LabelField(sentiment)
return Instance(fields)
```

Model

```
@Model.register("bert_classifier")
class BertClassifier(Model):
    def __init__(
        self,
        vocab: Vocabulary,
        embedder: TextFieldEmbedder,
        pooler: Seq2VecEncoder,
        freeze_encoder: bool = True,
    ) -> None:
        super().__init__(vocab)

        self.vocab = vocab
        self.embedder = embedder
        self.pooler = pooler
        self.freeze_encoder = freeze_encoder

        for parameter in self.embedder.parameters():
            parameter.requires_grad = not self.freeze_encoder

        in_features = self.pooler.get_output_dim()
        out_features = vocab.get_vocab_size(namespace="labels")

        self._classification_layer = torch.nn.Linear(in_features, out_features)
        self._accuracy = CategoricalAccuracy()
        self._loss = torch.nn.CrossEntropyLoss()
```

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```

Fine tune or not

Model

```python
def forward(  # type: ignore
    self, tokens: Dict[str, torch.Tensor], label: torch.IntTensor = None
) -> Dict[str, torch.Tensor]:

    # (batch_size, max_len, embedding_dim)
    embeddings = self.embedder(tokens)

    # get the pooled representation of the tokens in each sentence
    # e.g. [CLS] rep, mean pool, ...
    # (batch_size, embedding_dim)
    sentence_representation = self.pooler(embeddings)

    # apply classification layer
    # (batch_size, num_labels)
    logits = self._classification_layer(sentence_representation)

    probs = torch.nn.functional.softmax(logits, dim=-1)

    output_dict = {"logits": logits, "probs": probs}

    if label is not None:
        loss = self._loss(logits, label.long().view(-1))
        output_dict["loss"] = loss
        self._accuracy(logits, label)

    return output_dict
```

NB: frozen embeddings can be pre-computed for efficiency

Where was BERT?

- In the TextFieldEmbedder!
- In run_classifying.py: initialized a PretrainedTransformerEmbedder
  - AllenNLP has wrappers around HuggingFace
  - But note: to extract more from a model, you’ll probably need to write your own class, using the existing ones as inspiration

Config file (classifying_experiment.jsonnet)

```
local bert_model = "bert-base-uncased";
{
    "dataset_reader": {
        "type": "sst_reader",
        "tokenizer": {
            "type": "pretrained_transformer",
            "model_name": bert_model,
        },
        "token_indexers": {
            "tokens": {
                "type": "pretrained_transformer",
                "model_name": bert_model,
            }
        }
    },
    "train_data_path": "sst/trees/train.txt",
    "validation_data_path": "sst/trees/dev.txt",
```

`@DatasetReader.register(“sst_reader”)`

Arguments to SSTReader!

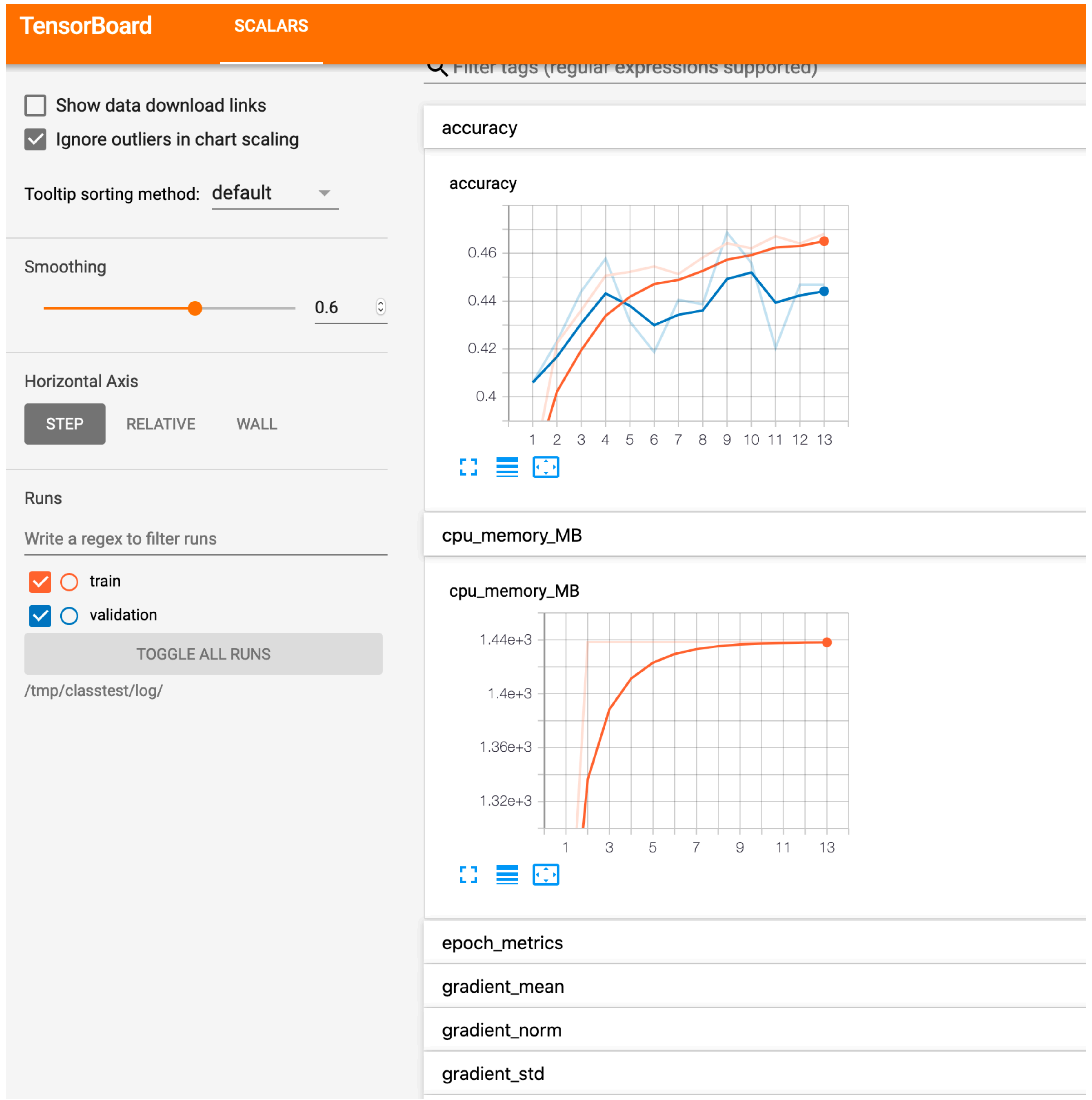
Config file (classifying_experiment.jsonnet)

```
    "model": {
        "type": "bert_classifier",
        "embedder": {
            "type": "basic",
            "token_embedders": {
                "tokens": {
                    "type": "pretrained_transformer",
                    "model_name": bert_model
                }
            }
        },
        "pooler": {
            # NB: for probing, cls_pooler and boe_pooler are good choices
            # bert_pooler actually does more than what is wanted in that scenario
            "type": "cls_pooler",
            "embedding_dim": 768,
        },
        "freeze_encoder": true,
    },
    "data_loader": {
        "batch_size": 32
    },
    "trainer": {
        "optimizer": {
            "type": "adam",
            "lr": 0.001
        },
        "validation_metric": "+accuracy",
        "checkpointer": {
            "keep_most_recent_by_count": 1
        },
        "num_epochs": 30,
        "grad_norm": 10.0,
        "patience": 5,
        "cuda_device": -1
    }
}
```

```
allennlp train classifying_experiment.jsonnet \
  --serialization-dir test \
  --include-package classifying
```

TensorBoard

```
tensorboard --logdir /serialization_dir/log
```



Use SSH port forwarding to [view server-side results locally]()

Tagging

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- The repository also has an example of training a [semantic tagger]()
  - Like POS tagging, but with a richer set of “semantic” tags

ANA anaphoric	PRO	anaphoric & deictic pronouns: *he, she, I, him*
	DEF	definite: *the, lo*[IT], *der*[DE]
	HAS	possessive pronoun: *my, her*
	REF	reflexive & reciprocal pron.: *herself, each_other*
	EMP	emphasizing pronouns: *himself*
ACT speech act	GRE	greeting & parting: *hi, bye*
	ITJ	interjections, exclamations: *alas, ah*
	HES	hesitation: *err*
	QUE	interrogative: *who, which, ?*
ATT attribute	QUC*	concrete quantity: *two, six_million, twice*
	QUV*	vague quantity: *millions, many, enough*
	COL*	colour: *red, crimson, light_blue, chestnut_brown*
	IST	intersective: *open, vegetarian, quickly*
	SST	subsective: *skillful* surgeon, *tall* kid
	PRI	privative: *former, fake*
	DEG*	degree: 2 meters *tall*, 20 years *old*
	INT	intensifier: *very, much, too, rather*
	REL	relation: *in, on, ’s, of, after*
	SCO	score: *3-0*, grade *A*
COM comparative	EQU	equative: *as* tall as John, whales *are* mammals
	MOR	comparative positive: *better, more*
	LES	comparative negative: *less, worse*
	TOP	superlative positive: *most, mostly*
	BOT	superlative negative: *worst, least*
	ORD	ordinal: *1st, 3rd, third*
UNE unnamed entity	CON	concept: *dog, person*
	ROL	role: *student, brother, prof., victim*
	GRP*	group: John *{,}* Mary *and* Sam gathered, a *group* of people
DXS deixis	DXP*	place deixis: *here, this, above*
	DXT*	temporal deixis: *just, later, tomorrow*
	DXD*	discourse deixis: *latter, former, above*
LOG logical	ALT	alternative & repetitions: *another, different, again*
	XCL	exclusive: *only, just*
	NIL	empty semantics: *{.}, to, of*
	DIS	disjunction & exist. quantif.: *a, some, any, or*
	IMP	implication: *if, when, unless*
	AND	conjunction & univ. quantif.: *every, and, who, any*

NOT	negation: *not, no, neither, without*	MOD modality
NEC	necessity: *must, should, have* to	
POS	possibility: *might, could, perhaps, alleged, can*	
SUB	subordinate relations: *that, while, because*	DSC discourse
COO	coordinate relations: *so, {,}, {;}, and*	
APP	appositional relations: *{,}, which, {(}, {—}*	
BUT	contrast: *but, yet*	
PER	person: *Axl_Rose, Sherlock_Holmes*	NAM named entity
GPE	geo-political entity: *Paris, Japan*	
GPO*	geo-political origin: *Parisian, French*	
GEO	geographical location: *Alps, Nile*	
ORG	organization: *IKEA, EU*	
ART	artifact: *iOS_7*	
HAP	happening: *Eurovision_2017*	
UOM	unit of measurement: *meter, $, %, degree_Celsius*	
CTC*	contact information: *112, info@mail.com*	
URL	URL: `http://pmb.let.rug.nl`	
LIT*	literal use of names: his name is *John*	
NTH*	other names: table *1a*, equation *(1)*	
EXS	untensed simple: to *walk*, is *eaten, destruction*	EVE events
ENS	present simple: we *walk*, he *walks*	
EPS	past simple: *ate, went*	
EXG	untensed progressive: is *running*	
EXT	untensed perfect: has *eaten*	
NOW	present tense: *is* skiing, *do* ski, *has* skied, *now*	TNS tense & aspect
PST	past tense: *was* baked, *had* gone, *did* go	
FUT	future tense: *will, shall*	
PRG*	progressive: has been *being* treated, *aan_het*[NL]	
PFT*	perfect: has *been* going/done	
DAT*	full date: *27.04.2017, 27/04/17*	TIM temporal entity
DOM	day of month: *27th* December	
YOC	year of century: *2017*	
DOW	day of week: *Thursday*	
MOY	month of year: *April*	
DEC	decade: *80s, 1990s*	
CLO	clocktime: *8:45_pm, 10_o’clock, noon*	

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- Issue: the data comes with its own tokenization:
  - BERT: ['the', 'ya', '##zuka', 'are', 'the', 'japanese', 'mafia', ‘.’]

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- The repository also has an example of training a [semantic tagger]
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- Need to get word-level representations out of BERT’s *subword* representations

Tagging: Modeling

- Used to be complicated, BUT:
- They’ve added a PretrainedMismatchedTransformerEmbedder (and a corresponding PretrainedMismatchedTransformerIndexer for tokens)
  - Handles all of the mis-alignment between dataset tokens and model tokens for you!
  - How to pool subwords—>words:
    - `sub_token_mode` kwarg: default = avg, but can do first/last, etc

Tagging: Modeling

```python
@Model.register("subword_word_tagger")
class SubwordWordTagger(Model):

    # TODO: document!

    def __init__(
        self,
        embedder: TextFieldEmbedder,
        vocab: Vocabulary = None,
        freeze_encoder: bool = True,
    ):
        super().__init__(vocab)

        self._embedder = embedder
        self._freeze_encoder = freeze_encoder
        # turn off gradients if don't want to fine tune encoder
        for parameter in self._embedder.parameters():
            parameter.requires_grad = not self._freeze_encoder

        self.classifier = TimeDistributed(
            torch.nn.Linear(
                in_features=embedder.get_output_dim(),
                out_features=vocab.get_vocab_size("labels"),
            )
        )

        self.accuracy = CategoricalAccuracy()
```

```python
def forward(
    self, sentence: Dict[str, torch.Tensor], labels: torch.Tensor = None
) -> Dict[str, torch.Tensor]:

    # (batch_size, max_seq_len, embedding_dim)
    embeddings = self._embedder(sentence)

    # get mask to keep track of which tokens are padding
    # prevent them from contributing to loss
    # (batch_size, max_word_seq_len)
    word_mask = get_text_field_mask(sentence)

    # (batch_size, max_word_seq_len, num_labels)
    logits = self.classifier(embeddings)

    outputs = {"logits": logits}

    if labels is not None:
        self.accuracy(logits, labels, word_mask)
        outputs["loss"] = sequence_cross_entropy_with_logits(
            logits, labels, word_mask
        )

    return outputs
```

On These Libraries

- If you're using transformer-based LMs, I strongly recommend HuggingFace
- On the other hand, it's possible that learning AllenNLP's abstractions may cost you more time than it saves in the short term
- As always, try and use the best tool for the job at hand
- One more that makes fine-tuning and/or diagnostic classification easy:
  - jiant

Other tools for experiment management

- Disclaimer: I've never used them!
  - Might be over-kill in the short term
- Guild (entirely local): https://guild.ai/
- CodaLab: https://codalab.org/
- Weights and Biases: https://www.wandb.com/
- Neptune: https://neptune.ai/

Using GPUs on Patas

Setting up local environment

- Three GPU nodes:
  - 2xTesla P40
  - 8xTesla M10
  - 2xQuadro 8000
- For info on setting up your local environment to use these nodes in a fairly painless way:
  - https://www.shane.st/teaching/575/spr22/patas-gpu.pdf

Condor job file for patas

```
executable = run_exp_gpu.sh
getenv = True
error = exp.error
log = exp.log
notification = always
transfer_executable = false
request_memory = 8*1024
request_GPUs = 1
+Research = True
Queue
```

Example executable

```
#!/bin/sh
conda activate my-project

allennlp train tagging_experiment.jsonnet --serialization-dir test \
  --include-package tagging \
  --overrides "{'trainer': {'cuda_device': 1}}"
```