Chapter 4
Word Embeddings and Recurrent NNs

4.1 Word Embeddings for Language Models

- Variable $E_{1,n} = (E_1 \dots E_n)$
  - E_i = a word
- Value $e_{1,n}$
  - E.g. $e_{1,6}$ = (We live in a small world)
    e_1 = We, e_2 = live, …
- Probability Model

$$p(\text{We live in a small World}) = p(\text{We})p(\text{live}|\text{We})p(\text{in}|\text{We live})\cdots$$

  - Generally

$$p(E_{1,n} = e_{1,n}) = \prod_{j=1}^{j=n} p(E_j = e_j | E_{1,j-1} = e_{1,j-1})$$

- Tokenization
  - Breaking the strings into a sequence of words
  - Vocabulary set V
    - Punctuation(final period .) is a word
    - *UNK* is unknown words
      - E.g. “132,423” in the sentence “The population of Providence is 132,423.”

- Penn Treebank(PTB)
  - news articles from the Wall Street Journal.
  - Files
    - ptb.train.txt, ptb.test.txt, ptb.valid.txt
  - Train data
    - 929589 words
  - Test data
    - 82430 words
  - Vocabulary set V
    - 10000 words

aer banknote berlitz calloway centrust cluett fromstein gitano guterman hydro-quebec ipo kia memotec mlx nahb punts rake regatta rubens sim snack-food ssangyong swapo wachter
pierre <unk> N years old will join the board as a nonexecutive director nov. N
mr. <unk> is chairman of <unk> n.v. the dutch publishing group

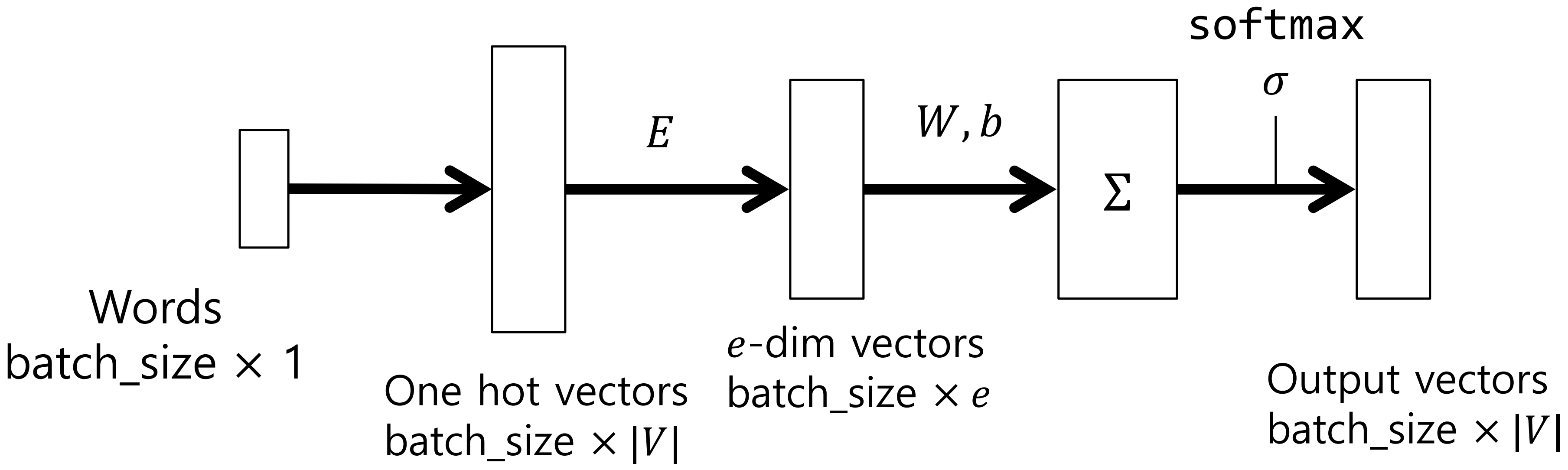
- Probability Model
  - Bigram model

$$p\left(E_{1,n} = e_{1,n}\right) = p(E_1 = e_1) \prod_{j=2}^{j=n} p\left(E_j = e_j \middle| E_{j-1} = e_{j-1}\right)$$

  - Sentence padding
    - Put a imaginary word “STOP” at the beginning of every sentence

$$p\left(E_{1,n} = e_{1,n}\right) = \prod_{j=1}^{j=n} p\left(E_j = e_j \middle| E_{j-1} = e_{j-1}\right)$$

- Neural Network
  - Word embedding
    - word → index → one hot vector → e-dimensional vector
    - $e = 20,\ 100$ or 1000



- Words embedding
  - Cosine similarity
    - $\cos(\boldsymbol{x}, \boldsymbol{y}) = \frac{\boldsymbol{x} \cdot \boldsymbol{y}}{\|\boldsymbol{x}\| \|\boldsymbol{y}\|}$
    - Cosine of angle between $\boldsymbol{x}$ and $\boldsymbol{y}$

Word Numbers	Word	Largest Cosine Similarity	Most Similar
0	under		
1	above	0.362	0
2	the	–0.160	0
3	a	0.127	2
4	recalls	0.479	1
5	says	0.553	4
6	rules	–0.066	4
7	laws	0.523	6
8	computer	0.249	2
9	machine	0.333	8

4.2 Building Feed-Forward Language Models

```
inpt = tf.placeholder(tf.int32, shape=[batchSz])
answr = tf.placeholder(tf.int32, shape=[batchSz])
E = tf.Variable(tf.random_normal([vocabSz, embedSz], stddev = 0.1))
embed = tf.nn.embedding_lookup(E, inpt)
```

```
xEnt = tf.nn.sparse_softmax_cross_entropy_with_logits(logits=logits,labels=answr)
loss = tf.reduce_sum(xEnt)
```

4.3 Improving Feed-Forward Language Models

1. Adding layer

2. Trigram model

```
embed2 = tf.nn.embedding_lookup(E, inpt2)
both = tf.concat([embed,embed2], 1)
```

4.4 Overfitting

- Regularization
  - Early stopping
  - Dropout
  - L2 regularization

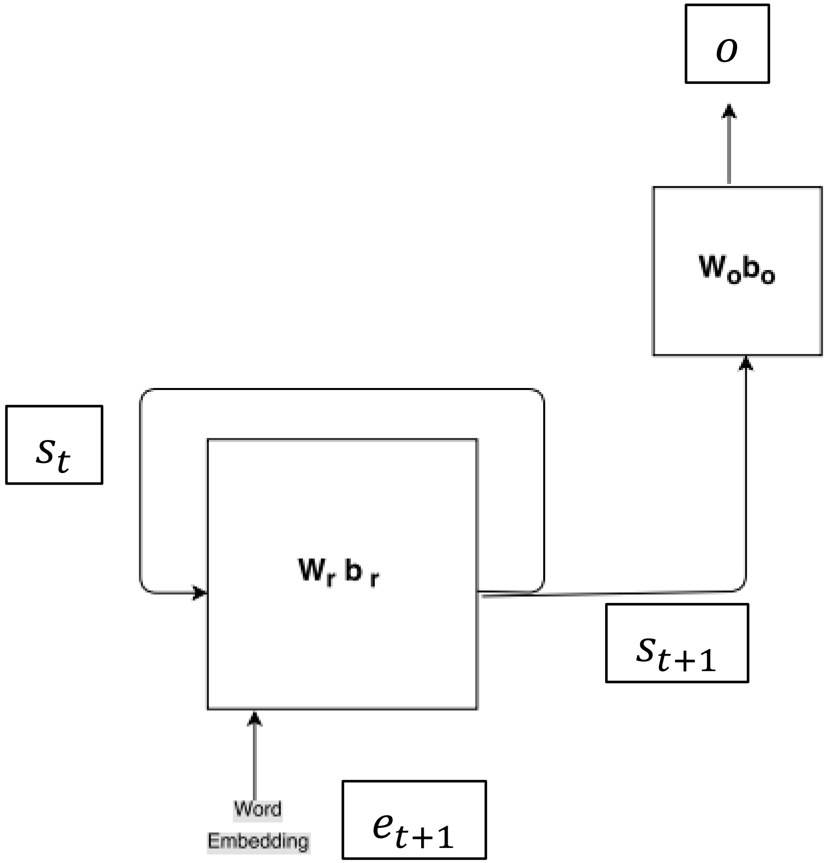
Epoch	1	2	3	4	5	6	7	10	15	20	30
Train	197	122	100	87	78	72	67	56	45	41	35
Dev	172	152	145	143	143	143	145	149	159	169	182

Figure 4.3: Overfitting in a language model

Epoch	1	2	3	4	5	6	7	10	15	20	30
Dropout	213	182	166	155	150	144	139	131	122	118	114
L2 Reg	180	163	155	148	144	140	137	130	123	118	112

Figure 4.4: Language-model perplexity when using regularization

4.5 Recurrent Networks

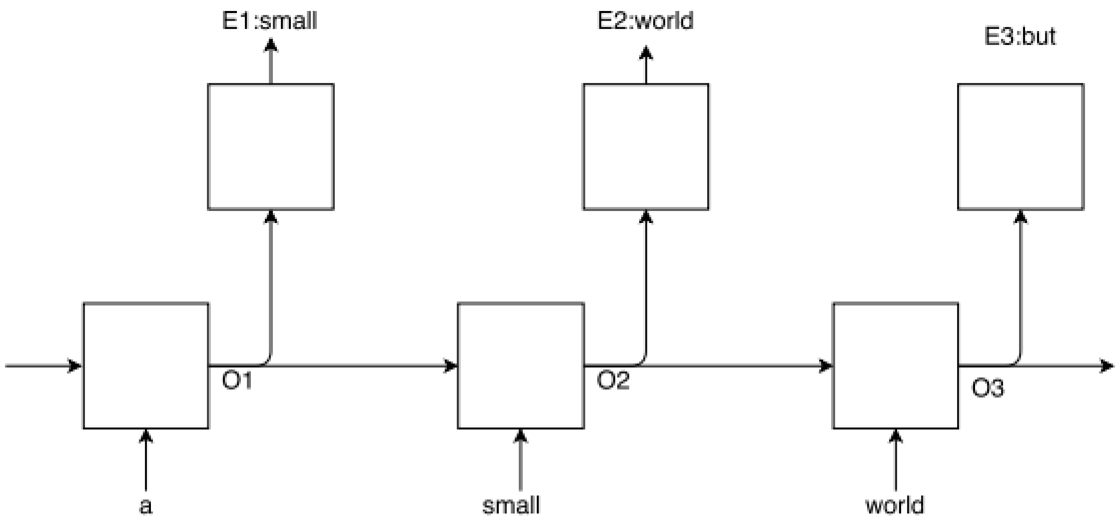


RNN(recurrent neural network

$$s_0 = 0$$
$$s_{t+1} = \rho((e_{t+1} \cdot s_t)W_r + b_r)$$
$$o = \sigma(s_{t+1}W_0 + b_0)$$

ρ: relu
σ: cross-entropy
$\cdot$: concatenation

It is a small world but I like it that way



batch 1
batch 2

STOP	It	is	a	small	world
but	I	like	it	that	way

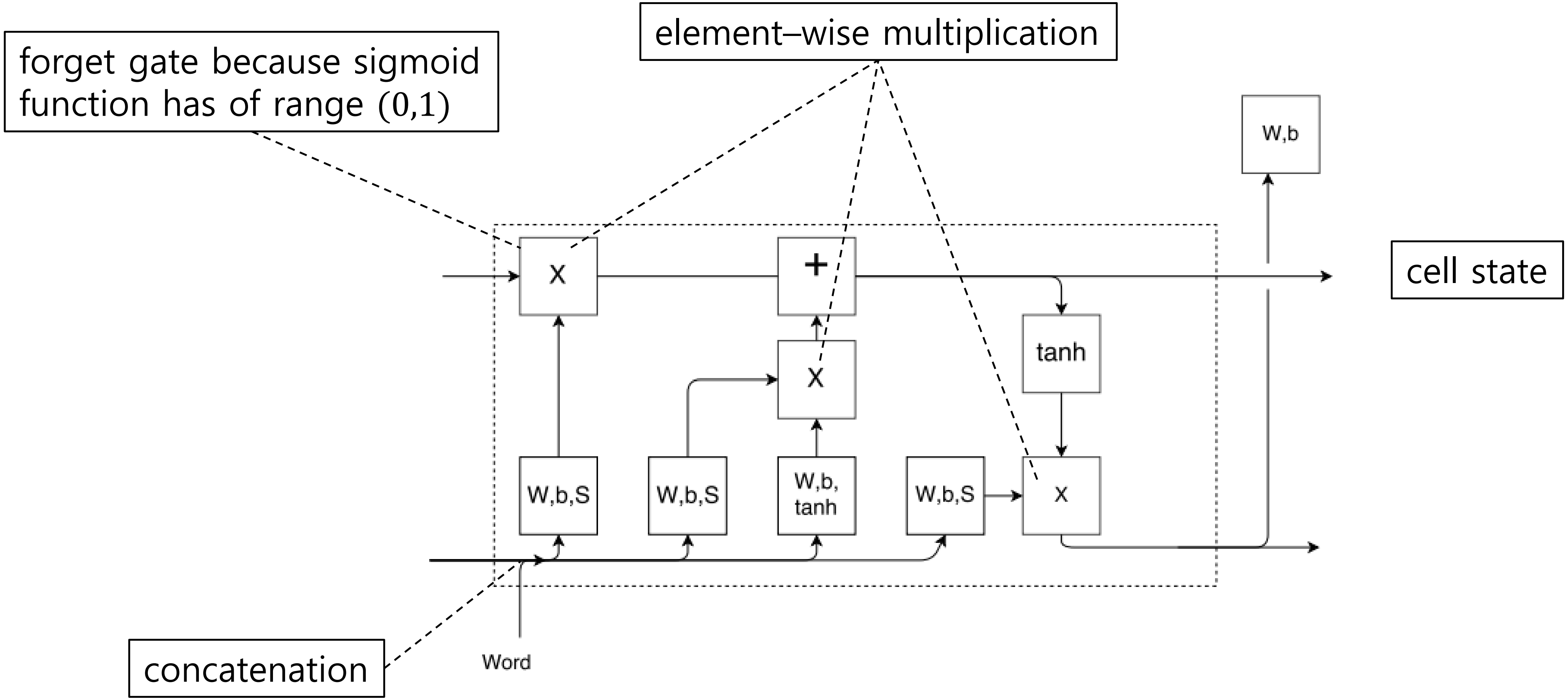
STOP	It	is
but	I	like

a	small	world
it	that	way

Batch size = 2
Window size = 3

```
rnn= tf.contrib.rnn.BasicRNNCell(rnnSz)
initialState = rnn.zero_state(batchSz, tf.float32)
outputs, nextState = tf.nn.dynamic_rnn(rnn, embeddings,
                                       initial_state=initialState)
```

4.6 Long Short-Term Memory



- TF program
  - replace

```
tf.contrib.rnn.BasicRNNCell(rnnSz)
```

    with

```
tf.contrib.rnn.LSTMCell(rnnSz)
```