Transfer Learning

March 4th, 2021
UW DATA 598

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AI2

Slides adapted from…

Transfer Learning in Natural Language Processing

June 2, 2019
NAACL-HLT 2019

Sebastian Ruder

AllenNLP

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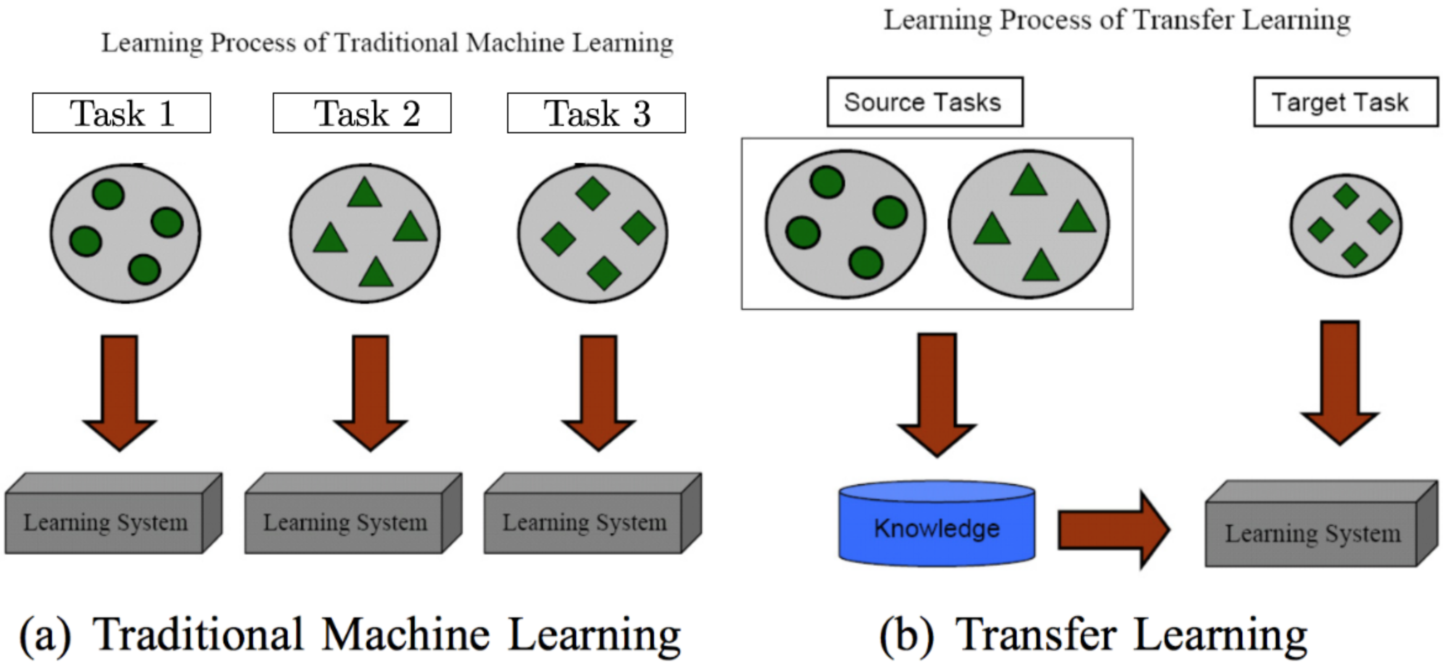
Thomas Wolf

What is transfer learning?



Pan and Yang (2010)

Preliminaries

- Focus: Natural Language Processing
- Goal: provide broad overview of methods in transfer learning
    - focusing on the most empirically successful methods *in NLP (as of 2019)*
- Demo:
    - Transfer learning from language model to a text classification task in NLP

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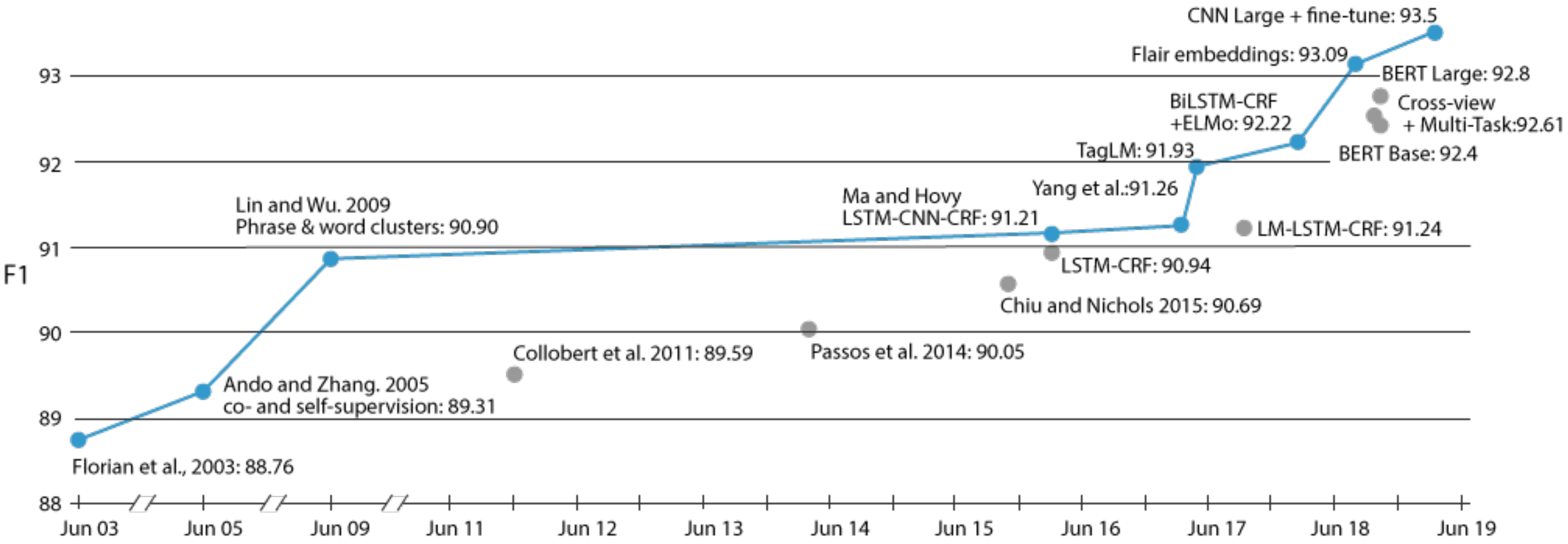
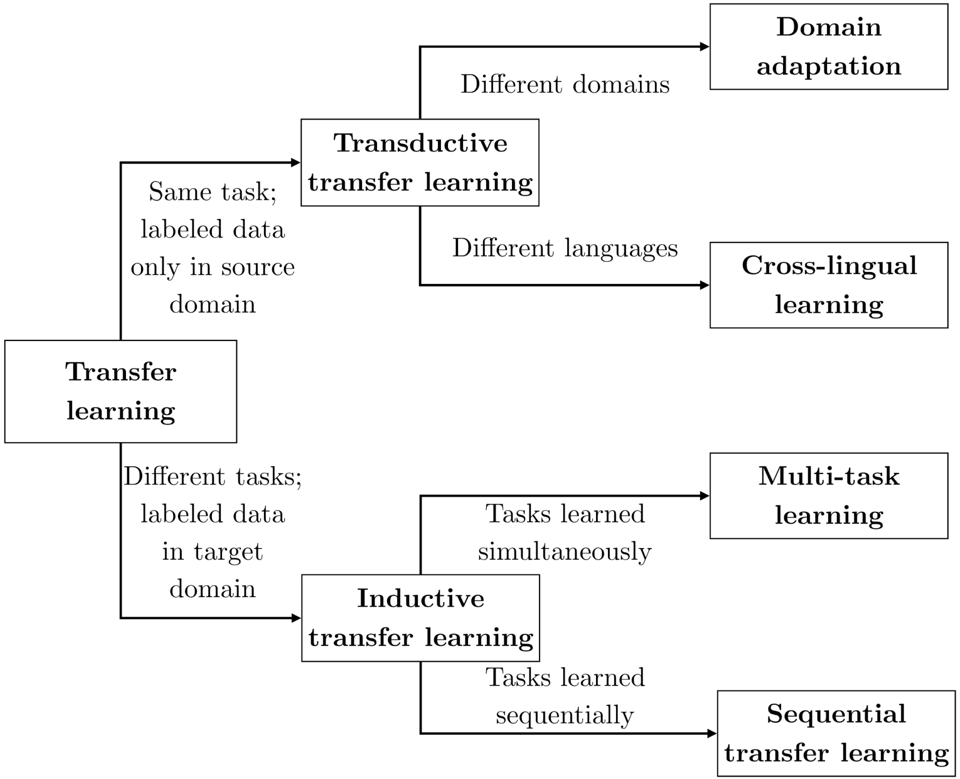
- Empirically, transfer learning has resulted in state-of-the-art performance
  - for many supervised NLP tasks (e.g. classification, information extraction, Q&A, etc).

Why transfer learning (in NLP)? Empirically...

Performance on Named Entity Recognition (NER) on CoNLL-2003 (English) over time



Types of transfer learning in NLP



Ruder (2019)

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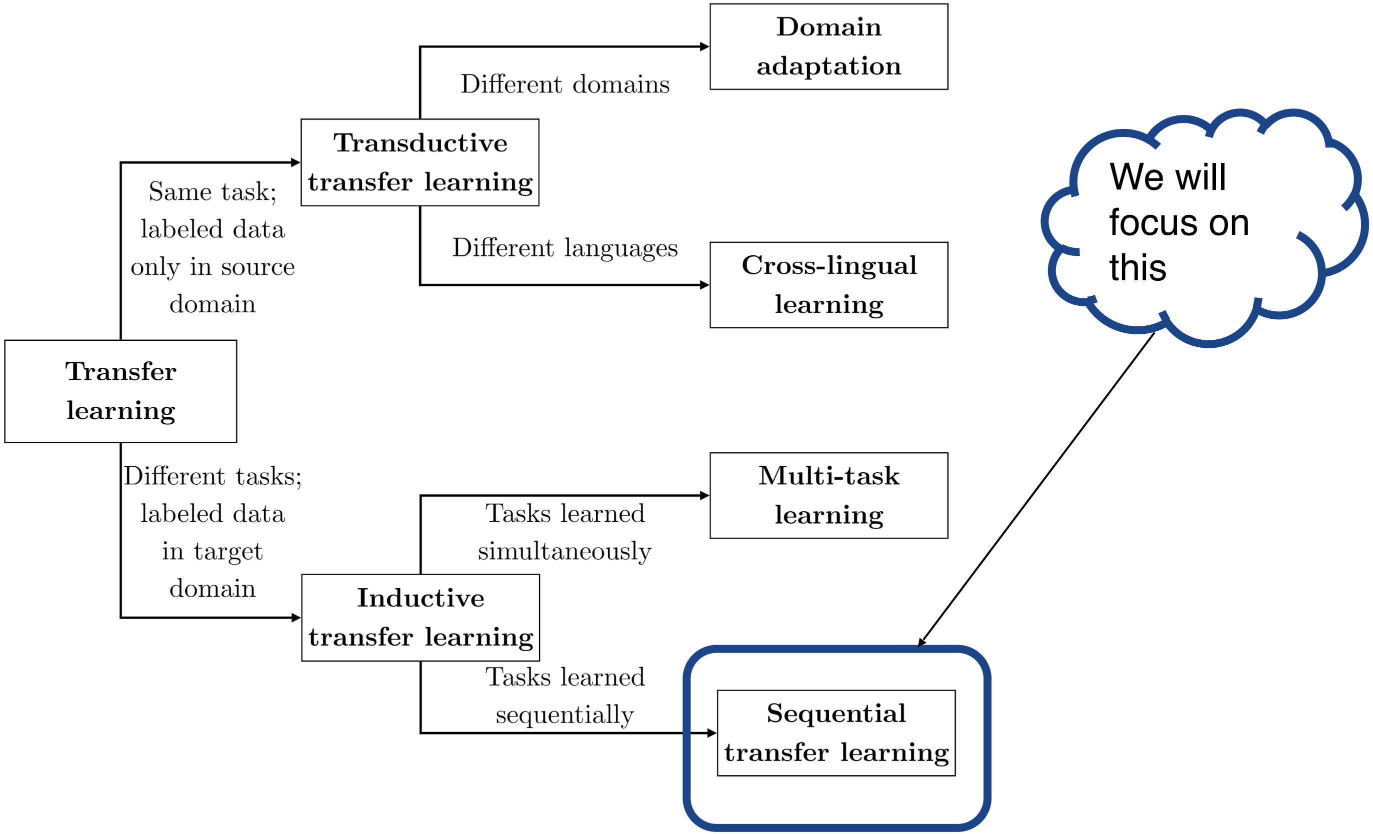


Ruder (2019)

Agenda

[1] Introduction

[2] Pretraining

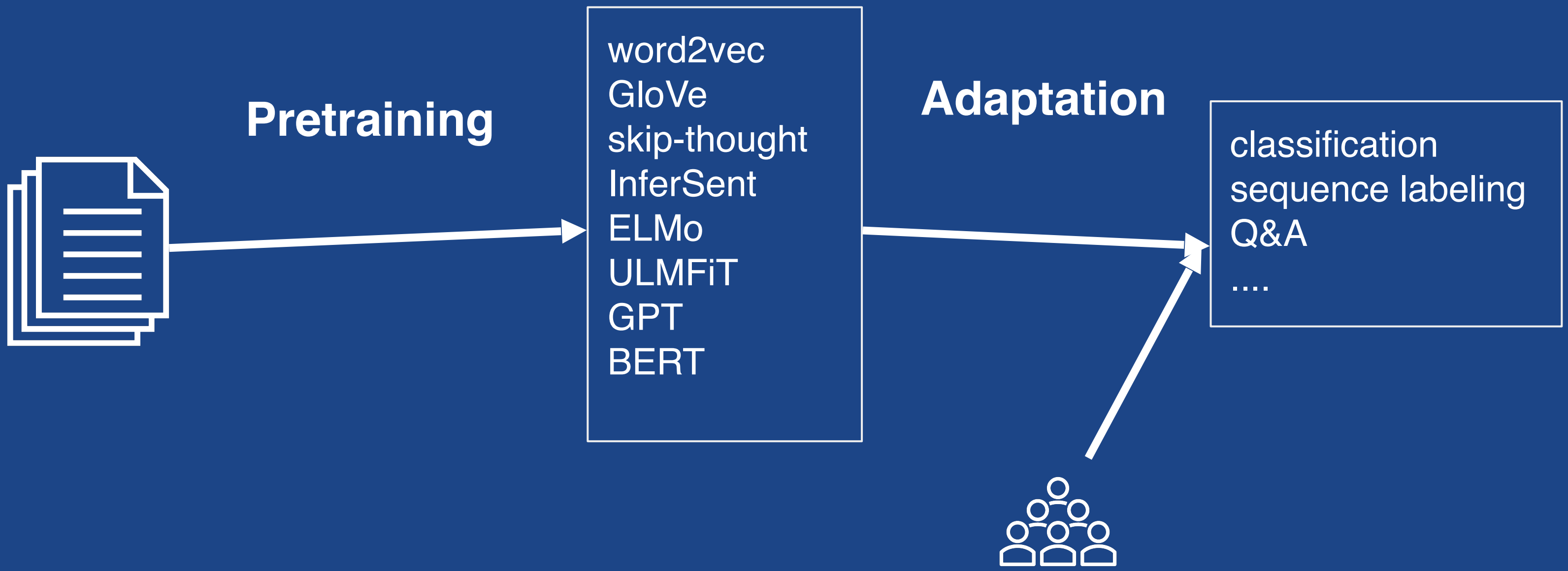
[3] What’s in a representation?

[4] Adaptation

1. Introduction

Sequential transfer learning

Learn on one task / dataset, then transfer to another task / dataset



Pretraining tasks and datasets

- ❑ Unlabeled data and self-supervision
- ❑ Supervised pretraining

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  - NLI for sentence representations
  - Task-specific—transfer from one Q&A dataset to another

Concrete example—word vectors

Word embedding methods (e.g. word2vec) learn one vector per word:

cat = [0.1, -0.2, 0.4, …]

dog = [0.2, -0.1, 0.7, …]

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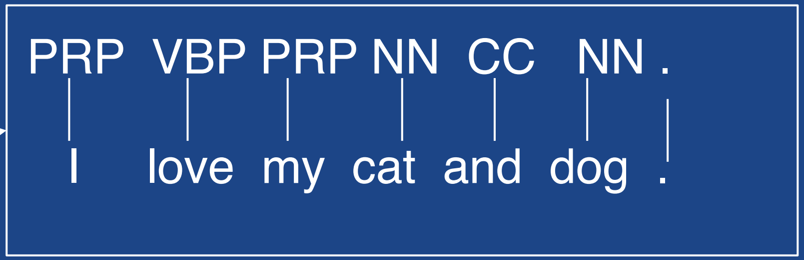

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PRP	VBP	PRP	NN	CC	NN	.
I	love	my	cat	and	dog	.

I love my cat and dog . }-> “positive"

Major Themes

Major themes: From words to words-in-context

Word vectors

cats = [0.2, -0.3, …]

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We have two cats. } [-1.2, 0.0, …]

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Word-in-context vectors

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- Doesn't require human annotation
- Many languages have enough text to learn high capacity model
- Versatile—can learn both sentence and word representations with a variety of objective functions

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- ❑ Word vectors can be pooled across contexts, but often outperformed by other methods
- ❑ In contextual word vectors, bidirectional context important

In general:

- ❑ Similar pretraining and target tasks → best results

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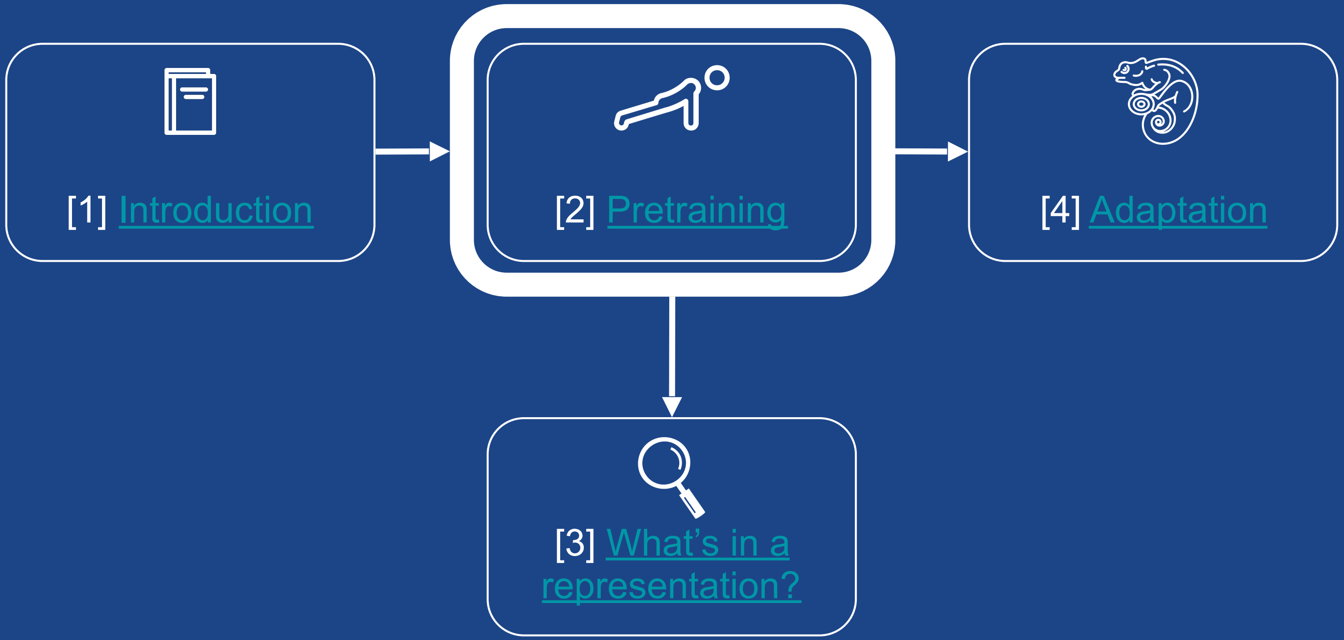
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2. Pretraining

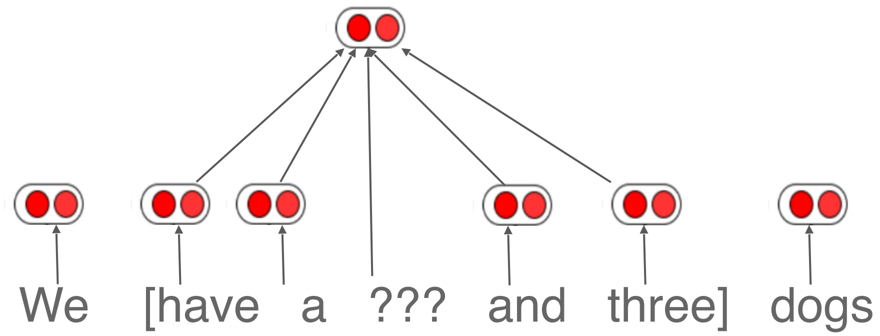
Image credit: Creative Stall

Overview

- ❑ Language model pretraining
- ❑ Word vectors (types)
- ❑ Contextual word vectors (tokens)
- ❑ Self-supervised and Supervised pretraining

LM pretraining

word2vec, Mikolov et al (2013)



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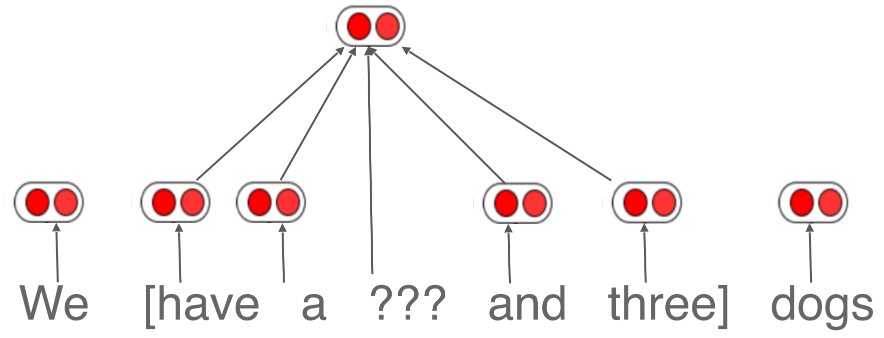
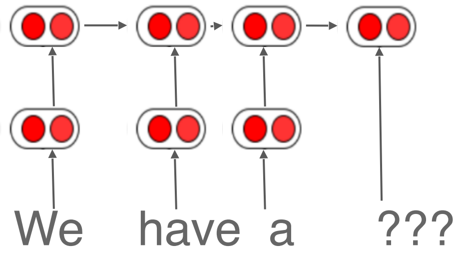


ELMo, Peters et al. 2018, ULMFiT (Howard & Ruder 2018), GPT (Radford et al. 2018)



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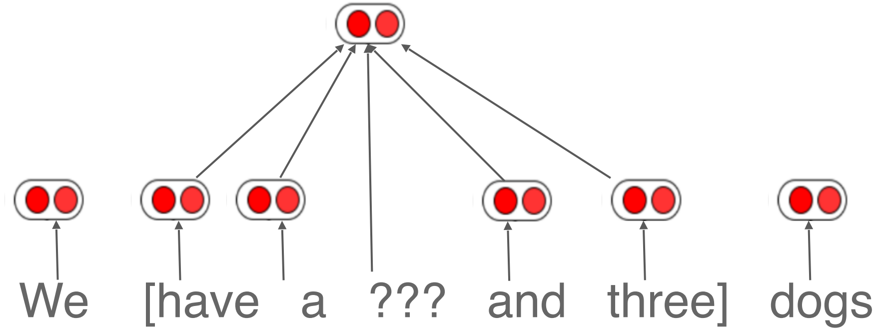

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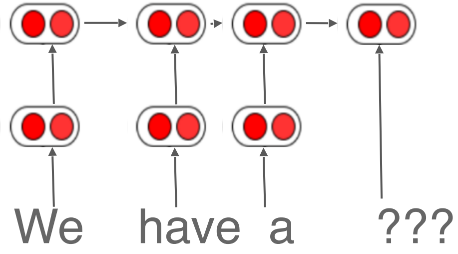
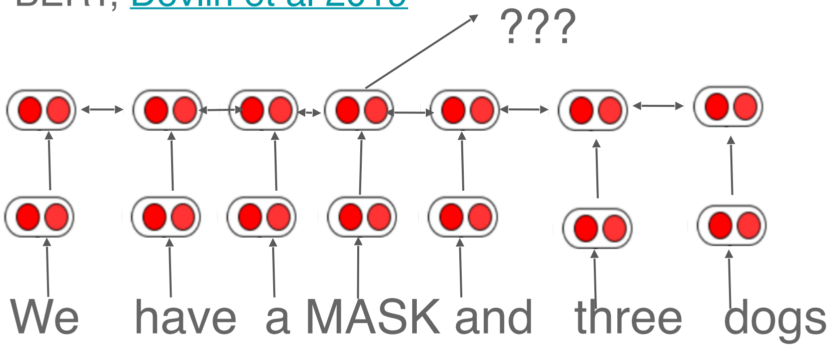


BERT, Devlin et al 2019



Word vectors

Why embed words?

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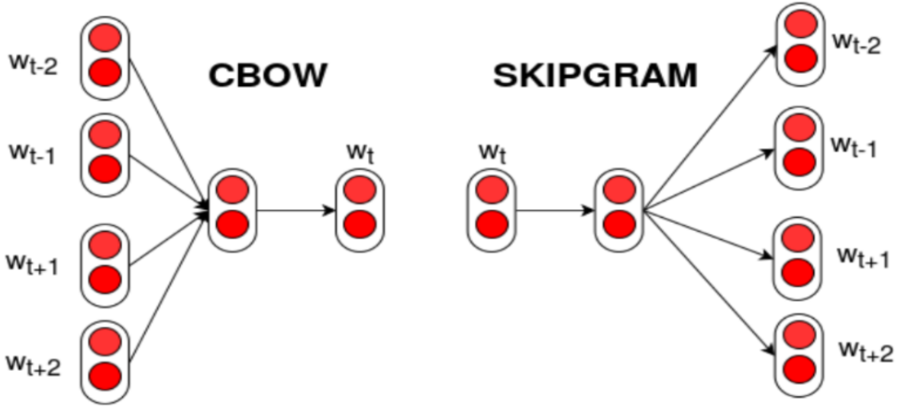
- Embeddings are themselves parameters—can be learned
- Sharing representations across tasks
- Lower dimensional space
  - Better for computation—difficult to handle sparse vectors.

word2vec

Efficient algorithm + large scale training → high quality word vectors

(Mikolov et al., 2013)



$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c, j\neq 0} logp(w_t|w_{t+j})$$

$$\frac{1}{T}\sum_{t=1}^{T}\sum_{-c\leq j\leq c, j\neq 0} logp(w_{t+j}|w_t)$$

See also:

- Pennington et al. (2014): GloVe
- Bojanowski et al. (2017): fastText

Contextual word vectors

Contextual word vectors - Motivation

Word vectors compress all contexts into a *single vector*

Nearest neighbor GloVe vectors to "**play**"

VERB	NOUN	ADJ
playing	game	multiplayer
played	games	
	players	
	football	

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VERB	NOUN	ADJ	??
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played	games		(theatrical)
	players		Play
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Contextual word vectors - Key Idea

- ✦ Instead of learning one vector per word type, learn a vector that depends on context

f(play | The kids play a game in the park.)

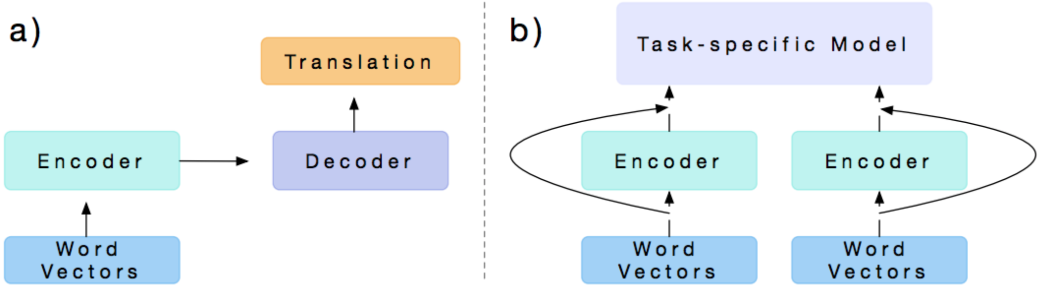
!=

f(play | The Broadway play premiered yesterday.)

- ✦ Many approaches based on language models.
  - ✦ We'll only look at a few.

Pretraining Tasks

Supervised Pretraining: CoVe



(McCann et al, NeurIPS 2017)

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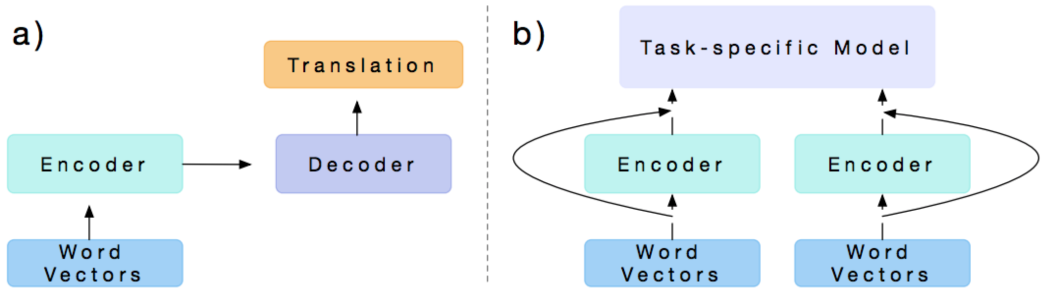

Pretrain bidirectional encoder with MT supervision, extract LSTM states

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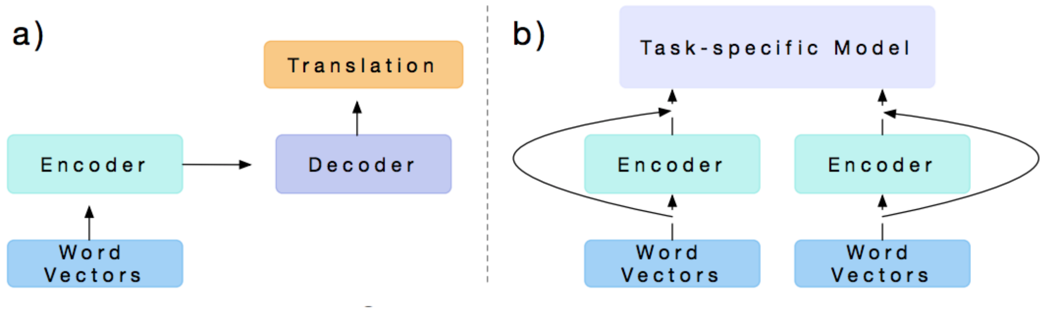


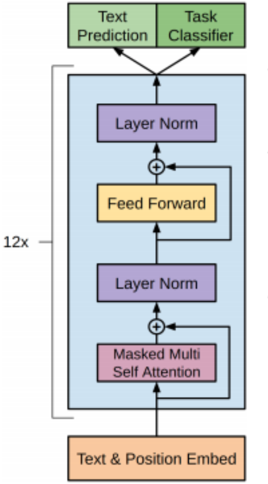
Dataset	Random	GloVe	GloVe+ Char	GloVe+ CoVe-S	GloVe+ CoVe-M	GloVe+ CoVe-L	GloVe+ Char+CoVe-L
SST-2	84.2	88.4	90.1	89.0	90.9	91.1	**91.2**
SST-5	48.6	53.5	52.2	54.0	54.7	54.5	**55.2**
IMDb	88.4	91.1	91.3	90.6	91.6	91.7	**92.1**
TREC-6	88.9	94.9	94.7	94.7	95.1	95.8	**95.8**
TREC-50	81.9	89.2	89.8	89.6	89.6	90.5	**91.2**
SNLI	82.3	87.7	87.7	87.3	87.5	87.9	**88.1**
SQuAD	65.4	76.0	78.1	76.5	77.1	79.5	**79.9**

Pretrain bidirectional encoder with MT supervision, extract LSTM states

Adding CoVe with GloVe gives improvements for classification, NLI, Q&A

(McCann et al, NeurIPS 2017)

Self-supervised Pretraining: GPT



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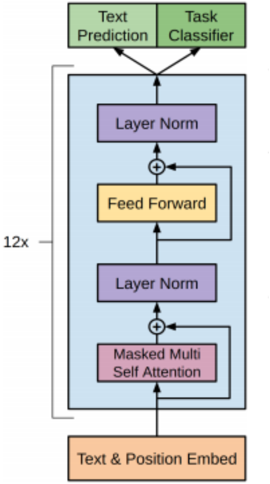

Pretrain large 12-layer **left-to-right** Transformer Language Model.

[(Radford et al., 2018)](#)

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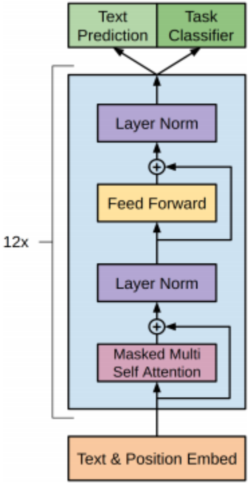

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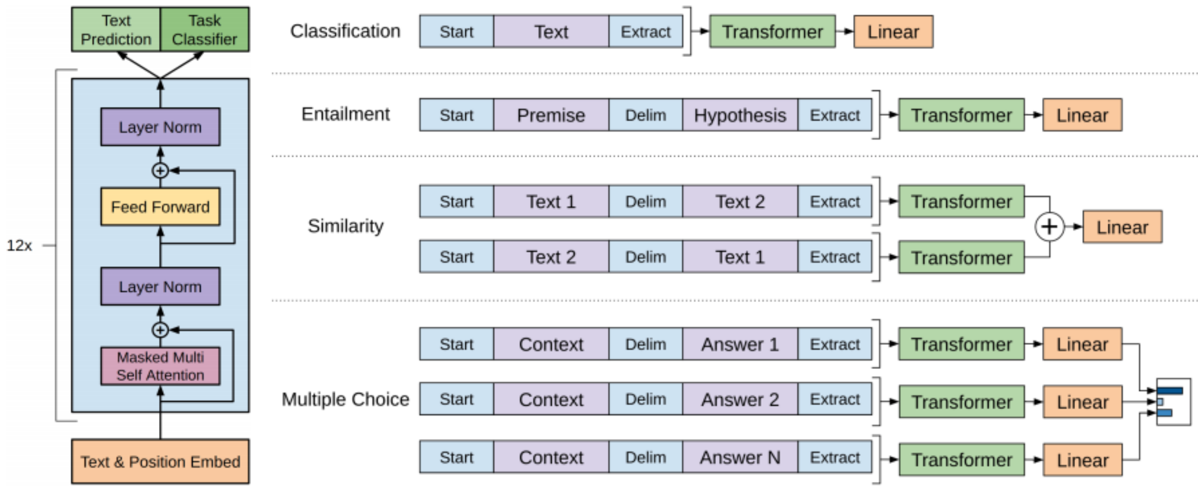

Method	MNLI-m	MNLI-mm	SNLI	SciTail	QNLI	RTE
ESIM + ELMo [44] (5x)	-	-	89.3	-	-	-
CAFE [58] (5x)	80.2	79.0	89.3	-	-	-
Stochastic Answer Network [35] (3x)	80.6	80.1	-	-	-	-
CAFE [58]	78.7	77.9	88.5	83.3		
GenSen [64]	71.4	71.3	-	-	82.3	59.2
Multi-task BiLSTM + Attn [64]	72.2	72.1	-	-	82.1	**61.7**
Finetuned Transformer LM (ours)	**82.1**	**81.4**	**89.9**	**88.3**	**88.1**	56.0

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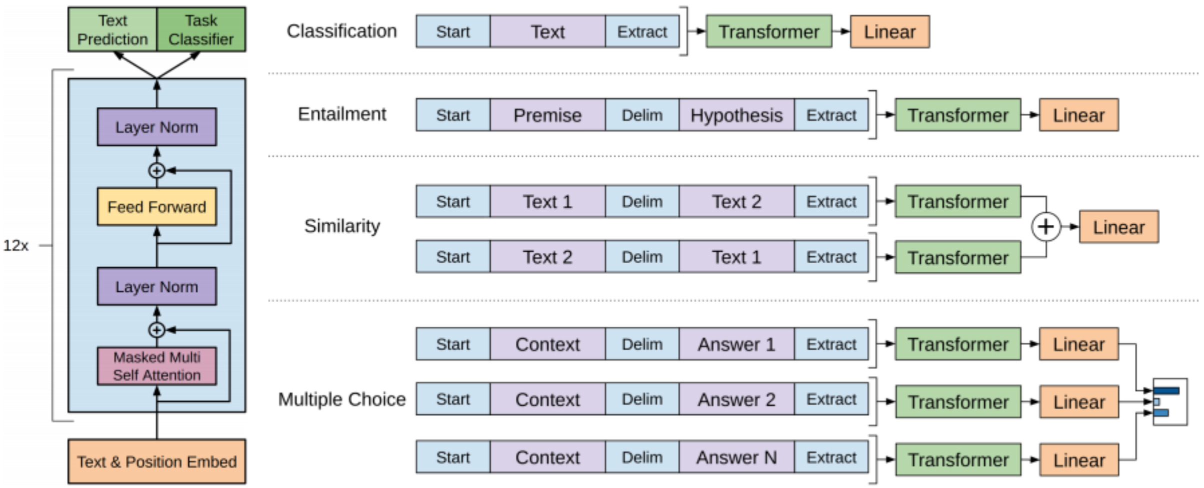

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More variants of GPT: 2 and 3!

(Radford et al., 2018)

Self-supervised Pretraining: BERT

BERT pretrains both sentence and contextual word representations, using **masked LM** and **next sentence prediction**. BERT-large has 340M parameters, 24 layers!

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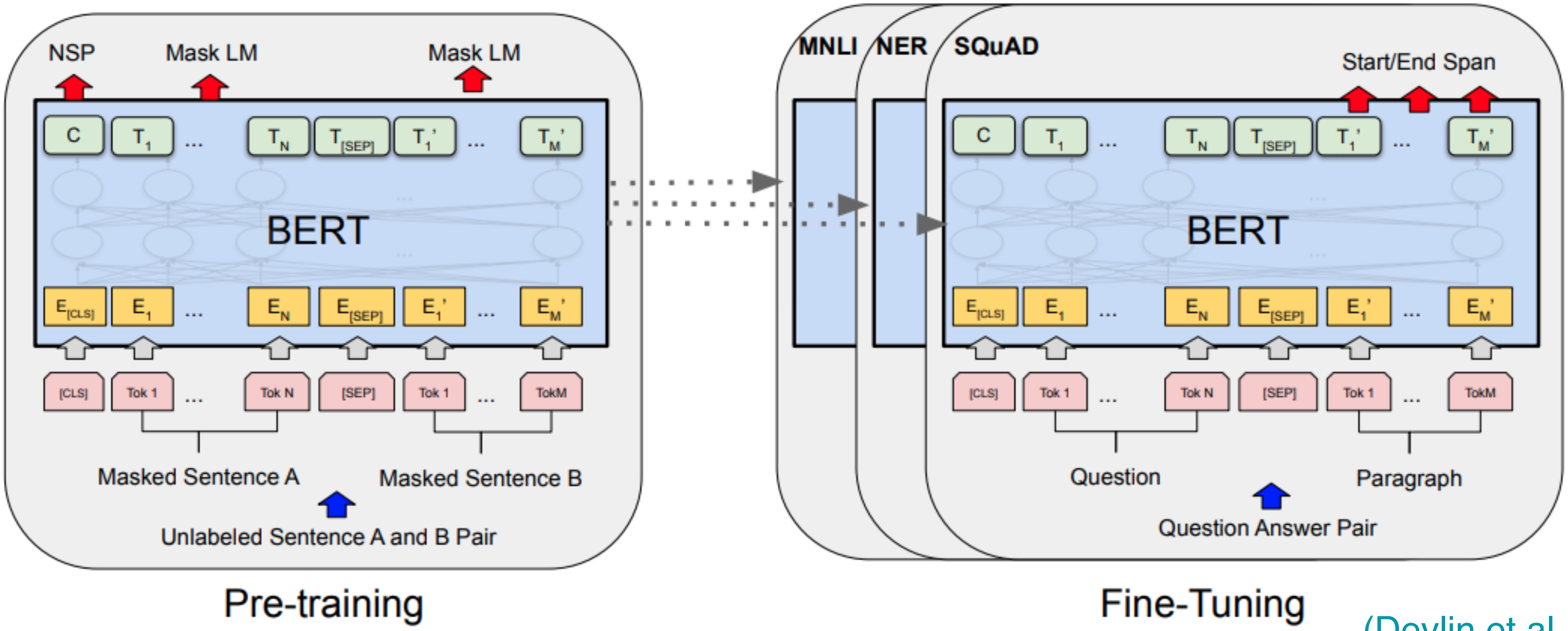

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- Given enough data, a huge model, and enough compute, can do a reasonable job!
- Empirically works better than translation: “Language Modeling Teaches You More Syntax than Translation Does” (Zhang et al. 2018)

Hands-on #1:
Pretraining a Transformer Language Model

Image credit: Chanaky

Hands-on: Overview

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  - ❑ Expose all the details in a simple, concise and self-contained code-base
  - ❑ Show that transfer learning can be simple (less hand-engineering) & fast (pretrained model)
- ❑ Plan
  - ❑ Build a GPT-2 / BERT model
  - ❑ Pretrain it on a rather large corpus with ~100M words
  - ❑ Adapt it for a target task (question categorization) to get SOTA performances

Hands-on pre-training

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- ❏ applying a succession of transformer blocks with:
  - ❏ layer normalisation
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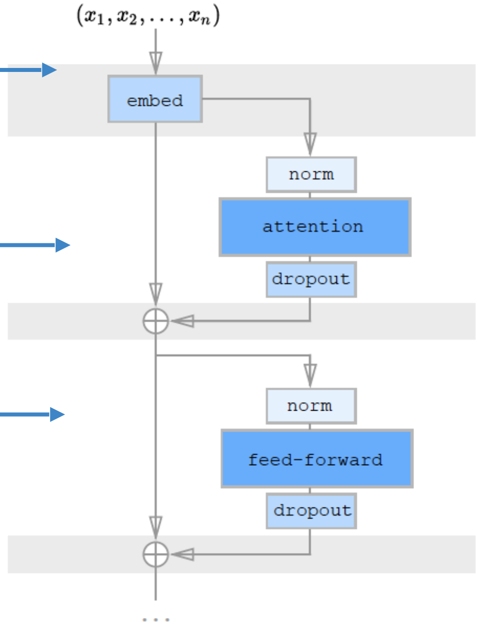

Illustration from (Child et al, 2019)

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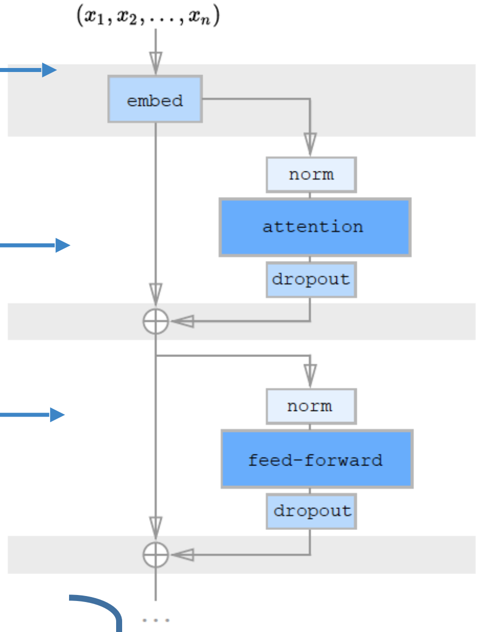


Main differences between GPT/GPT-2/BERT are the objective functions:

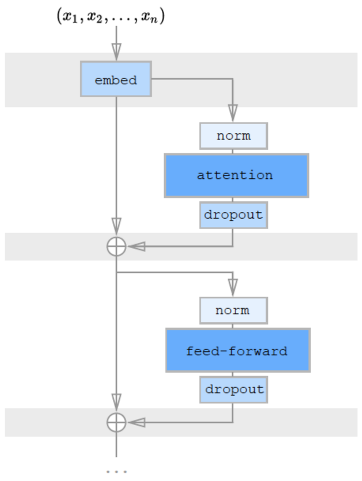
- ❑ causal language modeling for GPT
- ❑ masked language modeling for BERT (+ next sentence prediction)

We'll play with both

Illustration from (Child et al, 2019)

Hands-on pre-training

Let’s code the backbone of our model!




```python
import torch
import torch.nn as nn

class Transformer(nn.Module):
    def __init__(self, embed_dim, hidden_dim, num_embeddings, num_max_positions, num_heads, num_layers, dropout, causal):
        super().__init__()
        self.causal = causal
        self.tokens_embeddings = nn.Embedding(num_embeddings, embed_dim)
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        self.dropout = nn.Dropout(dropout)

        self.attentions, self.feed_forwards = nn.ModuleList(), nn.ModuleList()
        self.layer_norms_1, self.layer_norms_2 = nn.ModuleList(), nn.ModuleList()
        for _ in range(num_layers):
            self.attentions.append(nn.MultiheadAttention(embed_dim, num_heads, dropout=dropout))
            self.feed_forwards.append(nn.Sequential(nn.Linear(embed_dim, hidden_dim),
                                                    nn.ReLU(),
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            self.layer_norms_1.append(nn.LayerNorm(embed_dim, eps=1e-12))
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    def forward(self, x, padding_mask=None):

        positions = torch.arange(len(x), device=x.device).unsqueeze(-1)
        h = self.tokens_embeddings(x)
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        h = self.dropout(h)

        attn_mask = None
        if self.causal:
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Hands-on pre-training

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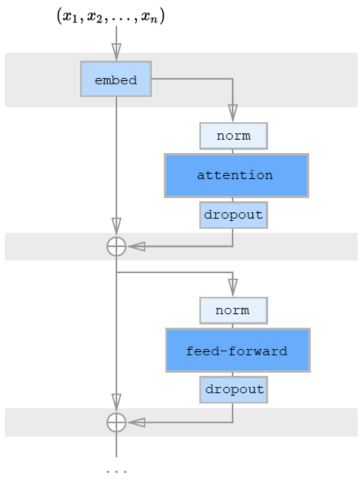


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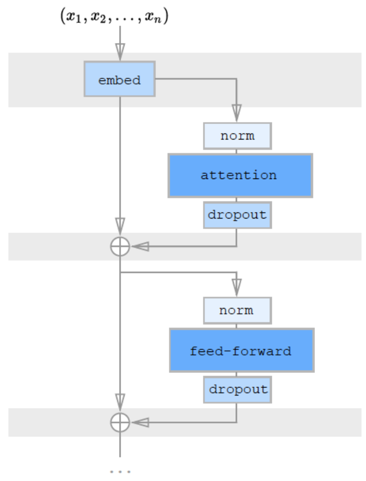


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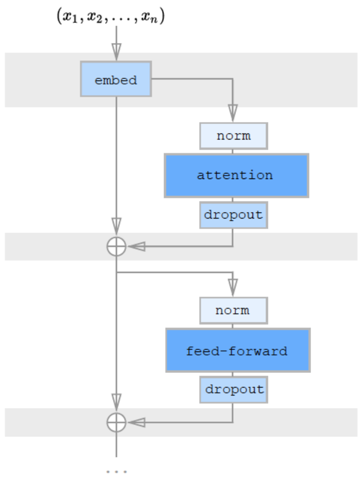


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Hands-on pre-training

Two attention masks?

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Hands-on pre-training

Two attention masks?

- `padding_mask` masks the padding tokens. It is specific to each sample in the batch:

I	love	Mom	'	s	cooking
I	love	you	too	!	
No	way				
This	is	the	shit		
Yes					

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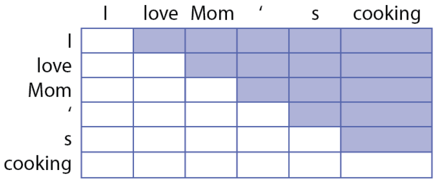
- `attn_mask` is the same for all samples in the batch. It masks the previous tokens for causal transformers:

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Hands-on pre-training

To pretrain our model, we need to add a few elements: a head, a loss and initialize weights.

```
class TransformerWithLMHead(nn.Module):
    def __init__(self, config):
        """ Transformer with a language modeling head on top (tied weights) """
        super().__init__()
        self.config = config
        self.transformer = Transformer(config.embed_dim, config.hidden_dim, config.num_embeddings,
                                       config.num_max_positions, config.num_heads, config.num_layers,
                                       config.dropout, causal=not config.mlm)

        self.lm_head = nn.Linear(config.embed_dim, config.num_embeddings, bias=False)
        self.apply(self.init_weights)
        self.tie_weights()

    def tie_weights(self):
        self.lm_head.weight = self.transformer.tokens_embeddings.weight

    def init_weights(self, module):
        """ initialize weights - nn.MultiheadAttention is already initalized by PyTorch (xavier) """
        if isinstance(module, (nn.Linear, nn.Embedding, nn.LayerNorm)):
            module.weight.data.normal_(mean=0.0, std=self.config.initializer_range)
        if isinstance(module, (nn.Linear, nn.LayerNorm)) and module.bias is not None:
            module.bias.data.zero_()

    def forward(self, x, labels=None, padding_mask=None):
        """ x has shape [seq length, batch], padding_mask has shape [batch, seq length] """
        hidden_states = self.transformer(x, padding_mask)
        logits = self.lm_head(hidden_states)

        if labels is not None:
            shift_logits = logits[:-1] if self.transformer.causal else logits
            shift_labels = labels[1:] if self.transformer.causal else labels
            loss_fct = nn.CrossEntropyLoss(ignore_index=-1)
            loss = loss_fct(shift_logits.view(-1, shift_logits.size(-1)), shift_labels.view(-1))
            return logits, loss

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```

Hands-on pre-training

To pretrain our model, we need to add a few elements: a head, a loss and initialize weights.

We add these elements with a pretraining model encapsulating our model.

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Hands-on pre-training

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1. **A pretraining head** on top of our core model: we choose a language modeling head with tied weights

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            module.weight.data.normal_(mean=0.0, std=self.config.initializer_range)
        if isinstance(module, (nn.Linear, nn.LayerNorm)) and module.bias is not None:
            module.bias.data.zero_()

    def forward(self, x, labels=None, padding_mask=None):
        """ x has shape [seq length, batch], padding_mask has shape [batch, seq length] """
        hidden_states = self.transformer(x, padding_mask)
        logits = self.lm_head(hidden_states)

        if labels is not None:
            shift_logits = logits[:-1] if self.transformer.causal else logits
            shift_labels = labels[1:] if self.transformer.causal else labels
            loss_fct = nn.CrossEntropyLoss(ignore_index=-1)
            loss = loss_fct(shift_logits.view(-1, shift_logits.size(-1)), shift_labels.view(-1))
            return logits, loss

        return logits
```

Hands-on pre-training

To pretrain our model, we need to add a few elements: a head, a loss and initialize weights.

We add these elements with a pretraining model encapsulating our model.

1. **A pretraining head** on top of our core model: we choose a language modeling head with tied weights

2. **Initialize** the weights

```
class TransformerWithLMHead(nn.Module):
    def __init__(self, config):
        """ Transformer with a language modeling head on top (tied weights) """
        super().__init__()
        self.config = config
        self.transformer = Transformer(config.embed_dim, config.hidden_dim, config.num_embeddings,
                                       config.num_max_positions, config.num_heads, config.num_layers,
                                       config.dropout, causal=not config.mlm)

        self.lm_head = nn.Linear(config.embed_dim, config.num_embeddings, bias=False)
        self.apply(self.init_weights)
        self.tie_weights()

    def tie_weights(self):
        self.lm_head.weight = self.transformer.tokens_embeddings.weight

    def init_weights(self, module):
        """ initialize weights - nn.MultiheadAttention is already initalized by PyTorch (xavier) """
        if isinstance(module, (nn.Linear, nn.Embedding, nn.LayerNorm)):
            module.weight.data.normal_(mean=0.0, std=self.config.initializer_range)
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We add these elements with a pretraining model encapsulating our model.

1. **A pretraining head** on top of our core model: we choose a language modeling head with tied weights

2. **Initialize** the weights

3. Define a **loss function**: we choose a cross-entropy loss on current (or next) token predictions

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    def __init__(self, config):
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        super().__init__()
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Hands-on pre-training

Now let's take care of our data and configuration

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from pytorch_pretrained_bert import BertTokenizer, cached_path

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from collections import namedtuple

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               0.1     , 0.02            , 16         , 2.5e-4, 1.0 , 50      , 1000    ,
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```
dataset_file = cached_path("https://s3.amazonaws.com/datasets.huggingface.co/wikitext-103/"
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# Convert our encoded dataset to torch.tensors and reshape in blocks of the transformer's input length
for split_name in ['train', 'valid']:
    tensor = torch.tensor(datasets[split_name], dtype=torch.long)
    num_sequences = (tensor.size(0) // args.num_max_positions) * args.num_max_positions
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```
model = TransformerWithLMHead(args).to(args.device)
optimizer = torch.optim.Adam(model.parameters(), lr=args.lr)
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We'll use a pre-defined open vocabulary tokenizer: BERT's model cased tokenizer.

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Use a large dataset for pre-training: WikiText-103 with 103M tokens (Merity et al., 2017).

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```

Instantiate our model and optimizer

```
model = TransformerWithLMHead(args).to(args.device)
optimizer = torch.optim.Adam(model.parameters(), lr=args.lr)
```

Hands-on pre-training

And we're done: let's train!

```python
import os
from torch.utils.data import DataLoader
from ignite.engine import Engine, Events
from ignite.metrics import RunningAverage
from ignite.handlers import ModelCheckpoint
from ignite.contrib.handlers import CosineAnnealingScheduler, create_lr_scheduler_with_warmup, ProgressBar

dataloader = DataLoader(datasets['train'], batch_size=args.batch_size, shuffle=True)

# Define training function
def update(engine, batch):
    model.train()
    batch = batch.transpose(0, 1).contiguous().to(args.device)  # to shape [seq length, batch]
    logits, loss = model(batch, labels=batch)
    loss = loss / args.gradient_accumulation_steps
    loss.backward()
    torch.nn.utils.clip_grad_norm_(model.parameters(), args.max_norm)
    if engine.state.iteration % args.gradient_accumulation_steps == 0:
        optimizer.step()
        optimizer.zero_grad()
    return loss.item()
trainer = Engine(update)

# Add progressbar with loss
RunningAverage(output_transform=lambda x: x).attach(trainer, "loss")
ProgressBar(persist=True).attach(trainer, metric_names=['loss'])

# Learning rate schedule: linearly warm-up to lr and then decrease the learning rate to zero with cosine
cos_scheduler = CosineAnnealingScheduler(optimizer, 'lr', args.lr, 0.0, len(dataloader) * args.n_epochs)
scheduler = create_lr_scheduler_with_warmup(cos_scheduler, 0.0, args.lr, args.n_warmup)
trainer.add_event_handler(Events.ITERATION_STARTED, scheduler)

# Save checkpoints and training config
checkpoint_handler = ModelCheckpoint(args.log_dir, 'checkpoint', save_interval=1, n_saved=5)
trainer.add_event_handler(Events.EPOCH_COMPLETED, checkpoint_handler, {'mymodel': model})
torch.save(args, os.path.join(args.log_dir, 'training_args.bin'))
```

```python
trainer.run(train_dataloader, max_epochs=args.n_epochs)
```

Epoch [1/50] [365/28874] 1%| , loss=2.30e+00 [03:43<4:52:22]

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```python
trainer.run(train_dataloader, max_epochs=args.n_epochs)
```

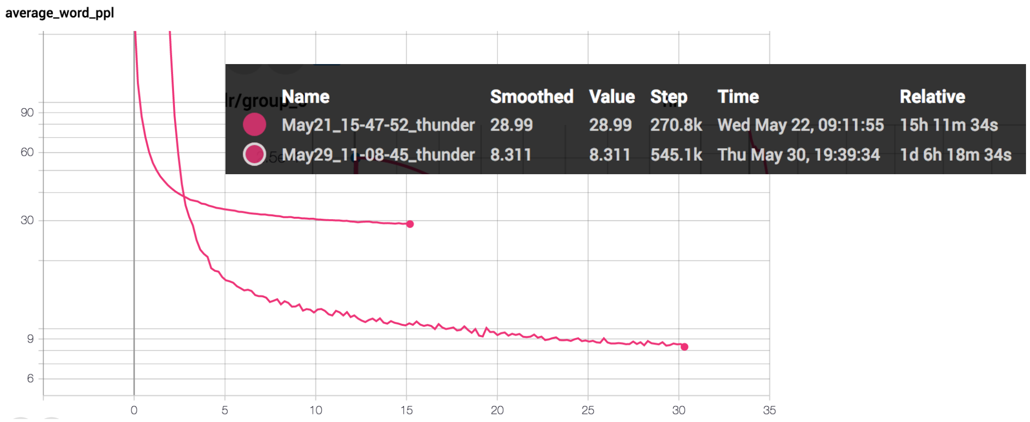
Go! → Epoch [1/50] [365/28874] 1%| , loss=2.30e+00 [03:43<4:52:22]

Hands-on pre-training — Concluding remarks

- On pretraining
  - **Intensive**: in our case 5h–20h on 8 V100 GPUs (few days w. 1 V100) to reach a good perplexity ⇨ share your pretrained models
  - **Robust to the choice of hyper-parameters (**apart from needing a warm-up for transformers)
  - Language modeling is a hard task, your model should **not have enough capacity to overfit** if your dataset is large enough ⇨ you can just start the training and let it run.
  - **Masked-language modeling**: typically 2-4 times slower to train than causal LM
    We only mask 15% of the tokens ⇨ smaller signal

Hands-on pre-training — Concluding remarks

- First model:
  - **exactly the one** we built together ⇨ a 50M parameters causal Transformer
  - Trained 15h on 8 V100
  - Reached a **word-level perplexity of 29** on wikitext-103 validation set (quite competitive)
- Second model:
  - Same model but trained with a **masked-language modeling** objective (see the repo)
  - Trained 30h on 8 V100
  - Reached a “masked-word” perplexity of 8.3 on wikitext-103 validation set



Model	#Params	Validation PPL	Test PPL
Grave et al. (2016b) – LSTM	-	-	48.7
Bai et al. (2018) – TCN	-	-	45.2
Dauphin et al. (2016) – GCNN-8	-	-	44.9
Grave et al. (2016b) – LSTM + Neural cache	-	-	40.8
Dauphin et al. (2016) – GCNN-14	-	-	37.2
Merity et al. (2018) – 4-layer QRNN	151M	32.0	33.0
Rae et al. (2018) – LSTM + Hebbian + Cache	-	29.7	29.9
Ours – Transformer-XL Standard	151M	**23.1**	**24.0**
Baevski & Auli (2018) – adaptive input◇	247M	19.8	20.5
Ours – Transformer-XL Large	257M	**17.7**	**18.3**

Wikitext-103 Validation/Test PPL

Dai et al., 2018

Agenda

[1] Introduction

[2] Pretraining

[4] Adaptation

[3] What's in a representation?

3. What is in a Representation?

Image credit: Caique Lima

Why care about what is in a representation?

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- Alternative to Extrinsic evaluation with downstream tasks
  - Complex, diverse with task-specific quirks

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- Alternative to Extrinsic evaluation with downstream tasks
  - Complex, diverse with task-specific quirks

- Measures language-awareness of representations
  - To generalize to other tasks, new inputs
  - As intermediates for possible improvements to pretraining

[Swayamdipta, 2019]

Why care about what is in a representation?

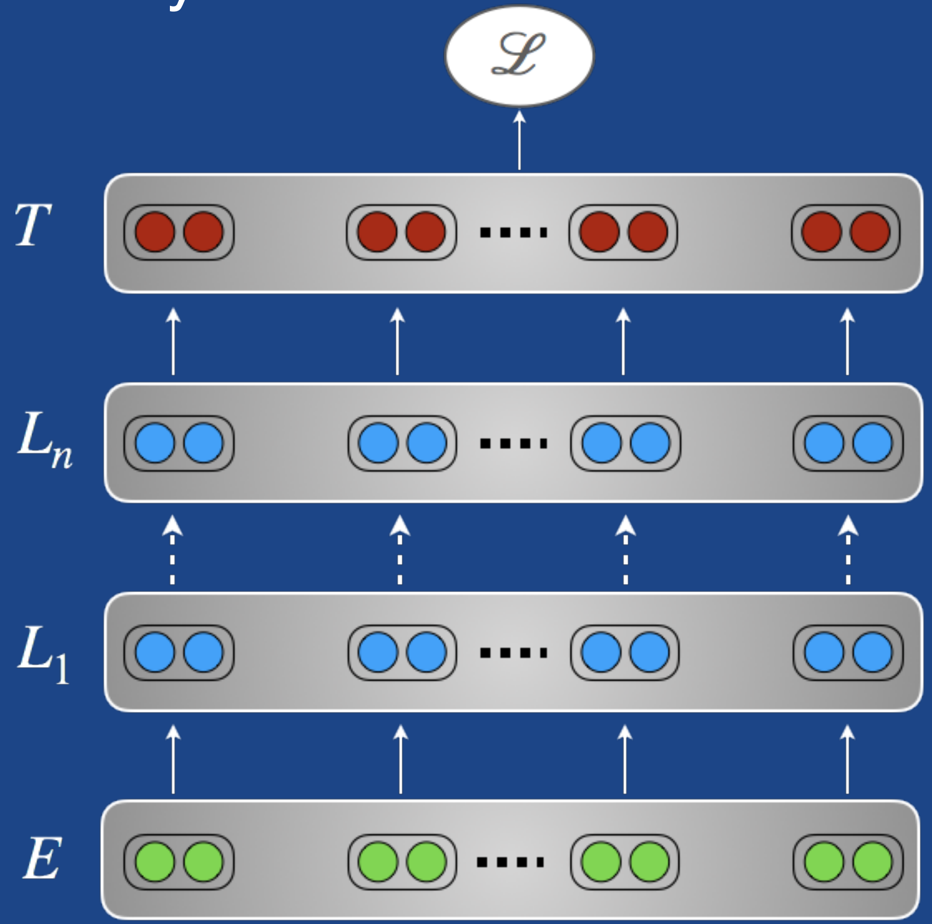
- ❏ Alternative to Extrinsic evaluation with downstream tasks
  - ❏ Complex, diverse with task-specific quirks

- ❏ Measures language-awareness of representations
  - ❏ To generalize to other tasks, new inputs
  - ❏ As intermediates for possible improvements to pretraining

- ❏ Interpretability!
  - ❏ Are we getting our results because of the right reasons?
  - ❏ Uncovering biases...

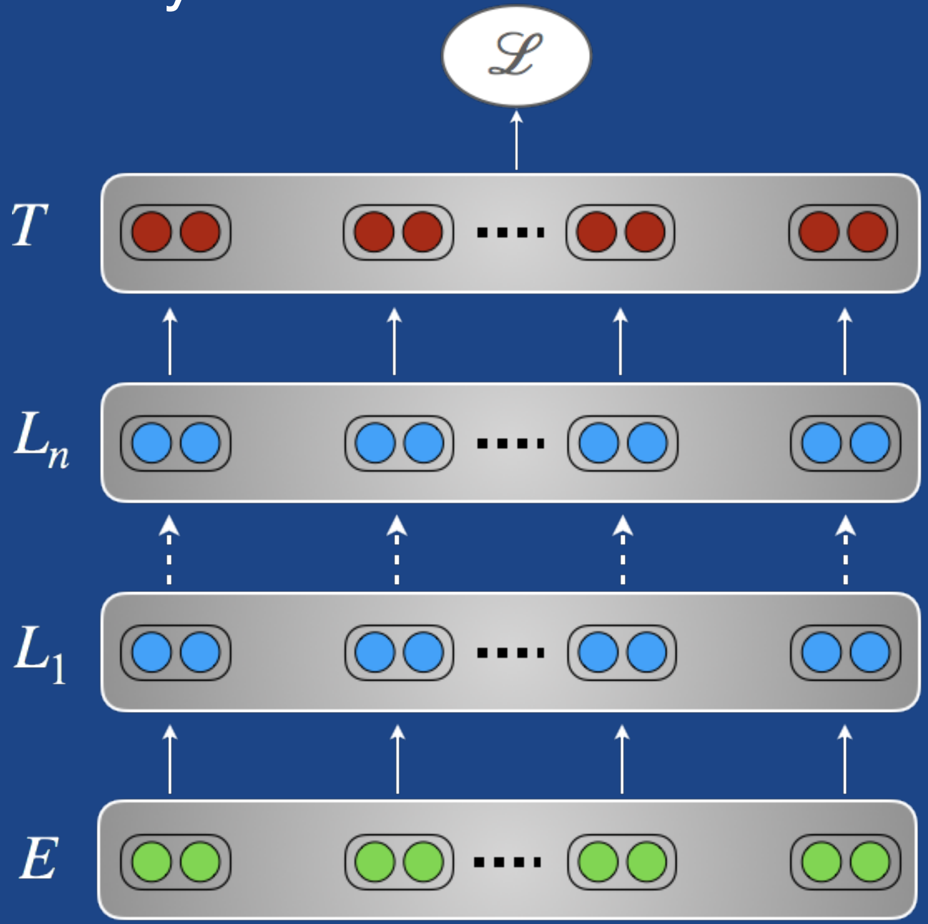
Swayamdipta, 2019

What to analyze?



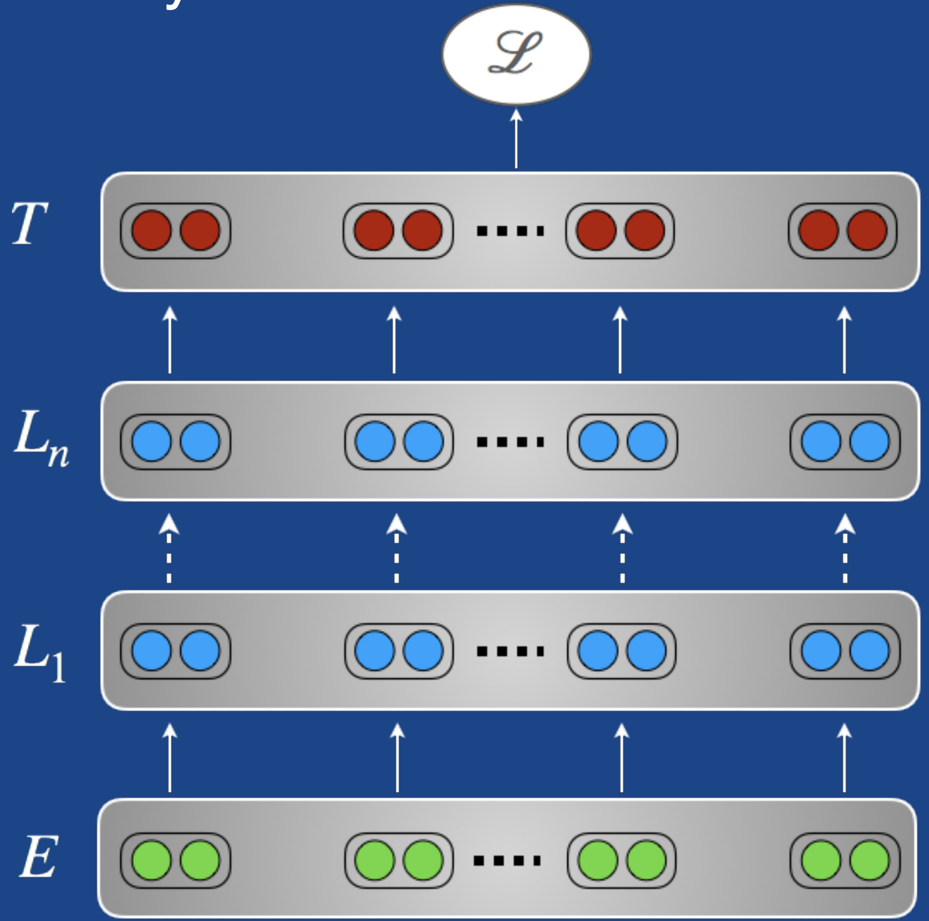
What to analyze?

- Embeddings
  - Word
  - Contextualized



What to analyze?

- Embeddings
  - Word
  - Contextualized
- Network Activations



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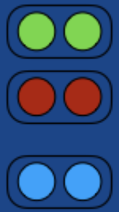

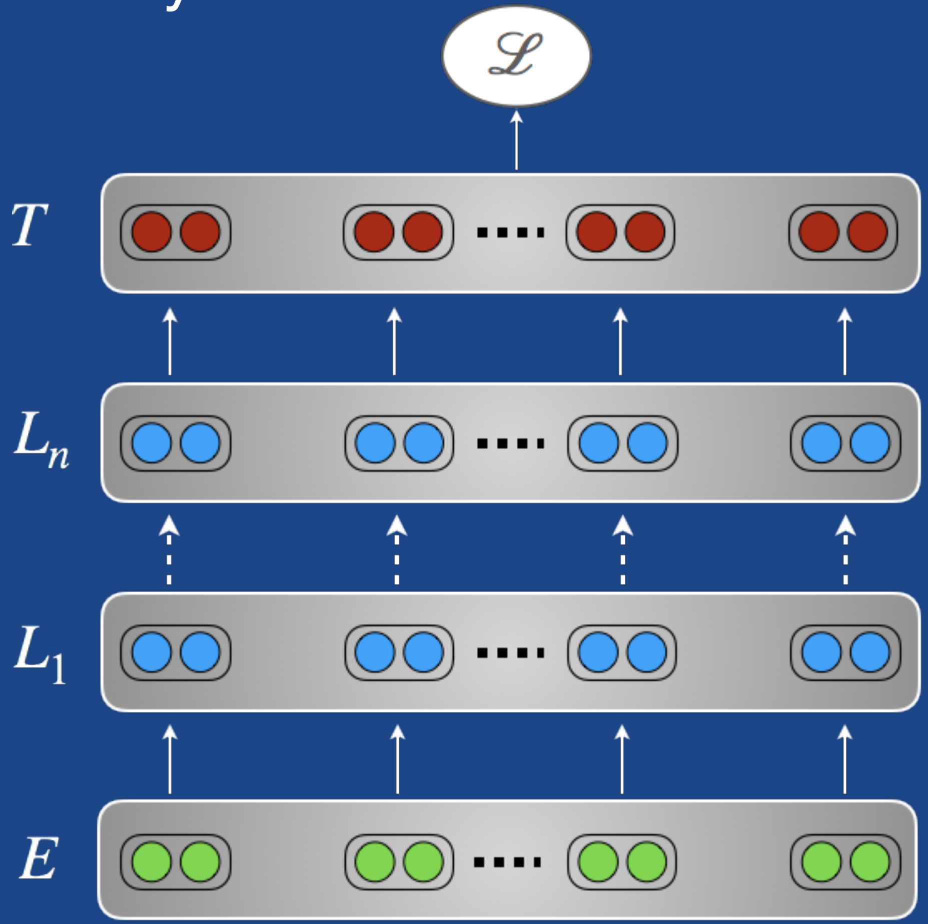

- ❑ Embeddings
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  - ❑ Contextualized
- ❑ Network Activations

- ❑ Alterations:
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What to analyze?

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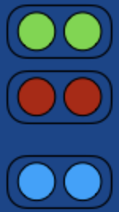

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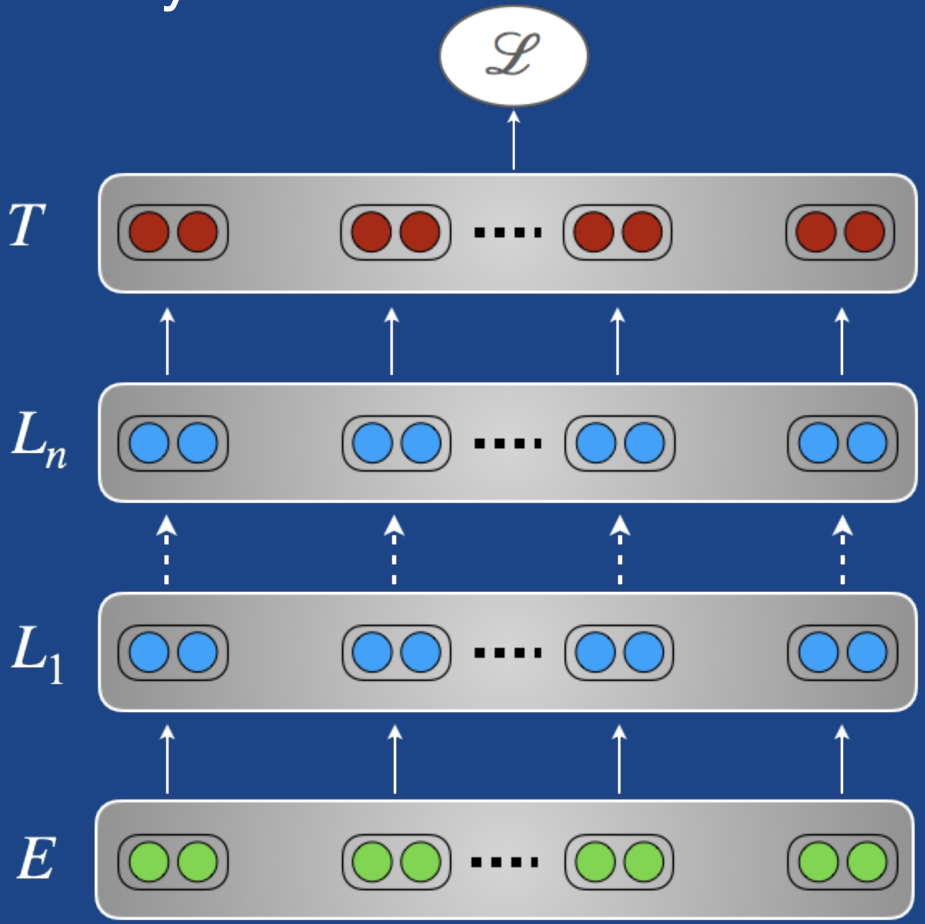

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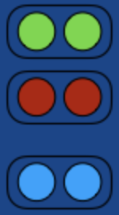

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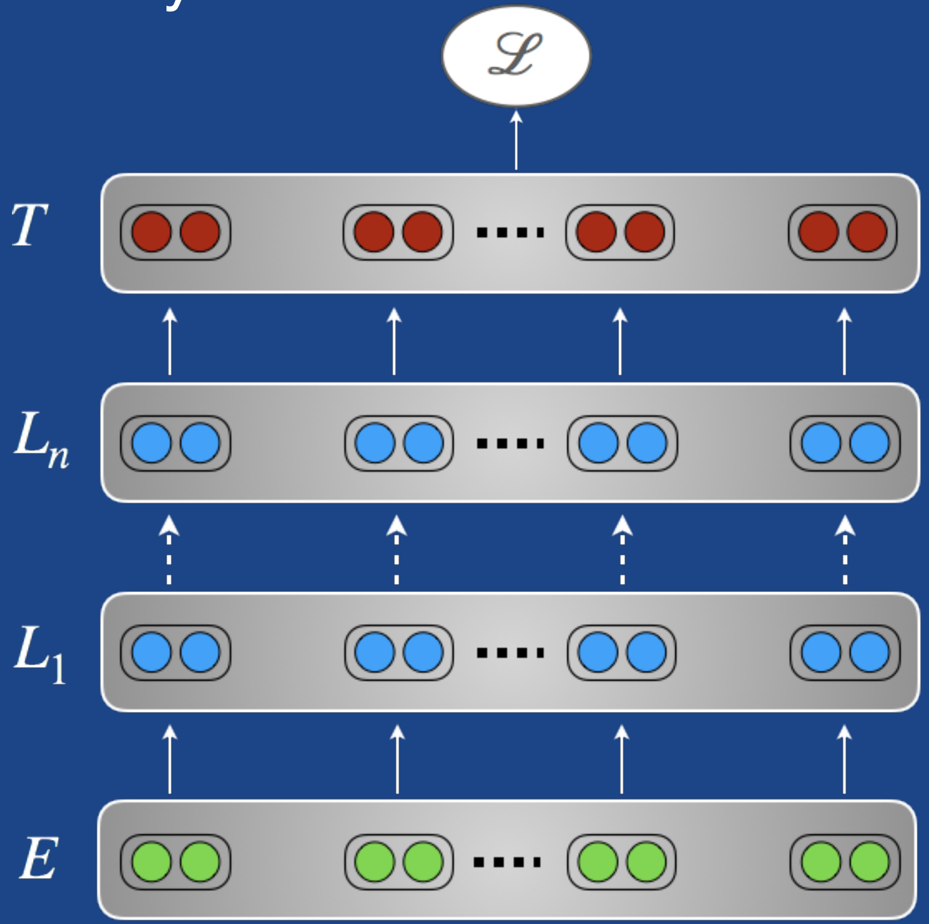
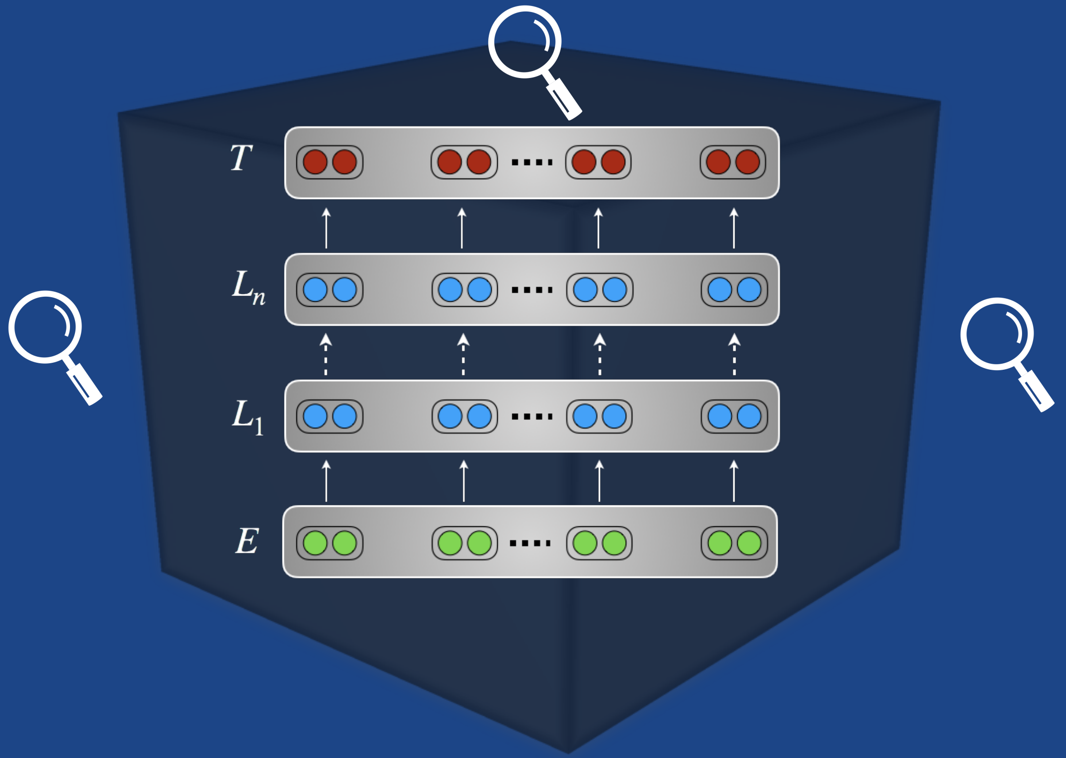


Analysis Method 1: Visualization

Hold the embeddings / network activations static or **frozen**



Visualizing Embedding Geometries

- Plotting embeddings **faithfully** into a lower dimensional (2D/3D) space
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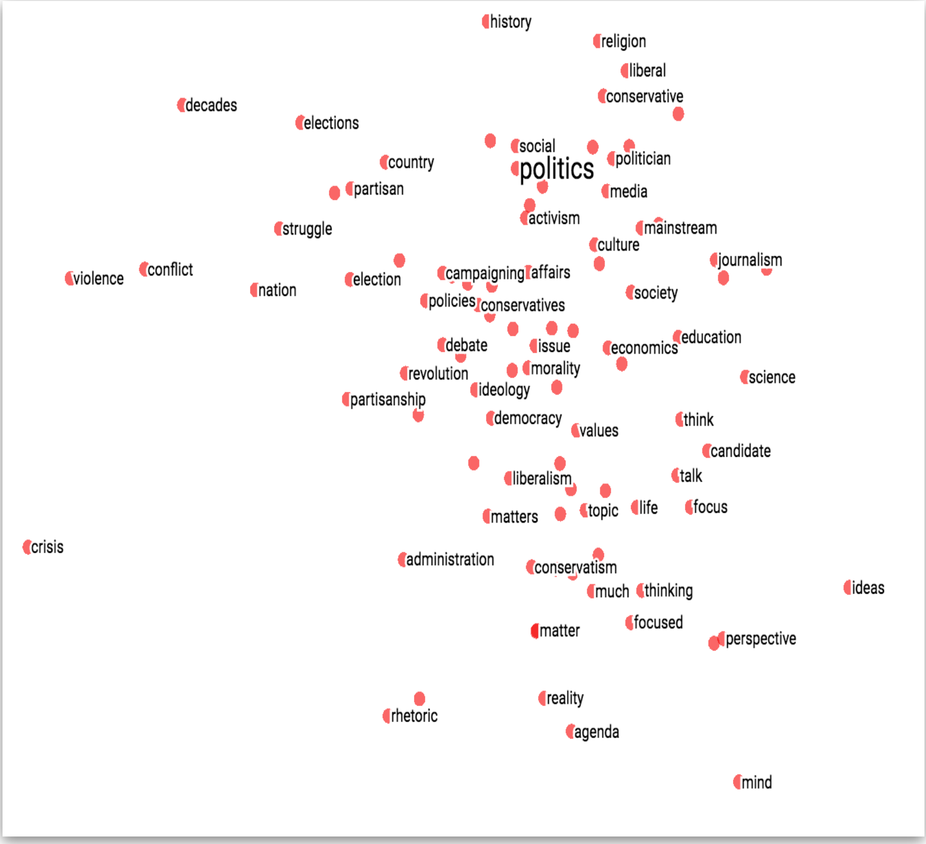

Image: [Tensorflow]

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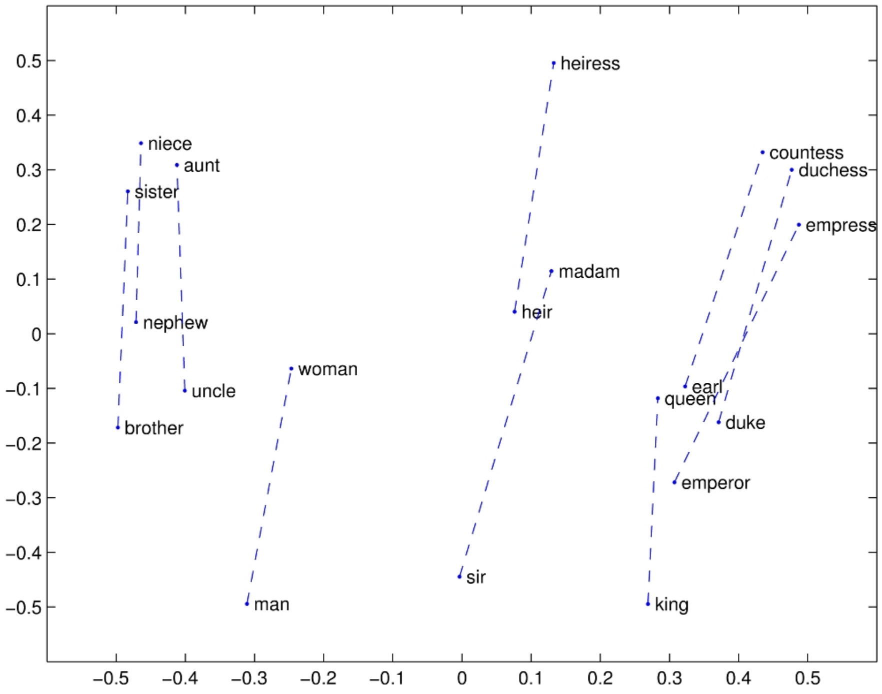
  - Spatial relations
  - $w_{king} - w_{man} + w_{woman} \sim w_{queen}$



Pennington et al., 2014

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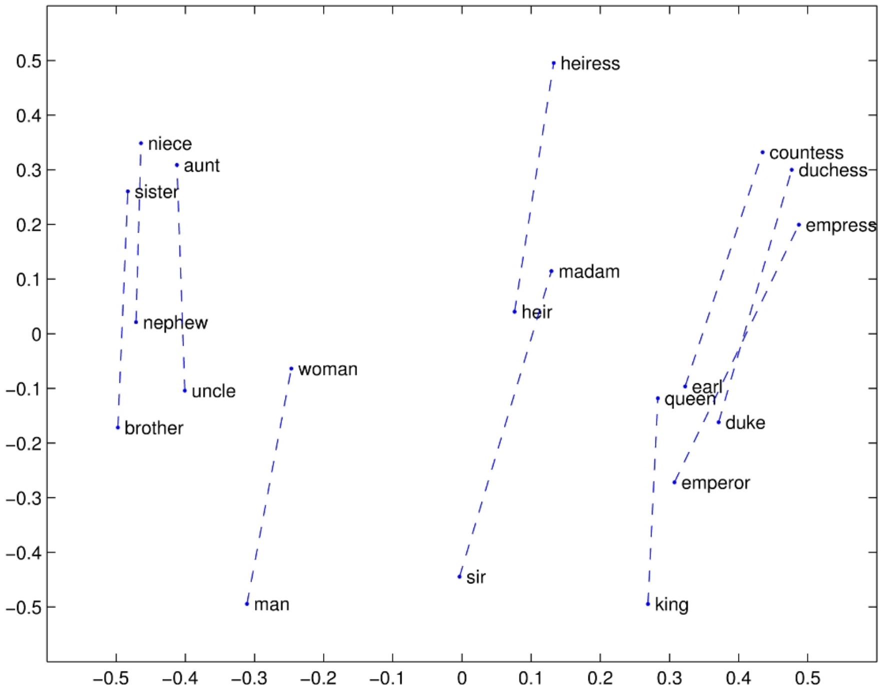
- High-level view of lexical semantics
  - Only a limited number of examples
  - Connection to other tasks is unclear Goldberg, 2017



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Visualizing Neuron Activations

- Neuron activation values correlate with features / labels

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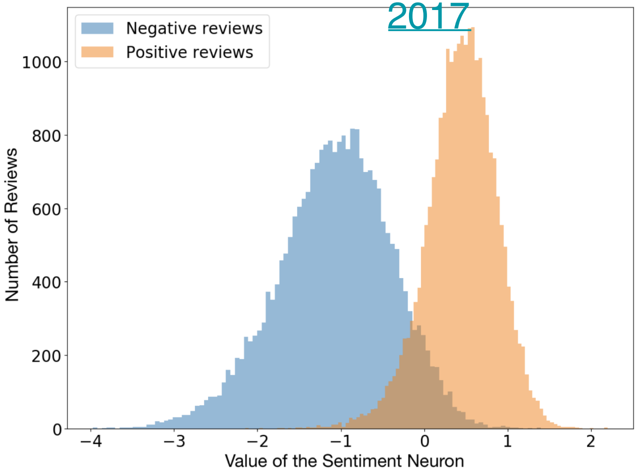
[Radford et al., 2017]



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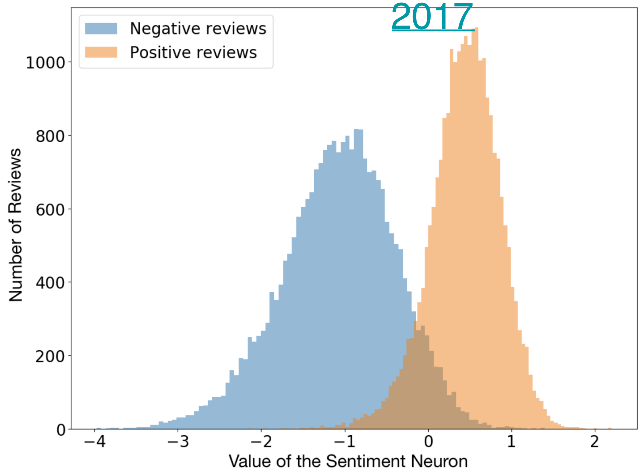
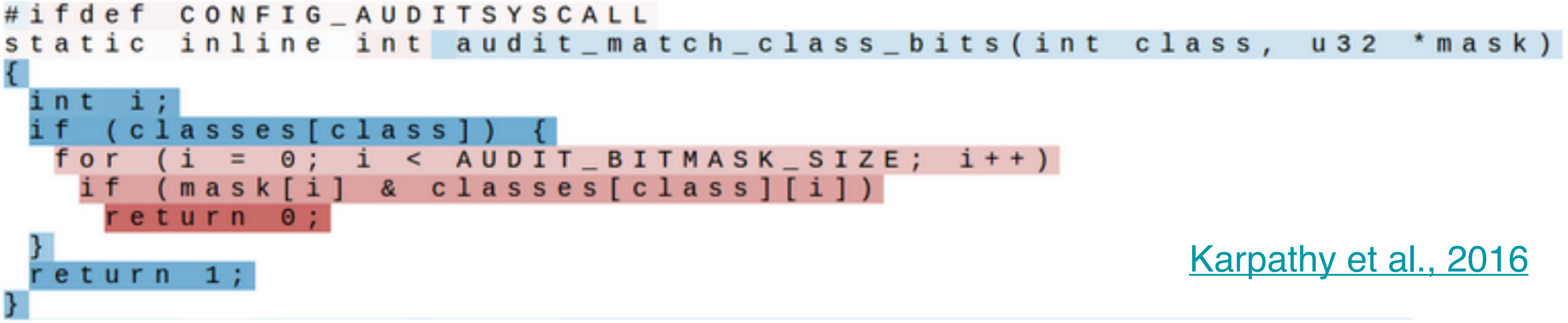



Cell that is sensitive to the depth of an expression:

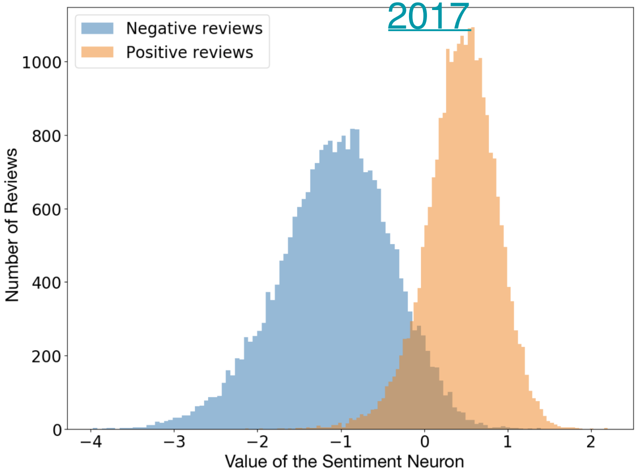
```
#ifdef CONFIG_AUDITSYSCALL
static inline int audit_match_class_bits(int class, u32 *mask)
{
 int i;
 if (classes[class]) {
  for (i = 0; i < AUDIT_BITMASK_SIZE; i++)
   if (mask[i] & classes[class][i])
    return 0;
 }
 return 1;
}
```

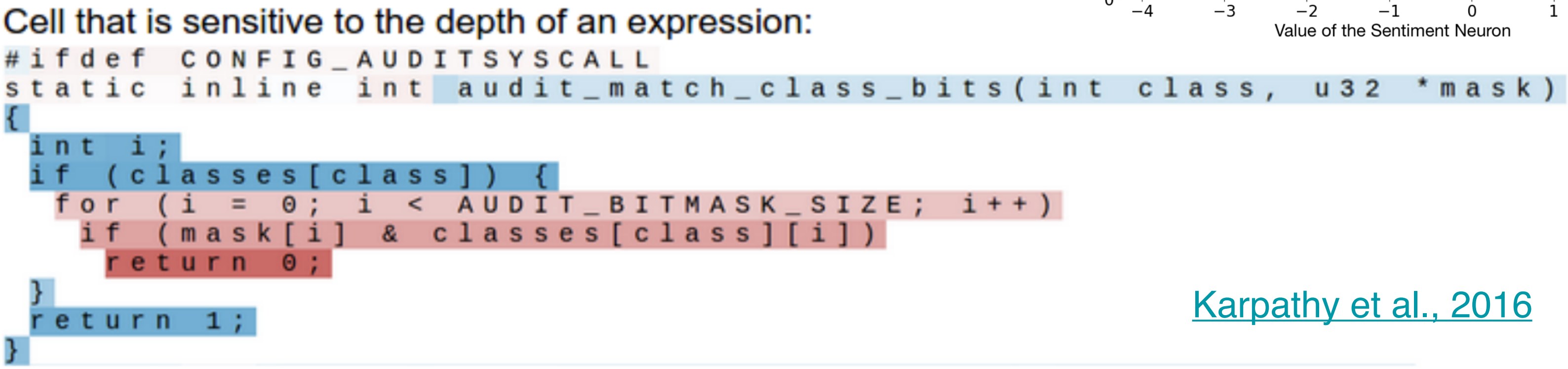
[Karpathy et al., 2016](#)

Visualizing Neuron Activations

- Neuron activation values correlate with features / labels
- Indicates learning of recognizable features
  - How to select which neuron? Hard to scale!
  - Interpretable != Important (Morcos et al., 2018)

Radford et al., 2017





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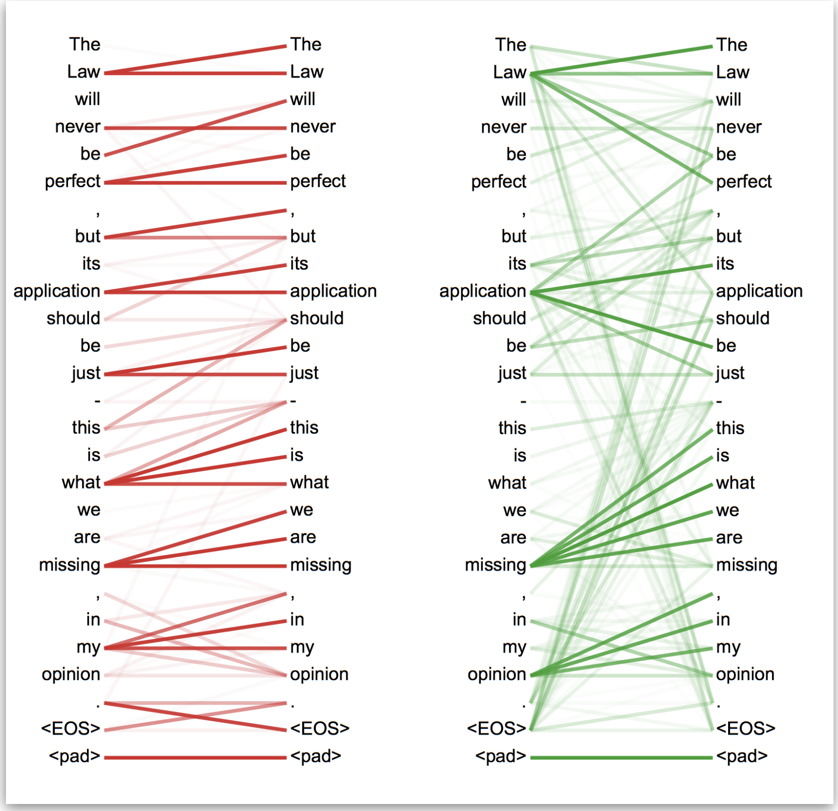

Vaswani et al., 2017

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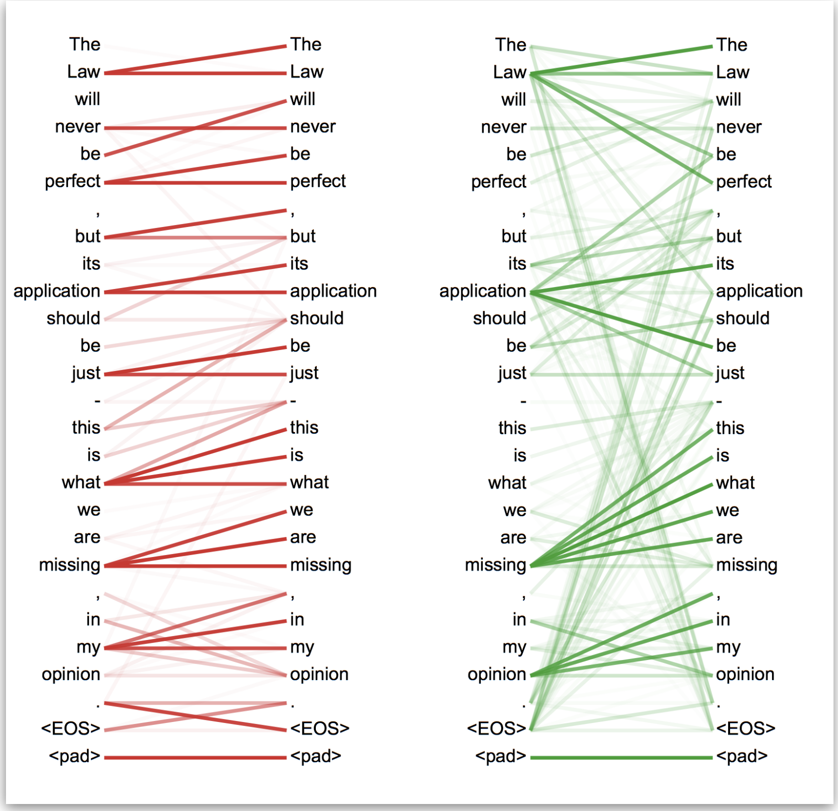

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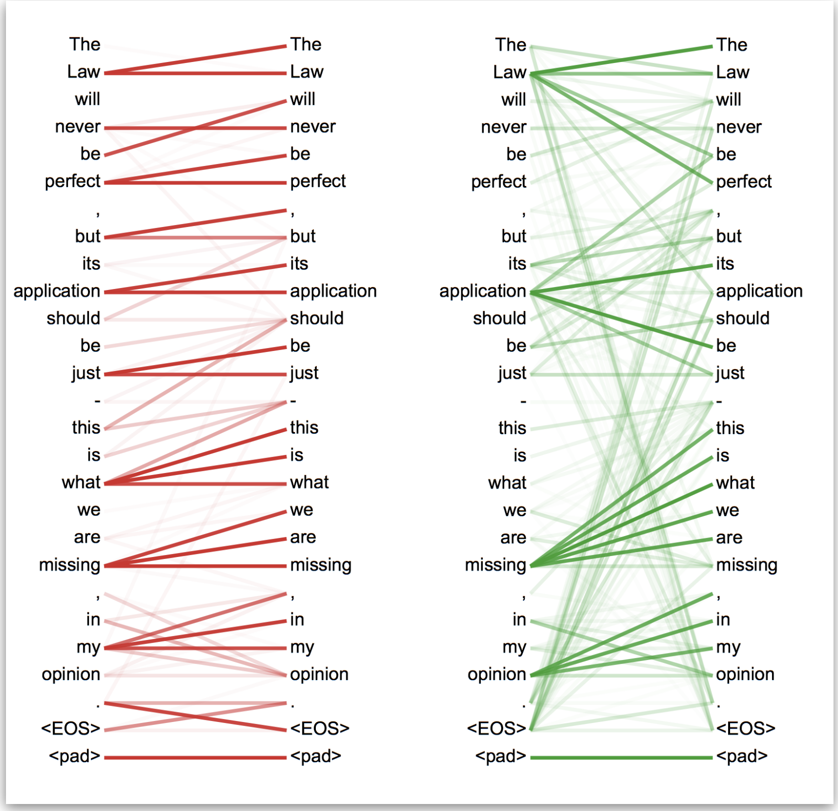

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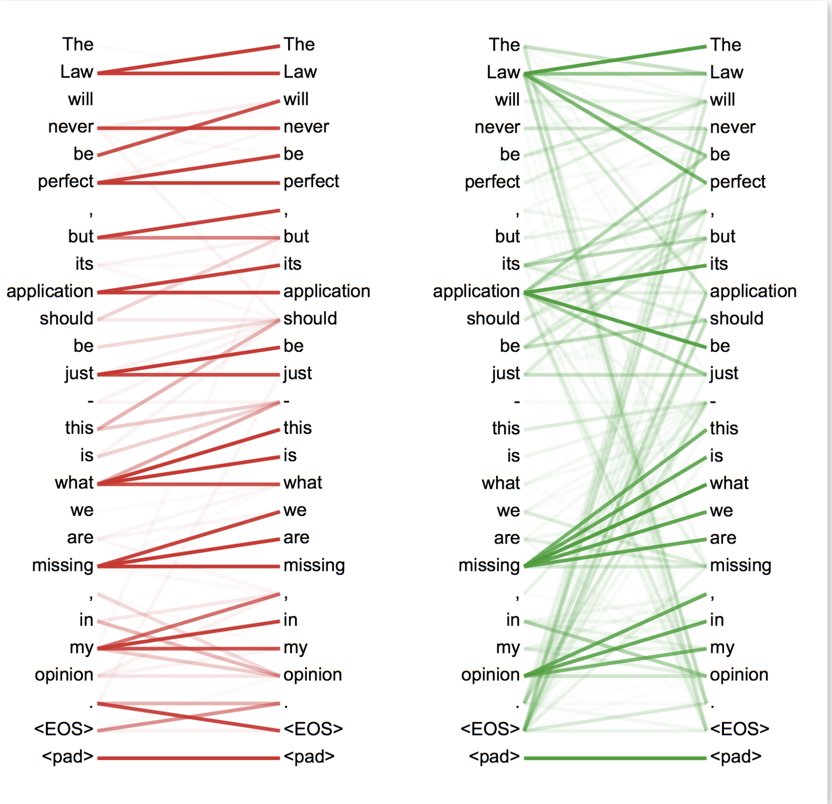

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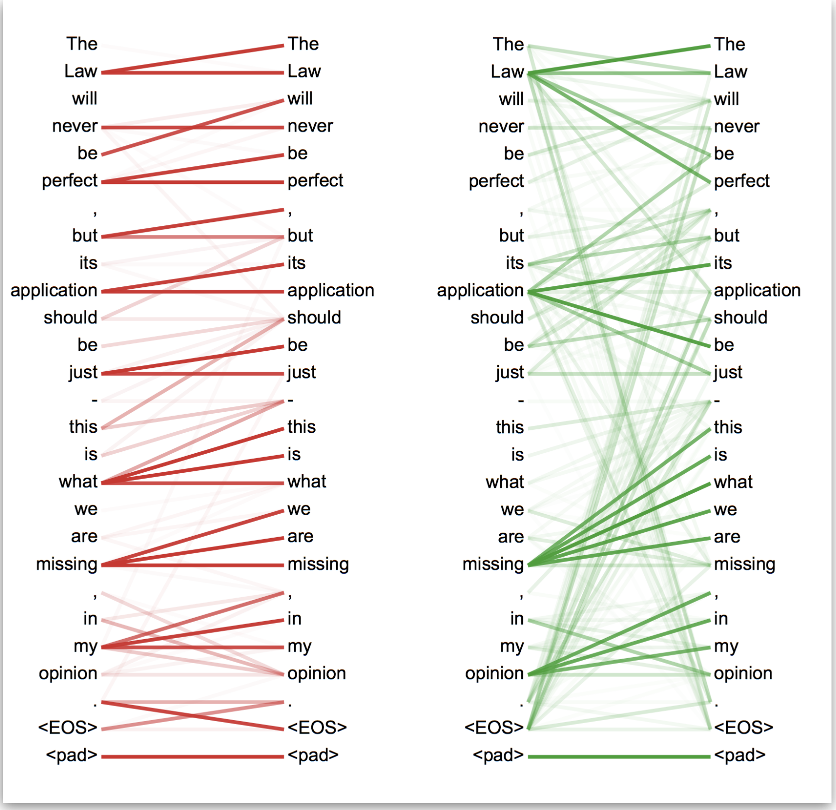
- Sheds light on architectures
  - Having sophisticated attention mechanisms can be a good thing!
  - Layer-specific (layer 5 / layer 6 in fig.)
- Interpretation can be tricky
  - Few examples only - cherry picking?
  - Robust **corpus-wide** trends? Next!



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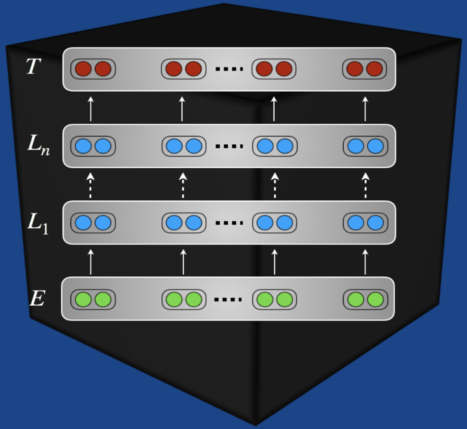
Analysis Method 2: Behavioral Probes



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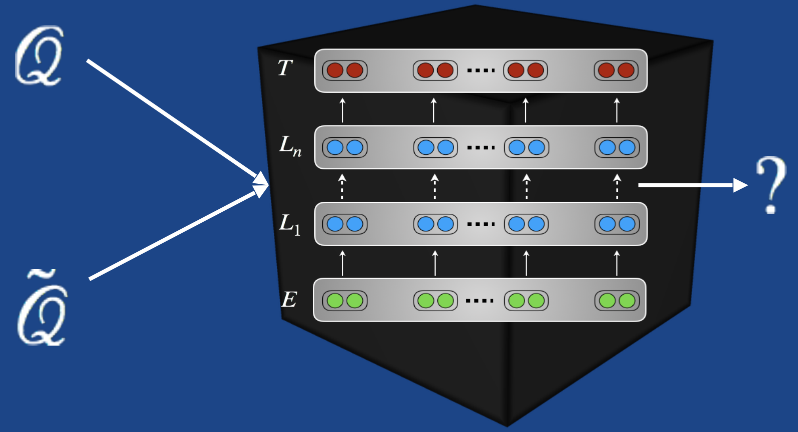

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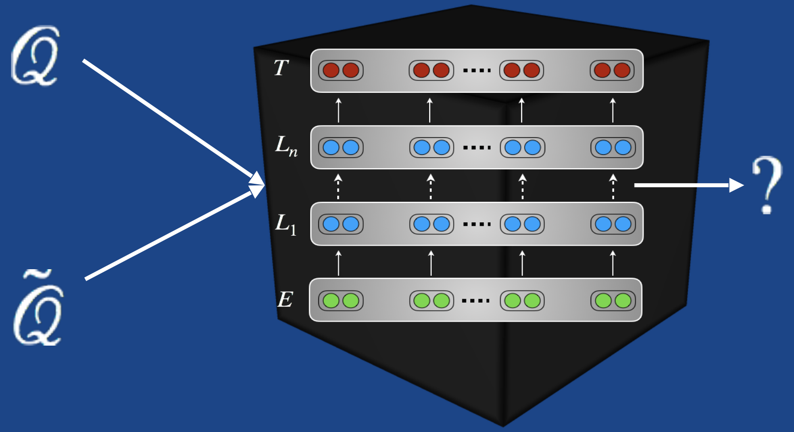

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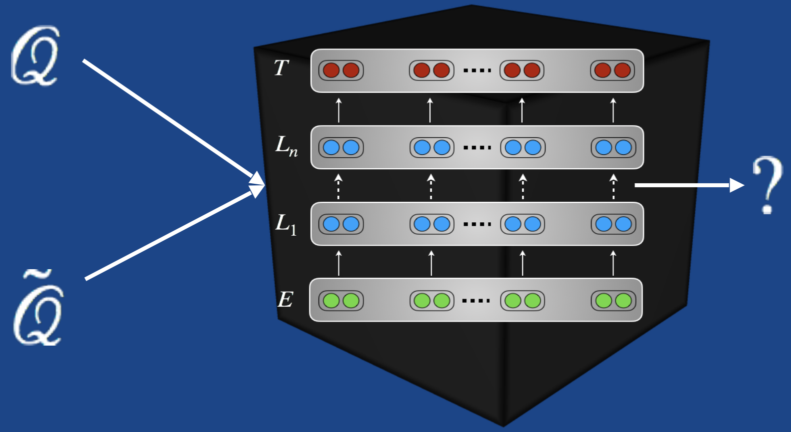

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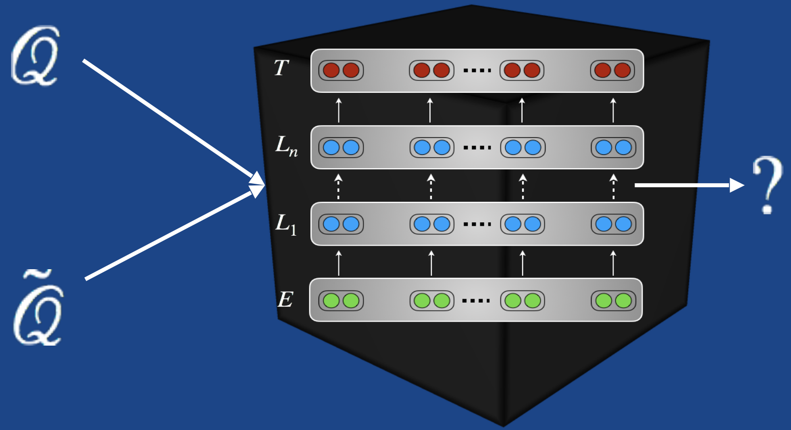

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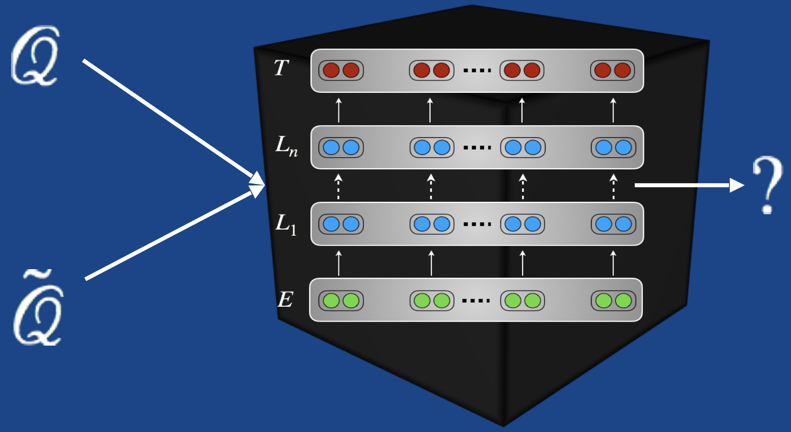

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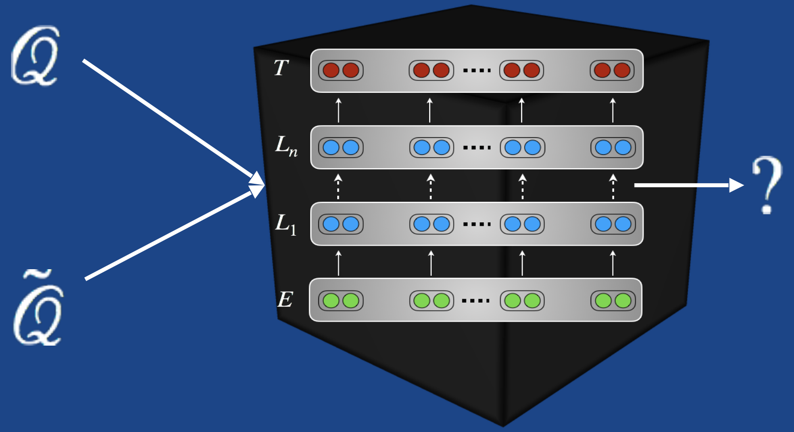

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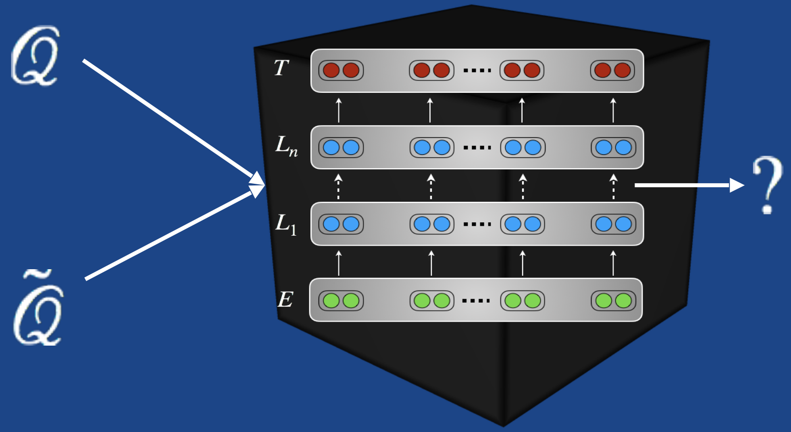

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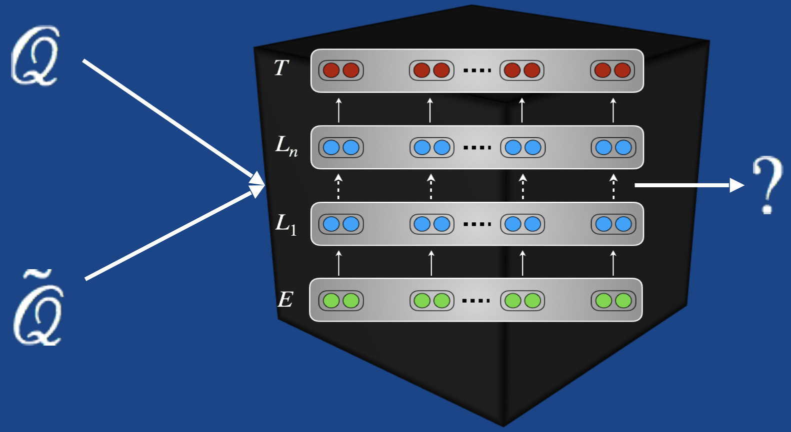

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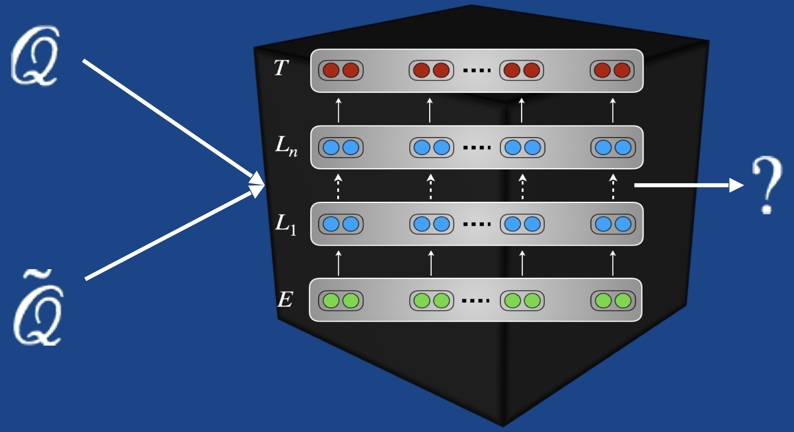

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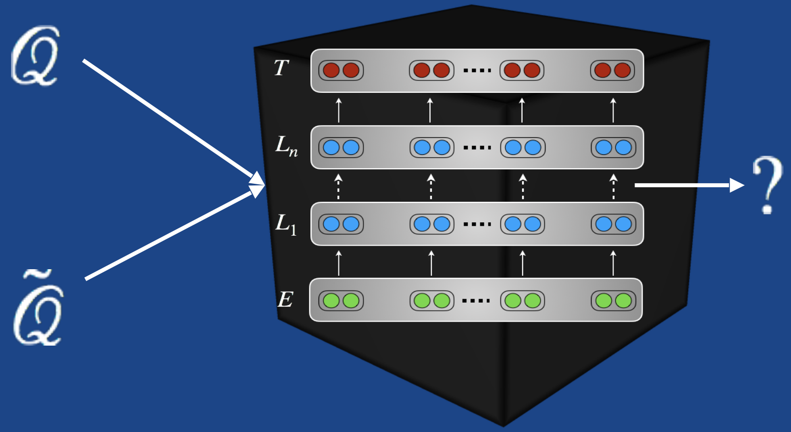

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  - Nonce sentences might be too different from original...

Kuncoro et al. 2018

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Analysis Method 3: Classifier Probes

Hold the embeddings / network

activations static and

train a **simple supervised**

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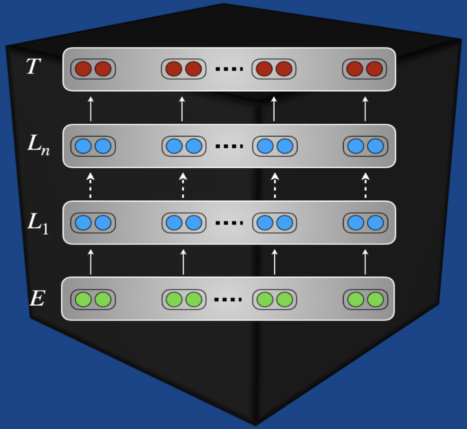

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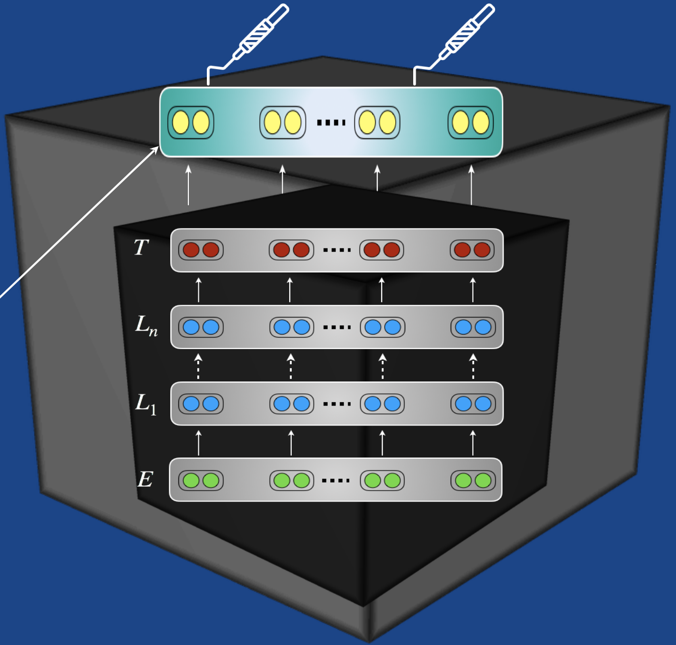
Probe classification task
(Linear / MLP)



Probing Surface-level Features

Zhang et al. 2018; Liu et al., 2018; Conneau et al., 2018

Probing Surface-level Features

- Given a sentence, predict properties such as
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  - Is a word in the sentence?
- Given a word in a sentence predict properties such as:
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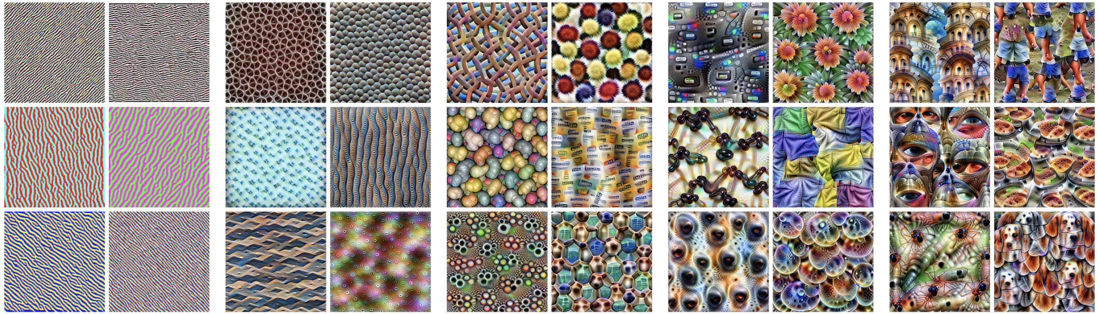
Probing: Layers of the network



Edges (layer conv2d0) **Textures** (layer mixed3a) **Patterns** (layer mixed4a) **Parts** (layers mixed4b & mixed4c) **Objects** (layers mixed4d & mixed4e)

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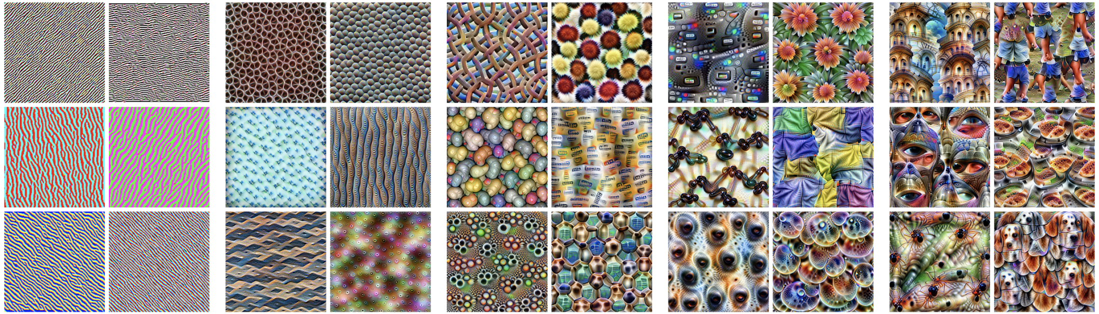

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- **RNN** layers: General linguistic properties
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  - Middle layers: **syntax**
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  - Also see Tenney et. al., 2019

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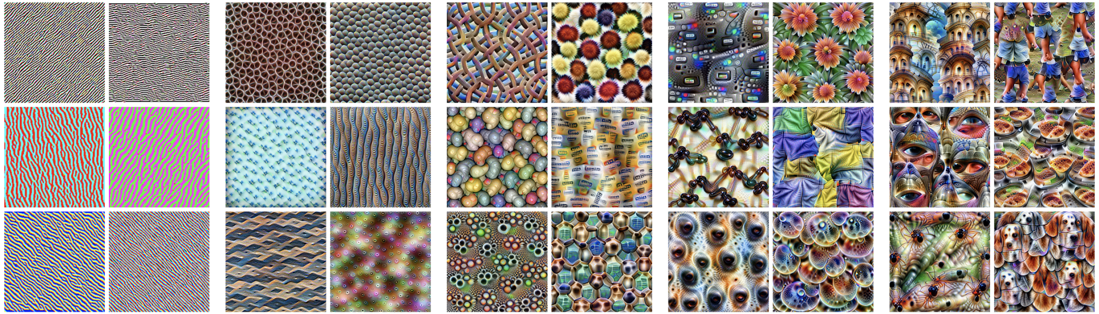

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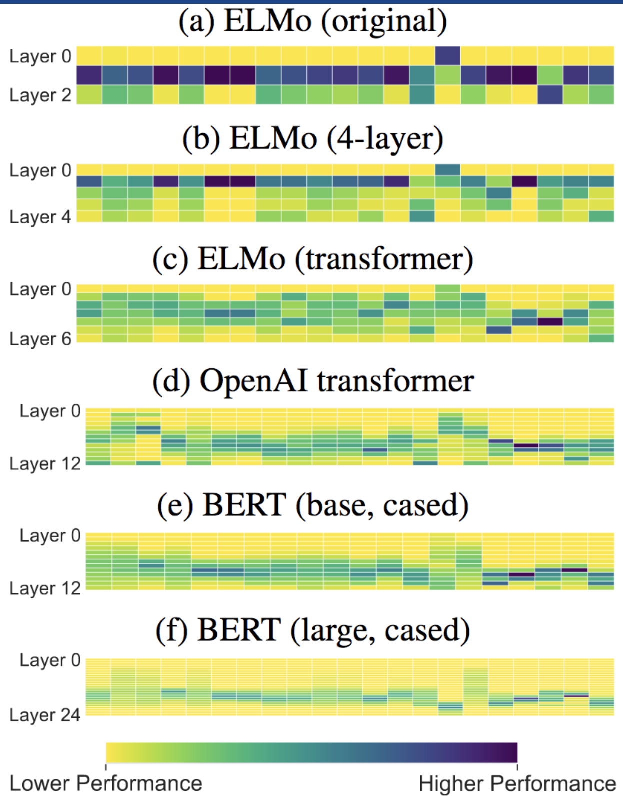
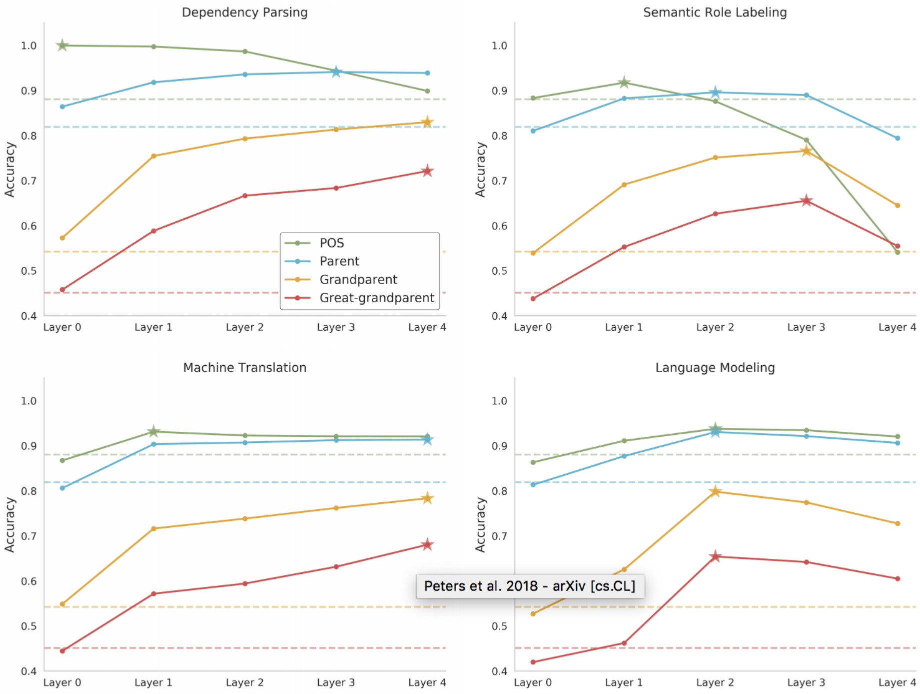


Fig. from Liu et al. (NAACL 2019)

Probing: Pretraining Objectives

- Language modeling **outperforms** other unsupervised and supervised objectives.
    - Machine Translation
    - Dependency Parsing
    - Skip-thought
- **Low-resource** settings (size of training data) might result in opposite trends.



Zhang et al., 2018; Blevins et al., 2018; Liu et al., 2019;

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- Network architectures determine what is in a representation
  - Syntax and BERT Transformer (Tenney et al., 2019; Goldberg, 2019)
  - Different layer-wise trends across architectures

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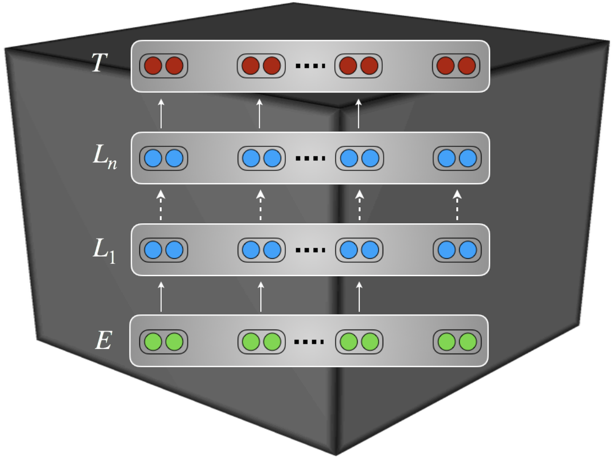
  - behavioral: design of input sentences
- Should we be using **probes as evaluation metrics**?
  - might defeat the purpose...

Analysis Method 4: Model Alterations

- Progressively erase or mask network components
  - Word embedding dimensions
  - Hidden units
  - Input - words / phrases



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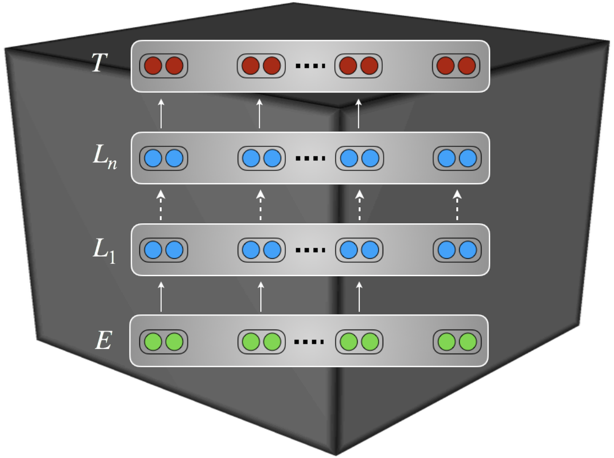


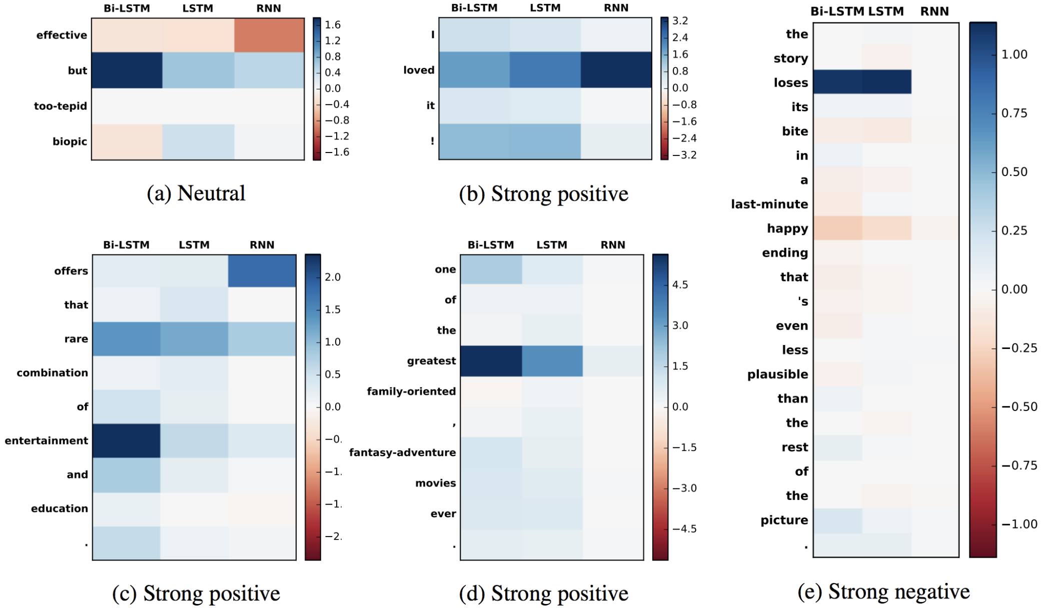
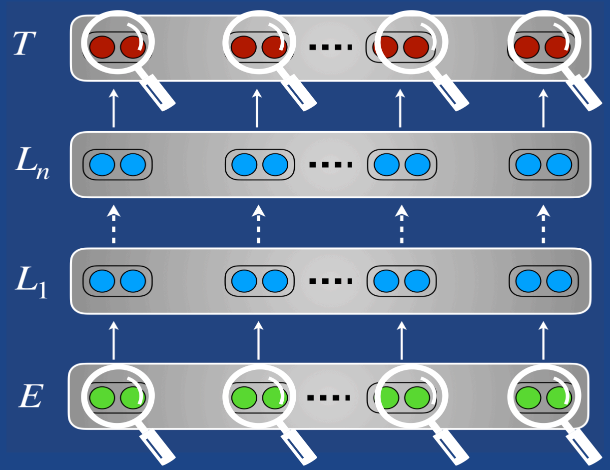


Figure 5: Heatmap of word importance (computed using Eq. 1) in sentiment analysis.

[Li et al., 2016]

So, what is in a representation?



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- Depends on how you look at it!
  - **Visualization**:
    - **bird’s eye view**
    - **few** samples -- might call to mind cherry-picking
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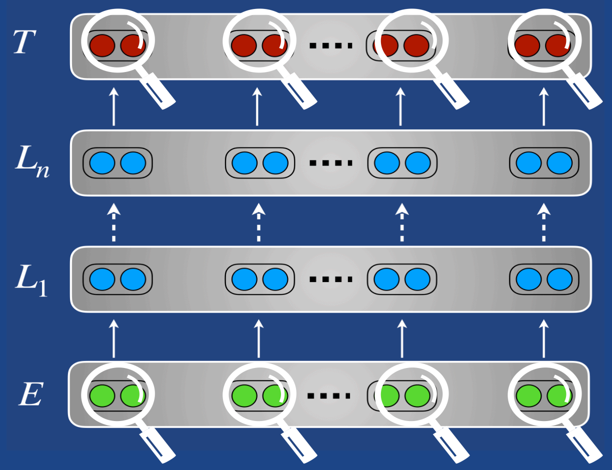

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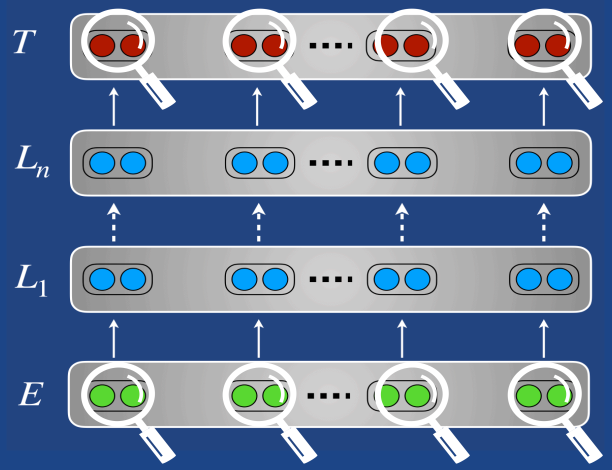
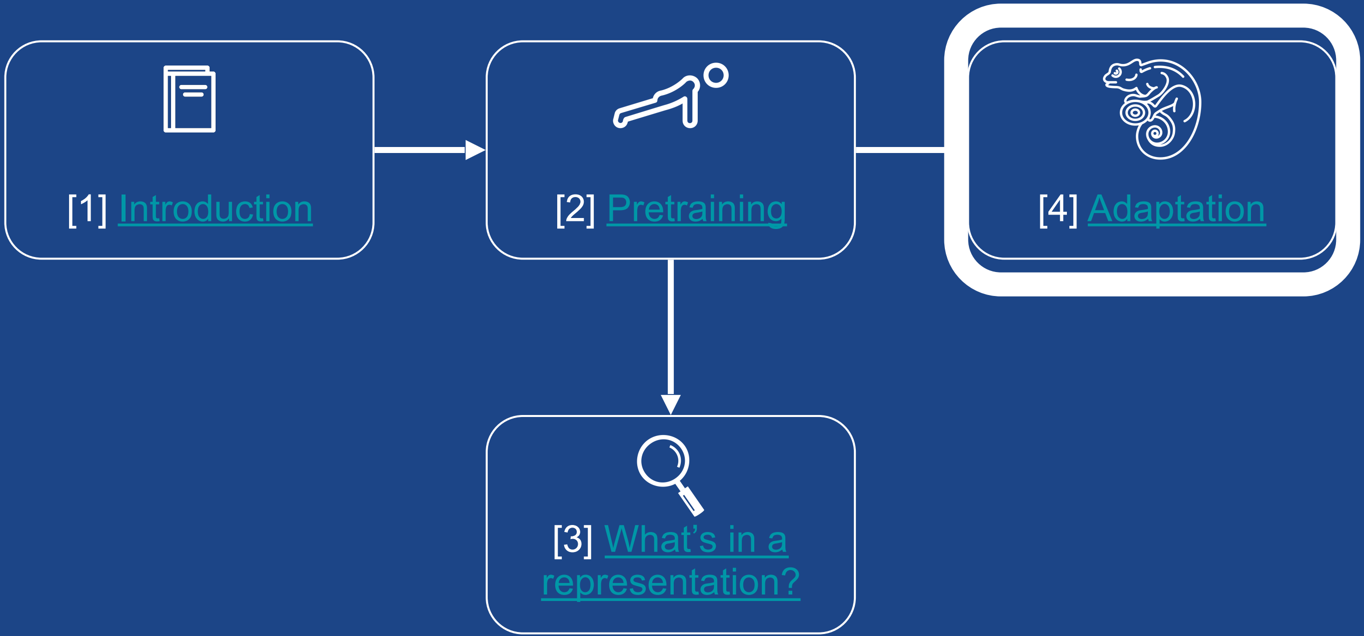
- Analysis methods as tools to aid model development!



Agenda

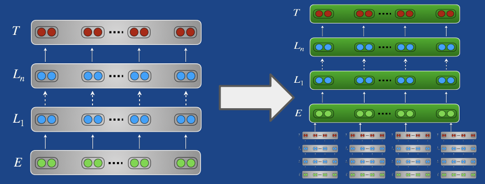

[1] Introduction
[2] Pretraining
[3] What's in a representation?
[4] Adaptation

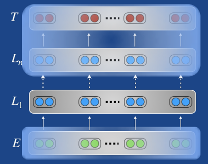
4. Adaptation

Image credit: Ben Didier

4 – How to adapt the pretrained model

Several orthogonal directions we can make decisions on:





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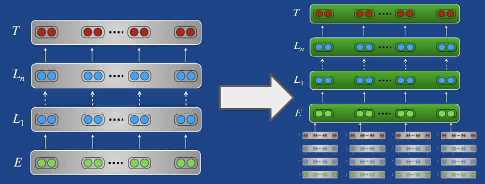
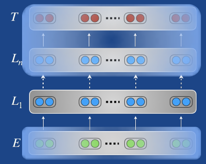
   How much to change the pretrained model architecture for adaptation





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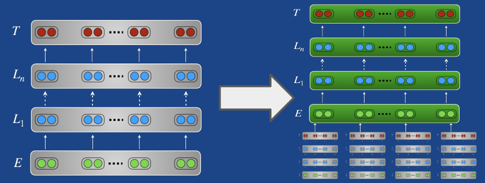

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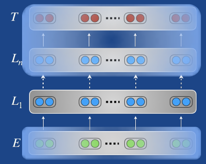

2. **Optimization** schemes?
   Which weights to train during adaptation and following what schedule

4.1 – Architecture

Two general options:

Image credit:
Darmawansyah

4.1 – Architecture

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A. **Keep** pretrained model **internals unchanged**:
   Add classifiers on top, embeddings at the bottom, use outputs as features

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Image credit: Darmawansyah

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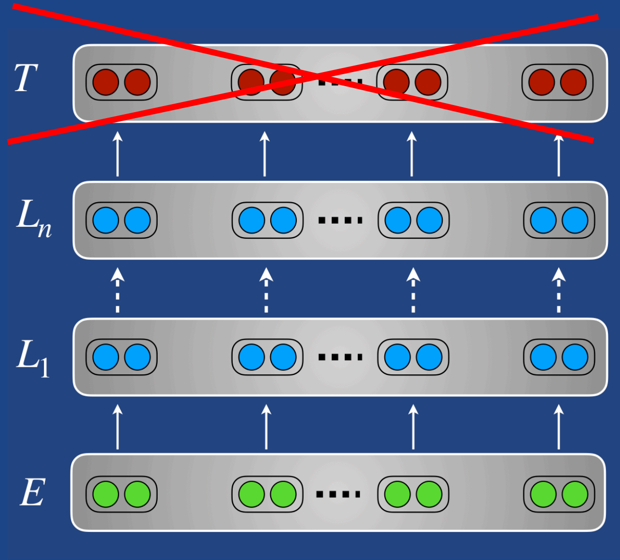
4.1.A – Architecture: Keep model **unchanged**

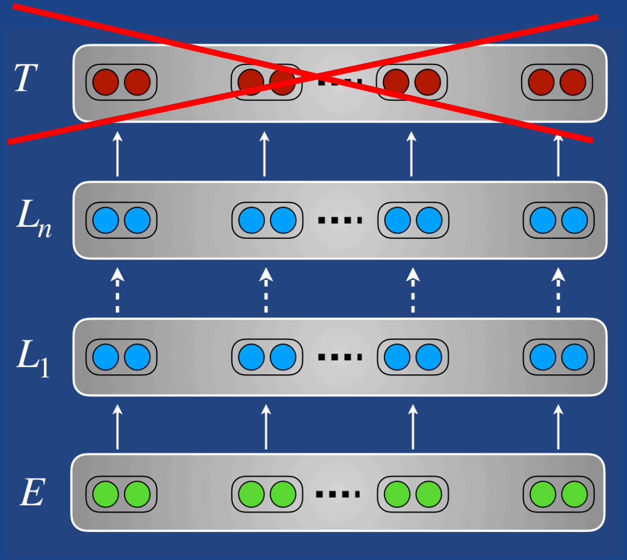
General workflow:



4.1.A – Architecture: Keep model **unchanged**

General workflow:

1. **Remove pretraining task head** if not useful for target task
    a. **Example**: remove softmax classifier from pretrained LM
    b. **Not always needed**: some adaptation schemes re-use the pretraining objective/task, e.g. for **multi-task learning**



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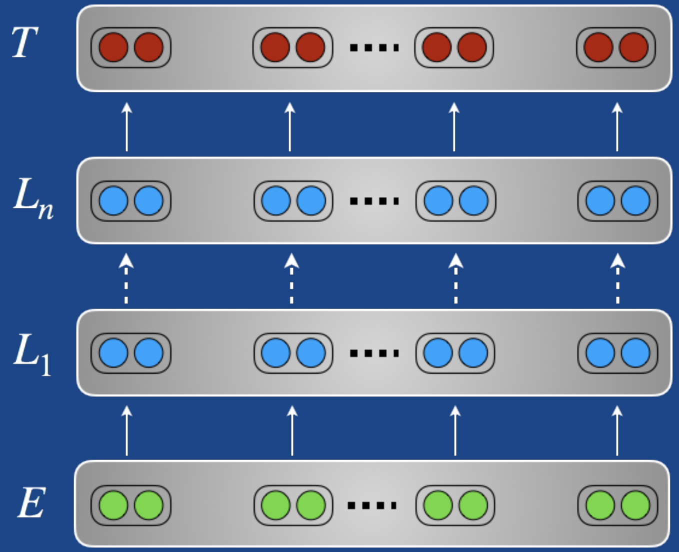

Also known as finetuning*

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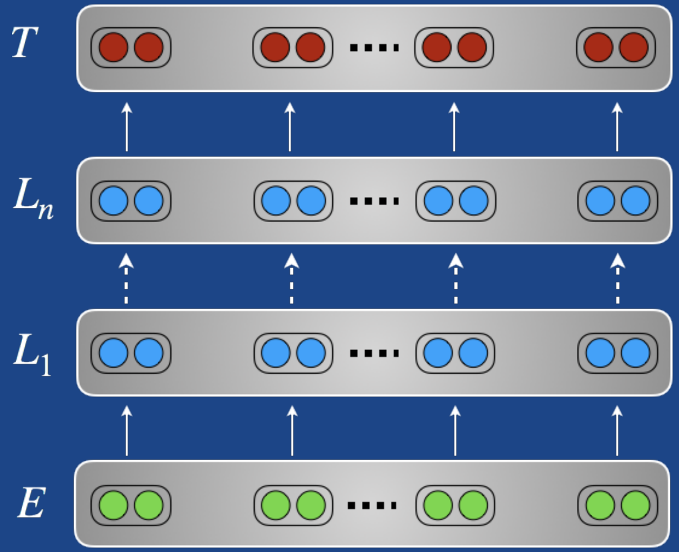

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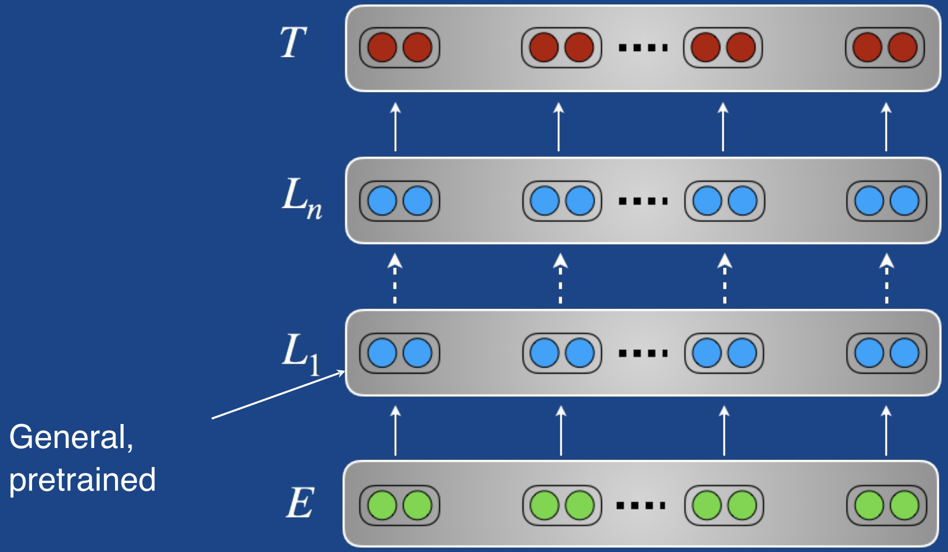

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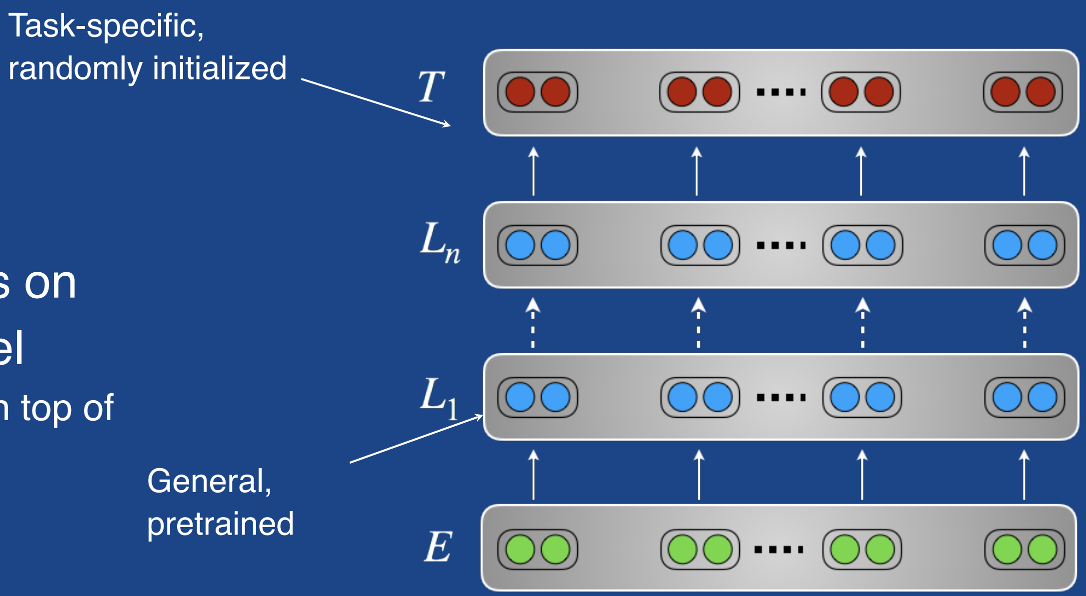

Also known as finetuning*

Hands-on #2:
Adapting our pretrained model

Image credit: Chanaky

Hands-on: Model adaptation

Let's see how a simple fine-tuning scheme can be implemented with our pretrained model:

- Plan
  - Start from our Transformer language model
  - Adapt the model to a target task:
    - *keep the model **core unchanged**, load the pretrained weights*
    - *add a linear layer **on top**, newly initialized*
    - *use additional embeddings **at the bottom**, newly initialized*

Hands-on: Model adaptation

Adaptation task

- ❑ We select a text classification task as the downstream task
- ❑ TREC-6: The Text REtrieval Conference (TREC) Question Classification (Li et al., COLING 2002)
- ❑ TREC consists of open-domain, fact-based questions divided into broad semantic categories contains 5500 labeled training questions & 500 testing questions with 6 labels:
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Ex:

★ How did serfdom develop in and then leave Russia ? —> *DESCRIPTION*
★ What films featured the character Popeye Doyle ? —> *ENTITY*

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	Model	Test
TREC-6	CoVe (McCann et al., 2017)	4.2
	TBCNN (Mou et al., 2015)	4.0
	LSTM-CNN (Zhou et al., 2016)	3.9
	ULMFiT (ours)	**3.6**

Transfer learning models shine on this type of low-resource task

(Howard and Ruder, ACL 2018)

Hands-on: Model adaptation

First adaptation scheme

Hands-on: Model adaptation

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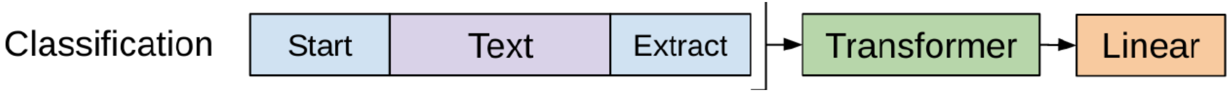
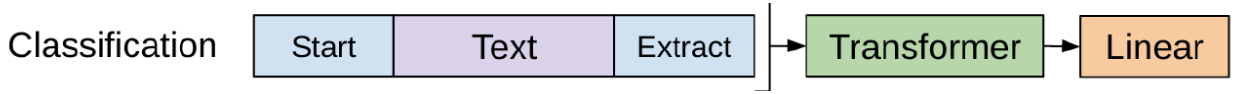


(Radford et al., 2018)

Hands-on: Model adaptation

First adaptation scheme



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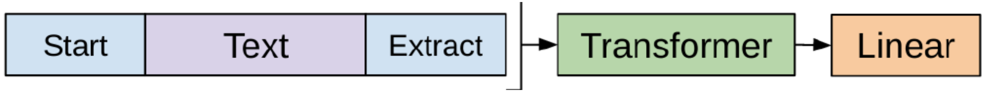
Hands-on: Model adaptation

First adaptation scheme

Classification



- ❏ Modifications:
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- ❏ Computation flow:
  - ❏ Model input: the tokenized question with a classification token at the end
  - ❏ Extract the last hidden-state associated to the classification token
  - ❏ Pass the hidden-state in a linear layer and softmax to obtain class probabilities

(Radford et al., 2018)

Hands-on: Model adaptation

```python
AdaptationConfig = namedtuple('AdaptationConfig',
  field_names="num_classes, dropout, initializer_range, batch_size, lr, max_norm, n_epochs,"
              "n_warmup, valid_set_prop, gradient_accumulation_steps, device,"
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               6          , 0.1    , 0.02              , 16        , 6.5e-5, 1.0    , 3,
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import random
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Hands-on: Model adaptation

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– 6 classes in TREC-6

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```

I	love	Mom	'	s	cooking	[CLS]
I	love	you	too	!	[CLS]	
No	way	[CLS]				
This	is	the	one	[CLS]		
Yes	[CLS]					

Hands-on: Model adaptation

Fine-tuning hyper-parameters:

– 6 classes in TREC-6

– Other fine tuning hyper parameters from Radford et al., 2018

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adapt_args = AdaptationConfig(
               6          , 0.1     , 0.02               , 16         , 6.5e-5, 1.0    , 3,
               10      , 0.1          , 1, "cuda" if torch.cuda.is_available() else "cpu",
               "./"    , "./dataset_cache.bin")
```

Let's load and prepare our dataset:

- trim to the transformer input size & add a classification token at the end of each sample,
- pad to the left,
- convert to tensors.

```
import random
from torch.utils.data import TensorDataset, random_split

dataset_file = cached_path("https://s3.amazonaws.com/datasets.huggingface.co/trec/"
                           "trec-tokenized-bert.bin")
datasets = torch.load(dataset_file)

for split_name in ['train', 'test']:

    # Trim the samples to the transformer's input length minus 1 & add a classification token
    datasets[split_name] = [x[:args.num_max_positions-1] + [tokenizer.vocab['[CLS]']]
                            for x in datasets[split_name]]

    # Pad the dataset to max length
    padding_length = max(len(x) for x in datasets[split_name])
    datasets[split_name] = [x + [tokenizer.vocab['[PAD]']] * (padding_length - len(x))
                            for x in datasets[split_name]]

    # Convert to torch.Tensor and gather inputs and labels
    tensor = torch.tensor(datasets[split_name], dtype=torch.long)
    labels = torch.tensor(datasets[split_name + '_labels'], dtype=torch.long)
    datasets[split_name] = TensorDataset(tensor, labels)

# Create a validation dataset from a fraction of the training dataset
valid_size = int(adapt_args.valid_set_prop * len(datasets['train']))
train_size = len(datasets['train']) - valid_size
valid_dataset, train_dataset = random_split(datasets['train'], [valid_size, train_size])

train_loader = DataLoader(train_dataset, batch_size=adapt_args.batch_size, shuffle=True)
valid_loader = DataLoader(valid_dataset, batch_size=adapt_args.batch_size, shuffle=False)
test_loader = DataLoader(datasets['test'], batch_size=adapt_args.batch_size, shuffle=False)
```

I	love	Mom	'	s	cooking	[CLS]
I	love	you	too	!	[CLS]	
No	way	[CLS]				
This	is	the	one	[CLS]		
Yes	[CLS]					

Hands-on: Model adaptation

Adapt our model architecture

```
class TransformerWithClfHead(nn.Module):
    def __init__(self, config, fine_tuning_config):
        super().__init__()
        self.config = fine_tuning_config
        self.transformer = Transformer(config.embed_dim, config.hidden_dim, config.num_embeddings,
                                       config.num_max_positions, config.num_heads, config.num_layers,
                                       fine_tuning_config.dropout, causal=not config.mlm)

        self.classification_head = nn.Linear(config.embed_dim, fine_tuning_config.num_classes)

        self.apply(self.init_weights)

    def init_weights(self, module):
        if isinstance(module, (nn.Linear, nn.Embedding, nn.LayerNorm)):
            module.weight.data.normal_(mean=0.0, std=self.config.initializer_range)
        if isinstance(module, (nn.Linear, nn.LayerNorm)) and module.bias is not None:
            module.bias.data.zero_()

    def forward(self, x, clf_tokens_mask, clf_labels=None, padding_mask=None):
        hidden_states = self.transformer(x, padding_mask)

        clf_tokens_states = (hidden_states * clf_tokens_mask.unsqueeze(-1).float()).sum(dim=0)
        clf_logits = self.classification_head(clf_tokens_states)

        if clf_labels is not None:
            loss_fct = nn.CrossEntropyLoss(ignore_index=-1)
            loss = loss_fct(clf_logits.view(-1, clf_logits.size(-1)), clf_labels.view(-1))
            return clf_logits, loss
        return clf_logits
```

```
# If you have pretrained a model in the first section, you can use its weigths
# state_dict = model.state_dict()

# Otherwise, just load pretrained model weigths (and reload the training config as well)
state_dict = torch.load(cached_path("https://s3.amazonaws.com/models.huggingface.co/"
                                    "naacl-2019-tutorial/model_checkpoint.pth"), map_location='cpu')
args = torch.load(cached_path("https://s3.amazonaws.com/models.huggingface.co/"
                              "naacl-2019-tutorial/model_training_args.bin"))

adaptation_model = TransformerWithClfHead(config=args, fine_tuning_config=adapt_args).to(adapt_args.device)

incompatible_keys = adaptation_model.load_state_dict(state_dict, strict=False)
print(f"Parameters discarded from the pretrained model: {incompatible_keys.unexpected_keys}")
print(f"Parameters added in the adaptation model: {incompatible_keys.missing_keys}")
```

```
Parameters discarded from the pretrained model: ['lm_head.weight']
Parameters added in the adaptation model: ['classification_head.weight', 'classification_head.bias']
```

Hands-on: Model adaptation

Adapt our model architecture

Keep our pretrained model unchanged as the backbone.

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    def __init__(self, config, fine_tuning_config):
        super().__init__()
        self.config = fine_tuning_config
        self.transformer = Transformer(config.embed_dim, config.hidden_dim, config.num_embeddings,
                                       config.num_max_positions, config.num_heads, config.num_layers,
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Hands-on: Model adaptation

Adapt our model architecture

Keep our pretrained model unchanged as the backbone.

Replace the pre-training head (language modeling) with the classification head:
A linear layer, which takes as input the hidden-state of the [CLF] token (using a mask)

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class TransformerWithClfHead(nn.Module):
    def __init__(self, config, fine_tuning_config):
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                                       config.num_max_positions, config.num_heads, config.num_layers,
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    def init_weights(self, module):
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Hands-on: Model adaptation

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        self.classification_head = nn.Linear(config.embed_dim, fine_tuning_config.num_classes)

        self.apply(self.init_weights)

    def init_weights(self, module):
        if isinstance(module, (nn.Linear, nn.Embedding, nn.LayerNorm)):
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        if isinstance(module, (nn.Linear, nn.LayerNorm)) and module.bias is not None:
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        if clf_labels is not None:
            loss_fct = nn.CrossEntropyLoss(ignore_index=-1)
            loss = loss_fct(clf_logits.view(-1, clf_logits.size(-1)), clf_labels.view(-1))
            return clf_logits, loss
        return clf_logits
```

* Initialize all the weights of the model.

```
# If you have pretrained a model in the first section, you can use its weigths
# state_dict = model.state_dict()

# Otherwise, just load pretrained model weigths (and reload the training config as well)
state_dict = torch.load(cached_path("https://s3.amazonaws.com/models.huggingface.co/"
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adaptation_model = TransformerWithClfHead(config=args, fine_tuning_config=adapt_args).to(adapt_args.device)

incompatible_keys = adaptation_model.load_state_dict(state_dict, strict=False)
print(f"Parameters discarded from the pretrained model: {incompatible_keys.unexpected_keys}")
print(f"Parameters added in the adaptation model: {incompatible_keys.missing_keys}")
```

```
Parameters discarded from the pretrained model: ['lm_head.weight']
Parameters added in the adaptation model: ['classification_head.weight', 'classification_head.bias']
```

Hands-on: Model adaptation

Adapt our model architecture

Keep our pretrained model unchanged as the backbone.

Replace the pre-training head (language modeling) with the classification head:
A linear layer, which takes as input the hidden-state of the [CLF] token (using a mask)

```
class TransformerWithClfHead(nn.Module):
    def __init__(self, config, fine_tuning_config):
        super().__init__()
        self.config = fine_tuning_config
        self.transformer = Transformer(config.embed_dim, config.hidden_dim, config.num_embeddings,
                                       config.num_max_positions, config.num_heads, config.num_layers,
                                       fine_tuning_config.dropout, causal=not config.mlm)

        self.classification_head = nn.Linear(config.embed_dim, fine_tuning_config.num_classes)

        self.apply(self.init_weights)

    def init_weights(self, module):
        if isinstance(module, (nn.Linear, nn.Embedding, nn.LayerNorm)):
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        hidden_states = self.transformer(x, padding_mask)

        clf_tokens_states = (hidden_states * clf_tokens_mask.unsqueeze(-1).float()).sum(dim=0)
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        if clf_labels is not None:
            loss_fct = nn.CrossEntropyLoss(ignore_index=-1)
            loss = loss_fct(clf_logits.view(-1, clf_logits.size(-1)), clf_labels.view(-1))
            return clf_logits, loss
        return clf_logits
```

* Initialize all the weights of the model.
* Reload common weights from the pretrained model.

```
# If you have pretrained a model in the first section, you can use its weigths
# state_dict = model.state_dict()

# Otherwise, just load pretrained model weigths (and reload the training config as well)
state_dict = torch.load(cached_path("https://s3.amazonaws.com/models.huggingface.co/"
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adaptation_model = TransformerWithClfHead(config=args, fine_tuning_config=adapt_args).to(adapt_args.device)

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```

```
Parameters discarded from the pretrained model: ['lm_head.weight']
Parameters added in the adaptation model: ['classification_head.weight', 'classification_head.bias']
```

Hands-on: Model adaptation

Our fine-tuning code:

```python
optimizer = torch.optim.Adam(adaptation_model.parameters(), lr=adapt_args.lr)

# Training function and trainer
def update(engine, batch):
    adaptation_model.train()
    batch, labels = (t.to(adapt_args.device) for t in batch)
    inputs = batch.transpose(0, 1).contiguous()  # to shape [seq length, batch]
    _, loss = adaptation_model(inputs, clf_tokens_mask=(inputs == tokenizer.vocab['[CLS]']), clf_labels=labels,
                               padding_mask=(batch == tokenizer.vocab['[PAD]']))
    loss = loss / adapt_args.gradient_accumulation_steps
    loss.backward()
    torch.nn.utils.clip_grad_norm_(adaptation_model.parameters(), adapt_args.max_norm)
    if engine.state.iteration % adapt_args.gradient_accumulation_steps == 0:
        optimizer.step()
        optimizer.zero_grad()
    return loss.item()
trainer = Engine(update)

# Evaluation function and evaluator (evaluator output is the input of the metrics)
def inference(engine, batch):
    adaptation_model.eval()
    with torch.no_grad():
        batch, labels = (t.to(adapt_args.device) for t in batch)
        inputs = batch.transpose(0, 1).contiguous()  # to shape [seq length, batch]
        clf_logits = adaptation_model(inputs, clf_tokens_mask=(inputs == tokenizer.vocab['[CLS]']),
                                      padding_mask=(batch == tokenizer.vocab['[PAD]']))
    return clf_logits, labels
evaluator = Engine(inference)

# Attache metric to evaluator & evaluation to trainer: evaluate on valid set after each epoch
Accuracy().attach(evaluator, "accuracy")
@trainer.on(Events.EPOCH_COMPLETED)
def log_validation_results(engine):
    evaluator.run(valid_loader)
    print(f"Validation Epoch: {engine.state.epoch} Error rate: {100*(1 - evaluator.state.metrics['accuracy'])}")

# Learning rate schedule: linearly warm-up to lr and then to zero
scheduler = PiecewiseLinear(optimizer, 'lr', [(0, 0.0), (adapt_args.n_warmup, adapt_args.lr),
                                              (len(train_loader)*adapt_args.n_epochs, 0.0)])
trainer.add_event_handler(Events.ITERATION_STARTED, scheduler)

# Add progressbar with loss
RunningAverage(output_transform=lambda x: x).attach(trainer, "loss")
ProgressBar(persist=True).attach(trainer, metric_names=['loss'])

# Save checkpoints and finetuning config
checkpoint_handler = ModelCheckpoint(adapt_args.log_dir, 'finetuning_checkpoint', save_interval=1, require_empty=False)
trainer.add_event_handler(Events.EPOCH_COMPLETED, checkpoint_handler, {'mymodel': adaptation_model})
torch.save(args, os.path.join(adapt_args.log_dir, 'fine_tuning_args.bin'))
```

Hands-on: Model adaptation

Our fine-tuning code:

A simple training update function:
** prepare inputs: transpose and* *<u>build padding & classification token masks</u>*
** we have options to clip and accumulate gradients*

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    loss = loss / adapt_args.gradient_accumulation_steps
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Hands-on: Model adaptation

Our fine-tuning code:

A simple training update function:
** prepare inputs: transpose and <u>build padding & classification token masks</u>*
** we have options to clip and accumulate gradients*

We will evaluate on our validation and test sets:
** validation: after each epoch*
** test: at the end*

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optimizer = torch.optim.Adam(adaptation_model.parameters(), lr=adapt_args.lr)

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torch.save(args, os.path.join(adapt_args.log_dir, 'fine_tuning_args.bin'))
```

Hands-on: Model adaptation – Results

We can now fine-tune our model on TREC:

Hands-on: Model adaptation – Results

We can now fine-tune our model on TREC:

```
[50] trainer.run(train_loader, max_epochs=adapt_args.n_epochs)
```

```
Epoch [1/3]  [307/307] 100%| , loss=3.85e-01 [01:10<00:00]
Validation Epoch: 1 Error rate: 9.174311926605505
Epoch [2/3]  [307/307] 100%| , loss=1.73e-01 [01:10<00:00]
Validation Epoch: 2 Error rate: 5.871559633027523
Epoch [3/3]  [307/307] 100%| , loss=9.63e-02 [01:10<00:00]
Validation Epoch: 3 Error rate: 5.688073394495408
<ignite.engine.engine.State at 0x7ff4c8b385f8>
```

```
evaluator.run(test_loader)
print(f"Test Results - Error rate: {100*(1.00 - evaluator.state.metrics['accuracy']):.3f}")
```

```
Test Results - Error rate: 3.600
```

Hands-on: Model adaptation – Results

We can now fine-tune our model on TREC:

```
[50] trainer.run(train_loader, max_epochs=adapt_args.n_epochs)
```

```
Epoch [1/3]  [307/307] 100%| , loss=3.85e-01 [01:10<00:00]
Validation Epoch: 1 Error rate: 9.174311926605505
Epoch [2/3]  [307/307] 100%| , loss=1.73e-01 [01:10<00:00]
Validation Epoch: 2 Error rate: 5.871559633027523
Epoch [3/3]  [307/307] 100%| , loss=9.63e-02 [01:10<00:00]
Validation Epoch: 3 Error rate: 5.688073394495408
<ignite.engine.engine.State at 0x7ff4c8b385f8>
```

```
evaluator.run(test_loader)
print(f"Test Results - Error rate: {100*(1.00 - evaluator.state.metrics['accuracy']):.3f}")
```

```
Test Results - Error rate: 3.600
```

	Model	Test
TREC-6	CoVe (McCann et al., 2017)	4.2
	TBCNN (Mou et al., 2015)	4.0
	LSTM-CNN (Zhou et al., 2016)	3.9
	ULMFiT (ours)	**3.6**

We are at the state-of-the-art (ULMFiT)

Hands-on: Model adaptation – Results

We can now fine-tune our model on TREC:

```
[50] trainer.run(train_loader, max_epochs=adapt_args.n_epochs)

Epoch [1/3] [307/307] 100%|, loss=3.85e-01 [01:10<00:00]
Validation Epoch: 1 Error rate: 9.174311926605505
Epoch [2/3] [307/307] 100%|, loss=1.73e-01 [01:10<00:00]
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We are at the state-of-the-art (ULMFiT)

Remarks:

- ❏ The error rate goes down quickly! After one epoch we already have >90% accuracy.
  - ⇨ Fine-tuning is highly **data efficient** in Transfer Learning
- ❏ We took our pre-training & fine-tuning hyper-parameters straight from the literature on related models.
  - ⇨ Fine-tuning is often **robust** to the exact choice of hyper-parameters

Hands-on: Model adaptation – Results

Let's conclude this hands-on with a few additional words on robustness & variance.

Hands-on: Model adaptation – Results

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- Large pretrained models (e.g. BERT large) are prone to degenerate performance when fine-tuned on tasks with small training sets.

Hands-on: Model adaptation – Results

Let's conclude this hands-on with a few additional words on robustness & variance.

- Large pretrained models (e.g. BERT large) are prone to degenerate performance when fine-tuned on tasks with small training sets.
- Observed behavior is often "on-off": it either works very well or doesn't work at all.

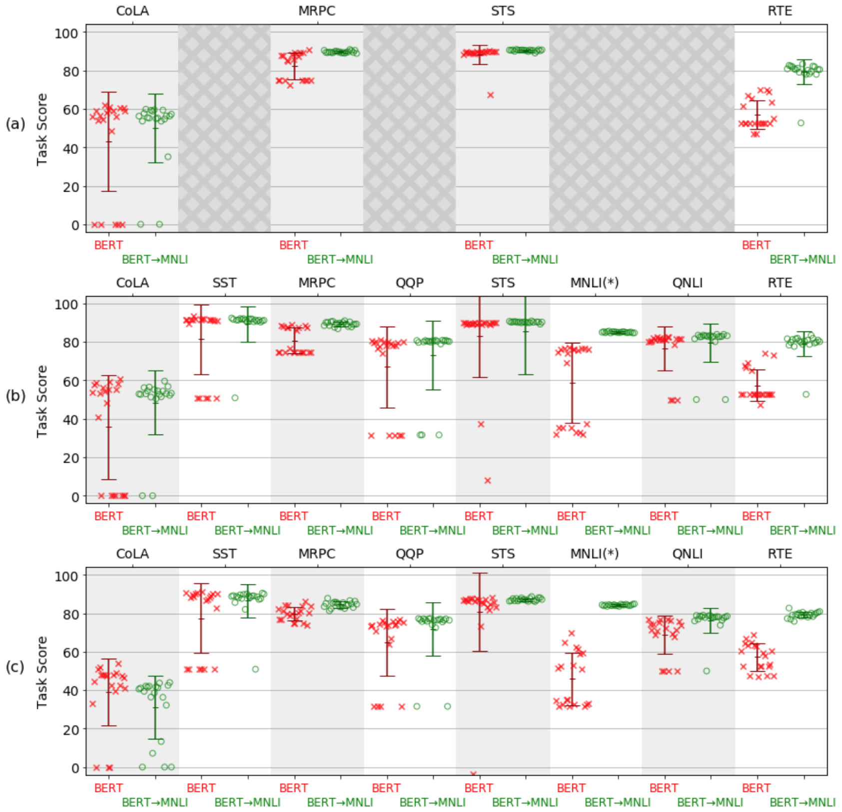


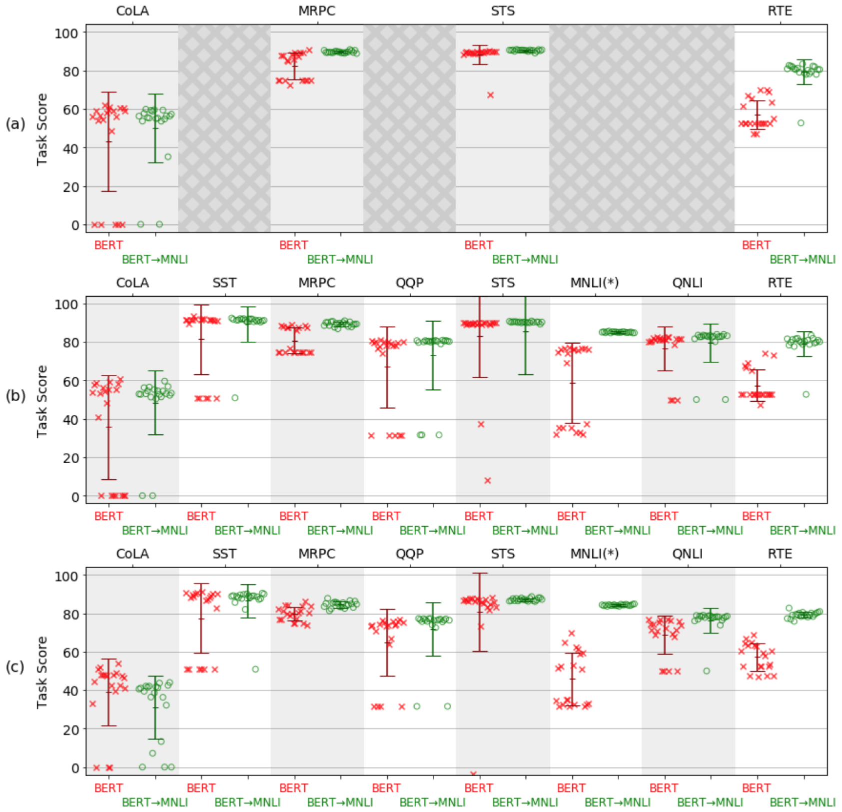
Figure 1: Distribution of task scores across 20 random restarts for BERT, and BERT with intermediary fine-tuning on MNLI. Each cross represents a single run. Error lines show mean±1std. (a) Fine-tuned on all data, for tasks with <10k training examples. (b) Fine-tuned on no more than 5k examples for each task. (c) Fine-tuned on no more than 1k examples for each task. (*) indicates that the intermediate task is the same as the target task.

Phang et al., 2018

Hands-on: Model adaptation – Results

Let’s conclude this hands-on with a few additional words on robustness & variance.

- Large pretrained models (e.g. BERT large) are prone to degenerate performance when fine-tuned on tasks with small training sets.
- Observed behavior is often “on-off”: it either works very well or doesn’t work at all.
- Understanding the conditions and causes of this behavior (models, adaptation schemes) is an open research question.



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[Phang et al., 2018]

4.2 – Optimization

Image credit: ProSymbols, purplestudio, Markus, Alfredo

4.2 – Optimization

Several directions when it comes to the optimization itself:

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A. Choose **which weights** we should update
   Feature extraction, fine-tuning, adapters

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4.2 – Optimization

Several directions when it comes to the optimization itself:

A. Choose **which weights** we should update
Feature extraction, fine-tuning, adapters

B. Consider **practical trade-offs**
Space and time complexity, performance

Image credit: ProSymbols, purplestudio, Markus, Alfredo

4.2.A – Optimization: Which weights?

The main question: **To tune or not to tune (the pretrained weights)?**

Image credit: purplestudio

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A. **Do not change** pretrained weights

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4.2.A – Optimization: Which weights?

The main question: **To tune or not to tune (the pretrained weights)?**

A. **Do not change** pretrained weights
   Feature extraction, adapters

B. **Change** pretrained weights
   Fine-tuning

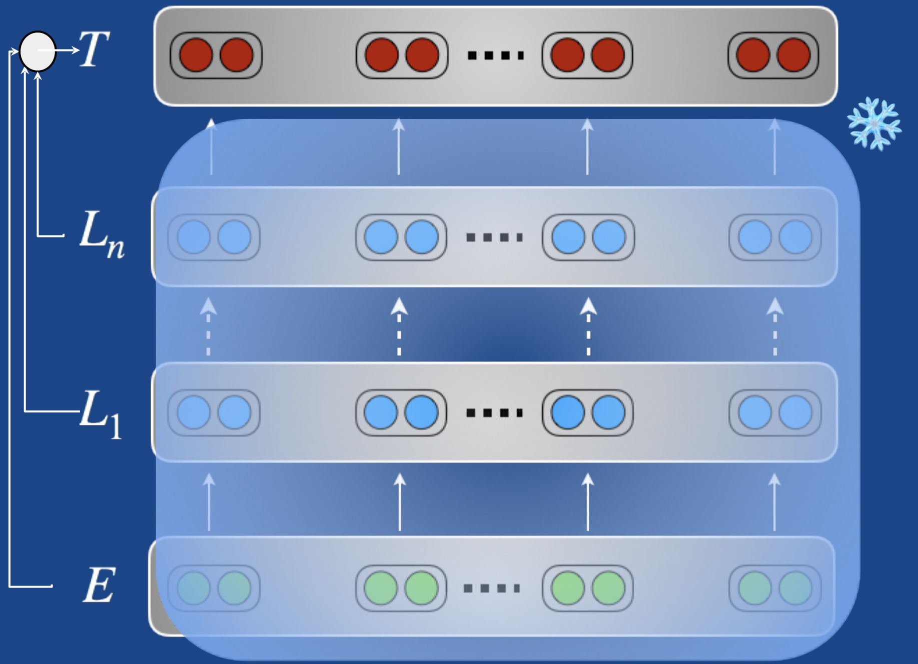
Image credit: purplestudio

4.2.A – Optimization: Which weights?

Don't touch the pretrained weights!

Feature extraction:

- ❑ Weights are **frozen**
- ❑ A **linear classifier** is trained on top of the pretrained representations
- ❑ **Don't just use features of the top layer!**
- ❑ Learn a **linear combination** of layers (Peters et al., NAACL 2018, Ruder et al., AAAI 2019)

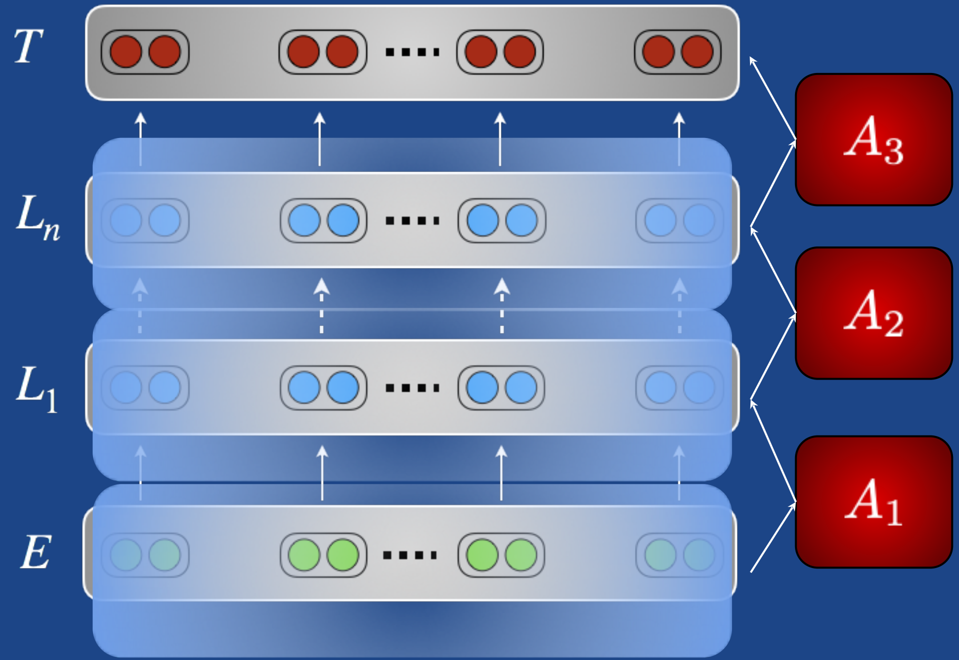


4.2.A – Optimization: Which weights?

Don't touch the pretrained weights!

Adapters

- Task-specific modules that are added **in between** existing layers
- Only adapters are trained



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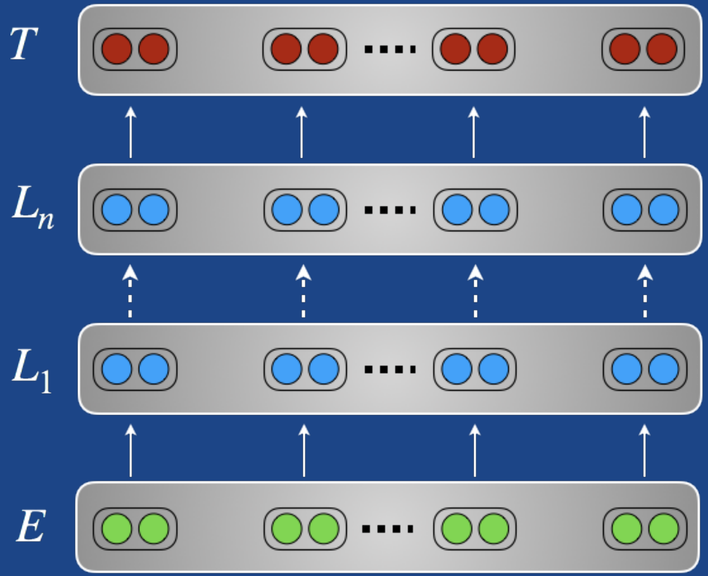

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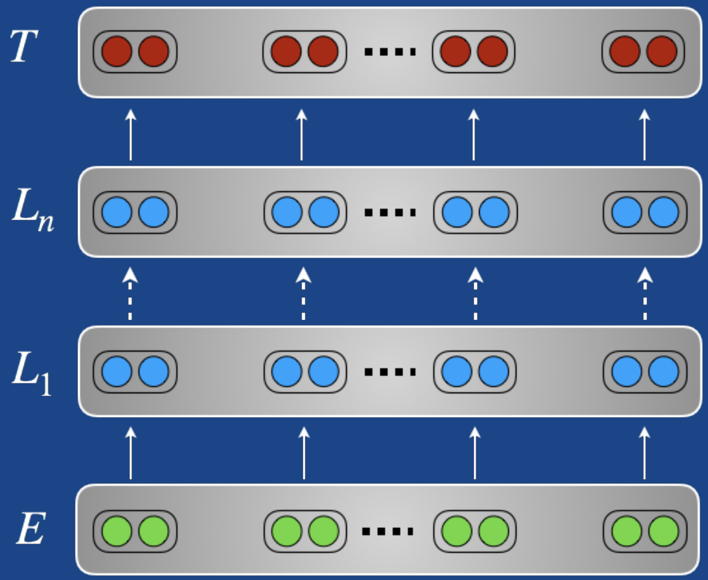
Fine-tuning:



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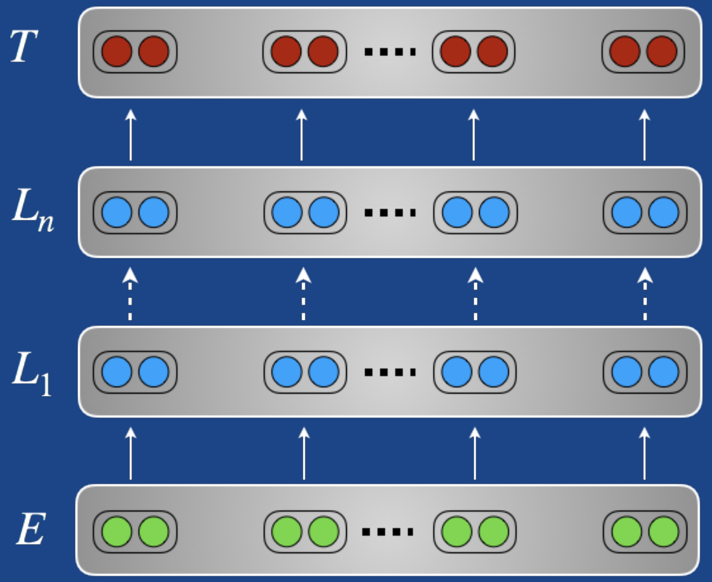
Fine-tuning:

- Pretrained weights are used as **initialization** for parameters of the downstream model



4.2.A – Optimization: Which weights?

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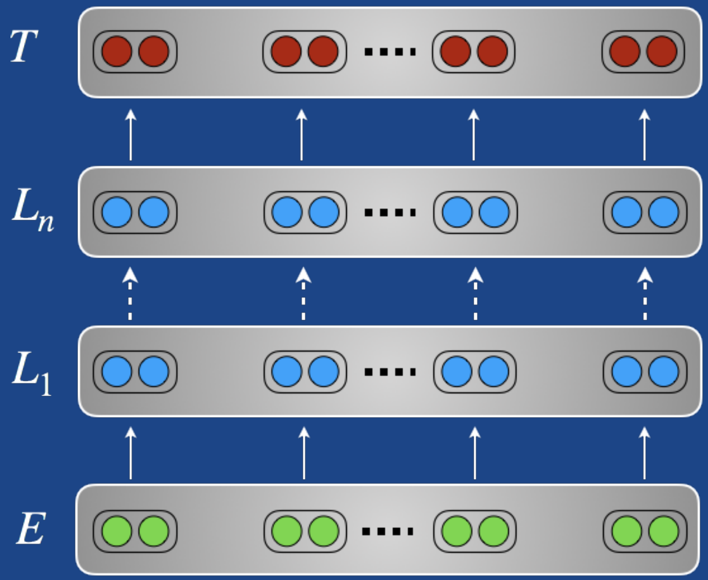
Fine-tuning:

- ❑ Pretrained weights are used as **initialization** for parameters of the downstream model
- ❑ The **whole pretrained architecture** is trained during the adaptation phase



4.2.B – Optimization: Trade-offs

Several trade-offs when choosing which weights to update:

Image credit: Alfredo

4.2.B – Optimization: Trade-offs

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A. **Space** complexity
   Task-specific modifications, additional parameters, parameter reuse

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Several trade-offs when choosing which weights to update:

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B. **Time** complexity

   Training time

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4.2.B – Optimization: Trade-offs

Several trade-offs when choosing which weights to update:

A. **Space** complexity

   Task-specific modifications, additional parameters, parameter reuse

B. **Time** complexity

   Training time

C. **Performance**

Image credit: Alfredo

4.2.B – Optimization trade-offs: Space

Task-specific modifications

Feature extraction ⟷ **Adapters** ⟷ **Fine-tuning**

Many — Few

4.2.B – Optimization trade-offs: Space

Task-specific modifications

Feature extraction **Adapters** **Fine-tuning**

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Parameter reuse

Feature extraction — **Adapters** — **Fine-tuning**

All — None

4.2.B – Optimization trade-offs: Time

Training time

Feature extraction **Adapters** **Fine-tuning**

Slow ⟷ Fast

4.2.B – Optimization trade-offs: Performance

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- Rule of thumb: If task source and target tasks are **dissimilar***, use feature extraction (Peters et al., 2019)

*dissimilar: certain capabilities (e.g. modelling inter-sentence relations) are beneficial for target task, but pretrained model lacks them

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- ❑ Otherwise, feature extraction and fine-tuning often perform similar
- ❑ Fine-tuning BERT on textual similarity tasks works significantly better
- ❑ Adapters achieve performance competitive with fine-tuning
- ❑ Anecdotally, Transformers are easier to fine-tune (less sensitive to hyper-parameters) than recurrent neural nets (e.g. LSTMs)

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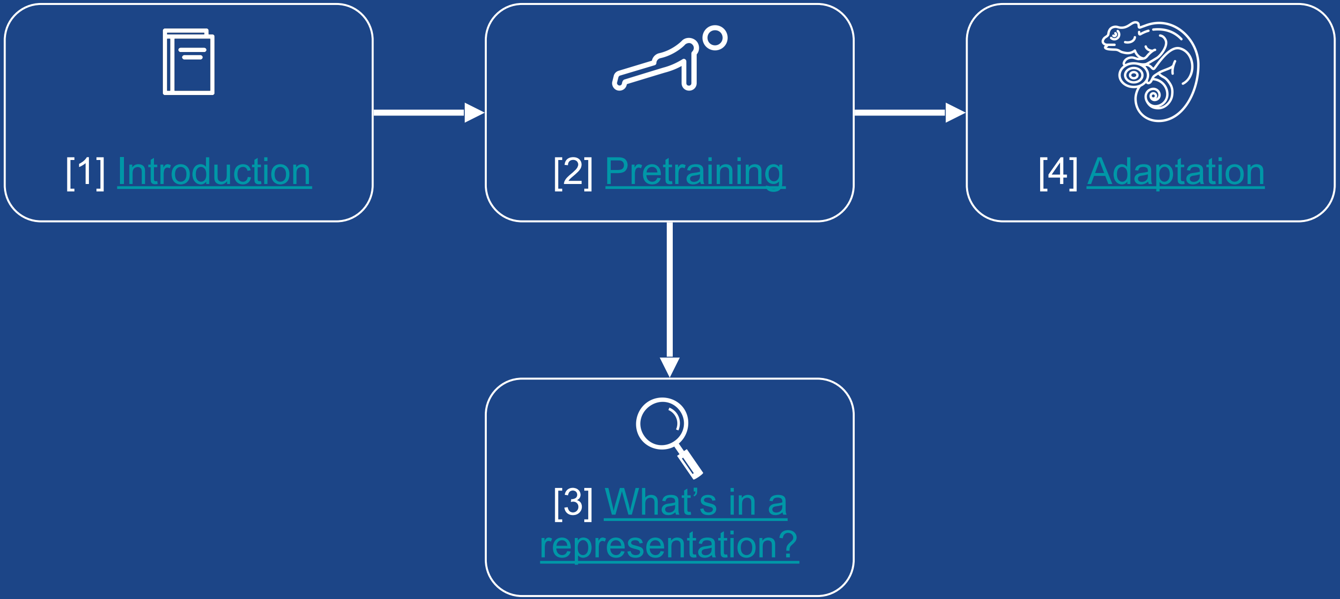
In summary


[1] Introduction
[2] Pretraining
[4] Adaptation
[3] What's in a representation?

Pretraining tasks

Pretraining tasks

More diverse self-supervised objectives

Pretraining tasks

More diverse self-supervised objectives

- computer vision

Example:

Sampling a patch and a neighbour and predicting their spatial configuration ([Doersch et al., ICCV 2015](#))

Image colorization ([Zhang et al., ECCV 2016](#))

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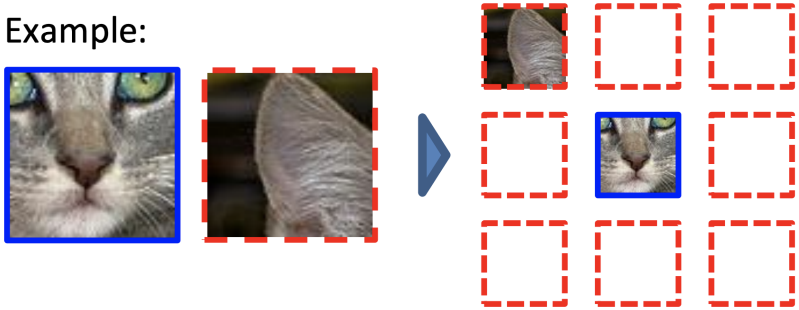

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- Self-supervision in language mostly based on word co-occurrence (Ando and Zhang, 2005) Instead, supervision on different levels of meaning

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- Self-supervision in language mostly based on word co-occurrence (Ando and Zhang, 2005) Instead, supervision on different levels of meaning
  - Discourse, document, sentence, etc.
  - Using other signals, e.g. meta-data

Pretraining tasks

Pretraining tasks

Need for grounded representations

Pretraining tasks

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- Limits of distributional hypothesis—difficult to learn certain types of information from raw text
  - Human reporting bias: not stating the obvious (Gordon and Van Durme, AKBC 2013)
  - Common sense isn't written down
  - No grounding to other modalities

Pretraining tasks

Need for grounded representations

- Limits of distributional hypothesis—difficult to learn certain types of information from raw text
  - Human reporting bias: not stating the obvious (Gordon and Van Durme, AKBC 2013)
  - Common sense isn't written down
  - No grounding to other modalities
- Possible solutions:
  - Incorporate other structured knowledge (e.g. knowledge bases like ERNIE, Zhang et al 2019)
  - Multimodal learning (e.g. with visual representations like VideoBERT, Sun et al. 2019)
  - Interactive/human-in-the-loop approaches (e.g. dialog, Hancock et al. 2018)

Continual learning

- Current transfer learning **performs adaptation once**.
- Ultimately, we'd like to have models that continue to **retain and accumulate knowledge** across many tasks (Yogatama et al., 2019).
- No distinction between pretraining and adaptation; just **one stream of tasks**.
- Main challenge towards this: **Catastrophic forgetting**.

Thank you!
Questions?

Email: swabhas@allenai.org

https://swabhs.com

@swabhz

Other Resources:
Colab
Full tutorial Video
Tutorial
Slides