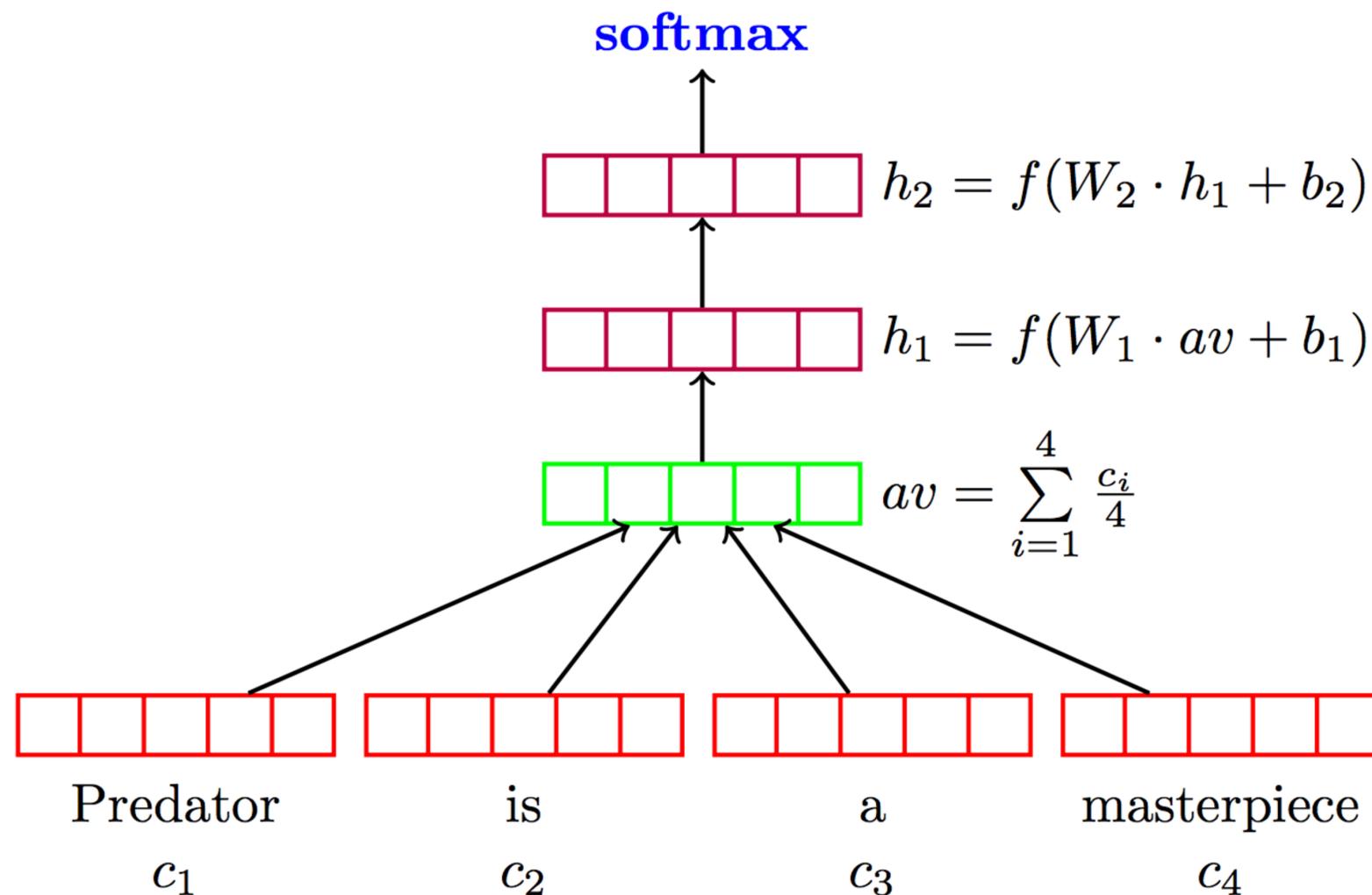


Applying Embeddings

- ▶ First layer of your network: map from word indices to embeddings
- ▶ Approach 1: learn these embeddings as parameters from your data
 - ▶ Often works pretty well
- ▶ Approach 2: initialize word embeddings using GloVe, keep fixed
 - ▶ Faster because no need to update these parameters
- ▶ Approach 3: initialize word embeddings GloVe, fine-tune
 - ▶ Works best for some tasks
- ▶ Can also evaluate embeddings intrinsically on tasks like word similarity

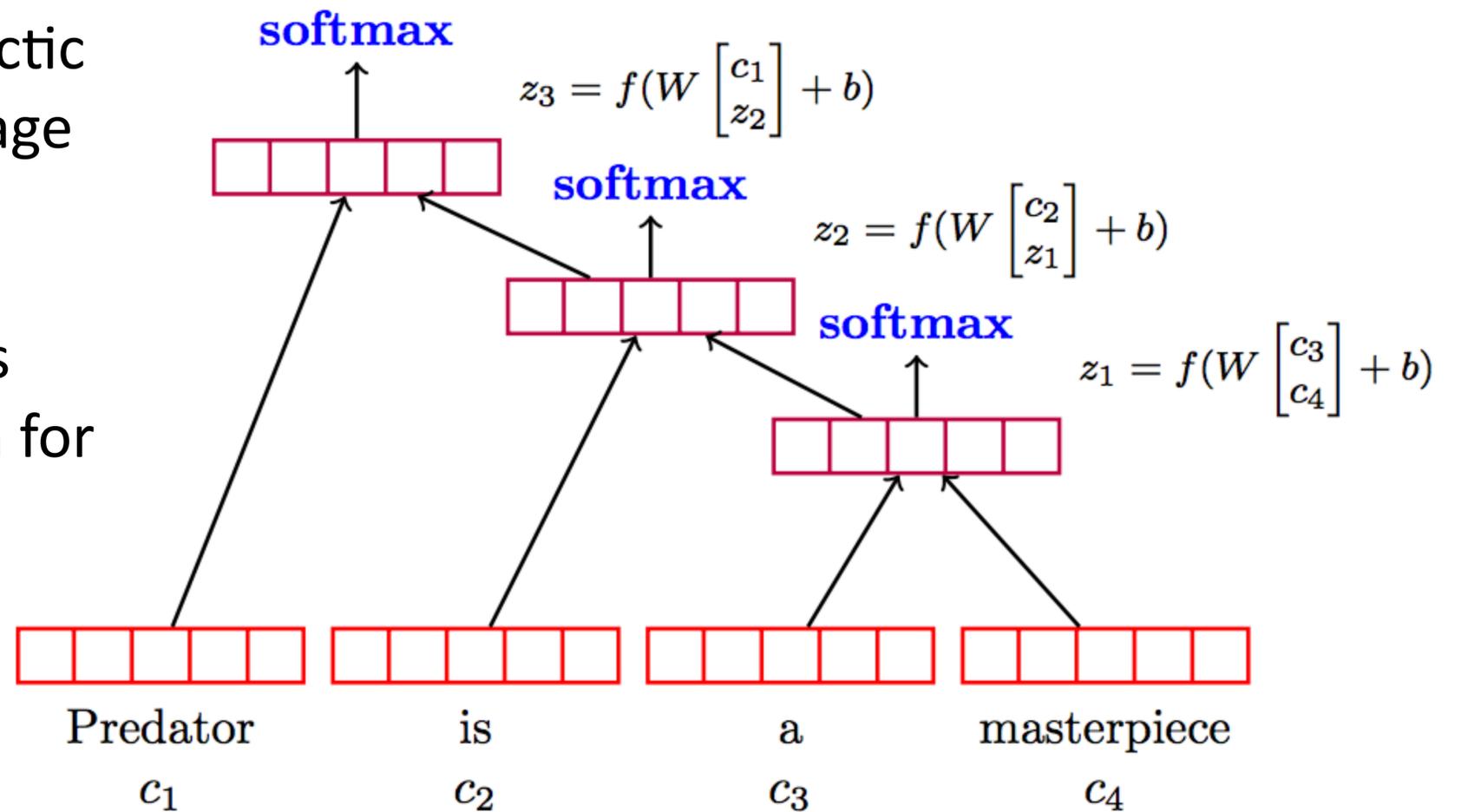
Deep Averaging Networks

- ▶ Deep Averaging Networks: feedforward neural network on average of word embeddings from input



Deep Averaging Networks

- ▶ Contradicts a widely-held view that we need to model syntactic structure to represent language
- ▶ Simple averaging can work as well as syntactic composition for some problems!



Deep Averaging Networks

| | Model | RT | SST fine | SST bin | IMDB | Time (s) | |
|---------------------------------|-----------------|-------------|-------------|-------------|-------------|--------------|-------------------------|
| No pretrained embeddings | DAN-ROOT | — | 46.9 | 85.7 | — | 31 | Iyer et al. (2015) |
| | DAN-RAND | 77.3 | 45.4 | 83.2 | 88.8 | 136 | |
| | DAN | 80.3 | 47.7 | 86.3 | 89.4 | 136 | |
| Bag-of-words | NBOW-RAND | 76.2 | 42.3 | 81.4 | 88.9 | 91 | Wang and Manning (2012) |
| | NBOW | 79.0 | 43.6 | 83.6 | 89.0 | 91 | |
| | BiNB | — | 41.9 | 83.1 | — | — | |
| | NBSVM-bi | 79.4 | — | — | 91.2 | — | |
| Tree-structured neural networks | RecNN* | 77.7 | 43.2 | 82.4 | — | — | Kim (2014) |
| | RecNTN* | — | 45.7 | 85.4 | — | — | |
| | DRecNN | — | 49.8 | 86.6 | — | 431 | |
| | TreeLSTM | — | 50.6 | 86.9 | — | — | |
| | DCNN* | — | 48.5 | 86.9 | 89.4 | — | |
| | PVEC* | — | 48.7 | 87.8 | 92.6 | — | |
| | CNN-MC | 81.1 | 47.4 | 88.1 | — | 2,452 | |
| WRRBM* | — | — | — | 89.2 | — | | |

Deep Averaging Networks

| Sentence | DAN | DRecNN | Ground Truth |
|---|----------|----------|--------------|
| who knows what exactly godard is on about in this film , but his words and images do n't have to add up to mesmerize you. | positive | positive | positive |
| it's so good that its relentless , polished wit can withstand not only inept school productions , but even oliver parker 's movie adaptation | negative | positive | positive |
| too bad , but thanks to some lovely comedic moments and several fine performances, it's not a total loss | negative | negative | positive |
| this movie was not good | negative | negative | negative |
| this movie was good | positive | positive | positive |
| this movie was bad | negative | negative | negative |
| the movie was not bad | negative | negative | positive |

- ▶ Will return to compositionality with syntax and LSTMs