CS11-747 Neural Networks for NLP

Multi-task, Multi-lingual Learning

Graham Neubig

Carnegie Mellon University

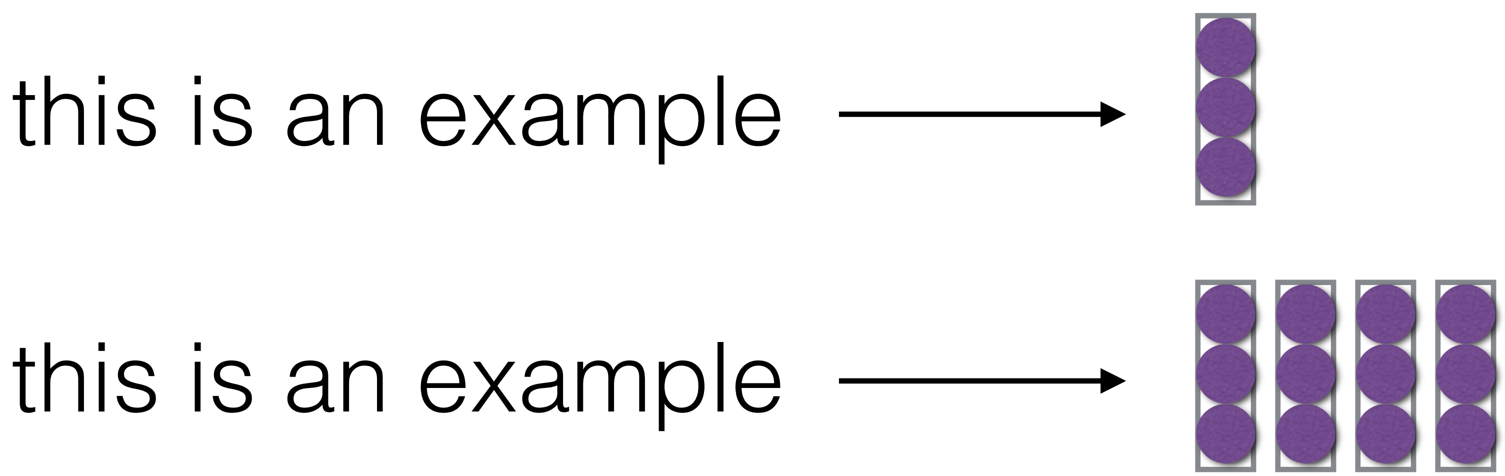
Language Technologies Institute

Site

https://phontron.com/class/nn4nlp2018/

Remember, Neural Nets are Feature Extractors!

- Create a vector representation of sentences or words for use in downstream tasks



- In many cases, the same representation can be used in multiple tasks (e.g. word embeddings)

Types of Learning

- **Multi-task learning** is a general term for training on multiple tasks

- **Transfer learning** is a type of multi-task learning where we only really care about one of the tasks

- **Domain adaptation** is a type of transfer learning, where the output is the same, but we want to handle different topics or genres, etc.

When to Multi-task?

Plethora of Tasks in NLP

- In NLP, there are a plethora of tasks, each requiring different varieties of data
  - **Only text:** e.g. language modeling
  - **Naturally occurring data:** e.g. machine translation
  - **Hand-labeled data:** e.g. most analysis tasks
- And each in many languages, many domains!

Rule of Thumb 1: Multitask to Increase Data

- Perform multi-tasking when one of your two tasks has many fewer data

- **General domain → specific domain**
(e.g. web text → medical text)

- **High-resourced language → low-resourced language**
(e.g. English → Telugu)

- **Plain text → labeled text**
(e.g. LM -> parser)

Rule of Thumb 2:

- Perform multi-tasking when your **tasks are related**

  common optimal hypothesis class, i.e. tasks have the same inductive bias.

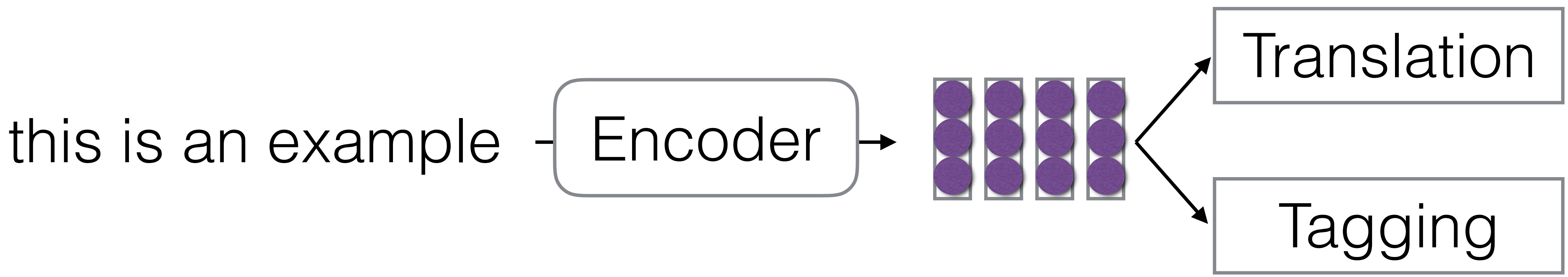
  could use the same features to make a decision

- e.g. predicting eye gaze and summarization (Klerke et al. 2016)

Methods for Multi-task Learning

Standard Multi-task Learning

- Train representations to do well on multiple tasks at once

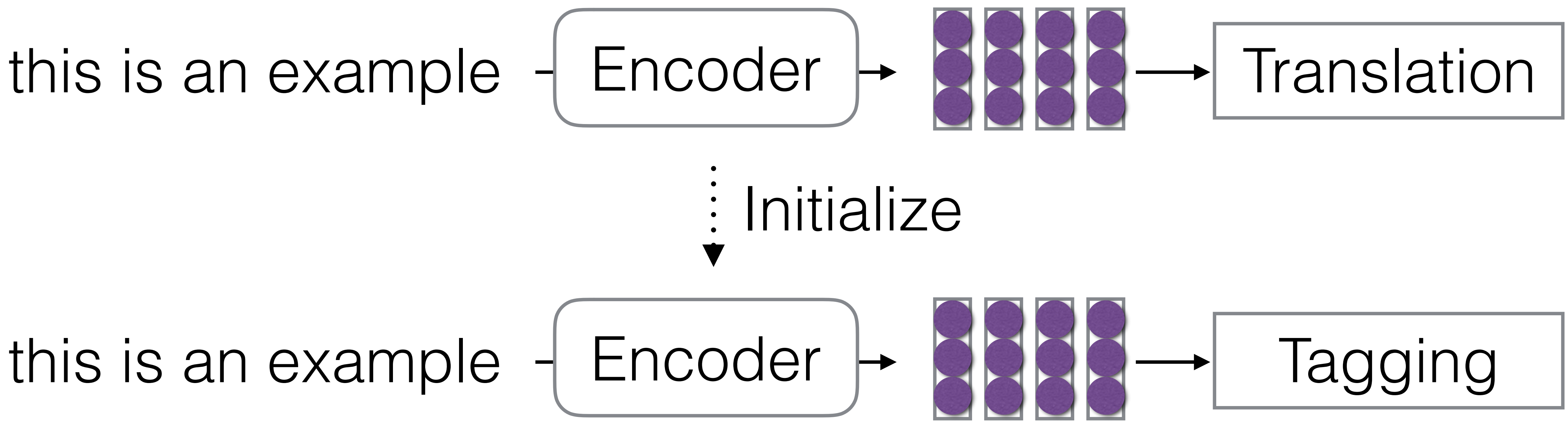


- In general, as simple as randomly choosing minibatch from one of multiple tasks

- Many many examples, starting with Collobert and Weston (2011)

Pre-training

- First train on one task, then train on another



- Widely used in word embeddings (Turian et al. 2010)

- Also pre-training sentence representations (Dai et al. 2015)

Examples of Pre-training Encoders

- Common to pre-train encoders for downstream tasks, common to use:
- **Language models** (Dai and Le 2015)
- **Translation models** (McCann et al. 2017)
- **Bidirectional LMs** (Peters et al. 2017)
- **Masked LMs** (Devlin et al. 2019)

Regularization for Pre-training
(e.g. Barone et al. 2017)

- Pre-training relies on the fact that we won't move too far from the initialized values

- We need some form of regularization to ensure this

  - **Early stopping:** implicit regularization — stop when the model starts to overfit

  - **Explicit regularization:** L2 on difference from initial parameters

$$\theta_{adapt} = \theta_{pre} + \theta_{diff} \qquad \ell(\theta_{adapt}) = \sum_{\langle X,Y \rangle \in \langle \mathcal{X},\mathcal{Y} \rangle} -\log P(Y \mid X; \theta_{adapt}) + ||\theta_{diff}||$$

  - **Dropout:** Also implicit regularization, works pretty well

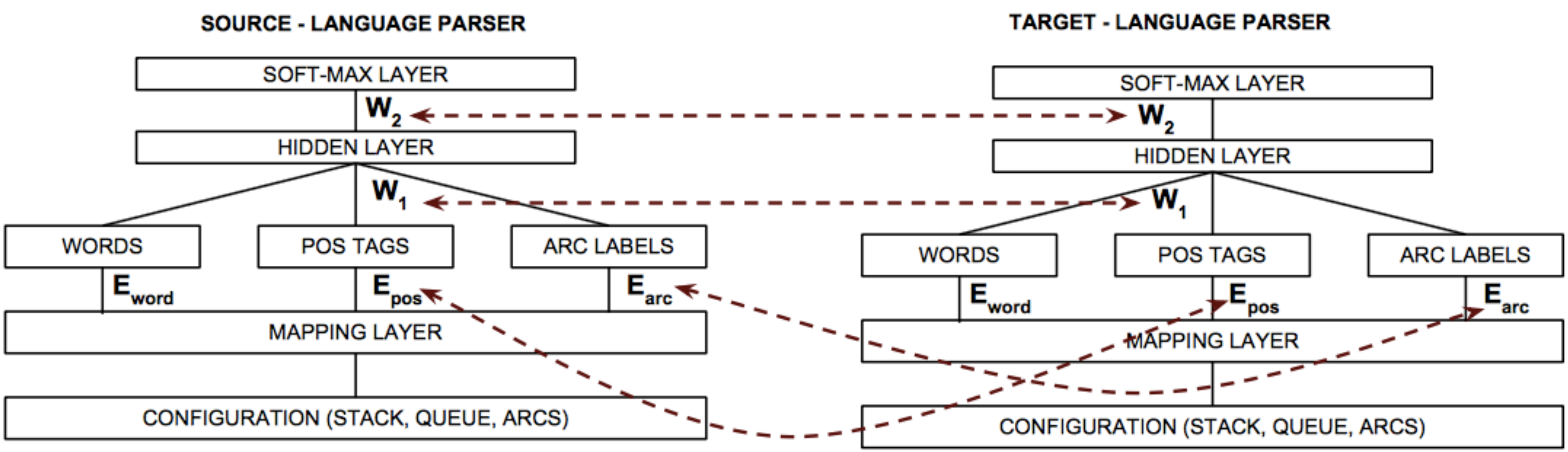
Selective Parameter Adaptation

- Sometimes it is better to adapt only some of the parameters
- e.g. in cross-lingual transfer for neural MT, Zoph et al. (2016) examine best parameters to adapt

Setting	Dev BLEU	Dev PPL
No retraining	0.0	112.6
Retrain source embeddings	7.7	24.7
+ source RNN	11.8	17.0
+ target RNN	14.2	14.5
+ target attention	**15.0**	13.9
+ target input embeddings	14.7	**13.8**
+ target output embeddings	13.7	14.4

Soft Parameter Tying

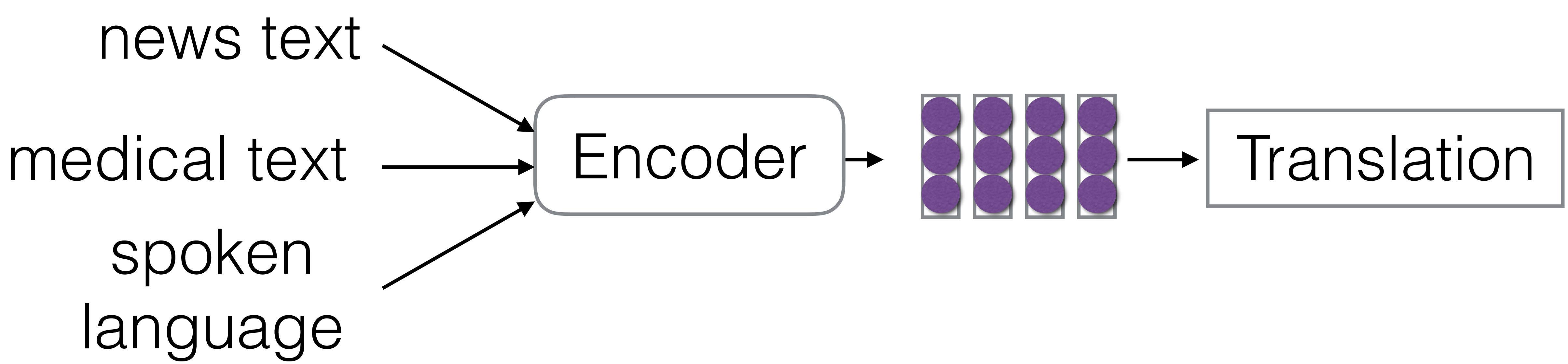
- It is also possible to share parameters loosely between various tasks
- Parameters are regularized to be closer, but not tied in a hard fashion (e.g. Duong et al. 2015)



Domain Adaptation

Domain Adaptation

- Basically one task, but incoming data could be from very different distributions



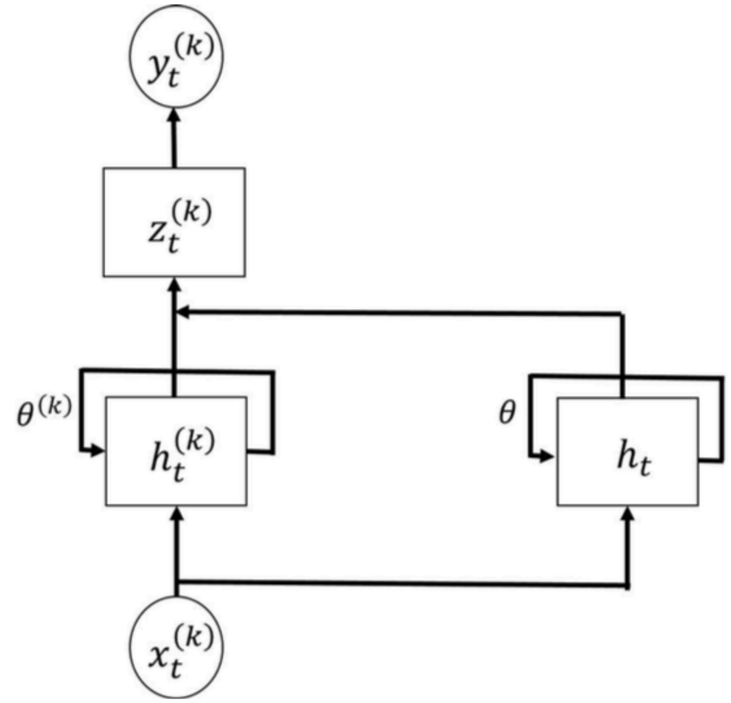
- Often have big grab-bag of all domains, and want to tailor to a specific domain
- Two settings: **supervised and unsupervised**

Supervised/Unsupervised Adaptation

- **Supervised adaptation:** have data in target domain
  - Simple pre-training on all data, tailoring to domain-specific data (Luong et al. 2015)
  - Learning domain-specific networks/features
- **Unsupervised adaptations:** no data in target domain
  - Matching distributions over features

Supervised Domain Adaptation through Feature Augmentation

- e.g. Train general-domain and domain-specific feature extractors, then sum their results (Kim et al. 2016)



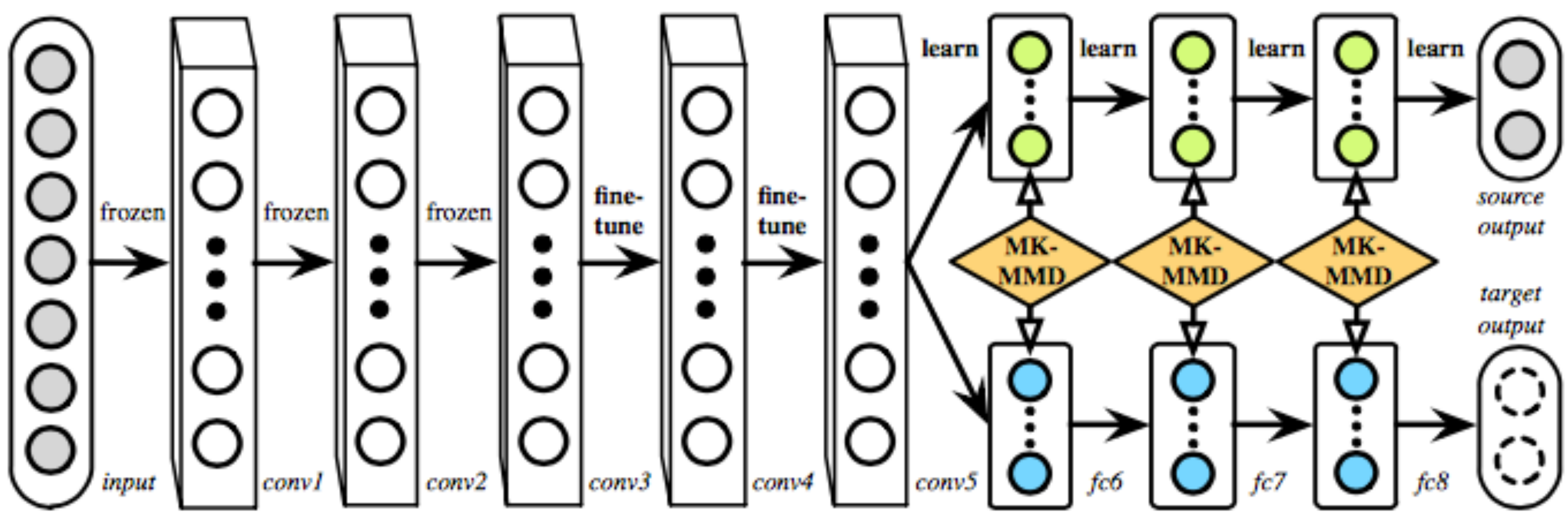
- Append a domain tag to input (Chu et al. 2016)

<news> news text

<med> medical text

Unsupervised Learning through Feature Matching

- Adapt the latter layers of the network to match labeled and unlabeled data using multi-kernel mean maximum discrepancy (Long et al. 2015)

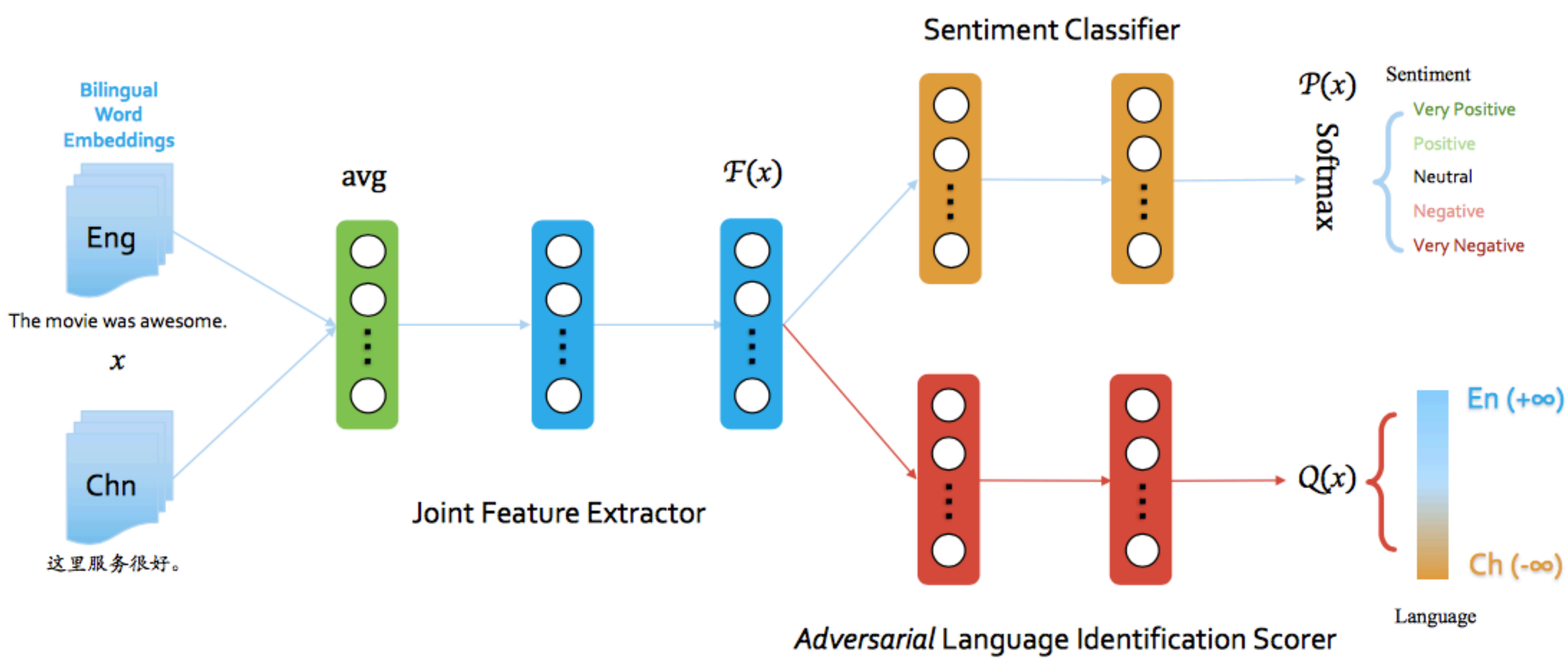


- Similarly, adversarial nets (Ganin et al. 2016)

Multi-lingual Models

Multilingual Inputs

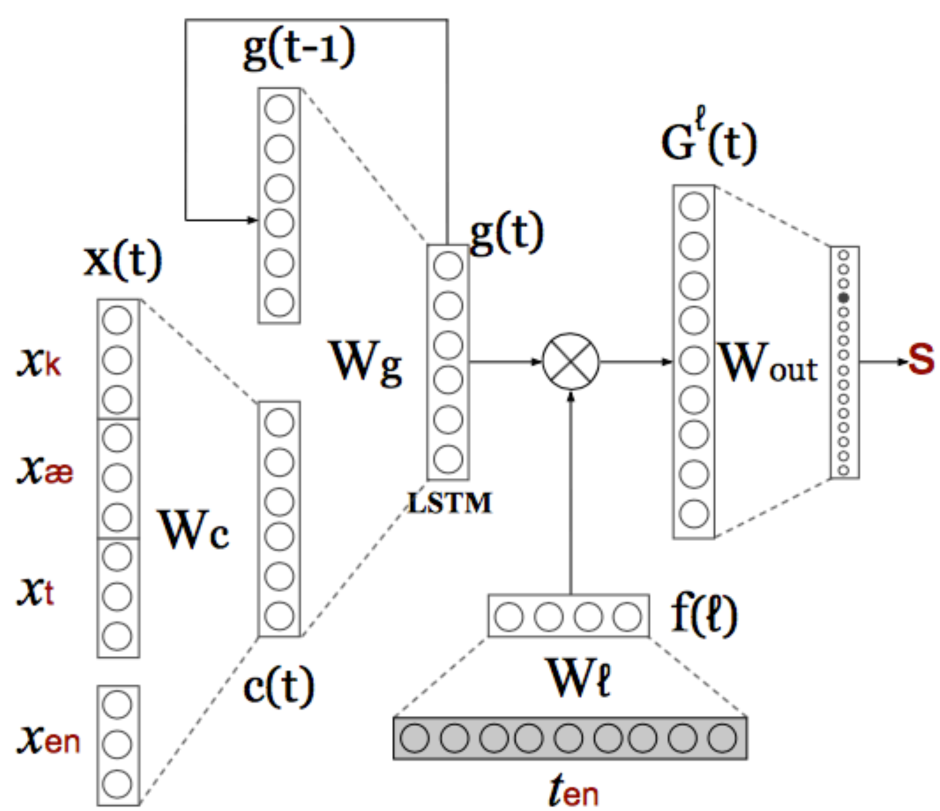
- Often as simple as training a single (large) encoder
- Optionally: use adversarial objective to help ensure that information is shared (Chen et al. 2016)



- Quite successful in a number of tasks

Multilingual Structured Prediction/ Multilingual Outputs

- Things are harder when predicting a sequence of actions (parsing) or words (MT) in different languages
- One simple method: add embedding of the expected output to your model (e.g. Tsvetkov et al. 2016)



Multi-lingual Sequence-to-sequence Models

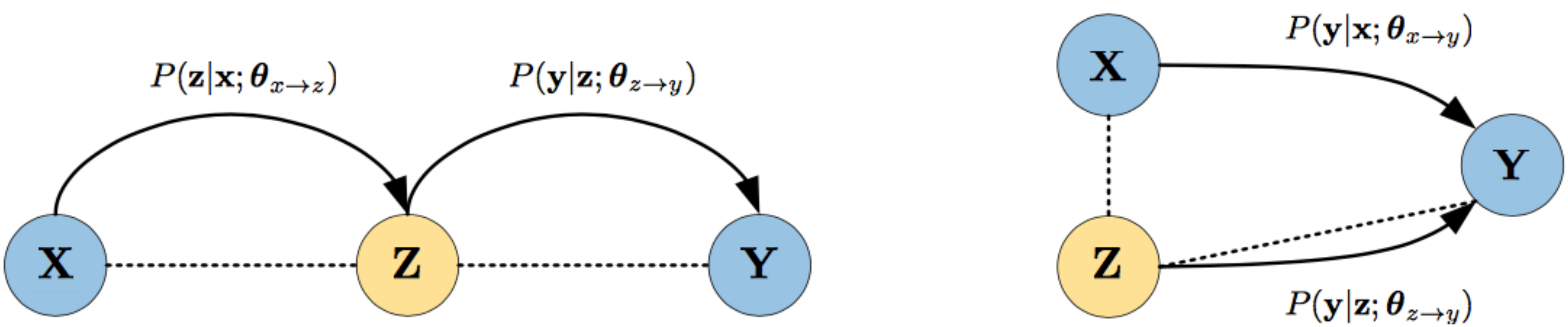
- It is possible to translate into several languages by adding a tag about the target language (Johnson et al. 2016, Ha et al. 2016)

  <fr> this is an example → ceci est un exemple
  <ja> this is an example → これは例です

- Potential to allow for **"zero-shot"** learning: train on fr↔en and ja↔en, and use on fr↔ja
  - Works, but not as effective as translating fr→en→ja

Teacher-student Networks for Multilingual Adaptation (Chen et al. 2017)

- Use a better pivoted model to “teach” a worse zero-shot model to translate well



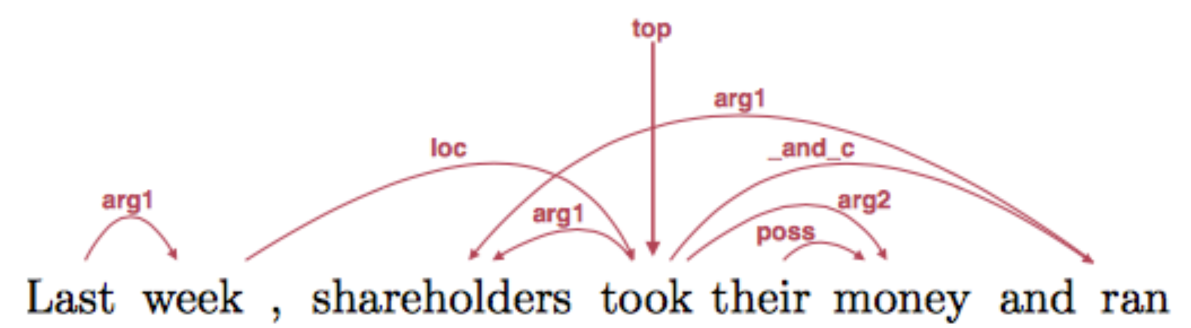
Multi-task Models

Types of Multi-tasking

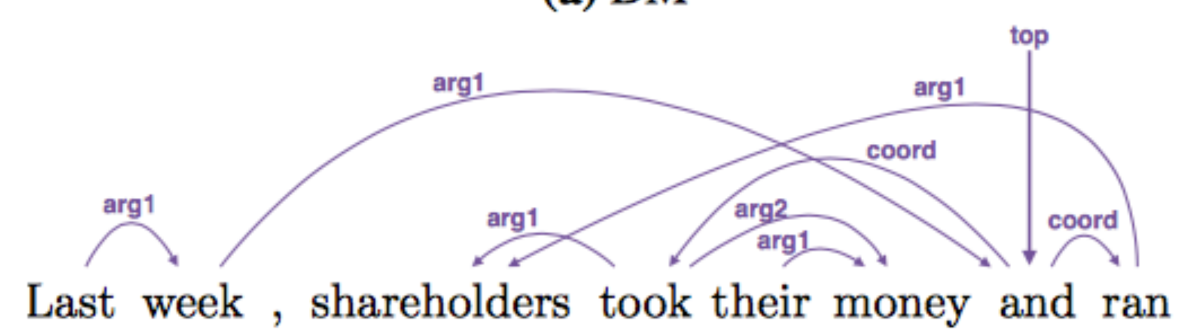
- Most common: train on plain text or translated text, use information for syntactic analysis task
- Also, training on multiple annotation tasks
- Other examples:
    - Training with multiple annotation standards
    - Training w/ different layers for different tasks

Multiple Annotation Standards

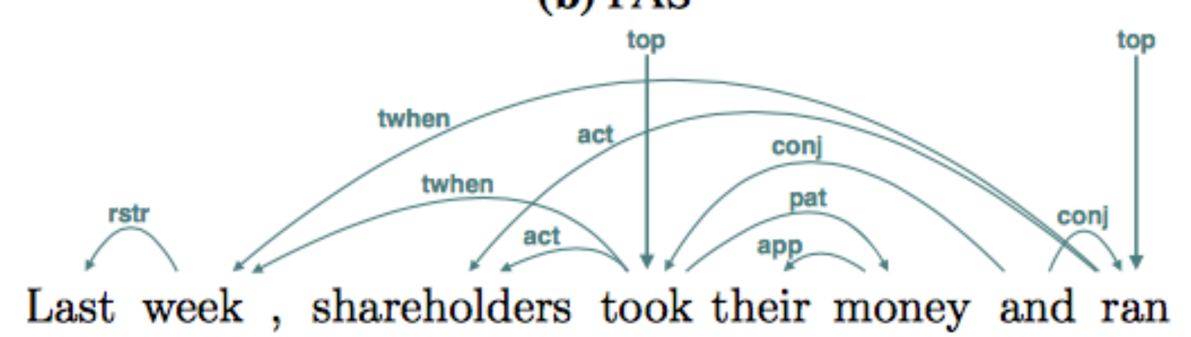
- For analysis tasks, it is possible to have different annotation standards
- Solution: train models that adjust to annotation standards for tasks such as semantic parsing (Peng et al. 2017).
- We can even adapt to individual annotators! (Guan et al. 2017)



(a) DM



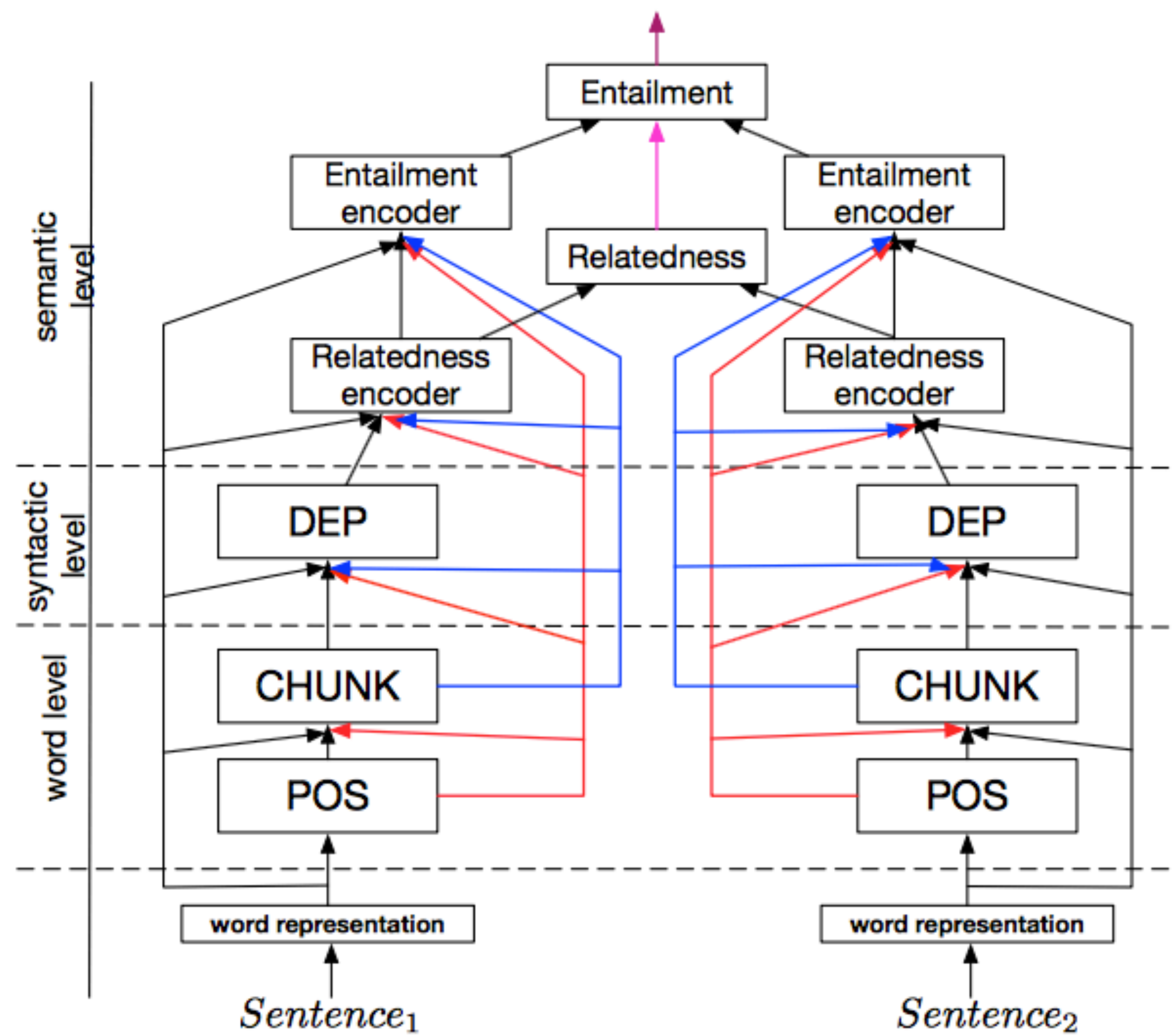
(b) PAS



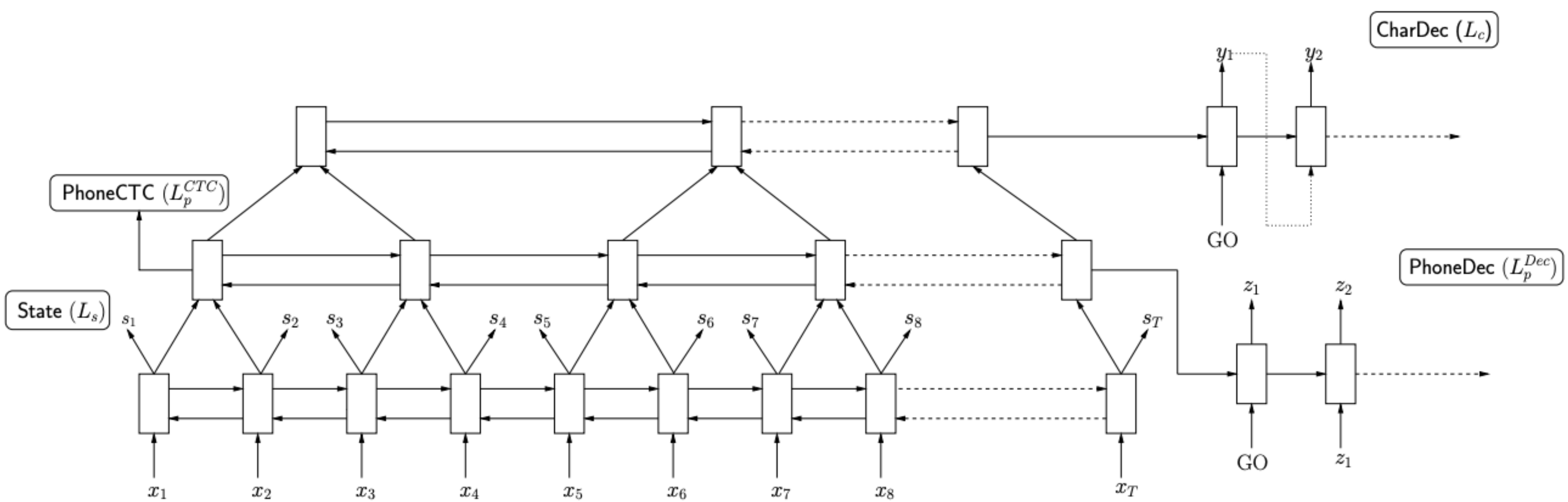
(c) PSD

Different Layers for Different Tasks (Hashimoto et al. 2017)

- Depending on the complexity of the task we might need deeper layers
- Choose the layers to use based on the level of semantics required



Different Layers for Different Tasks (Toshniwal et al 2017)



Summary of design dimensions

Order

1. First X —> Y, then X —> Z (transfer, pretraining)
   using pre-trained BERT/ELMo/other embeddings falls in this category!

2. Alternate between X —> Y and X —> Z
   (most common)

3. Jointly train on triplets X —> {Y,Z}
   (rare due to data scarcity)
   -maybe sharing different layers: X —> Y —> Z

4. Variations: X —> Y —> X
   Reconstruction: (Tu et al 2017)

Summary of design dimensions

Parameter Sharing

1. None (soft tying through regularization)

2. Some, e.g.:
   - only encoder (typical: X—>Y,Z)
   - embedding layer (e.g. BERT)

3. All (using tag for task/language)

4. Learn which parameters to share e.g.
   sluice network (Ruder et al. 2019)

Questions?