Practical Neural Networks for NLP

Chris Dyer, Yoav Goldberg, Graham Neubig

November 1, 2016

EMNLP

Previous Part

- DyNet
- Feed Forward Networks
- RNNs

- All pretty standard, can do very similar in TF / Theano / Keras.

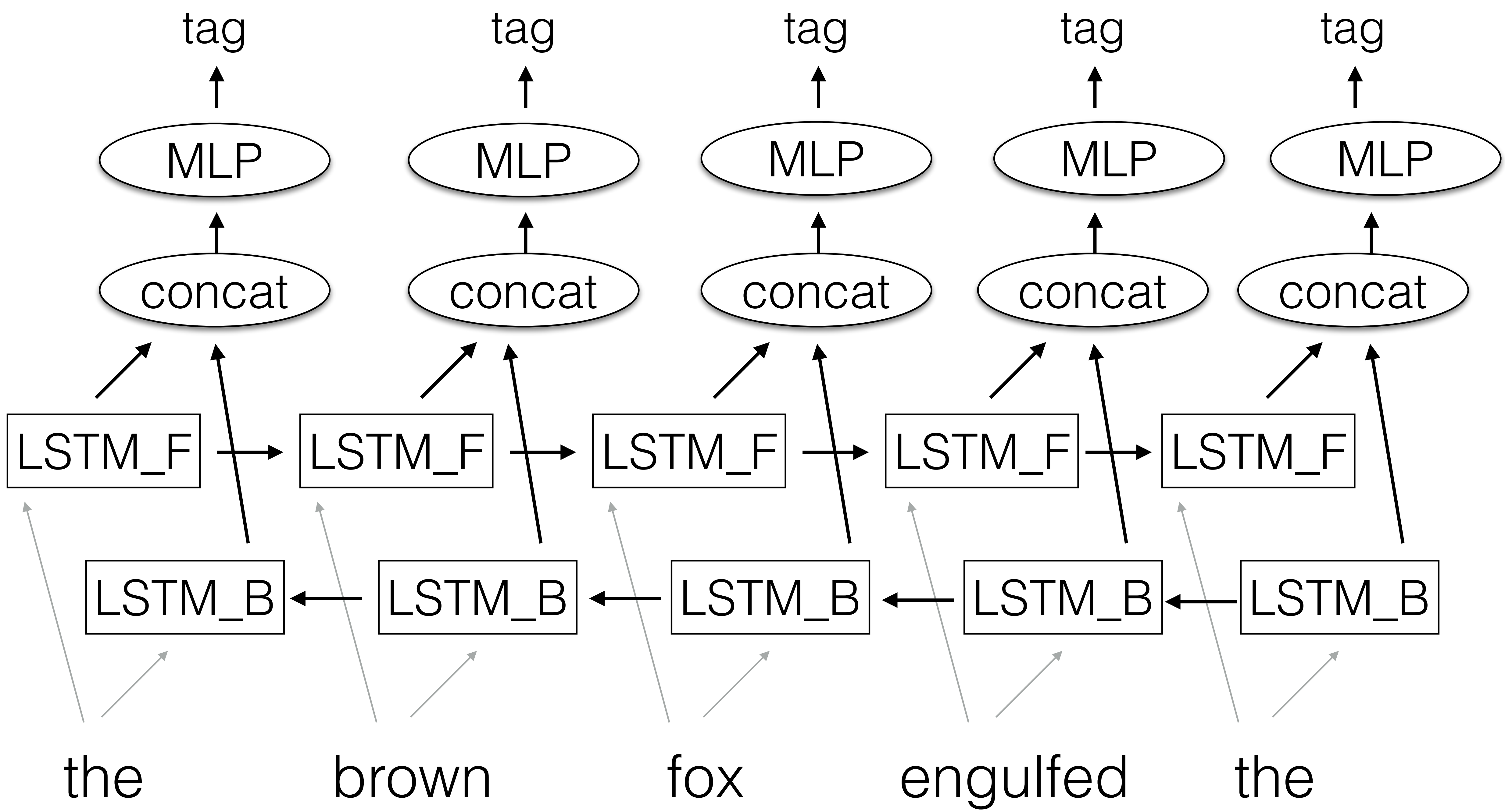
This Part

- Where DyNet shines -- dynamically structured networks.
- Things that are cumbersome / hard / ugly in other frameworks.

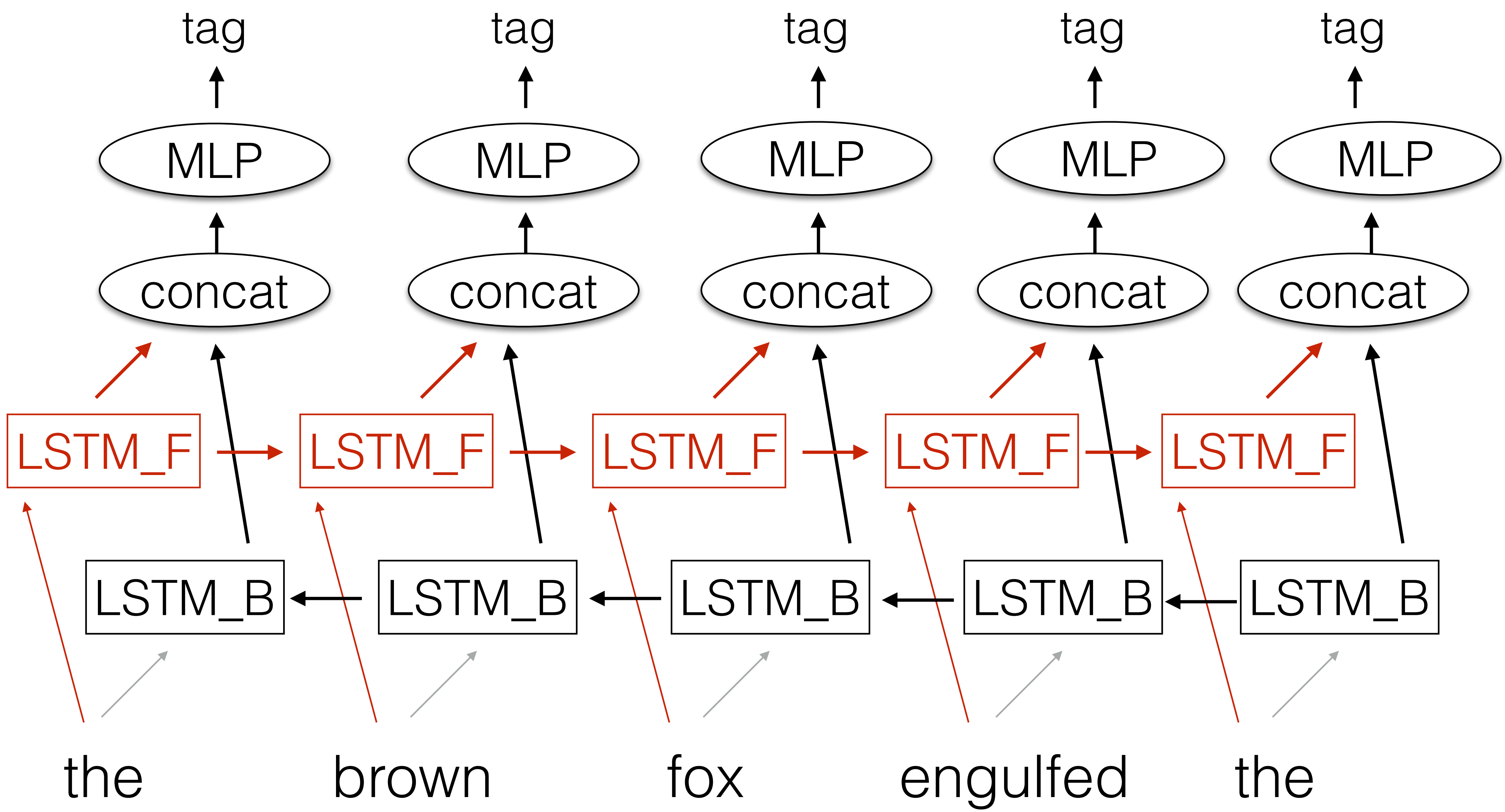
Outline

- **Part 2: Case Studies**
  - Tagging with bidirectional RNNs
  - Transition-based dependency parsing
  - Structured prediction meets deep learning

BiLSTM Tagger



BiLSTM Tagger



```
WORDS_LOOKUP = model.add_lookup_parameters((nwords, 128))
fwdRNN = dy.LSTMBuilder(1,   128,   50, model)
```

layers in-dim out-dim

```
dy.renew_cg()
# initialize the RNNs
f_init = fwdRNN.initial_state()

wembs = [word_rep(w) for w in words]

fw_exps = []
s = f_init
for we in wembs:
    s = s.add_input(we)
    fw_exps.append(s.output())
```

```
WORDS_LOOKUP = model.add_lookup_parameters((nwords, 128))
fwdRNN = dy.LSTMBuilder(1,  128,  50, model)
```

layers in-dim out-dim

```
dy.renew_cg()
# initialize the RNNs
f_init = fwdRNN.initial_state()

wembs = [word_rep(w) for w in words]

fw_exps = []
s = f_init
for we in wembs:
    s = s.add_input(we)
    fw_exps.append(s.output())
```

```
WORDS_LOOKUP = model.add_lookup_parameters((nwords, 128))
fwdRNN = dy.LSTMBuilder(1,  128,  50, model)
```

layers in-dim out-dim

```
def word_rep(w):
    w_index = vw.w2i[w]
    return WORDS_LOOKUP[w_index]
```

```
dy.renew_cg(
# initialize
f_init = fwd

wembs = [word_rep(w) for w in words]

fw_exps = []
s = f_init
for we in wembs:
    s = s.add_input(we)
    fw_exps.append(s.output())
```

```
WORDS_LOOKUP = model.add_lookup_parameters((nwords, 128))
fwdRNN = dy.LSTMBuilder(1,  128,  50, model)
```

layers in-dim out-dim

```
dy.renew_cg()
# initialize the RNNs
f_init = fwdRNN.initial_state()

wembs = [word_rep(w) for w in words]

fw_exps = []
s = f_init
for we in wembs:
    s = s.add_input(we)
    fw_exps.append(s.output())
```

```
WORDS_LOOKUP = model.add_lookup_parameters((nwords, 128))
fwdRNN = dy.LSTMBuilder(1,  128,  50, model)
```

layers   in-dim   out-dim

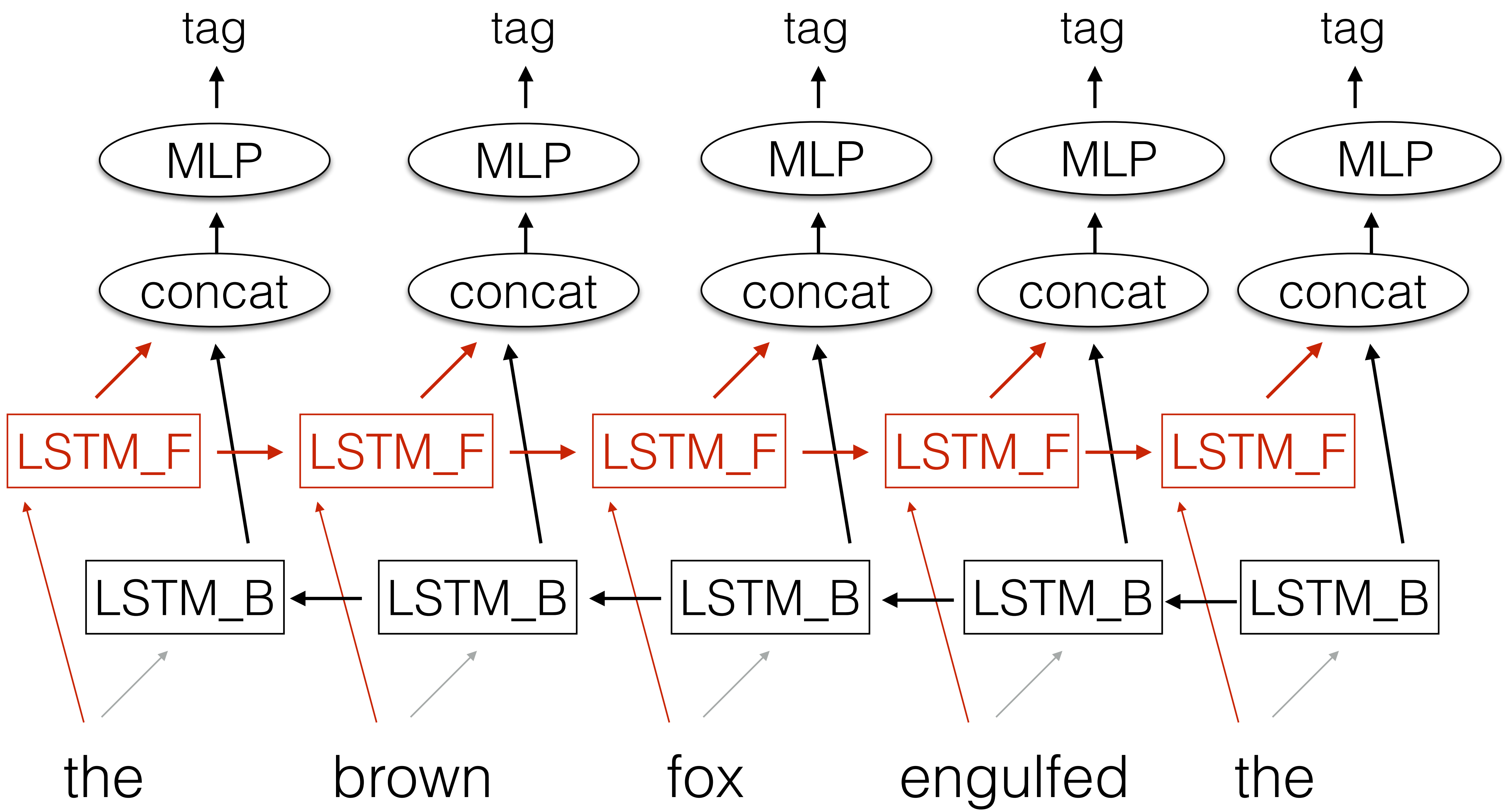
```
dy.renew_cg()
# initialize the RNNs
f_init = fwdRNN.initial_state()

wembs = [word_rep(w) for w in words]

fw_exps = f_init.transduce(wembs)
```

```
WORDS_LOOKUP = model.add_lookup_parameters((nwords, 128))
fwdRNN = dy.LSTMBuilder(1,  128,  50, model)
```

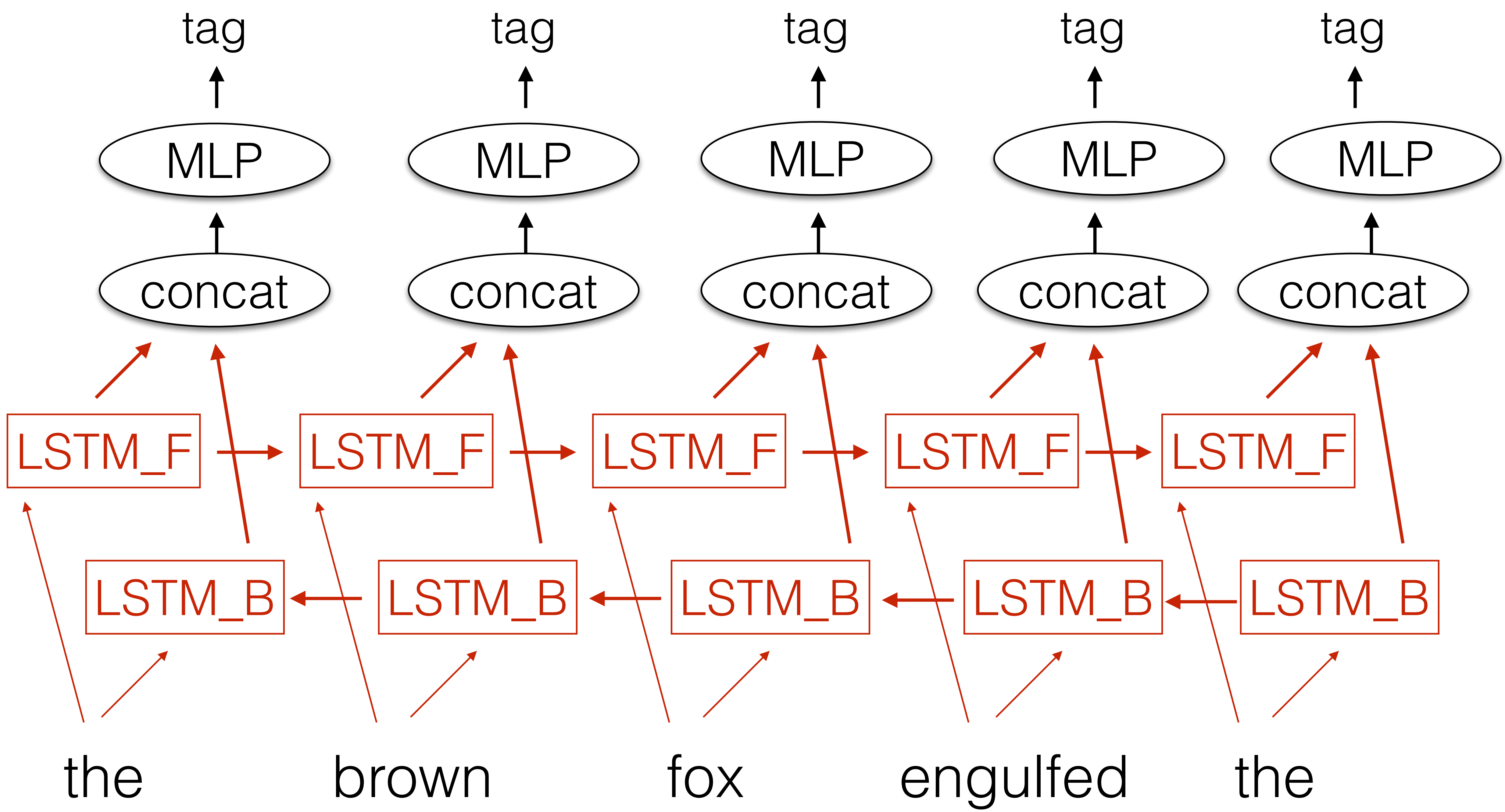
layers in-dim out-dim

```
dy.renew_cg()
# initialize the RNNs
f_init = fwdRNN.initial_state()

wembs = [word_rep(w) for w in words]

fw_exps = f_init.transduce(wembs)
```

BiLSTM Tagger

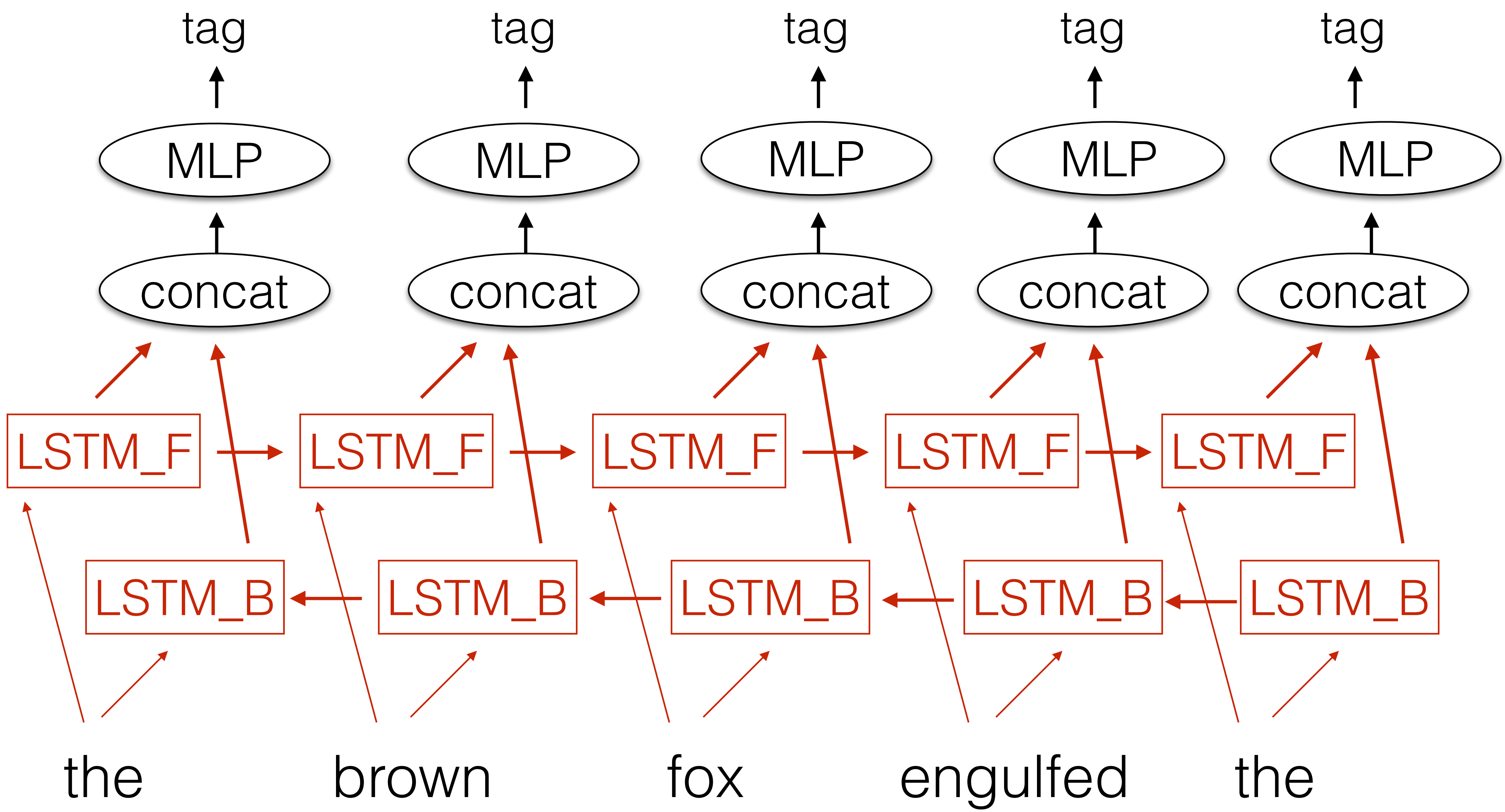


BiLSTM Tagger

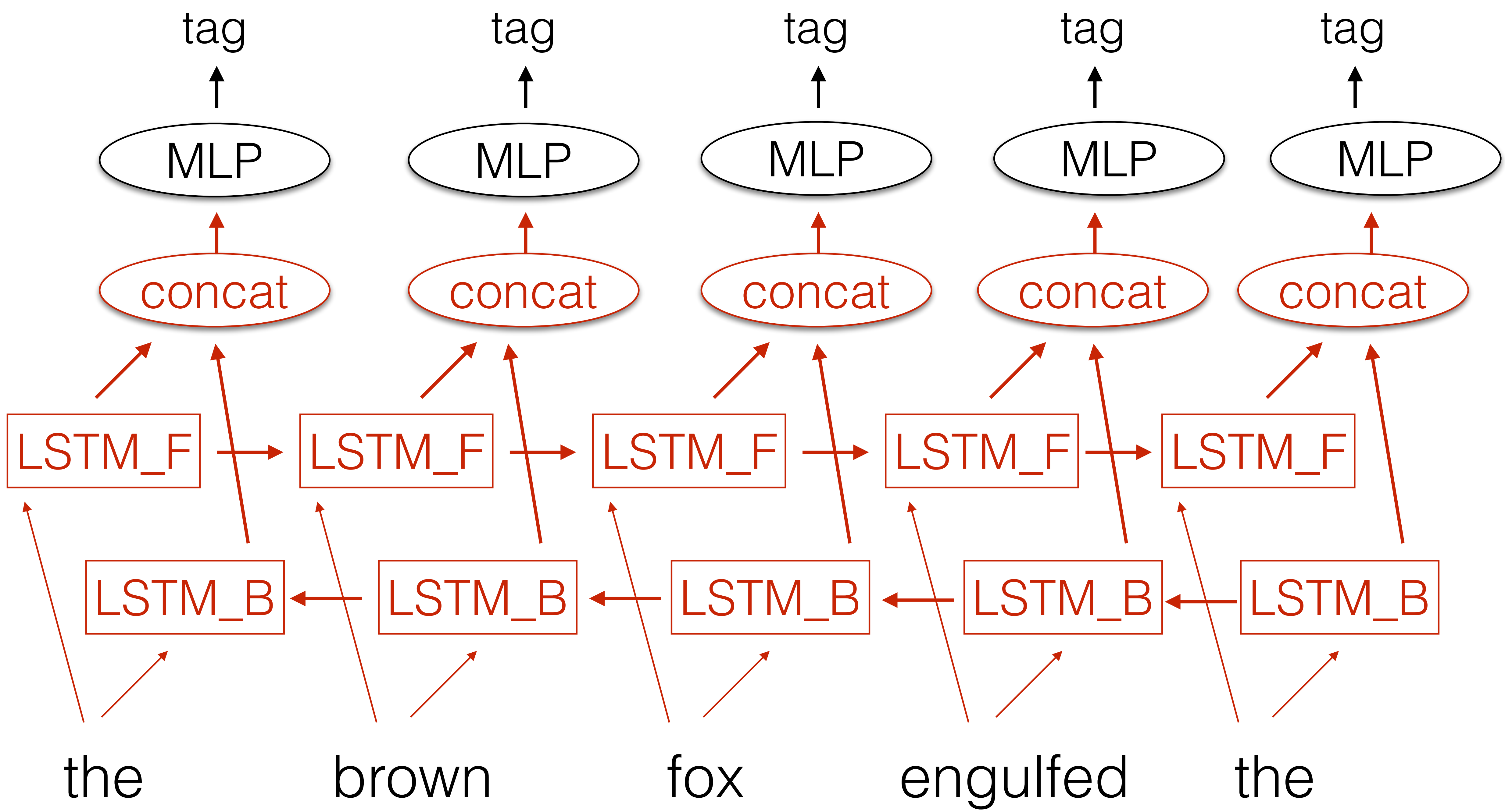


```python
WORDS_LOOKUP = model.add_lookup_parameters((nwords, 128))
fwdRNN = dy.LSTMBuilder(1, 128, 50, model)
bwdRNN = dy.LSTMBuilder(1, 128, 50, model)



dy.renew_cg()
# initialize the RNNs
f_init = fwdRNN.initial_state()
b_init = bwdRNN.initial_state()

wembs = [word_rep(w) for w in words]

fw_exps = f_init.transduce(wembs)
bw_exps = b_init.transduce(reversed(wembs))
```

BiLSTM Tagger



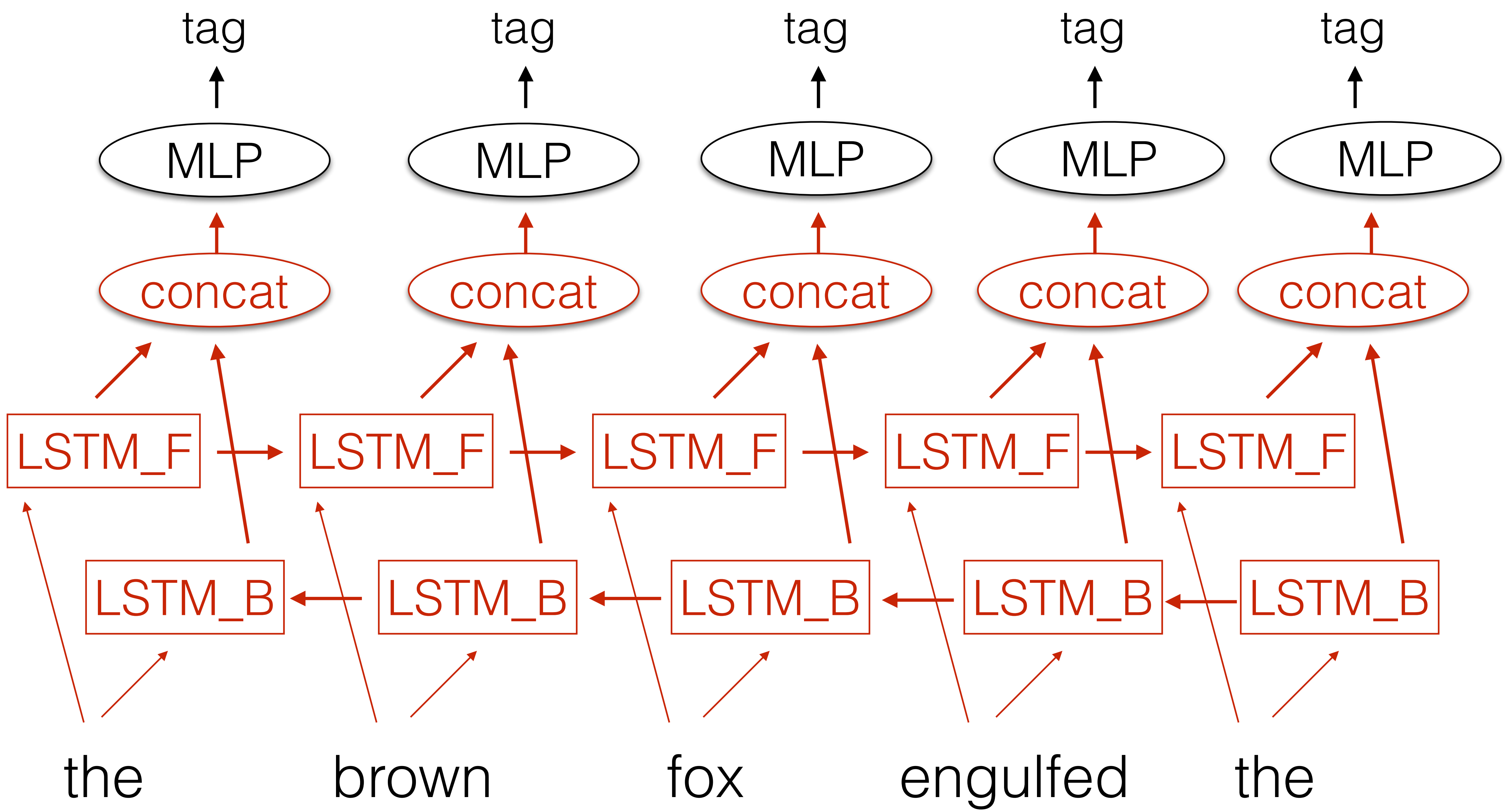
BiLSTM Tagger



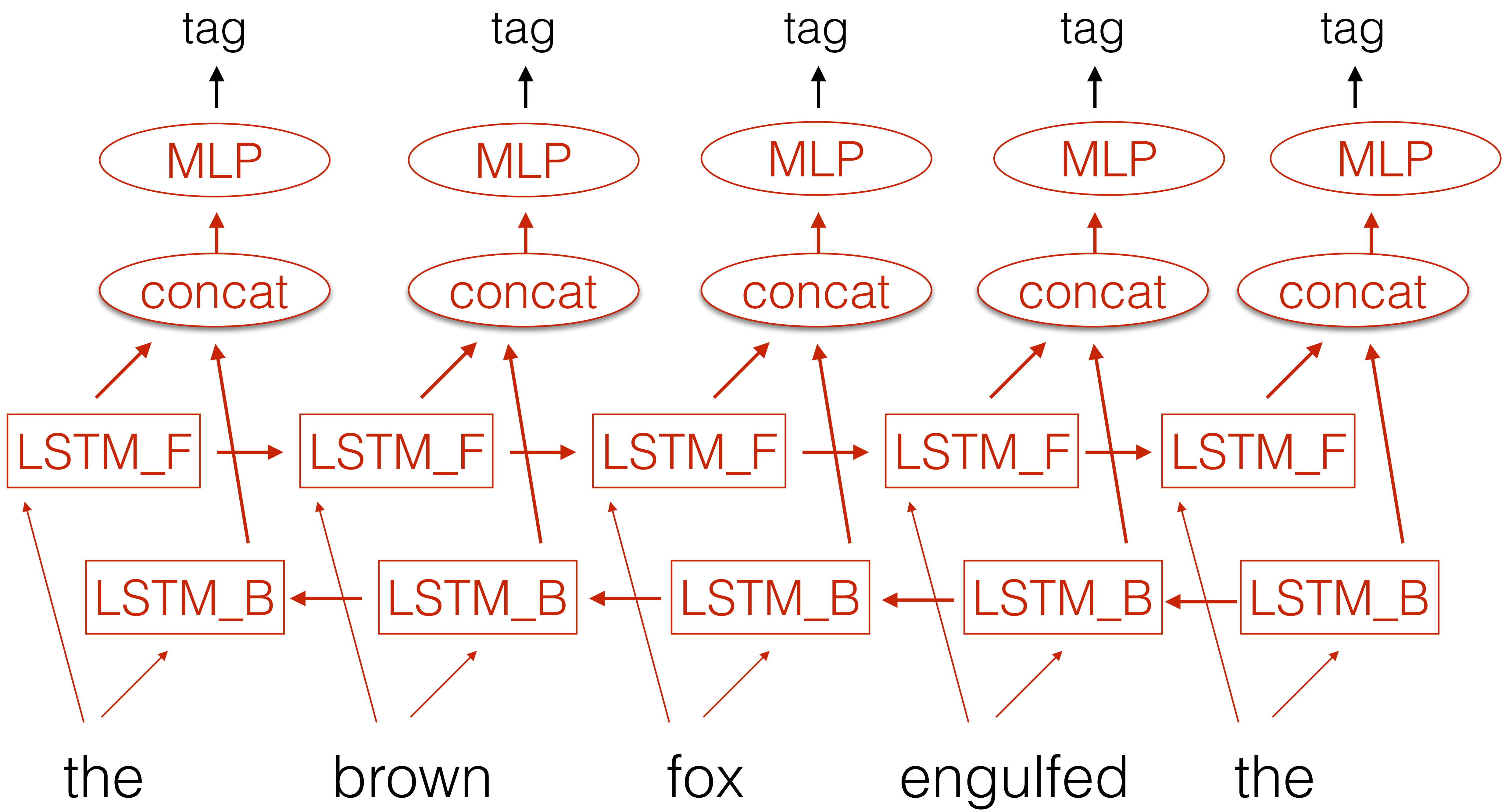
```
WORDS_LOOKUP = model.add_lookup_parameters((nwords, 128))
fwdRNN = dy.LSTMBuilder(1, 128, 50, model)
bwdRNN = dy.LSTMBuilder(1, 128, 50, model)
```

```
dy.renew_cg()
# initialize the RNNs
f_init = fwdRNN.initial_state()
b_init = bwdRNN.initial_state()

wembs = [word_rep(w) for w in words]

fw_exps = f_init.transduce(wembs)
bw_exps = b_init.transduce(reversed(wembs))

# biLSTM states
bi = [dy.concatenate([f,b]) for f,b in zip(fw_exps,
                                           reversed(bw_exps))]
```

BiLSTM Tagger



BiLSTM Tagger



```
WORDS_LOOKUP = model.add_lookup_parameters((nwords, 128))
fwdRNN = dy.LSTMBuilder(1, 128, 50, model)
bwdRNN = dy.LSTMBuilder(1, 128, 50, model)
pH = model.add_parameters((32, 50*2))
pO = model.add_parameters((ntags, 32))
```

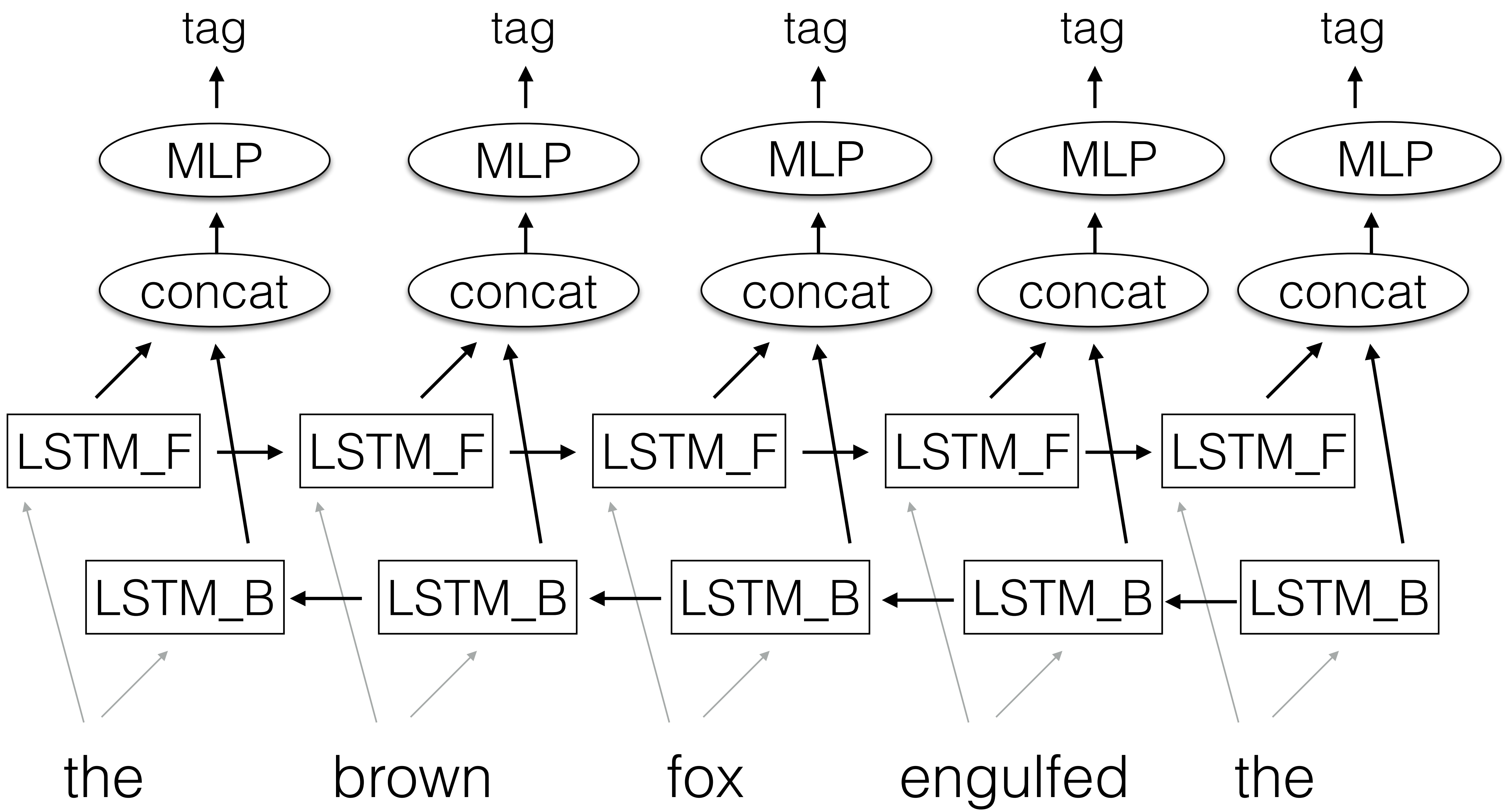
```
dy.renew_cg()
# initialize the RNNs
f_init = fwdRNN.initial_state()
b_init = bwdRNN.initial_state()
wembs = [word_rep(w) for w in words]
fw_exps = f_init.transduce(wembs)
bw_exps = b_init.transduce(reversed(wembs))

# biLSTM states
bi = [dy.concatenate([f,b]) for f,b in zip(fw_exps,
                                          reversed(bw_exps))]
# MLPs
H = dy.parameter(pH)
O = dy.parameter(pO)
outs = [O*(dy.tanh(H * x)) for x in bi]
```

```
WORDS_LOOKUP = model.add_lookup_parameters((nwords, 128))
fwdRNN = dy.LSTMBuilder(1, 128, 50, model)
bwdRNN = dy.LSTMBuilder(1, 128, 50, model)
pH = model.add_parameters((32, 50*2))
pO = model.add_parameters((ntags, 32))
```

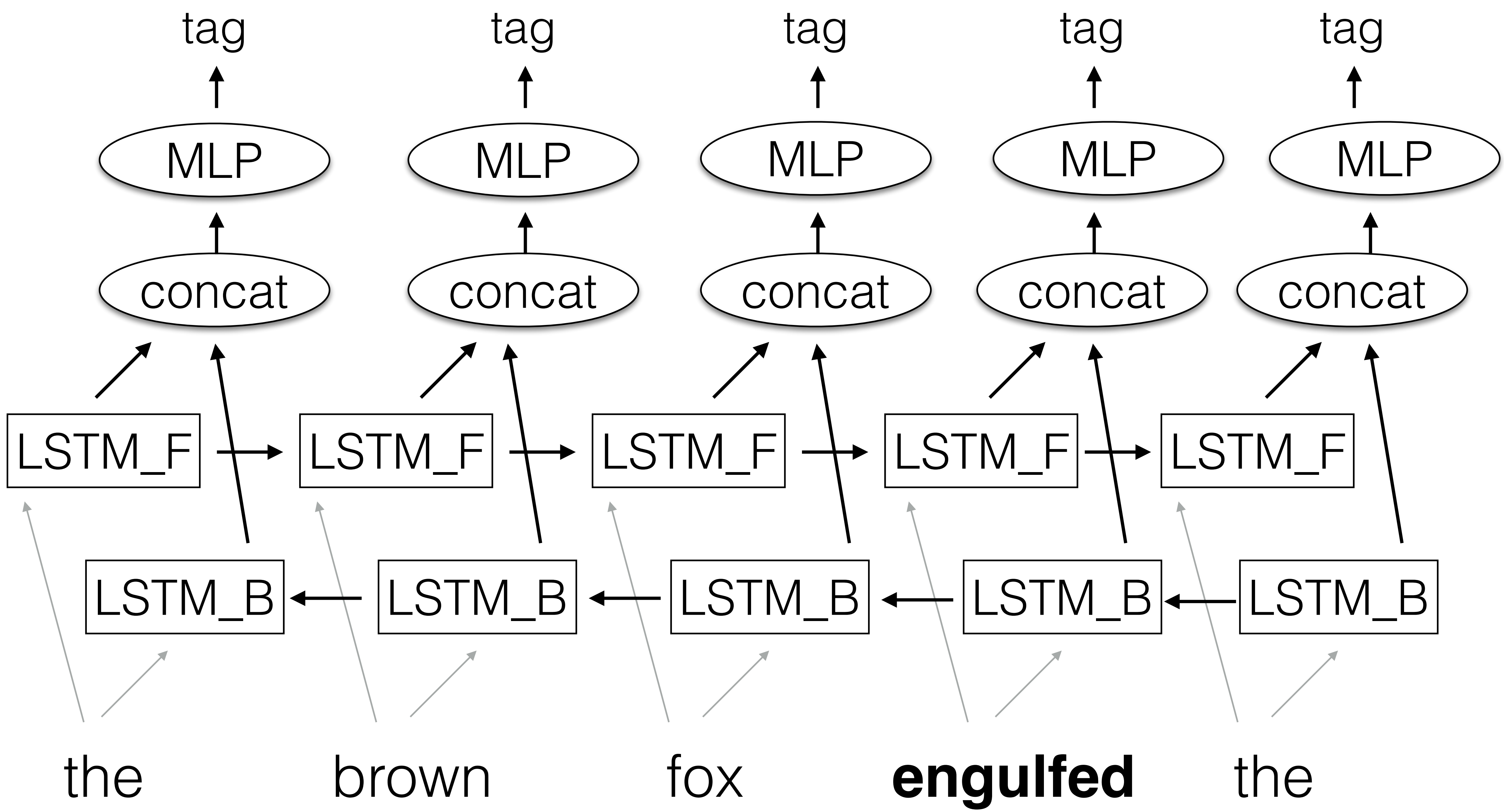
```
dy.renew_cg()
# initialize the RNNs
f_init = fwdRNN.initial_state()
b_init = bwdRNN.initial_state()
wembs = [word_rep(w) for w in words]
fw_exps = f_init.transduce(wembs)
bw_exps = b_init.transduce(reversed(wembs))

# biLSTM states
bi = [dy.concatenate([f,b]) for f,b in zip(fw_exps,
                                          reversed(bw_exps))]
# MLPs
H = dy.parameter(pH)
O = dy.parameter(pO)
outs = [O*(dy.tanh(H * x)) for x in bi]
```

```
WORDS_LOOKUP = model.add_lookup_parameters((nwords, 128))

def word_rep(w):
    w_index = vw.w2i[w]
    return WORDS_LOOKUP[w_index]

dy.renew_cg()
# initialize the RNNs
f_init = fwdRNN.initial_state()
b_init = bwdRNN.initial_state()
wembs = [word_rep(w) for w in words]
fw_exps = f_init.transduce(wembs)
bw_exps = b_init.transduce(reversed(wembs))

# biLSTM states
bi = [dy.concatenate([f,b]) for f,b in zip(fw_exps,
                                            reversed(bw_exps))]
# MLPs
H = dy.parameter(pH)
O = dy.parameter(pO)
outs = [O*(dy.tanh(H * x)) for x in bi]
```

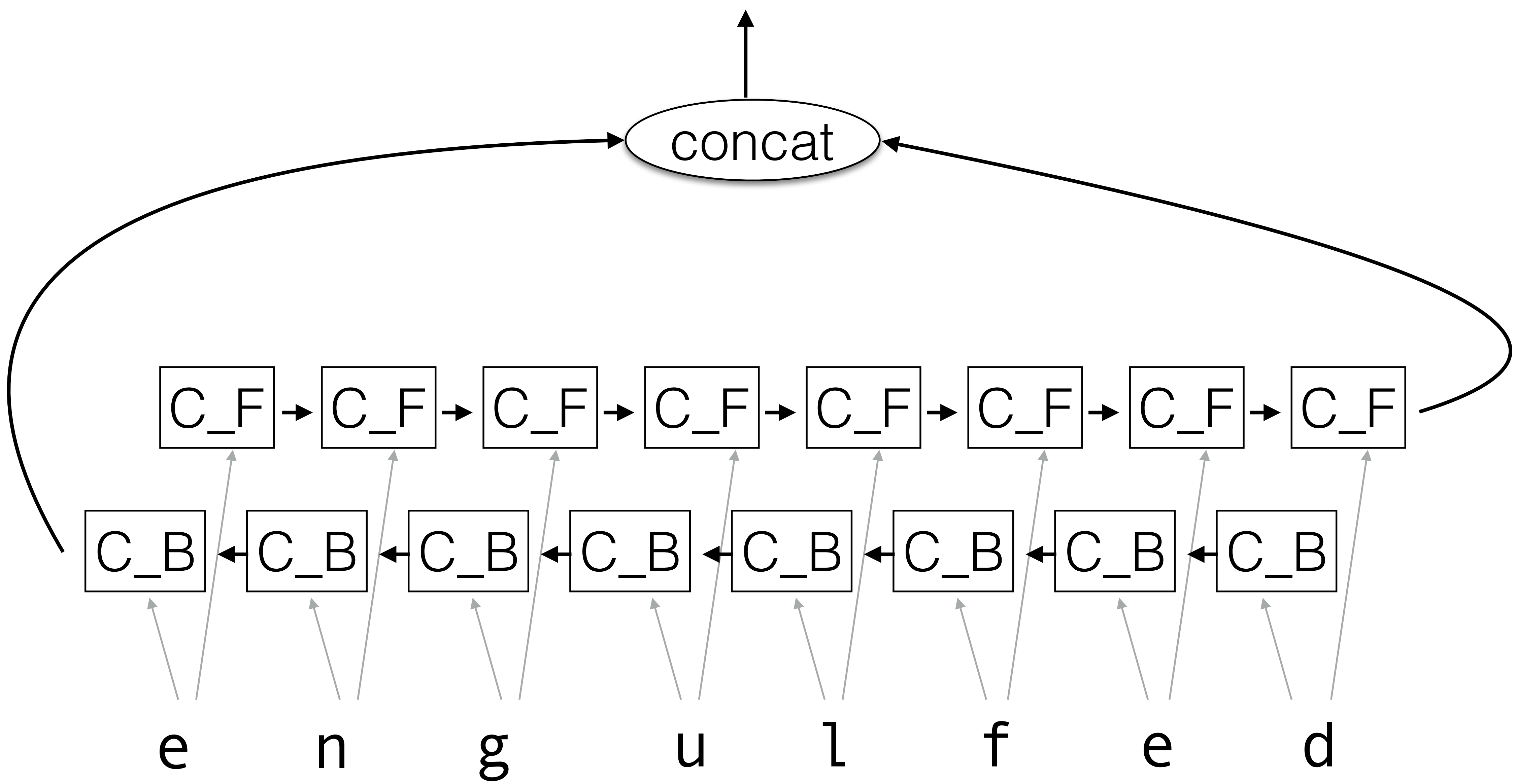
BiLSTM Tagger



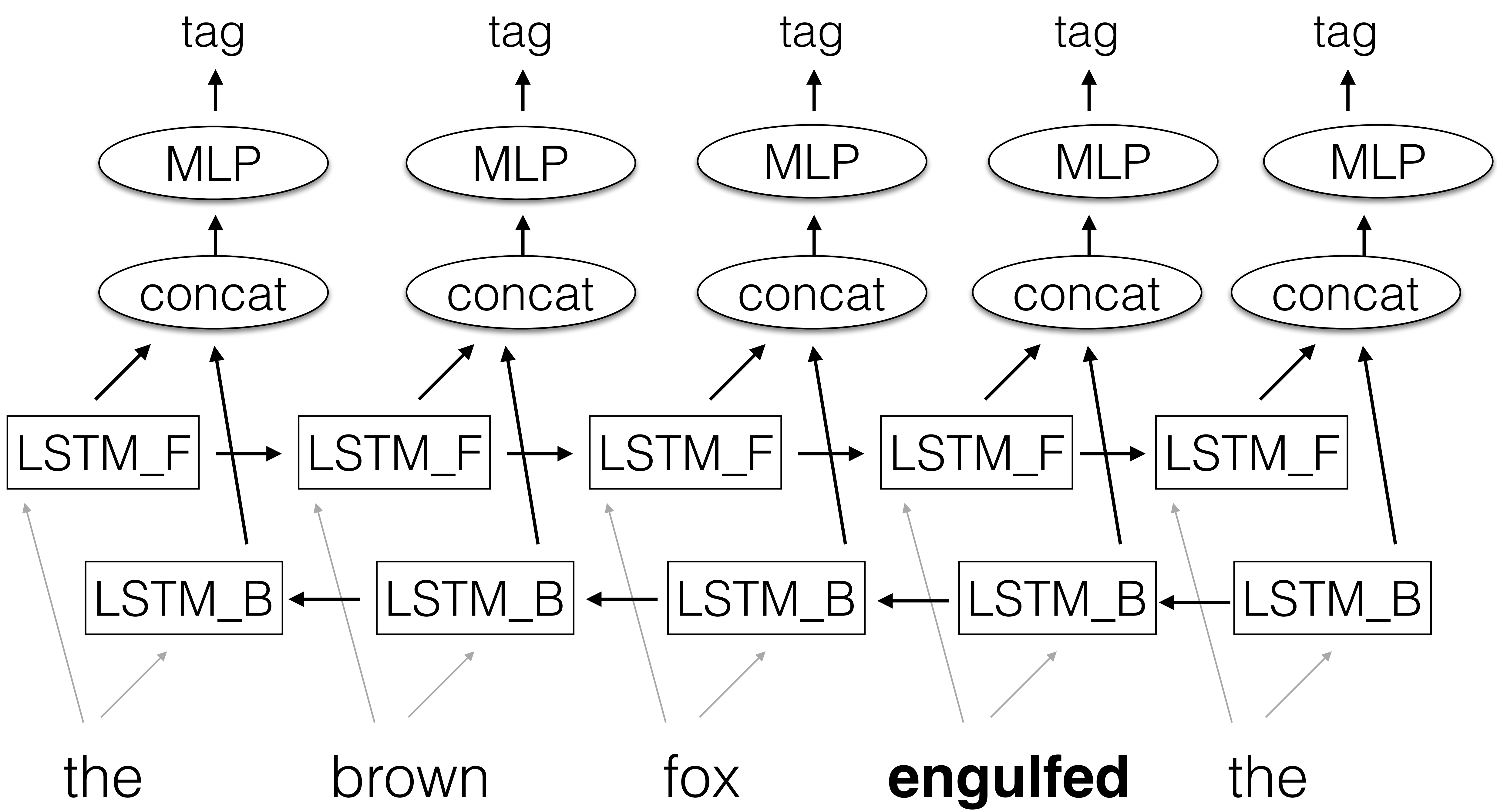
BiLSTM Tagger



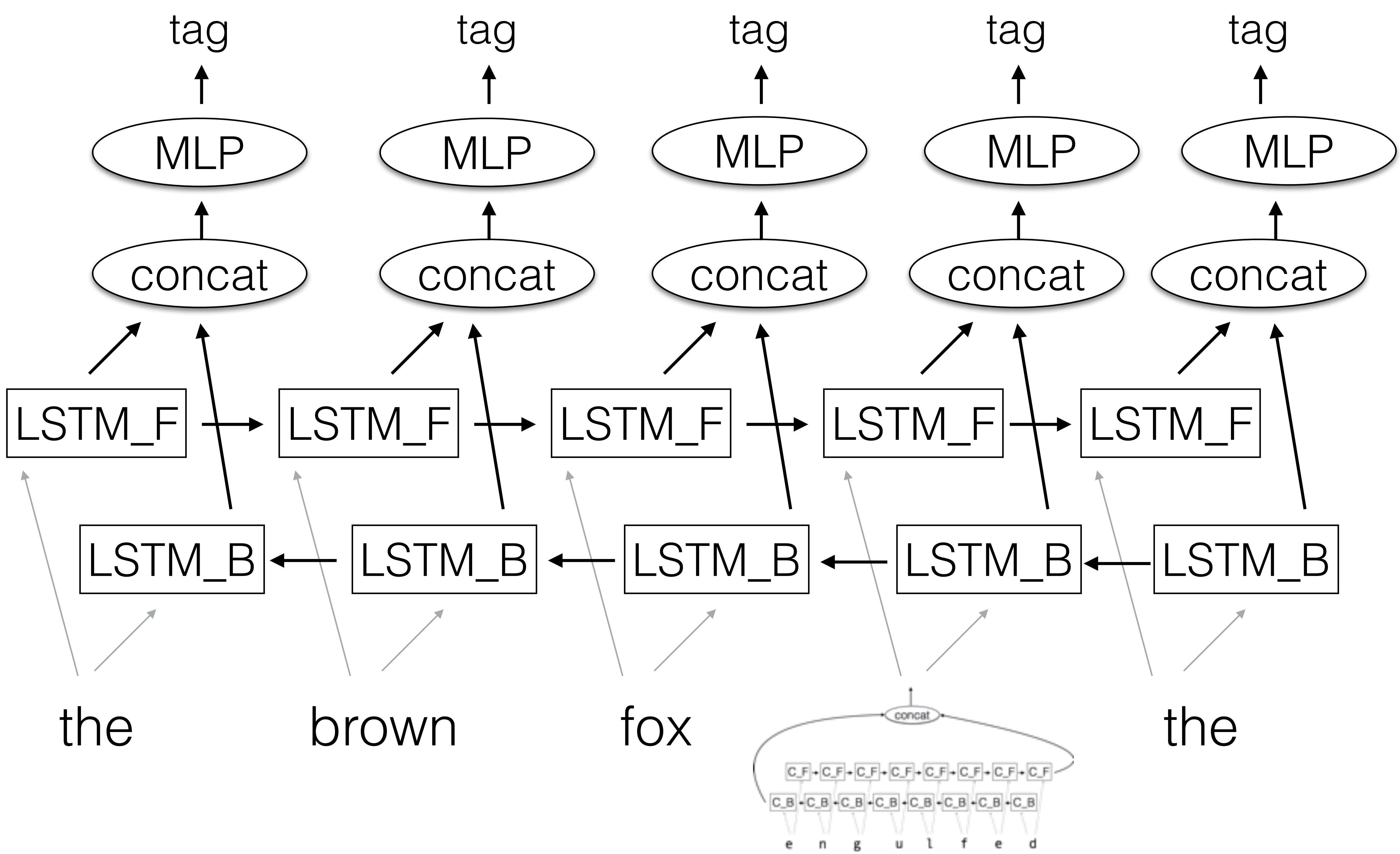
Back off to char-LSTM for rare words



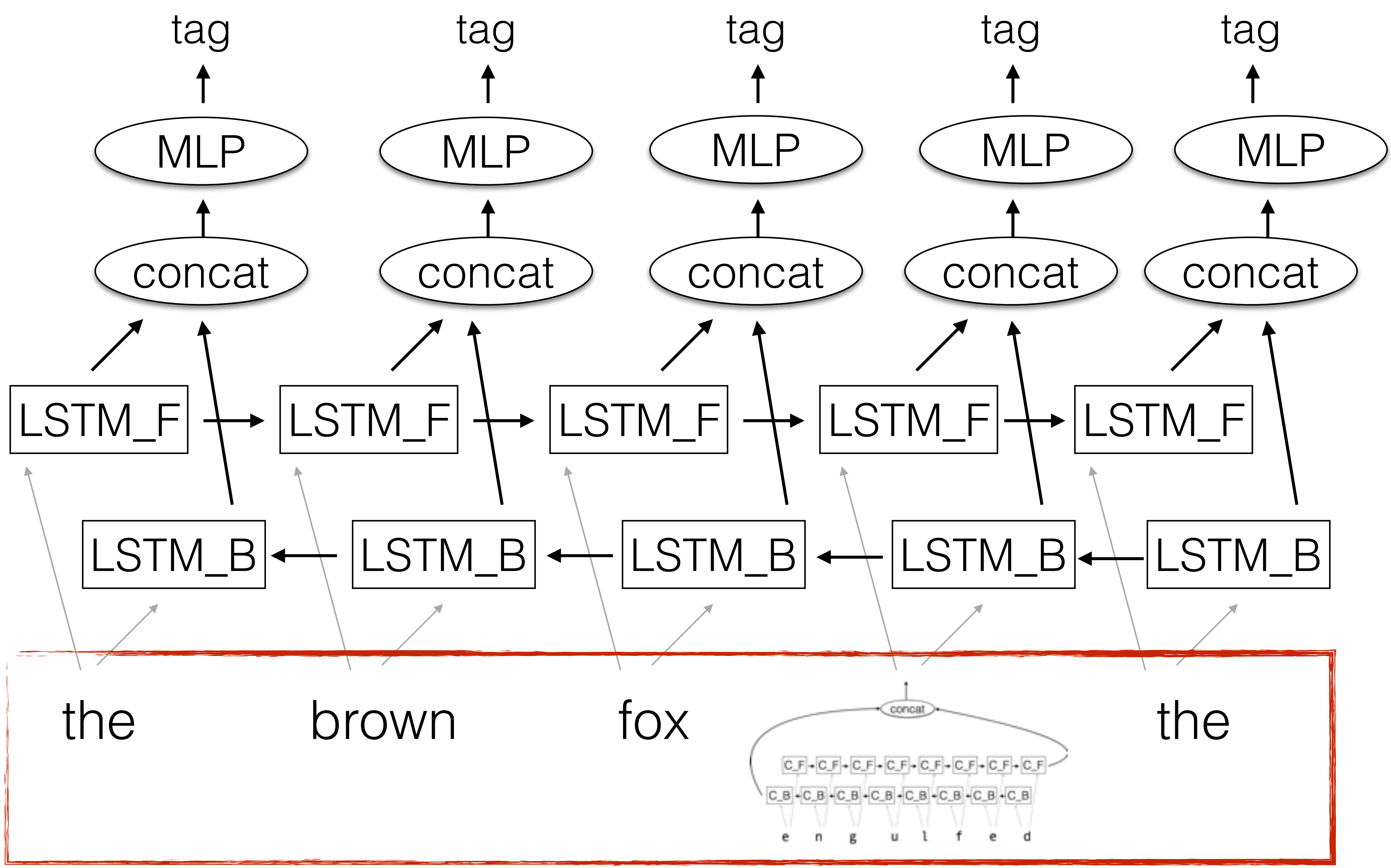
BiLSTM Tagger



BiLSTM Tagger



BiLSTM Tagger



```
WORDS_LOOKUP = model.add_lookup_parameters((nwords, 128))
CHARS_LOOKUP = model.add_lookup_parameters((nchars, 20))
cFwdRNN = dy.LSTMBuilder(1, 20, 64, model)
cBwdRNN = dy.LSTMBuilder(1, 20, 64, model)
```

```
WORDS_LOOKUP = model.add_lookup_parameters((nwords, 128))
CHARS_LOOKUP = model.add_lookup_parameters((nchars, 20))
cFwdRNN = dy.LSTMBuilder(1, 20, 64, model)
cBwdRNN = dy.LSTMBuilder(1, 20, 64, model)


def word_rep(w):
    w_index = vw.w2i[w]
    return WORDS_LOOKUP[w_index]
```

```
WORDS_LOOKUP = model.add_lookup_parameters((nwords, 128))
CHARS_LOOKUP = model.add_lookup_parameters((nchars, 20))
cFwdRNN = dy.LSTMBuilder(1, 20, 64, model)
cBwdRNN = dy.LSTMBuilder(1, 20, 64, model)
```

```
def word_rep(w):
    w_index = vw.w2i[w]
    return WORDS_LOOKUP[w_index]
```

```
def word_rep(w, cf_init, cb_init):
    if wc[w] > 5:
        w_index = vw.w2i[w]
        return WORDS_LOOKUP[w_index]
    else:
        char_ids = [vc.w2i[c] for c in w]
        char_embs = [CHARS_LOOKUP[cid] for cid in char_ids]
        fw_exps = cf_init.transduce(char_embs)
        bw_exps = cb_init.transduce(reversed(char_embs))
        return dy.concatenate([ fw_exps[-1], bw_exps[-1] ])
```

```python
def build_tagging_graph(words):
    dy.renew_cg()
    # initialize the RNNs
    f_init = fwdRNN.initial_state()
    b_init = bwdRNN.initial_state()

    cf_init = cFwdRNN.initial_state()
    cb_init = cBwdRNN.initial_state()

    wembs = [word_rep(w, cf_init, cb_init) for w in words]

    fws = f_init.transduce(wembs)
    bws = b_init.transduce(reversed(wembs))

    # biLSTM states
    bi = [dy.concatenate([f,b]) for f,b in zip(fws, reversed(bws))]

    # MLPs
    H = dy.parameter(pH)
    O = dy.parameter(pO)
    outs = [O*(dy.tanh(H * x)) for x in bi]
    return outs
```

```python
def tag_sent(words):
    vecs = build_tagging_graph(words)
    vecs = [dy.softmax(v) for v in vecs]
    probs = [v.npvalue() for v in vecs]
    tags = []
    for prb in probs:
        tag = np.argmax(prb)
        tags.append(vt.i2w[tag])
    return zip(words, tags)
```

```python
def sent_loss(words, tags):
    vecs = build_tagging_graph(words)
    losses = []
    for v,t in zip(vecs,tags):
        tid = vt.w2i[t]
        loss = dy.pickneglogsoftmax(v, tid)
        losses.append(loss)
    return dy.esum(losses)
```

```python
num_tagged = cum_loss = 0
for ITER in xrange(50):
    random.shuffle(train)
    for i,s in enumerate(train,1):
        if i > 0 and i % 500 == 0:   # print status
            trainer.status()
            print cum_loss / num_tagged
            cum_loss = num_tagged = 0
        if i % 10000 == 0:           # eval on dev
            good = bad = 0.0
            for sent in dev:
                words = [w for w,t in sent]
                golds = [t for w,t in sent]
                tags = [t for w,t in tag_sent(words)]
                for go,gu in zip(golds,tags):
                    if go == gu: good +=1
                    else: bad+=1
            print good/(good+bad)
        # train on sent
        words = [w for w,t in s]
        golds = [t for w,t in s]

        loss_exp =  sent_loss(words, golds)
        cum_loss += loss_exp.scalar_value()
        num_tagged += len(golds)
        loss_exp.backward()
        trainer.update()
```

```python
num_tagged = cum_loss = 0
for ITER in xrange(50):
    random.shuffle(train)
    for i,s in enumerate(train,1):
        if i > 0 and i % 500 == 0:   # print status
            trainer.status()
            print cum_loss / num_tagged
            cum_loss = num_tagged = 0
        if i % 10000 == 0:           # eval on dev
            good = bad = 0.0
            for sent in dev:
                words = [w for w,t in sent]
                golds = [t for w,t in sent]
                tags = [t for w,t in tag_sent(words)]
                for go,gu in zip(golds,tags):
                    if go == gu: good +=1
                    else: bad+=1
            print good/(good+bad)
        # train on sent
        words = [w for w,t in s]
        golds = [t for w,t in s]

        loss_exp =  sent_loss(words, golds)
        cum_loss += loss_exp.scalar_value()
        num_tagged += len(golds)
        loss_exp.backward()
        trainer.update()
```

progress reports

training

Outline

- **Part 2: Case Studies**
  - Tagging with bidirectional RNNs
  - Transition-based dependency parsing
  - Structured prediction meets deep learning

Transition-Based Parsing

Stack	Buffer	Action
	I saw her duck	

Stack	Buffer	Action
	I saw her duck	SHIFT

Stack	Buffer	Action
	I saw her duck	SHIFT
I	saw her duck	

Stack	Buffer	Action
	I saw her duck	SHIFT
I	saw her duck	SHIFT

Stack	Buffer	Action
	I saw her duck	SHIFT
I	saw her duck	SHIFT
I saw	her duck	

Stack	Buffer	Action
	I saw her duck	SHIFT
I	saw her duck	SHIFT
I saw	her duck	REDUCE-L

Stack	Buffer	Action
	I saw her duck	SHIFT
I	saw her duck	SHIFT
I saw	her duck	REDUCE-L
I saw		

Stack	Buffer	Action
	I saw her duck	SHIFT
I	saw her duck	SHIFT
I saw	her duck	REDUCE-L
I saw	her duck	

Stack	Buffer	Action
	I saw her duck	**SHIFT**
I	saw her duck	**SHIFT**
I saw	her duck	**REDUCE-L**
I saw	her duck	**SHIFT**

Stack	Buffer	Action
	I saw her duck	SHIFT
I	saw her duck	SHIFT
I saw	her duck	REDUCE-L
I saw	her duck	SHIFT
I saw her	duck	

Stack	Buffer	Action
	I saw her duck	SHIFT
I	saw her duck	SHIFT
I saw	her duck	REDUCE-L
I saw	her duck	SHIFT
I saw her	duck	SHIFT

Stack	Buffer	Action
	I saw her duck	SHIFT
I	saw her duck	SHIFT
I saw	her duck	REDUCE-L
I saw	her duck	SHIFT
I saw her	duck	SHIFT
I saw her duck		

Stack	Buffer	Action
	I saw her duck	SHIFT
I	saw her duck	SHIFT
I saw	her duck	REDUCE-L
I saw	her duck	SHIFT
I saw her	duck	SHIFT
I saw her duck		REDUCE-L

Stack	Buffer	Action
	I saw her duck	SHIFT
I	saw her duck	SHIFT
I saw	her duck	REDUCE-L
I saw	her duck	SHIFT
I saw her	duck	SHIFT
I saw her duck		REDUCE-L
I saw her duck		

Stack	Buffer	Action
	I saw her duck	SHIFT
I	saw her duck	SHIFT
I saw	her duck	REDUCE-L
I saw	her duck	SHIFT
I saw her	duck	SHIFT
I saw her duck		REDUCE-L
I saw her duck		REDUCE-R

Stack	Buffer	Action
	I saw her duck	SHIFT
I	saw her duck	SHIFT
I saw	her duck	REDUCE-L
I saw	her duck	SHIFT
I saw her	duck	SHIFT
I saw her duck		REDUCE-L
I saw her duck		REDUCE-R
I saw her duck		

Transition-based parsing

- Build trees by pushing words ("**shift**") onto a stack and combing elements at the top of the stack into a syntactic constituent ("**reduce**")
- ***Given current stack and buffer of unprocessed words, what action should the algorithm take?***

Transition-based parsing

- Build trees by pushing words ("**shift**") onto a stack and combing elements at the top of the stack into a syntactic constituent ("**reduce**")
- ***Given current stack and buffer of unprocessed words, what action should the algorithm take?***

Let's use a neural network!

Transition-based parsing

`tokens` is the sentence to be parsed.
`oracle_actions` is a list of {`SHIFT`, `REDUCE_L`, `REDUCE_R`}.

```
def parse(self, tokens, oracle_actions):
```

Transition-based parsing

`tokens` is the sentence to be parsed.
`oracle_actions` is a list of {`SHIFT`, `REDUCE_L`, `REDUCE_R`}.

```
def parse(self, tokens, oracle_actions):
    buffer = []
    stack = []
```

Transition-based parsing

`tokens` is the sentence to be parsed.
`oracle_actions` is a list of {`SHIFT`, `REDUCE_L`, `REDUCE_R`}.

```
def parse(self, tokens, oracle_actions):
    buffer = []
    stack = []
    for tok in reversed(tokens):
        buffer.append(tok)
```

Transition-based parsing

`tokens` is the sentence to be parsed.
`oracle_actions` is a list of {`SHIFT`, `REDUCE_L`, `REDUCE_R`}.

```
def parse(self, tokens, oracle_actions):
    buffer = []
    stack = []
    for tok in reversed(tokens):
        buffer.append(tok)

    while not (len(stack) == 1 and len(buffer) == 0):
```

Transition-based parsing

`tokens` is the sentence to be parsed.
`oracle_actions` is a list of {`SHIFT`, `REDUCE_L`, `REDUCE_R`}.

```
def parse(self, tokens, oracle_actions):
    buffer = []
    stack = []
    for tok in reversed(tokens):
        buffer.append(tok)

    while not (len(stack) == 1 and len(buffer) == 0):
        action_probs = model(stack, buffer)
        action = oracle_actions.pop()
        loss += pick(action_probs, action)
```

Transition-based parsing

`tokens` is the sentence to be parsed.
`oracle_actions` is a list of {`SHIFT`, `REDUCE_L`, `REDUCE_R`}.

```
def parse(self, tokens, oracle_actions):
    buffer = []
    stack = []
    for tok in reversed(tokens):
        buffer.append(tok)

    while not (len(stack) == 1 and len(buffer) == 0):
        action_probs = model(stack, buffer)
        action = oracle_actions.pop()
        loss += pick(action_probs, action)

        # execute the action to update the parser state
        if action == SHIFT:
            next_token = buffer.pop()
            stack.append(next_token)
```

Transition-based parsing

`tokens` is the sentence to be parsed.
`oracle_actions` is a list of {`SHIFT`, `REDUCE_L`, `REDUCE_R`}.

```
def parse(self, tokens, oracle_actions):
    buffer = []
    stack = []
    for tok in reversed(tokens):
        buffer.append(tok)

    while not (len(stack) == 1 and len(buffer) == 0):
        action_probs = model(stack, buffer)
        action = oracle_actions.pop()
        loss += pick(action_probs, action)

        # execute the action to update the parser state
        if action == SHIFT:
            next_token = buffer.pop()
            stack.append(next_token)
        else: # one of the REDUCE actions
            right = stack.pop() # pop a stack state
            left = stack.pop()  # pop another stack state
            # figure out which is the head and which is the modifier
            head, modifier = (left, right) if action == REDUCE_R else (right, left)
```

Transition-based parsing

`tokens` is the sentence to be parsed.
`oracle_actions` is a list of {`SHIFT`, `REDUCE_L`, `REDUCE_R`}.

```
def parse(self, tokens, oracle_actions):
    buffer = []
    stack = []
    for tok in reversed(tokens):
        buffer.append(tok)

    while not (len(stack) == 1 and len(buffer) == 0):
        action_probs = model(stack, buffer)
        action = oracle_actions.pop()
        loss += pick(action_probs, action)

        # execute the action to update the parser state
        if action == SHIFT:
            next_token = buffer.pop()
            stack.append(next_token)
        else: # one of the REDUCE actions
            right = stack.pop() # pop a stack state
            left = stack.pop()  # pop another stack state
            # figure out which is the head and which is the modifier
            head, modifier = (left, right) if action == REDUCE_R else (right, left)
            tree=compose(head, modifier)
```

Transition-based parsing

`tokens` is the sentence to be parsed.
`oracle_actions` is a list of {`SHIFT`, `REDUCE_L`, `REDUCE_R`}.

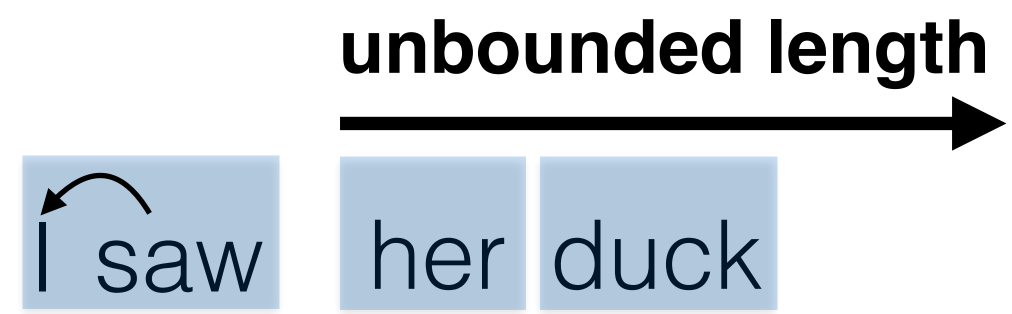
```python
def parse(self, tokens, oracle_actions):
    buffer = []
    stack = []
    for tok in reversed(tokens):
        buffer.append(tok)

    while not (len(stack) == 1 and len(buffer) == 0):
        action_probs = model(stack, buffer)
        action = oracle_actions.pop()
        loss += pick(action_probs, action)

        # execute the action to update the parser state
        if action == SHIFT:
            next_token = buffer.pop()
            stack.append(next_token)
        else: # one of the REDUCE actions
            right = stack.pop() # pop a stack state
            left = stack.pop()  # pop another stack state
            # figure out which is the head and which is the modifier
            head, modifier = (left, right) if action == REDUCE_R else (right, left)
            tree=compose(head, modifier)
            stack.append(tree)
```

Transition-based parsing

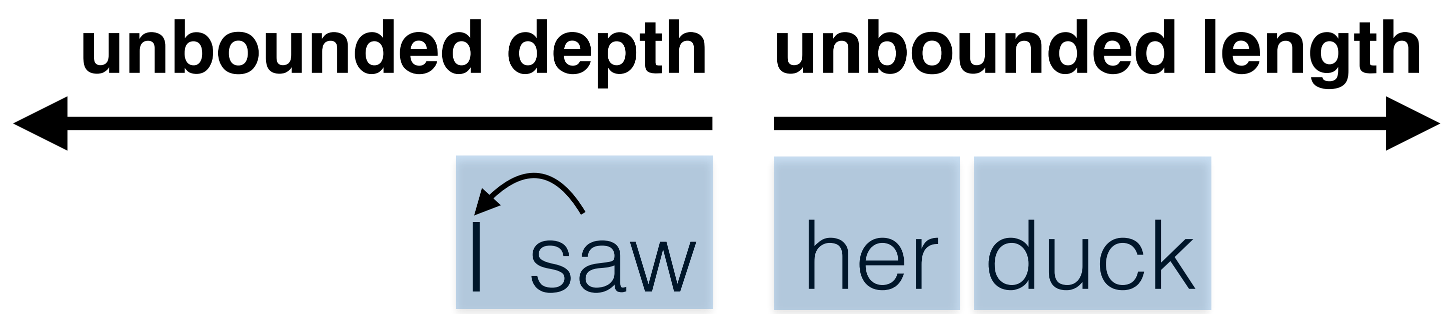
- This is a good problem for dynamic networks!
  - Different sentences trigger different parsing states
  - The state that needs to be embedded is complex (sequences, trees, sequences of trees)
  - The parsing algorithm has fairly complicated flow control and data structures

Transition-based parsing
Challenges

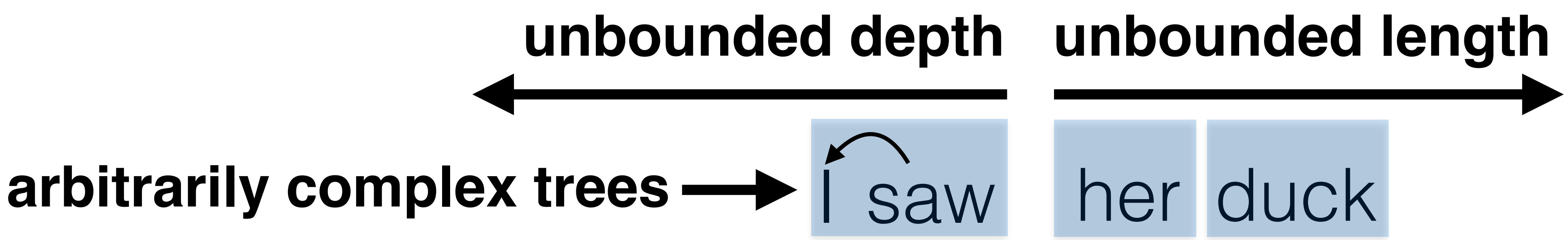
Transition-based parsing
Challenges



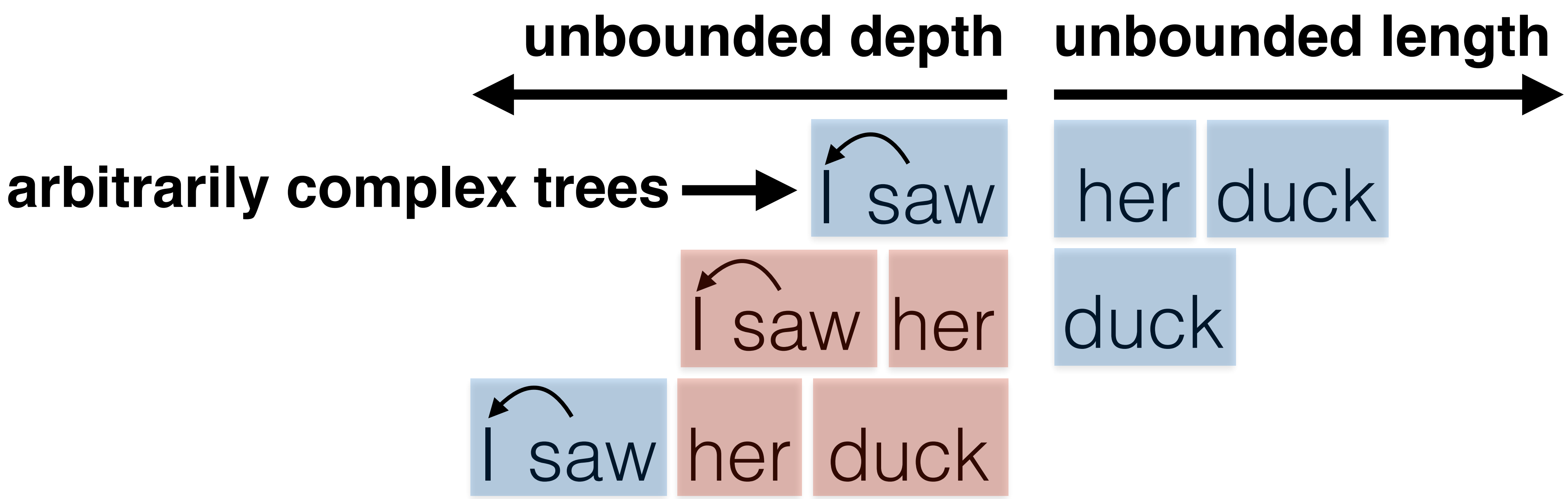
Transition-based parsing
Challenges



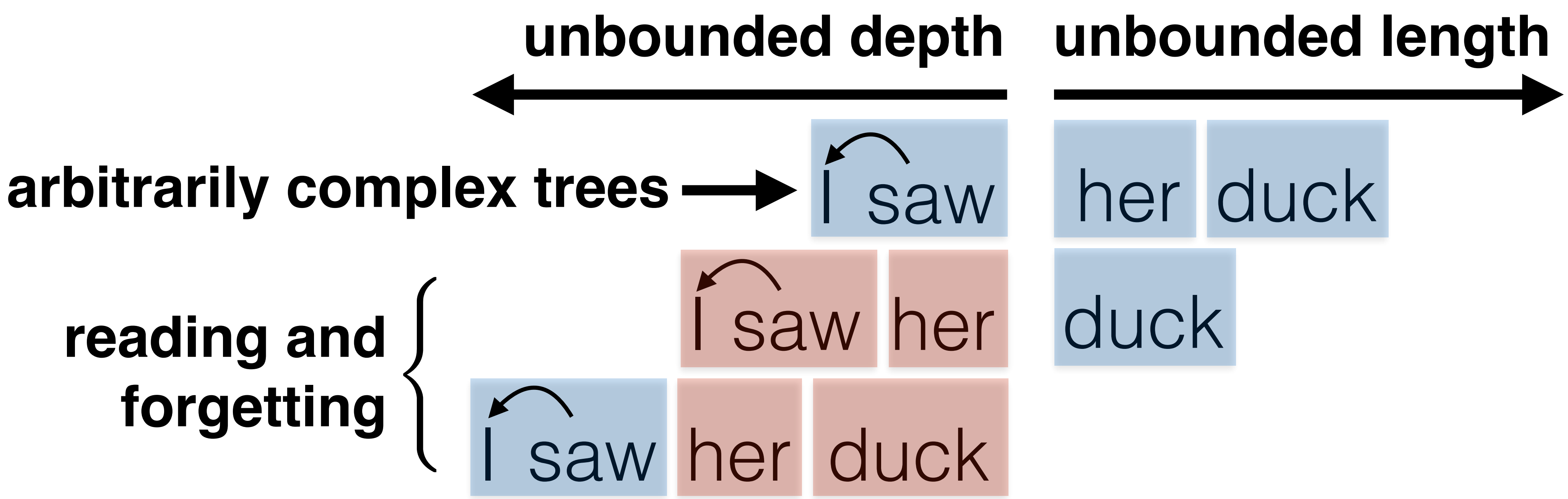
Transition-based parsing
Challenges



Transition-based parsing
Challenges



Transition-based parsing
Challenges



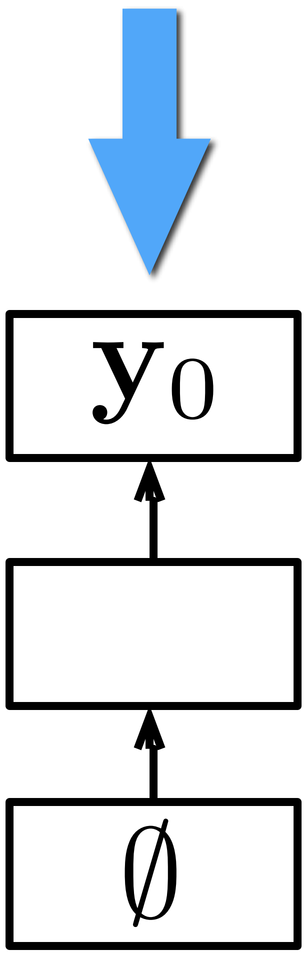
Transition-based parsing
State embeddings

- We can embed words
- Assume we can embed tree fragments
- The contents of the buffer are just a sequence
  - which we periodically “shift” from
- The contents of the stack is just a sequence
  - which we periodically pop from and push to
- Sequences -> use RNNs to get an encoding!
- But running an RNN for each state will be expensive. **Can we do better?**

Transition-based parsing
Stack RNNs

- Augment RNN with a **stack pointer**
- Three ***constant-time*** operations
  - **`push`** - read input, add to top of stack
  - **`pop`** - move stack pointer back
  - **`embedding`** - return the RNN state at the location of the stack pointer (which summarizes its current contents)

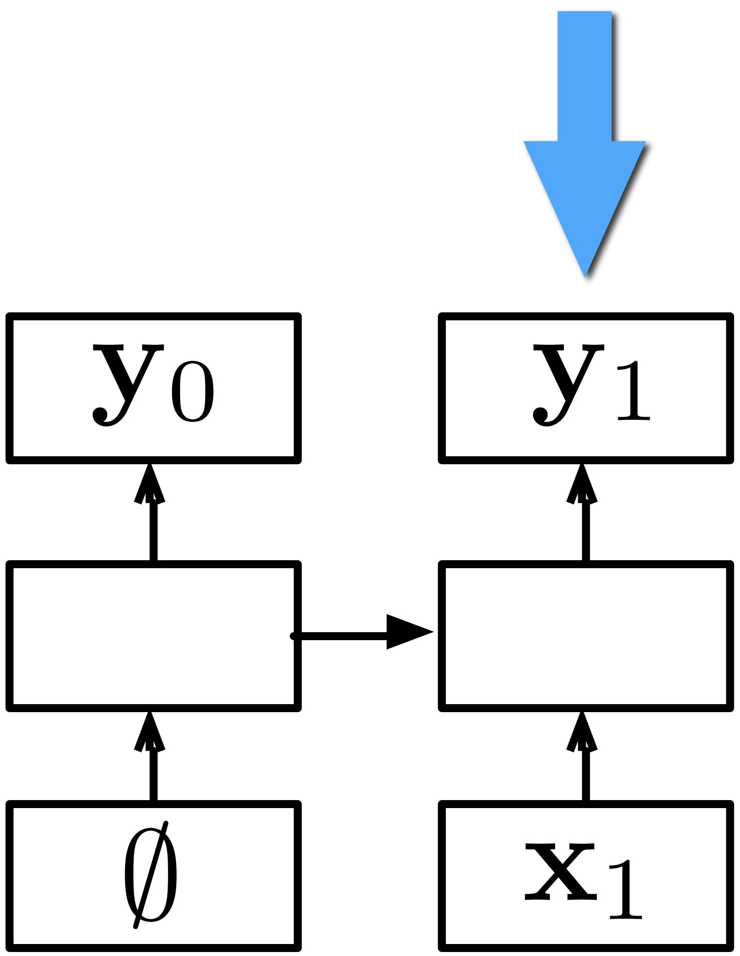
Transition-based parsing
Stack RNNs



DyNet:

```
s=[rnn.inital_state()]
s.append[s[-1].add_input(x1)
s.pop()
s.append[s[-1].add_input(x2)
s.pop()
s.append[s[-1].add_input(x3)
```

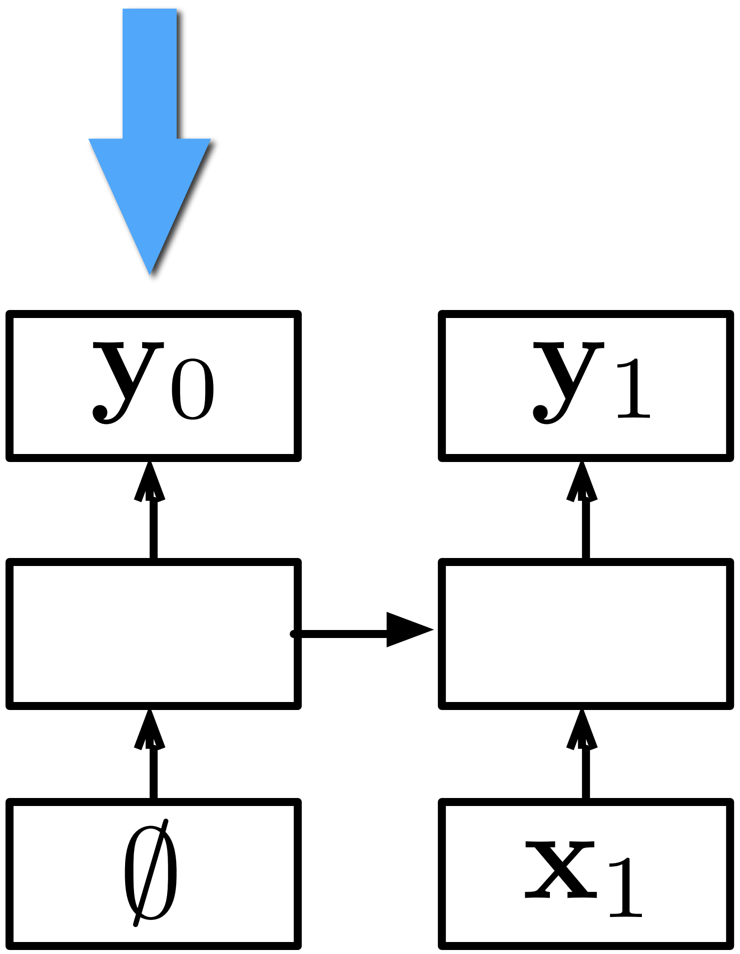
Transition-based parsing
Stack RNNs



DyNet:

```
s=[rnn.inital_state()]
s.append[s[-1].add_input(x1)
s.pop()
s.append[s[-1].add_input(x2)
s.pop()
s.append[s[-1].add_input(x3)
```

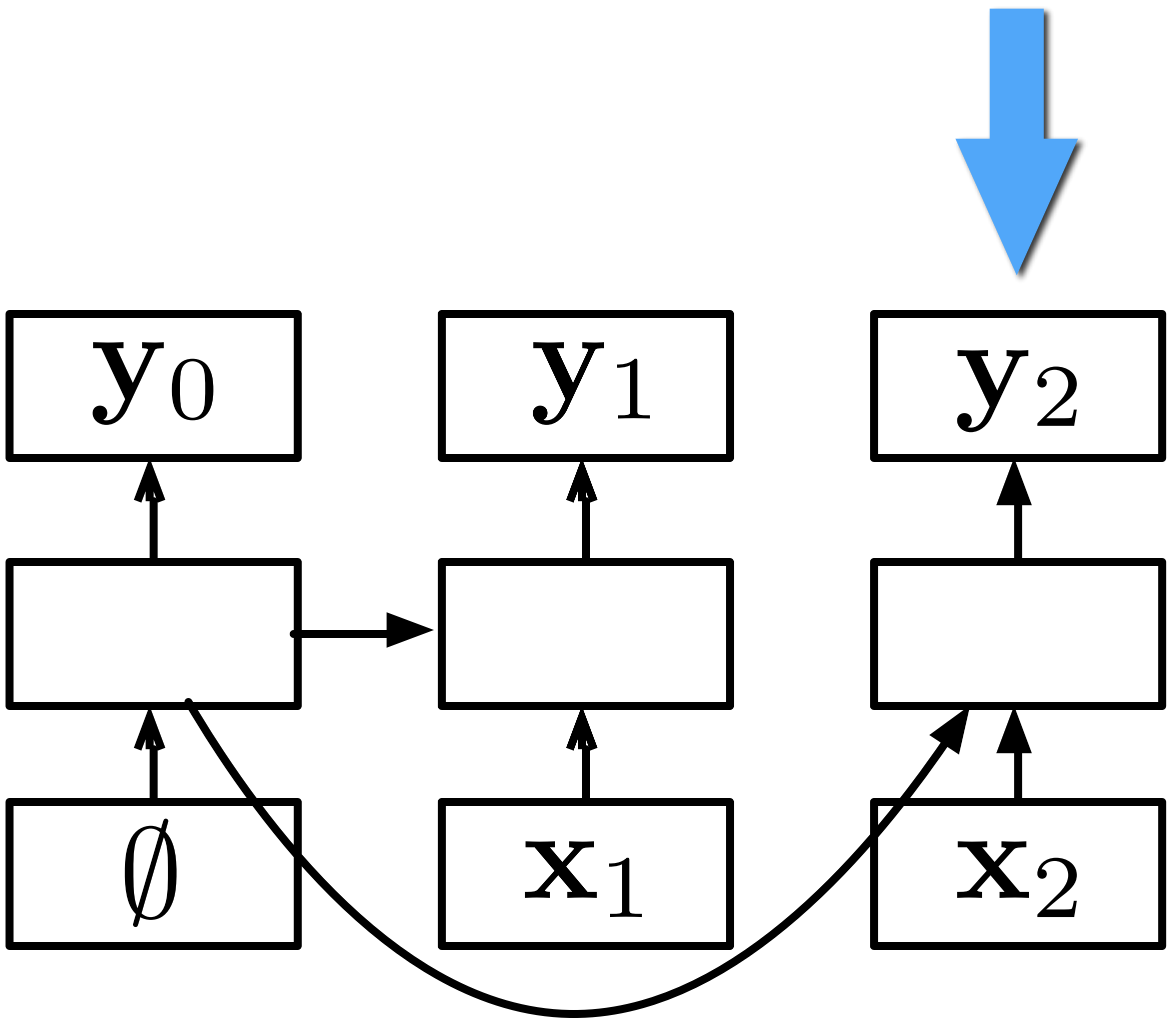
Transition-based parsing
Stack RNNs



DyNet:

```
s=[rnn.inital_state()]
s.append[s[-1].add_input(x1)
s.pop()
s.append[s[-1].add_input(x2)
s.pop()
s.append[s[-1].add_input(x3)
```

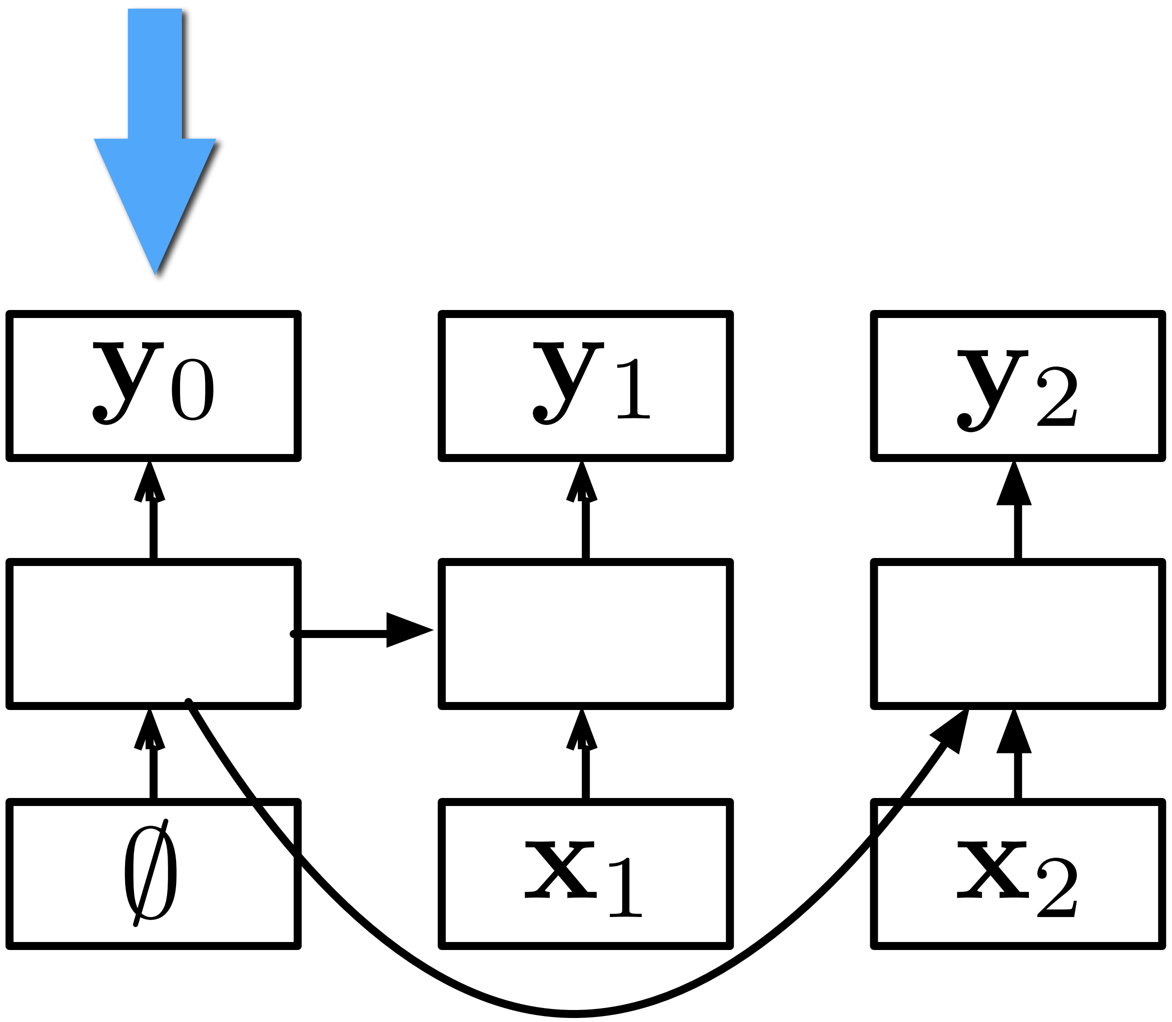
Transition-based parsing
Stack RNNs



DyNet:

```
s=[rnn.inital_state()]
s.append[s[-1].add_input(x1)
s.pop()
s.append[s[-1].add_input(x2)
s.pop()
s.append[s[-1].add_input(x3)
```

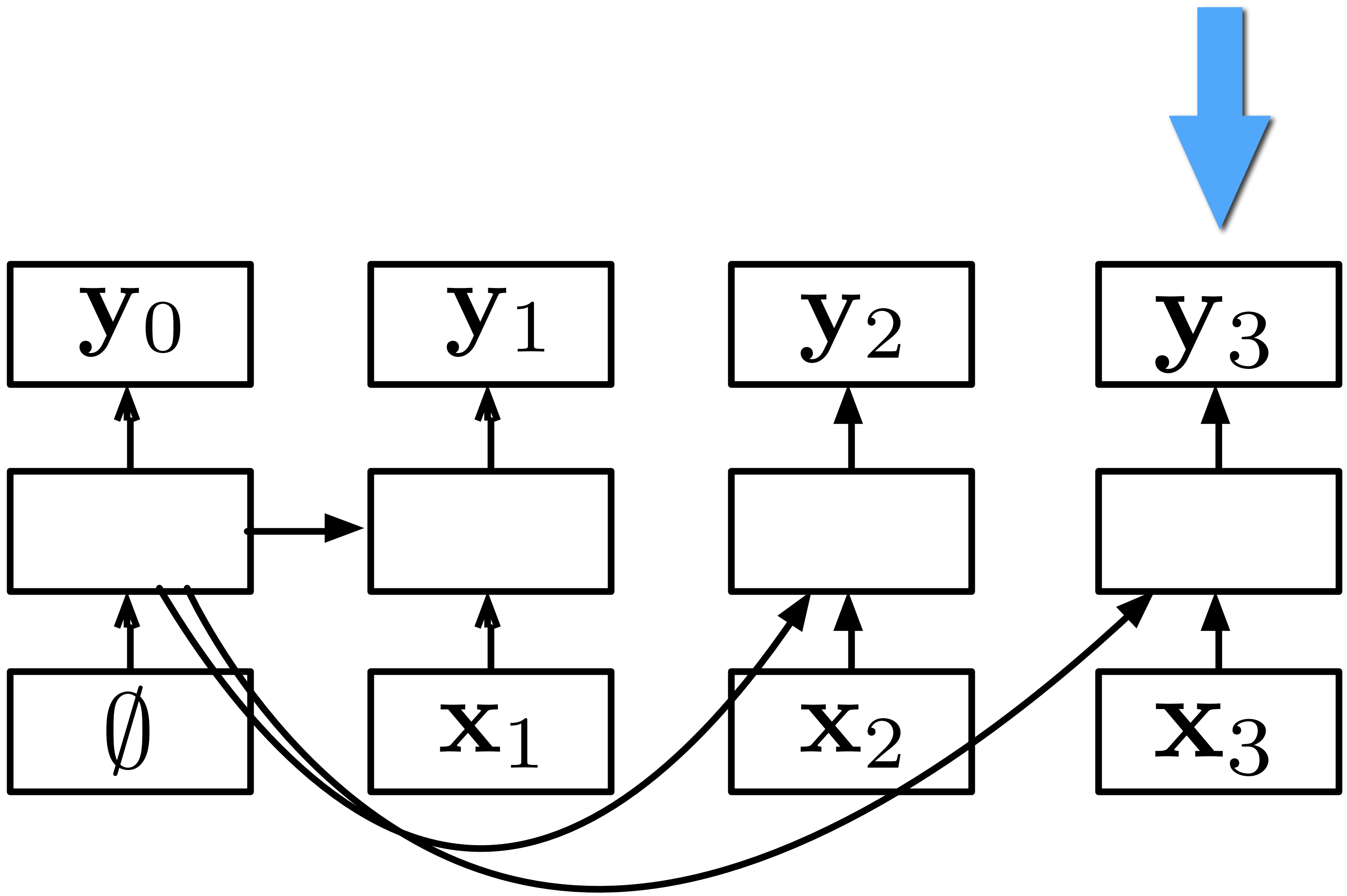
Transition-based parsing
Stack RNNs



DyNet:

```
s=[rnn.inital_state()]
s.append[s[-1].add_input(x1)
s.pop()
s.append[s[-1].add_input(x2)
s.pop()
s.append[s[-1].add_input(x3)
```

Transition-based parsing
Stack RNNs



DyNet:

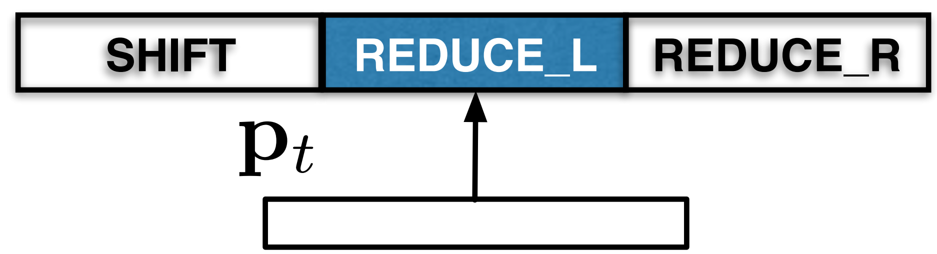
```
s=[rnn.inital_state()]
s.append[s[-1].add_input(x1)
s.pop()
s.append[s[-1].add_input(x2)
s.pop()
s.append[s[-1].add_input(x3)
```

Transition-based parsing

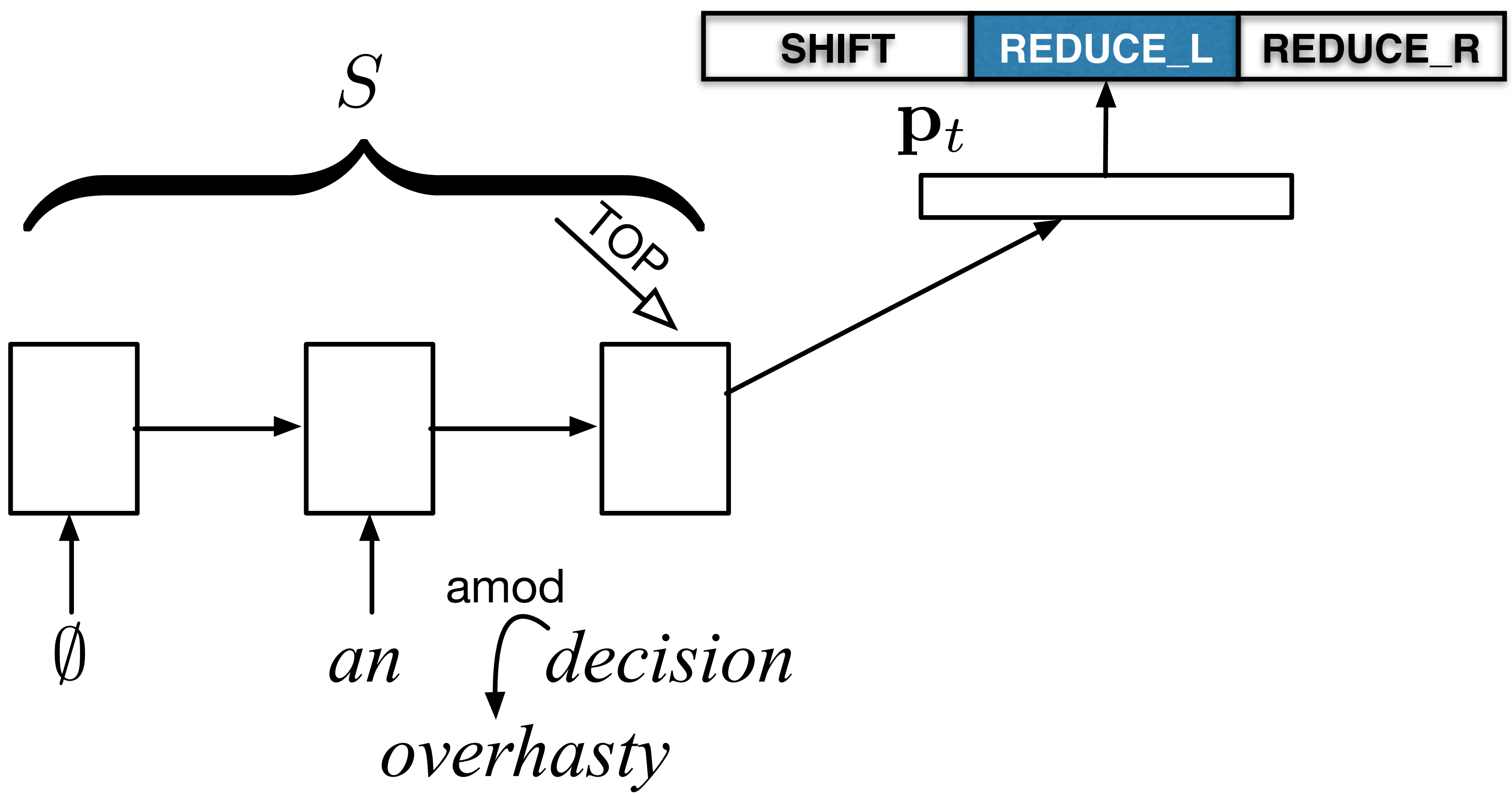
DyNet wrapper implementation:

```
class StackRNN(object):
    def __init__(self, rnn, p_empty_embedding = None):
        self.s = [(rnn.initial_state(), None)]
        self.empty = None
        if p_empty_embedding:
            self.empty = dy.parameter(p_empty_embedding)
    def push(self, expr, extra=None):
        self.s.append((self.s[-1][0].add_input(expr), extra))
    def pop(self):
        return self.s.pop()[1] # return "extra" (i.e., whatever the caller wants or None)
    def embedding(self):
        # work around since inital_state.output() is None
        return self.s[-1][0].output() if len(self.s) > 1 else self.empty
    def __len__(self):
        return len(self.s) - 1
```

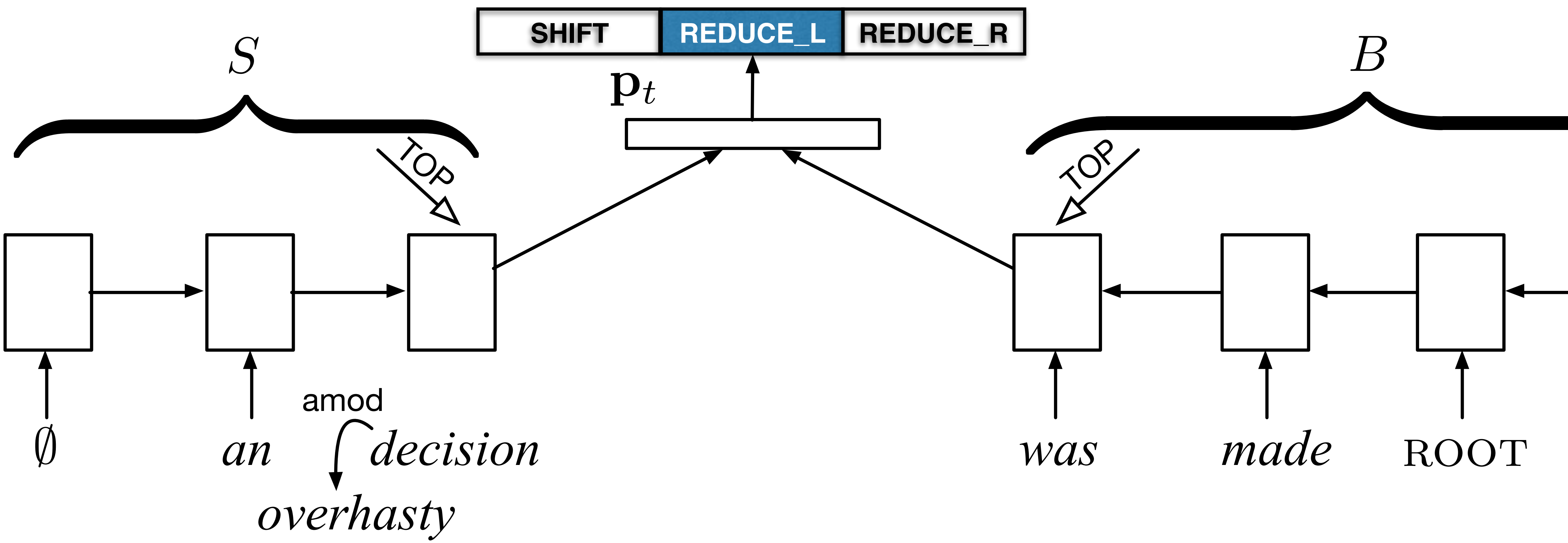
Transition-based parsing
Representing the state



Transition-based parsing
Representing the state



Transition-based parsing
Representing the state



Transition-based parsing
Syntactic compositions

$$head$$

$$\mathbf{h}$$

Transition-based parsing

Syntactic compositions

$$\textit{modifier} \qquad\qquad \textit{head}$$

$$\mathbf{m} \qquad\qquad\qquad \mathbf{h}$$

Transition-based parsing
Syntactic compositions

$$\mathbf{c} = \tanh(\mathbf{W}[\mathbf{h}; \mathbf{m}] + \mathbf{b})$$

modifier *head*

$\mathbf{m}$ $\mathbf{h}$

Transition-based parsing

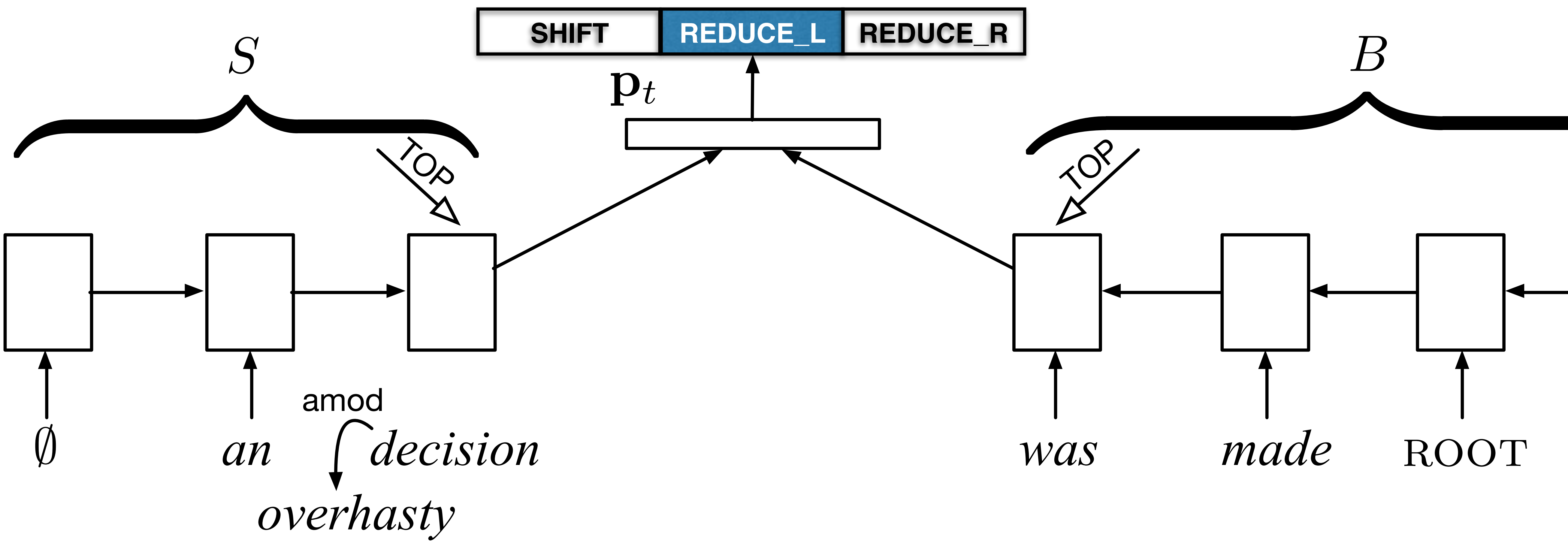
Syntactic compositions

```
# execute the action to update the parser state
if action == SHIFT:
    tok_embedding, token = buffer.pop()
    stack.push(tok_embedding, (tok_embedding, token))
else: # one of the REDUCE actions
    right = stack.pop() # pop a stack state
    left = stack.pop()  # pop another stack state
    # figure out which is the head and which is the modifier
    head, modifier = (left, right) if action == REDUCE_R else (right, left)

    # compute composed representation
    head_rep, head_tok = head
    mod_rep, mod_tok = modifier
    composed_rep = dy.tanh(W_comp * dy.concatenate([head_rep, mod_rep]) + b_comp)

    stack.push(composed_rep, (composed_rep, head_tok))
```

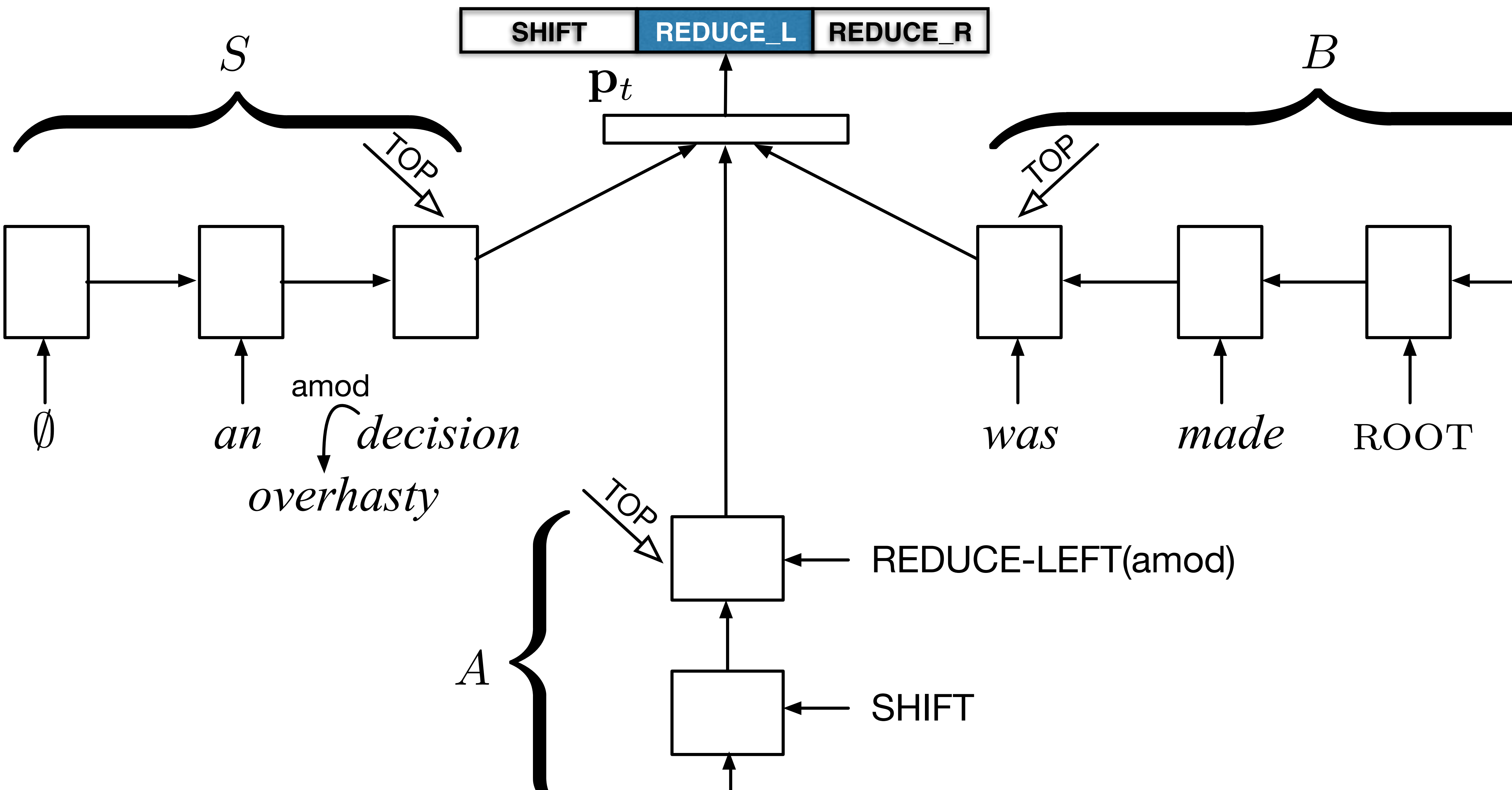
It is very easy to experiment with different composition functions.

Code Tour

Transition-based parsing
Representing the state



Transition-based parsing
Representing the state



Transition-based parsing
Pop quiz

- How should we add this functionality?

Outline

- **Part 2: Case Studies**
  - Tagging with bidirectional RNNs
  - Transition-based dependency parsing
  - Structured prediction meets deep learning

Training with Structured Objectives

What do we Know So Far?

- How to create relatively complicated models
- How to optimize them given an oracle action sequence

Local vs. Global Inference

Local vs. Global Inference

- What if optimizing local decisions doesn’t lead to good global decisions?

Local vs. Global Inference

- What if optimizing local decisions doesn't lead to good global decisions?

time flies like an arrow

Local vs. Global Inference

- What if optimizing local decisions doesn't lead to good global decisions?

time	flies	like	an	arrow
NN	VBZ	PRP	DET	NN

Local vs. Global Inference

- What if optimizing local decisions doesn't lead to good global decisions?

time	flies	like	an	arrow
NN	VBZ	PRP	DET	NN
NN	NNP	VB	DET	NN

Local vs. Global Inference

- What if optimizing local decisions doesn't lead to good global decisions?

time	flies	like	an	arrow
NN	VBZ	PRP	DET	NN
NN	NNP	VB	DET	NN
VB	NNP	PRP	DET	NN

Local vs. Global Inference

- What if optimizing local decisions doesn't lead to good global decisions?

	time	flies	like	an	arrow		
P(	NN	VBZ	PRP	DET	NN	) =	0.4
P(	NN	NNP	VB	DET	NN	) =	0.3
P(	VB	NNP	PRP	DET	NN	) =	0.3

Local vs. Global Inference

- What if optimizing local decisions doesn't lead to good global decisions?

	time	flies	like	an	arrow	
P(	NN	VBZ	PRP	DET	NN	) = 0.4
P(	NN	NNP	VB	DET	NN	) = 0.3
P(	VB	NNP	PRP	DET	NN	) = 0.3
	↓					
	NN					

Local vs. Global Inference

- What if optimizing local decisions doesn't lead to good global decisions?

	time	flies	like	an	arrow	
P(	NN	VBZ	PRP	DET	NN	) = 0.4
P(	NN	NNP	VB	DET	NN	) = 0.3
P(	VB	NNP	PRP	DET	NN	) = 0.3
	↓	↓				
	NN	NNP				

Local vs. Global Inference

- What if optimizing local decisions doesn't lead to good global decisions?

	time	flies	like	an	arrow	
P(	NN	VBZ	PRP	DET	NN	) = 0.4
P(	NN	NNP	VB	DET	NN	) = 0.3
P(	VB	NNP	PRP	DET	NN	) = 0.3
	NN	NNP	PRP			

Local vs. Global Inference

- What if optimizing local decisions doesn't lead to good global decisions?

	time	flies	like	an	arrow		
P(	NN	VBZ	PRP	DET	NN	)	= 0.4
P(	NN	NNP	VB	DET	NN	)	= 0.3
P(	VB	NNP	PRP	DET	NN	)	= 0.3
	↓	↓	↓	↓			
	NN	NNP	PRP	DET			

Local vs. Global Inference

- What if optimizing local decisions doesn't lead to good global decisions?

	time	flies	like	an	arrow		
P(	NN	VBZ	PRP	DET	NN	)	= 0.4
P(	NN	NNP	VB	DET	NN	)	= 0.3
P(	VB	NNP	PRP	DET	NN	)	= 0.3
	↓	↓	↓	↓	↓		
	NN	NNP	PRP	DET	NN		

Local vs. Global Inference

- What if optimizing local decisions doesn't lead to good global decisions?

	time	flies	like	an	arrow		
P(	NN	VBZ	PRP	DET	NN	)	= 0.4
P(	NN	NNP	VB	DET	NN	)	= 0.3
P(	VB	NNP	PRP	DET	NN	)	= 0.3
	↓	↓	↓	↓	↓		
	NN	NNP	PRP	DET	NN		

- Simple solution: input last label (e.g. RNNLM)
  → Modeling search is difficult, can lead down garden paths

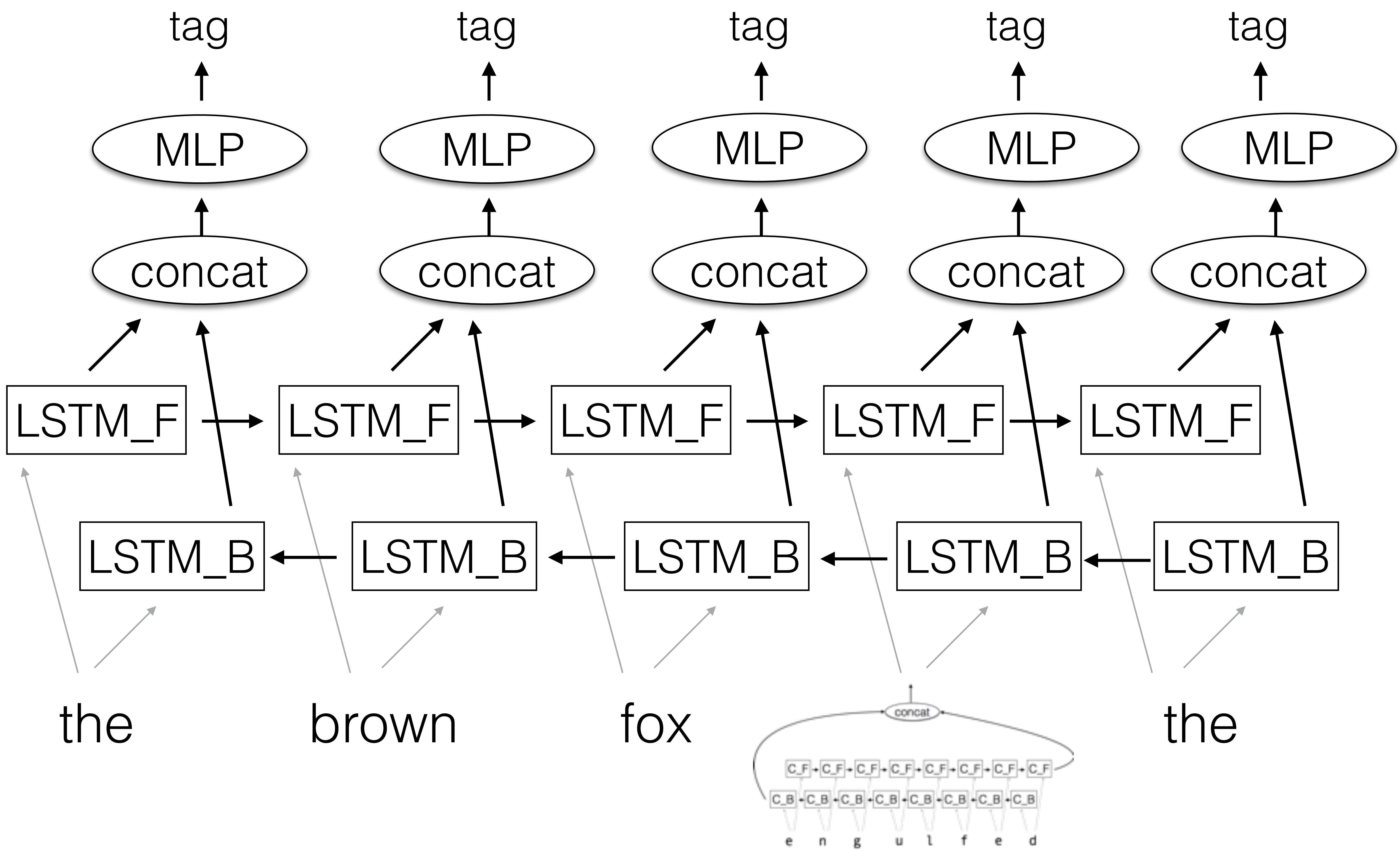
Local vs. Global Inference

- What if optimizing local decisions doesn't lead to good global decisions?

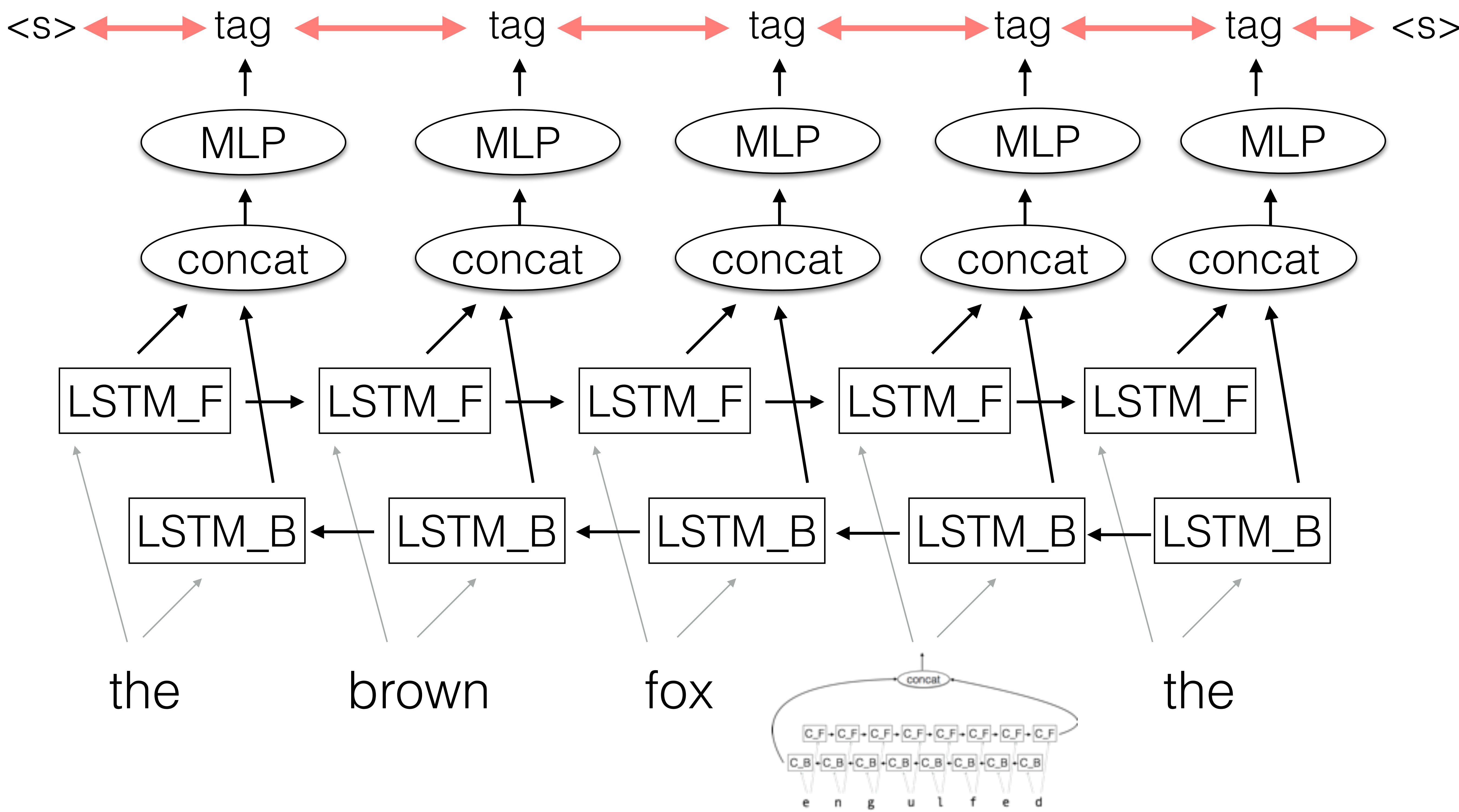
	time	flies	like	an	arrow	
P(	NN	VBZ	PRP	DET	NN	) = 0.4
P(	NN	NNP	VB	DET	NN	) = 0.3
P(	VB	NNP	PRP	DET	NN	) = 0.3
	↓	↓	↓	↓	↓	
	NN	NNP	PRP	DET	NN	

- Simple solution: input last label (e.g. RNNLM)
  → Modeling search is difficult, can lead down garden paths
- Better solutions: global objectives
  - Phrase Structure Parsing (Durrett et al. 2015), Named Entity Recognition (Lample et. al 2016), Dependency Parsing (Kiperwaser et al. 2016)

BiLSTM Tagger w/ Tag Bigram Parameters



BiLSTM Tagger w/ Tag Bigram Parameters



From Local to Global

- Standard BiLSTM loss function:

$$\log P(\boldsymbol{y}|\boldsymbol{x}) = \sum_i \log P(y_i|\boldsymbol{x})$$

$$s(\boldsymbol{y}, \boldsymbol{x}) = \sum_i s_e(y_i, \boldsymbol{x})$$

$$s(\boldsymbol{y}, \boldsymbol{x}) = \sum_i (s_e(y_i, \boldsymbol{x}) + s_t(y_{i-1}, y_i))$$

From Local to Global

- Standard BiLSTM loss function:

$$\log P(\boldsymbol{y}|\boldsymbol{x}) = \sum_i \log P(y_i|\boldsymbol{x})$$

$$s(\boldsymbol{y}, \boldsymbol{x}) = \sum_i s_e(y_i, \boldsymbol{x})$$

- With transition features:

$$s(\boldsymbol{y}, \boldsymbol{x}) = \sum_i (s_e(y_i, \boldsymbol{x}) + s_t(y_{i-1}, y_i))$$

From Local to Global

- Standard BiLSTM loss function:

$$\log P(\boldsymbol{y}|\boldsymbol{x}) = \sum_i \log P(y_i|\boldsymbol{x})$$

$\updownarrow$ log emission probs as scores

$$s(\boldsymbol{y}, \boldsymbol{x}) = \sum_i s_e(y_i, \boldsymbol{x})$$

- With transition features:

$$s(\boldsymbol{y}, \boldsymbol{x}) = \sum_i (s_e(y_i, \boldsymbol{x}) + s_t(y_{i-1}, y_i))$$

From Local to Global

- Standard BiLSTM loss function:

$$\log P(\boldsymbol{y}|\boldsymbol{x}) = \sum_i \log P(y_i|\boldsymbol{x})$$

log emission probs as scores

$$s(\boldsymbol{y}, \boldsymbol{x}) = \sum_i s_e(y_i, \boldsymbol{x})$$

- With transition features:

$$s(\boldsymbol{y}, \boldsymbol{x}) = \sum_i (s_e(y_i, \boldsymbol{x}) + s_t(y_{i-1}, y_i))$$

transition scores

How do We Train?

How do We Train?

- Cannot simply enumerate all possibilities and do backprop

How do We Train?

- Cannot simply enumerate all possibilities and do backprop
- Solutions using dynamic programming: structured perceptron, conditional random fields, margin-based methods

How do We Train?

- Cannot simply enumerate all possibilities and do backprop
- Solutions using dynamic programming: structured perceptron, conditional random fields, margin-based methods

Structured Perceptron Overview

Structured Perceptron Overview

time flies like an arrow

Structured Perceptron Overview

time flies like an arrow

Reference
NN VBZ PRP DET NN

Structured Perceptron Overview

$$\hat{\boldsymbol{y}} = \underset{\boldsymbol{y}}{\text{argmax}}\ \text{score}(\boldsymbol{y}|\boldsymbol{x};\theta)$$

time flies like an arrow

Reference
NN VBZ PRP DET NN

Hypothesis
NN NNP VB DET NN

Structured Perceptron Overview

$$\hat{\boldsymbol{y}} = \underset{\boldsymbol{y}}{\operatorname{argmax}}\ \operatorname{score}(\boldsymbol{y}|\boldsymbol{x};\theta)$$

time flies like an arrow

Reference
NN VBZ PRP DET NN

$\neq$

Hypothesis
NN NNP VB DET NN

Structured Perceptron Overview

$$\hat{\boldsymbol{y}} = \underset{\boldsymbol{y}}{\text{argmax}} \; \text{score}(\boldsymbol{y}|\boldsymbol{x};\theta)$$

time flies like an arrow

Reference
NN VBZ PRP DET NN

$\neq$

Hypothesis
NN NNP VB DET NN

Update!

Structured Perceptron Overview

$$\hat{\boldsymbol{y}} = \underset{\boldsymbol{y}}{\operatorname{argmax}} \operatorname{score}(\boldsymbol{y}|\boldsymbol{x};\theta)$$

time flies like an arrow

Reference
NN VBZ PRP DET NN

$\neq$

Hypothesis
NN NNP VB DET NN

Update!

Perceptron Loss

$$\ell_{\text{percep}}(\boldsymbol{x},\boldsymbol{y},\theta) = \max(\operatorname{score}(\hat{\boldsymbol{y}}|\boldsymbol{x};\theta) - \operatorname{score}(\boldsymbol{y}|\boldsymbol{x};\theta), 0)$$

Structured Perceptron in DyNet

```
def viterbi_sent_loss(words, tags):
    vecs = build_tagging_graph(words)
    vit_tags, vit_score = viterbi_decoding(vecs, tags)
    if vit_tags != tags:
        ref_score = forced_decoding(vecs, tags)
        return vit_score - ref_score
    else:
        return dy.scalarInput(0)
```

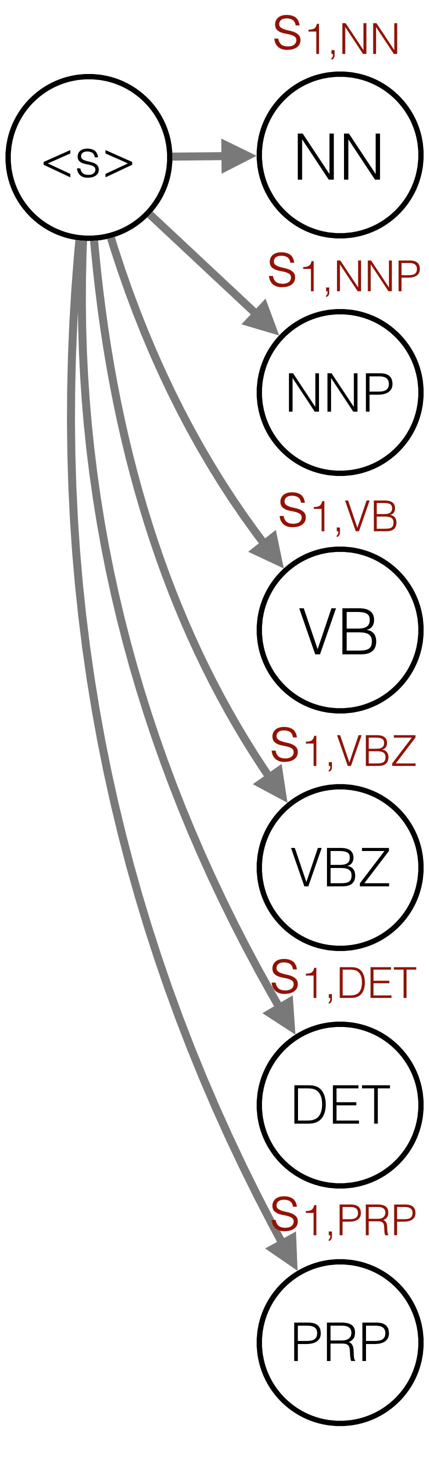
Viterbi Algorithm

time flies like an arrow

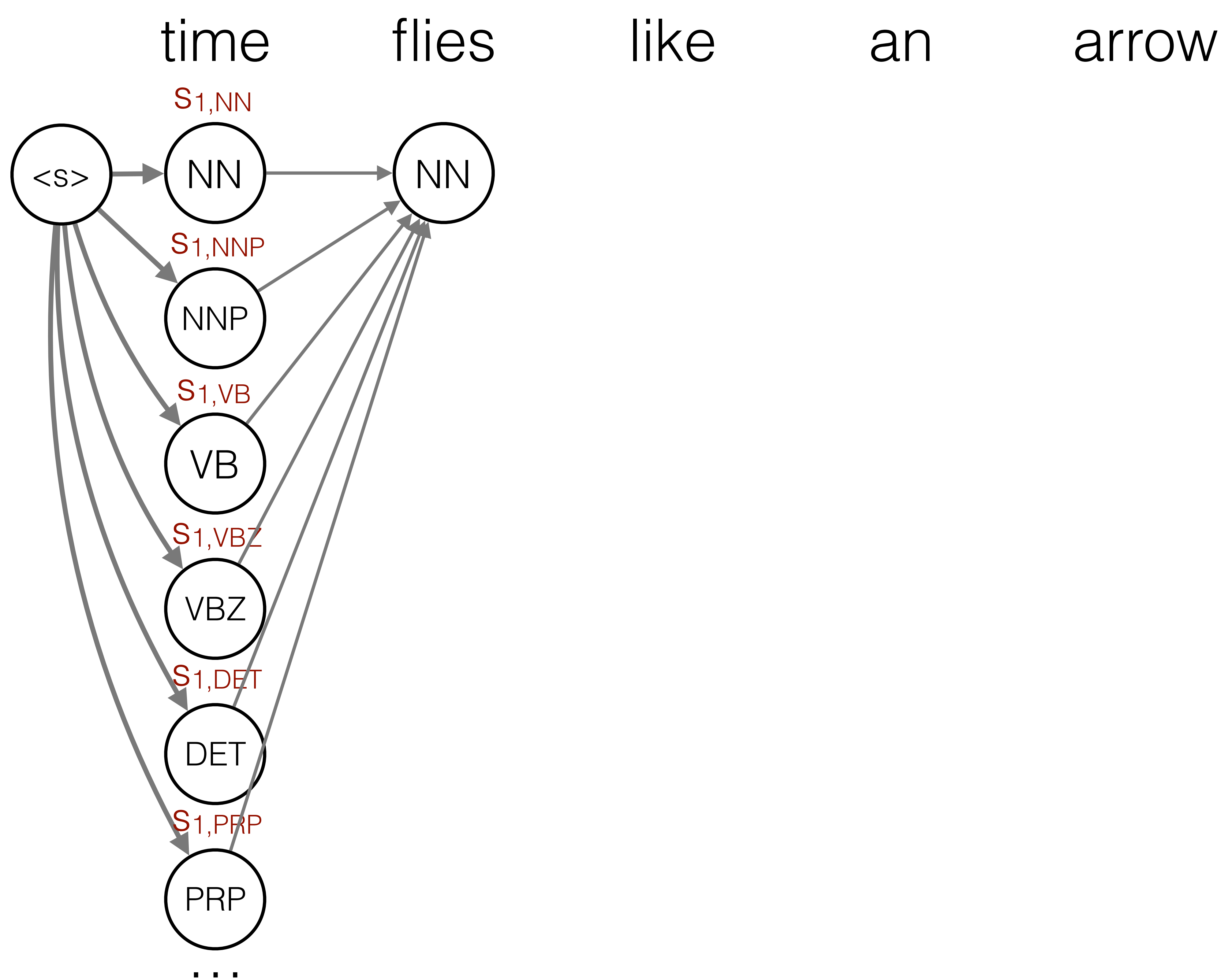
<s>

Viterbi Algorithm

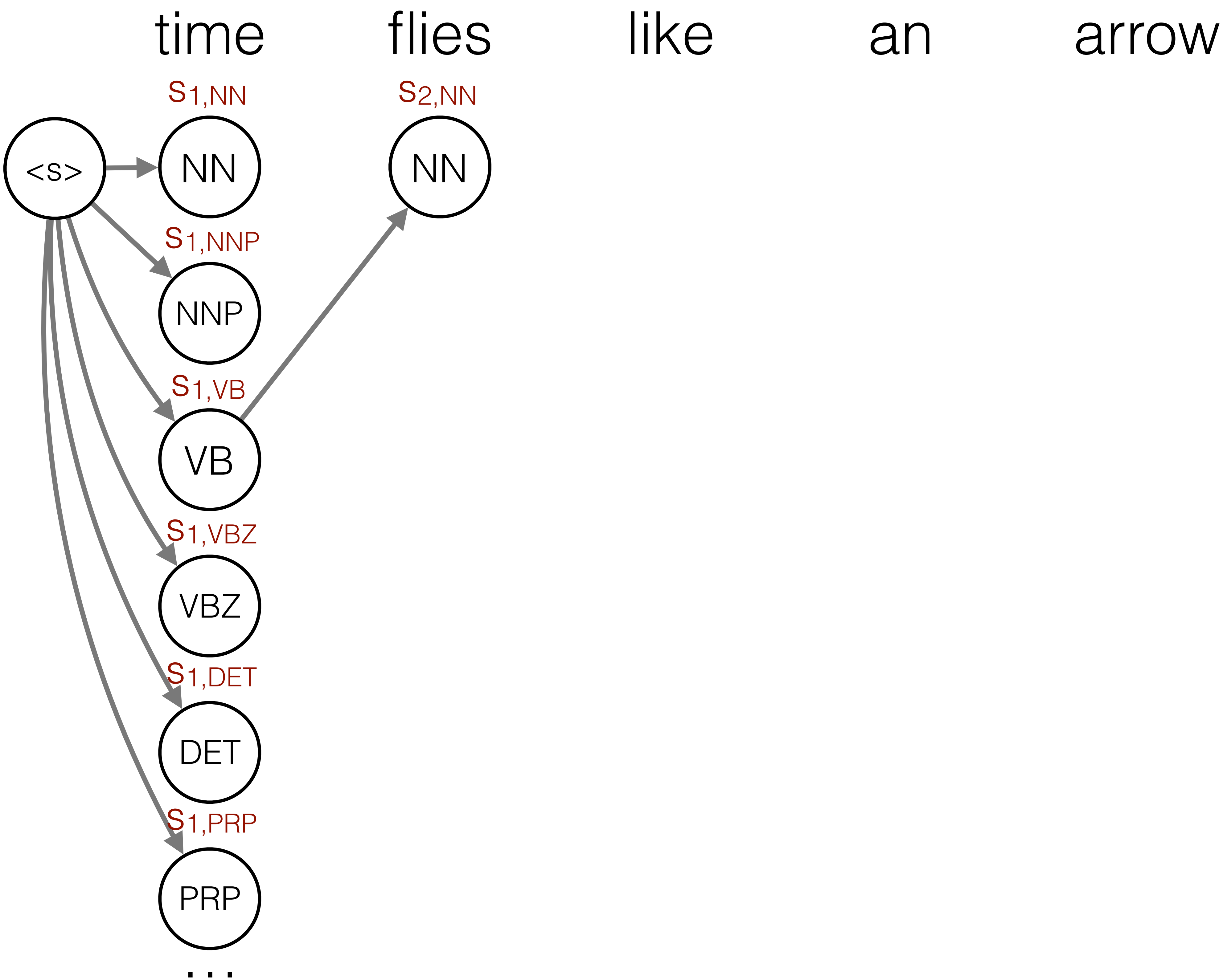
time flies like an arrow



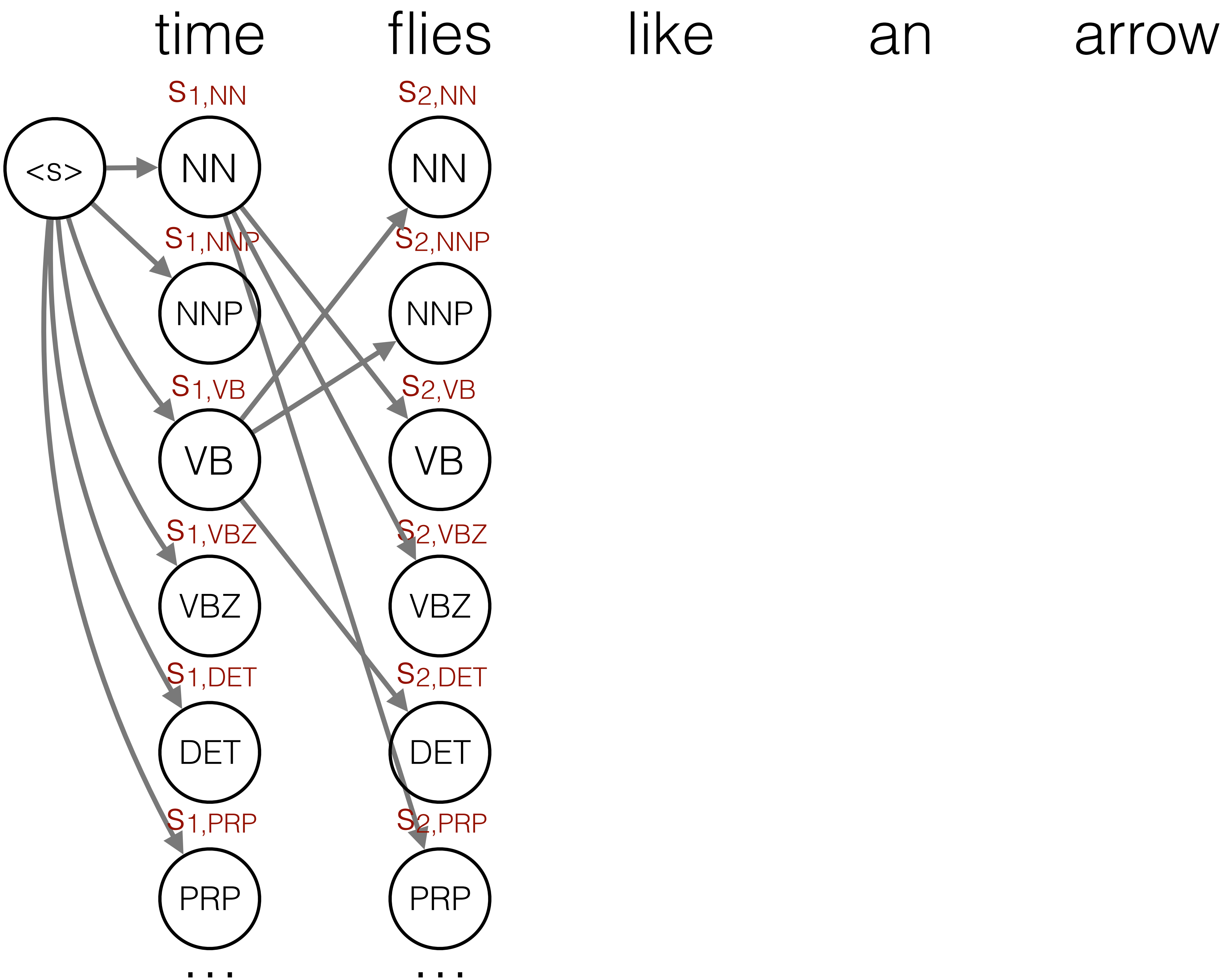
Viterbi Algorithm



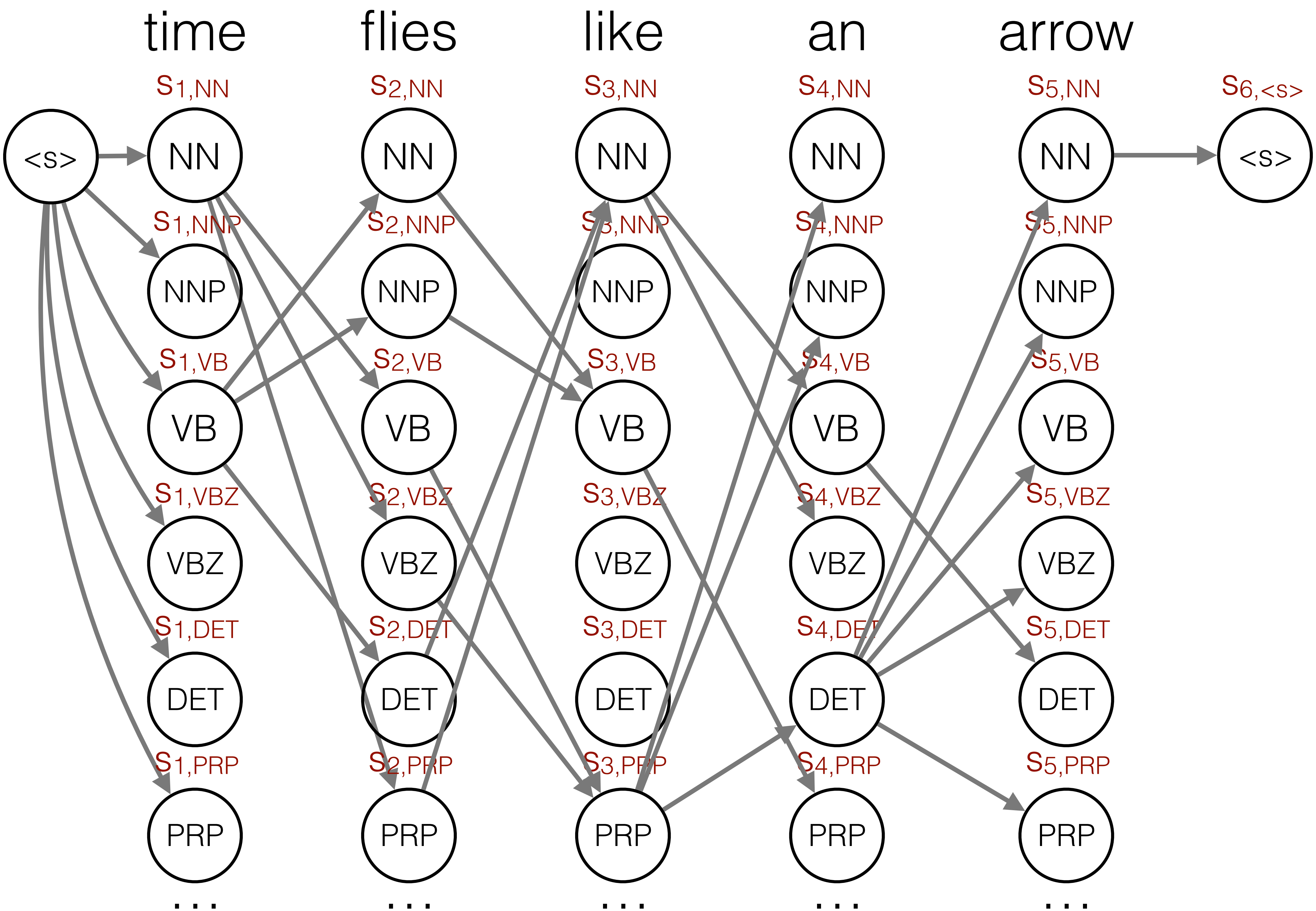
Viterbi Algorithm



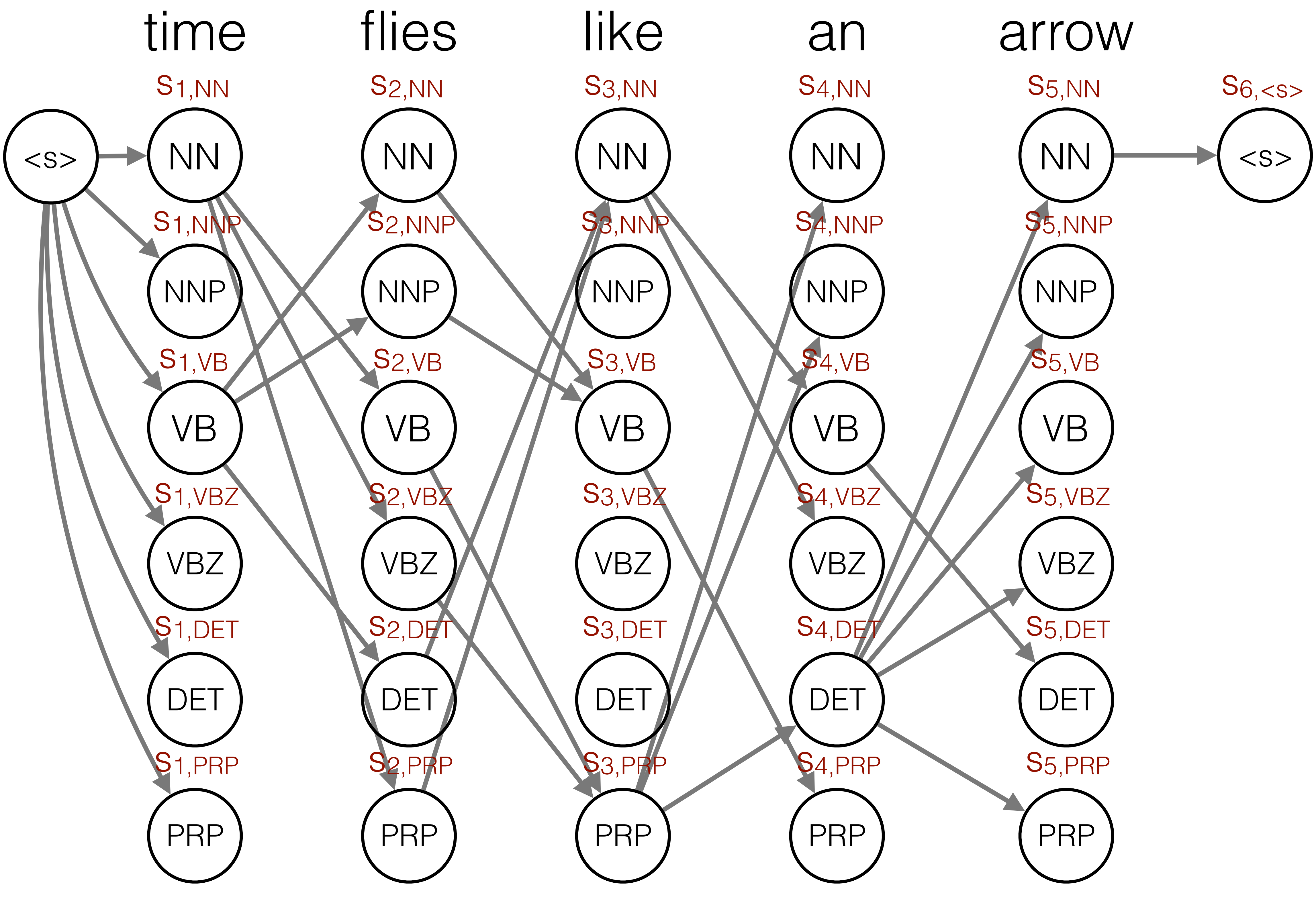
Viterbi Algorithm



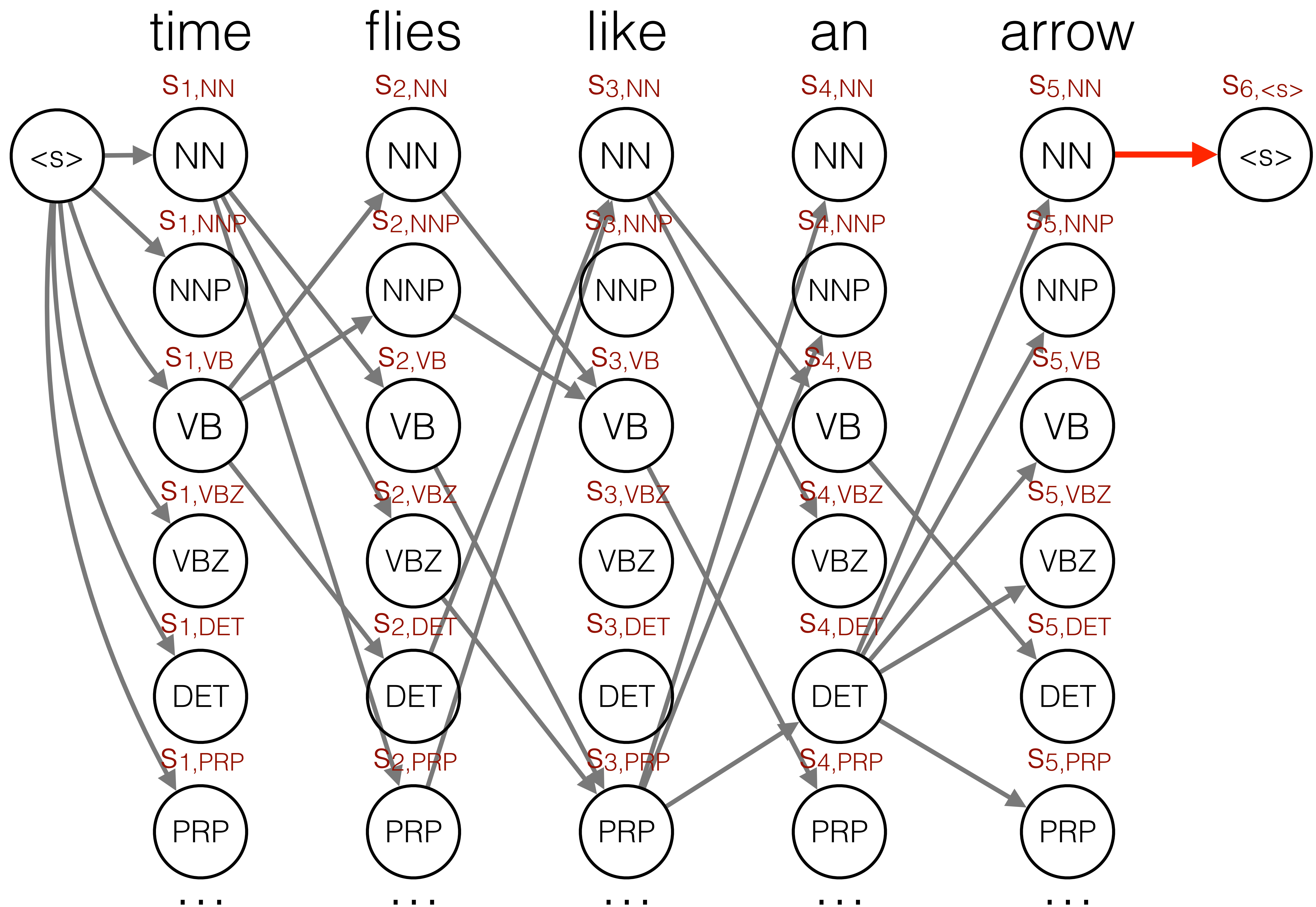
Viterbi Algorithm



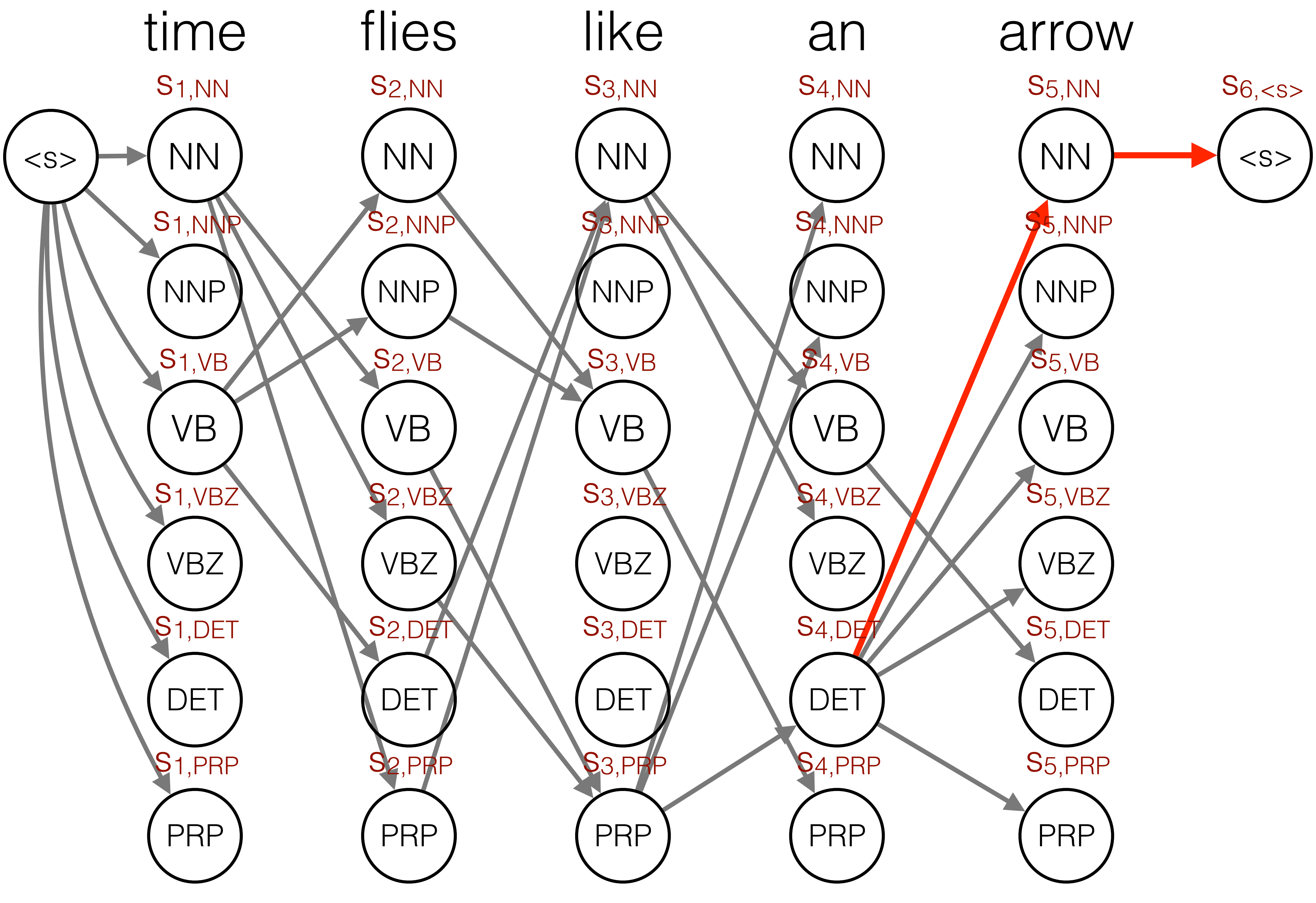
Viterbi Algorithm



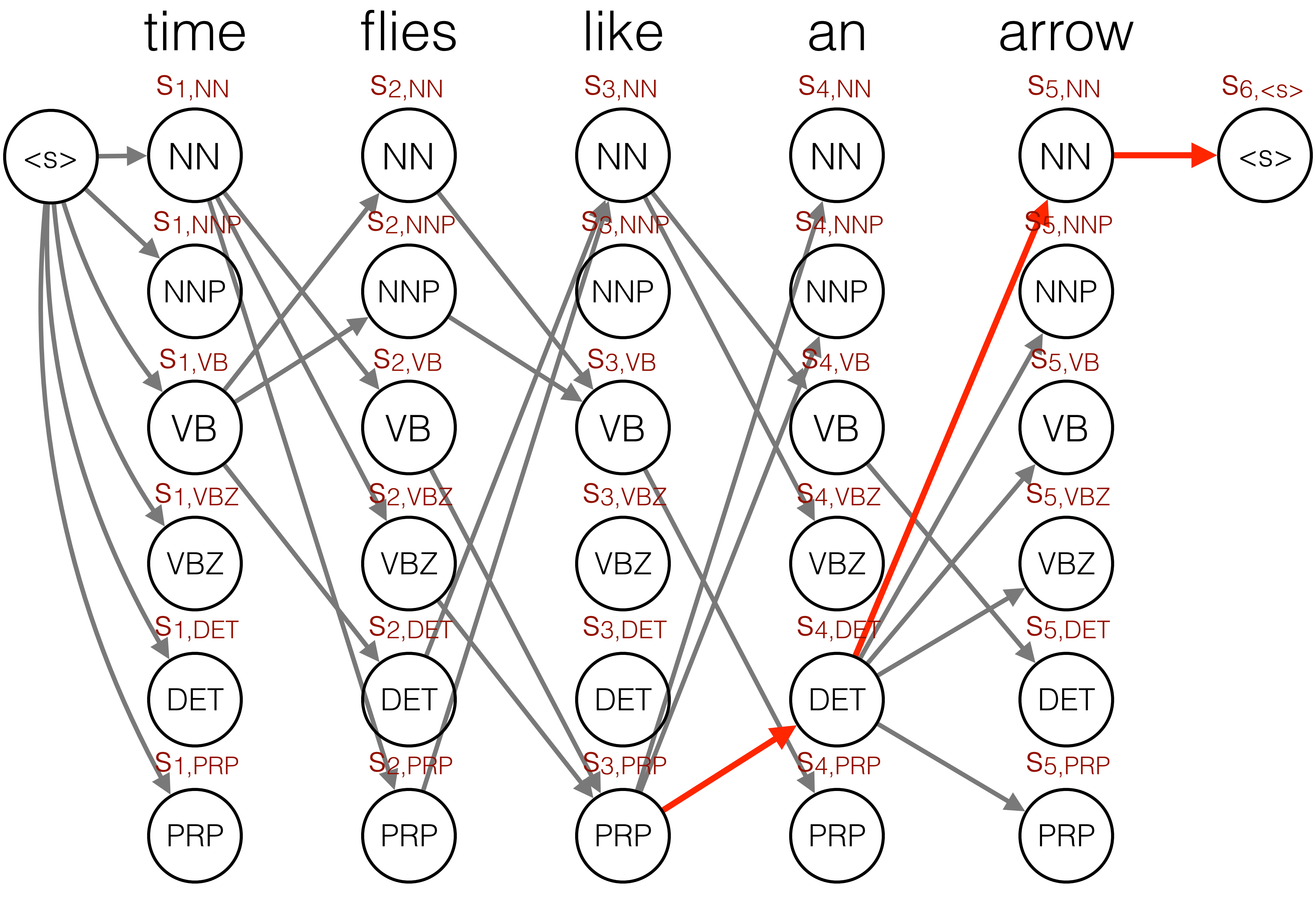
Viterbi Algorithm



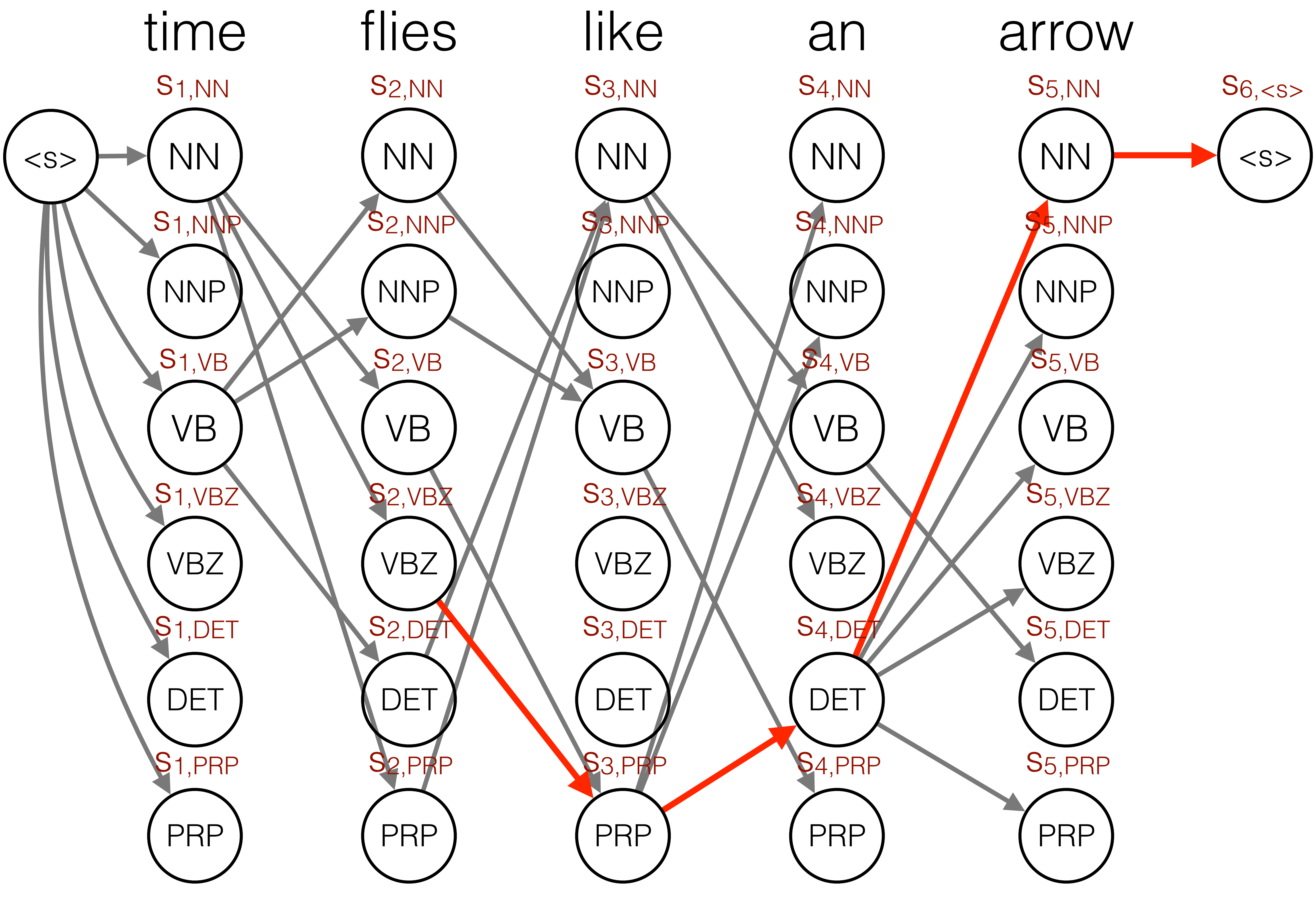
Viterbi Algorithm



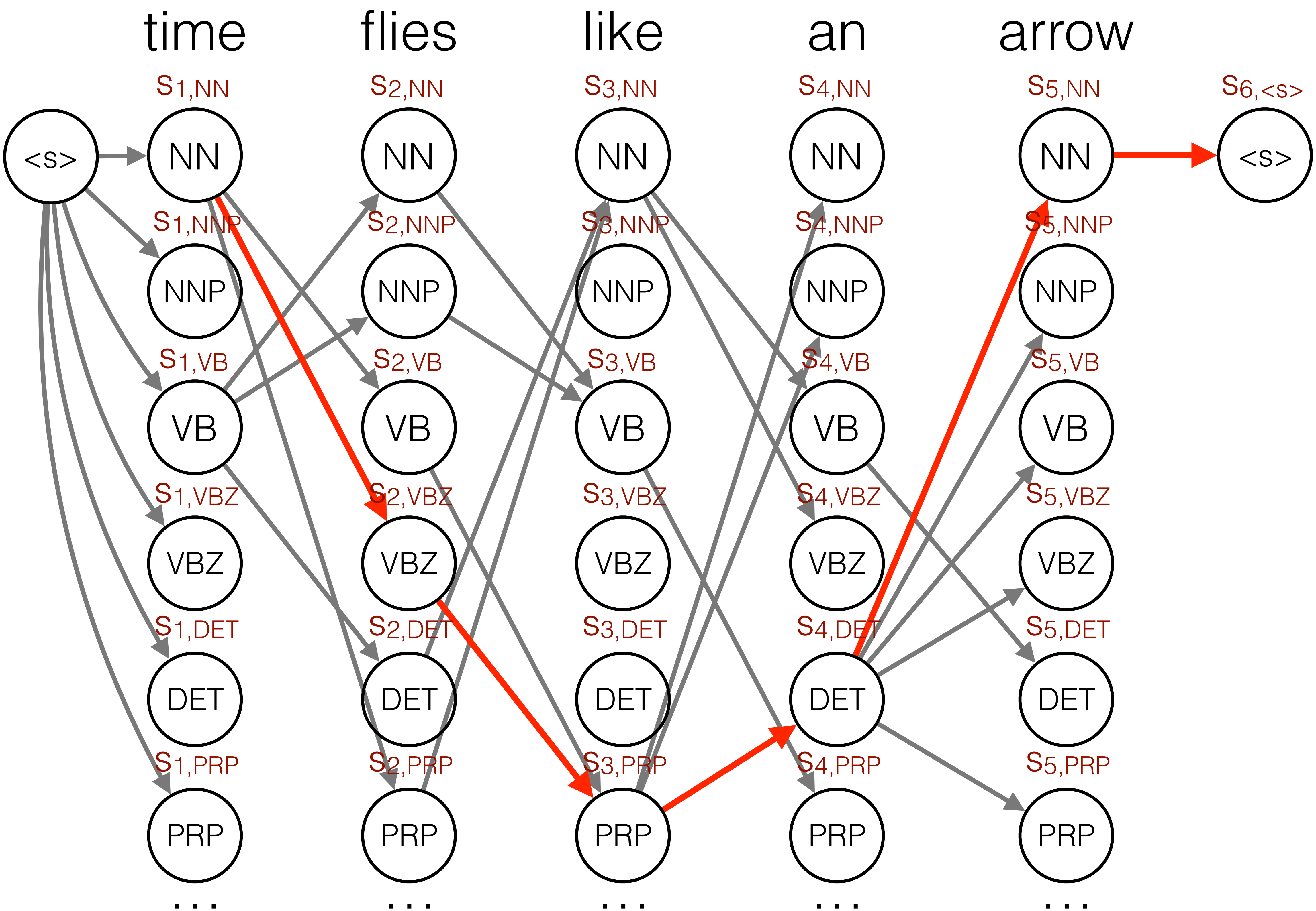
Viterbi Algorithm



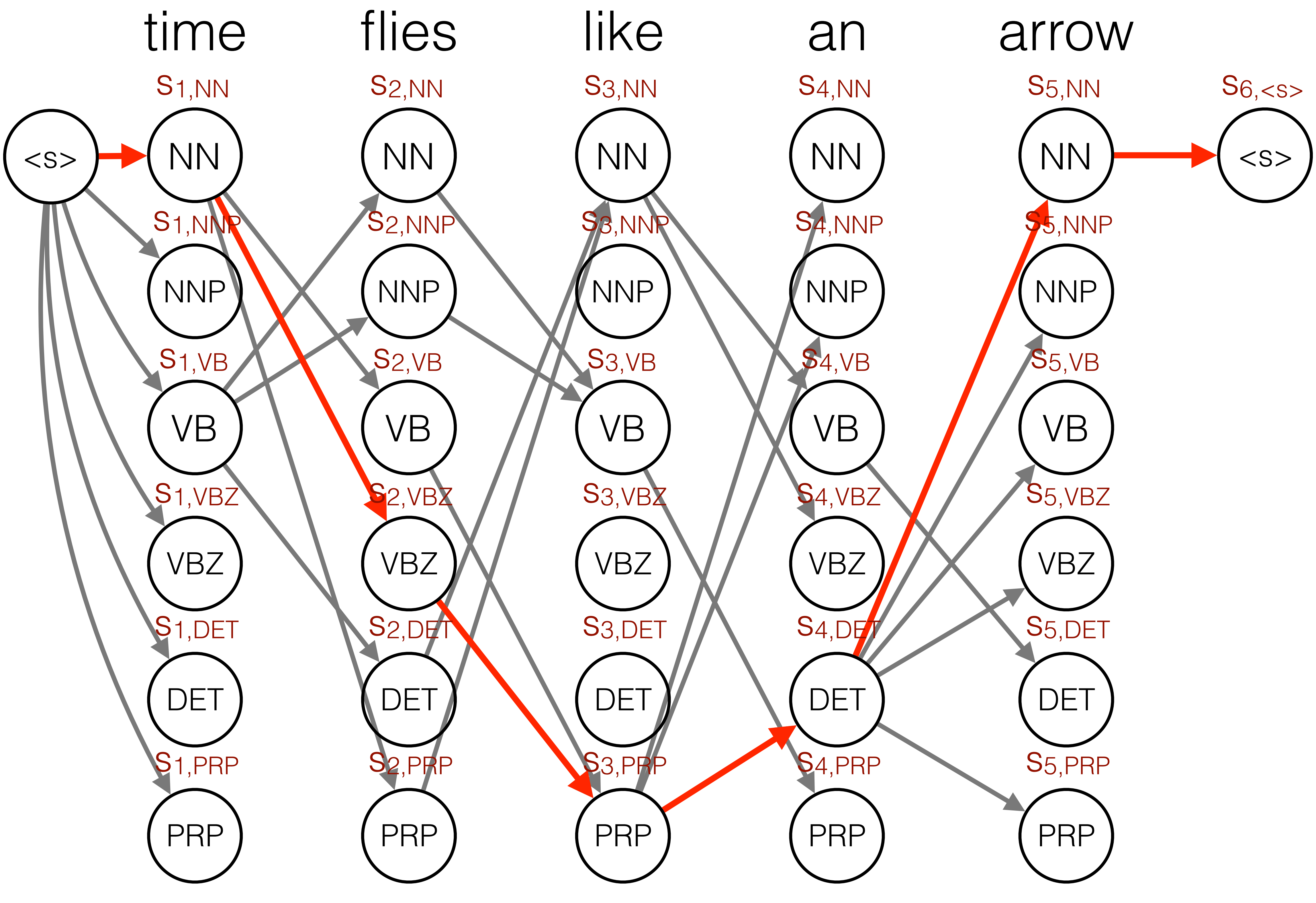
Viterbi Algorithm



Viterbi Algorithm



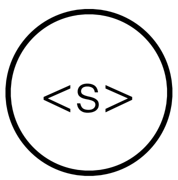
Viterbi Algorithm



Code

Viterbi Initialization Code

time flies like an arrow



Viterbi Initialization Code

Viterbi Initialization Code

time flies like an arrow

$s_{0,<s>} = 0$

<s>

$s_{0,NN} = -\infty$

NN

$s_{0,NNP} = -\infty$

NNP

$s_{0,VB} = -\infty$

VB

$s_{0,VBZ} = -\infty$

VBZ

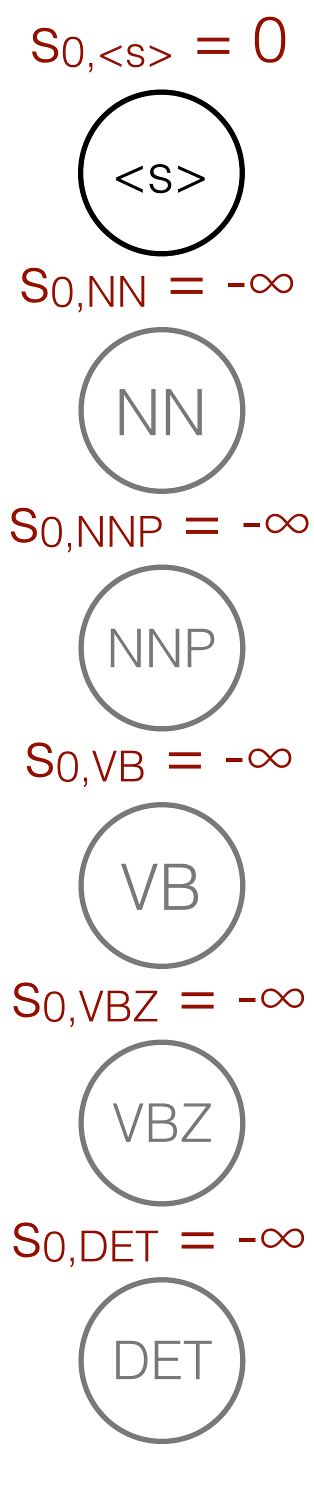
$s_{0,DET} = -\infty$

DET

…

Viterbi Initialization Code

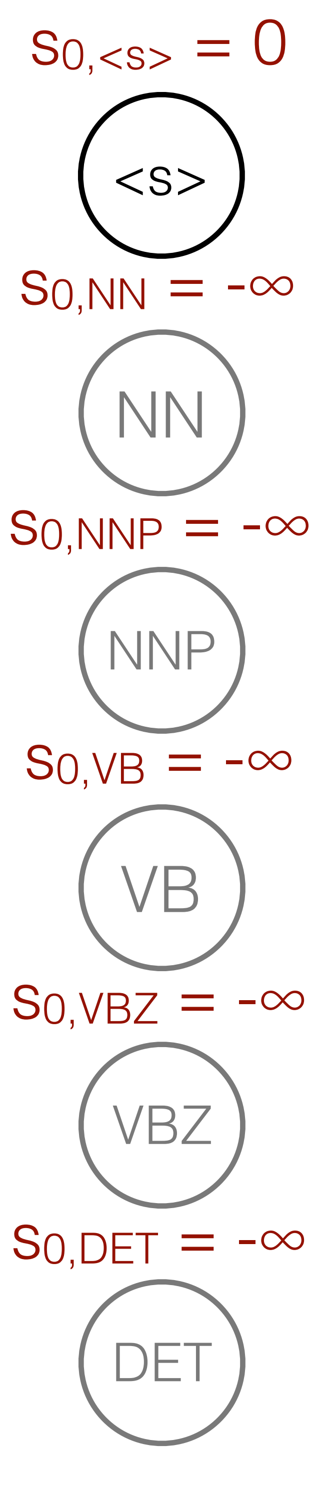
time flies like an arrow



$$\boldsymbol{s}_0 = [0, -\infty, -\infty, \ldots]^{\mathrm{T}}$$

Viterbi Initialization Code

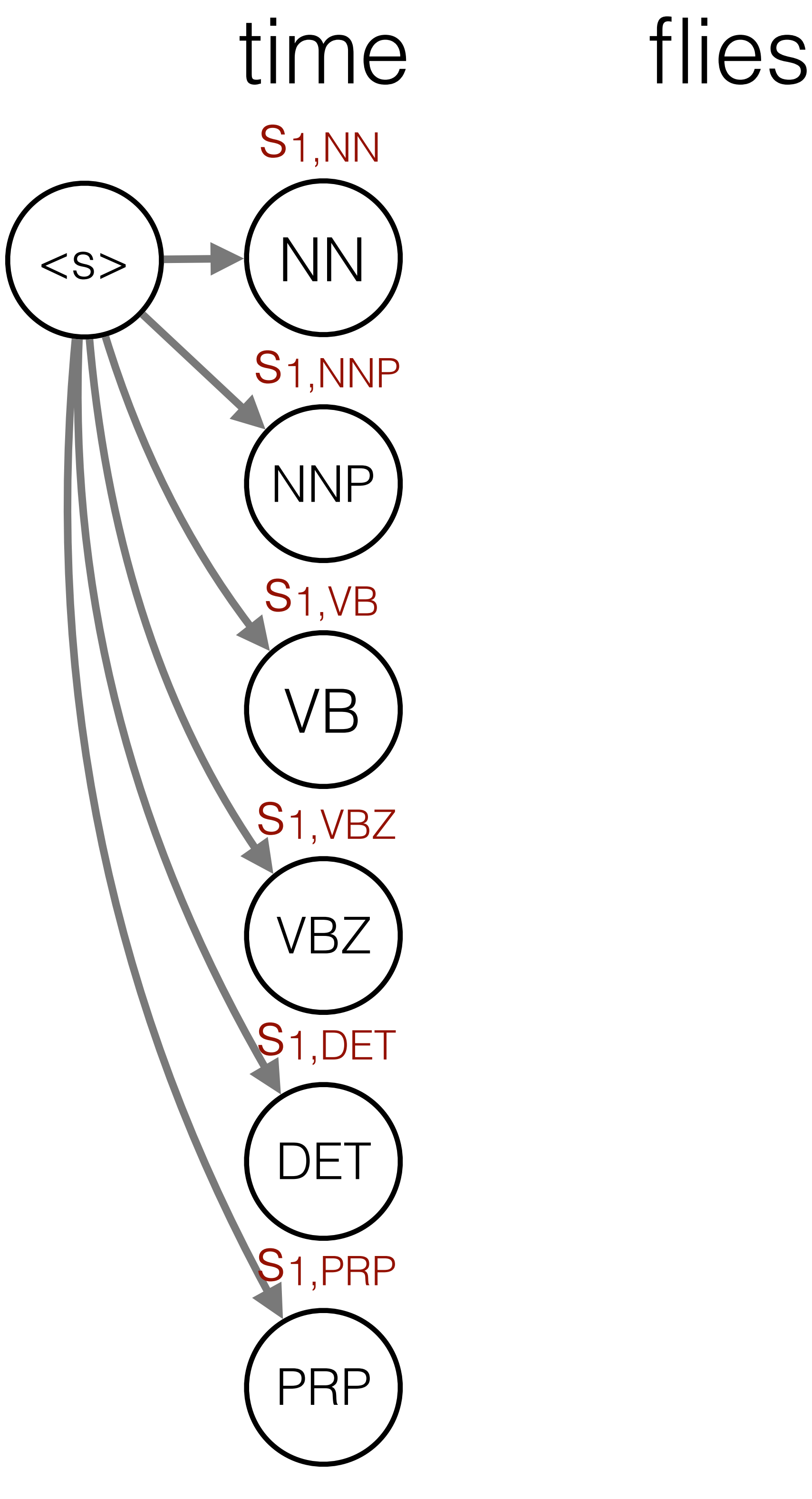
time flies like an arrow



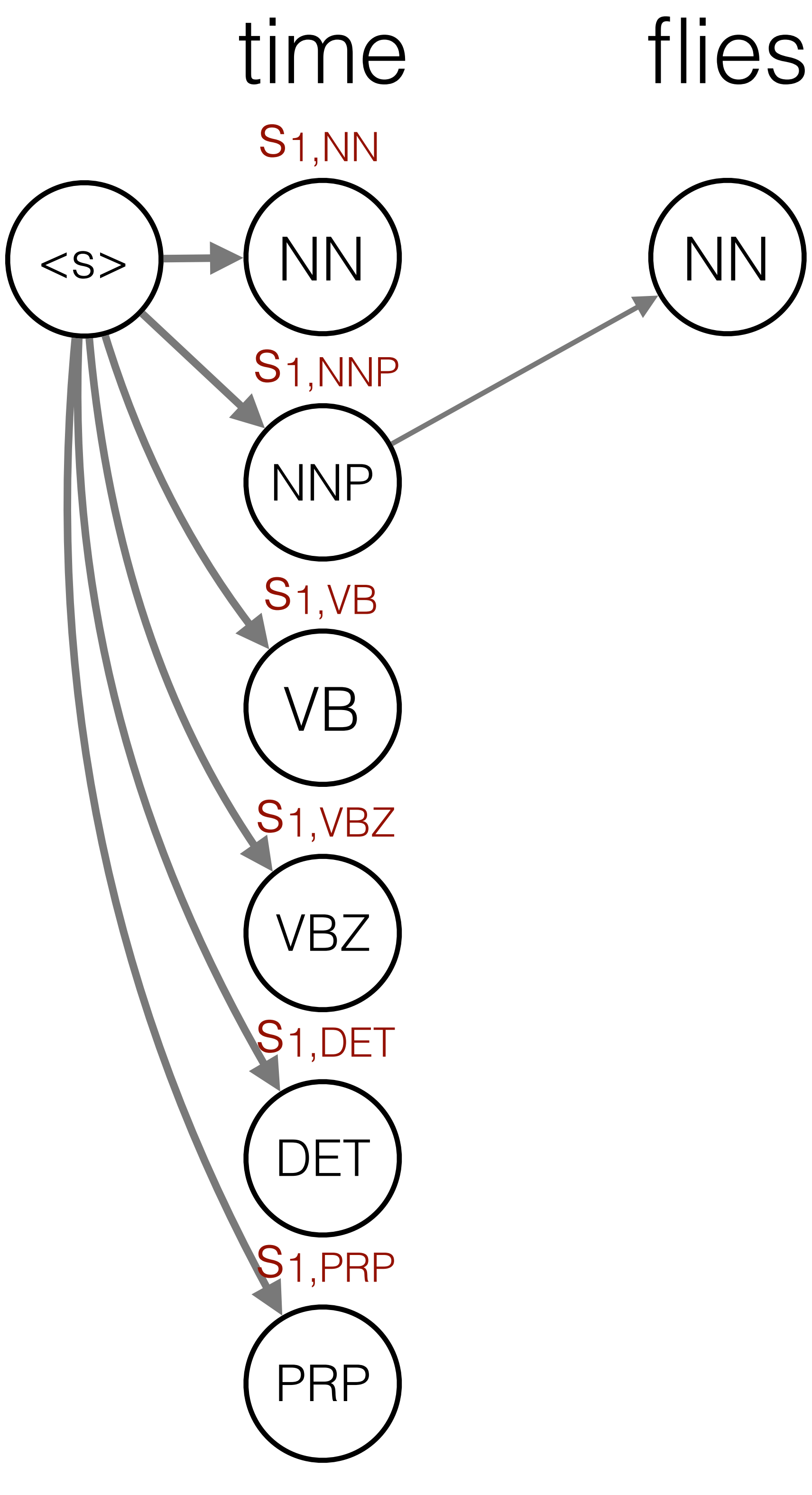
$$\boldsymbol{s}_0 = [0, -\infty, -\infty, \ldots]^{\mathrm{T}}$$

```
init_score = [SMALL_NUMBER] * ntags
init_score[S_T] = 0
for_expr = dy.inputVector(init_score)
```

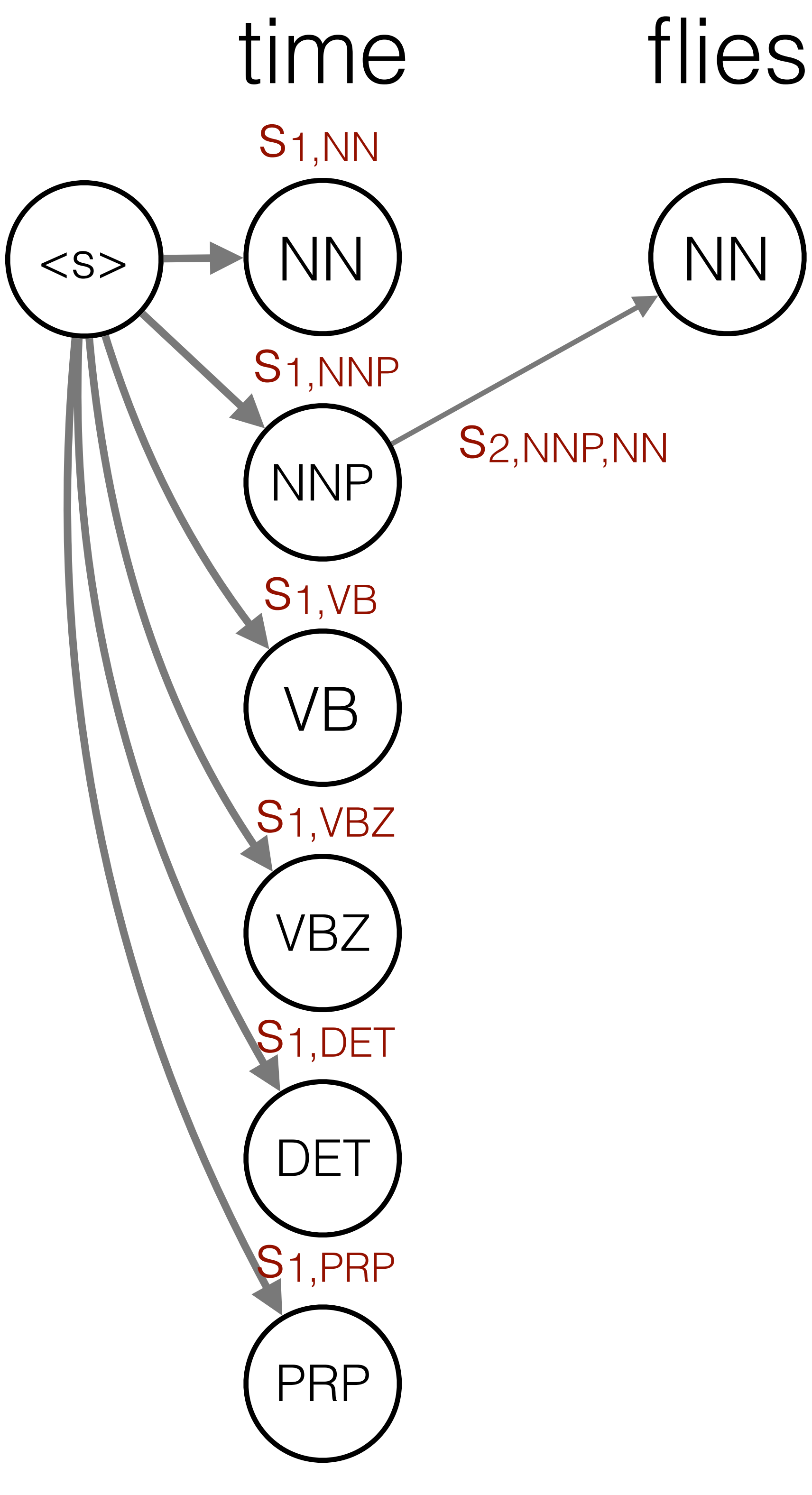
Viterbi Forward Step



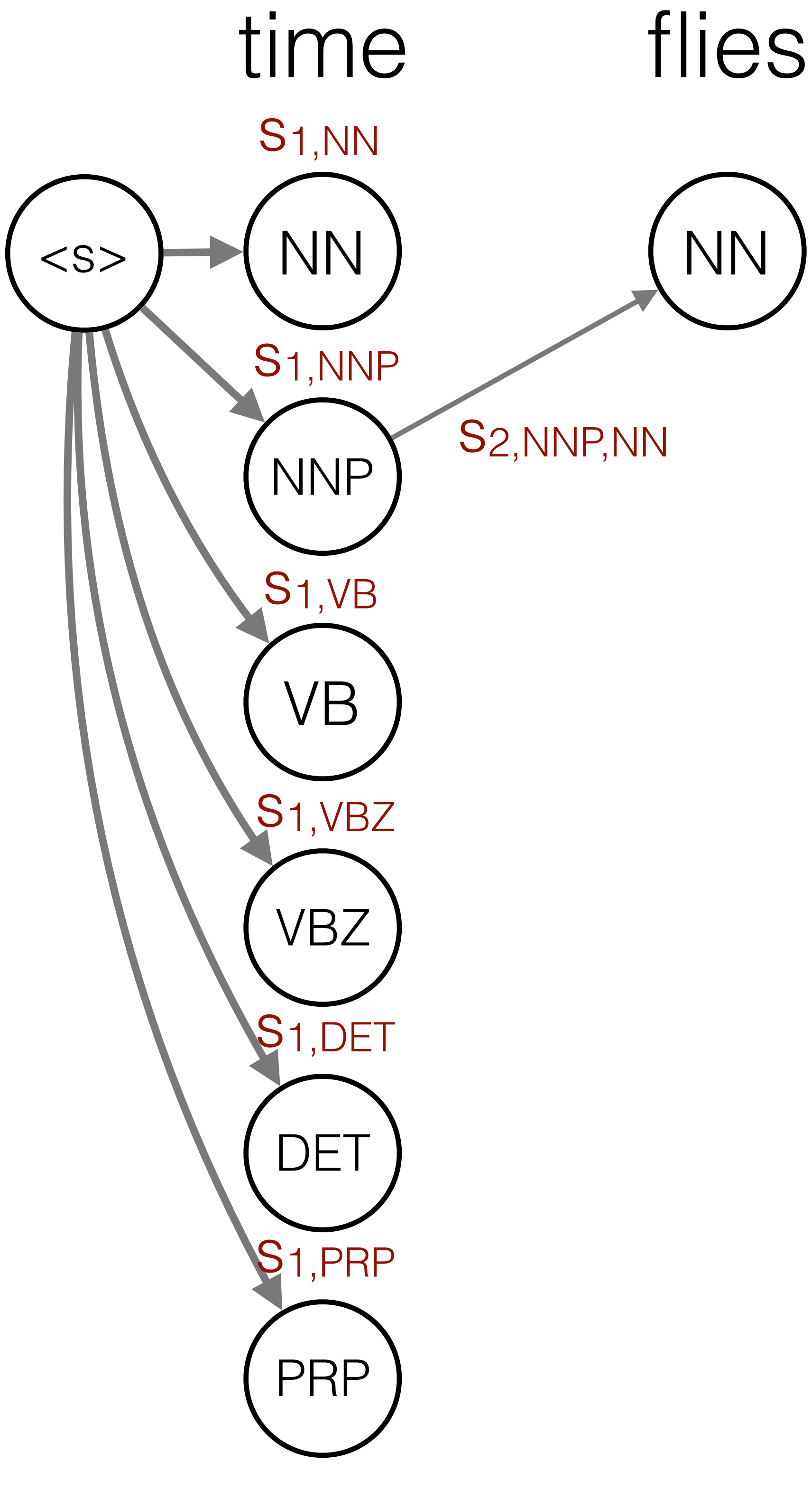
Viterbi Forward Step



Viterbi Forward Step

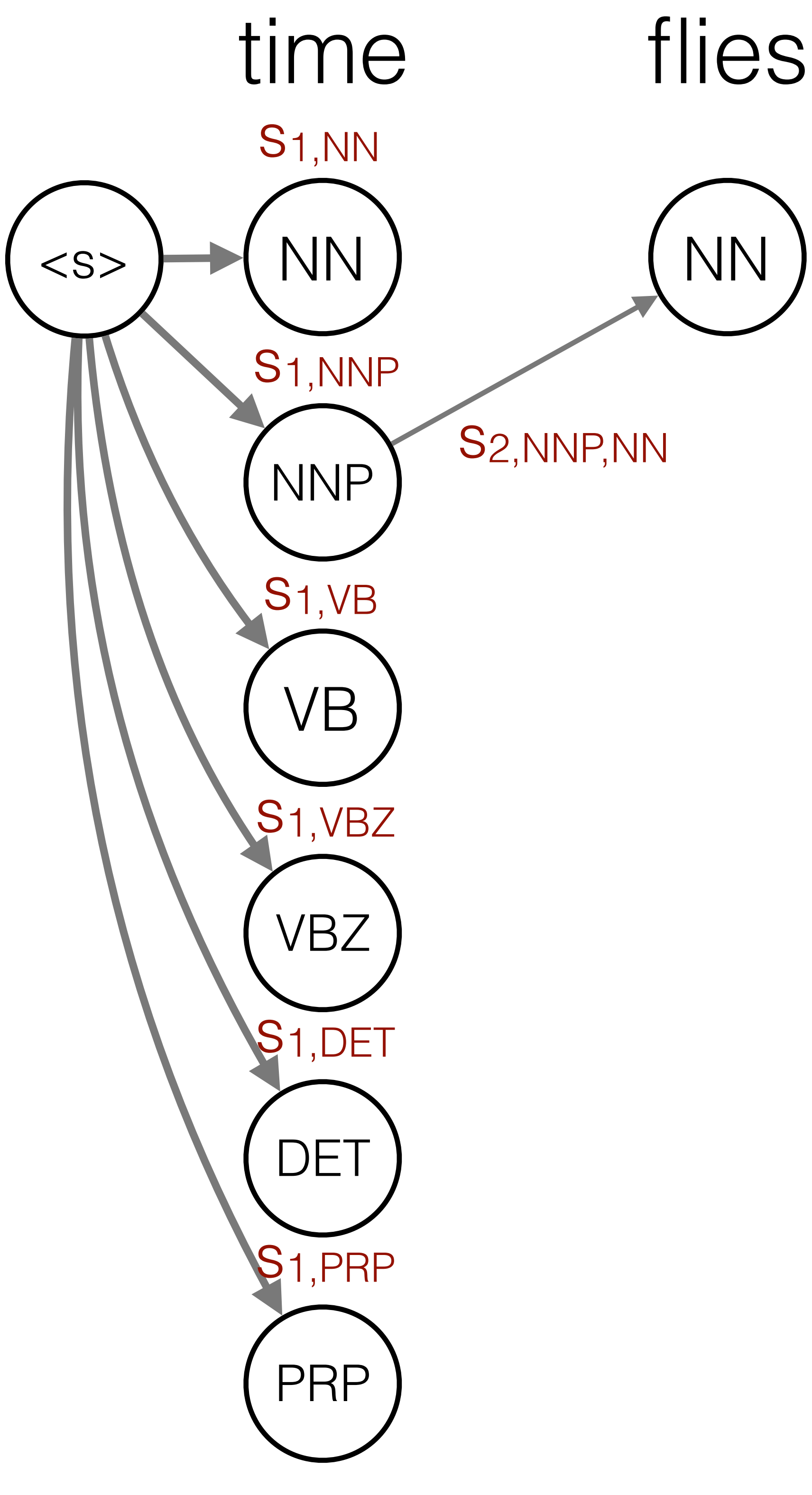


Viterbi Forward Step



$$\sum_i (s_e(y_i, \boldsymbol{x}) + s_t(y_{i-1}, y_i))$$

Viterbi Forward Step



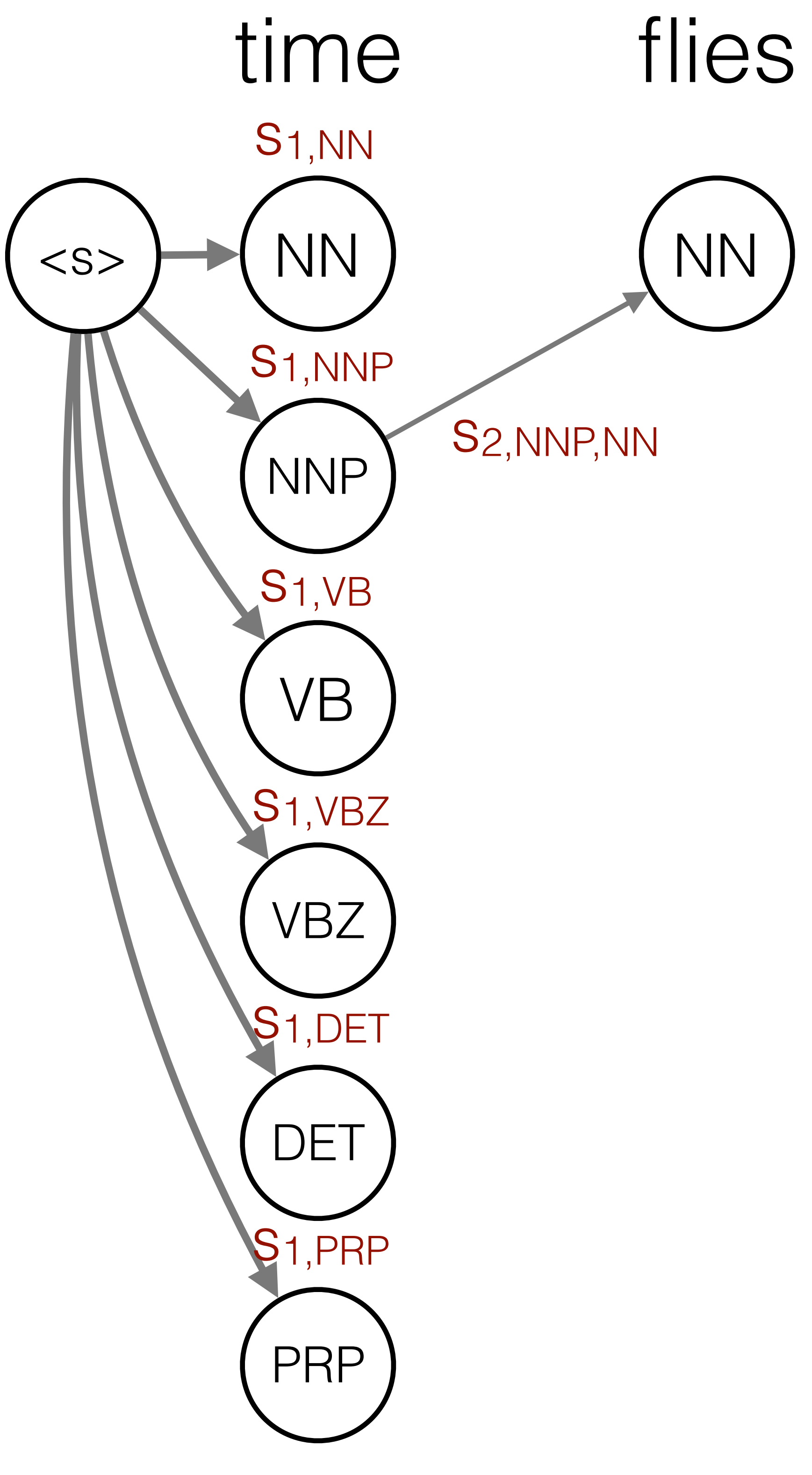
$$\sum_i (s_e(y_i, \boldsymbol{x}) + s_t(y_{i-1}, y_i))$$

i = 2 (time step)

j = NNP (previous POS)

k = NN (next POS)

Viterbi Forward Step



$$\sum_i (s_e(y_i, \boldsymbol{x}) + s_t(y_{i-1}, y_i))$$

forward transition

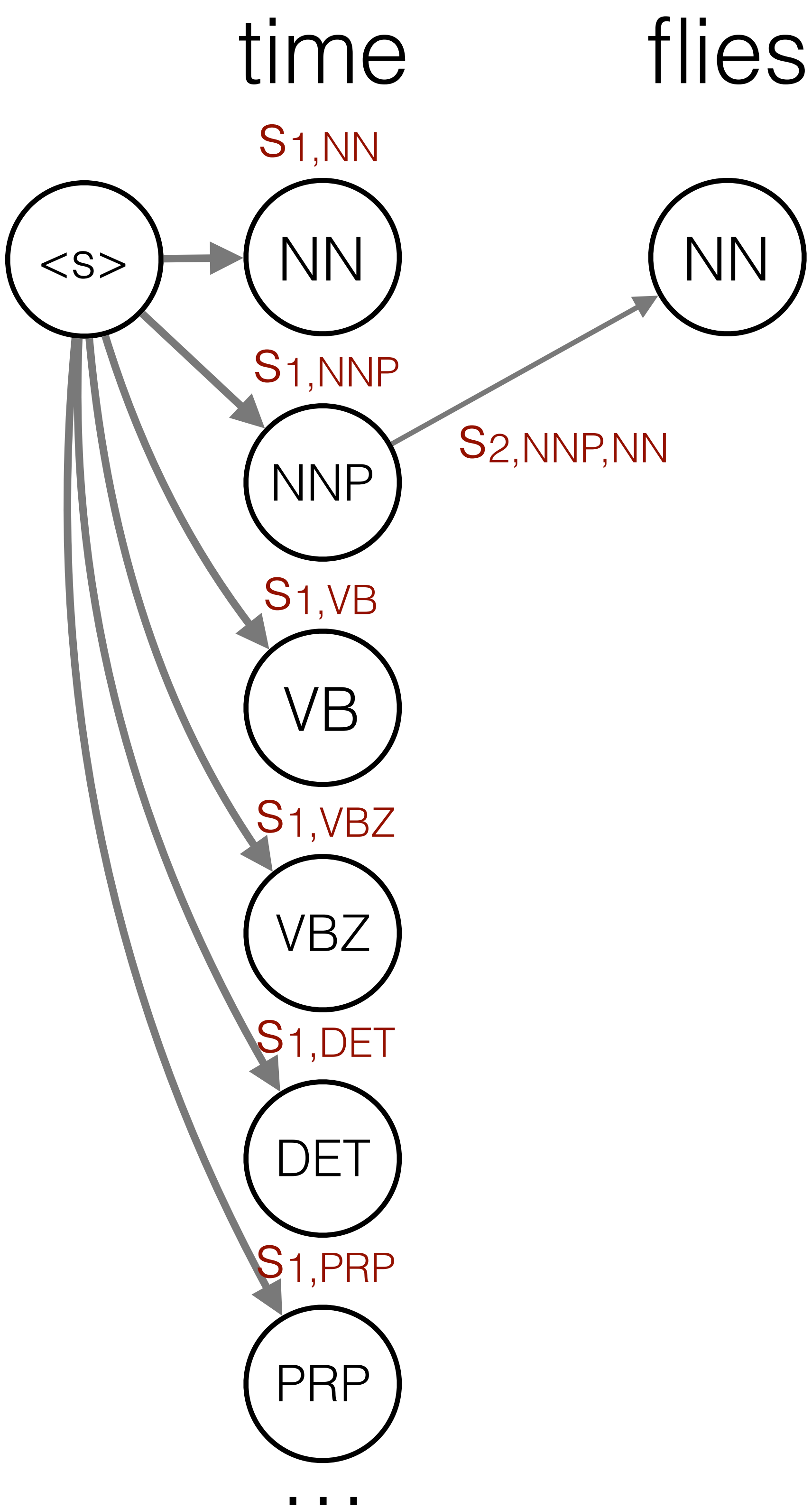
emission

i = 2 (time step)

j = NNP (previous POS)

k = NN (next POS)

Viterbi Forward Step



$$\sum_i (s_e(y_i, \boldsymbol{x}) + s_t(y_{i-1}, y_i))$$

$$s_{f,i,j,k} = s_{f,i-1,j} + s_{e,i,k} + s_{t,j,k}$$

forward transition

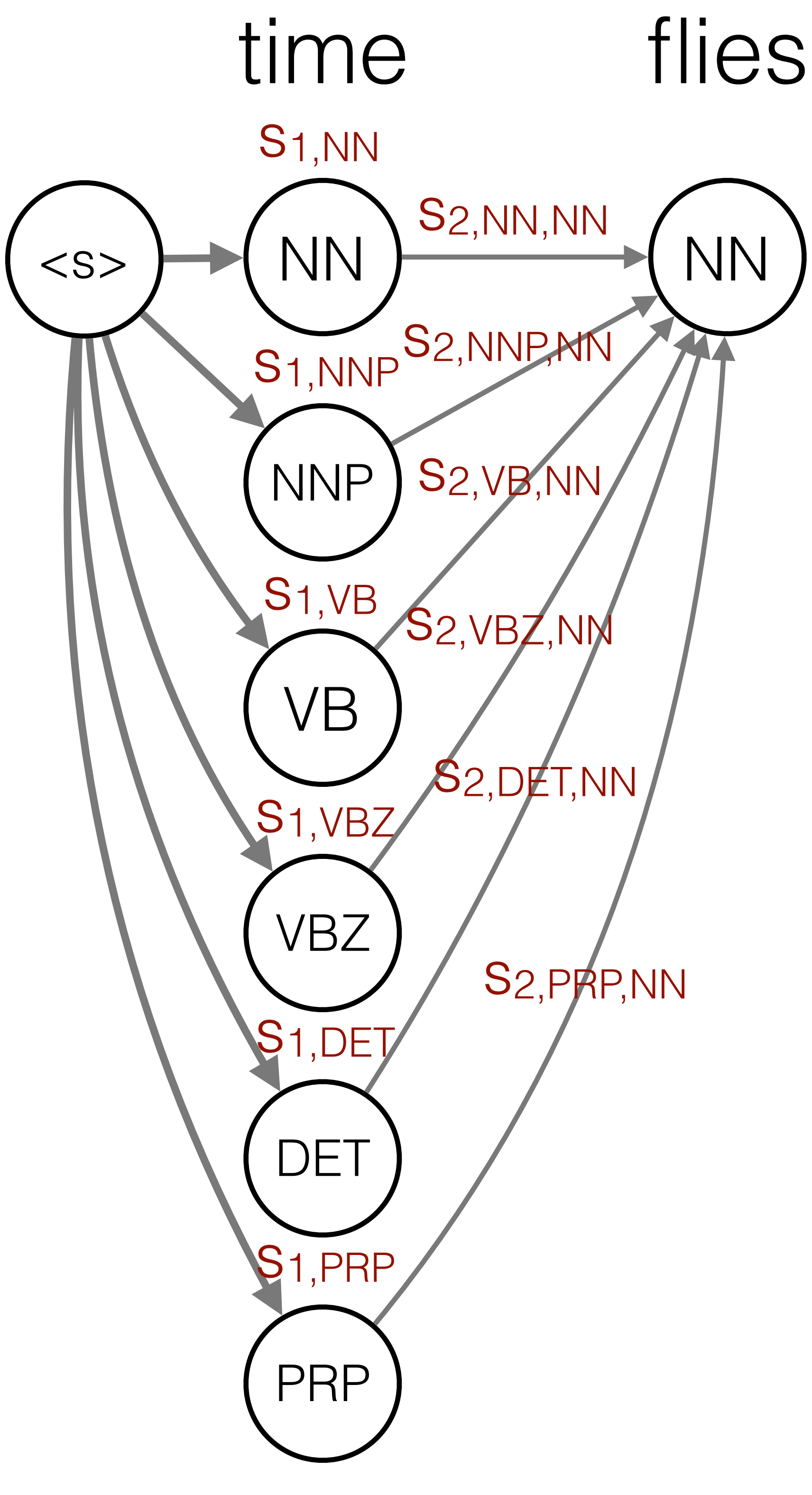
emission

i = 2 (time step)

j = NNP (previous POS)

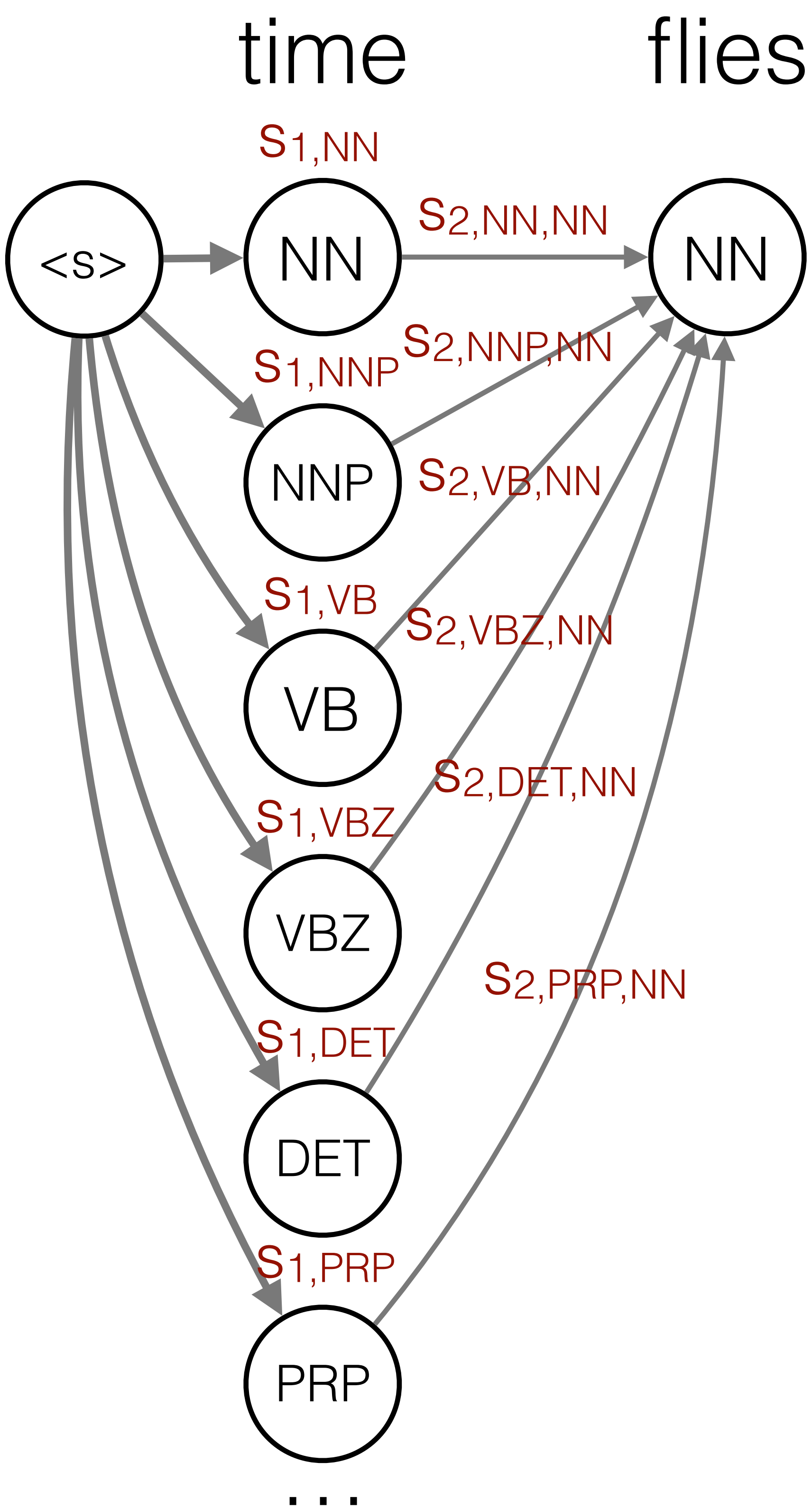
k = NN (next POS)

Viterbi Forward Step



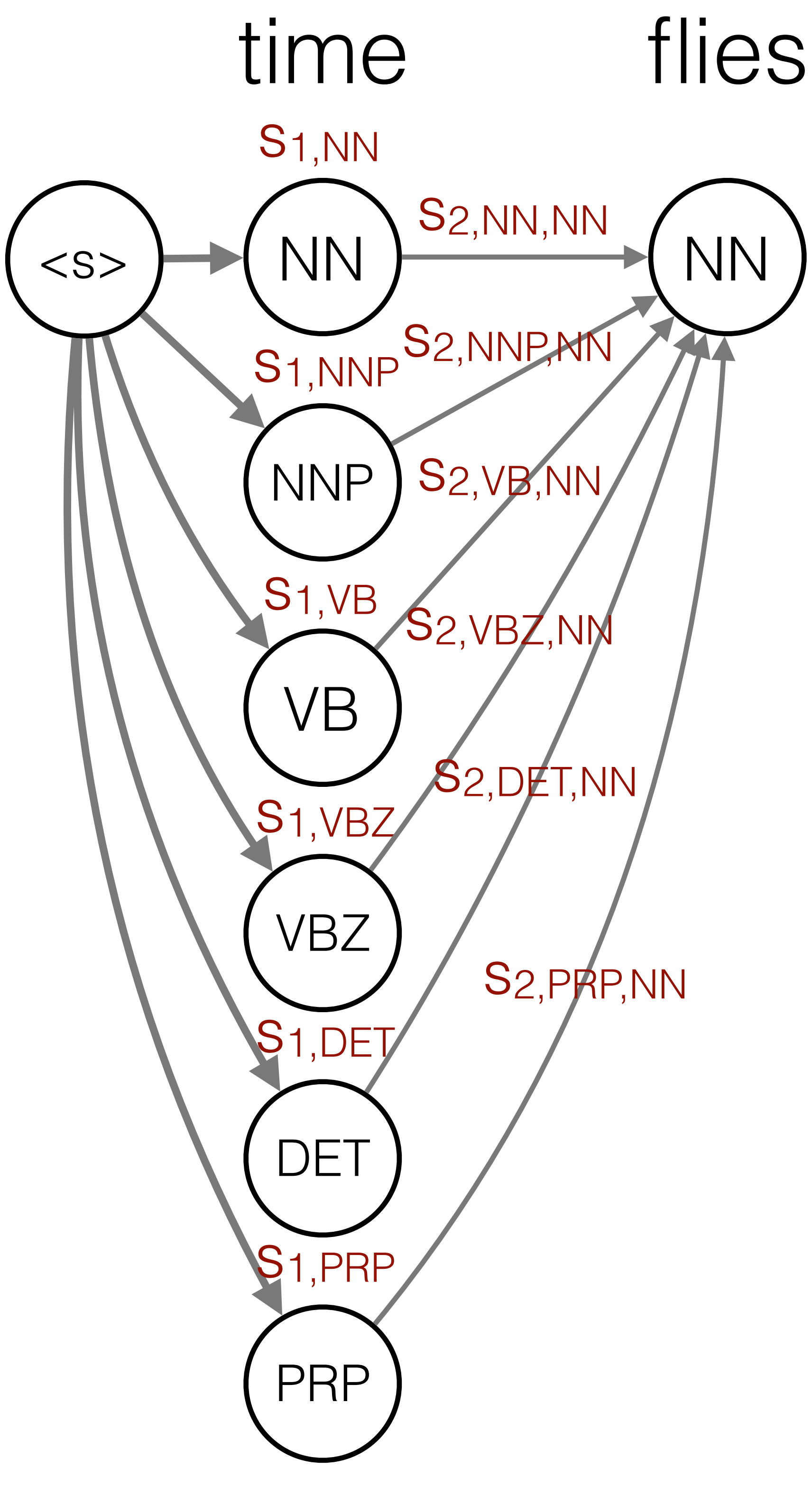
$$s_{f,i,j,k} = s_{f,i-1,j} + s_{e,i,k} + s_{t,j,k}$$

Viterbi Forward Step



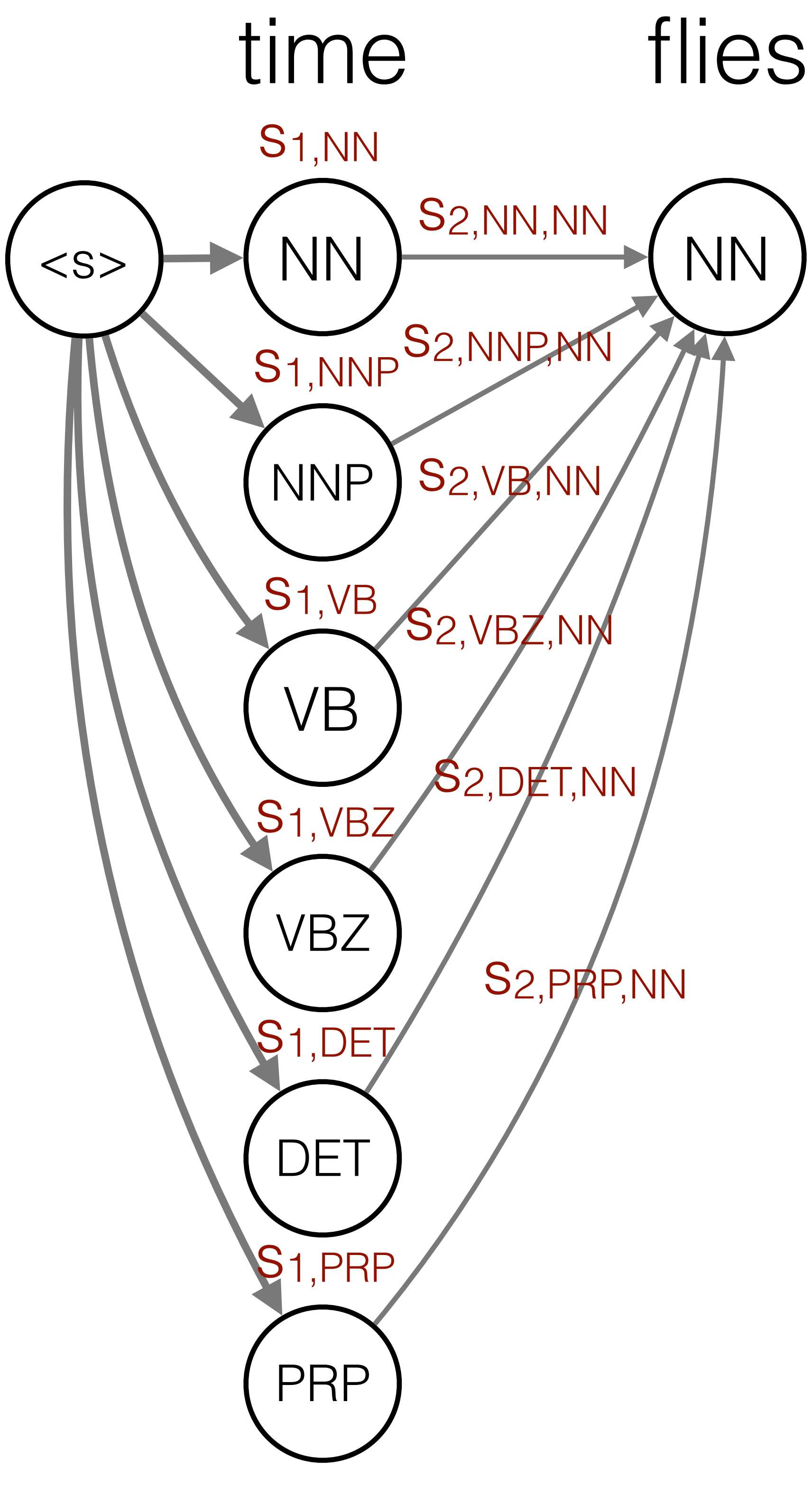
$$s_{f,i,j,k} = s_{f,i-1,j} + s_{e,i,k} + s_{t,j,k}$$

Viterbi Forward Step



$$s_{f,i,j,k} = s_{f,i-1,j} + s_{e,i,k} + s_{t,j,k}$$

Viterbi Forward Step

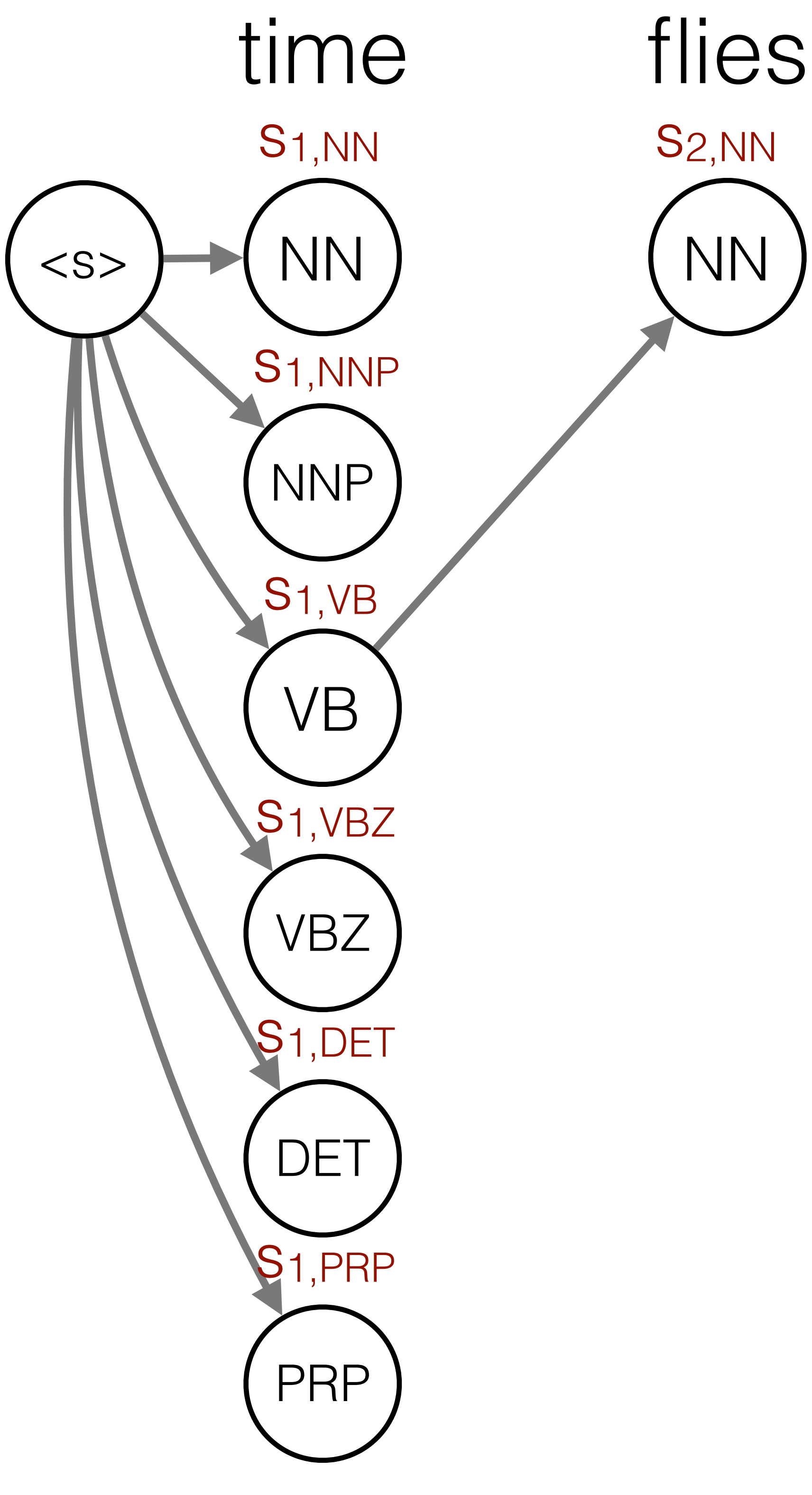


$$s_{f,i,j,k} = s_{f,i-1,j} + s_{e,i,k} + s_{t,j,k}$$

$$\Big\downarrow \text{ vectorize}$$

$$\boldsymbol{s}_{f,i,k} = \boldsymbol{s}_{f,i-1} + s_{e,i,k} + \boldsymbol{s}_{t,k}$$

Viterbi Forward Step

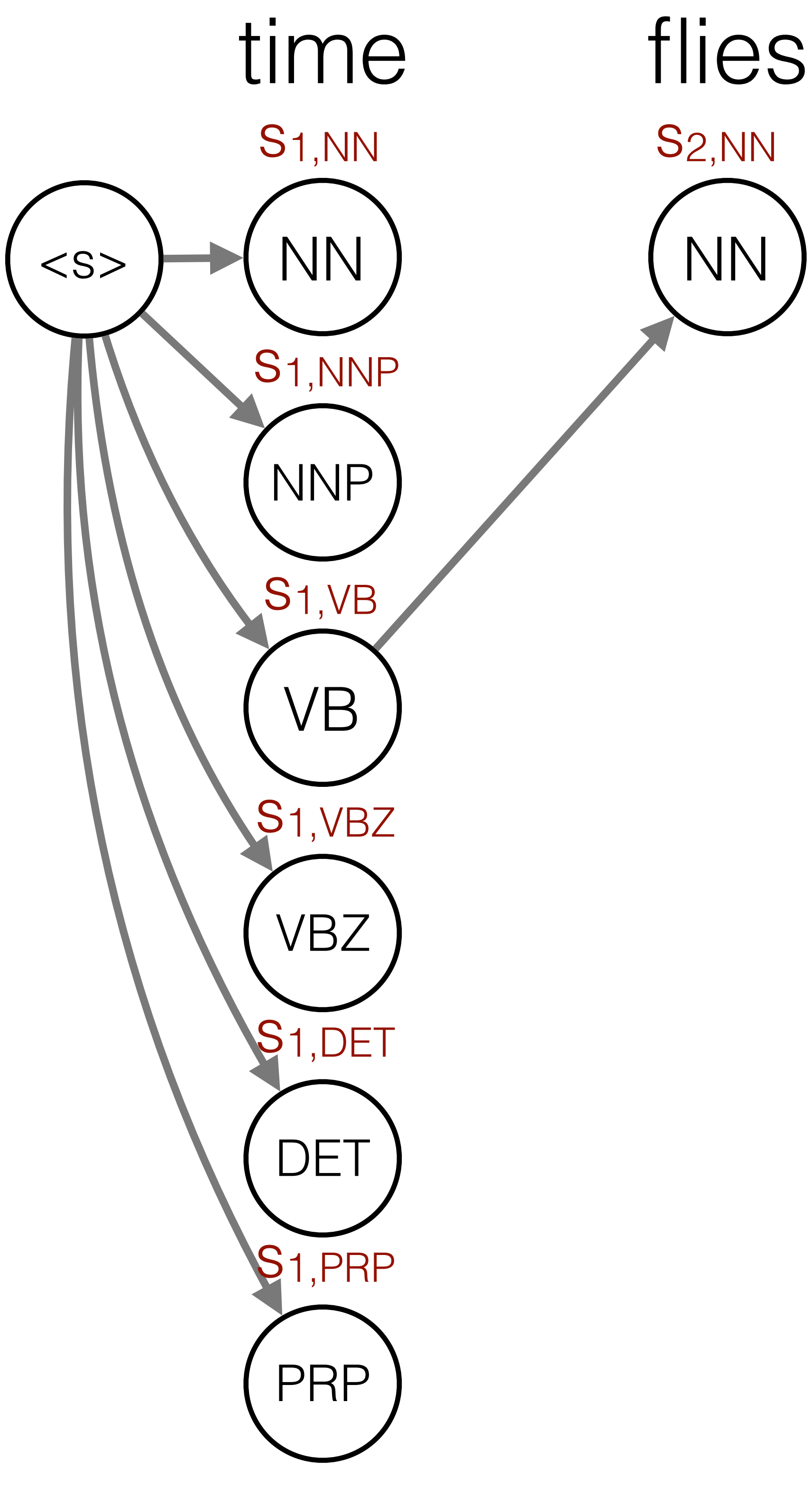


$$s_{f,i,j,k} = s_{f,i-1,j} + s_{e,i,k} + s_{t,j,k}$$

↓ vectorize

$$\boldsymbol{s}_{f,i,k} = \boldsymbol{s}_{f,i-1} + s_{e,i,k} + \boldsymbol{s}_{t,k}$$

Viterbi Forward Step



$$s_{f,i,j,k} = s_{f,i-1,j} + s_{e,i,k} + s_{t,j,k}$$

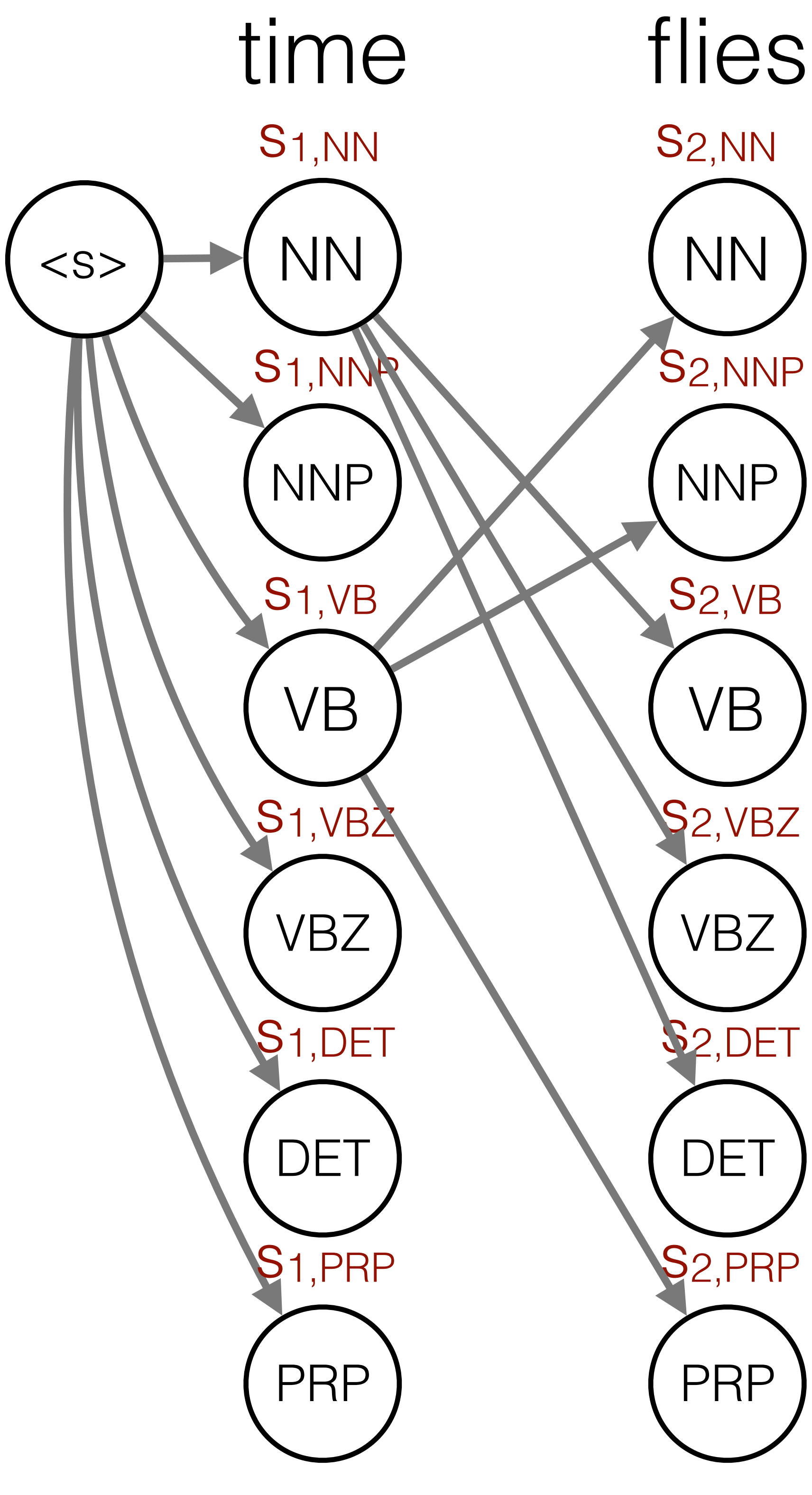
↓ vectorize

$$\boldsymbol{s}_{f,i,k} = \boldsymbol{s}_{f,i-1} + s_{e,i,k} + \boldsymbol{s}_{t,k}$$

↓ max

$$s_{f,i,k} = \max(\boldsymbol{s}_{f,i,k})$$

Viterbi Forward Step



$$s_{f,i,j,k} = s_{f,i-1,j} + s_{e,i,k} + s_{t,j,k}$$

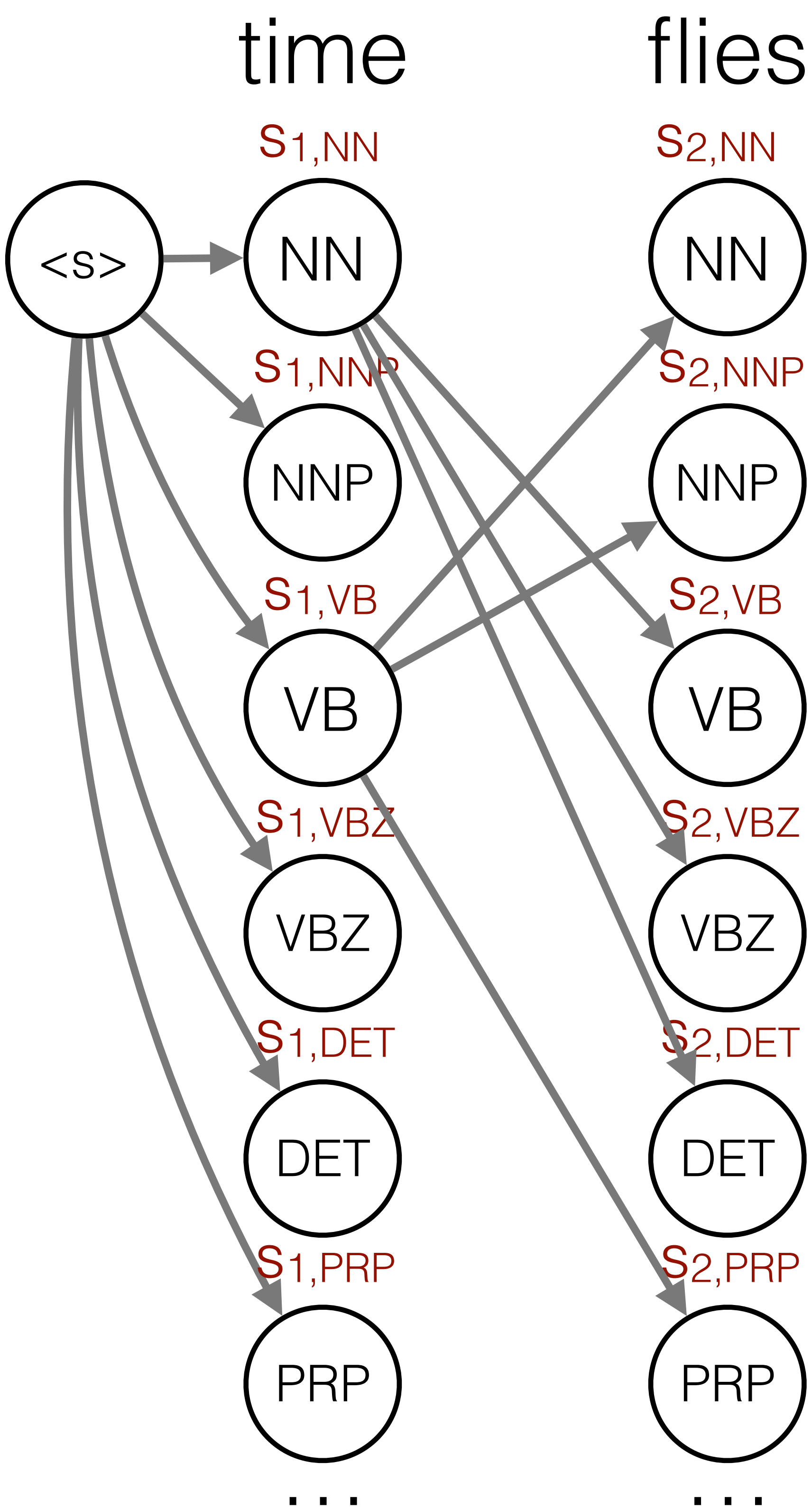
↓ vectorize

$$\boldsymbol{s}_{f,i,k} = \boldsymbol{s}_{f,i-1} + s_{e,i,k} + \boldsymbol{s}_{t,k}$$

↓ max

$$s_{f,i,k} = \max(\boldsymbol{s}_{f,i,k})$$

Viterbi Forward Step



$$s_{f,i,j,k} = s_{f,i-1,j} + s_{e,i,k} + s_{t,j,k}$$

↓ vectorize

$$\boldsymbol{s}_{f,i,k} = \boldsymbol{s}_{f,i-1} + s_{e,i,k} + \boldsymbol{s}_{t,k}$$

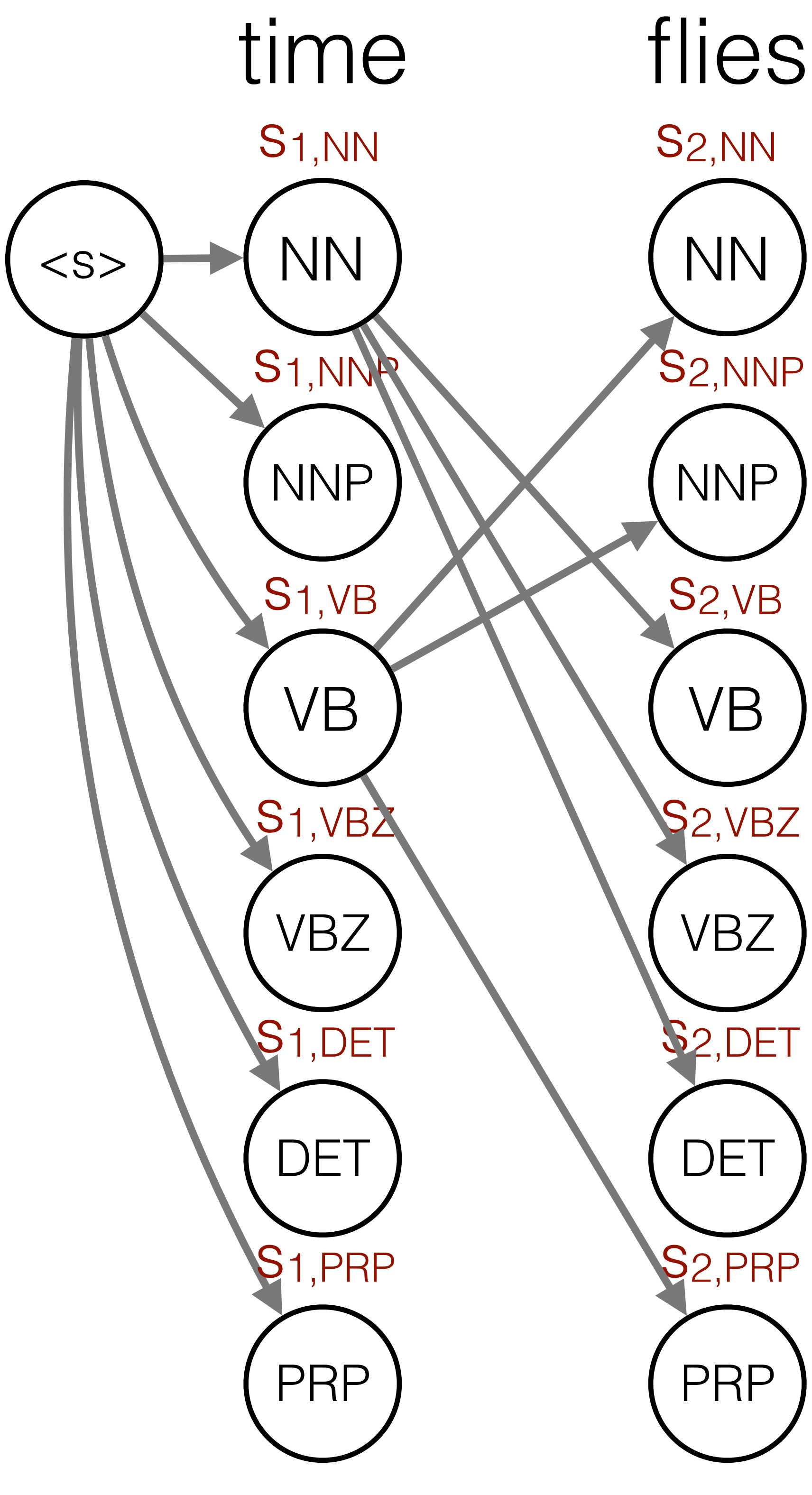
↓ max

$$s_{f,i,k} = \max(\boldsymbol{s}_{f,i,k})$$

↓ concat

$$\boldsymbol{s}_{f,i} = \text{concat}(s_{f,i,1}, s_{f,i,2}, \ldots)$$

Viterbi Forward Step



$$s_{f,i,j,k} = s_{f,i-1,j} + s_{e,i,k} + s_{t,j,k}$$

vectorize

$$\boldsymbol{s}_{f,i,k} = \boldsymbol{s}_{f,i-1} + s_{e,i,k} + \boldsymbol{s}_{t,k}$$

max

$$s_{f,i,k} = \max(\boldsymbol{s}_{f,i,k})$$

recurse

concat

$$\boldsymbol{s}_{f,i} = \text{concat}(s_{f,i,1}, s_{f,i,2}, \ldots)$$

Transition Matrix in DyNet

Add additional parameters

```
TRANS_LOOKUP = model.add_lookup_parameters((ntags, ntags))
```

Initialize at sentence start

```
trans_exprs = [TRANS_LOOKUP[tid] for tid in range(ntags)]
```

Viterbi Forward in DyNet

```
# Perform the forward pass through the sentence
for i, vec in enumerate(vecs):
    my_best_ids = []
    my_best_exprs = []
    for next_tag in range(ntags):
        # Calculate vector for single next tag
        next_single_expr = for_expr + trans_exprs[next_tag]
        next_single = next_single_expr.npvalue()
        # Find and save the best score
        my_best_id = np.argmax(next_single)
        my_best_ids.append(my_best_id)
        my_best_exprs.append(dy.pick(next_single_expr, my_best_id))
    # Concatenate vectors and add emission probs
    for_expr = dy.concatenate(my_best_exprs) + vec
    # Save the best ids
    best_ids.append(my_best_ids)
```

and do similar for final “<s>” tag

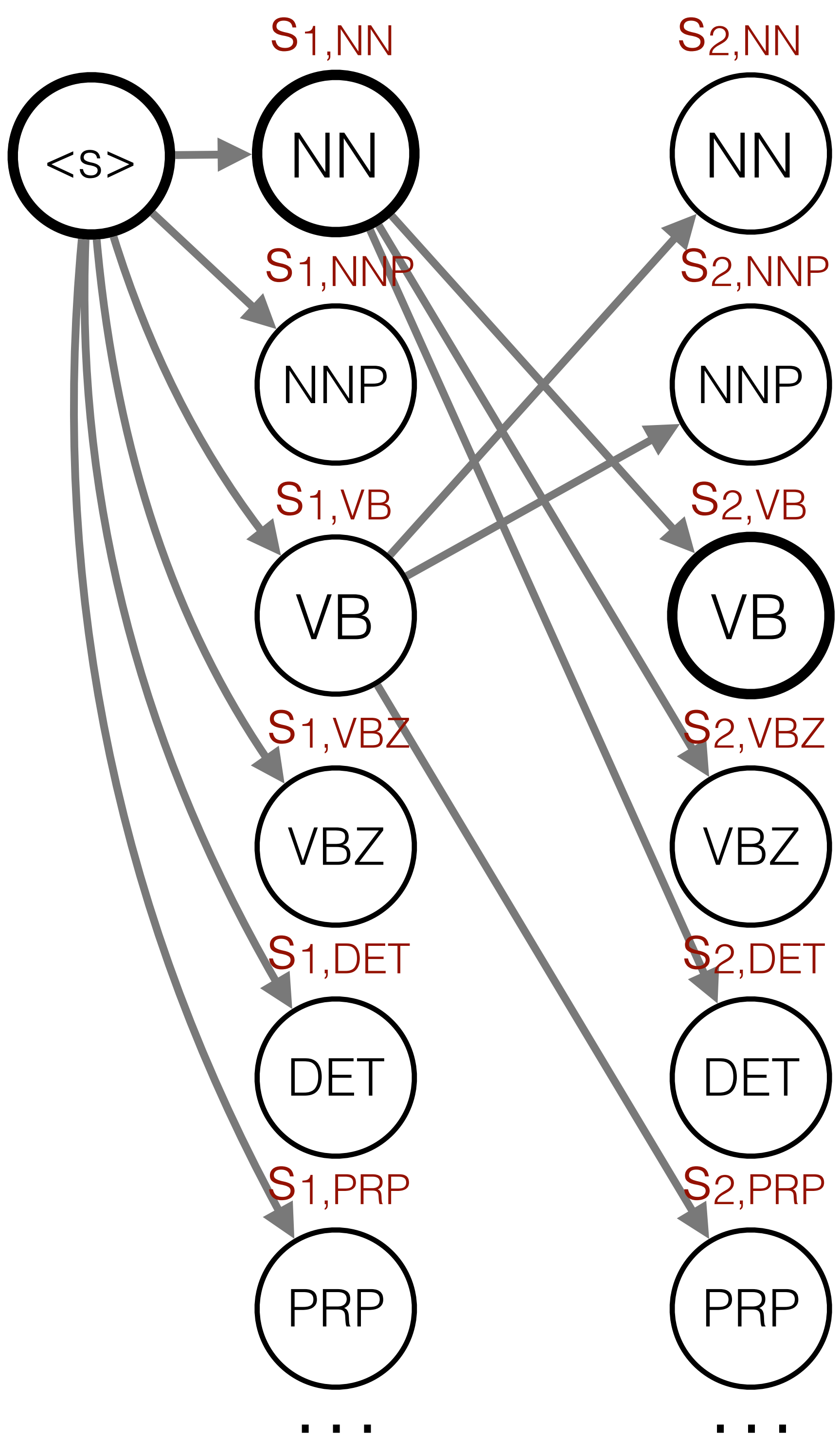
Viterbi Backward

```
# Perform the reverse pass
best_path = [vt.i2w[my_best_id]]
for my_best_ids in reversed(best_ids):
    my_best_id = my_best_ids[my_best_id]
    best_path.append(vt.i2w[my_best_id])
best_path.pop() # Remove final <s>
best_path.reverse()

# Return the best path and best score as an expression
return best_path, best_expr
```

Calculating Reference Scores

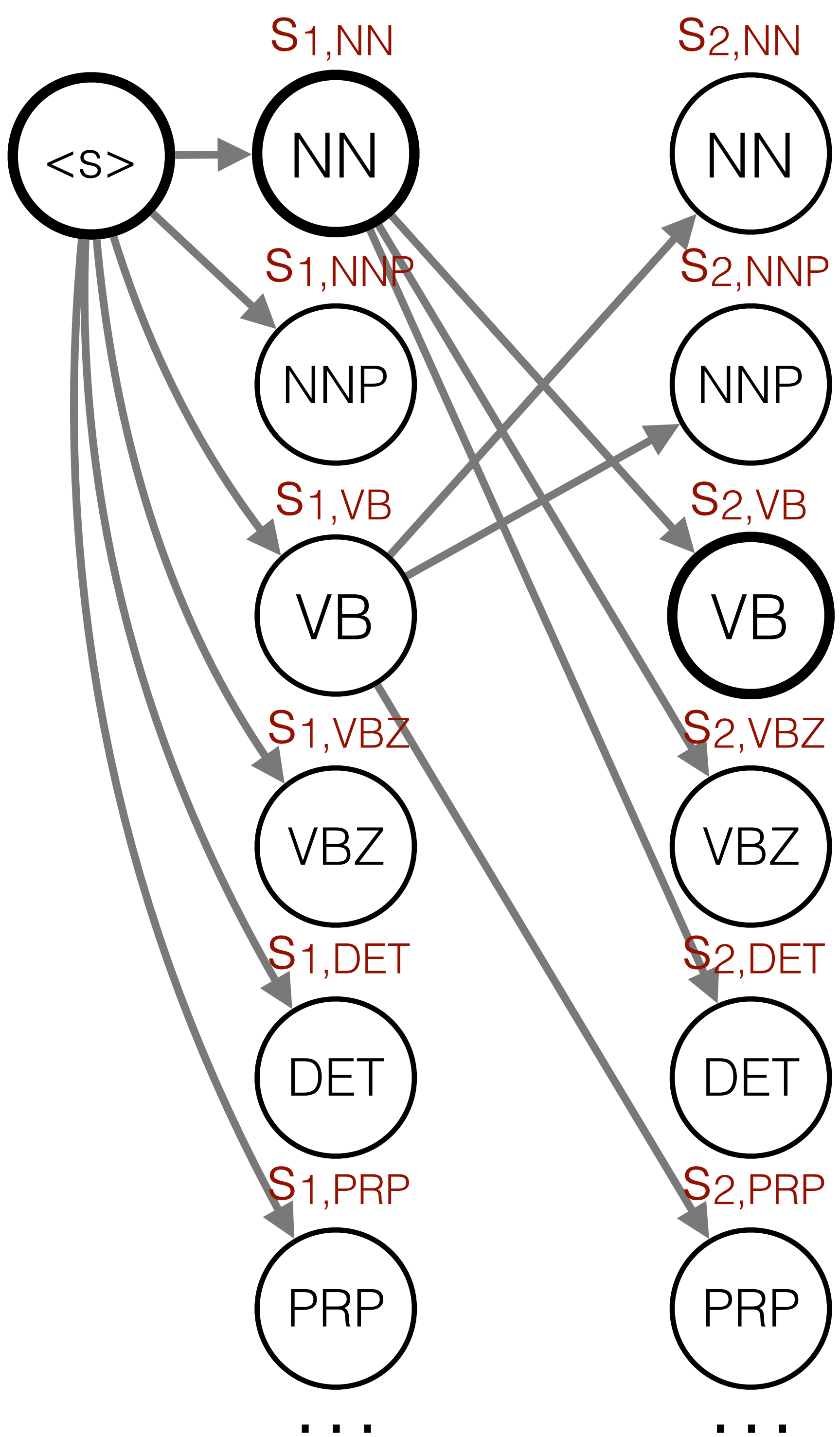
```
def forced_decoding(vecs, tags):
    # Initialize
    for_expr = dy.scalarInput(0)
    for_tag = S_T
    # Perform the forward pass through the sentence
    for i, vec in enumerate(vecs):
        my_tag = vt.w2i[tags[i]]
        my_trans = dy.pick(TRANS_LOOKUP[my_tag], for_tag)
        for_expr = for_expr + my_trans + vec[my_tag]
        for_tag = my_tag
    for_expr = for_expr + dy.pick(TRANS_LOOKUP[S_T], for_tag)
    return for_expr
```

Loss Augmented Inference



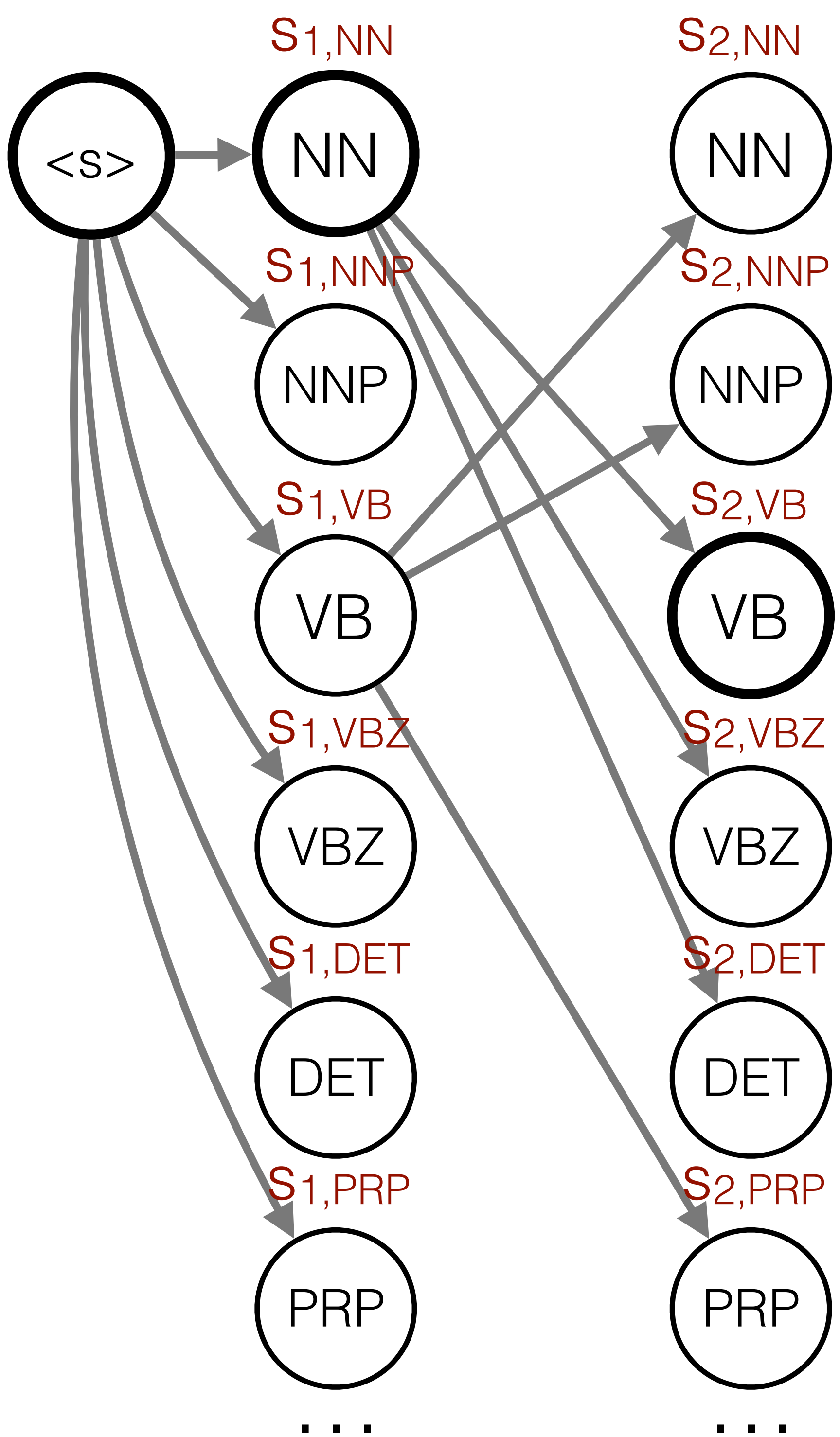
Loss Augmented Inference

- Idea: we want the model to be **really sure** about the best path



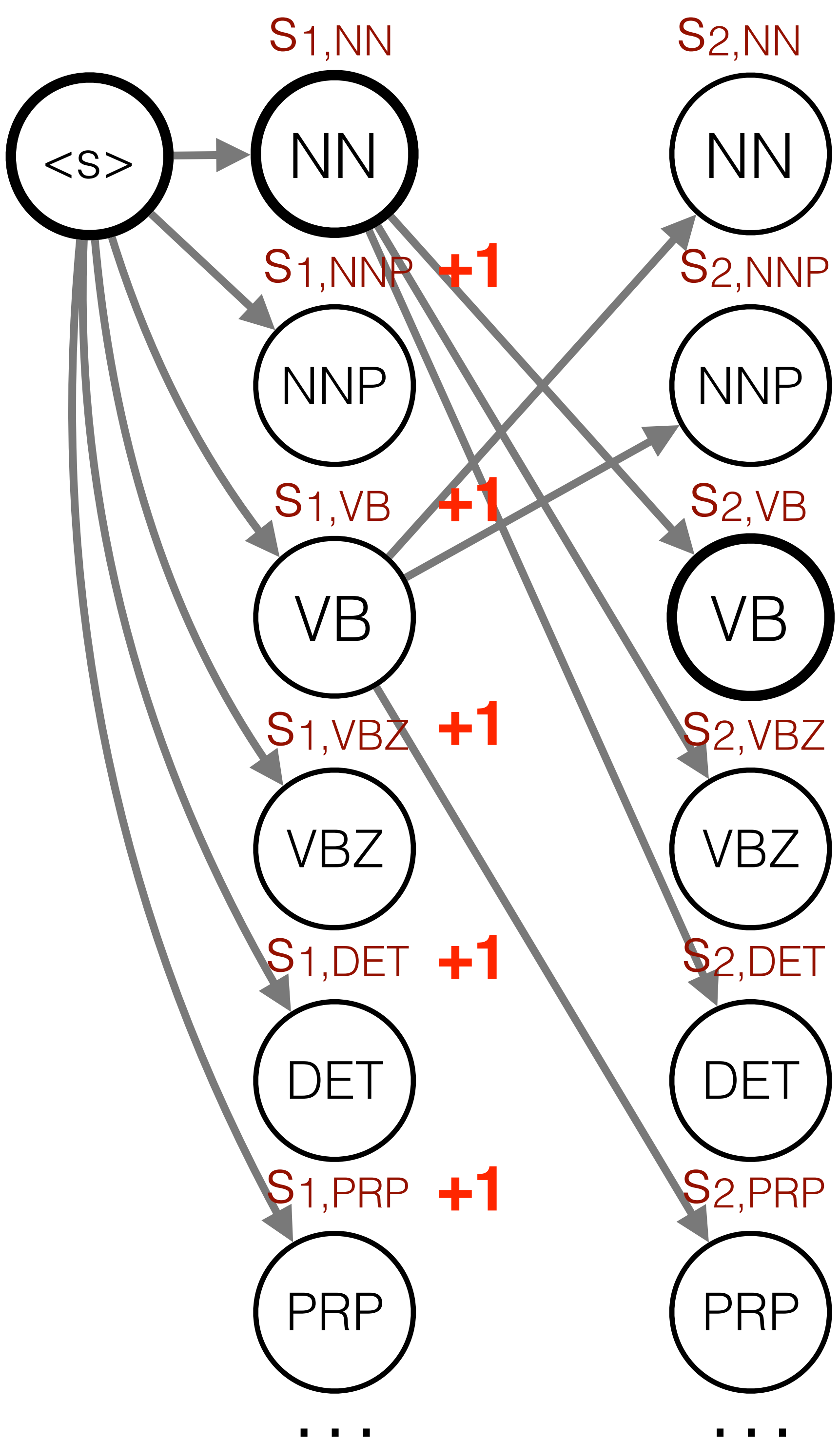
Loss Augmented Inference

- Idea: we want the model to be **really sure** about the best path
- During search, give bonus to all but correct tag



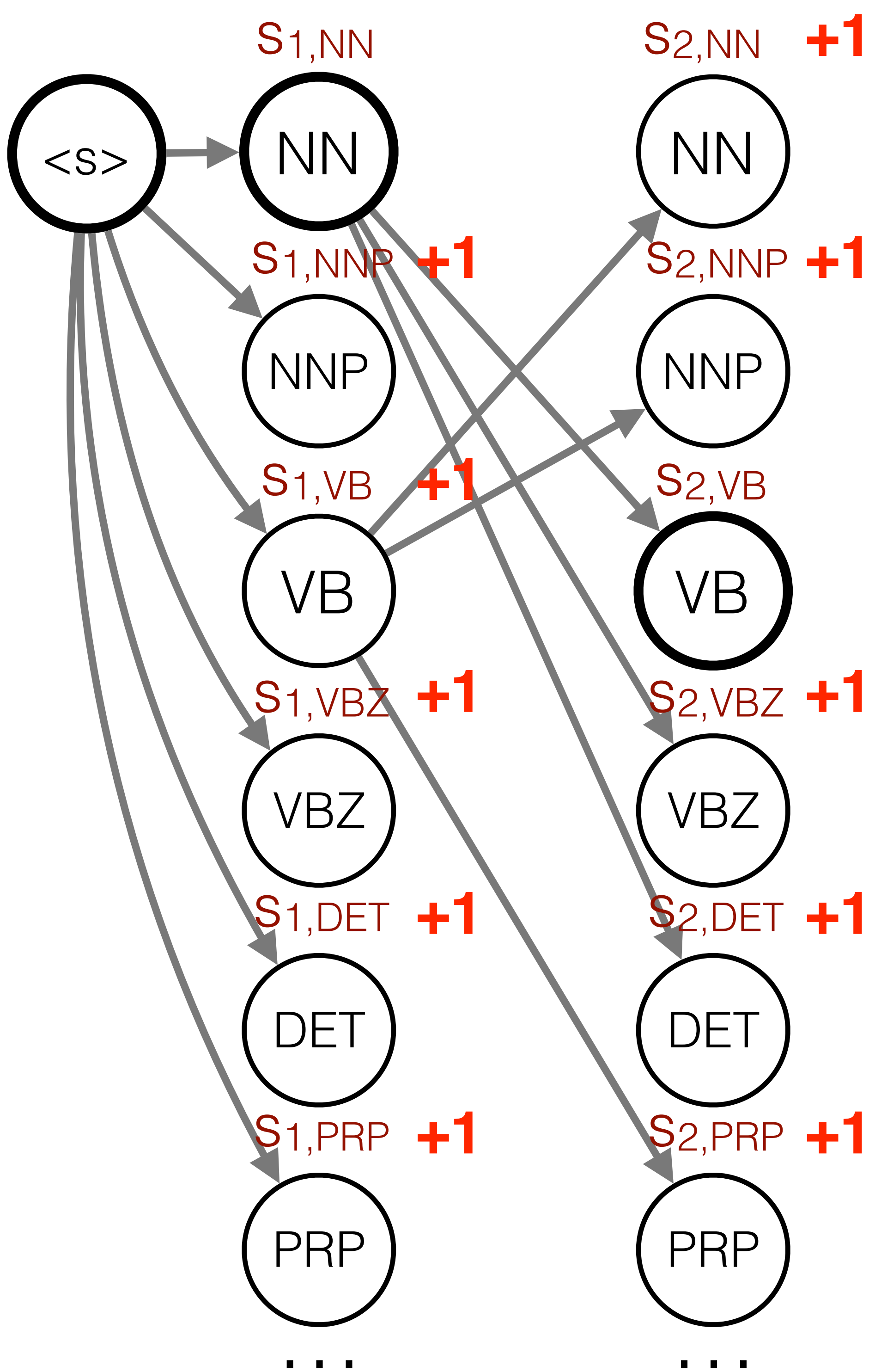
Loss Augmented Inference

- Idea: we want the model to be **really sure** about the best path
- During search, give bonus to all but correct tag



Loss Augmented Inference

- Idea: we want the model to be **really sure** about the best path
- During search, give bonus to all but correct tag



Loss Augmented Inference in DyNet

```
def viterbi_decoding(vecs, gold_tags = []):
    ...
    for i, vec in enumerate(vecs):
        ...
        for_expr = dy.concatenate(my_best_exprs) + vec
        if MARGIN != 0 and len(gold_tags) != 0:
            # Add vector where all but correct are MARGIN
            adjust = [MARGIN] * ntags
            adjust[vt.w2i[gold_tags[i]]] = 0
            for_expr = for_expr + dy.inputVector(adjust)
```

Caveat: Downsides of Structured Training

Caveat: Downsides of Structured Training

- Structured training allows for richer models

Caveat: Downsides of Structured Training

- Structured training allows for richer models
- **But,** it has disadvantages
  - Speed: requires more complicated algorithms
  - Stability: often can't enumerate whole hypothesis space

Caveat: Downsides of Structured Training

- Structured training allows for richer models
- **But,** it has disadvantages
    - Speed: requires more complicated algorithms
    - Stability: often can't enumerate whole hypothesis space
- One solution: initialize with ML, continue with structured training

Conclusion

Training NNs for NLP

Training NNs for NLP

- We want the flexibility to handle the structures we like

Training NNs for NLP

- We want the flexibility to handle the structures we like
- We want to write code the way that we think about models

Training NNs for NLP

- We want the flexibility to handle the structures we like
- We want to write code the way that we think about models
- DyNet gives you the tools to do so!

Training NNs for NLP

- We want the flexibility to handle the structures we like
- We want to write code the way that we think about models
- DyNet gives you the tools to do so!
- We welcome contributors to make it even better