Neural Language Model

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∗Contents are based on materials created by Noah Smith

Reference Content

- Noah Smith. CSE 517: Natural Language Processing
  https://courses.cs.washington.edu/courses/cse517/16wi/

"One Hot" Vectors

- Arbitrarily order the words in $\mathcal{V}$, giving each an index in $\{1, \ldots, V\}$
- Let $e_i \in \mathbb{R}^V$ contain all zeros, with the exception of a 1 in position i
- This is the "one hot" vector for the ith word in $\mathcal{V}$

$$\mathbf{e}_i = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

Feedforward Neural Network Language Model

Bengio et al. (2003)

- Define the n-gram probability as follows:

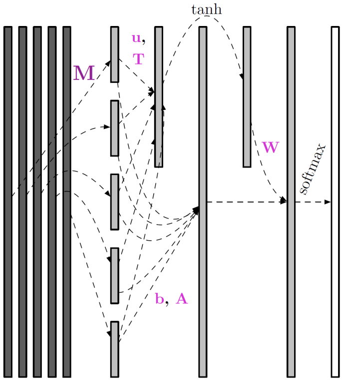
$$P(\langle v_1, \ldots, v_V \rangle | \langle h_1, \ldots, h_{n-1} \rangle) = n_\nu(\langle v_1, \ldots, v_V \rangle | \langle \mathbf{e}_{h_1}, \ldots, \mathbf{e}_{h_{n-1}} \rangle) =$$

$$\text{softmax}\left(\underset{V}{\mathbf{b}} + \sum_{i=1}^{n-1} \underset{V}{\mathbf{e}_{h_i}^\top} \underset{V \times d}{\mathbf{M}} \underset{d \times V}{\mathbf{A}_i} + \underset{V \times H}{\mathbf{W}} \tanh\left(\underset{H}{\mathbf{u}} + \sum_{i=1}^{n-1} \underset{V}{\mathbf{e}_{h_i}^\top} \underset{V \times d}{\mathbf{M}} \underset{d \times H}{\mathbf{T}_i} \right) \right)$$

  where $\langle h_1, \ldots, h_{n-1} \rangle$ are $(n-1)$ previous symbols $\langle w_{i-1}, \ldots, w_{i-n+1} \rangle$, $\mathbf{e}_{h_i} \in \mathbb{R}^V$ is a one hot vector and H is the number of "hidden units" in the neural network (a "hyperparameter")
- Parameters in neural network n_ν
  - $\mathbf{M} \in \mathbb{R}^{V \times d}$: "embeddings" (row vectors), one for every word in $\mathcal{V}$
  - Forward NN parameters: $\mathbf{b} \in \mathbb{R}^V$, $\mathbf{A} \in \mathbb{R}^{(n-1) \times d \times V}$ $(\mathbf{A}_i \in \mathbb{R}^{d \times V})$, $\mathbf{W} \in \mathbb{R}^{V \times H}$, $\mathbf{u} \in \mathbb{R}^H$, $\mathbf{T} \in \mathbb{R}^{(n-1) \times d \times H}$ $(\mathbf{T}_i \in \mathbb{R}^{d \times H})$

Breaking It Down

$$P(\langle v_1,\ldots,v_V\rangle|\langle h_1,\ldots,h_{n-1}\rangle) = n_\nu(\langle v_1,\ldots,v_V\rangle|\langle \mathbf{e}_{h_1},\ldots,\mathbf{e}_{h_{n-1}}\rangle) =$$
$$\mathit{softmax}\left(\underset{V}{\mathbf{b}} + \sum_{i=1}^{n-1} \underset{V}{\mathbf{e}_{h_i}^\top} \underset{V\times d}{\mathbf{M}} \underset{d\times V}{\mathbf{A}_i} + \underset{V\times H}{\mathbf{W}} \tanh\left(\underset{H}{\mathbf{u}} + \sum_{i=1}^{n-1} \underset{V}{\mathbf{e}_{h_i}^\top} \underset{V\times d}{\mathbf{M}} \underset{d\times H}{\mathbf{T}_i}\right)\right)$$



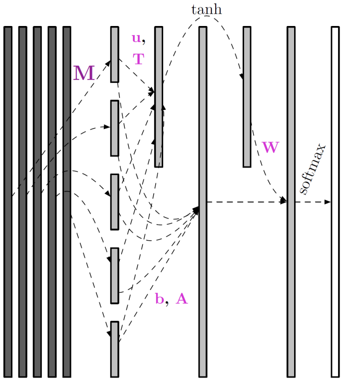
- Look up each of the history words $h_i, \forall i \in \{1,\ldots,n-1\}$ in $\mathbf{M}$; keep two copies.

$$\underset{V}{\mathbf{e}_{h_i}^\top} \underset{V\times d}{\mathbf{M}}$$

$$P(\langle v_1,\dots,v_V\rangle|\langle h_1,\dots,h_{n-1}\rangle) = n_\nu(\langle v_1,\dots,v_V\rangle|\langle \mathbf{e}_{h_1},\dots,\mathbf{e}_{h_{n-1}}\rangle) =$$
$$\mathit{softmax}\left(\underset{V}{\mathbf{b}} + \sum_{i=1}^{n-1} \underset{V}{\mathbf{e}_{h_i}^{T}} \underset{V\times d}{\mathbf{M}} \underset{d\times V}{\mathbf{A}_i} + \underset{V\times H}{\mathbf{W}} \tanh\left(\underset{H}{\mathbf{u}} + \sum_{i=1}^{n-1} \underset{V}{\mathbf{e}_{h_i}^{T}} \underset{V\times d}{\mathbf{M}} \underset{d\times H}{\mathbf{T}_i}\right)\right)$$

- Look up each of the history words $h_i, \forall i \in \{1,\dots,n-1\}$ in $\mathbf{M}$; keep two copies.
- Rename them as m_{h_i}

$$\underset{V}{\mathbf{e}_{h_i}^{\top}} \underset{V\times d}{\mathbf{M}} = \underset{d}{m_{h_i}}$$

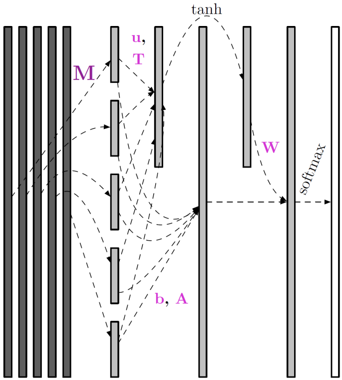


- Apply an affine transformation to the history-word embeddings ($\mathbf{u}$, $\mathbf{T}$)

$$\underset{V}{\mathbf{e}_{h_i}^{\top}} \underset{V \times d}{\mathbf{M}} = \underset{d}{m_{h_i}}$$

$$\underset{H}{\mathbf{u}} + \sum_{i=1}^{n-1} \underset{d}{m_{h_i}} \underset{d \times H}{\mathbf{T}_i}$$

$$P(\langle v_1, \ldots, v_V \rangle | \langle h_1, \ldots, h_{n-1} \rangle) = n_\nu(\langle v_1, \ldots, v_V \rangle | \langle \mathbf{e}_{h_1}, \ldots, \mathbf{e}_{h_{n-1}} \rangle) =$$
$$softmax\left(\underset{V}{\mathbf{b}} + \sum_{i=1}^{n-1} \underset{V}{\mathbf{e}_{h_i}^T} \underset{V \times d}{\mathbf{M}} \underset{d \times V}{\mathbf{A}_i} + \underset{V \times H}{\mathbf{W}} \tanh\left(\underset{H}{\mathbf{u}} + \sum_{i=1}^{n-1} \underset{V}{\mathbf{e}_{h_i}^T} \underset{V \times d}{\mathbf{M}} \underset{d \times H}{\mathbf{T}_i}\right)\right)$$



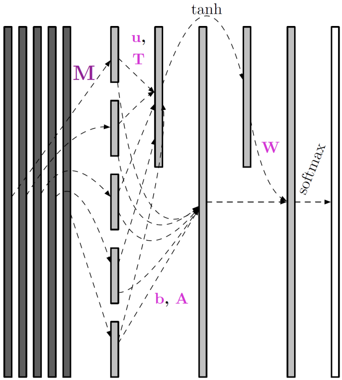
- Apply an affine transformation to the history-word embeddings ($\mathbf{u}$, $\mathbf{T}$)
- and a tanh nonlinearity

$$\underset{V}{\mathbf{e}_{h_i}^{\top}} \underset{V \times d}{\mathbf{M}} = \underset{d}{m_{h_i}}$$

$$\tanh\left(\underset{H}{\mathbf{u}} + \sum_{i=1}^{n-1} \underset{d}{m_{h_i}} \underset{d \times H}{\mathbf{T}_i}\right)$$

$$P(\langle v_1, \ldots, v_V \rangle | \langle h_1, \ldots, h_{n-1} \rangle) = n_\nu(\langle v_1, \ldots, v_V \rangle | \langle \mathbf{e}_{h_1}, \ldots, \mathbf{e}_{h_{n-1}} \rangle) =$$

$$softmax\left(\underset{V}{\mathbf{b}} + \sum_{i=1}^{n-1} \underset{V}{\mathbf{e}_{h_i}^{T}} \underset{V \times d}{\mathbf{M}} \underset{d \times V}{\mathbf{A}_i} + \underset{V \times H}{\mathbf{W}} \tanh\left(\underset{H}{\mathbf{u}} + \sum_{i=1}^{n-1} \underset{V}{\mathbf{e}_{h_i}^{T}} \underset{V \times d}{\mathbf{M}} \underset{d \times H}{\mathbf{T}_i}\right)\right)$$



Breaking It Down

- Apply an affine transformation to everything ($\mathbf{b}$, $\mathbf{A}$, $\mathbf{W}$)

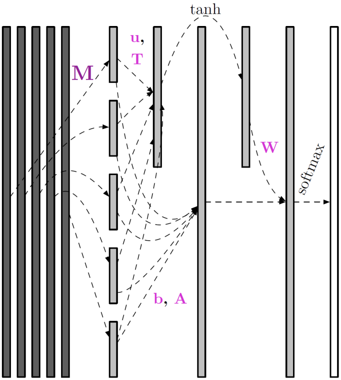
$$\underset{V}{\mathbf{e}_{h_i}^{\top}} \underset{V \times d}{\mathbf{M}} = \underset{d}{m_{h_i}}$$

$$\underset{V}{\mathbf{b}} + \sum_{i=1}^{n-1} \underset{d}{m_{h_i}} \underset{d \times V}{\mathbf{A}_i} +$$

$$\underset{V \times H}{\mathbf{W}} \tanh\left(\underset{H}{\mathbf{u}} + \sum_{i=1}^{n-1} \underset{d}{m_{h_i}} \underset{d \times H}{\mathbf{T}_i} \right)$$

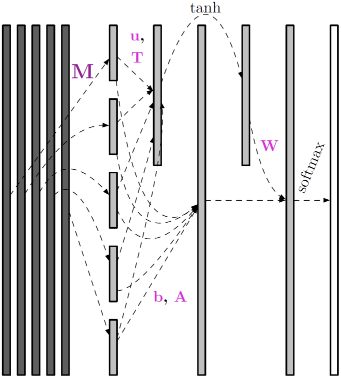
$$P(\langle v_1, \ldots, v_V \rangle | \langle h_1, \ldots, h_{n-1} \rangle) = n_\nu(\langle v_1, \ldots, v_V \rangle | \langle \mathbf{e}_{h_1}, \ldots, \mathbf{e}_{h_{n-1}} \rangle) =$$

$$softmax\left(\underset{V}{\mathbf{b}} + \sum_{i=1}^{n-1} \underset{V}{\mathbf{e}_{h_i}^{T}} \underset{V \times d}{\mathbf{M}} \underset{d \times V}{\mathbf{A}_i} + \underset{V \times H}{\mathbf{W}} \tanh\left(\underset{H}{\mathbf{u}} + \sum_{i=1}^{n-1} \underset{V}{\mathbf{e}_{h_i}^{T}} \underset{V \times d}{\mathbf{M}} \underset{d \times H}{\mathbf{T}_i} \right) \right)$$



Breaking It Down

$$P(\langle v_1,\ldots,v_V\rangle|\langle h_1,\ldots,h_{n-1}\rangle) = n_\nu(\langle v_1,\ldots,v_V\rangle|\langle \mathbf{e}_{h_1},\ldots,\mathbf{e}_{h_{n-1}}\rangle) =$$
$$softmax\left(\underset{V}{\mathbf{b}} + \sum_{i=1}^{n-1} \underset{V}{\mathbf{e}_{h_i}^T} \underset{V\times d}{\mathbf{M}} \underset{d\times V}{\mathbf{A}_i} + \underset{V\times H}{\mathbf{W}} \tanh\left(\underset{H}{\mathbf{u}} + \sum_{i=1}^{n-1} \underset{V}{\mathbf{e}_{h_i}^T} \underset{V\times d}{\mathbf{M}} \underset{d\times H}{\mathbf{T}_i}\right)\right)$$



- Apply a softmax transformation to make the vector sum to one.

$$\text{softmax}\left(\underset{V}{\mathbf{b}} + \sum_{i=1}^{n-1} \underset{d}{m_{h_i}} \underset{d\times V}{\mathbf{A}_i}\right.$$
$$\left. + \underset{V\times H}{\mathbf{W}} \tanh\left(\underset{H}{\mathbf{u}} + \sum_{i=1}^{n-1} \underset{d}{m_{h_i}} \underset{d\times H}{\mathbf{T}_i}\right)\right)$$

Breaking It Down

$$\text{softmax}\left(\underset{V}{\mathbf{b}} + \sum_{i=1}^{n-1} \underset{V}{\mathbf{e}_{h_i}^\top} \underset{V \times d}{\mathbf{M}} \underset{d \times V}{\mathbf{A}_i} + \underset{V \times H}{\mathbf{W}} \tanh\left(\underset{H}{\mathbf{u}} + \sum_{i=1}^{n-1} \underset{V}{\mathbf{e}_{h_i}^\top} \underset{V \times d}{\mathbf{M}} \underset{d \times H}{\mathbf{T}_i}\right)\right)$$

- Like a log-linear language model with two kinds of features:
  - Concatenation of context-word embeddings vectors $((\mathbf{m}_{h_1}, \ldots, \mathbf{m}_{h_{n-1}})$, mapped by $\mathbf{A} = (\mathbf{A}_1^\top, \ldots, \mathbf{A}_{n-1}^\top)^\top)$
  - tanh-affine transformation of the above
- New parameters arise from (i) embeddings and (ii) affine transformation "inside" the nonlinearity.

Number of Parameters

$$\text{softmax}\left(\underset{V}{\mathbf{b}} + \sum_{i=1}^{n-1} \underset{V}{\mathbf{e}_{h_i}^\top} \underset{V \times d}{\mathbf{M}} \underset{d \times V}{\mathbf{A}_i} + \underset{V \times H}{\mathbf{W}} \tanh\left(\underset{H}{\mathbf{u}} + \sum_{i=1}^{n-1} \underset{V}{\mathbf{e}_{h_i}^\top} \underset{V \times d}{\mathbf{M}} \underset{d \times H}{\mathbf{T}_i}\right)\right)$$

$$D = \underbrace{Vd}_{\mathbf{M}} + \underbrace{V}_{\mathbf{b}} + \underbrace{(n-1)dV}_{\mathbf{A}} + \underbrace{VH}_{\mathbf{W}} + \underbrace{H}_{\mathbf{u}} + \underbrace{(n-1)dH}_{\mathbf{T}}$$

- For Bengio et al. (2003):
  - $V \approx 18,000$ (after OOV processing)
  - $d \in \{30, 60\}$
  - $H \in \{50, 100\}$
  - $n - 1 = 5$
- So $D = 461V + 30,100 = 8.3M$ parameters, compared to $O(V^n)$ for classical n-gram models
  - Forcing $\mathbf{A} = 0$ eliminated $300V$ parameters and performed a bit better, but was slower to converge
  - If we averaged m_{h_i} instead of concatenating, we'd get to $221V + 6,100$ (this is a variant of "continuous bag of words," Mikolov et al. (2013))

Important Idea: Words as Vectors

- The idea of “embedding” words in $\mathbb{R}^d$ is much older than neural language models. You should think of this as a generalization of the discrete view of $\mathcal{V}$
- Deerwester et al. (1990) explored dimensionality reduction techniques for information retrieval-style querying of text collections
- Considerable ongoing research on learning word representations to capture linguistic similarity (Turney and Pantel (2010)); this is known as **vector space semantics**

Parameter Estimation

- Bad news for neural language models:
  - Log-likelihood function is not concave
  - Calculating log-likelihood and its gradient is very expensive (5 epochs took 3 weeks on 40 CPUs, in Bengio et al. (2003))
- Good news:
  - n_ν is differentiable with respect to $\mathbf{M}$ (from which its inputs come) and ν (its parameters), so gradient-based methods are available
  - Essential: the chain rule from calculus (sometimes called "backpropagation")
  - Lots more details in Bengio et al. (2003) and (for NNs more generally) in Goldberg (2016)

Overview

Next Up

- More examples of neural language models (in brief):
  - The log-bilinear language model
  - Recurrent neural network language models

Log-Bilinear Language Model

Mnih and Hinton (2007)

- In neural language model developed by Bengio et al. (2003):

$$P(\langle v_1, \ldots, v_V \rangle | \langle h_1, \ldots, h_{n-1} \rangle) = n_\nu(\langle v_1, \ldots, v_V \rangle | \langle \mathbf{e}_{h_1}, \ldots, \mathbf{e}_{h_{n-1}} \rangle) =$$

$$\text{softmax}\left(\underset{V}{\mathbf{b}} + \sum_{i=1}^{n-1} \underset{V}{\mathbf{e}_{h_i}^\top} \underset{V \times d}{\mathbf{M}} \underset{d \times V}{\mathbf{A}_i} + \underset{V \times H}{\mathbf{W}} \tanh\left(\underset{H}{\mathbf{u}} + \sum_{i=1}^{n-1} \underset{V}{\mathbf{e}_{h_i}^\top} \underset{V \times d}{\mathbf{M}} \underset{d \times H}{\mathbf{T}_i} \right) \right)$$

- we haven't considered the current word

- Define the n-gram probability as follows, for each $v \in \mathcal{V}$:

$$P(v|\langle h_1, \ldots, h_{n-1}\rangle) = \frac{\exp\left(\sum_{i=1}^{n-1}\left(\underbrace{\mathbf{m}_{h_i}^\top}_{d}\underbrace{\mathbf{A}}_{d\times d} + \underbrace{\mathbf{b}}_{d}\right)^\top \underbrace{\mathbf{m}_v}_{d} + c_v\right)}{\sum_{v'\in\mathcal{V}}\exp\left(\sum_{i=1}^{n-1}\left(\underbrace{\mathbf{m}_{h_i}^\top}_{d}\underbrace{\mathbf{A}}_{d\times d} + \underbrace{\mathbf{b}}_{d}\right)^\top \underbrace{\mathbf{m}_{v'}}_{d} + c_{v'}\right)}$$

- Number of parameters: $\underbrace{Vd}_{\mathbf{M}} + \underbrace{(n-1)d^2}_{\mathbf{A}} + \underbrace{d}_{\mathbf{b}} + \underbrace{V}_{\mathbf{c}}$
- The predicted word's probability depends on its vector $\mathbf{m}_v$, not just on the vectors of the history words
- Training this model involves a sum over the vocabulary (like log-linear models we saw earlier)
- Later work explored variations to make learning faster

Observations about Neural Language Models (So Far)

- There's no knowledge built in that the most recent word h_{n-1} should generally be more informative than earlier ones
  - This has to be learned
- In addition to choosing n, also have to choose dimensionalities like d and H
- Parameters of these models are hard to interpret
  - Example: ℓ_2-norm of $\mathbf{A}_i$ and $\mathbf{T}_i$ in the feedforward model correspond to the importance of history position i
  - Individual word embeddings can be clustered and dimensions can be analyzed (e.g., Tsvetkov et al. (2015))
- Architectures are not intuitive
- Still, impressive perplexity gains got people's interest

Recurrent Neural Network

- Each input element is understood to be an element of a sequence: $\{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_l\}$
- At each timestep t:
  - The tth input element $\mathbf{x}_t$ is processed alongside the previous state $\mathbf{s}_{t-1}$ to calculate the new state $\mathbf{s}_t$
  - The tth output is a function of the state $\mathbf{s}_t$
  - The same functions are applied at each iteration:

$$\mathbf{s}_t = f_{\text{recurrent}}(\mathbf{x}_t, \mathbf{s}_{t-1})$$

$$\mathbf{y}_t = f_{\text{output}}(\mathbf{s}_t)$$

- In RNN language models, words and histories are represented as vectors (respectively, $\mathbf{x}_t = \mathbf{e}_{h_t}$ and $\mathbf{s}_t$).

RNN Language Model

- The original version, by Mikolov et al. (2010) used a "simple" RNN architecture along these lines:

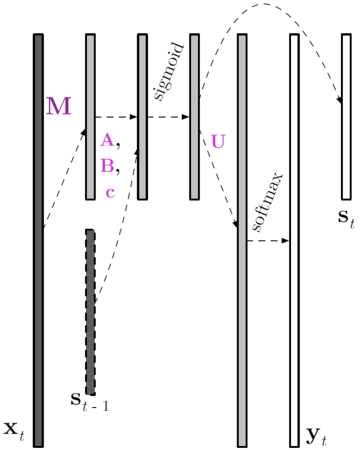
$$\mathbf{s}_t = f_{\text{recurrent}}(\mathbf{e}_{x_t}, \mathbf{s}_{t-1}) =$$

$$\textit{sigmoid}\left(\left(\mathbf{e}_{x_t}^\top \mathbf{M}\right)^\top \mathbf{A} + \mathbf{s}_{t-1}^\top \mathbf{B} + \mathbf{c}\right)$$

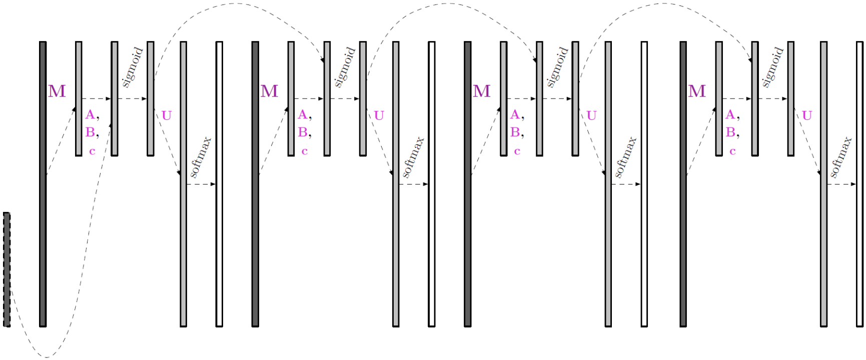
$$\mathbf{y}_t = f_{\text{output}}(\mathbf{s}_t) = \text{softmax}(\mathbf{s}_t^\top \mathbf{U})$$

$$P(v|h_1, \ldots, h_{n-1}) = [\mathbf{y}_t]_v$$

- Note: this is not an n-gram (Markov) model!



RNN Model Visualization



Comparison: Probabilistic vs. Connectionist Modeling

	Probabilistic	**Connectionist**
What do we engineer?	features, assumptions	architectures
Theory?	as N gets large	not really
Interpretation of parameters?	often easy	usually hard

Parting Shots

- I said very little about estimating the parameters
  - At present, this requires a lot of engineering
  - New libraries to help you are coming out all the time
  - Many of them use GPUs to speed things up
- This progression is worth reflecting on:

	history:	**represented as:**
before 1996	(n-1)-gram	discrete
1996–2003	(n-1)-gram	feature vector
2003–2010	(n-1)-gram	embedded vector
since 2010	unrestricted	embedded vector

Overview

Neural Language Model Results (Bengio et al. (2003))

	n	c	h	m	direct	mix	train.	valid.	test.
MLP1	5		50	60	yes	no	182	284	268
MLP2	5		50	60	yes	yes		275	257
MLP3	5		0	60	yes	no	201	327	310
MLP4	5		0	60	yes	yes		286	272
MLP5	5		50	30	yes	no	209	296	279
MLP6	5		50	30	yes	yes		273	259
MLP7	3		50	30	yes	no	210	309	293
MLP8	3		50	30	yes	yes		284	270
MLP9	5		100	30	no	no	175	280	276
MLP10	5		100	30	no	yes		265	**252**
Del. Int.	3						31	352	336
Kneser-Ney back-off	3							334	323
Kneser-Ney back-off	4							332	321
Kneser-Ney back-off	5							332	321
class-based back-off	3	150						348	334
class-based back-off	3	200						354	340
class-based back-off	3	500						326	**312**
class-based back-off	3	1000						335	319
class-based back-off	3	2000						343	326
class-based back-off	4	500						327	312
class-based back-off	5	500						327	312

Table 1: Comparative results on the Brown corpus. The deleted interpolation trigram has a test perplexity that is 33% above that of the neural network with the lowest validation perplexity. The difference is 24% in the case of the best n-gram (a class-based model with 500 word classes). n : order of the model. c : number of word classes in class-based n-grams. h : number of hidden units. m : number of word features for MLPs, number of classes for class-based n-grams. *direct*: whether there are direct connections from word features to outputs. *mix*: whether the output probabilities of the neural network are mixed with the

Model	Parameters	Validation	Test
Mikolov & Zweig (2012) - KN-5	2M‡	–	141.2
Mikolov & Zweig (2012) - KN5 + cache	2M‡	–	125.7
Mikolov & Zweig (2012) - RNN	6M‡	–	124.7
Mikolov & Zweig (2012) - RNN-LDA	7M‡	–	113.7
Mikolov & Zweig (2012) - RNN-LDA + KN-5 + cache	9M‡	–	92.0
Zaremba et al. (2014) - LSTM (medium)	20M	86.2	82.7
Zaremba et al. (2014) - LSTM (large)	66M	82.2	78.4
Gal & Ghahramani (2016) - Variational LSTM	20M	–	78.6
Gal & Ghahramani (2016) - Variational LSTM	66M	–	73.4
Kim et al. (2016) - CharCNN	19M	–	78.9
Merity et al. (2016) - Pointer Sentinel-LSTM	21M	72.4	70.9
Grave et al. (2016) - LSTM	–	–	82.3
Grave et al. (2016) - LSTM + continuous cache pointer	–	–	72.1
Inan et al. (2016) - Variational LSTM (tied) + augmented loss	24M	75.7	73.2
Inan et al. (2016) - Variational LSTM (tied) + augmented loss	51M	71.1	68.5
Zilly et al. (2016) - Variational RHN (tied)	23M	67.9	65.4
Zoph & Le (2016) - NAS Cell (tied)	25M	–	64.0
Zoph & Le (2016) - NAS Cell (tied)	54M	–	62.4
Melis et al. (2017) - 4-layer skip connection LSTM (tied)	24M	60.9	58.3
AWD-LSTM - 3-layer LSTM (tied)	24M	60.0	57.3
AWD-LSTM - 3-layer LSTM (tied) + continuous cache pointer	24M	53.9	52.8

Table 1: Single model perplexity on validation and test sets for the Penn Treebank language modeling task. Parameter numbers with ‡ are estimates based upon our understanding of the model and with reference to (Merity et al., 2016). Models noting *tied* use weight tying on the embedding and softmax weights. Our model, AWD-LSTM, stands for AvSGD Weight-Dropped LSTM.

Further Reading

- Goldberg (2016). A primer on neural network models for natural language processing.

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