Writing Code for NLP Research

EMNLP 2018

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ALLEN INSTITUTE
for ARTIFICIAL INTELLIGENCE

Who we are

Matt Gardner ([@nlpmattg]())

Matt is a research scientist on AllenNLP. He was the original architect of AllenNLP, and he co-hosts the NLP Highlights podcast.

Mark Neumann ([@markneumannnn]())

Mark is a research engineer on AllenNLP. He helped build AllenNLP and its precursor DeepQA with Matt, and has implemented many of the models in the demos.

Joel Grus ([@joelgrus]())

Joel is a research engineer on AllenNLP, although you may know him better from "I Don't Like Notebooks" or from "Fizz Buzz in Tensorflow" or from his book *Data Science from Scratch*.

Outline

- How to write code when prototyping
- Developing good processes

BREAK

- How to write reusable code for NLP
- Case Study: A Part-of-Speech Tagger
- Sharing Your Research

What we expect you know already

What we expect you know already

modern (neural) NLP

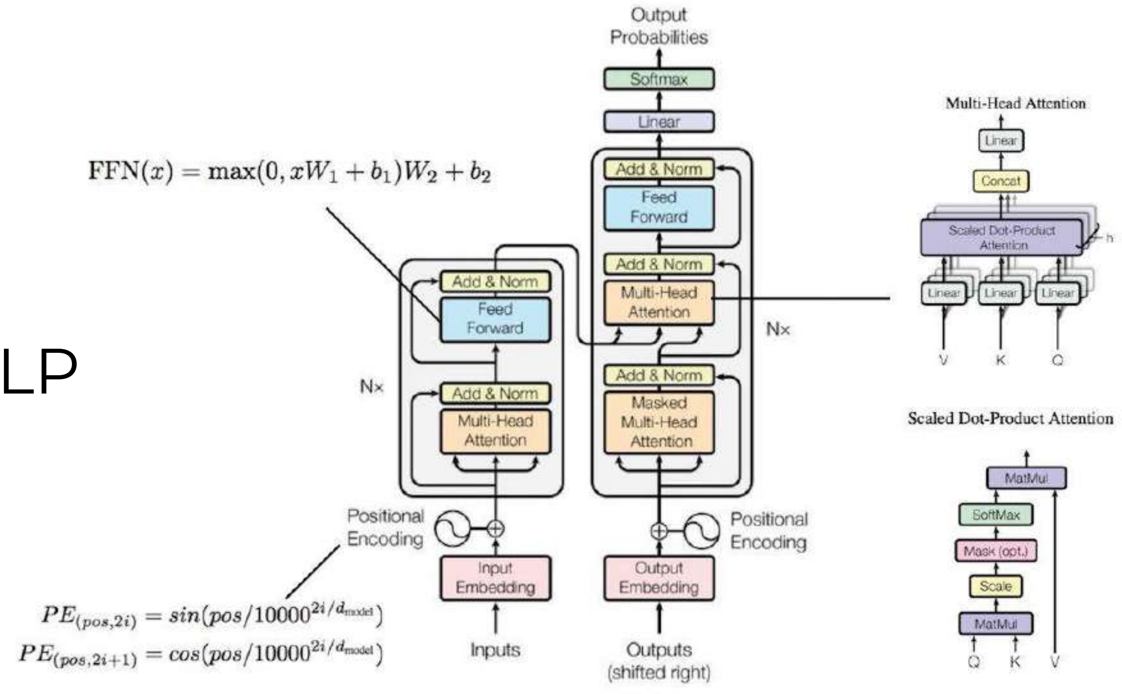
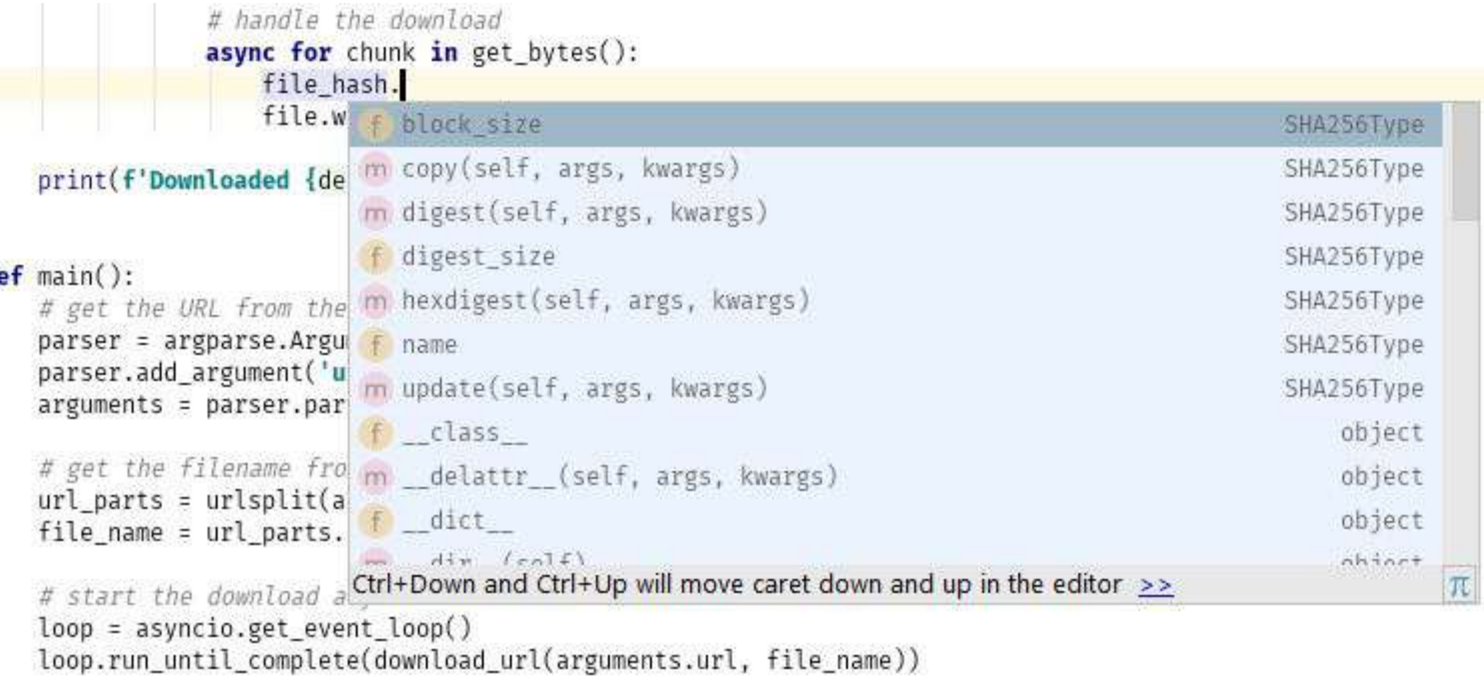


Figure 1: The Transformer - model architecture.

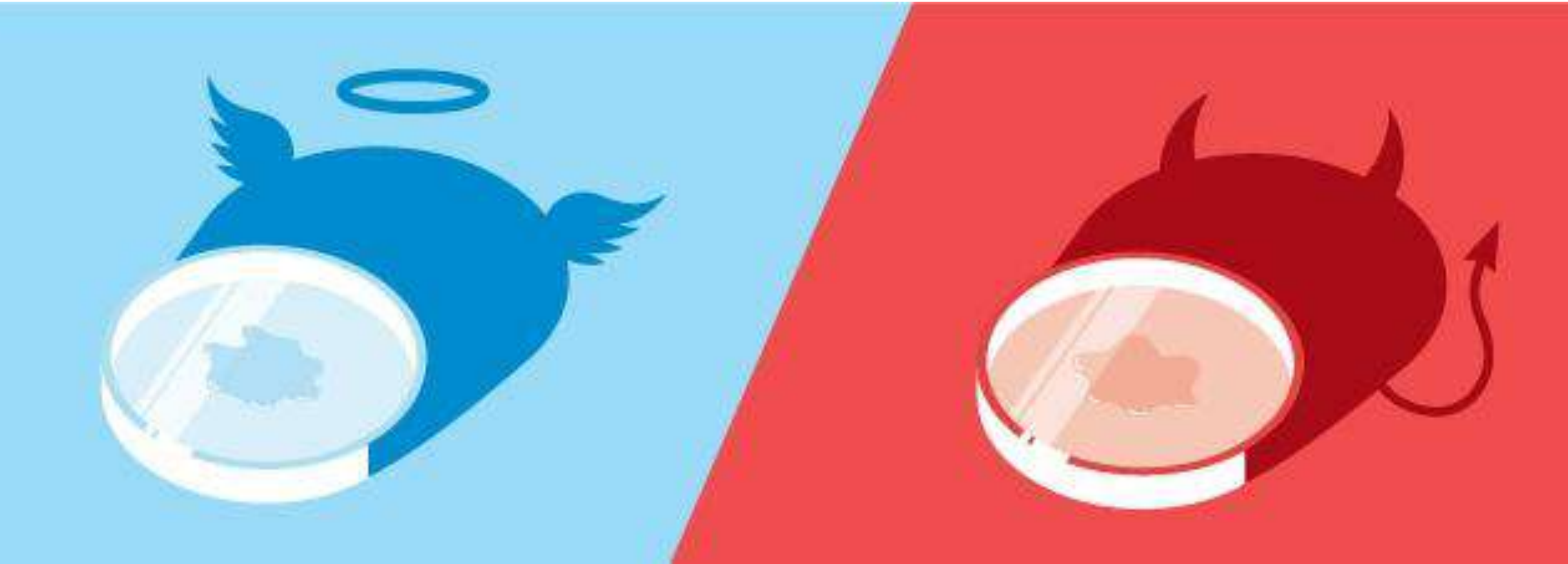
What we expect you know already



Python

What we expect you know already

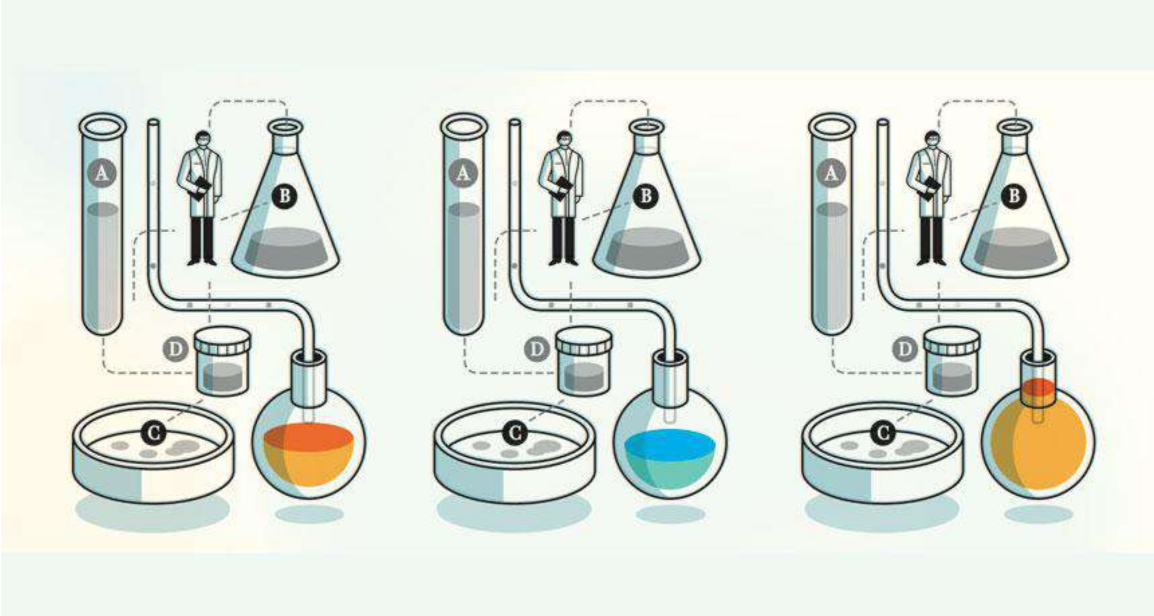
the difference between good science and bad science



What you'll learn today

What you'll learn today

how to write code in a way that facilitates good science and reproducible experiments



What you'll learn today

how to write code in a way that makes your life easier

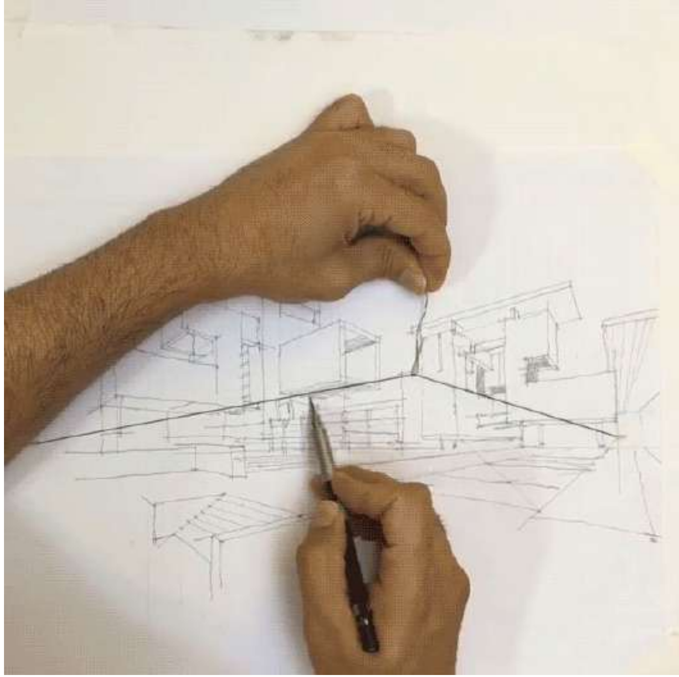
The Elephant in the Room: AllenNLP

- This is not a tutorial *about* AllenNLP
- But (obviously, seeing as we wrote it) AllenNLP represents our experiences and opinions about how best to write research code
- Accordingly, we'll use it in most of our examples
- And we hope you'll come out of this tutorial wanting to give it a try
- But our goal is that you find the tutorial useful even if you never use AllenNLP

Two modes of writing research code

1: prototyping

2: writing components



Prototyping New Models

Main goals during prototyping

- Write code quickly

- Run experiments, keep track of what you tried

- Analyze model behavior - did it do what you wanted?

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- **Write code quickly**

- Run experiments, keep track of what you tried

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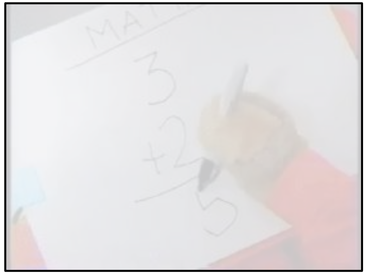
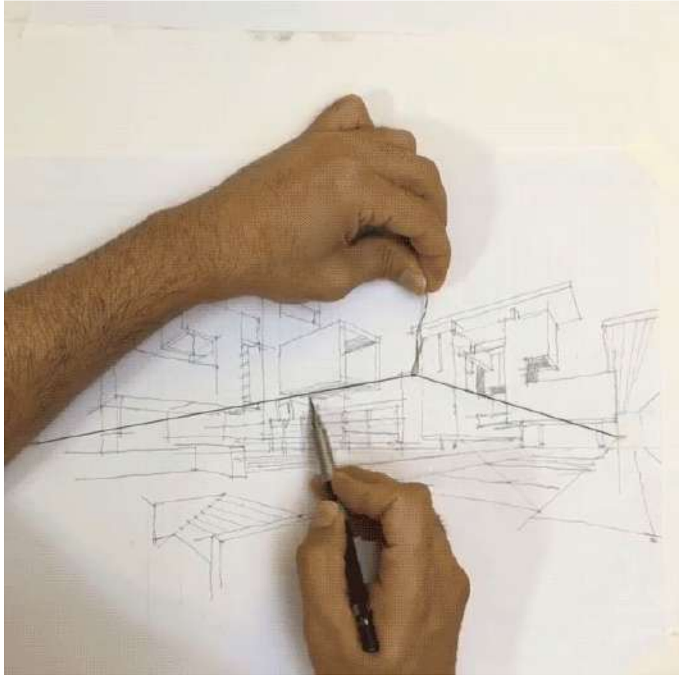


Writing code quickly - Use a framework!



Writing code quickly - Use a framework!

- Training loop?

Writing code quickly - Use a framework!

- Training loop?

```
model = LSTMTagger(EMBEDDING_DIM, HIDDEN_DIM,
                   len(word_to_ix), len(tag_to_ix))
loss_function = nn.NLLLoss()
optimizer = optim.SGD(model.parameters(), lr=0.1)
validation_losses = []
patience = 10
for epoch in range(1000):
    training_loss = 0.0
    validation_loss = 0.0

    for dataset, training in [(training_data, True),
                              (validation_data, False)]:
        correct = total = 0
        torch.set_grad_enabled(training)
        t = tqdm.tqdm(dataset)
        for i, (sentence, tags) in enumerate(t):
            model.zero_grad()
            model.hidden = model.init_hidden()

            sentence_in = prepare_sequence(sentence, word_to_ix)
            targets = prepare_sequence(tags, tag_to_ix)

            tag_scores = model(sentence_in)

            loss = loss_function(tag_scores, targets)
            predictions = tag_scores.max(-1)[1]
            correct += (predictions == targets).sum().item()
            total += len(targets)
            accuracy = correct / total

            if training:
                loss.backward()
                training_loss += loss.item()
                t.set_postfix(training_loss=training_loss/(i + 1),
                              accuracy=accuracy)
                optimizer.step()
            else:
                validation_loss += loss.item()
                t.set_postfix(validation_loss=validation_loss/(i + 1),
                              accuracy=accuracy)

    validation_losses.append(validation_loss)

    if (patience and
            len(validation_losses) >= patience and
            validation_losses[-patience] ==
                min(validation_losses[-patience:])):
        print("patience reached, stopping early")
        break
```

Writing code quickly - Use a framework!

- Tensorboard logging?
- Model checkpointing?
- Complex data processing, with smart batching?
- Computing span representations?
- Bi-directional attention matrices?

- Easily thousands of lines of code!

Writing code quickly - Use a framework!

- Don’t start from scratch! Use someone else’s components.

Writing code quickly - Use a framework!

- But...

Writing code quickly - Use a framework!

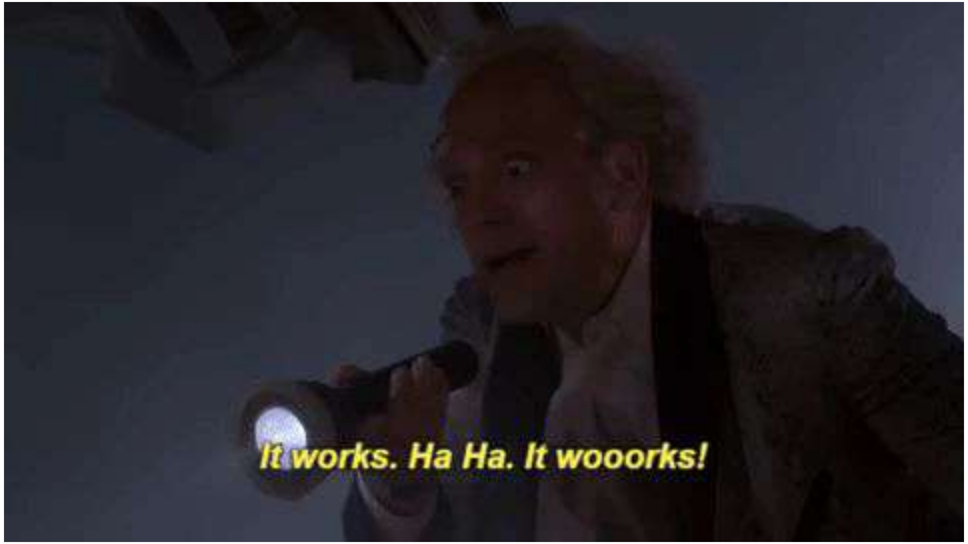
- But...

- Make sure you can bypass the abstractions when you need to

Writing code quickly - Get a good starting place

Writing code quickly - Get a good starting place

- First step: get a baseline running



- This is good research practice, too

Writing code quickly - Get a good starting place

- Could be someone else's code... as long as you can read it

```
with tf.variable_scope("char"):
    Acx = tf.nn.embedding_lookup(char_emb_mat, self.cx)  # [N, M, JX, W, dc]
    Acq = tf.nn.embedding_lookup(char_emb_mat, self.cq)  # [N, JQ, W, dc]
    Acx = tf.reshape(Acx, [-1, JX, W, dc])
    Acq = tf.reshape(Acq, [-1, JQ, W, dc])

    filter_sizes = list(map(int, config.out_channel_dims.split(',')))
    heights = list(map(int, config.filter_heights.split(',')))
    assert sum(filter_sizes) == dco
    with tf.variable_scope("conv"):
        xx = multi_conv1d(Acx, filter_sizes, heights, "VALID",  self.is_train, config.keep_prob, scope="xx")
        if config.share_cnn_weights:
            tf.get_variable_scope().reuse_variables()
            qq = multi_conv1d(Acq, filter_sizes, heights, "VALID", self.is_train, config.keep_prob, scope="xx")
        else:
            qq = multi_conv1d(Acq, filter_sizes, heights, "VALID", self.is_train, config.keep_prob, scope="qq")
        xx = tf.reshape(xx, [-1, M, JX, dco])
        qq = tf.reshape(qq, [-1, JQ, dco])
```

Writing code quickly - Get a good starting place

- Could be someone else's code... as long as you can read it

```
encoded_question = self._dropout(self._phrase_layer(embedded_question, question_lstm_mask))
encoded_passage = self._dropout(self._phrase_layer(embedded_passage, passage_lstm_mask))
encoding_dim = encoded_question.size(-1)

# Shape: (batch_size, passage_length, question_length)
passage_question_similarity = self._matrix_attention(encoded_passage, encoded_question)
# Shape: (batch_size, passage_length, question_length)
passage_question_attention = util.masked_softmax(passage_question_similarity, question_mask)
# Shape: (batch_size, passage_length, encoding_dim)
passage_question_vectors = util.weighted_sum(encoded_question, passage_question_attention)

# We replace masked values with something really negative here, so they don't affect the
# max below.
masked_similarity = util.replace_masked_values(passage_question_similarity,
                                               question_mask.unsqueeze(1),
                                               -1e7)
```

Writing code quickly - Get a good starting place

- Even better if this code already modularizes what you want to change

```
def __init__(self, vocab: Vocabulary,
             text_field_embedder: TextFieldEmbedder,
             num_highway_layers: int,
             phrase_layer: Seq2SeqEncoder,
             similarity_function: SimilarityFunction,
             modeling_layer: Seq2SeqEncoder,
             span_end_encoder: Seq2SeqEncoder,
             dropout: float = 0.2,
             mask_lstms: bool = True,
             initializer: InitializerApplicator = InitializerApplicator(),
             regularizer: Optional[RegularizerApplicator] = None) -> None:
```

Add ELMo / BERT here

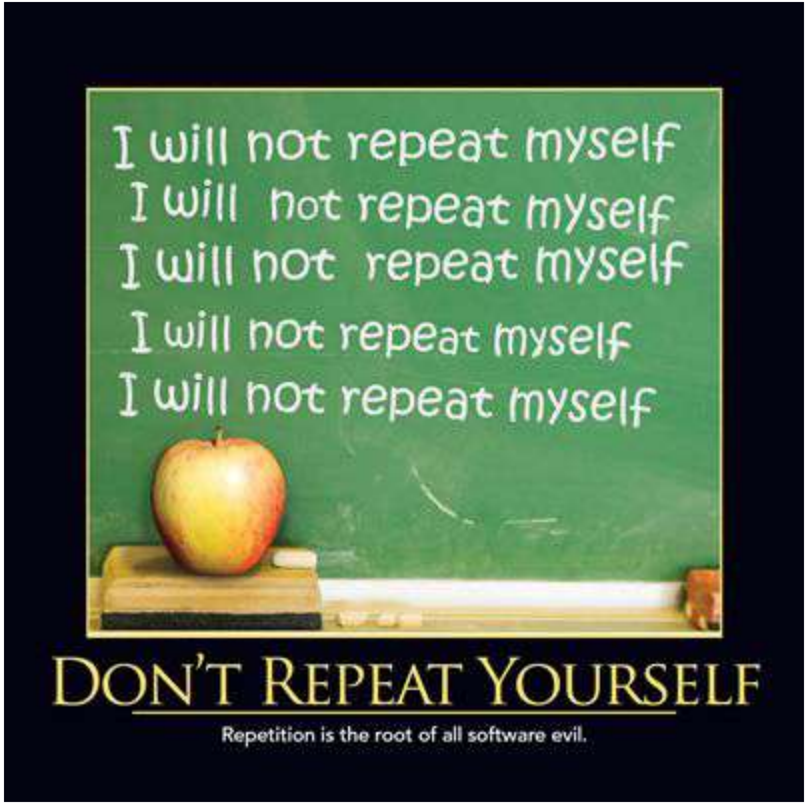
Writing code quickly - Get a good starting place

ON THE OTHER HAND

- Re-implementing a SOTA baseline is incredibly helpful for understanding what's going on, and where some decisions might have been made better

Writing code quickly - Copy first, refactor later

- CS degree:



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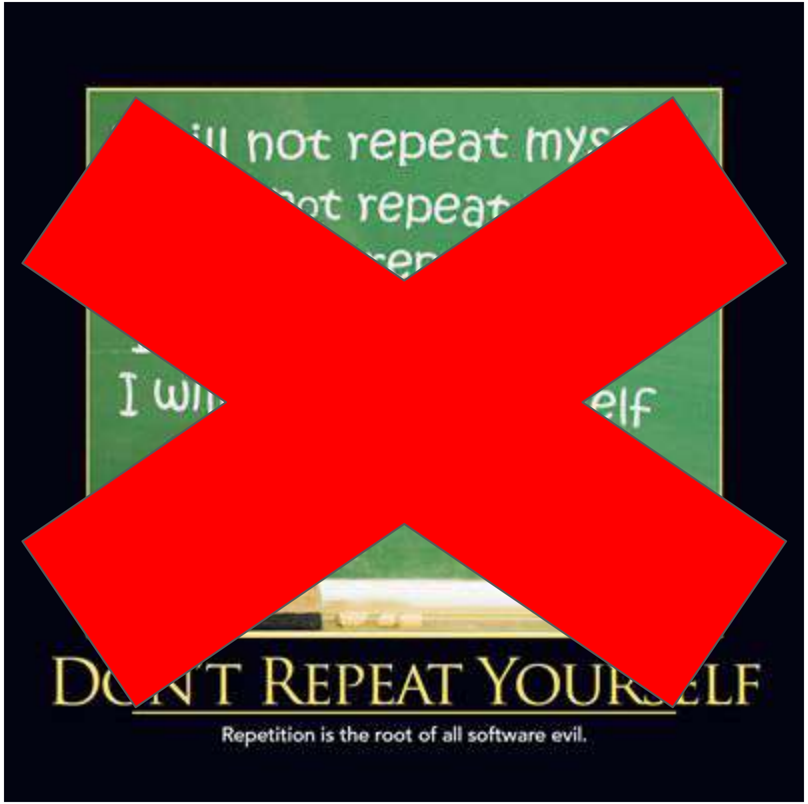

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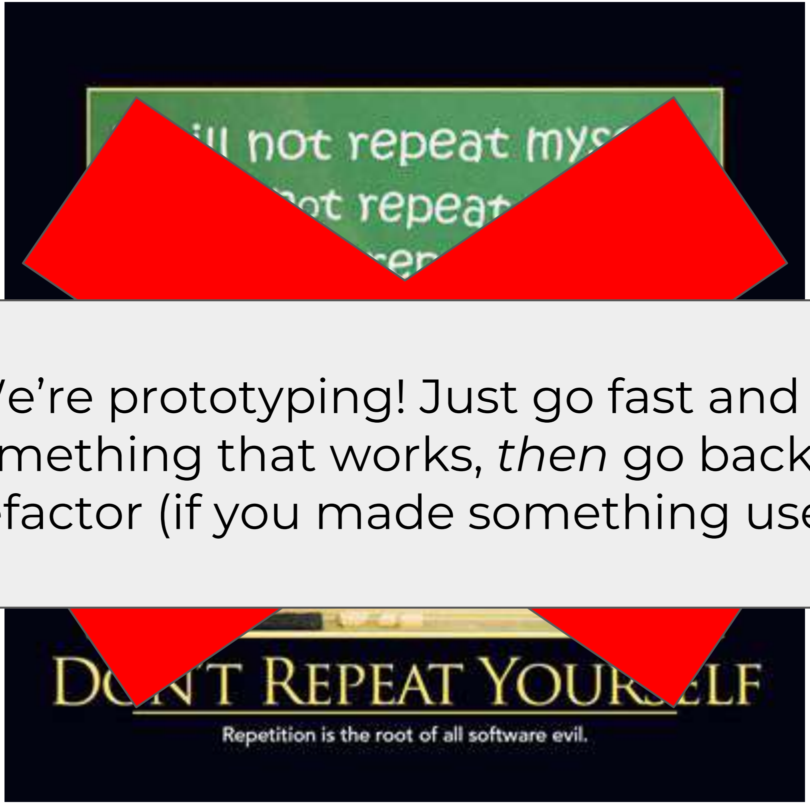

We’re prototyping! Just go fast and find something that works, *then* go back and refactor (if you made something useful)

Writing code quickly - Copy first, refactor later

- Really bad idea: using inheritance to share code for related models

```
class MemoryNetwork(TextTrainer):
    class SoftmaxMemoryNetwork(MemoryNetwork):
    class MultipleTrueFalseMemoryNetwork(MemoryNetwork):
        class MultipleTrueFalseSimilarity(MultipleTrueFalseMemoryNetwork):
        class MultipleTrueFalseDecomposableAttention(MultipleTrueFalseMemoryNetwork):
    class QuestionAnswerMemoryNetwork(MemoryNetwork):
```

- Instead: just copy the code, figure out how to share later, if it makes sense

Writing code quickly - *Do* use good code style

- CS degree:

```
/**
* Code Readability
*/
if (readable()) {
    be_happy();
} else {
    refactor();
}
```

Writing code quickly - *Do* use good code style

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Writing code quickly - *Do* use good code style

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    Acx = tf.reshape(Acx, [-1, JX, W, dc])
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    filter_sizes = list(map(int, config.out_channel_dims.split(',')))
    heights = list(map(int, config.filter_heights.split(',')))
    assert sum(filter_sizes) == dco
    with tf.variable_scope("conv"):
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Writing code quickly - *Do* use good code style

Meaningful names

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Shape comments on tensors

Writing code quickly - *Do* use good code style

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Comments describing non-obvious logic

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```

Write code for *people*,
not machines

Writing code quickly - Minimal testing (but not *no* testing)

- CS degree:

Writing code quickly - Minimal testing (but not *no* testing)

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Writing code quickly - Minimal testing (but not *no* testing)

- A test that checks experimental behavior is a waste of time

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                                               -1e7)
```

Writing code quickly - Minimal testing (but not *no* testing)

- But, some parts of your code aren't experimental

```
class TestSquadReader:
    @pytest.mark.parametrize("lazy", (True, False))
    def test_read_from_file(self, lazy):
        reader = SquadReader(lazy=lazy)
        instances = ensure_list(reader.read(AllenNlpTestCase.FIXTURES_ROOT / 'data' / 'squad.json'))
        assert len(instances) == 5

        assert [t.text for t in instances[0].fields["question"].tokens[:3]] == ["To", "whom", "did"]
        assert [t.text for t in instances[0].fields["passage"].tokens[:3]] == ["Architecturally", ",", "the"]
        assert [t.text for t in instances[0].fields["passage"].tokens[-3:]] == ["of", "Mary", "."]
        assert instances[0].fields["span_start"].sequence_index == 102
        assert instances[0].fields["span_end"].sequence_index == 104

        assert [t.text for t in instances[1].fields["question"].tokens[:3]] == ["What", "sits", "on"]
        assert [t.text for t in instances[1].fields["passage"].tokens[:3]] == ["Architecturally", ",", "the"]
        assert [t.text for t in instances[1].fields["passage"].tokens[-3:]] == ["of", "Mary", "."]
        assert instances[1].fields["span_start"].sequence_index == 17
        assert instances[1].fields["span_end"].sequence_index == 23
```

Writing code quickly - Minimal testing (but not *no* testing)

- And even experimental parts can have useful tests

```
class AtisSemanticParserTest(ModelTestCase):
    def setUp(self):
        super(AtisSemanticParserTest, self).setUp()
        self.set_up_model(str(self.FIXTURES_ROOT / "semantic_parsing" / "atis" / "experiment.json"),
                          str(self.FIXTURES_ROOT / "data" / "atis" / "sample.json"))

    @flaky
    def test_atis_model_can_train_save_and_load(self):
        self.ensure_model_can_train_save_and_load(self.param_file)
```

Writing code quickly - Minimal testing (but not *no* testing)

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```

Makes sure data processing works consistently, that tensor operations run, gradients are non-zero

Writing code quickly - Minimal testing (but not *no* testing)

- And even experimental parts can have useful tests

Run on small test fixtures, so debugging cycle is seconds, not minutes

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```

Writing code quickly - How much to hard-code?

- Which one should I do?

```python
class MyModel(Model):
    def __init__(self):
        self.input_embedding = Embedding(100)
        self.encoder = LSTM(100, 200)
        self.my_novel_bits = ...
```

```python
class MyModel(Model):
    def __init__(self,
                 input_embedding: TextFieldEmbedder,
                 encoder: Seq2SeqEncoder):
        self.input_embedding = input_embedding
        self.encoder = encoder
        self.my_novel_bits = ...
```

Writing code quickly - How much to hard-code?

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I’m just prototyping! Why shouldn’t I just hard-code an embedding layer?

```
class MyModel(Model):
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```

Why so abstract?

Writing code quickly - How much to hard-code?

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        self.input_embedding = input_embedding
        self.encoder = encoder
        self.my_novel_bits = ...
```

On the parts that aren't what you're focusing on, you start simple. Later add ELMo, etc., *without rewriting your code.*

Writing code quickly - How much to hard-code?

- Which one should I do?

```python
class MyModel(Model):
    def __init__(self):
        self.input_embedding = Embedding(1
        self.encoder = LSTM(100, 200)
        self.my_novel_bits = ...
```

```python
class MyModel(Model):
    def __init__(self,
                 input_embedding: TextFieldEmbedder,
                 encoder: Seq2SeqEncoder):
        self.input_embedding = input_embedding
        self.encoder = encoder
        self.my_novel_bits = ...
```

This also makes controlled experiments easier (both for you and for people who come after you).

Writing code quickly - How much to hard-code?

- Which one should I do?

```
class MyModel(Model):
    def __init__(self):
        self.input_embedding = Embedding(1
        self.encoder = LSTM(100, 200)
        self.my_novel_bits = ...
```

And it helps you think more clearly about the pieces of your model.

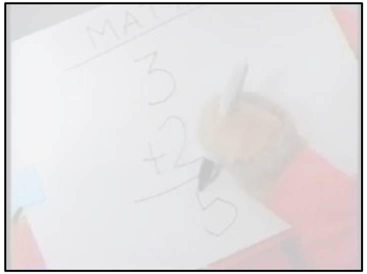
```
class MyModel(Model):
    def __init__(self,
                 input_embedding: TextFieldEmbedder,
                 encoder: Seq2SeqEncoder):
        self.input_embedding = input_embedding
        self.encoder = encoder
        self.my_novel_bits = ...
```

Main goals during prototyping

- Write code quickly

- **Run experiments, keep track of what you tried**

- Analyze model behavior - did it do what you wanted?



Running experiments - Keep track of what you ran

- You run a lot of stuff when you're prototyping, it can be hard to keep track of what happened when, and with what code

Running experiments - Keep track of what you ran

Experimenter	git SHA	Background Search Method	Model	Dataset	Train Acc	Validation Acc	Notes
Pradeep	fc8d6ca3	Lucene	QAMNS (50d)	Intermediate	0.3114	0.3045	patience=20
Pradeep	fc8d6ca3	Lucene	QAMNS (300d)	Intermediate	0.8317	0.3864	patience=20
Pradeep	fc8d6ca3	BOW-LSH question+answers Glove 50d	QAMNS (50d)	Intermediate	0.3008	0.35	patience=20
Pradeep	fc8d6ca3	BOW-LSH question+answers Glove 50d	QAMNS (300d)	Intermediate	0.7466	0.4227	patience=20
Pradeep	fc8d6ca3	BOW-LSH question+answers Glove 300d	QAMNS (50d)	Intermediate	0.3946	0.3591	patience=20
Pradeep	fc8d6ca3	BOW-LSH question+answers Glove 300d	QAMNS (300d)	Intermediate	0.7311	0.4227	patience=20
Pradeep	fc8d6ca3	BOW-LSH+IDF question+answers Glove 300d	QAMNS (300d)	Intermediate	0.7446	0.4227	patience=20
Pradeep	fc8d6ca3	BOW-LSH+IDF question+answers Paragram 300d	QAMNS (300d)	Intermediate	0.7853	0.3955	patience=20
Pradeep	fc8d6ca3	Lucene	QAMNS (300d)	SciQ	0.5551	0.571	patience=6
Pradeep	fc8d6ca3	BOW-LSH question+answers Glove 300d	QAMNS (300d)	SciQ	0.5434	0.524	patience=6

Running experiments - Keep track of what you ran

This is important!

Experimenter	git SHA	Background Searc	[illegible]	[illegible]	in Acc	Validation Acc	Notes
Pradeep	fc8d6ca3	Lucene	[illegible]	[illegible]	0.3114	0.3045	patience=20
Pradeep	fc8d6ca3	Lucene	QAMNS (300d)	Intermediate	0.8317	0.3864	patience=20
Pradeep	fc8d6ca3	BOW-LSH question+answers Glove 50d	QAMNS (50d)	Intermediate	0.3008	0.35	patience=20
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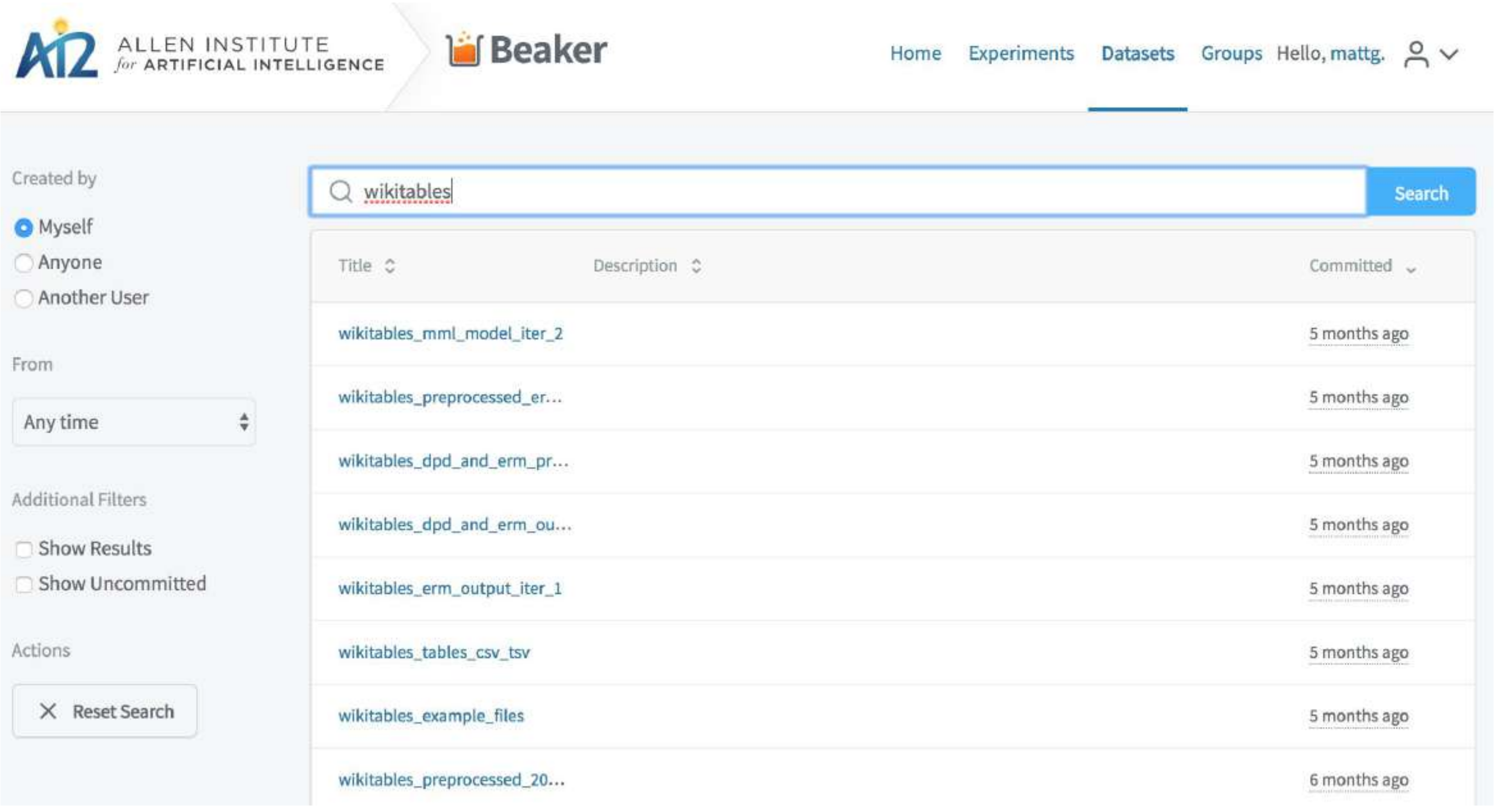
Running experiments - Keep track of what you ran

Beaker

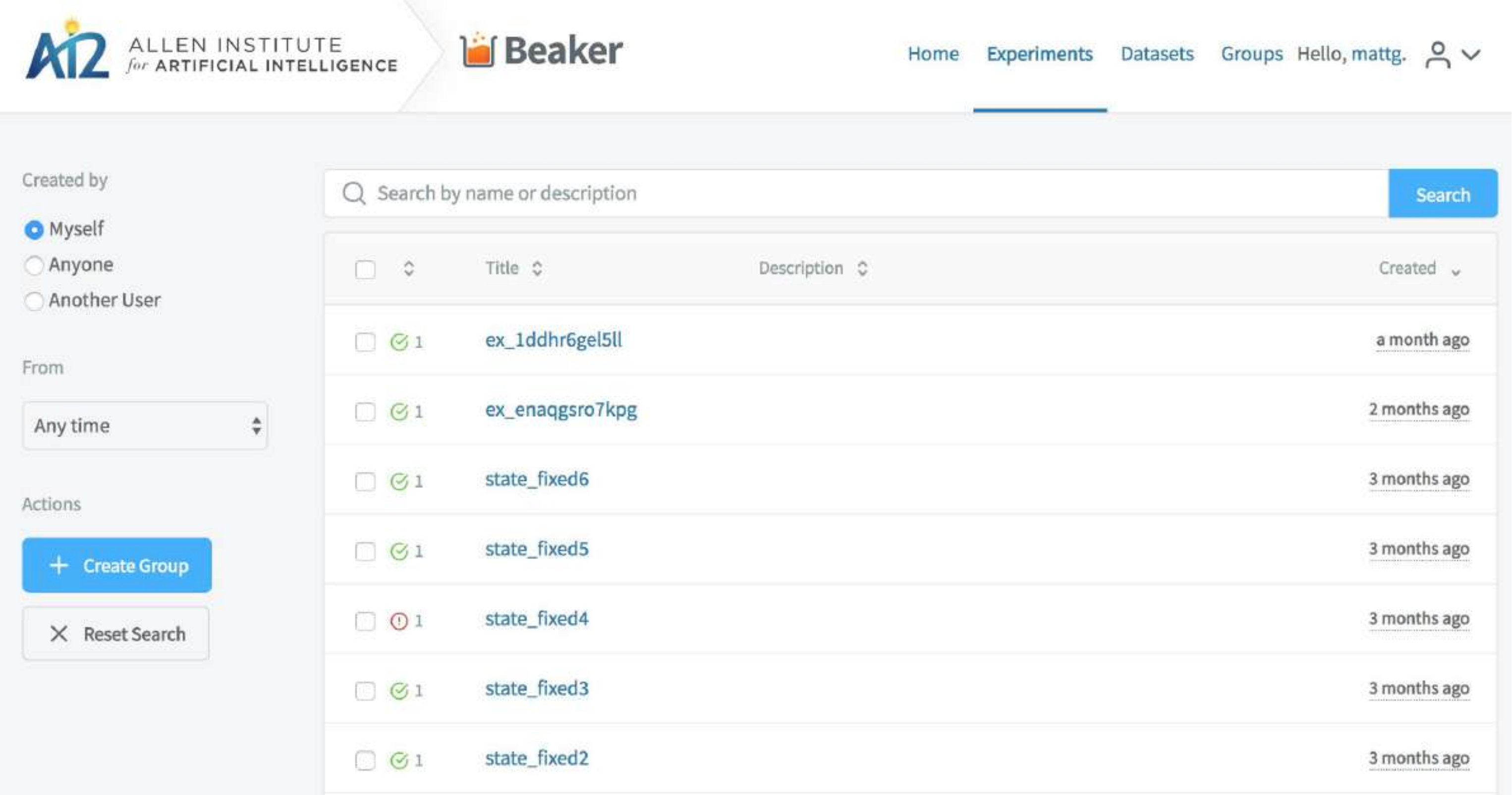
from AI2 ALLEN INSTITUTE for ARTIFICIAL INTELLIGENCE

- Currently in invite-only alpha; public beta coming soon
- https://github.com/allenai/beaker
- https://beaker-pub.allenai.org

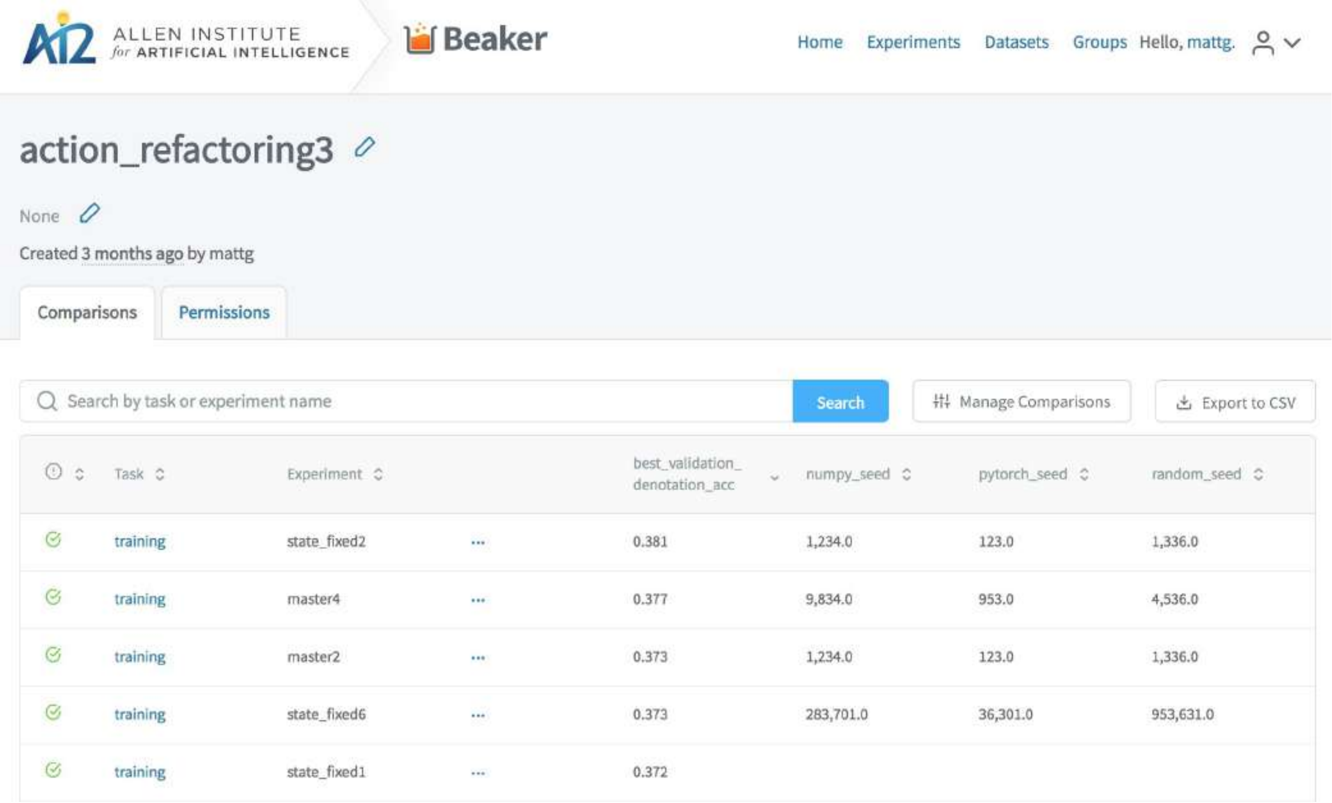
Running experiments - Keep track of what you ran



Running experiments - Keep track of what you ran



Running experiments - Keep track of what you ran



Running experiments - Controlled experiments

- Which one gives more understanding?

Model	Ensemble Size	Dev.	Test
Neelakantan et al. (2017)	1	34.1	34.2
Haug et al. (2017)	1	-	34.8
Pasupat and Liang (2015)	1	37.0	37.1
Neelakantan et al. (2017)	15	37.5	37.7
Haug et al. (2017)	15	-	38.7
Our Parser	1	42.7	43.3
Our Parser	5	-	**45.9**

Table 1: Development and test set accuracy of our semantic parser compared to prior work on WIKITABLEQUESTIONS.

Model	Dev. Accuracy
Full model	42.7
token features, no similarity	28.1
all features, no similarity	37.8
similarity only, no features	27.5

Table 3: Development accuracy of ablated parser variants trained without parts of the entity linking module.

Running experiments - Controlled experiments

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Table 1: Development and test set accuracy of our semantic parser compared to prior work on WIKITABLEQUESTIONS.

Important for putting your work in context

Table 3: Development accuracy of ablated parser variants trained without parts of the entity linking module.

Running experiments - Controlled experiments

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Our Parser	5	-	**45.9**

Table 1: Development and test set accuracy of our semantic parser compared to prior work on WIKITABLEQUESTIONS.

But… too many moving parts, hard to know *what caused the difference*

Table 3: Development accuracy of ablated parser variants trained without parts of the entity linking module.

Running experiments - Controlled experiments

- Which one gives more understanding?

Model	Ensemble Size	Dev.	Test
Our Parser	1	42.7	43.3
Our Parser	5	-	**45.9**

Very controlled experiments, varying one thing: we can make causal claims

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Model	Ensemble Size	Dev.	Test
Our Parser	1	42.7	43.3
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Table 1: Development and test set accuracy of our semantic parser compared to prior work on WIKITABLEQUESTIONS.

How do you set up your code for this?

Model	Dev. Accuracy
Full model	42.7
token features, no similarity	28.1
all features, no similarity	37.8
similarity only, no features	27.5

Table 3: Development accuracy of ablated parser variants trained without parts of the entity linking module.

Running experiments - Controlled experiments

```
class CrfTagger(Model):
    def __init__(self, vocab: Vocabulary,
                 text_field_embedder: TextFieldEmbedder,
                 encoder: Seq2SeqEncoder,
                 label_namespace: str = "labels",
                 feedforward: Optional[FeedForward] = None,
                 label_encoding: Optional[str] = None,
                 constraint_type: Optional[str] = None,
                 include_start_end_transitions: bool = True,
                 constrain_crf_decoding: bool = None,
                 calculate_span_f1: bool = None,
                 dropout: Optional[float] = None,
                 verbose_metrics: bool = False,
                 initializer: InitializerApplicator = InitializerApplicator(),
                 regularizer: Optional[RegularizerApplicator] = None) -> None:
        ...
```

Running experiments - Controlled experiments

```
class CrfTagger(Model):
    def __init__(self, vocab: Vocabulary,
                 text_field_embedder: TextFieldEmbe
                 encoder: Seq2SeqEncoder,
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                 feedforward: Optional[FeedForward] = None,
                 label_encoding: Optional[str] = None,
                 constraint_type: Optional[str] = None,
                 include_start_end_transitions: bool = True,
                 constrain_crf_decoding: bool = None,
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                 dropout: Optional[float] = None,
                 verbose_metrics: bool = False,
                 initializer: InitializerApplicator = InitializerApplicator(),
                 regularizer: Optional[RegularizerApplicator] = None) -> None:
        ...
```

Possible ablations

Running experiments - Controlled experiments

```
class CrfTagger(Model):
    def __init__(self, vocab: Vocabulary,
                 text_field_embedder: TextFieldEmbedder,
                 encoder: Seq2SeqEncoder,
                 label_namespace: str = "labels",
                 feedforward: Optional[FeedForward]
                 label_encoding: Optional[str] = No
                 constraint_type: Optional[str] = None,
                 include_start_end_transitions: bool = True,
                 constrain_crf_decoding: bool = None,
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                 verbose_metrics: bool = False,
                 initializer: InitializerApplicator = InitializerApplicator(),
                 regularizer: Optional[RegularizerApplicator] = None) -> None:
        ...
```

GloVe vs. character CNN vs. ELMo vs. BERT

Running experiments - Controlled experiments

```
class CrfTagger(Model):
    def __init__(self, vocab: Vocabulary,
                 text_field_embedder: TextFieldEmbedder,
                 encoder: Seq2SeqEncoder,
                 label_namespace: str = "labels",
                 feedforward: Optional[FeedForward]
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                 dropout: Optional[float] = None,
                 verbose_metrics: bool = False,
                 initializer: InitializerApplicator = InitializerApplicator(),
                 regularizer: Optional[RegularizerApplicator] = None) -> None:
        ...
```

LSTM vs. Transformer vs. GatedCNN vs. QRNN

Running experiments - Controlled experiments

- Not good: modifying code to run different variants; hard to keep track of what you ran
- Better: configuration files, or separate scripts, or something

```
"model": {
  "type": "crf_tagger",
  "label_encoding": "BIOUL",
  "constrain_crf_decoding": true,
  "calculate_span_f1": true,
  "dropout": 0.5,
  "include_start_end_transitions": false,
  "text_field_embedder": {
    "token_embedders": {
      "tokens": {
          "type": "embedding",
          "embedding_dim": 50,
          "pretrained_file": "https://s3-us-w
          "trainable": true
      },
```

```
"model": {
  "type": "crf_tagger",
  "constraint_type": "BIOUL",
  "dropout": 0.5,
  "include_start_end_transitions": false,
  "text_field_embedder": {
    "token_embedders": {
      "tokens": {
          "type": "embedding",
          "embedding_dim": 50,
          "pretrained_file": "https://s3-us-west-
          "trainable": true
      },
      "elmo":{
          "type": "elmo_token_embedder",
      "options_file": "https://s3-us-west-2.amazo
      "weight_file": "https://s3-us-west-2.amazon
          "do_layer_norm": false,
          "dropout": 0.0
      },
```

Main goals during prototyping

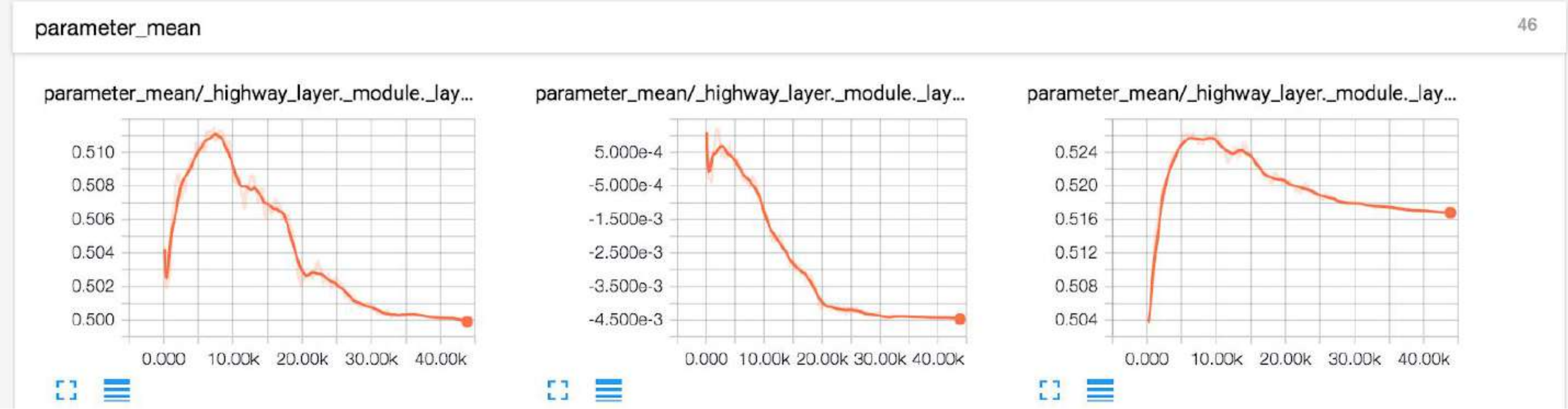
- Write code quickly

- Run experiments, keep track of what you tried

- **Analyze model behavior - did it do what you wanted?**

Analyze results - Tensorboard

- Crucial tool for understanding model behavior during training
- There is no better visualizer. If you don't use this, start now.



Analyze results - Tensorboard

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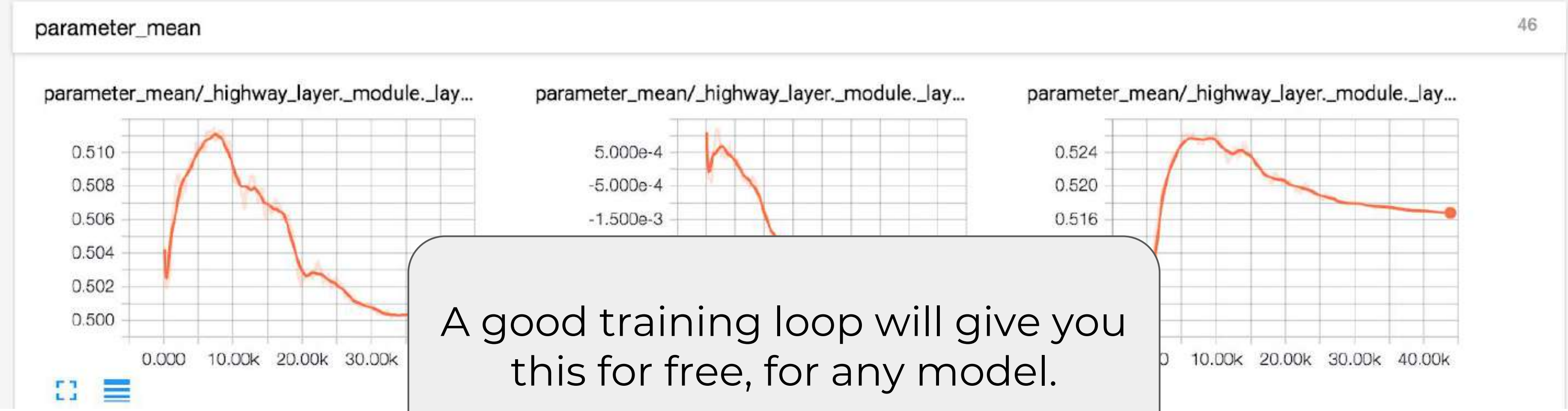
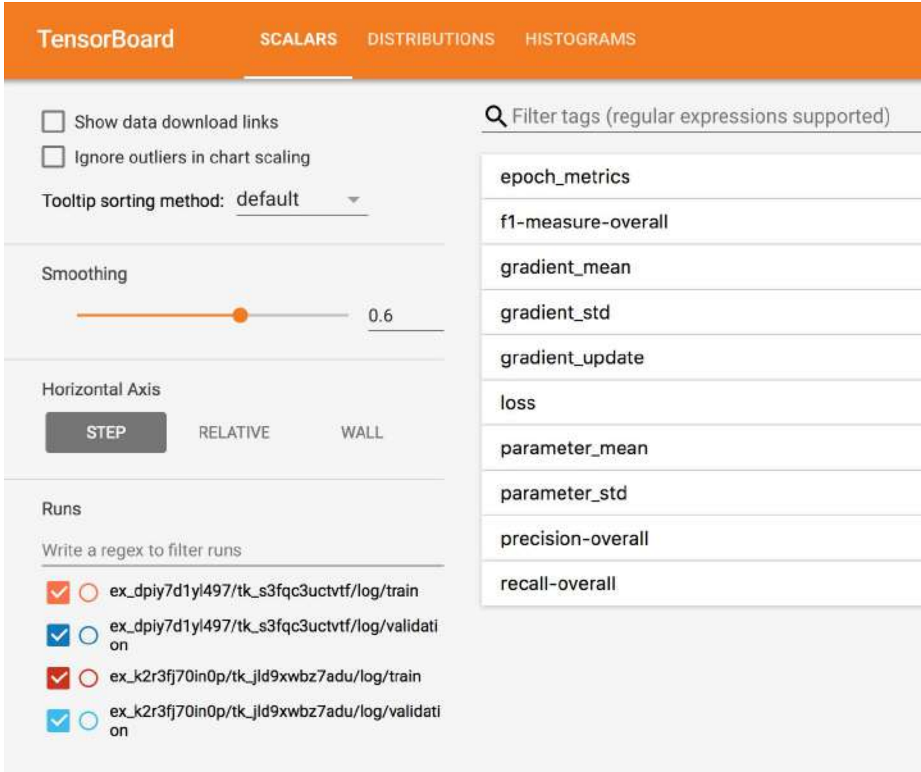


A good training loop will give you this for free, for any model.

Analyze results - Tensorboard

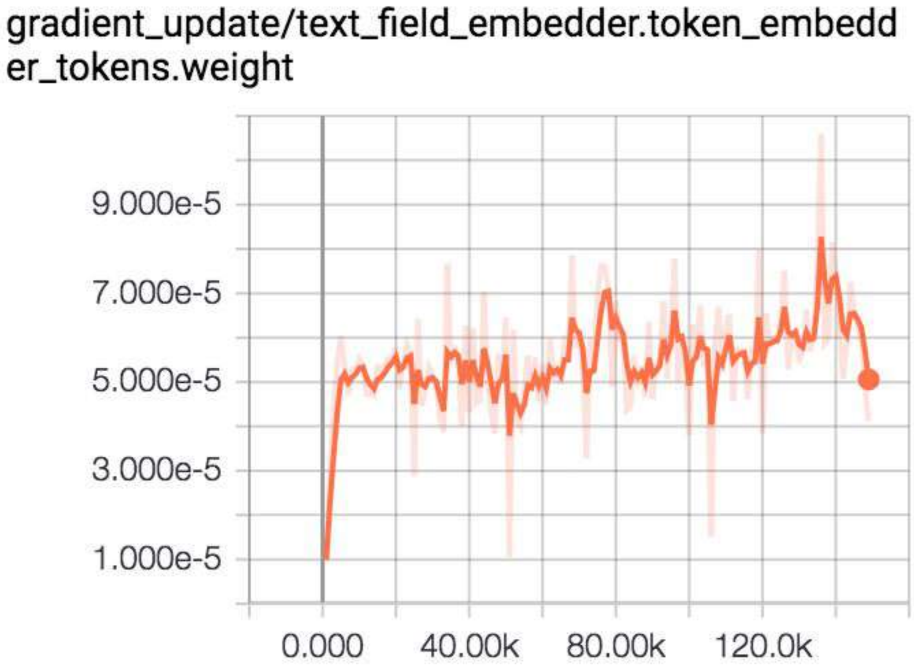
- Metrics
  - Loss
  - Accuracy etc.
- Gradients
  - Mean values
  - Std values
  - Actual update values
- Parameters
  - Mean values
  - Std values
- Activations
  - Log problematic activations



Analyze results - Tensorboard

Tensorboard will find optimisation bugs for you **for free.**

Here, the gradient for the embedding is 2 orders of magnitude different from the rest of the gradients.



Analyze results - Tensorboard

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different fron
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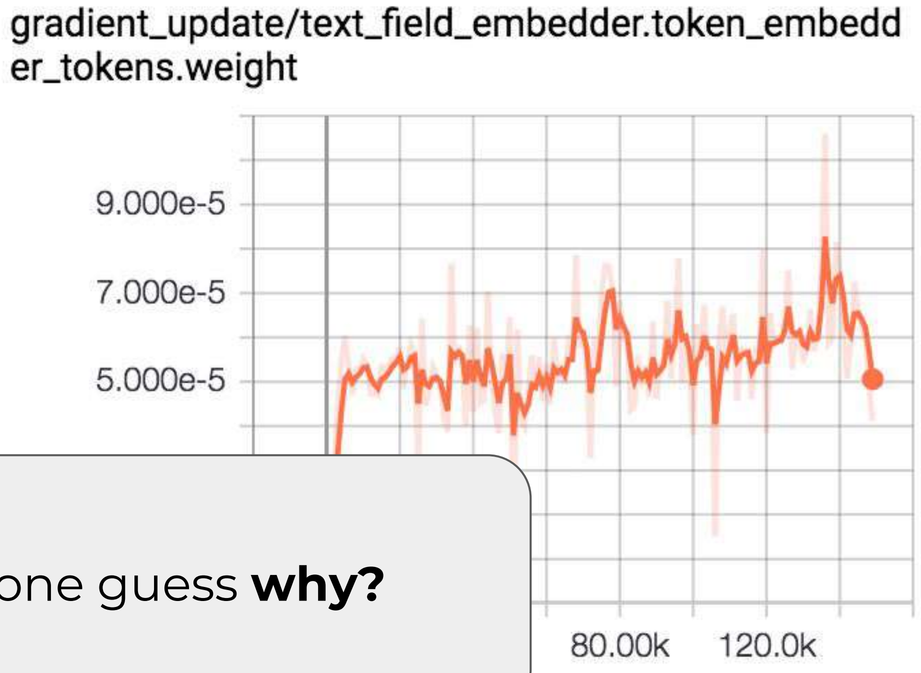
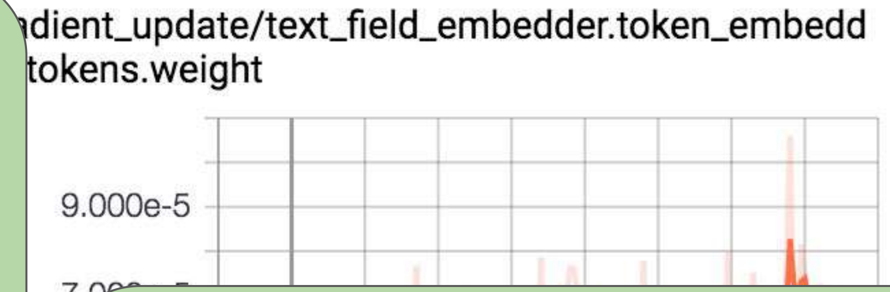


Can anyone guess **why?**

Analyze results - Tensorboard

Embeddings have **sparse gradients** (only some embeddings are updated), but the momentum coefficients from ADAM are calculated for the whole embedding every time.



orders of magnitude different from the rest of the gradients.

Solution:

```
from allennlp.training.optimizers import DenseSparseAdam
```

(uses sparse accumulators for gradient moments)

Analyze results - Look at your data!

- Good:

```
input:  {"passage": "The Matrix is a 1999 science fiction
action film written and directed by The Wachowskis, starri
ng Keanu Reeves, Laurence Fishburne, Carrie-Anne Moss, Hug
o Weaving, and Joe Pantoliano.", "question": "Who stars in
 The Matrix?"}
prediction:  {"best_span": [17, 33], "best_span_str": "Kea
nu Reeves, Laurence Fishburne, Carrie-Anne Moss, Hugo Weav
ing, and Joe Pantoliano" }

mattg@dhcp-057215:allennlp$
```

Analyze results - Look at your data!

- Better:

Passage

The Matrix is a 1999 science fiction action film written and directed by The Wachowskis, starring Keanu Reeves, Laurence Fishburne, Carrie-Anne Moss, Hugo Weaving, and Joe Pantoliano.

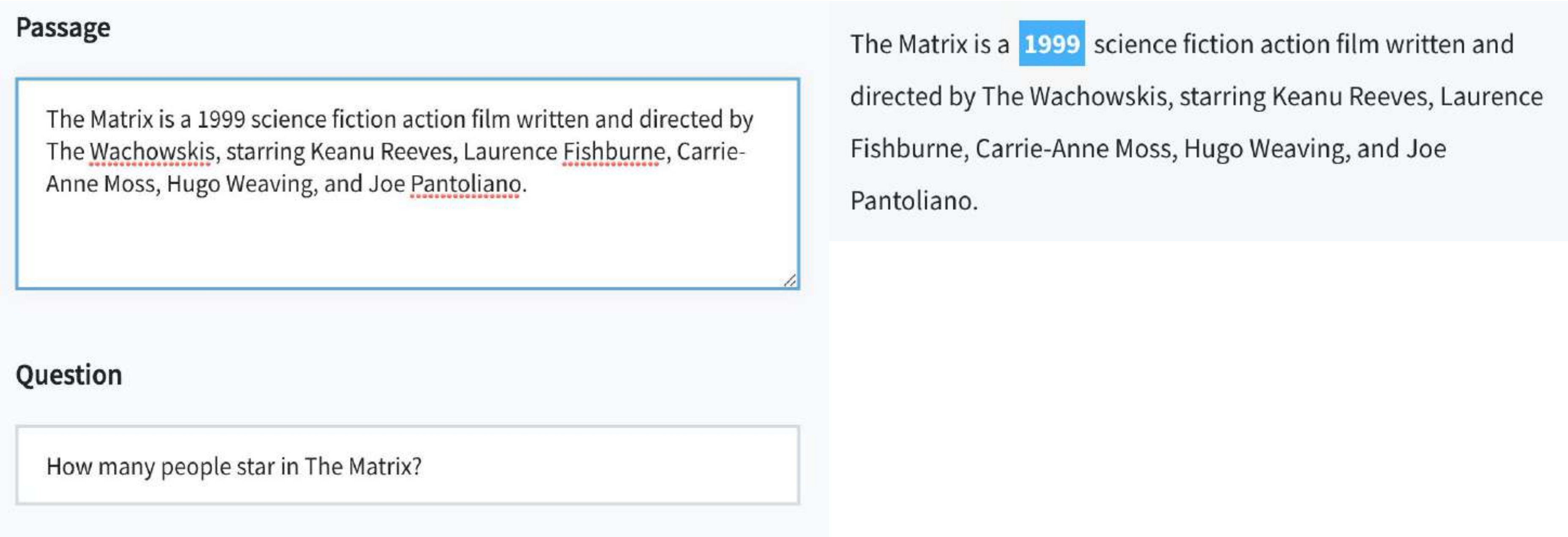
Question

Who stars in The Matrix?

The Matrix is a 1999 science fiction action film written and directed by The Wachowskis, starring **Keanu Reeves, Laurence Fishburne, Carrie-Anne Moss, Hugo Weaving, and Joe Pantoliano**.

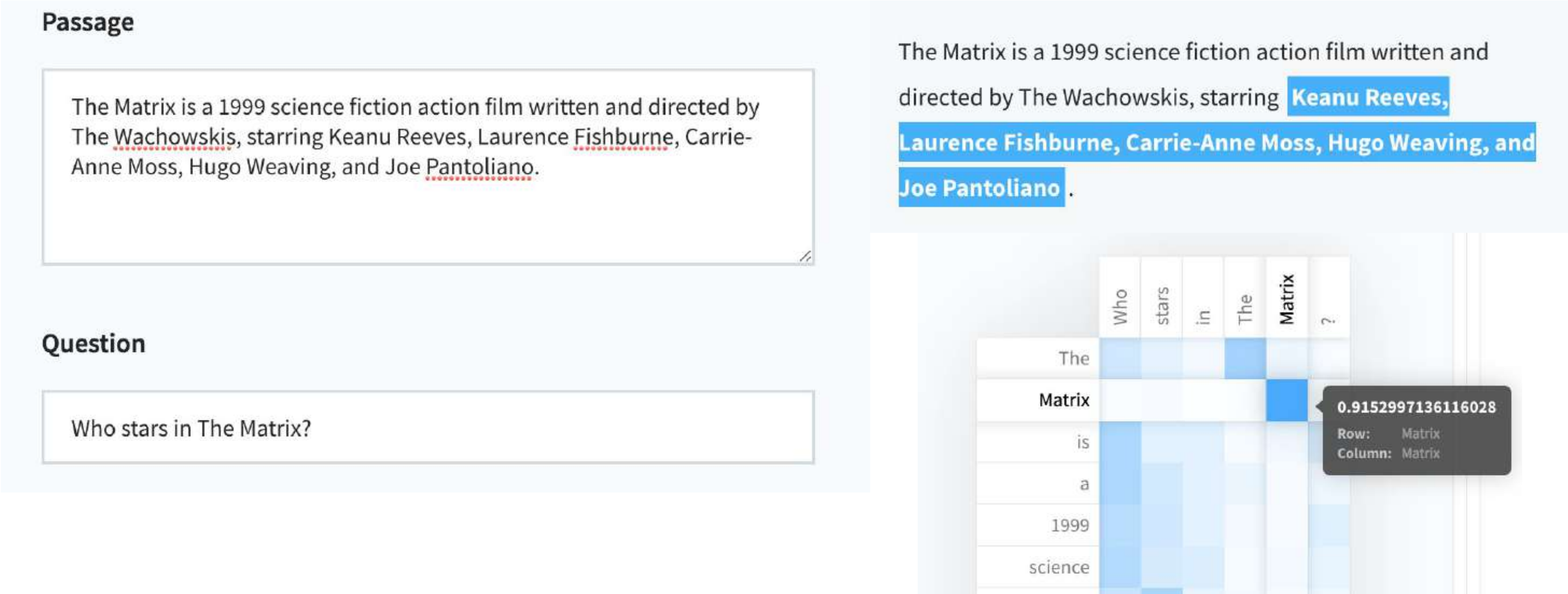
Analyze results - Look at your data!

- Better:



Analyze results - Look at your data!

- Best:



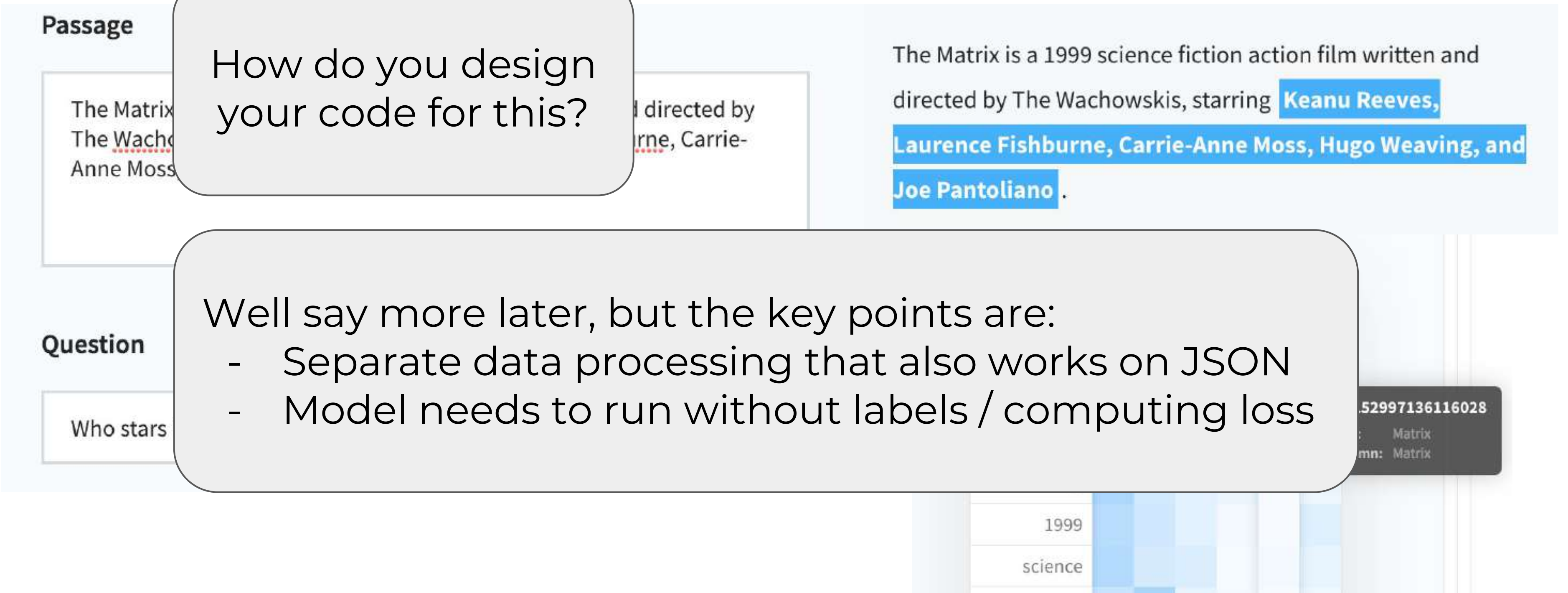
Analyze results - Look at your data!

- Best:

How do you design your code for this?

Analyze results - Look at your data!

- Best:



How do you design your code for this?

Well say more later, but the key points are:
- Separate data processing that also works on JSON
- Model needs to run without labels / computing loss

Key point during prototyping:
The components that you use matter. A lot.

We’ll give specific thoughts on designing components after the break

Developing Good Processes

Source Control

We Hope You're Already Using Source Control!

makes it easy to safely experiment with code changes

- if things go wrong, just revert!

We Hope You're Already Using Source Control!

- makes it easy to collaborate

We Hope You're Already Using Source Control!

- makes it easy to revisit older versions of your code

We Hope You're Already Using Source Control!

- makes it easy to implement code reviews

That's right, code reviews!

About Code Reviews

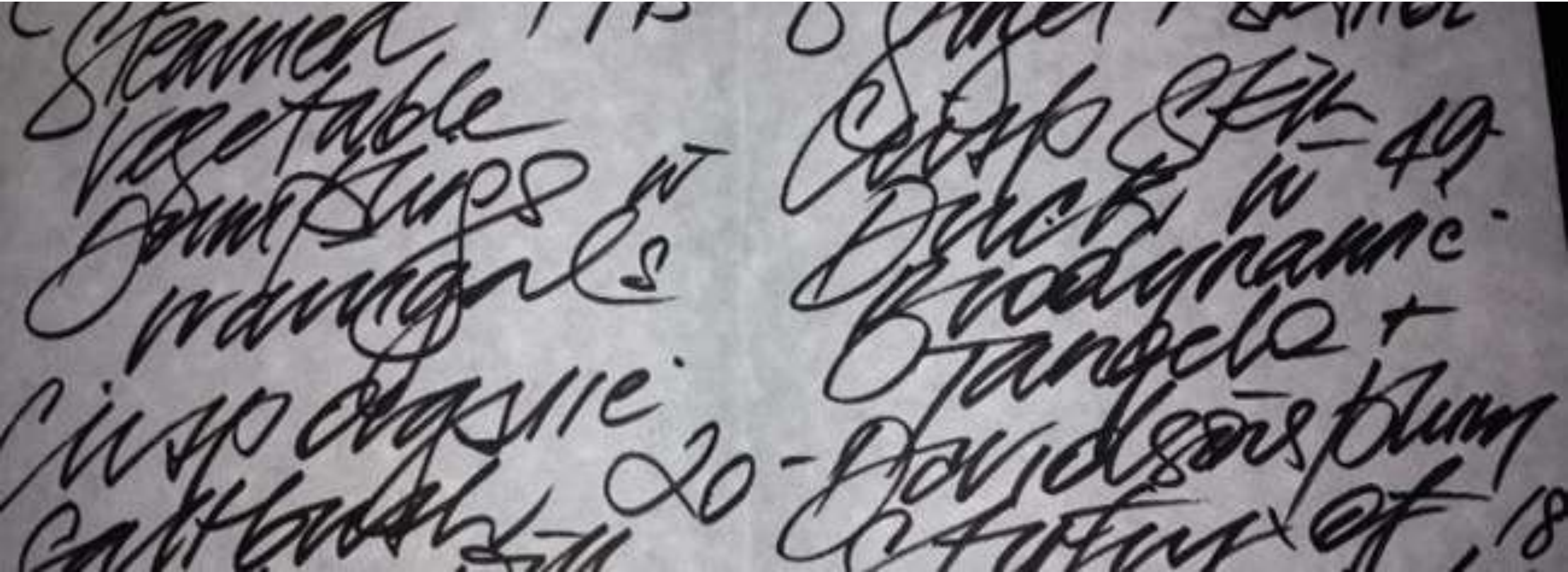
- code reviewers find mistakes

About Code Reviews

- code reviewers point out improvements

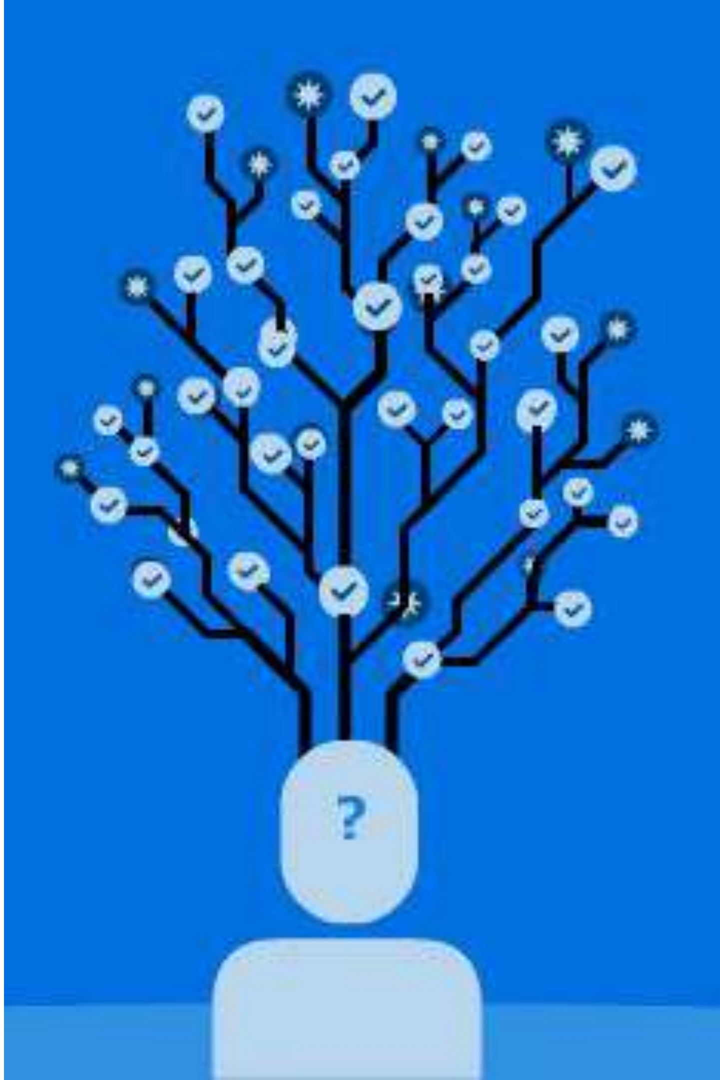
About Code Reviews

- code reviewers force you to make your code readable



About Code Reviews

and clear, readable code allows your code reviews to be discussions of your *modeling decisions*



About Code Reviews

- code reviewers can be your scapegoat when it turns out your results are wrong because of a bug

Continuous Integration

(+ Build Automation)

Continuous Integration (+ Build Automation)

Continuous Integration

always be merging (into a branch)

Build Automation

always be running your tests (+ other checks)

(this means you have to write tests)

Example: Typical AllenNLP PR

```
[17:35:34]   The build is removed from the queue to be prepared for the start
[17:35:34] ▶ Collecting changes in 1 VCS root
[17:35:34]   Starting the build on the agent agent-1
[17:35:35]   Clearing temporary directory: /local/deploy/agent1/temp/buildTmp
[17:35:35] ▶ Publishing internal artifacts
[17:35:35]   Clean build enabled: removing old files from /local/deploy/agent1
[17:35:35]   Checkout directory: /local/deploy/agent1/work/98197cf33cb401e5
[17:35:35] ▶ Updating sources: auto checkout (on agent)  (1s)
[17:35:36] ▶ Step 1/9: Docker Build (Docker)  (8s)
[17:35:45] ▶ Step 2/9: Docker Push SHA (Command Line)
[17:35:45] ▶ Step 3/9: Unit Tests (pytest) (Command Line)  (6m:28s)
[17:42:13] ▶ Step 4/9: Linter (pylint) (Command Line)  (1m:51s)
[17:44:05] ▶ Step 5/9: Type Checker (mypy) (Command Line)  (33s)
[17:44:38] ▶ Step 6/9: Build Docs (Command Line)  (1m:26s)
[17:46:05] ▶ Step 7/9: Check Docs (Command Line)  (4s)
[17:46:10] ▶ Step 8/9: Check Links (Command Line)
[17:46:10] ▶ Step 9/9: Sniff Tests (Command Line)  (4m:25s)
[17:50:35] ▶ Publishing artifacts
[17:50:35] ▶ Publishing internal artifacts
[17:50:36]   Build finished
```

if you're not building a
library that lots of
other people rely on,
you probably don't
need all these steps

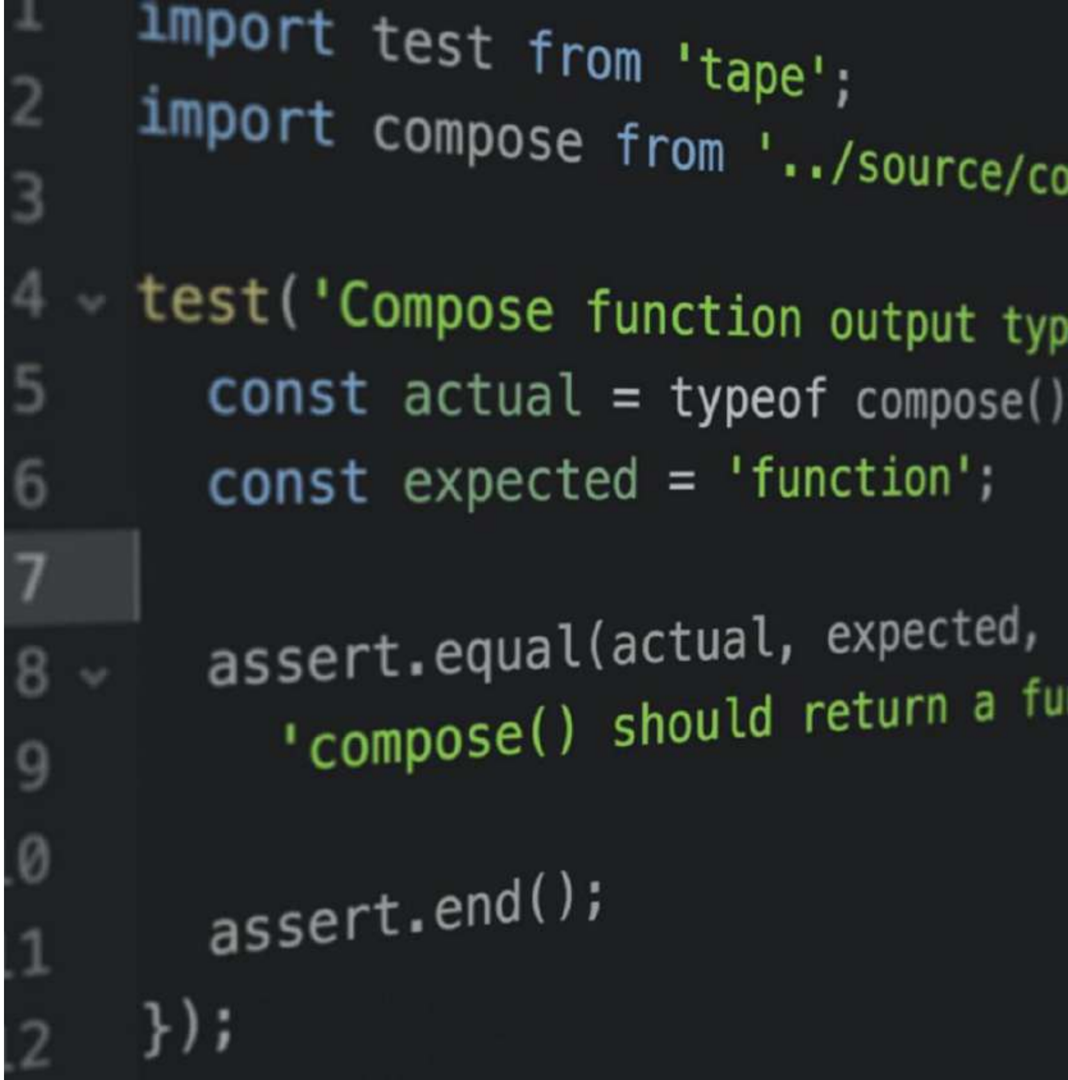
but you do need some
of them

Testing Your Code

What do we mean by "test your code"?

Write Unit Tests

a **unit test** is an *automated check* that a small part of your code works correctly



What should I test?

If You're Prototyping, Test the Basics

Prototyping? Test the Basics

```python
def test_read_from_file(self):
    conll_reader = Conll2003DatasetReader()
    instances = conll_reader.read('data/conll2003.txt'))
    instances = ensure_list(instances)

    expected_labels = ['I-ORG', 'O', 'I-PER', 'O', 'O', 'I-LOC', 'O']

    fields = instances[0].fields
    tokens = [t.text for t in fields['tokens'].tokens]
    assert tokens == ['U.N.', 'official', 'Ekeus', 'heads', 'for', 'Baghdad', '.']
    assert fields["tags"].labels == expected_labels

    fields = instances[1].fields
    tokens = [t.text for t in fields['tokens'].tokens]
    assert tokens == ['AI2', 'engineer', 'Joel', 'lives', 'in', 'Seattle', '.']
    assert fields["tags"].labels == expected_labels
```

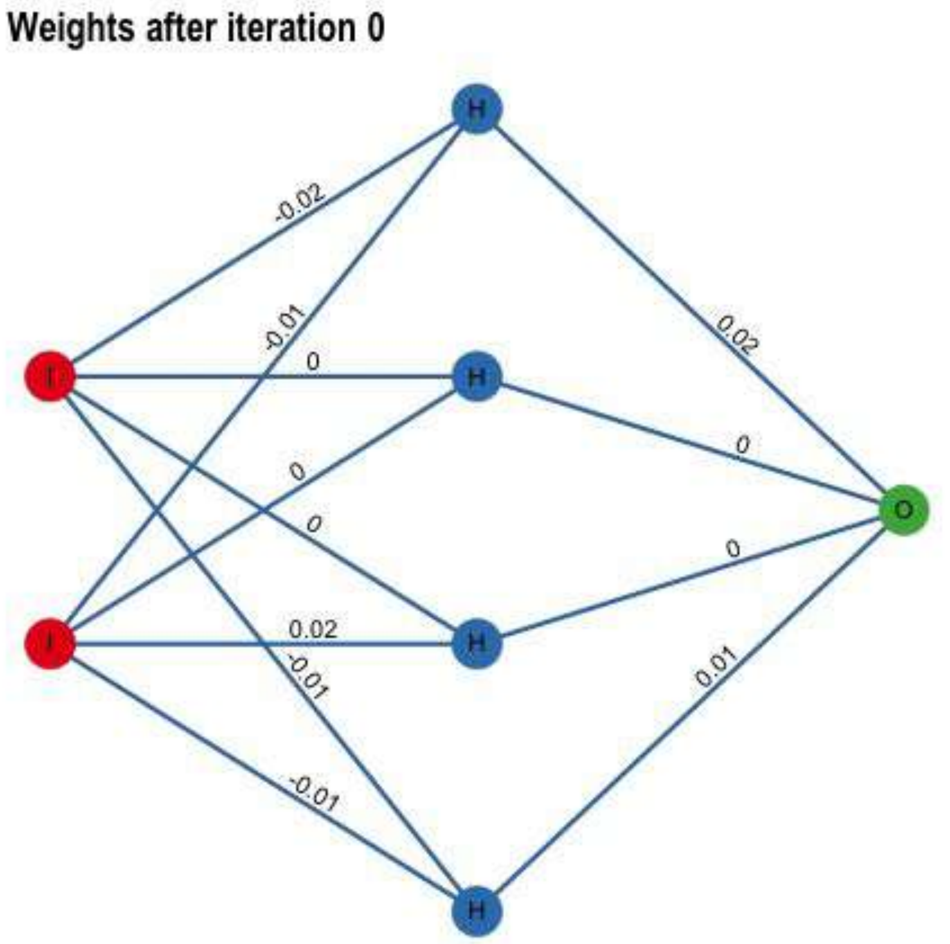
Prototyping? Test the Basics

```
def test_forward_pass_runs_correctly(self):
    output_dict = self.model(**self.training_tensors)
    tags = output_dict['tags']
    assert len(tags) == 2
    assert len(tags[0]) == 7
    assert len(tags[1]) == 7
    for example_tags in tags:
        for tag_id in example_tags:
            tag = idx_to_token[tag_id]
             assert tag in {'O', 'I-ORG', 'I-PER', 'I-LOC'}
```

If You're Writing Reusable Components, Test Everything

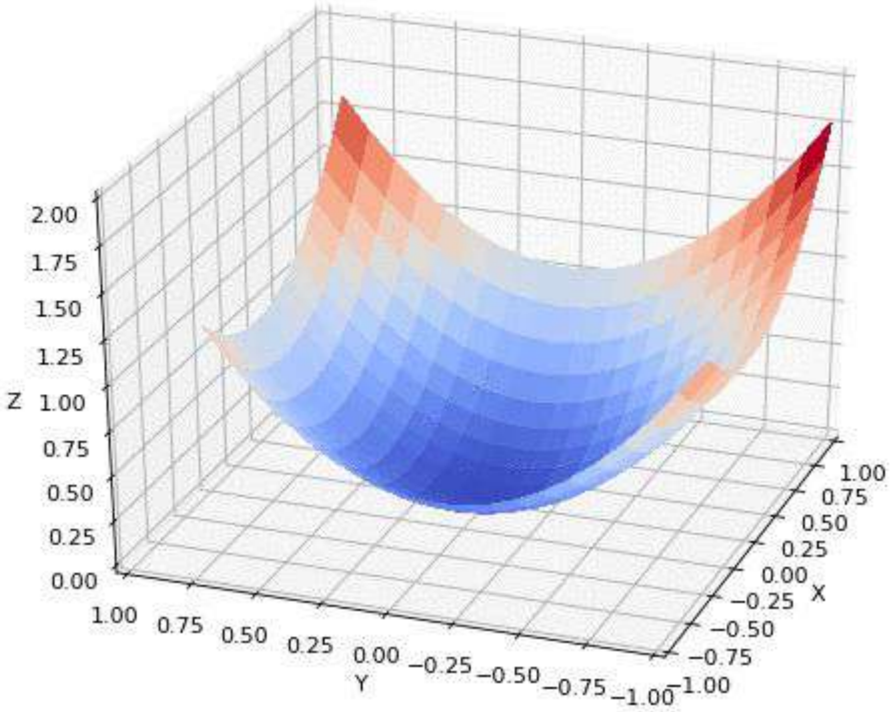
Test Everything

test your model can train, save, and load



Test Everything

test that it's computing / backpropagating gradients



Test Everything

but how?

Use Test Fixtures

create tiny datasets that look like the real thing

```
The###DET dog###NN ate###V
the###DET apple###NN
```

```
Everybody###NN read###V
that###DET book###NN
```

Use Test Fixtures

use them to create tiny pretrained models

It’s ok if the weights are essentially random. We’re not testing that the model is any **good.**

Use Test Fixtures

- write unit tests that use them to run your data pipelines and models
  - detect logic errors
  - detect malformed outputs
  - detect incorrect outputs

Use your knowledge to write clever tests

```
def test_attention_is_normalised_correctly(self):
    input_dim = 7
    sequence_tensor = torch.randn([2, 5, input_dim])
    extractor = SelfAttentiveSpanExtractor(input_dim=input_dim)
    # In order to test the attention, we'll make the weight which
    # computes the logits zero, so the attention distribution is
    # uniform over the sentence. This lets us check that the
    # computed spans are just the averages of their representations.
    extractor._global_attention._module.weight.data.fill_(0.0)
    extractor._global_attention._module.bias.data.fill_(0.0)
    span_representations = extractor(sequence_tensor,

    spans = span_representations[0]
    mean_embeddings = sequence_tensor[0, 1:4, :].mean
    numpy.testing.assert_array_almost_equal(spans[0].
                                            mean_embeddings.data.numpy())
```

Attention is hard to test because it relies on parameters

Use your knowledge to write clever tests

```
def test_attention_is_normalised_correctly(self):
    input_dim = 7
    sequence_tensor = torch.randn([2, 5, input_dim])
    extractor = SelfAttentiveSpanExtractor(input_dim=input_dim)
    # In order to test the attention, we'll make the weight which
    # computes the logits zero, so the attention distribution is
    # uniform over the sentence. This lets us check that the
    # computed spans are just the averages of their representations.
    extractor._global_attention._module.weight.data.fill_(0.0)
    extractor._global_attention._module.bias.data.fill_(0.0)
    span_representations = extractor(sequence_tensor

    spans = span_representations[0]
    mean_embeddings = sequence_tensor[0, 1:4, :].me
    numpy.testing.assert_array_almost_equal(spans[0
                                            mean_em
```

Idea: Make the parameters deterministic so you can test **everything** else

Pre-Break Summary

- Two Modes of Writing Research Code
  - Difference between prototyping and building components
  - When should you transition?
  - Good ways to analyse results
- Developing Good Processes
  - How to write good tests
  - How to know what to test
  - Why you should do code reviews

BREAK

please fill out our survey:
`https://tinyurl.com/emnlp-tutorial-survey`

will tweet out link to slides after talk
@ai2_allennlp

Reusable Components

What are the right abstractions for NLP?

The Right Abstractions

- AllenNLP now has more than 20 models in it
  - some simple
  - some complex
- Some abstractions have consistently proven useful
- (Some haven't)

Things That We Use A Lot

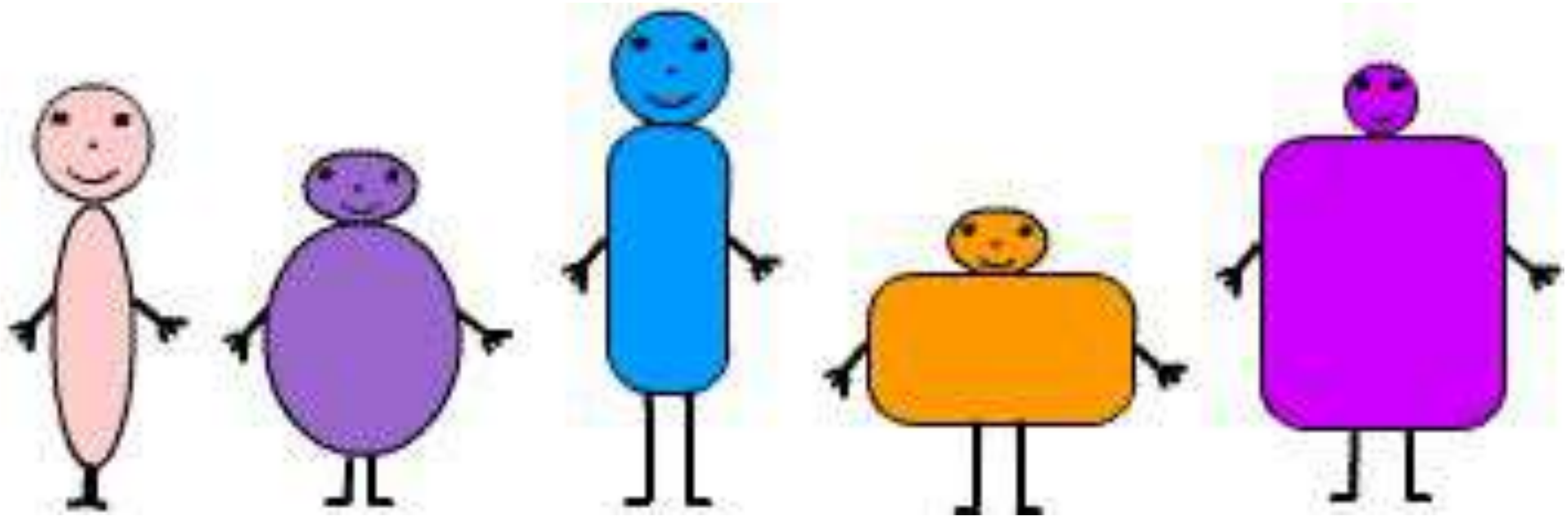
- training a model
- mapping words (or characters, or labels) to indexes
- summarizing a sequence of tensors with a single tensor

Things That Require a Fair Amount of Code

- training a model
- (some ways of) summarizing a sequence of tensors with a single tensor
- some neural network modules

Things That Have Many Variations

- turning a word (or a character, or a label) into a tensor
- summarizing a sequence of tensors with a single tensor
- transforming a sequence of tensors into a sequence of tensors

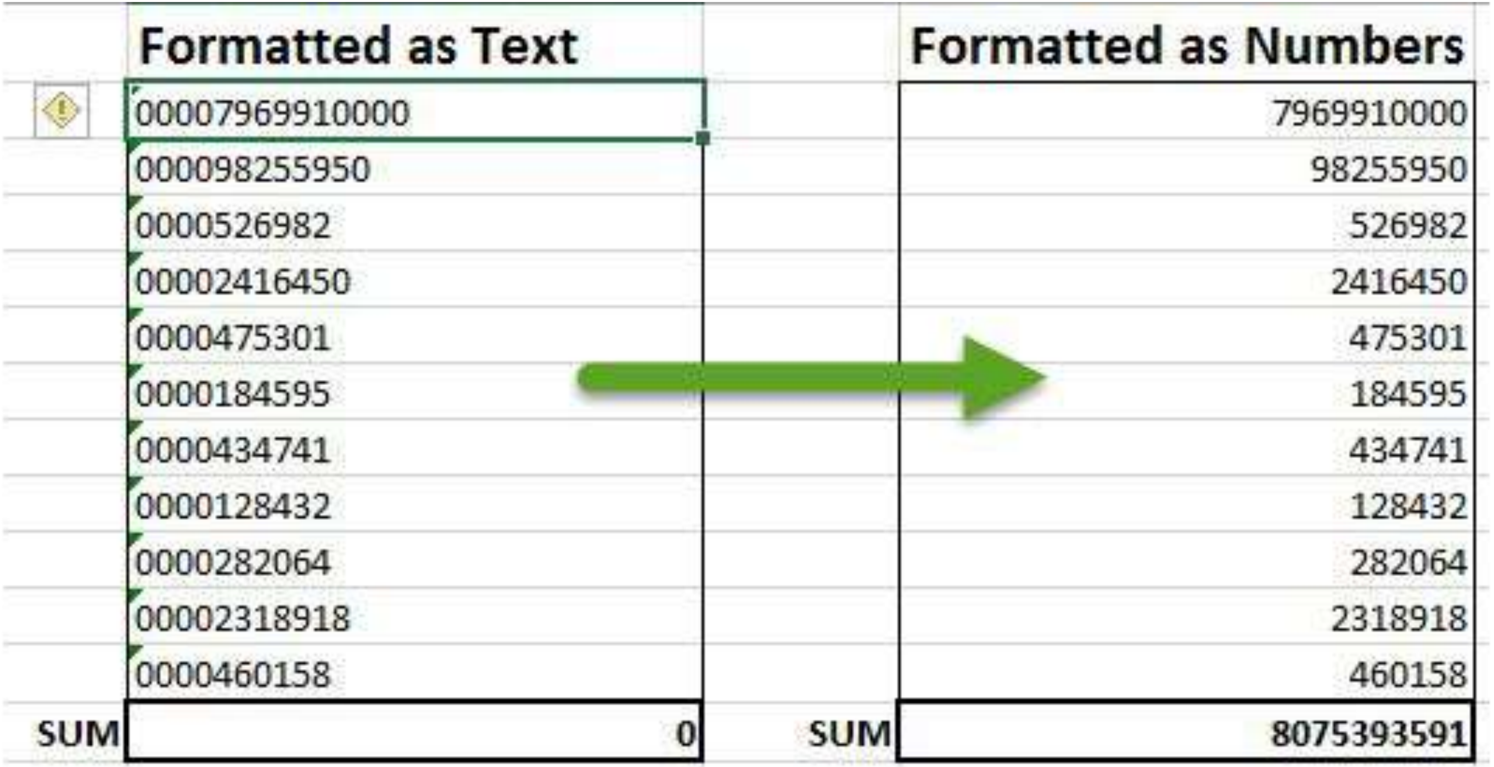


Things that reflect our higher-level thinking

- we'll have some inputs:
  - text, almost certainly
  - tags/labels, often
  - spans, sometimes
- we need some ways of *embedding* them as tensors
  - one hot encoding
  - low-dimensional embeddings
- we need some ways of dealing with sequences of tensors
  - sequence in -> sequence out (e.g. all outputs of an LSTM)
  - sequence in -> tensor out (e.g. last output of an LSTM)

Along the way, we need to worry about some things that make NLP tricky

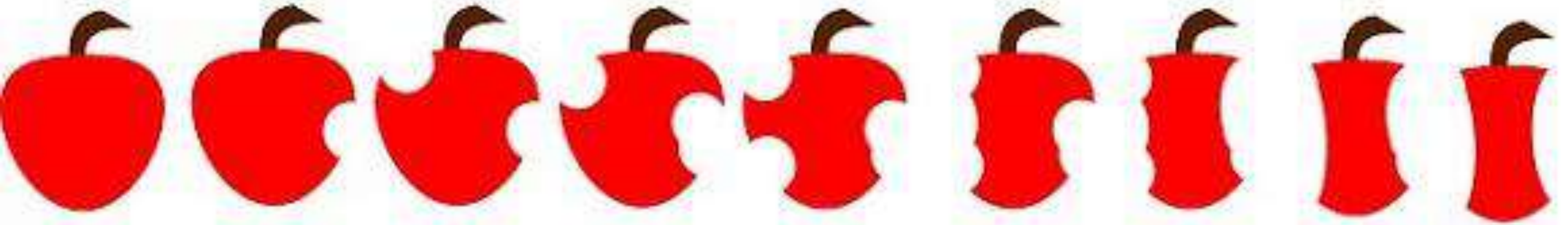
Inputs are *text*, but neural models want *tensors*



	Formatted as Text		Formatted as Numbers
	00007969910000		7969910000
	000098255950		98255950
	0000526982		526982
	00002416450		2416450
	0000475301		475301
	0000184595		184595
	0000434741		434741
	0000128432		128432
	0000282064		282064
	00002318918		2318918
	0000460158		460158
SUM	0	SUM	8075393591

Inputs are *sequences* of things

and order matters



Inputs can vary in length

Some sentences are short.

Whereas other sentences are so long that by the time you finish reading them you've already forgotten what they started off talking about and you have to go back and read them a second time in order to remember the parts at the beginning.

Reusable Components in AllenNLP

AllenNLP is built on PyTorch

AllenNLP is built on PyTorch

and is inspired by the question "what higher-level components would help NLP researchers do their research better + more easily?"

AllenNLP is built on PyTorch

under the covers, every piece of a model is a `torch.nn.Module` and every number is part of a `torch.Tensor`

AllenNLP is built on PyTorch

but we want you to be able to reason at a higher level most of the time hence the higher level concepts

the Model

```
class Model(torch.nn.Module, Registrable):
    def __init__(self,
                 vocab: Vocabulary,
                 regularizer: RegularizerApplicator = None) -> None: ...


    def forward(self, *inputs) -> Dict[str, torch.Tensor]: ...


    def get_metrics(self, reset: bool = False) -> Dict[str, float]: ...


    @classmethod
    def load(cls,
             config: Params,
             serialization_dir: str,
             weights_file: str = None,
             cuda_device: int = -1) -> 'Model': ...
```

Model.forward

```python
def forward(self, *inputs) -> Dict[str, torch.Tensor]: ...
```

- returns a dict [!]
- by convention, `"loss"` tensor is what the training loop will optimize
- but as a dict entry, `"loss"` is completely optional
  - which is good, since at inference / prediction time you don't have one
- can also return predictions, model internals, or any other outputs you'd want in an output dataset or a demo

every NLP project needs a Vocabulary

```python
class Vocabulary(Registrable):

   def __init__(self,
                counter: Dict[str, Dict[str, int]] = None,
                min_count: Dict[str, int] = None,
                max_vocab_size: Union[int, Dict[str, int]] = None,
                non_padded_namespaces: Iterable[str] = DEFAULT_NON_PADDED_NAMESPACES,
                pretrained_files: Optional[Dict[str, str]] = None,
                only_include_pretrained_words: bool = False,
                tokens_to_add: Dict[str, List[str]] = None,
                min_pretrained_embeddings: Dict[str, int] = None) -> None: ...

   @classmethod
   def from_instances(cls, instances: Iterable['Instance'], ...) -> 'Vocabulary': ...

   def add_token_to_namespace(self, token: str, namespace: str = 'tokens') -> int: ...

   def get_token_index(self, token: str, namespace: str = 'tokens') -> int: ...

   def get_token_from_index(self, index: int, namespace: str = 'tokens') -> str: ...
       return self._index_to_token[namespace][index]

   def get_vocab_size(self, namespace: str = 'tokens') -> int: ...
       return len(self._token_to_index[namespace])
```

a Vocabulary is built from Instances

```
class Instance(Mapping[str, Field]):
   def __init__(self, fields: MutableMapping[str, Field]) -> None: ...

   def add_field(self, field_name: str, field: Field, vocab: Vocabulary = None) -> None: ...

   def count_vocab_items(self, counter: Dict[str, Dict[str, int]]): ...

   def index_fields(self, vocab: Vocabulary) -> None: ...

   def get_padding_lengths(self) -> Dict[str, Dict[str, int]]: ...

   def as_tensor_dict(self,
                      padding_lengths: Dict[str, Dict[str, int]] = None) -> Dict[str, DataArray]:
```

an Instance is a collection of Fields

a Field contains a data element and knows how to turn it into a tensor

```
class Field(Generic[DataArray]):
    def count_vocab_items(self, counter: Dict[str, Dict[str, int]]): ...

    def index(self, vocab: Vocabulary): ...

    def get_padding_lengths(self) -> Dict[str, int]: ...

    def as_tensor(self, padding_lengths: Dict[str, int]) -> DataArray: ...

    def empty_field(self) -> 'Field': ...

    def batch_tensors(self, tensor_list: List[DataArray]) -> DataArray:  ...
```

Many kinds of Fields

- TextField: represents a sentence, or a paragraph, or a question, or ...
- LabelField: represents a single label (e.g. "entailment" or "sentiment")
- SequenceLabelField: represents the labels for a sequence (e.g. part-of-speech tags)
- SpanField: represents a span (start, end)
- IndexField: represents a single integer index
- ListField[T]: for repeated fields
- MetadataField: represents anything (but not tensorizable)

Example: an Instance for SNLI

```
def text_to_instance(self,
                     premise: str,
                     hypothesis: str,
                     label: str = None) -> Instance:

    fields: Dict[str, Field] = {}

    premise_tokens = self._tokenizer.tokenize(premise)
    hypothesis_tokens = self._tokenizer.tokenize(hypothesis)

    fields['premise'] = TextField(premise_tokens, self._token_indexers)
    fields['hypothesis'] = TextField(hypothesis_tokens, self._token_indexers)

    if label:
        fields['label'] = LabelField(label)

    metadata = {"premise_tokens": [x.text for x in premise_tokens],
                "hypothesis_tokens": [x.text for x in hypothesis_tokens]}
    fields["metadata"] = MetadataField(metadata)

    return Instance(fields)
```

Example: an Instance for SQuAD

```python
def make_reading_comprehension_instance(question_tokens: List[Token],
                                        passage_tokens: List[Token],
                                        token_indexers: Dict[str, TokenIndexer],
                                        token_spans: List[Tuple[int, int]] = None) -> Instance:

    fields: Dict[str, Field] = {}

    fields['passage'] = TextField(passage_tokens, token_indexers)
    fields['question'] = TextField(question_tokens, token_indexers)

    if token_spans:
        # There may be multiple answer annotations, so we pick the one that occurs the most.
        candidate_answers: Counter = Counter()
        for span_start, span_end in token_spans:
            candidate_answers[(span_start, span_end)] += 1
        span_start, span_end = candidate_answers.most_common(1)[0][0]

        fields['span_start'] = IndexField(span_start, passage_field)
        fields['span_end'] = IndexField(span_end, passage_field)

    return Instance(fields)
```

What's a TokenIndexer?

- how to represent text in our model is one of the fundamental decisions in doing NLP
- many ways, but pretty much always want to turn text into indices
- many choices
  - sequence of unique `token_ids` (or id for OOV) from a vocabulary
  - sequence of sequence of `character_ids`
  - sequence of ids representing byte-pairs / word pieces
  - sequence of `pos_tag_ids`
- might want to use several
- this is (deliberately) independent of the choice about how to *embed* these as tensors

And don't forget `DatasetReader`

- "given a path [usually but not necessarily to a file], produce `Instances`"
- decouples your modeling code from your data-on-disk format
- two pieces:
    - `text_to_instance`: creates an instance from named inputs ("passage", "question", "label", etc..)
    - `read`: parses data from a file and (typically) hands it to `text_to_instance`
- new dataset -> create a new DatasetReader (not too much code), but keep the model as-is
- same dataset, new model -> just re-use the DatasetReader
- default is to read all instances into memory, but base class handles laziness if you want it

Library also handles batching, via `DataIterator`

- `BasicIterator` just shuffles (optionally) and produces fixed-size batches
- `BucketIterator` groups together instances with similar "length" to minimize padding
- (Correctly padding and sorting instances that contain a variety of fields is slightly tricky; a lot of the API here is designed around getting this right)
- Maybe someday we'll have a working `AdaptiveIterator` that creates variable GPU-sized batches

Tokenizer

- Single abstraction for both word-level and character-level tokenization
- Possibly this wasn't the right decision!
- Pros:
  - easy to switch between words-as-tokens and characters-as-tokens in the same model
- Cons:
  - non-standard names + extra complexity
  - doesn’t seem to get used this way at all

back to the Model

Model is a subclass of torch.nn.Module

- so if you give it members that are `torch.nn.Parameters` or are themselves `torch.nn.Modules`, all the optimization will just work*
- for reasons we'll see in a bit, we'll also *inject* any model component that we might want to configure
- and AllenNLP provides NLP / deep-learning abstractions that allow us not to reinvent the wheel

*usually on the first try it won't "just work", but usually that's your fault not PyTorch's

TokenEmbedder

- turns ids (the outputs of your TokenIndexers) into tensors
- many options:
  - learned word embeddings
  - pretrained word embeddings
  - contextual embeddings (e.g. ELMo)
  - character embeddings + Seq2VecEncoder

Seq2VecEncoder

```
(batch_size, sequence_length, embedding_dim)
```

```
(batch_size, embedding_dim)
```

- bag of words
- (last output of) LSTM
- CNN + pooling

Seq2SeqEncoder

```
(batch_size, sequence_length, embedding_dim)
```

```
(batch_size, sequence_length, embedding_dim)
```

- LSTM (and friends)
- self-attention
- do-nothing

Wait, Two Different Abstractions for RNNs?

- Conceptually, RNN-for-Seq2Seq is different from RNN-for-Seq2Vec
- In particular, the class of possible replacements for the former is different from the class of replacements for the latter
- That is, "RNN" is not the right abstraction for NLP!

Attention

```
(batch_size, sequence_length, embedding_dim),

(batch_size, embedding_dim)
```

```
(batch_size, sequence_length)
```

- dot product ($x^T y$)
- bilinear ($x^T W y$)
- linear ($[x;y;x*y;...]^T w$)

MatrixAttention

```
(batch_size, sequence_length1, embedding_dim),

(batch_size, sequence_length2, embedding_dim)
```

⇩

```
(batch_size, sequence_length1, sequence_length2)
```

- dot product ($x^T y$)
- bilinear ($x^T W y$)
- linear ($[x;y;x*y;...]^T w$)

Attention and MatrixAttention

- These look similar - you could imagine sharing the similarity computation code
- We did this at first - code sharing, yay!
- But it was very memory inefficient - code sharing isn't always a good idea
- You could also imagine having a single Attention abstraction that also works for attention matrices
- But then you have a muddied and confusing input/output spec
- So, again, more duplicated (or at least very similar) code, but in this case that's probably the right decision, especially for efficiency

SpanExtractor

Span Indices `(batch_size, num_spans, 2)`

Sequence of Text `(batch_size, sequence_length, embedding_dim)`

Embedded Spans `(batch_size, num_spans, embedding_dim)`

- Many modern NLP models use representations of spans of text
  - Used by the Constituency Parser and the Co-reference model in AllenNLP
  - We generalised this after needing it again to implement the Constituency Parser.
- Lots of ways to represent a span:
  - Difference of endpoints
  - Concatenation of endpoints (etc)
  - Attention over intermediate words

This seems like a lot of abstractions!

- But in most cases it's pretty simple:
  - create a DatasetReader that generates the Instances you want
    - (if you're using a standard dataset, likely one already exists)
  - create a Model that turns Instances into predictions and a loss
    - use off-the-shelf components => can often write little code
  - create a JSON config and use the AllenNLP training code
  - (and also often a Predictor, coming up next)
- We'll go through a detailed example at the end of the tutorial
- And you can write as much PyTorch as you want when the built-in components don't do what you need

Abstractions just to make your life nicer

Declarative syntax

```
"model": {
   "type": "crf_tagger",
   "label_encoding": "BIOUL",
   "constrain_crf_decoding": true,
   "calculate_span_f1": true,
   "dropout": 0.5,
   "include_start_end_transitions": false,
   "text_field_embedder": {
     "token_embedders": {
       "tokens": {
           "type": "embedding",
           "embedding_dim": 50,
           "pretrained_file": "glove.6B.50d.txt.gz",
           "trainable": true
       },
```

most AllenNLP objects can be instantiated from Jsonnet blobs

```
           "token_characters": {
               "type": "character_encoding",
               "embedding": {
                   "embedding_dim": 16
               },
               "encoder": {
                   "type": "cnn",
                   "embedding_dim": 16,
                   "num_filters": 128,
                   "ngram_filter_sizes": [3],
                   "conv_layer_activation": "relu"
               }
             }
          },
       },
       "encoder": {
           "type": "lstm",
           "input_size": 50 + 128,
           "hidden_size": 200,
           "num_layers": 2,
           "dropout": 0.5,
           "bidirectional": true
       },
     },
```

Declarative syntax

- allows us to specify an entire experiment using JSON
- allows us to change architectures without changing code

```
"encoder": {
    "type": "lstm",
    "input_size": 50 + 128,
    "hidden_size": 200,
    "num_layers": 2,
    "dropout": 0.5,
    "bidirectional": true
},
```

```
"encoder": {
    "type": "gru",
    "input_size": 50 + 128,
    "hidden_size": 200,
    "num_layers": 1,
    "dropout": 0.5,
    "bidirectional": true
},
```

```
"encoder": {
    "type": "pass_through",
    "input_dim": 50 + 128
},
```

Declarative syntax

How does it work?

- Registrable
  - retrieve a class by its name
- FromParams
  - instantiate a class instance from JSON

Registrable

```
class Model(torch.nn.Module, Registrable):
...


@Model.register("bidaf")
class BidirectionalAttentionFlow(Model): ...

@Model.register("decomposable_attention")
class DecomposableAttention(Model): ...

@Model.register("simple_tagger")
class SimpleTagger(Model):
```

returns the class itself

```
model = Model.by_name("bidaf")(param1,
                               param2,
                               ...)
```

- so now, given a model "type" (specified in the JSON config), we can programmatically retrieve the class
- remaining problem: how do we programmatically call the constructor?

Model config, again

```
"model": {
   "type": "crf_tagger",
   "label_encoding": "BIOUL",
   "constrain_crf_decoding": true,
   "calculate_span_f1": true,
   "dropout": 0.5,
   "include_start_end_transitions": false,
   "text_field_embedder": {
     "token_embedders": {
       "tokens": {
           "type": "embedding",
           "embedding_dim": 50,
           "pretrained_file": "glove.6B.50d.txt.gz",
           "trainable": true
       },
       "token_characters": {
           "type": "character_encoding",
           "embedding": {
               "embedding_dim": 16
           },
           "encoder": {
               "type": "cnn",
               "embedding_dim": 16,
               "num_filters": 128,
               "ngram_filter_sizes": [3],
               "conv_layer_activation": "relu"
           }
         }
     },
   },
   "encoder": {
       "type": "lstm",
       "input_size": 50 + 128,
       "hidden_size": 200,
       "num_layers": 2,
       "dropout": 0.5,
       "bidirectional": true
   },
},
```

from_params, originally

```python
@Model.register("crf_tagger")
class CrfTagger(Model):
    def __init__(
        self,
        vocab: Vocabulary,
        text_field_embedder: TextFieldEmbedder,
        encoder: Seq2SeqEncoder,
        label_namespace: str = "labels",
        constraint_type: str = None,
        include_start_end_transitions: bool = True,
        dropout: float = None,
        initializer: InitializerApplicator = None,
        regularizer: Optional[RegularizerApplicator] = None
    ) -> None:
    ...
```

- have to write all the parameters twice
- better make sure you use the same default values in both places!
- tedious + error-prone
- the way from_params works should (in most cases) be obvious from the constructor

```python
@classmethod
def from_params(cls,
                vocab: Vocabulary,
                params: Params) -> 'CrfTagger':
    embedder_params = params.pop("text_field_embedder")
    text_field_embedder = TextFieldEmbedder.from_params(vocab,
                                                        embedder_params)
    encoder = Seq2SeqEncoder.from_params(params.pop("encoder"))
    label_namespace = params.pop("label_namespace", "labels")
    constraint_type = params.pop("constraint_type", None)
    dropout = params.pop("dropout", None)
    include_start_end_transitions = \
            params.pop("include_start_end_transitions", True)
    initializer_params = params.pop('initializer', [])
    initializer = InitializerApplicator.from_params(initializer_params)
    regularizer_params = params.pop('regularizer', [])
    regularizer = RegularizerApplicator.from_params(regularizer_params)


    params.assert_empty(cls.__name__)


    return cls(vocab=vocab,
               text_field_embedder=text_field_embedder,
               encoder=encoder,
               label_namespace=label_namespace,
               constraint_type=constraint_type,
               dropout=dropout,
               include_start_end_transitions=include_start_end_transitions,
               initializer=initializer,
```

from_params, now

```
class FromParams:
   @classmethod
   def from_params(cls: Type[T], params: Params, **extras) -> T:
       from allennlp.common.registrable import Registrable  # import here to avoid circular imports

       if params is None: return None

       registered_subclasses = Registrable._registry.get(cls)

       if registered_subclasses is not None:
           as_registrable = cast(Type[Registrable], cls)
           default_to_first_choice = as_registrable.default_implementation is not None
           choice = params.pop_choice("type",
                                      choices=as_registrable.list_available(),
                                      default_to_first_choice=default_to_first_choice)
           subclass = registered_subclasses[choice]

           if not takes_arg(subclass.from_params, 'extras'):
               extras = {k: v for k, v in extras.items() if takes_arg(subclass.from_params, k)}

           return subclass.from_params(params=params, **extras)
       else:
           if cls.__init__ == object.__init__:
               kwargs: Dict[str, Any] = {}
           else:
               kwargs = create_kwargs(cls, params, **extras)

           return cls(**kwargs)  # type: ignore
```

from_params, now

```python
def create_kwargs(cls: Type[T], params: Params, **extras) -> Dict[str, Any]:
    """
    Given some class, a `Params` object, and potentially other keyword arguments,
    create a dict of keyword args suitable for passing to the class's constructor.

    The function does this by finding the class's constructor, matching the constructor
    arguments to entries in the `params` object, and instantiating values for the parameters
    using the type annotation and possibly a from_params method.

    Any values that are provided in the `extras` will just be used as is.
    For instance, you might provide an existing `Vocabulary` this way.
    """
    ...
```

Trainer

```python
class Trainer(Registrable):
    def __init__(
        self,
        model: Model,
        optimizer: torch.optim.Optimizer,
        iterator: DataIterator,
        train_dataset: Iterable[Instance],
        validation_dataset: Optional[Iterable[Instance]] = None,
        patience: Optional[int] = None,
        validation_metric: str = "-loss",
        validation_iterator: DataIterator = None,
        shuffle: bool = True,
        num_epochs: int = 20,
        serialization_dir: Optional[str] = None,
        num_serialized_models_to_keep: int = 20,
        keep_serialized_model_every_num_seconds: int = None,
        model_save_interval: float = None,
        cuda_device: Union[int, List] = -1,
        grad_norm: Optional[float] = None,
        grad_clipping: Optional[float] = None,
        learning_rate_scheduler: LearningRateScheduler = None,
        summary_interval: int = 100,
        histogram_interval: int = None,
        should_log_parameter_statistics: bool = True,
        should_log_learning_rate: bool = False) -> None:
```

- configurable training loop with tons of options
    - your favorite PyTorch optimizer
    - early stopping
    - many logging options
    - many serialization options
    - learning rate schedulers
- (almost all of them optional)
- as always, configuration happens in your JSON experiment config

Model archives

- training loop produces a model.tar.gz
  - config.json + vocabulary + trained model weights
- can be used with command line tools to evaluate on test datasets or to make predictions
- can be used to power an interactive demo

Making Predictions

Predictor

- models are tensor-in, tensor-out
- for creating a web demo, want JSON-in, JSON-out
- same for making predictions interactively
- Predictor is just a simple JSON wrapper for your model

```
@Predictor.register('sentence-tagger')
class SentenceTaggerPredictor(Predictor):
    def __init__(self,
                 model: Model,
                 dataset_reader: DatasetReader) -> None:
        super().__init__(model, dataset_reader)
        self._tokenizer = SpacyWordSplitter(language='en_core_web_sm',
                                            pos_tags=True)

    def predict(self, sentence: str) -> JsonDict:
        return self.predict_json({"sentence" : sentence})

    @overrides
    def _json_to_instance(self, json_dict: JsonDict) -> Instance:
        sentence = json_dict["sentence"]
        tokens = self._tokenizer.split_words(sentence)
        return self._dataset_reader.text_to_instance(tokens)
```

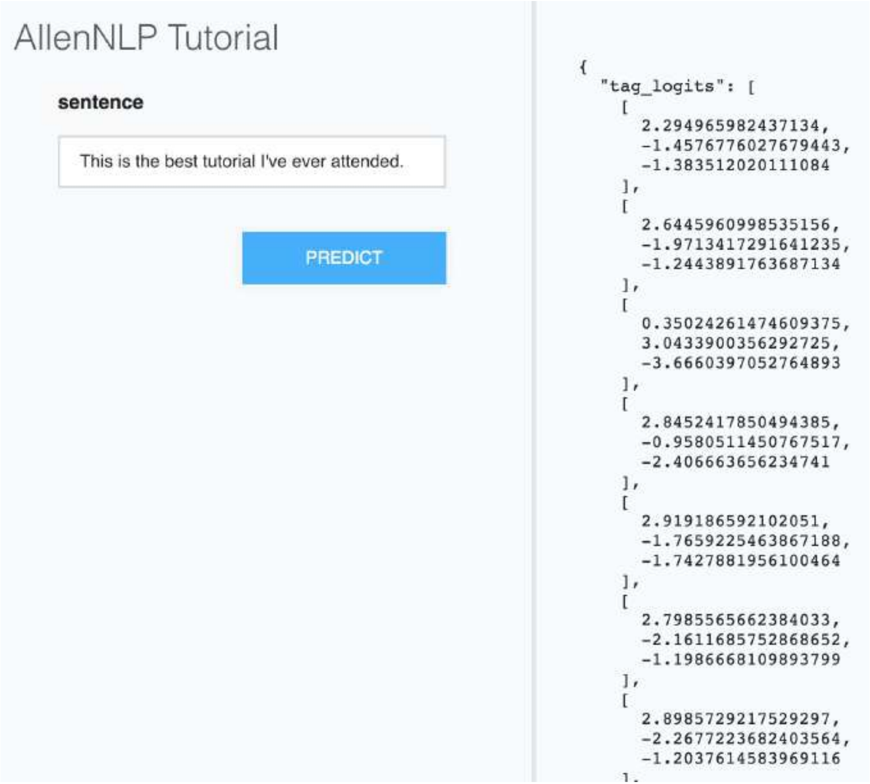
and this is enabled by all of our models taking *optional* labels and returning an optional loss and also various model internals and interesting results

this is (partly) why we split out text_to_instance as its own function in the dataset reader

Serving a demo

With this setup, serving a demo is easy.

- DatasetReader gives us `text_to_instance`
- Labels are optional in the model and dataset reader
- Model returns an arbitrary dict, so can get and visualize model internals
- Predictor wraps it all in JSON
- Archive lets us load a pre-trained model in a server
- Even better: pre-built UI components (using React) to visualize standard pieces of a model, like attentions, or span labels



We don't have it all figured out!

still figuring out some abstractions that we may not have correct

- regularization and initialization
- models with pretrained components
- more complex training loops
    - e.g. multi-task learning
- Caching preprocessed data
- Expanding vocabulary / embeddings at test time
- Discoverability of config options

you can *do* all these things, but almost certainly not in the most optimal / generalizable way

Case study

"an LSTM for part-of-speech tagging"

(based on the official PyTorch tutorial)

EXAMPLE: AN LSTM FOR PART-OF-SPEECH

In this section, we will use an LSTM to get part of speech tags. We
Backward or anything like that, but as a (challenging) exercise to t
Viterbi could be used after you have seen what is going on.

The model is as follows: let our input sentence be $w_1, \dots, w_M$, w
T be our tag set, and y_i the tag of word w_i. Denote our predictior

This is a structure prediction, model, where our output is a seque

To do the prediction, pass an LSTM over the sentence. Denote th
Also, assign each tag a unique index (like how we had word_to_ix i
section). Then our prediction rule for $\hat{y}_i$ is

$$\hat{y}_i = \text{argmax}_j \, (\log \text{Softmax}(Ah_i + b)$$

That is, take the log softmax of the affine map of the hidden state
that has the maximum value in this vector. Note this implies imme
the target space of A is $|T|$.

Prepare data:

```
def prepare_sequence(seq, to_ix):
    idxs = [to_ix[w] for w in seq]
    return torch.tensor(idxs, dtype=torch.long)


training_data = [
    ("The dog ate the apple".split(), ["DET", "NN", "
    ("Everybody read that book".split(), ["NN", "V",
]
word_to_ix = {}
for sent, tags in training_data:
    for word in sent:
```

The Problem

Given a training dataset that looks like

```
The###DET dog###NN ate###V the###DET apple###NN
Everybody###NN read###V that###DET book###NN
```

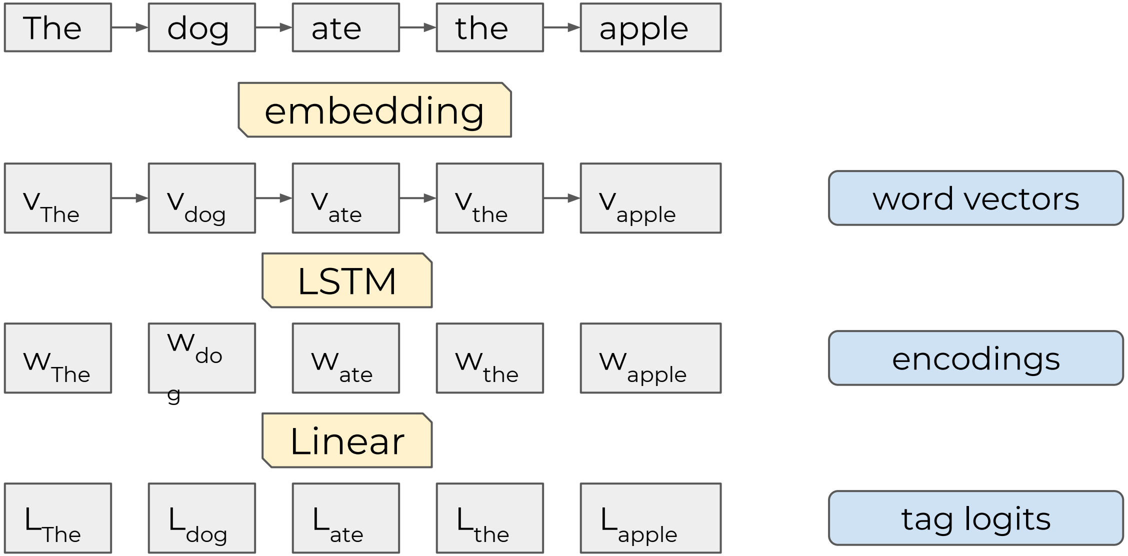
learn to predict part-of-speech tags

With a Few Enhancements to Make Things More Realistic

- read data from files
- check performance on a separate validation dataset
- use `tqdm` to track training progress
- implement early stopping based on validation loss
- track accuracy as we're training

Start With a Simple Baseline Model

- compute a vector embedding for each word
- feed the sequence of embeddings into an LSTM
- feed the hidden states into a feed-forward layer to produce a sequence of logits



v0: numpy

aka "this is why we use libraries"

v0: numpy (aka "this is why we use libraries")

```python
class LSTM:
    def __init__(self, input_size: int, hidden_size: int) -> None:
        self.params = {
            # forget gate
            "w_f": np.random.randn(input_size, hidden_size)
            "b_f": np.random.randn(hidden_size)
            "u_f": np.random.randn(hidden_size, hidden_size)

            # external input gate
            "w_g": np.random.randn(input_size, hidden_size)
            "b_g": np.random.randn(hidden_size)
            "u_g": np.random.randn(hidden_size, hidden_size)

            # output gate
            "w_q": np.random.randn(input_size, hidden_size)
            "b_q": np.random.randn(hidden_size)
            "u_q": np.random.randn(hidden_size, hidden_size)

            # usual params
            "w": np.random.randn(input_size, hidden_size)
            "b": np.random.randn(hidden_size)
            "u": np.random.randn(hidden_size, hidden_size)
        }

        self.grads = {name: None for name in self.params}
```

v1: PyTorch

v1: PyTorch - Load Data

```python
def load_data(file_path: str) -> List[Tuple[str, str]]:
    """
    One sentence per line, formatted like

        The###DET dog###NN ate###V the###DET apple###NN

    Returns a list of pairs (tokenized_sentence, tags)
    """
    data = []

    with open(file_path) as f:
        for line in f:
            pairs = line.strip().split()
            sentence, tags = zip(*(pair.split("###") for pair in pairs))
            data.append((sentence, tags))

    return data
```

seems reasonable

v1: PyTorch - Define Model

```
class LSTMTagger(nn.Module):
    def __init__(self, embedding_dim: int, hidden_dim: int, vocab_size: int, tagset_size: int) -> None:
        super().__init__()
        self.hidden_dim = hidden_dim

        self.word_embeddings = nn.Embedding(vocab_size, embedding_dim)

        # The LSTM takes word embeddings as inputs,
        # and outputs hidden states with dimensionality hidden_dim.
        self.lstm = nn.LSTM(embedding_dim, hidden_dim)

        # The linear layer that maps from hidden state space to tag space
        self.hidden2tag = nn.Linear(hidden_dim, tagset_size)
        self.hidden = self.init_hidden()

    def forward(self, sentence: torch.Tensor) -> torch.Tensor:
        embeds = self.word_embeddings(sentence)
        lstm_out, self.hidden = self.lstm(embeds.view(len(sentence), 1, -1), self.hidden)
        tag_space = self.hidden2tag(lstm_out.view(len(sentence), -1))
        tag_scores = F.log_softmax(tag_space, dim=1)
        return tag_scores
```

much nicer than writing our own LSTM!

v1: PyTorch - Train Model

this part is maybe less than ideal

```
model = LSTMTagger(EMBEDDING_DIM, HIDDEN_DIM,
                   len(word_to_ix), len(tag_to_ix))
loss_function = nn.NLLLoss()
optimizer = optim.SGD(model.parameters(), lr=0.1)

validation_losses = []
patience = 10

for epoch in range(1000):
   training_loss = 0.0
   validation_loss = 0.0

   for dataset, training in [(training_data, True),
                             (validation_data, False)]:
       correct = total = 0
       torch.set_grad_enabled(training)
       t = tqdm.tqdm(dataset)
       for i, (sentence, tags) in enumerate(t):
           model.zero_grad()
           model.hidden = model.init_hidden()

           sentence_in = prepare_sequence(sentence, word_to_ix)
           targets = prepare_sequence(tags, tag_to_ix)

           tag_scores = model(sentence_in)

           loss = loss_function(tag_scores, targets)

           predictions = tag_scores.max(-1)[1]
           correct += (predictions == targets).sum().item()
           total += len(targets)
           accuracy = correct / total

           if training:
               loss.backward()
               training_loss += loss.item()
               t.set_postfix(training_loss=training_loss/(i + 1),
                             accuracy=accuracy)
               optimizer.step()
           else:
               validation_loss += loss.item()
               t.set_postfix(validation_loss=validation_loss/(i + 1),
                             accuracy=accuracy)

   validation_losses.append(validation_loss)

   if (patience and
           len(validation_losses) >= patience and
           validation_losses[-patience] ==
               min(validation_losses[-patience:])):
       print("patience reached, stopping early")
       break
```

v2: AllenNLP

(but without config files)

v2: AllenNLP - Dataset Reader

```
class PosDatasetReader(DatasetReader):
   def __init__(self, token_indexers: Dict[str, TokenIndexer] = None) -> None:
       super().__init__(lazy=False)
       self.token_indexers = token_indexers or {"tokens": SingleIdTokenIndexer()}

   def text_to_instance(self, tokens: List[Token], tags: List[str] = None) -> Instance:
       sentence_field = TextField(tokens, self.token_indexers)
       fields = {"sentence": sentence_field}

       if tags:
           label_field = SequenceLabelField(labels=tags, sequence_field=sentence_field)
           fields["labels"] = label_field

       return Instance(fields)

   def _read(self, file_path: str) -> Iterator[Instance]:
       with open(file_path) as f:
           for line in f:
               pairs = line.strip().split()
               sentence, tags = zip(*(pair.split("###") for pair in pairs))
               yield self.text_to_instance([Token(word) for word in sentence], tags)
```

v2: AllenNLP - Model

```python
class LstmTagger(Model):
    def __init__(self, word_embeddings: TextFieldEmbedder, encoder: Seq2SeqEncoder, vocab: Vocabulary) -> None:
        super().__init__(vocab)
        self.word_embeddings = word_embeddings
        self.encoder = encoder
        self.hidden2tag = torch.nn.Linear(in_features=encoder.get_output_dim(),
                                          out_features=vocab.get_vocab_size('labels'))
        self.accuracy = CategoricalAccuracy()

    def forward(self, sentence: Dict[str, torch.Tensor], labels: torch.Tensor = None) -> torch.Tensor:
        mask = get_text_field_mask(sentence)
        embeddings = self.word_embeddings(sentence)
        encoder_out = self.encoder(embeddings, mask)

        tag_logits = self.hidden2tag(encoder_out)
        output = {"tag_logits": tag_logits}

        if labels is not None:
            self.accuracy(tag_logits, labels, mask)
            output["loss"] = sequence_cross_entropy_with_logits(tag_logits, labels, mask)

        return output

    def get_metrics(self, reset: bool = False) -> Dict[str, float]:
        return {"accuracy": self.accuracy.get_metric(reset)}
```

v2: AllenNLP - Training

```
reader = PosDatasetReader()
train_dataset =
reader.read(cached_path('https://raw.githubusercontent.com/allenai/allennlp/master/tutorials/tagger/training.txt'))
validation_dataset = reader.read(
        cached_path(https://raw.githubusercontent.com/allenai/allennlp/master/tutorials/tagger/validation.txt'))

vocab = Vocabulary.from_instances(train_dataset + validation_dataset)

EMBEDDING_DIM = 6
HIDDEN_DIM = 6

token_embedding = Embedding(num_embeddings=vocab.get_vocab_size('tokens'), embedding_dim=EMBEDDING_DIM)
word_embeddings = BasicTextFieldEmbedder({"tokens": token_embedding})
lstm = PytorchSeq2SeqWrapper(torch.nn.LSTM(EMBEDDING_DIM, HIDDEN_DIM, batch_first=True))
model = LstmTagger(word_embeddings, lstm, vocab)

optimizer = optim.SGD(model.parameters(), lr=0.1)
iterator = BucketIterator(batch_size=2, sorting_keys=[("sentence", "num_tokens")])
iterator.index_with(vocab)

trainer = Trainer(model=model, optimizer=optimizer, iterator=iterator,
                  train_dataset=train_dataset, validation_dataset=validation_dataset,
                  patience=10, num_epochs=1000)

trainer.train()
```

this is where the config-driven approach would make our lives a lot easier

v3: AllenNLP + config

v3: AllenNLP - config

```
local embedding_dim = 6;
local hidden_dim = 6;
local num_epochs = 1000;
local patience = 10;
local batch_size = 2;
local learning_rate = 0.1;

{
   "train_data_path": "...",
   "validation_data_path": "...",
   "dataset_reader": { "type": "pos-tutorial" },
   "model": {
       "type": "lstm-tagger",
       "word_embeddings": {
           "token_embedders": {
               "tokens": {
                   "type": "embedding",
                   "embedding_dim": embedding_dim
               }
           }
       },
       "encoder": {
           "type": "lstm",
           "input_size": embedding_dim,
           "hidden_size": hidden_dim
       }
   },
"iterator": {
       "type": "bucket",
       "batch_size": batch_size,
       "sorting_keys": [["sentence", "num_tokens"]]
   },
   "trainer": {
       "num_epochs": num_epochs,
       "optimizer": {
           "type": "sgd",
           "lr": learning_rate
       },
       "patience": patience
   }
}
```

```
params = Params.from_file('...')
serialization_dir = tempfile.mkdtemp()
model = train_model(params, serialization_dir)
```

Augmenting the Tagger with Character-Level Features

EXERCISE: AUGMENTING THE LSTM PA
WITH CHARACTER-LEVEL FEATURES

In the example above, each word had an embedding, which
model. Let's augment the word embeddings with a represe
the word. We expect that this should help significantly, sinc
affixes have a large bearing on part-of-speech. For example
always tagged as adverbs in English.

To do this, let c_w be the character-level representation of v
as before. Then the input to our sequence model is the co
dimension 5, and c_w dimension 3, then our LSTM should ac

To get the character level representation, do an LSTM over
the final hidden state of this LSTM. Hints:

- There are going to be two LSTM's in your new model.
  scores, and the new one that outputs a character-level
- To do a sequence model over characters, you will have
  embeddings will be the input to the character LSTM.

Total running time of the script: (0 minutes 1.250 secon

Download Python source code: sequence_models_t

Download Jupyter notebook: sequence_models_tut

‹ Previous

v1: PyTorch

```
class LSTMTagger(nn.Module):
   def __init__(self, embedding_dim: int, hidden_dim: int,
                vocab_size: int, tagset_size: int) -> None:
       super().__init__()
       self.hidden_dim = hidden_dim

       self.word_embeddings = nn.Embedding(vocab_size,embedding_dim)

       # The LSTM takes word embeddings as inputs,
       # and outputs hidden states with dimensionality hidden_dim.
       self.lstm = nn.LSTM(embedding_dim, hidden_dim)

       # Linear layer that maps from hidden state space to tag space
       self.hidden2tag = nn.Linear(hidden_dim, tagset_size)
       self.hidden = self.init_hidden()

   def forward(self, sentence: torch.Tensor) -> torch.Tensor:
       embeds = self.word_embeddings(sentence)
       lstm_out, self.hidden = self.lstm(embeds.view(len(sentence), 1,
-1), self.hidden)
       tag_space = self.hidden2tag(lstm_out.view(len(sentence), -1))
       tag_scores = F.log_softmax(tag_space, dim=1)
       return tag_scores
```

add char_embedding_dim

add char_embedding layer = embedding + LSTM?

change LSTM input dim

compute char embeddings

concatenate inputs

we really have to change our model code and how it works

v1: PyTorch

```
class LSTMTagger(nn.Module):
   def __init__(self, embedding_dim: int, hidden_dim: int,
                vocab_size: int, tagset_size: int) -> None:
       super().__init__()
       self.hidden_dim = hidden_dim

       self.word_embeddings = nn.Embedding(vocab_size,embedding_dim)

       # The LSTM takes word embeddings as inputs,
       # and outputs hidden states with dimensionality hidden_dim.
       self.lstm = nn.LSTM(embedding_dim, hidden_dim)

       # Linear layer that maps from hidden state space to tag space
       self.hidden2tag = nn.Linear(hidden_dim, tagset_size)
       self.hidden = self.init_hidden()

   def forward(self, sentence: torch.Tensor) -> torch.Tensor:
       embeds = self.word_embeddings(sentence)
       lstm_out, self.hidden = self.lstm(embeds.view(len(sentence), 1,
-1), self.hidden)
       tag_space = self.hidden2tag(lstm_out.view(len(sentence), -1))
       tag_scores = F.log_softmax(tag_space, dim=1)
       return tag_scores
```

I'm not really that thrilled to do this exercise

v2: AllenNLP

```
reader = PosDatasetReader()

# ...

EMBEDDING_DIM = 6
HIDDEN_DIM = 6

# ...
token_embedding = Embedding(
    num_embeddings=vocab.get_vocab_size('tokens'),
    embedding_dim=EMBEDDING_DIM)


word_embeddings = BasicTextFieldEmbedder(
    {"tokens": token_embedding}
)

# ...
```

add a second token indexer

add an extra parameter

add a character embedder

use the character embedder

```
reader = PosDatasetReader(token_indexers={
    "tokens": SingleIdTokenIndexer(),
    "token_characters": TokenCharactersIndexer()
})

# ...

WORD_EMBEDDING_DIM = 5
CHAR_EMBEDDING_DIM = 3
EMBEDDING_DIM = WORD_EMBEDDING_DIM + CHAR_EMBEDDING_DIM
HIDDEN_DIM = 6

# ...
token_embedding = Embedding(
    num_embeddings=vocab.get_vocab_size('tokens'),
    embedding_dim=WORD_EMBEDDING_DIM)

char_embedding = TokenCharactersEncoder(
    embedding=Embedding(
        num_embeddings=vocab.get_vocab_size('token_characters'),
        embedding_dim=CHAR_EMBEDDING_DIM),
    encoder=PytorchSeq2VecWrapper(
        torch.nn.LSTM(CHAR_EMBEDDING_DIM, CHAR_EMBEDDING_DIM,
                      batch_first=True))

word_embeddings = BasicTextFieldEmbedder({
    "tokens": token_embedding,
    "token_characters": char_embedding})

# ...
```

no changes to the model itself!

v3: AllenNLP - config

```
local embedding_dim = 6;
local hidden_dim = 6;
local num_epochs = 1000;
local patience = 10;
local batch_size = 2;
local learning_rate = 0.1;

{
   "train_data_path": "...",
   "validation_data_path": "...",
   "dataset_reader": { "type": "pos-tutorial" },
   "model": {
       "type": "lstm-tagger",
       "word_embeddings": {
           "token_embedders": {
               "tokens": {
                   "type": "embedding",
                   "embedding_dim": embedding_dim
               }
           }
       },
       "encoder": {
           "type": "lstm",
           "input_size": embedding_dim,
           "hidden_size": hidden_dim
       }
   },
```

we can accomplish this with just a couple of minimal config changes

v3: AllenNLP - config

```
local embedding_dim = 6;
local hidden_dim = 6;
local num_epochs = 1000;
local patience = 10;
local batch_size = 2;
local learning_rate = 0.1;
```

```
local word_embedding_dim = 5;
local char_embedding_dim = 3;
local embedding_dim = word_embedding_dim + char_embedding_dim;
local hidden_dim = 6;
local num_epochs = 1000;
local patience = 10;
local batch_size = 2;
local learning_rate = 0.1;
```

add a couple of new Jsonnet variables

v3: AllenNLP - config

```
"dataset_reader": { "type": "pos-tutorial" }
```

```
"dataset_reader": {
    "type": "pos-tutorial",
    "token_indexers": {
        "tokens": { "type": "single_id" },
        "token_characters": { "type": "characters" }
    }
}
```

add a second token indexer

v3: AllenNLP - config

```
"model": {
    "type": "lstm-tagger",
    "word_embeddings": {
        "token_embedders": {
            "tokens": {
                "type": "embedding",
                "embedding_dim": embedding_dim
            }
```

add a corresponding token embedder

```
        }
    },
    "encoder": {
        "type": "lstm",
        "input_size": embedding_dim,
        "hidden_size": hidden_dim
    }
}
```

```
"model": {
    "type": "lstm-tagger",
    "word_embeddings": {
        "token_embedders": {
            "tokens": {
                "type": "embedding",
                "embedding_dim": word_embedding_dim
            },
            "token_characters": {
                "type": "character_encoding",
                "embedding": {
                    "embedding_dim": char_embedding_dim,
                },
                "encoder": {
                    "type": "lstm",
                    "input_size": char_embedding_dim,
                    "hidden_size": char_embedding_dim
                }
            }
        },
    },
    "encoder": {
        "type": "lstm",
        "input_size": embedding_dim,
        "hidden_size": hidden_dim
    }
}
```

For a one-time change this is maybe not such a big win.

But being able to experiment with lots of architectures without having to change any code (and with a reproducible JSON description of each experiment) is a huge boon to research! (we think)

Sharing Your Research

How to make it easy to release your code

In the least amount of time possible:

Simplify your workflow for installation and data

Make your code run anywhere*

ANACONDA

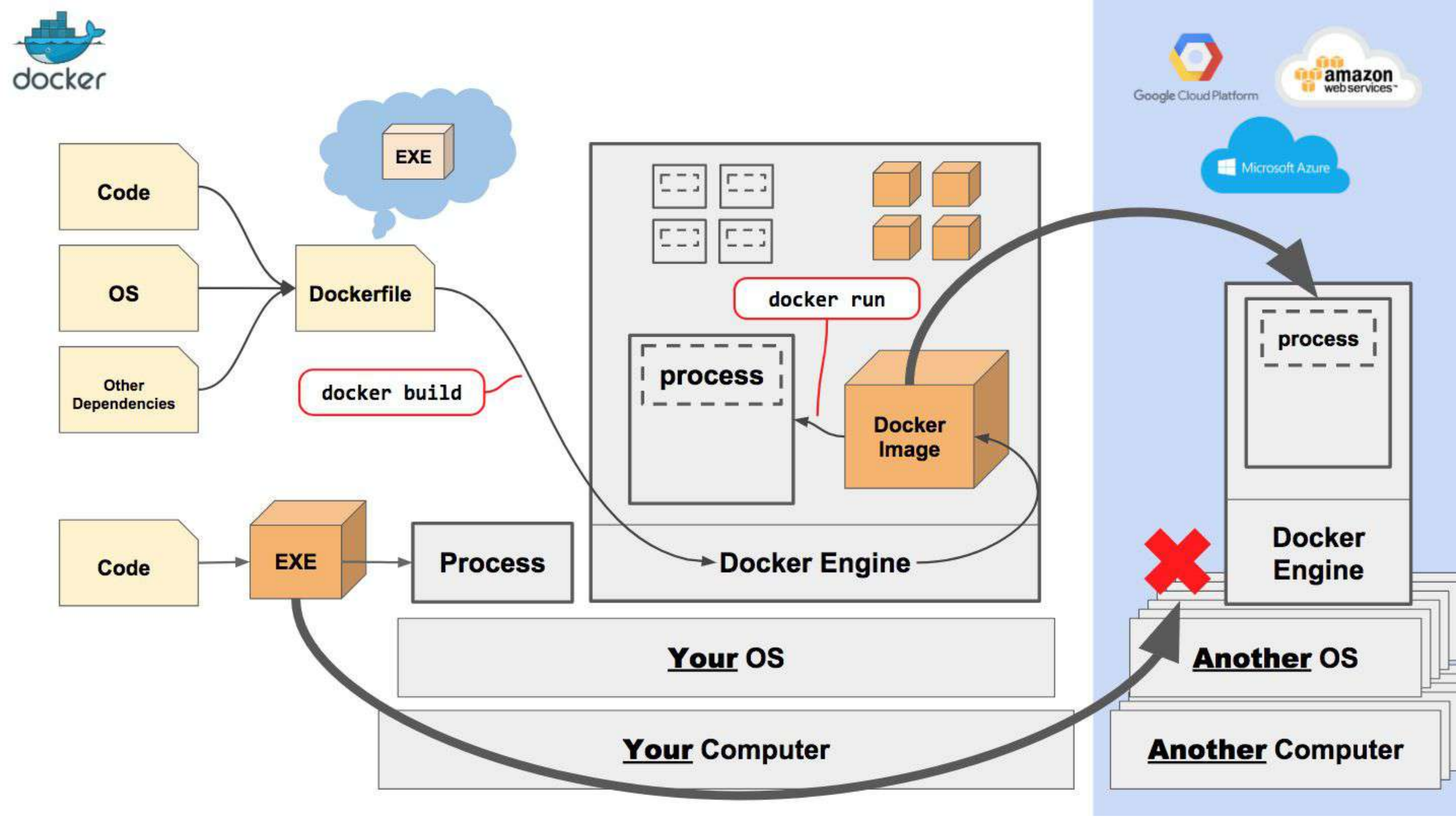
Isolated environments for your project

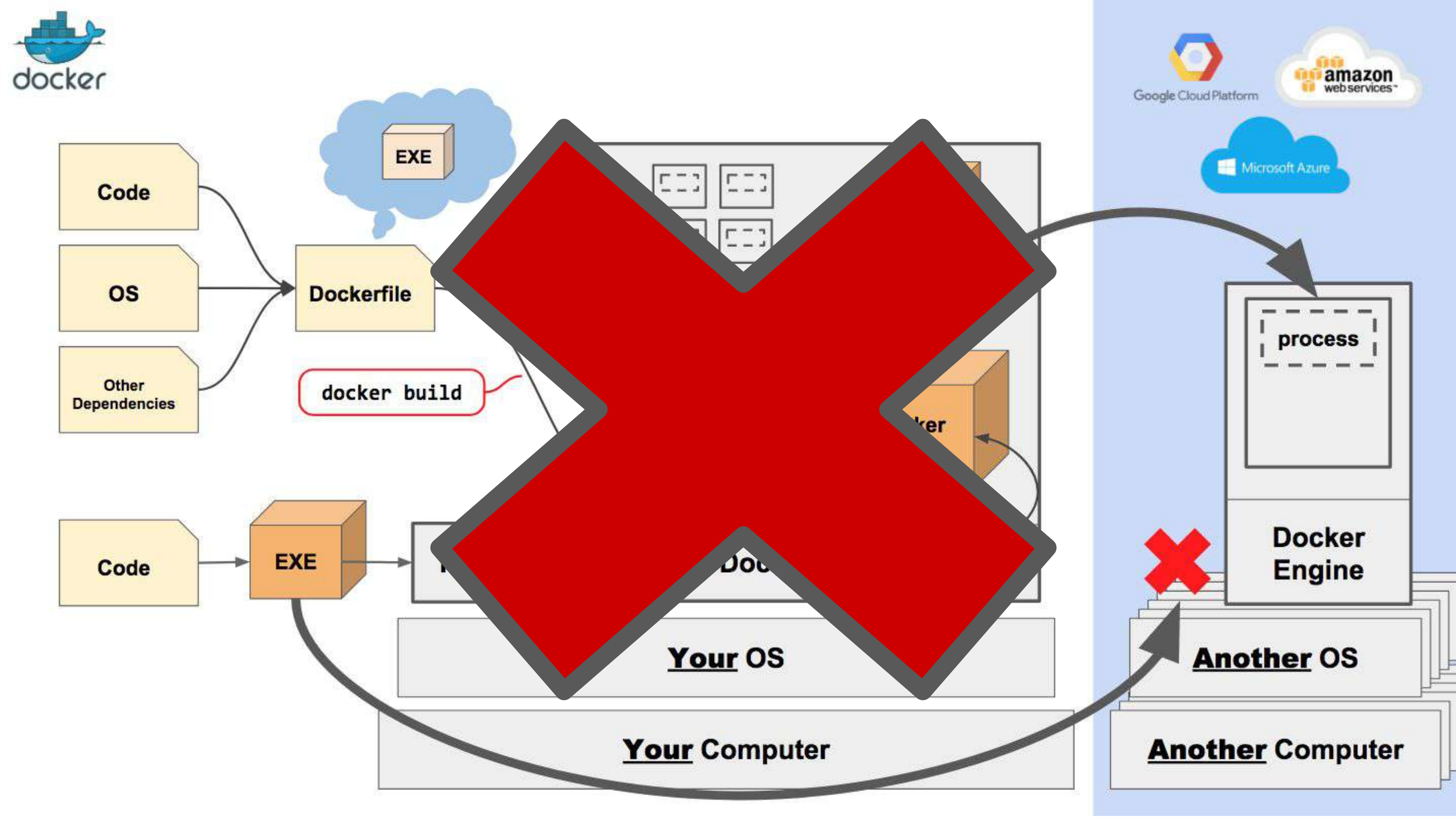
Docker

Objective: You don't feel like this about Docker

What does Docker Do?

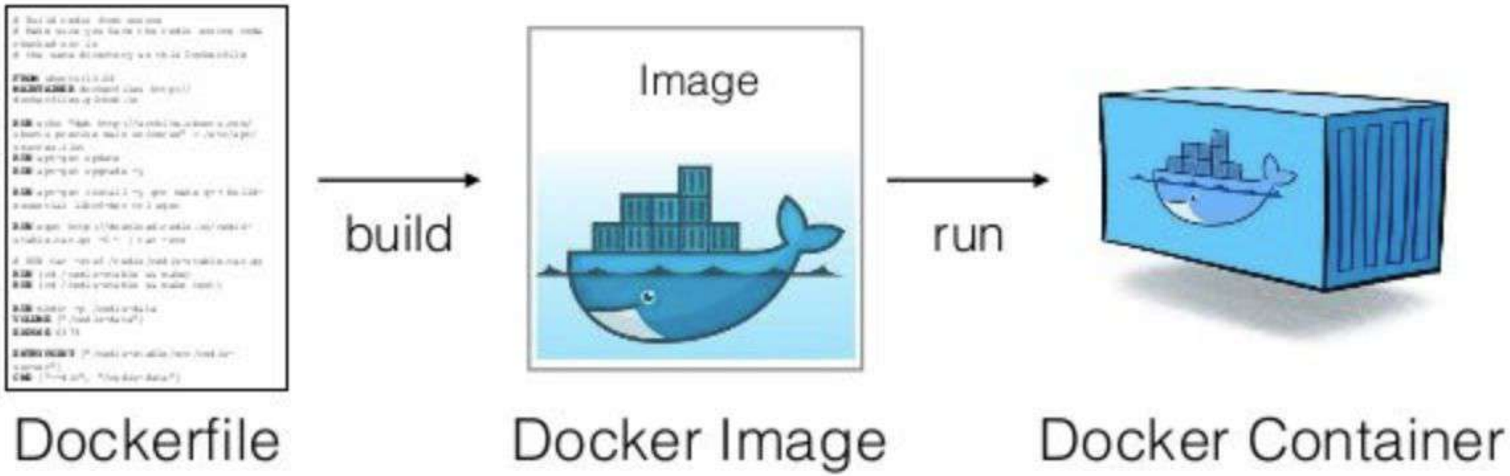
- Creates a virtual machine that will always run the same anywhere (In theory)
- Allows you to package up a virtual machine and some code and send it to someone, knowing the same thing will run
- Includes operating systems, dependencies for your code, your code etc.
- Let's you specify in a series of steps how to create this virtual machine and does clever caching when you change it.


docker
Google Cloud Platform
amazon web services
Microsoft Azure
EXE
Code
OS
Other Dependencies
Dockerfile
docker build
docker run
process
Docker Image
Docker Engine
Code
EXE
Process
Your OS
Your Computer
process
Docker Engine
Another OS
Another Computer



docker
Google Cloud Platform
amazon web services
Microsoft Azure
EXE
Code
OS
Other Dependencies
Dockerfile
docker build
process
Docker Engine
Code
EXE
Your OS
Another OS
Your Computer
Another Computer

3 Ideas: **Dockerfiles**, **Images** and **Containers**



Step 1: Write a Dockerfile

Here is a finished Dockerfile.

How does this work?

```
FROM python:3.6.3-jessie

ENV LC_ALL=C.UTF-8
ENV LANG=C.UTF-8


# This specifies where the current working
# directory is when we start copying files in.
WORKDIR /stage/allennlp

# Install base packages like gcc, git etc.
RUN apt-get update --fix-missing && apt-get install -y \
    bzip2 \
    ca-certificates \
    curl \
    gcc \
    git \
    libc-dev \
    libglib2.0-0 \
    libsm6 \
    libxext6 \
    libxrender1 \
    wget \
    libevent-dev \
    build-essential && \
    rm -rf /var/lib/apt/lists/*

# Optional argument to set an environment variable with the Git SHA
ARG SOURCE_COMMIT
ENV SOURCE_COMMIT $SOURCE_COMMIT

# This exposes port 8000 to outside of the Docker container.
# This is helful if you want to run a model server or something.
EXPOSE 8000

CMD ["/bin/bash"]
```

Step 1: Write a Dockerfile

```
COMMAND <command>
```

Step 1: Write a Dockerfile

$\boxed{\texttt{COMMAND}}$ `<command>`

Dockerfile commands are capitalised. Some important ones are: **`FROM`**, **`RUN`**, **`ENV`**, **`COPY`** and **`CMD`**

Step 1: Write a Dockerfile

```
FROM python:3.6.3-jessie
```

FROM includes another Dockerfile in your one. Here we start from a base Python Dockerfile.

Step 1: Write a Dockerfile

```
RUN pip install -r requirements.txt
```

RUN … runs a command. To use a command, it must be installed in a previous step!

Step 1: Write a Dockerfile

```
ENV LANG=C.UTF-8
```

ENV sets an environment variable which can be used inside the container.

Step 1: Write a Dockerfile

```
COPY my_research/ my_research/
```

COPY copies code from your current folder into the Docker image.

Step 1: Write a Dockerfile

```
COPY my_research/ my_research/
```

Do yourself a favour.
Don't change the names of things during this step.

Step 1: Write a Dockerfile

```
CMD [“/bin/bash”]
CMD [“python”, “my/script.py”]
```

CMD is what gets run when you ***run*** a built image.

Step 1: Write a Dockerfile

Here is a finished Dockerfile.

```
FROM python:3.6.3-jessie

ENV LC_ALL=C.UTF-8
ENV LANG=C.UTF-8


# This specifies where the current working
# directory is when we start copying files in.
WORKDIR /stage/allennlp

# Install base packages like gcc, git etc.
RUN apt-get update --fix-missing && apt-get install -y \
    bzip2 \
    ca-certificates \
    curl \
    gcc \
    git \
    libc-dev \
    libglib2.0-0 \
    libsm6 \
    libxext6 \
    libxrender1 \
    wget \
    libevent-dev \
    build-essential && \
    rm -rf /var/lib/apt/lists/*

# Optional argument to set an environment variable with the Git SHA
ARG SOURCE_COMMIT
ENV SOURCE_COMMIT $SOURCE_COMMIT

# This exposes port 8000 to outside of the Docker container.
# This is helful if you want to run a model server or something.
EXPOSE 8000

CMD ["/bin/bash"]
```

Step 2: Build your **Dockerfile** into an **Image**

```
docker build --tag <name> .
```

Step 2: Build your **Dockerfile** into an **Image**

```
docker build --tag <name> .
```

This is what you want the image to be called, e.g `markn/my-paper-code`.

Step 2: Build your **Dockerfile** into an **Image**

```
docker build --tag <name> .
```

You can see what images you have built already by running

```
docker images
```

Step 2: Build your **Dockerfile** into an **Image**

```
docker build --tag <name> .
```

This describes where docker should look for a Dockerfile. It can also be a URL.

Step 2: Build your **Dockerfile** into an **Image**

```
docker build --tag <name> .
```

If you've already built a line of your dockerfile before, Docker will remember and not build it again (so long as things before it haven't changed.)

```
Sending build context to Docker daemon  192.3MB
Step 1/32 : FROM python:3.6.3-jessie
 ---> 79e1dc9af1c1
Step 2/32 : ENV LC_ALL C.UTF-8
 ---> Using cache
 ---> 661329a57650
Step 3/32 : ENV LANG C.UTF-8
 ---> Using cache
 ---> 623908bc3a31
```

Step 2: Build your **Dockerfile** into an **Image**

```
docker build --tag <name> .
```

TIP: Put things that change more frequently (like your code) lower down in your Dockerfile.

```
Sending build context to Docker daemon  192.3MB
Step 1/32 : FROM python:3.6.3-jessie
 ---> 79e1dc9af1c1
Step 2/32 : ENV LC_ALL C.UTF-8
 ---> Using cache
 ---> 661329a57650
Step 3/32 : ENV LANG C.UTF-8
 ---> Using cache
 ---> 623908bc3a31
```

Step 3: Run your **Image** as a **Container**

```
docker run <image-name>
```

Step 3: Run your **Image** as a **Container**

```
docker run -it <image-name>
```

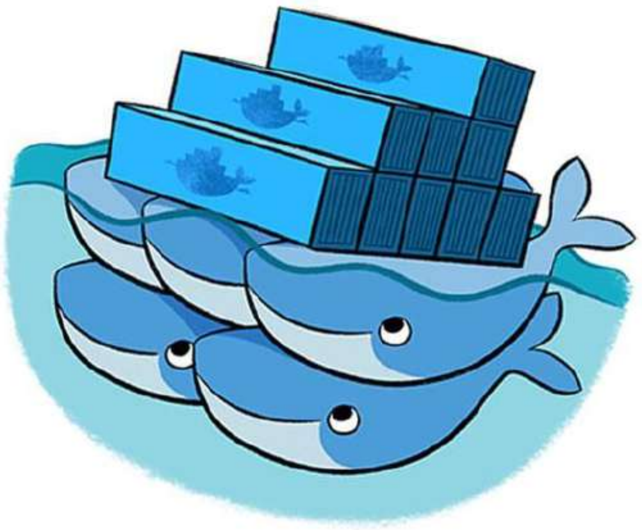
```
-i: interactive
-t: tty (with a terminal)
```

Step 3: Run your **Image** as a **Container**

```
docker run -it -e /bin/bash ...
```

These arguments will give you a command prompt inside any docker container, regardless of the CMD in the Dockerfile.

Optional Step 4: DockerHub



DockerHub is to **Docker** as **Github** is to **Git**

Docker automatically looks at dockerhub to find Docker images to run

```
docker push <image-name>
```

Pros of Docker

- Good for running CI - ALL your code dependencies are pinned, even system level stuff.
- Good for debugging people's problems with your code - just ask: Can you reproduce bug that in a Docker Container
- Great for deploying demos where you just need a model to run as a service.

Cons of Docker

- Docker is designed for production systems - it is very hard to debug inside a minimal docker container
- Takes up a lot of memory if you have a lot of large dependencies (e.g the JVM makes up about half of the AllenNLP Docker image)
- Just because your code is exactly reproducible doesn't mean that it's any good

Releasing your data

Use a simple file cache

First, download and unzip GloVe vectors from the Stanford NLP group website, with:

```
chmod +x download.sh; ./download.sh
```

Then prepare vocabulary and initial word vectors with:

```
python prepare_vocab.py dataset/tacred dataset/vocab --glove_dir dataset/glove
```

This will write vocabulary and word vectors as a numpy matrix into the dir `dataset/vocab`.

There are currently 27 CoreNLP Jar files you could download from the CoreNLP website

Data

We provide Quasar-T, SearchQA and TrivialQA dataset we used for the task in data/ directory. We preprocess the original data to make it satisfy the input format of our codes, and can be download at here.

To run our code, the dataset should be put in the folder data/ using the following format:

datasets/

- train.txt, dev.txt, test.txt: format for each line: {"question": quetion, "answers":[answer1, answer2, ...]}.
- train.json, dev.json, test.json: format [{"question": question, "document":document1},{"question": question, "document":document2}, ...].

embeddings/

- glove.840B.300d.txt: word vectors obtained from here.

corenlp/

- all jar files from Stanford Corenlp.

Use a simple file cache

```
embedding_file = cached_path(“embedding_url”)
datasets = cached_path(“dataset_url”)
```

Data

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embeddings/

- glove.840B.300d.txt: word vectors obtained from here.

corenlp/

- all jar files from Stanford Corenlp.

Use a simple file cache

But now I have to
write a file cache ....

Use a simple file cache

Copy this file into your project

```
from file_cache import cached_path
embeddings = cached_path(url)
```

Isolated (Python) environments

Python environments

Stable environments for Python can be tricky

This makes releasing code very annoying

Python environments

Docker is ideal, but not great for developing locally. For this, you should either use **virtualenvs** or **anaconda**.

Here we will talk about **anaconda**, because it's what we use.

Python environments

Anaconda is a very stable distribution of Python (amongst other things). Installing it is easy:

https://www.anaconda.com/

Python environments

One annoying install step - adding where you installed it to the **front** of your PATH environment variable.

```
export PATH=”/path/to/anaconda/bin:PATH”
```

Python environments

Now, your default `python` should be an anaconda one *(you did install python > 3.6, didn't you)*.

ANACONDA®

```
markn@markn ~ $ python
Python 3.6.3 |Anaconda, Inc.| (default, Oct  6 2017, 12:04:38)
[GCC 4.2.1 Compatible Clang 4.0.1 (tags/RELEASE_401/final)] on darwin
Type "help", "copyright", "credits" or "license" for more information.
>>>
```

Virtual environments

Every time you start a new project, make a new virtual environment which has only its dependencies in.

```
conda create -n
your-env-name
python=3.6
```

Virtual environments

Before you work on your project, run this command. This prepends the location of this particular copy of Python to your PATH.

```
source activate
your-project-name
```

```
pip install -r
requirements.txt
```

```
etc
```

Virtual environments

When you're done, or you want to work on a different project, run:

```
source deactivate
your-project-name
```

In Conclusion

In Conclusion

- Prototype fast (but still safely)
- Write production code safely (but still fast)
- Good processes => good science
- Use the right abstractions
- Check out AllenNLP

Thanks for Coming!

Questions?

please fill out our survey:
`https://tinyurl.com/emnlp-tutorial-survey`

will tweet out link to slides after talk
@ai2_allennlp