Libraries and Tools
🤗 Transformers, AllenNLP

LING575 Analyzing Neural Language Models

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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
- Interoperable with PyTorch or TensorFlow 2.0

Example: Tokenization

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

# OPTIONAL: if you want to have more information on what's happening under the hood, activate the logger as follows
import logging
logging.basicConfig(level=logging.INFO)

# Load pre-trained model tokenizer (vocabulary)
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')

# Tokenize input
text = "[CLS] Who was Jim Henson ? [SEP] Jim Henson was a puppeteer [SEP]"
tokenized_text = tokenizer.tokenize(text)

# Mask a token that we will try to predict back with `BertForMaskedLM`
masked_index = 8
tokenized_text[masked_index] = '[MASK]'
assert tokenized_text == ['[CLS]', 'who', 'was', 'jim', 'henson', '?', '[SEP]', 'jim', '[MASK]', 'was', 'a', 'puppet', '##eer', '[SEP]']

# Convert token to vocabulary indices
indexed_tokens = tokenizer.convert_tokens_to_ids(tokenized_text)
# Define sentence A and B indices associated to 1st and 2nd sentences (see paper)
segments_ids = [0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1]

# Convert inputs to PyTorch tensors
tokens_tensor = torch.tensor([indexed_tokens])
segments_tensors = torch.tensor([segments_ids])
```

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

Example: Forward Pass

```python
# Load pre-trained model (weights)
model = BertModel.from_pretrained('bert-base-uncased')

# Set the model in evaluation mode to deactivate the DropOut modules
# This is IMPORTANT to have reproducible results during evaluation!
model.eval()

# If you have a GPU, put everything on cuda
tokens_tensor = tokens_tensor.to('cuda')
segments_tensors = segments_tensors.to('cuda')
model.to('cuda')

# Predict hidden states features for each layer
with torch.no_grad():
    # See the models docstrings for the detail of the inputs
    outputs = model(tokens_tensor, token_type_ids=segments_tensors)
    # Transformers models always output tuples.
    # See the models docstrings for the detail of all the outputs
    # In our case, the first element is the hidden state of the last layer of the Bert model
    encoded_layers = outputs[0]
```

Outputs from the forward pass

- Outputs are always *tuples of Tensors*
  - BERT, by default, gives two things:
    - Top layer embeddings for each token.
      Shape: (batch_size, max_length, embedding_dimension)
    - Pooled representation: embedding of '[CLS]' token, passed through one tanh layer
      Shape: (batch_size, embedding_dimension)

Getting more out of a model

```
from transformers import BertConfig, BertModel

config = BertConfig(
  “bert-base-uncased”, output_attentions=True, output_hidden_states=True)

model = BertModel(config)
```

- Now, it’s a 4-tuple as output, additionally containing:
  - Hidden states. A tuple of tensors, one for each layer. Length: # layers
    Shape of each: `(batch_size, max_length, embedding_dimension)`
  - Attention heads: tuple of tensors, one for each layer. Length: # layers
    Shape of each: `(batch_size, num_heads, max_length, max_length)`

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
  - Read the docs carefully!

What the library does not do

- Anything related to training
  - Padding
  - Batching
  - Optimizing probe models, etc. Use PyTorch (or TF) for that

AllenNLP

https://allennlp.org/

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
  - https://allennlp.org/tutorials
  - https://github.com/jbarrow/allennlp_tutorial

Some Advantages

- Focus on modeling / experimenting, not writing boilerplate, e.g.:
- Training loop:

```
for each epoch:
  for each batch:
    get model outputs on batch
    compute loss
    compute gradients
    update parameters
```

- Not *that* complicated, but:
  - Early stopping
  - 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.

Overall Structure (Classification)

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

tokenizer = PretrainedTransformerTokenizer(
    model_string, do_lowercase=True)
token_indexer = PretrainedTransformerIndexer(
    model_string, do_lowercase=True)

reader = SSTDatasetReader(tokenizer, {"tokens": token_indexer})

train_dataset = reader.read('sst/trees/train.txt')
val_dataset = reader.read('sst/trees/dev.txt')

print(train_dataset[0])

vocab = Vocabulary.from_instances(train_dataset + val_dataset)

bert_token_embedder = PretrainedTransformerEmbedder(model_string)
bert_textfield_embedder = BasicTextFieldEmbedder(
    {"tokens": bert_token_embedder})

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

iterator = BucketIterator(
    sorting_keys=[("tokens", "num_tokens")],
    batch_size=32)
iterator.index_with(vocab)

trainer = Trainer(model=model,
                  optimizer=optim.Adam(model.parameters()),
                  serialization_dir='/tmp/test',
                  iterator=iterator,
                  train_dataset=train_dataset,
                  validation_dataset=val_dataset,
                  patience=5,
                  num_epochs=30)
trainer.train()
```

DatasetReader

Model

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://allenai.github.io/allennlp-docs/api/data/fields/field/
- 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

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

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

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

        in_features = self.embedder.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()
```

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)

    # the first embedding is for the [CLS] token
    # NOTE: this pre-supposes BERT encodings; not the most elegant!
    # (batch_size, embedding_dim)
    cls_embedding = embeddings[:, 0, :]

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

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

`@DatasetReader.register("sst_reader")`

Arguments to SSTReader!

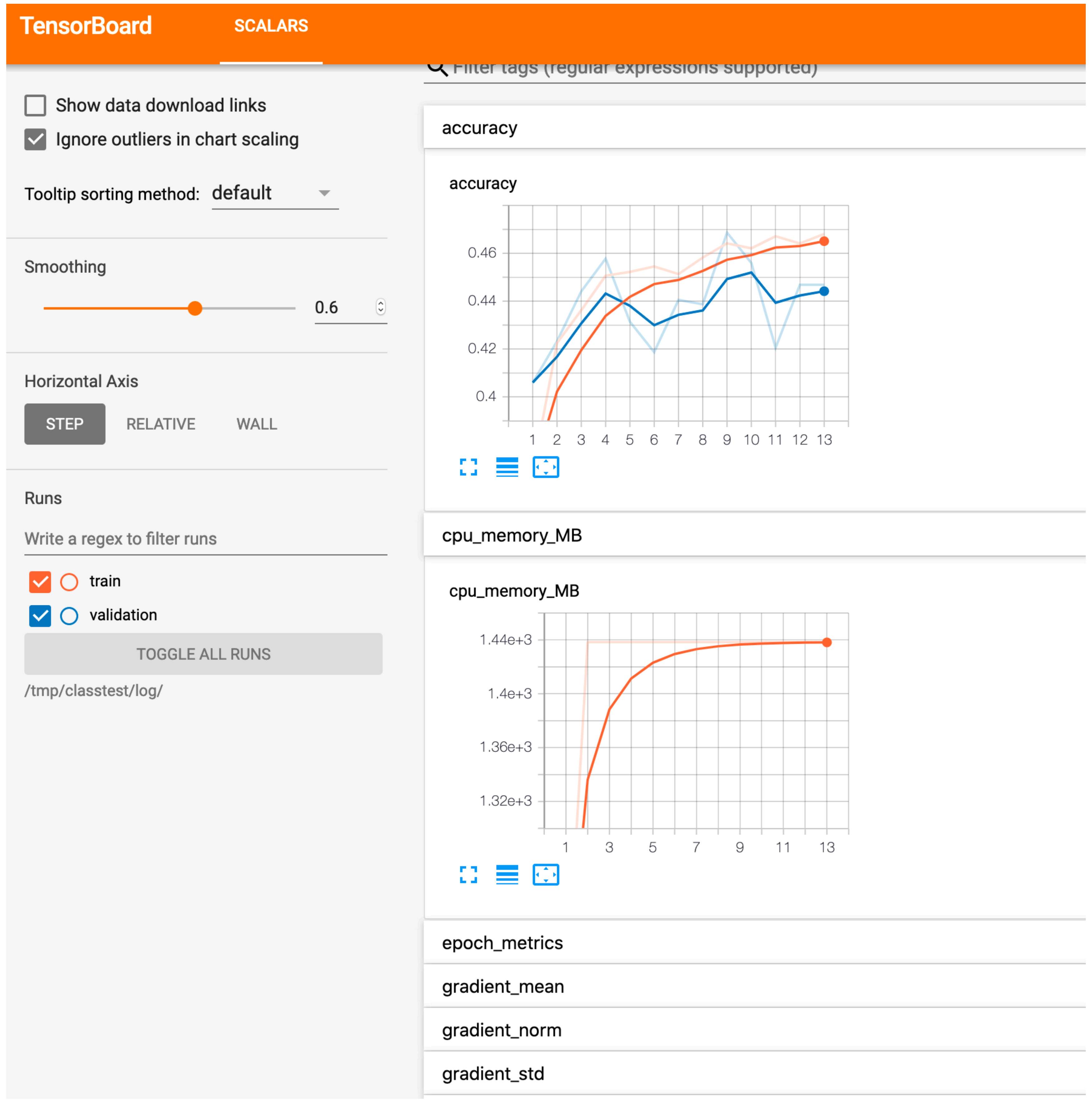
Config file (classifying_experiment.jsonnet)

```
    "model": {
        "type": "bert_classifier",
        "embedder": {
            "type": "basic",
            "tokens": {
                "type": "pretrained_transformer",
                "model_name": bert_model
            }
        },
        "freeze_encoder": true,
    },
    "iterator": {
        "type": "bucket",
        "sorting_keys": [["tokens", "num_tokens"]],
        "batch_size": 32
    },
    "trainer": {
        "optimizer": {
            "type": "adam",
            "lr": 0.001
        },
        "validation_metric": "+accuracy",
        "checkpointer": {
            "num_serialized_models_to_keep": 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

- The repository also has an example of training a *semantic tagger*
  - Like POS tagging, but with a richer set of “semantic” tags
- Issue: the data comes with its own tokenization:
  - BERT: ['the', 'ya', '##zuka', 'are', 'the', 'japanese', 'mafia', ‘.’]
- Need to get word-level representations out of BERT’s *subword* representations

```
DEF     The
CON     yakuza
ENS     are
DEF     the
GPO     Japanese
CON     mafia
NIL     .
~
```

Tagging: Modeling

- My example: keep track of which spans of BERT tokens the original words correspond to
  - Some complication in the DatasetReader because of this
- And then combine those representations with an arbitrary Seq2VecEncoder
- Since then (a few months ago), they've added a PretrainedMismatchedTransformerEmbedder that has essentially the same functionality
  - (Spans are pooled by summing, not by an arbitrary Seq2Vec)
  - Might be safest to use that (and corresponding MismatchedIndexer)

On These Libraries

- If you’re using transformer-based LMs, I strongly recommend HuggingFace
- But 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

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

- Two GPU nodes (getting a third one soon):
  - 2xTesla P40
  - 8xTesla M10
- For info on setting up your local environment to use these nodes in a fairly painless way:
  - https://www.shane.st/teaching/575/win20/patas-gpu.pdf
  - Pay attention to cudatoolkit version!!

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}}"
```