

# CSE 291 Assignment 2 BiLSTM CRF

## Download Data/Eval Script

```
In [1]: !wget https://raw.githubusercontent.com/sighsmile/conlleva/master/conlleva.py
!wget https://raw.githubusercontent.com/tberg12/cse291spr21/main/assignment2/train.data.quad
!wget https://raw.githubusercontent.com/tberg12/cse291spr21/main/assignment2/dev.data.quad
```

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```
In [1]: import conlleva
from tqdm import tqdm
import numpy as np
from collections import defaultdict, Counter
import torch
import torch.autograd as autograd
import torch.nn as nn
import torch.optim as optim
from torchtext.vocab import Vocab
from torch.nn.utils.rnn import pack_padded_sequence, pad_packed_sequence

torch.manual_seed(291)

device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(device)
```

cuda

## Data Preparation

```
In [2]: TRAIN_DATA = 'train.data.quad'
VALID_DATA = 'dev.data.quad'
UNK = '<unk>'
PAD = '<pad>'
START_TAG = "<start>" # you can add this explicitly or use it implicitly in your CRF layer
STOP_TAG = "<stop>" # you can add this explicitly or use it implicitly in your CRF layer

def read_conll_sentence(path):
    """ Read a CONLL-format sentence into vocab objects
    Args:
        :param path: path to CONLL-format data file
        :param word_vocab: Vocabulary object for source
        :param label_vocab: Vocabulary object for target
    """
    sent = [], []
    with open(path) as f:
        for line in f:
            line = line.strip().split()
            if line:
                # replace numbers with 0000
                word = line[0]
                word = '0000' if word.isnumeric() else word
```

```

        sent[0].append(word)
        sent[1].append(line[3])
    else:
        yield sent[0], sent[1]
        sent = [], []

def prepare_dataset(dataset, word_vocab, label_vocab):
    dataset = [
        [
            torch.tensor([word_vocab.stoi[word] for word in sent[0]], dtype=torch.long),
            torch.tensor([label_vocab.stoi[label] for label in sent[1]], dtype=torch.long),
        ]
        for sent in dataset
    ]
    return dataset

# load a list of sentences, where each word in the list is a tuple containing the word and
train_data = list(read_conll_sentence(TRAIN_DATA))
train_word_counter = Counter([word for sent in train_data for word in sent[0]])
train_label_counter = Counter([label for sent in train_data for label in sent[1]])
word_vocab = Vocab(train_word_counter, specials=(UNK, PAD), min_freq=2)
label_vocab = Vocab(train_label_counter, specials=(), min_freq=1)
train_data = prepare_dataset(train_data, word_vocab, label_vocab)
print('Train word vocab:', len(word_vocab), 'symbols.')
print('Train label vocab:', len(label_vocab), f'symbols: {list(label_vocab.stoi.keys())}')
valid_data = list(read_conll_sentence(VALID_DATA))
valid_data = prepare_dataset(valid_data, word_vocab, label_vocab)
print('Train data:', len(train_data), 'sentences.')
print('Valid data:', len(valid_data))

print(' '.join([word_vocab.itos[i.item()] for i in train_data[0][0]]))
print(' '.join([label_vocab.itos[i.item()] for i in train_data[0][1]]))

print(' '.join([word_vocab.itos[i.item()] for i in valid_data[1][0]]))
print(' '.join([label_vocab.itos[i.item()] for i in valid_data[1][1]]))
tag_to_ix = {"O": 0, "I-PER": 1, "I-ORG": 2, "I-LOC": 3, "I-MISC": 4, "B-MISC": 5, "B-ORG": 6, "B-PER": 7, "B-LOC": 8}
print(len(tag_to_ix))

```

Train word vocab: 3947 symbols.

Train label vocab: 8 symbols: ['O', 'I-PER', 'I-ORG', 'I-LOC', 'I-MISC', 'B-MISC', 'B-ORG', 'B-LOC']

Train data: 3420 sentences.

Valid data: 800

Pusan 0000 0000 0000 0000 0000 0000

I-ORG O O O O O O

Earlier this month , <unk> denied a Kabul government statement that the two sides had agreed to a ceasefire in the north .

O O O O I-PER O O I-LOC O O O O O O O O O O O O O O O

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## BiLSTMTagger

In [3]:

```

# Starter code implementing a BiLSTM Tagger
# which makes locally normalized, independent
# tag classifications at each time step

class BiLSTMTagger(nn.Module):
    def __init__(self, vocab_size, tag_vocab_size, embedding_dim, hidden_dim, dropout=0.3):
        super(BiLSTMTagger, self).__init__()

        self.embedding_dim = embedding_dim
        self.hidden_dim = hidden_dim

```

```

self.vocab_size = vocab_size
self.tagset_size = tag_vocab_size
self.word_embeds = nn.Embedding(vocab_size, embedding_dim).to(device)
self.bilstm = nn.LSTM(embedding_dim, hidden_dim // 2,
                      num_layers=1, bidirectional=True, batch_first=True).to(device)
# logistic regression
print("hidden_dim: ", hidden_dim)
print("target_size: ", tag_vocab_size)
self.tag_projection_layer = nn.Linear(hidden_dim, self.tagset_size).to(device)
self.dropout = nn.Dropout(p=dropout)

def init_hidden(self):
    return (torch.randn(2, 1, self.hidden_dim // 2).to(device),
            torch.randn(2, 1, self.hidden_dim // 2).to(device))

def compute_lstm_emission_features(self, sentence):
    hidden = self.init_hidden()
    embeds = self.word_embeds(sentence)
    #print(embeds.shape)
    #print(embeds)
    embeds = self.dropout(embeds)

    bilstm_out, hidden = self.bilstm(embeds, hidden)
    #print('before dropout: ', bilstm_out.shape)
    bilstm_out = self.dropout(bilstm_out)
    #print('after dropout: ', bilstm_out.shape)
    #print(bilstm_out)
    bilstm_out = bilstm_out
    bilstm_feats = self.tag_projection_layer(bilstm_out)
    return bilstm_feats

def forward(self, sentence):
    #input a sequence of tag, perform lstm and then logistic regression
    bilstm_feats = self.compute_lstm_emission_features(sentence)
    #print('forward: ', bilstm_feats.shape)
    #print('second: ', bilstm_feats.argmax(-1))
    return bilstm_feats.max(-1)[0].sum(), bilstm_feats.argmax(-1)

# compute the NLL -> negative likelihood loss
def loss(self, sentence, tags):
    #print('sentence length: ', sentence.shape)
    #print('tags length: ', tags.shape)
    bilstm_feats = self.compute_lstm_emission_features(sentence)
    #print('loss: ', bilstm_feats.shape)
    # transform predictions to (n_examples, n_classes) and ground truth to (n_examples, n_classes)
    return torch.nn.functional.cross_entropy(
        bilstm_feats.view(-1, self.tagset_size),
        tags.view(-1),
        reduction='sum'
    )

```

## Train / Eval loop

In [4]:

```

def argmax(vec):
    # return the argmax as a python int
    _, idx = torch.max(vec, 1)
    return idx.item()

def prepare_sequence(seq, to_ix):
    idxs = [to_ix[w] for w in seq]
    return torch.tensor(idxs, dtype=torch.long)

```

```

# Compute log sum exp in a numerically stable way for the forward algorithm
def log_sum_exp(vec):
    max_score = vec[0, argmax(vec)]
    max_score_broadcast = max_score.view(1, -1).expand(1, vec.size()[1])
    return max_score + \
        torch.log(torch.sum(torch.exp(vec - max_score_broadcast)))

```

In [7]:

```

class BiLSTMTagger3(nn.Module):
    def __init__(self, vocab_size, tag_to_ix, embedding_dim, hidden_dim, dropout=0.3):
        super(BiLSTMTagger3, self).__init__()

        self.embedding_dim = embedding_dim
        self.hidden_dim = hidden_dim
        self.vocab_size = vocab_size
        self.tag_to_ix = tag_to_ix
        self.tagset_size = len(tag_to_ix)

        self.word_embeds = nn.Embedding(vocab_size, embedding_dim).to(device)
        self.lstm = nn.LSTM(embedding_dim, hidden_dim // 2,
                             num_layers=1, bidirectional=True, batch_first=True).to(device)

        self.hidden2tag = nn.Linear(hidden_dim, self.tagset_size).to(device)
        self.dropout = nn.Dropout(p=dropout)

        self.transitions = nn.Parameter(
            torch.randn(self.tagset_size, self.tagset_size))

        self.transitions.data[tag_to_ix[START_TAG], :] = -10000
        self.transitions.data[:, tag_to_ix[STOP_TAG]] = -10000

        self.hidden = self.init_hidden()

    def init_hidden(self):
        return (torch.randn(2, 1, self.hidden_dim // 2).to(device),
                torch.randn(2, 1, self.hidden_dim // 2).to(device))

    def _forward_alg(self, feats):
        # Do the forward algorithm to compute the partition function
        init_alphas = torch.full((1, self.tagset_size), -10000.).to(device)
        # START_TAG has all of the score.
        init_alphas[0][self.tag_to_ix[START_TAG]] = 0.

        # Wrap in a variable so that we will get automatic backprop
        forward_var = init_alphas
        #print(feats.shape)
        # Iterate through the sentence
        for feat in feats:
            alphas_t = [] # The forward tensors at this timestep
            for next_tag in range(self.tagset_size):
                # broadcast the emission score: it is the same regardless of
                # the previous tag
                #print(next_tag)
                #print('feats shape', feats.shape)
                #print(feats)

                emit_score = feat[next_tag].view(
                    1, -1).expand(1, self.tagset_size)
                # the ith entry of trans_score is the score of transitioning to
                # next_tag from i
                trans_score = self.transitions[next_tag].view(1, -1)
                # The ith entry of next_tag_var is the value for the
                # edge (i -> next_tag) before we do log-sum-exp
                next_tag_var = forward_var + trans_score + emit_score

```

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        # The forward variable for this tag is log-sum-exp of all the
        # scores.
        alphas_t.append(log_sum_exp(next_tag_var).view(1))
        forward_var = torch.cat(alphas_t).view(1, -1)
        terminal_var = forward_var + self.transitions[self.tag_to_ix[STOP_TAG]]
        alpha = log_sum_exp(terminal_var)
        return alpha

def _get_lstm_features(self, sentence):
    self.hidden = self.init_hidden()
    #embeds = self.word_embeddings(sentence).view(len(sentence), 1, -1)
    embeds = self.word_embeddings(sentence)
    embeds = self.dropout(embeds)
    #print(embeds.shape)
    #print(embeds)
    lstm_out, self.hidden = self.lstm(embeds, self.hidden)
    #print('lstm_out', lstm_out.shape)
    lstm_out = lstm_out.squeeze(0)
    #print('lstm_out', lstm_out.shape)
    #lstm_out = lstm_out.view(len(sentence), self.hidden_dim)
    lstm_feats = self.hidden2tag(lstm_out)
    #print(lstm_feats.shape)

    return lstm_feats

def _score_sentence(self, feats, tags):
    # Gives the score of a provided tag sequence
    score = torch.zeros(1).to(device)
    #print(tags.shape)
    temp_tags = tags.squeeze(0)
    #print(temp_tags.shape)
    temp_tags = torch.cat([torch.tensor([self.tag_to_ix[START_TAG]],
                                         dtype=torch.long).to(device), temp_tags])

    #print(tags.shape)
    for i, feat in enumerate(feats):
        #print(i)
        score = score + \
            self.transitions[temp_tags[i + 1],
                             temp_tags[i]] + feat[temp_tags[i + 1]]
    score = score + self.transitions[self.tag_to_ix[STOP_TAG],
                                     temp_tags[-1]]

    return score

def _viterbi_decode(self, feats):
    backpointers = []

    # Initialize the viterbi variables in log space
    init_vvars = torch.full((1,
                             self.tagset_size), -10000.).to(device)
    init_vvars[0][self.tag_to_ix[START_TAG]] = 0

    # forward_var at step i holds the viterbi variables for step i-1
    forward_var = init_vvars
    for feat in feats:
        bptrs_t = [] # holds the backpointers for this step
        viterbivars_t = [] # holds the viterbi variables for this step

        for next_tag in range(self.tagset_size):
            # next_tag_var[i] holds the viterbi variable for tag i at the
            # previous step, plus the score of transitioning
            # from tag i to next_tag.
            # We don't include the emission scores here because the max
            # does not depend on them (we add them in below)
            next_tag_var = forward_var + self.transitions[next_tag]
            best_tag_id = argmax(next_tag_var)
            bptrs_t.append(best_tag_id)

```

```

        viterbivars_t.append(next_tag_var[0][best_tag_id].view(1))
        # Now add in the emission scores, and assign forward_var to the set
        # of viterbi variables we just computed
        forward_var = (torch.cat(viterbivars_t).to(device) + feat).view(1, -1)
        backpointers.append(bptrs_t)

    # Transition to STOP_TAG
    terminal_var = forward_var + self.transitions[self.tag_to_ix[STOP_TAG]]
    best_tag_id = argmax(terminal_var)
    path_score = terminal_var[0][best_tag_id]

    # Follow the back pointers to decode the best path.
    best_path = [best_tag_id]
    for bptrs_t in reversed(backpointers):
        best_tag_id = bptrs_t[best_tag_id]
        best_path.append(best_tag_id)
    # Pop off the start tag (we dont want to return that to the caller)
    start = best_path.pop()
    assert start == self.tag_to_ix[START_TAG] # Sanity check
    best_path.reverse()
    return path_score, best_path

def neg_log_likelihood(self, sentence, tags):
    feats = self._get_lstm_features(sentence)
    forward_score = self._forward_alg(feats)
    gold_score = self._score_sentence(feats, tags)
    return forward_score - gold_score

def forward(self, sentence): # dont confuse this with _forward_alg above.
    # Get the emission scores from the BiLSTM
    lstm_feats = self._get_lstm_features(sentence)

    # Find the best path, given the features.
    score, tag_seq = self._viterbi_decode(lstm_feats)
    return score, tag_seq

```

In [12]:

```

def train(model, train_data, valid_data, word_vocab, label_vocab, epochs, log_interval=25):
    losses_per_epoch = []
    for epoch in range(epochs):
        print(f'--- EPOCH {epoch} ---')
        model.train()
        losses_per_epoch.append([])
        for i, (sent, tags) in enumerate(train_data):
            model.zero_grad()
            sent, tags = sent.to(device), tags.to(device)
            # that is, for each sentence and its corresponding tag sequences
            sent = sent.unsqueeze(0)
            tags = tags.unsqueeze(0)
            #print(sent)
            loss = model.neg_log_likelihood(sent, tags)
            #loss = model.loss(sent, tags)
            loss.backward()
            optimizer.step()
            #print(i)
            losses_per_epoch[-1].append(loss.detach().cpu().item())
            if i > 0 and i % log_interval == 0:
                print(f'Avg loss over last {log_interval} updates: {np.mean(losses_per_epoch[-1])}')
        evaluate(model, valid_data, word_vocab, label_vocab)

def evaluate(model, dataset, word_vocab, label_vocab):
    model.eval()
    losses = []

```

```

scores = []
true_tags = []
pred_tags = []
sents = []
for i, (sent, tags) in enumerate(dataset):
    with torch.no_grad():
        sent, tags = sent.to(device), tags.to(device)
        sent = sent.unsqueeze(0)
        tags = tags.unsqueeze(0)
        losses.append(model.neg_log_likelihood(sent, tags).cpu().detach().item())
        #losses.append(model.loss(sent, tags).cpu().detach().item())
        score, pred_tag_seq = model(sent)
        scores.append(score.cpu().detach().numpy())
        temp = []
        temp.append(pred_tag_seq)
        pred_tag_seq = temp
        true_tags.append([label_vocab.itos[i] for i in tags.tolist()[0]])
        pred_tags.append([label_vocab.itos[i] for i in pred_tag_seq[0]])
        sents.append([word_vocab.itos[i] for i in sent[0]])

print('Avg evaluation loss:', np.mean(losses))
print(conlleval.evaluate([tag for tags in true_tags for tag in tags],
                        [tag for tags in pred_tags for tag in tags], verbose=True))
print('\n5 random evaluation samples:')
for i in np.random.randint(0, len(sents), size=5):
    print('SENT:', ' '.join(sents[i]))
    print('TRUE:', ' '.join(true_tags[i]))
    print('PRED:', ' '.join(pred_tags[i]))
return sents, true_tags, pred_tags

```

## Training

In [ ]:

In [13]:

```

%%time
# Train BiLSTM Tagger Baseline
model = BiLSTMTagger3(len(word_vocab), tag_to_ix, 128, 256).to(device)
#model = BiLSTMTagger(len(word_vocab), 8, 128, 256).to(device)
optimizer = optim.Adam(model.parameters(), lr=1e-3)
train(model, train_data, valid_data, word_vocab, label_vocab, epochs=30, log_interval=500)

```

--- EPOCH 0 ---

```

Avg loss over last 500 updates: 9.324693586349488
Avg loss over last 500 updates: 7.752459403514862
Avg loss over last 500 updates: 6.06698727941513
Avg loss over last 500 updates: 5.391325209379196
Avg loss over last 500 updates: 4.470411400556564
Avg loss over last 500 updates: 4.540101306200027
Avg evaluation loss: 4.3108238990604875
processed 11170 tokens with 1231 phrases; found: 792 phrases; correct: 507.
accuracy: 49.17%; (non-O)
accuracy: 89.46%; precision: 64.02%; recall: 41.19%; FB1: 50.12
          LOC: precision: 82.56%; recall: 44.35%; FB1: 57.71 195
          MISC: precision: 54.76%; recall: 23.96%; FB1: 33.33 84
          ORG: precision: 59.80%; recall: 38.76%; FB1: 47.04 199
          PER: precision: 57.64%; recall: 49.05%; FB1: 53.00 314
(64.01515151515152, 41.18602761982129, 50.12357884330203)

```

5 random evaluation samples:

```

SENT: There is nothing left for us but to be <unk> to <unk> for <unk> <unk> , " <unk> <unk>
> said.

```

```

TRUE: 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 I-ORG I-ORG 0 0

```

PRED: O O O O O O O O O O O O O O I-PER I-PER O O

SENT: Results of South Korean

TRUE: O O I-MISC I-MISC

PRED: O O I-MISC O

SENT: Extras ( <unk> <unk> <unk> ) 0000

TRUE: O O O O O O O

PRED: O O I-PER I-PER I-PER O O

SENT: 0000 - <unk> <unk>

TRUE: O O O O

PRED: O O O O

SENT: <unk> <unk> --- --- --- --- <unk> up <unk>

TRUE: I-LOC B-LOC O O O O O O O

PRED: O O O O O O O O O

--- EPOCH 1 ---

Avg loss over last 500 updates: 3.8126311416625978

Avg loss over last 500 updates: 4.14901714015007

Avg loss over last 500 updates: 3.3279778904914856

Avg loss over last 500 updates: 3.3117338461875914

Avg loss over last 500 updates: 2.650013731479645

Avg loss over last 500 updates: 2.8121376523971557

Avg evaluation loss: 3.237040534466505

processed 11170 tokens with 1231 phrases; found: 959 phrases; correct: 681.

accuracy: 62.22%; (non-O)

accuracy: 91.67%; precision: 71.01%; recall: 55.32%; FB1: 62.19

LOC: precision: 84.53%; recall: 61.71%; FB1: 71.34 265

MISC: precision: 79.82%; recall: 45.31%; FB1: 57.81 109

ORG: precision: 60.32%; recall: 49.51%; FB1: 54.38 252

PER: precision: 65.47%; recall: 59.08%; FB1: 62.11 333

(71.01147028154328, 55.320877335499596, 62.19178082191782)

5 random evaluation samples:

SENT: When we <unk> the shares we <unk> ...

TRUE: O O O O O O O O

PRED: O O O O O O O O

SENT: <unk> Bremen 0000 <unk> <unk> 0000

TRUE: I-ORG I-ORG O I-ORG I-ORG O

PRED: I-ORG I-ORG O I-ORG I-ORG O

SENT: Reuters has not verified these stories and does not vouch for their accuracy .

TRUE: I-ORG O O O O O O O O O O O O O

PRED: I-ORG O O O O O O O O O O O O O

SENT: SOCCER - <unk> <unk> IN <unk> FOR <unk> <unk> .

TRUE: O O I-LOC O O O O O O O

PRED: O O I-PER I-PER O O O O O O

SENT: It was the second arms <unk> this week .

TRUE: O O O O O O O O O

PRED: O O O O O O O O O

--- EPOCH 2 ---

Avg loss over last 500 updates: 2.5364945862293244

Avg loss over last 500 updates: 2.701589867115021

Avg loss over last 500 updates: 2.272822791337967

Avg loss over last 500 updates: 2.232509036540985

Avg loss over last 500 updates: 1.885722356081009

Avg loss over last 500 updates: 2.038311313152313

Avg evaluation loss: 2.9671986613422634

processed 11170 tokens with 1231 phrases; found: 1019 phrases; correct: 754.

accuracy: 66.57%; (non-O)

accuracy: 92.57%; precision: 73.99%; recall: 61.25%; FB1: 67.02

LOC: precision: 87.46%; recall: 71.07%; FB1: 78.42 295

MISC: precision: 81.03%; recall: 48.96%; FB1: 61.04 116

ORG: precision: 62.31%; recall: 52.77%; FB1: 57.14 260

PER: precision: 68.97%; recall: 65.04%; FB1: 66.95 348

(73.99411187438666, 61.25101543460602, 67.02222222222223)

5 random evaluation samples:

SENT: He would continue working on various <unk> and might meet " one state <unk> or another " .



TRUE: 0  
PRED: 0  
SENT: Johnson said that <unk> interest rates have already been <unk> by the election .  
TRUE: I-PER 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
PRED: I-PER 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
SENT: for , against , points ) :  
TRUE: 0 0 0 0 0 0 0  
PRED: 0 0 0 0 0 0 0  
SENT: " When I saw the new draw I did n't have to change my <unk> , " <unk> said . "  
TRUE: 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 I-PER 0 0 0  
PRED: 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 I-PER 0 0 0  
SENT: 9. <unk> <unk> ( China ) <unk>  
TRUE: 0 I-PER I-PER 0 I-LOC 0 0  
PRED: 0 I-PER I-PER 0 I-LOC 0 0  
--- EPOCH 3 ---

Avg loss over last 500 updates: 1.919104497909546  
Avg loss over last 500 updates: 2.109152201652527  
Avg loss over last 500 updates: 1.7381675925254823  
Avg loss over last 500 updates: 1.759016581773758  
Avg loss over last 500 updates: 1.5086341819763183  
Avg loss over last 500 updates: 1.660850250005722  
Avg evaluation loss: 2.836272454857826  
processed 11170 tokens with 1231 phrases; found: 998 phrases; correct: 774.  
accuracy: 68.34%; (non-0)  
accuracy: 93.54%; precision: 77.56%; recall: 62.88%; FB1: 69.45  
LOC: precision: 87.33%; recall: 72.18%; FB1: 79.03 300  
MISC: precision: 82.79%; recall: 52.60%; FB1: 64.33 122  
ORG: precision: 69.74%; recall: 51.79%; FB1: 59.44 228  
PER: precision: 72.41%; recall: 68.29%; FB1: 70.29 348  
(77.55511022044088, 62.875710804224205, 69.44818304172274)

5 random evaluation samples:

SENT: <unk> <unk> ( 11th ) , <unk> <unk> ( <unk> and 51st ) , <unk> <unk>  
TRUE: I-PER I-PER 0 0 0 0 I-PER I-PER 0 0 0 0 0 0 I-PER I-PER  
PRED: I-PER I-PER 0 0 0 0 I-PER I-PER 0 0 0 0 0 0 I-PER I-PER  
SENT: PRESS DIGEST - <unk> - AUG 0000 .  
TRUE: 0 0 0 I-LOC 0 0 0 0  
PRED: 0 0 0 0 0 0 0 0  
SENT: 0000 GMT  
TRUE: 0 I-MISC  
PRED: 0 I-MISC  
SENT: <unk> <unk> <unk> ( <unk> ) <unk> <unk> <unk> US / UK / <unk>  
TRUE: I-ORG 0 0 0 0 0 0 0 0 I-LOC 0 I-LOC 0 I-LOC  
PRED: 0 I-PER I-PER 0 0 0 0 0 0 I-ORG I-ORG I-ORG 0 0  
SENT: According to a new release from the governor , Wisconsin submitted a plan to the U.  
S. Department of <unk> and Human <unk> for administration of the new block <unk> system fo  
r welfare just minutes after President Bill Clinton signed the <unk> into law Thursday .  
TRUE: 0 0 0 0 0 0 0 0 0 0 I-LOC 0 0 0 0 0 0 I-ORG I-ORG I-ORG I-ORG I-ORG I-ORG I-ORG I-ORG 0 0 0 0  
0 0 0 0 0 0 0 0 0 0 I-PER I-PER 0 0 0 0 0 0 0  
PRED: 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 I-LOC I-LOC I-LOC 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0  
I-PER I-PER 0 0 0 0 0 0 0  
--- EPOCH 4 ---

Avg loss over last 500 updates: 1.5034452352523804  
Avg loss over last 500 updates: 1.678650174856186  
Avg loss over last 500 updates: 1.4139041152000427  
Avg loss over last 500 updates: 1.360803474187851  
Avg loss over last 500 updates: 1.212214565515518  
Avg loss over last 500 updates: 1.384278891801834  
Avg evaluation loss: 2.74378400683403  
processed 11170 tokens with 1231 phrases; found: 1022 phrases; correct: 779.  
accuracy: 69.33%; (non-0)  
accuracy: 93.52%; precision: 76.22%; recall: 63.28%; FB1: 69.15  
LOC: precision: 88.82%; recall: 74.38%; FB1: 80.96 304  
MISC: precision: 80.83%; recall: 50.52%; FB1: 62.18 120  
ORG: precision: 63.71%; recall: 53.75%; FB1: 58.30 259  
PER: precision: 72.86%; recall: 66.94%; FB1: 69.77 339

(76.22309197651663, 63.28188464662876, 69.15224145583666)

5 random evaluation samples:

SENT: -DOCSTART-

TRUE: O

PRED: O

SENT: 4. <unk> <unk> ( Kenya ) <unk>

TRUE: O I-PER I-PER O I-LOC O O

PRED: O I-PER I-PER O I-LOC O O

SENT: The Greek <unk> party 's executive bureau gave the <unk> light to Prime Minister <unk> <unk> to call <unk> elections , its general secretary <unk> <unk> told reporters .

TRUE: O I-MISC O O O O O O O O O O O I-PER I-PER O O O O O O O I-PER I-PER O O O

PRED: O I-MISC I-ORG I-ORG O O O O O O O O O O I-PER I-PER O O O O O O O O I-PER I-PER O O O

SENT: <unk> <unk> <unk> ( Netherlands ) <unk> <unk>

TRUE: O I-PER I-PER O I-LOC O I-ORG O

PRED: I-PER I-PER I-PER O I-LOC O O O

SENT: -DOCSTART-

TRUE: O

PRED: O

--- EPOCH 5 ---

Avg loss over last 500 updates: 1.2795283374786377

Avg loss over last 500 updates: 1.375453113079071

Avg loss over last 500 updates: 1.215940806388855

Avg loss over last 500 updates: 1.3309865157604217

Avg loss over last 500 updates: 1.002288314819336

Avg loss over last 500 updates: 1.19175581741333

Avg evaluation loss: 2.8216698206961155

processed 11170 tokens with 1231 phrases; found: 1069 phrases; correct: 796.

accuracy: 71.53%; (non-O)

accuracy: 93.50%; precision: 74.46%; recall: 64.66%; FB1: 69.22

LOC: precision: 87.54%; recall: 71.63%; FB1: 78.79 297

MISC: precision: 77.52%; recall: 52.08%; FB1: 62.31 129

ORG: precision: 62.85%; recall: 58.96%; FB1: 60.84 288

PER: precision: 71.83%; recall: 69.11%; FB1: 70.44 355

(74.4621141253508, 64.66287571080423, 69.21739130434783)

5 random evaluation samples:

SENT: First Union National Bank of <unk> <unk> suit .

TRUE: I-ORG I-ORG I-ORG I-ORG I-ORG I-ORG O O O

PRED: I-ORG I-ORG I-ORG I-ORG I-ORG I-ORG I-ORG O O

SENT: He spent a year under house arrest and was tried but <unk> last year on charges of ordering the murder of four <unk> in 0000 .

TRUE: O

PRED: O

SENT: Waqar Younis <unk> <unk> b Harris 0000

TRUE: I-PER I-PER O I-PER O I-PER O

PRED: I-PER I-PER I-PER I-PER O I-PER O

SENT: The <unk> are July <unk> , and the final September <unk> 0000 .

TRUE: O O O O O O O O O O O O O

PRED: O O O O O O O O O O I-ORG O O

SENT: Rangers 0000 <unk> United 0000

TRUE: I-ORG O I-ORG I-ORG O

PRED: I-ORG O I-ORG I-ORG O

--- EPOCH 6 ---

Avg loss over last 500 updates: 1.0786786432266235

Avg loss over last 500 updates: 1.2349101711511612

Avg loss over last 500 updates: 1.1458699822425842

Avg loss over last 500 updates: 1.0566541259288789

Avg loss over last 500 updates: 0.9335016398429871

Avg loss over last 500 updates: 1.1129399638175965

Avg evaluation loss: 2.930451305359602

processed 11170 tokens with 1231 phrases; found: 1090 phrases; correct: 818.

accuracy: 71.59%; (non-O)

accuracy: 93.78%; precision: 75.05%; recall: 66.45%; FB1: 70.49

LOC: precision: 88.82%; recall: 74.38%; FB1: 80.96 304



Avg loss over last 500 updates: 0.6583041189908981  
Avg loss over last 500 updates: 0.8643292055130005  
Avg evaluation loss: 3.1224144876003264  
processed 11170 tokens with 1231 phrases; found: 1077 phrases; correct: 819.  
accuracy: 71.81%; (non-O)  
accuracy: 93.95%; precision: 76.04%; recall: 66.53%; FB1: 70.97  
LOC: precision: 88.54%; recall: 76.58%; FB1: 82.13 314  
MISC: precision: 81.89%; recall: 54.17%; FB1: 65.20 127  
ORG: precision: 64.64%; recall: 58.96%; FB1: 61.67 280  
PER: precision: 71.91%; recall: 69.38%; FB1: 70.62 356  
(76.04456824512535, 66.53127538586516, 70.97053726169842)

5 random evaluation samples:

SENT: Martin <unk> , <unk> <unk> ( Sweden )  
TRUE: I-PER I-PER O I-PER I-PER O I-LOC O  
PRED: I-PER I-PER O I-PER I-PER O I-LOC O  
SENT: The court <unk> <unk> 's <unk> that <unk> 's <unk> from Denmark , where he was arrested in March last year at the request of German authorities , was illegal .  
TRUE: O O O I-PER O O O I-PER O O O I-LOC O O O O O O O O O O O O O I-MISC O O O O O  
PRED: O O O I-PER O O O I-ORG O O O I-LOC O O O O O O O O O O O O O I-MISC O O O O O  
SENT: <unk>  
TRUE: O  
PRED: O  
SENT: -DOCSTART-  
TRUE: O  
PRED: O  
SENT: An <unk> of <unk> has killed five people in the central Senegal town of <unk> , where health authorities have <unk> 0000 cases since August 0000 , a medical official said on Thursday .  
TRUE: O O O O O O O O O O O I-LOC O O I-LOC O O O O O O O O O O O O O O O O O O O  
PRED: O O O O O O O O O O O I-LOC O O I-LOC O O O O O O O O O O O O O O O O O O O  
--- EPOCH 9 ---

Avg loss over last 500 updates: 0.7717373546361923  
Avg loss over last 500 updates: 0.929089684009552  
Avg loss over last 500 updates: 0.8032551293373108  
Avg loss over last 500 updates: 0.8174836456775665  
Avg loss over last 500 updates: 0.612529159784317  
Avg loss over last 500 updates: 0.8102035324573517  
Avg evaluation loss: 3.0575619511306287  
processed 11170 tokens with 1231 phrases; found: 1133 phrases; correct: 835.  
accuracy: 74.61%; (non-O)  
accuracy: 93.97%; precision: 73.70%; recall: 67.83%; FB1: 70.64  
LOC: precision: 89.39%; recall: 76.58%; FB1: 82.49 311  
MISC: precision: 73.38%; recall: 53.12%; FB1: 61.63 139  
ORG: precision: 67.88%; recall: 60.59%; FB1: 64.03 274  
PER: precision: 65.77%; recall: 72.90%; FB1: 69.15 409  
(73.6981465136805, 67.83103168155971, 70.64297800338409)

5 random evaluation samples:

SENT: Standings ( tabulated under played , won , drawn , lost , goals  
TRUE: O O O O O O O O O O O O O O  
PRED: O O O O O O O O O O O O O O  
SENT: PARIS 1996-08-23  
TRUE: I-LOC O  
PRED: I-LOC O  
SENT: The PKK also <unk> into Turkey from <unk> in the <unk> of northern Iraq .  
TRUE: O I-ORG O O O I-LOC O O O O O O O I-LOC O  
PRED: O I-ORG O O O I-LOC O O O O O O O I-LOC O  
SENT: <unk> - <unk> <unk> figures <unk> to value of orders on books at end of period .  
TRUE: O O O O O O O O O O O O O O O O  
PRED: O O I-PER O O O O O O O O O O O O O  
SENT: 5. Steve Brown ( U.S. ) <unk>  
TRUE: O I-PER I-PER O I-LOC O O  
PRED: O I-PER I-PER O I-LOC O O  
--- EPOCH 10 ---  
Avg loss over last 500 updates: 0.6969414043426514

Avg loss over last 500 updates: 0.8385431489944458  
 Avg loss over last 500 updates: 0.7882229256629943  
 Avg loss over last 500 updates: 0.7522817523479461  
 Avg loss over last 500 updates: 0.6692605974674225  
 Avg loss over last 500 updates: 0.6750851354598999  
 Avg evaluation loss: 3.185546517819166  
 processed 11170 tokens with 1231 phrases; found: 1149 phrases; correct: 854.  
 accuracy: 74.83%; (non-O)  
 accuracy: 94.08%; precision: 74.33%; recall: 69.37%; FB1: 71.76  
     LOC: precision: 87.62%; recall: 77.96%; FB1: 82.51 323  
     MISC: precision: 80.45%; recall: 55.73%; FB1: 65.85 133  
     ORG: precision: 68.73%; recall: 61.56%; FB1: 64.95 275  
     PER: precision: 65.79%; recall: 74.53%; FB1: 69.89 418  
 (74.325500435161, 69.37449228269699, 71.76470588235294)

5 random evaluation samples:

SENT: SOCCER - <unk> <unk> <unk> <unk> <unk> MANCHESTER <unk> .  
 TRUE: O O I-PER O O O O I-LOC I-LOC O  
 PRED: O O I-ORG I-ORG I-ORG I-ORG I-ORG O O O  
 SENT: India <unk> <unk> ' 0000 sales , output up .  
 TRUE: I-LOC I-ORG O O O O O O O O  
 PRED: I-LOC O I-PER O O O O O O O  
 SENT: Newmont , in fact , will not <unk> from the Santa Fe acquisition on an earnings basi  
 s for at least two years , which also <unk> its <unk> to <unk> its offer .  
 TRUE: I-ORG O O O O O O O O O I-ORG I-ORG O O O O O O O O O O O O O O O O O O O  
 PRED: I-PER O O O O O O O O O I-ORG I-ORG O O O O O O O O O O O O O O O O O O O  
 SENT: -DOCSTART-  
 TRUE: O  
 PRED: O  
 SENT: Fox said the British government wanted an end to the alleged <unk> of its <unk> at D  
 haka airport by customs officials .  
 TRUE: I-PER O O I-MISC O O O O O O O O O O O O I-LOC O O O O O  
 PRED: I-PER O O I-MISC O O O O O O O O O O O O I-LOC O O O O O  
 --- EPOCH 11 ---  
 Avg loss over last 500 updates: 0.6967372241020202  
 Avg loss over last 500 updates: 0.7907397847175598  
 Avg loss over last 500 updates: 0.6878003034591674  
 Avg loss over last 500 updates: 0.657532648563385  
 Avg loss over last 500 updates: 0.556335406780243  
 Avg loss over last 500 updates: 0.6988385837078095  
 Avg evaluation loss: 3.116869171112776  
 processed 11170 tokens with 1231 phrases; found: 1140 phrases; correct: 846.  
 accuracy: 74.78%; (non-O)  
 accuracy: 94.00%; precision: 74.21%; recall: 68.72%; FB1: 71.36  
     LOC: precision: 89.69%; recall: 79.06%; FB1: 84.04 320  
     MISC: precision: 79.70%; recall: 55.21%; FB1: 65.23 133  
     ORG: precision: 59.42%; recall: 59.61%; FB1: 59.51 308  
     PER: precision: 71.24%; recall: 73.17%; FB1: 72.19 379  
 (74.21052631578947, 68.72461413484972, 71.3622943905525)

5 random evaluation samples:

SENT: 5. <unk> <unk> ( Russia ) <unk>  
 TRUE: O I-PER I-PER O I-LOC O O  
 PRED: O I-PER I-PER O I-LOC O O  
 SENT: Hong Kong 's Tsang sees growth , <unk> <unk> .  
 TRUE: I-LOC I-LOC O I-PER O O O O O O  
 PRED: I-LOC I-LOC O O O O O O O O  
 SENT: Moslem <unk> <unk> 0000 <unk> - agency .  
 TRUE: I-MISC O O O I-MISC O O O  
 PRED: I-MISC O O O O O O O  
 SENT: A hijacked Sudan Airways plane with 0000 passengers and crew on board was expected t  
 o land at London 's Stansted airport later on Tuesday morning , a police spokeswoman said  
 .  
 TRUE: O O I-ORG I-ORG O O O O O O O O O O O O I-LOC O I-LOC O O O O O O O O O O  
 PRED: O O I-ORG I-ORG O O O O O O O O O O O O I-LOC O I-LOC O O O O O O O O O O  
 SENT: 6. Michael <unk> ( U.S. ) <unk>

TRUE: O I-PER I-PER O I-LOC O O

PRED: O I-PER I-PER O I-LOC O O

--- EPOCH 12 ---

Avg loss over last 500 updates: 0.5625160057544708

Avg loss over last 500 updates: 0.688736927986145

Avg loss over last 500 updates: 0.658545393705368

Avg loss over last 500 updates: 0.624279503583908

Avg loss over last 500 updates: 0.5952160804271698

Avg loss over last 500 updates: 0.6750965361595154

Avg evaluation loss: 3.2722255070507527

processed 11170 tokens with 1231 phrases; found: 1120 phrases; correct: 838.

accuracy: 72.85%; (non-O)

accuracy: 94.06%; precision: 74.82%; recall: 68.07%; FB1: 71.29

LOC: precision: 88.24%; recall: 78.51%; FB1: 83.09 323

MISC: precision: 77.54%; recall: 55.73%; FB1: 64.85 138

ORG: precision: 65.31%; recall: 57.65%; FB1: 61.25 271

PER: precision: 69.33%; recall: 72.90%; FB1: 71.07 388

(74.82142857142857, 68.07473598700243, 71.28881327094852)

5 random evaluation samples:

SENT: <unk> <unk>

TRUE: I-ORG I-ORG

PRED: O O

SENT: He has since named a prime minister for the first time since early in his rule and ordered a crackdown on <unk> .

TRUE: O

PRED: O

SENT: <unk> ( <unk> <unk> ) <unk> 0000

TRUE: O O O O O O O

PRED: I-ORG O I-ORG I-ORG O I-ORG O

SENT: U.S. debt futures finished a <unk> <unk> session sharply lower , as the markets were <unk> by a stronger than expected rise in the August National Association of <unk> <unk> ( <unk> ) index for the Chicago area , traders and analysts said .

TRUE: I-LOC O I-ORG I-ORG I-ORG I-ORG I-ORG  
O I-ORG O O O O I-LOC O O O O O O O

PRED: I-LOC O I-ORG I-ORG I-ORG I-ORG I-ORG  
O I-ORG O O O O I-LOC O O O O O O O

SENT: The PKK also <unk> into Turkey from <unk> in the <unk> of northern Iraq .

TRUE: O I-ORG O O O I-LOC O O O O O O O I-LOC O

PRED: O I-ORG O O O I-LOC O O O O O O O I-LOC O

--- EPOCH 13 ---

Avg loss over last 500 updates: 0.5624189565181732

Avg loss over last 500 updates: 0.6365453751087189

Avg loss over last 500 updates: 0.5754836969375611

Avg loss over last 500 updates: 0.603867014169693

Avg loss over last 500 updates: 0.4931268653869629

Avg loss over last 500 updates: 0.6459541335105896

Avg evaluation loss: 3.4159583427011966

processed 11170 tokens with 1231 phrases; found: 1191 phrases; correct: 856.

accuracy: 75.77%; (non-O)

accuracy: 93.77%; precision: 71.87%; recall: 69.54%; FB1: 70.69

LOC: precision: 90.42%; recall: 77.96%; FB1: 83.73 313

MISC: precision: 70.32%; recall: 56.77%; FB1: 62.82 155

ORG: precision: 60.19%; recall: 60.59%; FB1: 60.39 309

PER: precision: 67.15%; recall: 75.34%; FB1: 71.01 414

(71.87237615449203, 69.53696181965881, 70.68538398018167)

5 random evaluation samples:

SENT: 6. Michael <unk> ( U.S. ) <unk>

TRUE: O I-PER I-PER O I-LOC O O

PRED: O I-PER I-PER O I-LOC O O

SENT: NEW YORK 1996-08-23

TRUE: I-LOC I-LOC O

PRED: I-LOC I-LOC O

SENT: -DOCSTART-

TRUE: O



PRED: I-PER O  
SENT: BEIJING 1996-12-06  
TRUE: I-LOC O  
PRED: I-LOC O  
SENT: <unk>  
TRUE: O  
PRED: O  
SENT: Tottenham 0000 0000 0000 0000 0000 0000 0000  
TRUE: I-ORG O O O O O O O  
PRED: I-ORG O O O O O O O  
--- EPOCH 16 ---

Avg loss over last 500 updates: 0.5316154316663743  
Avg loss over last 500 updates: 0.5638617334365845  
Avg loss over last 500 updates: 0.6231105732917785  
Avg loss over last 500 updates: 0.4700705800056458  
Avg loss over last 500 updates: 0.37194175958633424  
Avg loss over last 500 updates: 0.5451498885154724  
Avg evaluation loss: 3.425596902668476  
processed 11170 tokens with 1231 phrases; found: 1161 phrases; correct: 863.  
accuracy: 75.22%; (non-O)  
accuracy: 94.22%; precision: 74.33%; recall: 70.11%; FB1: 72.16  
LOC: precision: 89.66%; recall: 78.79%; FB1: 83.87 319  
MISC: precision: 79.26%; recall: 55.73%; FB1: 65.44 135  
ORG: precision: 60.06%; recall: 62.21%; FB1: 61.12 318  
PER: precision: 71.72%; recall: 75.61%; FB1: 73.61 389  
(74.33247200689061, 70.10560519902518, 72.1571906354515)

5 random evaluation samples:

SENT: SOCCER - PSV BEAT <unk> <unk> TO <unk> <unk> FROM <unk> .  
TRUE: O O I-ORG O I-ORG O O O O O I-ORG O  
PRED: O O I-ORG O I-ORG I-ORG O I-ORG O O O O  
SENT: " The plant is <unk> as <unk> , " Jose <unk> <unk> , director of <unk> , told Spanish state television .  
TRUE: O O O O O O O O O I-PER I-PER I-PER O O O O O O I-MISC O O O  
PRED: O O O O O O O O O I-PER I-PER I-PER O O O I-ORG O O I-MISC O O O  
SENT: -DOCSTART-  
TRUE: O  
PRED: O  
SENT: <unk> sources said feed <unk> demand was keeping <unk> with <unk> production and driving prices higher .  
TRUE: I-LOC O O O O O O O O O O O O O O O O  
PRED: O O O O O O O O O O O O O O O O  
SENT: CRICKET - ENGLAND <unk> <unk> FOR ONE-DAY <unk> .  
TRUE: O O I-LOC O O O O O O  
PRED: O O I-LOC O I-ORG O O O O  
--- EPOCH 17 ---

Avg loss over last 500 updates: 0.4674039533138275  
Avg loss over last 500 updates: 0.5557696592807769  
Avg loss over last 500 updates: 0.48278678131103514  
Avg loss over last 500 updates: 0.48371106362342836  
Avg loss over last 500 updates: 0.4126667063236237  
Avg loss over last 500 updates: 0.5237756986618042  
Avg evaluation loss: 3.558134785890579  
processed 11170 tokens with 1231 phrases; found: 1193 phrases; correct: 863.  
accuracy: 74.67%; (non-O)  
accuracy: 93.91%; precision: 72.34%; recall: 70.11%; FB1: 71.20  
LOC: precision: 86.14%; recall: 80.44%; FB1: 83.19 339  
MISC: precision: 72.67%; recall: 56.77%; FB1: 63.74 150  
ORG: precision: 62.79%; recall: 61.56%; FB1: 62.17 301  
PER: precision: 67.74%; recall: 73.98%; FB1: 70.73 403  
(72.33864207879296, 70.10560519902518, 71.2046204620462)

5 random evaluation samples:

SENT: June <unk> v British <unk> ( at Oxford , three days )  
TRUE: O O O I-ORG I-ORG O O I-LOC O O O O  
PRED: O I-ORG O I-ORG I-ORG O O I-LOC O O O O



SENT: <unk> 0000 0000 0000 0000 0000 0000  
 TRUE: I-ORG O O O O O O O  
 PRED: I-ORG O O O O O O O  
 SENT: From central Texas north to Kansas , <unk> throughout July and August have <unk> most of the <unk> conditions that <unk> the region earlier this year .  
 TRUE: O O I-LOC O O I-LOC O  
 PRED: O O I-LOC O O I-LOC O  
 SENT: There is nothing left for us but to be <unk> to <unk> for <unk> <unk> , " <unk> <unk> > said .  
 TRUE: O O O O O O O O O O O O O O O O O I-ORG I-ORG O O  
 PRED: O O O O O O O O O O O O O O O O O I-PER I-PER O O  
 SENT: Pakistani bourse to use new <unk> index .  
 TRUE: I-MISC O O O O O O O  
 PRED: I-MISC O O O O I-MISC O O  
 --- EPOCH 18 ---  
 Avg loss over last 500 updates: 0.4740509853363037  
 Avg loss over last 500 updates: 0.5172397384643554  
 Avg loss over last 500 updates: 0.5227785496711731  
 Avg loss over last 500 updates: 0.4226785435676575  
 Avg loss over last 500 updates: 0.39808293783664706  
 Avg loss over last 500 updates: 0.5073284511566162  
 Avg evaluation loss: 3.69926515892148  
 processed 11170 tokens with 1231 phrases; found: 1215 phrases; correct: 870.  
 accuracy: 76.10%; (non-O)  
 accuracy: 93.84%; precision: 71.60%; recall: 70.67%; FB1: 71.14  
     LOC: precision: 88.34%; recall: 79.34%; FB1: 83.60 326  
     MISC: precision: 74.31%; recall: 55.73%; FB1: 63.69 144  
     ORG: precision: 60.75%; recall: 63.52%; FB1: 62.10 321  
     PER: precision: 66.04%; recall: 75.88%; FB1: 70.62 424  
 (71.60493827160494, 70.67424857839156, 71.13654946852003)

5 random evaluation samples:

SENT: The <unk> parliament failed for a third and final time to elect a new state president on Tuesday , refusing a second mandate for <unk> <unk> Meri .  
 TRUE: O I-MISC O I-PER I-PER O  
 PRED: O I-PER O  
 SENT: Russian and rebel military <unk> finally met in Chechnya on Tuesday for delayed talks aimed at <unk> a ceasefire <unk> last week by President <unk> Yeltsin 's <unk> Alexander Lebed .  
 TRUE: I-MISC O O O O O O O I-LOC O O O O O O O O O O O O O O I-PER I-PER O O I-PER I-PER O  
 PRED: I-MISC O O O O O O O I-LOC O O O O O O O O O O O O O O I-PER I-PER O I-PER I-PER I-PER O  
 SENT: -- New York <unk> <unk> <unk> 0000 0000 0000  
 TRUE: O I-ORG I-ORG I-ORG I-ORG O O O O  
 PRED: O I-ORG I-ORG I-ORG I-ORG I-ORG O O O  
 SENT: -DOCSTART-  
 TRUE: O  
 PRED: O  
 SENT: <unk>  
 TRUE: O  
 PRED: O

--- EPOCH 19 ---  
 Avg loss over last 500 updates: 0.38547558069229126  
 Avg loss over last 500 updates: 0.47908888721466064  
 Avg loss over last 500 updates: 0.434932984828949  
 Avg loss over last 500 updates: 0.4043343040943146  
 Avg loss over last 500 updates: 0.32861188769340516  
 Avg loss over last 500 updates: 0.38310386300086974  
 Avg evaluation loss: 3.961290597617626  
 processed 11170 tokens with 1231 phrases; found: 1235 phrases; correct: 876.  
 accuracy: 76.98%; (non-O)  
 accuracy: 93.79%; precision: 70.93%; recall: 71.16%; FB1: 71.05  
     LOC: precision: 90.31%; recall: 79.61%; FB1: 84.63 320  
     MISC: precision: 71.62%; recall: 55.21%; FB1: 62.35 148  
     ORG: precision: 65.31%; recall: 62.54%; FB1: 63.89 294

```
PER: precision: 61.10%; recall: 78.32%; FB1: 68.65 473
(70.93117408906883, 71.16165718927701, 71.04622871046229)
```

5 random evaluation samples:

SENT: The <unk> of his other <unk> <unk> as " In the Year of January " ( 0000 ) , " The <unk> " ( 0000 ) , " <unk> <unk> " ( 0000 ) , " The <unk> <unk> " ( 0000 ) and " A World of <unk> " ( 0000 ) , followed by " The <unk> , " " <unk> <unk> " and , most recently , " A <unk> . "

```

TRUE: 0 0 0 0 0 0 0 0 0 0 I-MISC I-MISC I-MISC I-MISC I-MISC 0 0 0 0 0 0 I-MISC I-MISC 0 0 0
0 0 0 I-MISC I-MISC 0 0 0 0 0 0 I-MISC I-MISC I-MISC 0 0 0 0 0 0 I-MISC I-MISC I-MISC I-MI
SC 0 0 0 0 0 0 0 0 0 I-MISC I-MISC 0 0 0 I-MISC I-MISC 0 0 0 0 0 0 0 I-MISC I-MISC 0 0
PRED: 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 I-PER I-PER 0 0 0 0 0 0 0 I-
ORG I-ORG 0 0 0 0 0 0 0 0 0 I-MISC 0 0 0 0 0 0 0 0 0 0 0 0 0 I-MISC I-MISC 0 0 0 0 0 0 0 0
0 0 0

```

SENT: Summary of game played in the Spanish first division on Saturday : <unk> <unk> 0000  
( <unk> <unk> , <unk> minute ) Real Madrid 0000 ( <unk> Carlos <unk> ) .

TRUE: 0 0 0 0 0 0 I-MISC 0 I-MISC 0 0 0 I-ORG I-ORG 0 0 I-PER I-PER 0 0 0 0 I-ORG I-ORG 0  
0 I-PER I-PER 0 0 0

PRED: 0 0 0 0 0 0 I-MISC 0 0 0 0 0 I-PER I-PER 0 0 I-PER I-PER 0 I-PER 0 0 I-ORG I-ORG 0 0  
I-PER I-PER 0 0 0

SENT: Brazil - Giovanni ( <unk> ) , <unk> <unk> ( <unk> )

TRUE: I-LOC 0 I-PER 0 0 0 0 I-PER I-PER 0 0 0

PRED: I-LOC 0 I-PER 0 0 0 0 I-PER I-PER 0 I-ORG 0

SENT: <unk> 0000 0000 0000 0000 0000 0000 0000

TRUE: I-ORG 0 0 0 0 0 0 0

PRED: I-ORG 0 0 0 0 0 0 0

SENT: CRICKET - SRI LANKA BEAT <unk> <unk> 0000 <unk> IN ONE-DAY MATCH .

```
TRUE: 0 0 I-LOC I-LOC 0 I-LOC 0 0 0 0 0 0 0
```

PRED: 0 0 I-LOC I-LOC 0 I-ORG I-ORG 0 0 0 0 0 0

--- EPOCH 20 ---

Avg loss over last 500 updates: 0.48135097217559814

Avg loss over last 500 updates: 0.4950535833835602

Avg loss over last 500 updates: 0.5244938030242919

Avg loss over last 500 updates: 0.378475266456604

Avg loss over last 500 updates: 0.3657068989276886

Avg loss over last 500 updates: 0.47909418869018555

Avg evaluation loss: 3.67012115880847

```
processed 11170 tokens with 1231 phrases; found: 1194 phrases; correct: 858.
```

accuracy: 75.11%; (non-0)

accuracy: 93.75%; precision: 71.86%; recall: 69.70%; FB1: 70.76

LOC: precision: 86.63%; recall: 78.51%; FB1: 82.37 329

MISC: precision: 72.48%; recall: 56.25%; FB1: 63.34 149

ORG: precision: 60.56%; recall: 63.52%; FB1: 62.00 322

PER: precision: 68.53%; recall: 73.17%; FB1: 70.77 394

(71.85929648241206, 69.69943135662064, 70.76288659793815)

5 random evaluation samples:

SENT: A South African boy is writing back to an American girl whose message in a <unk> he found <unk> up on President Nelson <unk> 's <unk> prison island .

TRUE: 0 I-MISC I-MISC 0 0 0 0 0 0 I-MISC 0 0 0 0 0 0 0 0 0 0 0 0 I-PER I-PER 0 0 0 0 0

PRED: 0 I-MISC I-MISC 0 0 0 0 0 0 I-ORG 0 0 0 0 0 0 0 0 0 0 I-PER I-PER 0 I-MISC 0 0 0

SENT: <unk> <unk> 0000 - <unk> 0000 : <unk> of <unk> at \$ <unk> , 10,000 of <unk> at \$ <unk> , <unk> of <unk> at \$ <unk> .

TRUE: 0

PRED: I-PER I-PER O O I-PER O

SENT: In an interview following its first-half results , which included a less <unk> forecast for the second half of this year than it had made in the past , Sir Colin <unk> said <unk> had taken defensive action to <unk> it from <unk> markets .

```
TRUE: 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 I-PER I-PER O I-ORG O O  
O O O O O O O O O
```

[illegible]

SENT: <unk> 's autonomy was <unk> in 0000 and Serb police forces <unk> down on Albanian pr  
otests .

TRUE: I-LOC 0 0 0 0 0 0 0 I-MISC 0 0 0 0 0 I-MISC 0 0

PRED: I-ORG 0 0 0 0 0 0 0 I-MISC 0 0 0 0 0 I-MISC 0 0

SENT: - <unk> 0000 down <unk>  
 TRUE: O I-LOC O O O  
 PRED: O I-PER O O O  
 --- EPOCH 21 ---  
 Avg loss over last 500 updates: 0.438204106092453  
 Avg loss over last 500 updates: 0.45517674469947816  
 Avg loss over last 500 updates: 0.400373046875  
 Avg loss over last 500 updates: 0.3606664307117462  
 Avg loss over last 500 updates: 0.3681542270183563  
 Avg loss over last 500 updates: 0.3900785427093506  
 Avg evaluation loss: 3.8932757551968096  
 processed 11170 tokens with 1231 phrases; found: 1214 phrases; correct: 868.  
 accuracy: 76.49%; (non-O)  
 accuracy: 93.97%; precision: 71.50%; recall: 70.51%; FB1: 71.00  
           LOC: precision: 88.41%; recall: 79.89%; FB1: 83.94 328  
           MISC: precision: 75.91%; recall: 54.17%; FB1: 63.22 137  
           ORG: precision: 58.66%; recall: 62.87%; FB1: 60.69 329  
           PER: precision: 66.90%; recall: 76.15%; FB1: 71.23 420  
 (71.49917627677101, 70.51177904142973, 71.00204498977506)

5 random evaluation samples:

SENT: \* <unk> <unk> lost <unk> percent to 0000 francs after a morning trading <unk> during which it said it had approved plans to buy out its <unk> percent owned transport unit <unk> <unk> <unk> ( <unk> ) and <unk> shareholders to <unk> their shares .

TRUE: O O I-ORG O I-ORG I-ORG I-ORG  
 O I-ORG O O O O O O O O O

PRED: O I-ORG I-ORG O I-ORG I-ORG I-ORG  
 O I-ORG O O I-ORG O O O O O O

SENT: 1. <unk> 0000

TRUE: O I-PER O

PRED: O I-PER O

SENT: In the <unk> , between 0000 to 0000 percent of the muscle <unk> in one group of <unk> > produced <unk> for two weeks before <unk> .

TRUE: O

PRED: O O O O O O O O O O O O O O O O O I-ORG O O O O O O O O

SENT: <unk> <unk> ( <unk> , <unk> , <unk> ) , <unk> <unk> ( <unk> ) , Petr

TRUE: I-PER I-PER O O O O O O O O I-PER I-PER O O O O I-PER

PRED: I-PER I-PER O O O O O O O O I-PER I-PER O I-ORG O O I-PER

SENT: What was its right ( to the money ) <unk> do not know , " Rosati told a news confere nce .

TRUE: O O O O O O O O O O O O O O O O I-PER O O O O O

PRED: O O O O O O O O O O O O O O O O I-PER O O O O O

--- EPOCH 22 ---

Avg loss over last 500 updates: 0.4492936780452728  
 Avg loss over last 500 updates: 0.3838615689277649  
 Avg loss over last 500 updates: 0.42850667905807494  
 Avg loss over last 500 updates: 0.3253185479640961  
 Avg loss over last 500 updates: 0.2941946313381195  
 Avg loss over last 500 updates: 0.4442888958454132  
 Avg evaluation loss: 3.8677443878352644  
 processed 11170 tokens with 1231 phrases; found: 1195 phrases; correct: 862.  
 accuracy: 75.55%; (non-O)  
 accuracy: 94.03%; precision: 72.13%; recall: 70.02%; FB1: 71.06  
           LOC: precision: 86.09%; recall: 80.17%; FB1: 83.02 338  
           MISC: precision: 72.86%; recall: 53.12%; FB1: 61.45 140  
           ORG: precision: 58.43%; recall: 63.19%; FB1: 60.72 332  
           PER: precision: 71.43%; recall: 74.53%; FB1: 72.94 385  
 (72.13389121338912, 70.02437043054427, 71.06347897774114)

5 random evaluation samples:

SENT: <unk> Gold Inc was up C\$ <unk> to C\$ <unk> in trading of <unk> shares , while <unk> Gold Corp gained C\$ <unk> to C\$ 0000 in volume of <unk> shares .

TRUE: I-ORG I-ORG I-ORG O O I-MISC O O I-MISC O O O O O O O O I-ORG I-ORG I-ORG O I-MISC O  
 O I-MISC O O O O O O O O

PRED: I-ORG I-ORG I-ORG O O I-MISC O O I-MISC O O O O O O O O I-ORG I-ORG I-ORG O I-MISC O  
 O I-MISC O O O O O O O O

SENT: Chesterfield 0000 <unk> 0000  
TRUE: I-ORG O I-ORG O  
PRED: I-ORG O I-ORG O  
SENT: -DOCSTART-  
TRUE: O  
PRED: O  
SENT: U.S. debt futures end lower , <unk> by Chicago <unk> .  
TRUE: I-LOC O O O O O O O I-LOC I-ORG O  
PRED: I-LOC O O O O O O O I-LOC O O  
SENT: - Pakistan <unk> <unk> tonnes of <unk> <unk> yellow <unk> from <unk> Inc for \$ <unk>  
per tonne , <unk> U.S. Gulf , agents for the <unk> said .  
TRUE: O I-LOC O O O O O O O O I-ORG I-ORG O O O O O O O I-LOC I-LOC O O O O O O O  
PRED: O I-LOC O O O O I-ORG I-ORG O O O I-ORG I-ORG O O O O O O O I-LOC I-LOC O O O O I-OR  
G O O

--- EPOCH 23 ---

Avg loss over last 500 updates: 0.37144859838485716  
Avg loss over last 500 updates: 0.38163819003105165  
Avg loss over last 500 updates: 0.4294299356937408  
Avg loss over last 500 updates: 0.2975582957267761  
Avg loss over last 500 updates: 0.28728287744522096  
Avg loss over last 500 updates: 0.3545259051322937  
Avg evaluation loss: 4.057561903223395  
processed 11170 tokens with 1231 phrases; found: 1185 phrases; correct: 870.  
accuracy: 75.61%; (non-O)  
accuracy: 94.06%; precision: 73.42%; recall: 70.67%; FB1: 72.02  
LOC: precision: 89.41%; recall: 79.06%; FB1: 83.92 321  
MISC: precision: 76.19%; recall: 58.33%; FB1: 66.08 147  
ORG: precision: 64.11%; recall: 59.93%; FB1: 61.95 287  
PER: precision: 66.74%; recall: 77.78%; FB1: 71.84 430  
(73.41772151898735, 70.67424857839156, 72.01986754966889)

5 random evaluation samples:

SENT: Poland 's Foreign Minister <unk> Rosati will visit Yugoslavia on September 0000 and  
0000 to revive a <unk> between the two governments which was <unk> <unk> in 0000 , <unk> n  
ews agency reported on Friday .  
TRUE: I-LOC O O O I-PER I-PER O O I-LOC O O O O O O O O O O O O O O O O O O O I-ORG O O  
O O O O  
PRED: I-LOC O O O I-PER I-PER O O I-LOC O O O O O O O O O O O O O O O O O O O I-ORG O O  
O O O O  
SENT: But about 0000 university students were still <unk> outside the <unk> of their <unk>  
, <unk> said .  
TRUE: O O O O O O O O O O O O O O O O O O  
PRED: O O O O O O O O O O O O O O O O I-PER O O  
SENT: <unk> , <unk> .  
TRUE: I-LOC O I-LOC O  
PRED: O O I-PER O  
SENT: Australia at South Africa  
TRUE: I-LOC O I-LOC I-LOC  
PRED: I-LOC O I-LOC I-LOC  
SENT: They said the index could also rise towards <unk> if the <unk> share prices <unk> bu  
yers .  
TRUE: O O O O O O O O O O O O O O O O O  
PRED: O O O O O O O O O O O O O O O O O

--- EPOCH 24 ---

Avg loss over last 500 updates: 0.36597043061256407  
Avg loss over last 500 updates: 0.45555487847328185  
Avg loss over last 500 updates: 0.40572158312797546  
Avg loss over last 500 updates: 0.3514133563041687  
Avg loss over last 500 updates: 0.3342776668071747  
Avg loss over last 500 updates: 0.3343775763511658  
Avg evaluation loss: 4.276873261034488  
processed 11170 tokens with 1231 phrases; found: 1245 phrases; correct: 870.  
accuracy: 75.99%; (non-O)  
accuracy: 93.63%; precision: 69.88%; recall: 70.67%; FB1: 70.27  
LOC: precision: 87.27%; recall: 79.34%; FB1: 83.12 330  
MISC: precision: 75.68%; recall: 58.33%; FB1: 65.88 148

ORG: precision: 63.61%; recall: 60.91%; FB1: 62.23 294  
PER: precision: 59.83%; recall: 76.69%; FB1: 67.22 473  
(69.87951807228916, 70.67424857839156, 70.27463651050081)

5 random evaluation samples:

SENT: But <unk> said it would be " <unk> " against the other <unk> if only Balkan planes were <unk> in .

TRUE: O I-PER O O O O O O O O O O O O I-LOC O O O O O

PRED: O I-ORG O O O O O O O O O O O O O O O O O O

SENT: NEW YORK 1996-08-22

TRUE: I-LOC I-LOC O

PRED: I-LOC I-LOC O

SENT: <unk> newspapers said the men had been <unk> against " strategic <unk> and <unk> <unk> " but gave no other details .

TRUE: I-ORG O

PRED: O

SENT: " Now many Russian banks are strong and can make various <unk> of money <unk> , while <unk> traders are being ousted by more <unk> ones .

TRUE: O O O I-MISC O

PRED: O O O I-MISC O O O O O O O O O O O O I-ORG O O O O O O O O

SENT: Jose <unk> <unk> , who had drawn up the bill .

TRUE: I-PER I-PER I-PER O O O O O O O O

PRED: I-PER I-PER I-PER O O O O O O O O

--- EPOCH 25 ---

Avg loss over last 500 updates: 0.39553758096694946

Avg loss over last 500 updates: 0.3998786451816559

Avg loss over last 500 updates: 0.40556255626678467

Avg loss over last 500 updates: 0.32037803483009336

Avg loss over last 500 updates: 0.29176287245750426

Avg loss over last 500 updates: 0.35602904987335204

Avg evaluation loss: 4.165012877732515

processed 11170 tokens with 1231 phrases; found: 1210 phrases; correct: 880.

accuracy: 76.05%; (non-O)

accuracy: 94.15%; precision: 72.73%; recall: 71.49%; FB1: 72.10

LOC: precision: 87.84%; recall: 79.61%; FB1: 83.53 329

MISC: precision: 79.14%; recall: 57.29%; FB1: 66.47 139

ORG: precision: 65.10%; recall: 63.19%; FB1: 64.13 298

PER: precision: 64.64%; recall: 77.78%; FB1: 70.60 444

(72.72727272727273, 71.48659626320065, 72.10159770585827)

5 random evaluation samples:

SENT: Roe said he was <unk> by his forecast of a <unk> billion <unk> net for 0000 .

TRUE: I-PER O O O O O O O O O O O O O O O O

PRED: I-PER O O O O O O O O O O O O O O O O

SENT: <unk> <unk> 0000 0000 0000 0000 0000 0000 0000

TRUE: I-ORG I-ORG O O O O O O O

PRED: I-ORG I-ORG O O O O O O O

SENT: The <unk> of his other <unk> <unk> as " In the Year of January " ( 0000 ) , " The <unk> " ( 0000 ) , " <unk> <unk> " ( 0000 ) , " The <unk> <unk> " ( 0000 ) and " A World of <unk> " ( 0000 ) , followed by " The <unk> , " " <unk> <unk> " and , most recently , " A <unk> . "

TRUE: O O O O O O O O I-MISC I-MISC I-MISC I-MISC I-MISC O O O O O O I-MISC I-MISC O O O  
O O O I-MISC I-MISC O O O O O O I-MISC I-MISC I-MISC O O O O O O I-MISC I-MISC I-MISC I-MISC  
SC O O O O O O O O I-MISC I-MISC O O O I-MISC I-MISC O O O O O O O I-MISC I-MISC O O

PRED: O I-PER I-PER O O O O O O O I-  
ORG I-ORG O I-MISC I-MISC O O O O O O O O O O  
O

SENT: <unk> 0000 0000 0000 0000 0000 0000 0000

TRUE: I-ORG O O O O O O O O

PRED: I-ORG O O O O O O O O

SENT: It was the second arms <unk> this week .

TRUE: O O O O O O O O O

PRED: O O O O O O O O O

--- EPOCH 26 ---

Avg loss over last 500 updates: 0.3498471896648407

Avg loss over last 500 updates: 0.37959309267997743

Avg loss over last 500 updates: 0.3461668291091919  
Avg loss over last 500 updates: 0.32090911626815793  
Avg loss over last 500 updates: 0.262311635017395  
Avg loss over last 500 updates: 0.3424121060371399  
Avg evaluation loss: 4.212019420862198  
processed 11170 tokens with 1231 phrases; found: 1243 phrases; correct: 860.  
accuracy: 75.72%; (non-O)  
accuracy: 93.69%; precision: 69.19%; recall: 69.86%; FB1: 69.52  
LOC: precision: 82.52%; recall: 79.34%; FB1: 80.90 349  
MISC: precision: 68.75%; recall: 57.29%; FB1: 62.50 160  
ORG: precision: 60.78%; recall: 60.59%; FB1: 60.69 306  
PER: precision: 64.49%; recall: 74.80%; FB1: 69.26 428  
(69.18744971842317, 69.86190089358246, 69.52303961196442)

5 random evaluation samples:

SENT: -DOCSTART-

TRUE: O

PRED: O

SENT: As a result of <unk> we are looking at <unk> <unk> more <unk> to see if the profit margins are <unk> enough to <unk> things like <unk> security . "

TRUE: O

PRED: O

SENT: No arrests had been made , a police spokesman said .

TRUE: O O O O O O O O O O O

PRED: O O O O O O O O O O O

SENT: <unk> Bremen 0000 <unk> <unk> 0000

TRUE: I-ORG I-ORG O I-ORG I-ORG O

PRED: I-ORG I-ORG O I-ORG I-ORG O

SENT: AUG 0000 <unk> 'S <unk> 0000 <unk> 0000 <unk>

TRUE: O O O O O O O O O

PRED: O O I-ORG I-ORG I-ORG O I-ORG O O

--- EPOCH 27 ---

Avg loss over last 500 updates: 0.3462287621498108

Avg loss over last 500 updates: 0.3938676681518555

Avg loss over last 500 updates: 0.3202833204269409

Avg loss over last 500 updates: 0.28946461629867554

Avg loss over last 500 updates: 0.3295359447002411

Avg loss over last 500 updates: 0.2931487522125244

Avg evaluation loss: 4.178279275149107

processed 11170 tokens with 1231 phrases; found: 1188 phrases; correct: 863.

accuracy: 75.11%; (non-O)

accuracy: 94.15%; precision: 72.64%; recall: 70.11%; FB1: 71.35

LOC: precision: 86.65%; recall: 80.44%; FB1: 83.43 337

MISC: precision: 71.24%; recall: 56.77%; FB1: 63.19 153

ORG: precision: 63.01%; recall: 59.93%; FB1: 61.44 292

PER: precision: 68.47%; recall: 75.34%; FB1: 71.74 406

(72.64309764309765, 70.10560519902518, 71.35179826374535)

5 random evaluation samples:

SENT: <unk> 0000 <unk> 0000

TRUE: I-ORG O I-ORG O

PRED: I-ORG O I-ORG O

SENT: <unk>

TRUE: O

PRED: O

SENT: <unk> AT SAN FRANCISCO

TRUE: I-ORG O I-LOC I-LOC

PRED: I-ORG O I-LOC I-LOC

SENT: ( Aug 0000 ) ( Jul 0000 )

TRUE: O O O O O O O O

PRED: O O O O O O O O

SENT: " We <unk> to start international telephone business as soon as possible , " a company official told Reuters .

TRUE: O O O O O O O O O O O O O O O O O I-ORG O

PRED: O O O O O O O O O O O O O O O O O I-ORG O

--- EPOCH 28 ---

Avg loss over last 500 updates: 0.31965131902694705  
 Avg loss over last 500 updates: 0.3676064219474792  
 Avg loss over last 500 updates: 0.32074091863632204  
 Avg loss over last 500 updates: 0.3590176103115082  
 Avg loss over last 500 updates: 0.28661622190475466  
 Avg loss over last 500 updates: 0.29312648105621336  
 Avg evaluation loss: 4.250497308522463  
 processed 11170 tokens with 1231 phrases; found: 1219 phrases; correct: 864.  
 accuracy: 75.39%; (non-O)  
 accuracy: 93.84%; precision: 70.88%; recall: 70.19%; FB1: 70.53  
           LOC: precision: 87.16%; recall: 80.44%; FB1: 83.67 335  
           MISC: precision: 68.15%; recall: 55.73%; FB1: 61.32 157  
           ORG: precision: 58.39%; recall: 61.24%; FB1: 59.78 322  
           PER: precision: 68.40%; recall: 75.07%; FB1: 71.58 405  
 (70.87776866283839, 70.18683996750609, 70.53061224489797)

5 random evaluation samples:

SENT: .  
 TRUE: O  
 PRED: O  
 SENT: From central Texas north to Kansas , <unk> throughout July and August have <unk> mos  
 t of the <unk> conditions that <unk> the region earlier this year .  
 TRUE: O O I-LOC O O I-LOC O  
 PRED: O O I-LOC I-LOC O I-LOC O  
 SENT: -DOCSTART-  
 TRUE: O  
 PRED: O  
 SENT: The <unk> parliament failed for a third and final time to elect a new state presiden  
 t on Tuesday , refusing a second mandate for <unk> <unk> Meri .  
 TRUE: O I-MISC O I-PER I-PER O  
 PRED: O I-PER O  
 SENT: In July , the average rate on a <unk> <unk> rate mortgage was <unk> percent , below  
 June 's <unk> percent but still higher than February 's <unk> percent , the report <unk> .  
 TRUE: O  
 PRED: O  
 --- EPOCH 29 ---

Avg loss over last 500 updates: 0.26736956453323363  
 Avg loss over last 500 updates: 0.3369770126342773  
 Avg loss over last 500 updates: 0.40757529354095456  
 Avg loss over last 500 updates: 0.29582179522514346  
 Avg loss over last 500 updates: 0.2658300094604492  
 Avg loss over last 500 updates: 0.31865103435516356  
 Avg evaluation loss: 4.538428762853146  
 processed 11170 tokens with 1231 phrases; found: 1176 phrases; correct: 867.  
 accuracy: 75.39%; (non-O)  
 accuracy: 94.17%; precision: 73.72%; recall: 70.43%; FB1: 72.04  
           LOC: precision: 88.41%; recall: 79.89%; FB1: 83.94 328  
           MISC: precision: 76.03%; recall: 57.81%; FB1: 65.68 146  
           ORG: precision: 65.14%; recall: 60.26%; FB1: 62.61 284  
           PER: precision: 67.22%; recall: 76.15%; FB1: 71.41 418  
 (73.72448979591837, 70.43054427294882, 72.03988367262153)

5 random evaluation samples:

SENT: <unk> 1996-08-27  
 TRUE: I-LOC O  
 PRED: I-LOC O  
 SENT: It is an <unk> of Clinton 's strategic planning as he <unk> into the <unk> drive for  
 the Nov. 0000 presidential election .  
 TRUE: O O O O O I-PER O O O O O O O O O O O O O O O O O  
 PRED: O O O O O I-PER O O O O O O O O O O O O O O O O O  
 SENT: LOS ANGELES 0000 0000 <unk> 0000  
 TRUE: I-ORG I-ORG O O O O  
 PRED: I-ORG I-ORG O O O O  
 SENT: After I won I <unk> I could give them a little <unk> . "  
 TRUE: O O O O O O O O O O O O O O O O O O  
 PRED: O O O O O O O O O O O O O O O O O O

SENT: GLASGOW 1996-12-07  
TRUE: I-LOC O  
PRED: I-LOC O  
Wall time: 2h 43s

```
In [12]: df = pd.DataFrame(columns = ['LOC_crf', 'MISC_crf', 'ORG_crf', 'PER_crf'])
```

```
In [45]: df = df.append({'LOC' : 83.94, 'MISC_crf' : 65.68, 'ORG_crf' : 62.61 , 'PER_crf':71.41 },  
                      ignore_index = True)
```

```
In [53]: df
```

```
Out[53]:
```

	MISC_crf	ORG_crf	PER_crf	LOC_crf
0	33.33	47.04	53.00	57.71
1	57.81	54.38	62.11	71.34
2	61.04	57.14	66.95	78.42
3	64.33	59.44	70.29	79.03
4	62.18	58.30	69.77	80.96
5	62.31	60.84	70.44	78.79
6	64.17	62.94	69.65	80.96
7	66.06	62.10	72.18	83.46
8	65.20	61.67	70.62	82.13
9	61.63	64.03	69.15	82.49
10	65.85	64.95	69.89	82.51
11	65.23	59.51	72.19	84.04
12	64.85	61.25	71.07	83.09
13	62.82	60.39	71.01	83.73
14	62.24	59.32	70.82	82.15
15	64.46	61.13	72.77	82.13
16	65.44	61.12	73.61	83.87
17	63.74	62.17	70.73	83.19
18	63.69	62.10	70.62	83.60
19	62.35	63.89	68.65	84.63
20	63.34	62.00	70.77	82.37
21	63.22	60.69	71.23	83.94
22	61.45	60.72	72.94	83.02
23	66.08	61.95	71.84	83.92
24	65.88	62.23	67.22	83.12
25	66.47	64.13	70.60	83.53
26	62.50	60.69	69.26	80.90



	MISC_crf	ORG_crf	PER_crf	LOC_crf
<b>27</b>	63.19	61.44	71.74	83.43
<b>28</b>	61.32	59.78	71.58	83.67
<b>29</b>	65.68	62.61	71.41	83.94

In [195...

```
%%time
# Train BiLSTM Tagger Baseline
#model = BiLSTMTagger3(len(word_vocab), tag_to_ix, 128, 256).to(device)
model2 = BiLSTMTagger(len(word_vocab), 8, 128, 256).to(device)
optimizer = optim.Adam(model2.parameters(), lr=1e-3)
train(model2, train_data, valid_data, word_vocab, label_vocab, epochs=30, log_interval=500)
```

```
hidden_dim: 256
target_size: 8
--- EPOCH 0 ---
Avg loss over last 500 updates: 9.207625520944596
Avg loss over last 500 updates: 8.203925667714328
Avg loss over last 500 updates: 6.6126301279459145
Avg loss over last 500 updates: 5.7041344931358475
Avg loss over last 500 updates: 4.952978737355676
Avg loss over last 500 updates: 5.1556796167618595
Avg evaluation loss: 4.763876983722221
processed 11170 tokens with 1231 phrases; found: 736 phrases; correct: 471.
accuracy: 43.17%; (non-O)
accuracy: 89.62%; precision: 63.99%; recall: 38.26%; FB1: 47.89
          LOC: precision: 79.33%; recall: 39.12%; FB1: 52.40 179
          MISC: precision: 64.41%; recall: 19.79%; FB1: 30.28 59
          ORG: precision: 63.10%; recall: 34.53%; FB1: 44.63 168
          PER: precision: 56.06%; recall: 50.14%; FB1: 52.93 330
(63.99456521739131, 38.26157595450853, 47.89018810371123)

5 random evaluation samples:
SENT: ( <unk> ) 7-6 ( 7-4 )
TRUE: O O O O O O O
PRED: O O O O O O O
SENT: 10. <unk> <unk> ( Italy ) <unk> <unk> <unk>
TRUE: O I-PER I-PER O I-LOC O I-MISC I-MISC O
PRED: O I-PER I-PER O I-LOC O O O O
SENT: <unk> tested positive for the <unk> <unk> after the fifth stage of the Tour , in whi
ch he finished third overall .
TRUE: I-PER O O O O O O O O O O I-MISC O O O O O O O O
PRED: O O O O O O O O O O O O O O O O O O O
SENT: <unk> league matches on Sunday :
TRUE: O O O O O O
PRED: O O O O O O
SENT: Hong Kong 's Tsang sees growth , <unk> <unk> .
TRUE: I-LOC I-LOC O I-PER O O O O O O
PRED: I-LOC I-LOC O O O O O O O O
--- EPOCH 1 ---
Avg loss over last 500 updates: 4.386172959215066
Avg loss over last 500 updates: 4.940935809938179
Avg loss over last 500 updates: 4.182841504598487
Avg loss over last 500 updates: 3.832591070348799
Avg loss over last 500 updates: 3.3322007677918517
Avg loss over last 500 updates: 3.5130282022433237
Avg evaluation loss: 3.758712802360669
processed 11170 tokens with 1231 phrases; found: 953 phrases; correct: 644.
accuracy: 58.87%; (non-O)
accuracy: 91.95%; precision: 67.58%; recall: 52.32%; FB1: 58.97
          LOC: precision: 86.25%; recall: 57.02%; FB1: 68.66 240
          MISC: precision: 71.00%; recall: 36.98%; FB1: 48.63 100
```

ORG: precision: 54.51%; recall: 47.23%; FB1: 50.61 266  
PER: precision: 63.69%; recall: 59.89%; FB1: 61.73 347  
(67.57607555089193, 52.31519090170593, 58.97435897435898)

5 random evaluation samples:

SENT: <unk> 0000 <unk> 0000  
TRUE: I-ORG O I-ORG O  
PRED: I-ORG O I-ORG O  
SENT: 0000 - <unk> <unk> ( South Africa ) beat Todd <unk>  
TRUE: O O I-PER I-PER O I-LOC I-LOC O O I-PER I-PER  
PRED: O O I-PER I-PER O I-LOC I-LOC O O I-PER I-PER  
SENT: <unk> win 2-1 on aggregate .  
TRUE: I-ORG O O O O O  
PRED: O O O O O O  
SENT: NEW YORK 1996-08-22  
TRUE: I-LOC I-LOC O  
PRED: I-LOC I-LOC O  
SENT: <unk> <unk> ISS <unk> <unk> PAY DATE <unk>  
TRUE: O O O O O O O O  
PRED: O O O O O O O O  
--- EPOCH 2 ---

Avg loss over last 500 updates: 3.224115241336611  
Avg loss over last 500 updates: 3.6249761232665914  
Avg loss over last 500 updates: 3.0132237215502156  
Avg loss over last 500 updates: 3.0386997171622117  
Avg loss over last 500 updates: 2.5953576887795027  
Avg loss over last 500 updates: 2.795695305746527  
Avg evaluation loss: 3.416785683650573  
processed 11170 tokens with 1231 phrases; found: 1034 phrases; correct: 714.  
accuracy: 64.54%; (non-O)  
accuracy: 92.85%; precision: 69.05%; recall: 58.00%; FB1: 63.05  
LOC: precision: 83.88%; recall: 63.09%; FB1: 72.01 273  
MISC: precision: 78.95%; recall: 46.88%; FB1: 58.82 114  
ORG: precision: 58.16%; recall: 53.42%; FB1: 55.69 282  
PER: precision: 63.29%; recall: 62.60%; FB1: 62.94 365  
(69.0522243713733, 58.001624695369614, 63.046357615894046)

5 random evaluation samples:

SENT: -DOCSTART-  
TRUE: O  
PRED: O  
SENT: <unk> police shot dead six <unk> suspects as they tried to escape from <unk> in the  
northern city of <unk> , the national news agency reported on Friday .  
TRUE: I-MISC O O O O O O O O O O O O O O O O O O I-LOC O O O O O O O O O  
PRED: O O O O O O O O O O O O O O O O O O I-LOC O O O O O O O O O  
SENT: At Leicester : <unk> drawn .  
TRUE: O I-LOC O O O O  
PRED: O O O O O O  
SENT: The defeat put the <unk> out of the <unk> Cup .  
TRUE: O O O O I-MISC O O O I-MISC I-MISC O  
PRED: O O O O O O O O O I-MISC O  
SENT: He walked three and struck out three in winning for the 10th time in his last 0000 <  
unk> .  
TRUE: O O O O O O O O O O O O O O O O O O  
PRED: O O O O O O O O O O O O O O O O O O  
--- EPOCH 3 ---

Avg loss over last 500 updates: 2.446811728320189  
Avg loss over last 500 updates: 2.8625406725368676  
Avg loss over last 500 updates: 2.3376253051262608  
Avg loss over last 500 updates: 2.487354991577225  
Avg loss over last 500 updates: 2.083202376675463  
Avg loss over last 500 updates: 2.253242397779996  
Avg evaluation loss: 3.172191244728601  
processed 11170 tokens with 1231 phrases; found: 1062 phrases; correct: 754.  
accuracy: 67.68%; (non-O)  
accuracy: 93.28%; precision: 71.00%; recall: 61.25%; FB1: 65.77

LOC: precision: 86.24%; recall: 70.80%; FB1: 77.76 298  
MISC: precision: 78.69%; recall: 50.00%; FB1: 61.15 122  
ORG: precision: 57.89%; recall: 53.75%; FB1: 55.74 285  
PER: precision: 66.11%; recall: 63.96%; FB1: 65.01 357  
(70.99811676082862, 61.25101543460602, 65.76537287396424)

5 random evaluation samples:

SENT: <unk> <unk> <unk>

TRUE: O O O

PRED: I-PER O O

SENT: Iran <unk> <unk> <unk> Iran

TRUE: I-MISC I-MISC O O I-LOC

PRED: I-LOC O O O I-LOC

SENT: for , against , points ) :

TRUE: O O O O O O O

PRED: O O O O O O O

SENT: <unk> , 0000 , had complained of lower back <unk> since a trip to Taiwan in May , wh  
en <unk> forced her to go to <unk> <unk> <unk> for an <unk> .

TRUE: I-PER O O O O O O O O O O O O I-LOC O O O O O O O O O O I-LOC I-LOC I-LOC O O O O

PRED: I-PER O

SENT: Russian and rebel military <unk> finally met in Chechnya on Tuesday for delayed talk  
s aimed at <unk> a ceasefire <unk> last week by President <unk> Yeltsin 's <unk> Alexander  
Lebed .

TRUE: I-MISC O O O O O O O I-LOC O O O O O O O O O O O O O O I-PER I-PER O O I-PER I-PER  
O

PRED: I-MISC O O O O O O O I-LOC O O O O O O O O O O O O O O I-PER I-PER O O I-PER I-PER  
O

--- EPOCH 4 ---

Avg loss over last 500 updates: 2.055506019696447

Avg loss over last 500 updates: 2.437038330635055

Avg loss over last 500 updates: 1.9619857788445643

Avg loss over last 500 updates: 2.0284820533829637

Avg loss over last 500 updates: 1.7362450845651989

Avg loss over last 500 updates: 1.9579637778124224

Avg evaluation loss: 3.126044884925497

processed 11170 tokens with 1231 phrases; found: 1070 phrases; correct: 781.

accuracy: 69.93%; (non-O)

accuracy: 93.72%; precision: 72.99%; recall: 63.44%; FB1: 67.88

LOC: precision: 87.12%; recall: 70.80%; FB1: 78.12 295

MISC: precision: 81.45%; recall: 52.60%; FB1: 63.92 124

ORG: precision: 59.53%; recall: 57.98%; FB1: 58.75 299

PER: precision: 69.60%; recall: 66.40%; FB1: 67.96 352

(72.99065420560747, 63.444354183590576, 67.88352890047807)

5 random evaluation samples:

SENT: The Civil War <unk> <unk> is mostly <unk> joined by students during the school year

.

TRUE: O I-ORG I-ORG I-ORG I-ORG O O O O O O O O O O O

PRED: O I-MISC O I-ORG I-ORG O O O O O O O O O O O

SENT: He said at one point during a press conference : " I have seen my <unk> ( party mana  
ger ) for next week which , of course , does n't mean very much to me now . "

TRUE: O

PRED: O

SENT: Leeds v Wimbledon

TRUE: I-ORG O I-ORG

PRED: I-ORG O I-ORG

SENT: <unk> <unk> <unk> <unk>

TRUE: O O O I-MISC

PRED: O O O O

SENT: JOHANNESBURG 1996-08-26

TRUE: I-LOC O

PRED: I-LOC O

--- EPOCH 5 ---

Avg loss over last 500 updates: 1.7986285788665484

Avg loss over last 500 updates: 2.064853647189681

Avg loss over last 500 updates: 1.7076912592592957

Avg loss over last 500 updates: 1.7689334122504206  
Avg loss over last 500 updates: 1.4995551668749731  
Avg loss over last 500 updates: 1.7255591286968157  
Avg evaluation loss: 3.187378549123059  
processed 11170 tokens with 1231 phrases; found: 1104 phrases; correct: 792.  
accuracy: 70.43%; (non-O)  
accuracy: 93.66%; precision: 71.74%; recall: 64.34%; FB1: 67.84  
LOC: precision: 86.56%; recall: 72.73%; FB1: 79.04 305  
MISC: precision: 80.30%; recall: 55.21%; FB1: 65.43 132  
ORG: precision: 60.76%; recall: 57.00%; FB1: 58.82 288  
PER: precision: 65.17%; recall: 66.94%; FB1: 66.04 379  
(71.73913043478261, 64.33793663688058, 67.8372591006424)

5 random evaluation samples:

SENT: <unk> <unk> ( U.S. ) beat <unk> <unk> ( Netherlands ) 5-7 6-3 6-3  
TRUE: I-PER I-PER O I-LOC O O I-PER I-PER O I-LOC O O O O  
PRED: I-PER I-PER O I-LOC O O I-PER I-PER O I-LOC O O O O  
SENT: <unk> 1996-08-25  
TRUE: I-LOC O  
PRED: O O  
SENT: <unk> 0000 0000 0000 0000 0000 0000 0000  
TRUE: I-ORG O O O O O O O  
PRED: I-ORG O O O O O O O  
SENT: Following are some of the main factors likely to <unk> Indonesian stocks on Thursday  
:  
TRUE: O O O O O O O O O O I-MISC O O O O  
PRED: O O O O O O O O O O I-MISC O O O O  
SENT: -DOCSTART-  
TRUE: O  
PRED: O  
--- EPOCH 6 ---

Avg loss over last 500 updates: 1.516061978531084  
Avg loss over last 500 updates: 1.6888382547295686  
Avg loss over last 500 updates: 1.511420607591895  
Avg loss over last 500 updates: 1.6242827976404206  
Avg loss over last 500 updates: 1.3553802845773169  
Avg loss over last 500 updates: 1.6584229665811536  
Avg evaluation loss: 3.0778924888317274  
processed 11170 tokens with 1231 phrases; found: 1114 phrases; correct: 819.  
accuracy: 72.08%; (non-O)  
accuracy: 94.04%; precision: 73.52%; recall: 66.53%; FB1: 69.85  
LOC: precision: 87.66%; recall: 74.38%; FB1: 80.48 308  
MISC: precision: 83.08%; recall: 56.25%; FB1: 67.08 130  
ORG: precision: 57.63%; recall: 60.26%; FB1: 58.92 321  
PER: precision: 72.11%; recall: 69.38%; FB1: 70.72 355  
(73.51885098743267, 66.53127538586516, 69.8507462686567)

5 random evaluation samples:

SENT: <unk> 0000 COLORADO 0000  
TRUE: I-ORG O I-ORG O  
PRED: I-ORG O I-ORG O  
SENT: " The Foreign Ministry is trying to find out from the Greek embassy why Albanian ref  
ugees have been <unk> from Greece , " <unk> told Reuters .  
TRUE: O O I-ORG I-ORG O O O O O O I-MISC O O I-MISC O O O O O I-LOC O O I-PER O I-ORG O  
PRED: O O O I-ORG O O O O O O O I-MISC O O I-MISC O O O O O I-LOC O O I-PER O I-ORG O  
SENT: But he said a power struggle in Russia 's ruling <unk> could not be ruled out , whic  
h could <unk> further <unk> .  
TRUE: O O O O O O O I-LOC O O O O O O O O O O O O O O  
PRED: O O O O O O O I-LOC O O O O O O O O O O O O O O  
SENT: <unk> <unk> <unk> ( Netherlands ) <unk> <unk>  
TRUE: O I-PER I-PER O I-LOC O I-ORG O  
PRED: O I-PER I-PER O I-LOC O O O  
SENT: Halftime <unk> .  
TRUE: O O O  
PRED: O O O  
--- EPOCH 7 ---

Avg loss over last 500 updates: 1.3779640918101819  
Avg loss over last 500 updates: 1.5834947387945444  
Avg loss over last 500 updates: 1.2839705977744806  
Avg loss over last 500 updates: 1.4413288185103965  
Avg loss over last 500 updates: 1.2351025580366757  
Avg loss over last 500 updates: 1.4268885190182325  
Avg evaluation loss: 3.0831734830603508  
processed 11170 tokens with 1231 phrases; found: 1162 phrases; correct: 828.  
accuracy: 73.02%; (non-O)  
accuracy: 93.95%; precision: 71.26%; recall: 67.26%; FB1: 69.20  
LOC: precision: 86.03%; recall: 74.66%; FB1: 79.94 315  
MISC: precision: 75.00%; recall: 56.25%; FB1: 64.29 144  
ORG: precision: 57.10%; recall: 60.26%; FB1: 58.64 324  
PER: precision: 69.66%; recall: 71.54%; FB1: 70.59 379  
(71.25645438898451, 67.26238830219334, 69.20183869619724)

5 random evaluation samples:

SENT: With their fifth straight win , the Dodgers moved a <unk> ahead of the <unk> at the top of the <unk> <unk> <unk> behind <unk> ( <unk> ) , who allowed six hits and walked four with six <unk> .

TRUE: O O O O O O O I-ORG O O O O O O I-ORG O O O O O O O O O I-PER O O O O O O O O O O O O O O

PRED: O O O O O O O I-ORG O O O O O O O O O O O O I-ORG I-ORG I-ORG O O O I-ORG O O O O O O O O O O O O O

SENT: CHICAGO 0000 0000 .526 0000

TRUE: I-ORG O O O O

PRED: I-ORG O O O O

SENT: " <unk> seen <unk> <unk> his goals ...

TRUE: O O O I-PER O O O O

PRED: O O O O O O O O

SENT: Canada 's <unk> <unk> finished second in his Williams

TRUE: I-LOC O I-PER I-PER O O O O I-ORG

PRED: I-LOC O I-PER I-PER O O O O O

SENT: NEW YORK 1996-12-07

TRUE: I-LOC I-LOC O

PRED: I-LOC I-LOC O

--- EPOCH 8 ---

Avg loss over last 500 updates: 1.357581618527333

Avg loss over last 500 updates: 1.4985661709114633

Avg loss over last 500 updates: 1.2745562377289934

Avg loss over last 500 updates: 1.2496031929099594

Avg loss over last 500 updates: 1.154334063734751

Avg loss over last 500 updates: 1.3127732463782726

Avg evaluation loss: 3.1528406326202454

processed 11170 tokens with 1231 phrases; found: 1171 phrases; correct: 841.

accuracy: 73.07%; (non-O)

accuracy: 93.93%; precision: 71.82%; recall: 68.32%; FB1: 70.02

LOC: precision: 84.73%; recall: 77.96%; FB1: 81.21 334

MISC: precision: 75.68%; recall: 58.33%; FB1: 65.88 148

ORG: precision: 57.59%; recall: 60.59%; FB1: 59.05 323

PER: precision: 71.04%; recall: 70.46%; FB1: 70.75 366

(71.81895815542272, 68.31844029244517, 70.02497918401332)

5 random evaluation samples:

SENT: -DOCSTART-

TRUE: O

PRED: O

SENT: <unk> <unk> <unk> of South Africa defeated Tim <unk> of Britain 6-4 6-4 after a <unk> evening rain <unk> and <unk> Thomas <unk> of Sweden won his <unk> match , <unk> Petr <unk> of the Czech Republic 6-3 6-4 .

TRUE: O I-PER I-PER O I-LOC I-LOC O I-PER I-PER O I-LOC O O O O O O O O O O I-PER I-PER O I-LOC O O O O O O O I-PER I-PER O O I-LOC I-LOC O O O

PRED: O O O O I-LOC I-LOC O I-PER I-PER O I-LOC O O O O O O O O O O I-PER I-PER O I-LOC O O O O O O I-PER O O O I-LOC I-LOC O O O

SENT: ATLANTA AT PITTSBURGH

TRUE: I-ORG O I-LOC

PRED: I-ORG O I-LOC  
SENT: Suu Kyi , who <unk> a campaign forsanctions on <unk> 's government , was under hous  
e arrest for six years without being tried before being released in July 0000 .  
TRUE: I-PER I-PER O O O O O O O O I-LOC O  
PRED: I-PER I-PER O O O O O O O O I-ORG O  
SENT: <unk> <unk>  
TRUE: I-PER I-PER  
PRED: I-PER O  
--- EPOCH 9 ---

Avg loss over last 500 updates: 1.1769165323205653  
Avg loss over last 500 updates: 1.37241407262937  
Avg loss over last 500 updates: 1.1872848890557424  
Avg loss over last 500 updates: 1.062428315886572  
Avg loss over last 500 updates: 1.0239464682876303  
Avg loss over last 500 updates: 1.1727701357061724  
Avg evaluation loss: 3.2805274964013518  
processed 11170 tokens with 1231 phrases; found: 1148 phrases; correct: 831.  
accuracy: 73.35%; (non-O)  
accuracy: 94.14%; precision: 72.39%; recall: 67.51%; FB1: 69.86  
LOC: precision: 85.71%; recall: 77.69%; FB1: 81.50 329  
MISC: precision: 78.42%; recall: 56.77%; FB1: 65.86 139  
ORG: precision: 59.74%; recall: 58.96%; FB1: 59.34 303  
PER: precision: 68.70%; recall: 70.19%; FB1: 69.44 377  
(72.38675958188153, 67.50609260763608, 69.86128625472887)

5 random evaluation samples:  
SENT: Reading 0000 0000 0000 0000 0000 0000 0000  
TRUE: I-ORG O O O O O O O  
PRED: I-ORG O O O O O O O  
SENT: The cars will be <unk> <unk> by <unk> and <unk> <unk> <unk> <unk> , <unk> by a son o  
f President <unk> , which plans next year to start <unk> the <unk> in Indonesia .  
TRUE: O O O O O O O I-ORG O I-ORG I-ORG I-ORG I-ORG O O O O O O O I-PER O O O O O O O O O  
O O I-LOC O  
PRED: O O O O O O O O O O O I-PER O O O O O O O O I-PER O O O O O O O O O O O I-LOC O  
SENT: SOCCER - <unk> <unk> <unk> <unk> <unk> <unk> .  
TRUE: O O I-PER O I-ORG O O O O  
PRED: O O O O O O O O O  
SENT: <unk> <unk> 0000 0000 0000 0000 0000 0000 0000  
TRUE: I-ORG I-ORG O O O O O O O  
PRED: I-ORG I-ORG O O O O O O O  
SENT: <unk> said <unk> the meeting carried <unk> for Singapore , " however , this is <unk>  
<unk> as the <unk> <unk> may not <unk> lead to any additional investment and trade <unk> t  
o this region . "  
TRUE: I-PER O O O O O O O O I-LOC O  
PRED: I-PER O O O O O O O O I-LOC O  
--- EPOCH 10 ---

Avg loss over last 500 updates: 1.126772257849591  
Avg loss over last 500 updates: 1.3339204299108196  
Avg loss over last 500 updates: 1.1484673207211082  
Avg loss over last 500 updates: 1.0757857147213168  
Avg loss over last 500 updates: 0.9359214804280749  
Avg loss over last 500 updates: 1.0518884640757156  
Avg evaluation loss: 3.441275830005336  
processed 11170 tokens with 1231 phrases; found: 1122 phrases; correct: 820.  
accuracy: 72.41%; (non-O)  
accuracy: 94.19%; precision: 73.08%; recall: 66.61%; FB1: 69.70  
LOC: precision: 84.88%; recall: 75.76%; FB1: 80.06 324  
MISC: precision: 78.63%; recall: 53.65%; FB1: 63.78 131  
ORG: precision: 62.72%; recall: 58.63%; FB1: 60.61 287  
PER: precision: 68.95%; recall: 71.00%; FB1: 69.96 380  
(73.0837789661319, 66.61251015434605, 69.69825754356141)

5 random evaluation samples:  
SENT: <unk> of French first division  
TRUE: O O I-MISC O O  
PRED: O O I-MISC O O

SENT: PRESS DIGEST - <unk> - AUG 0000 .  
 TRUE: 0 0 0 I-LOC 0 0 0 0  
 PRED: 0 0 0 0 0 0 0 0  
 SENT: 6. <unk> <unk> ( Belgium ) Honda  
 TRUE: 0 I-PER I-PER 0 I-LOC 0 I-ORG  
 PRED: 0 I-PER I-PER 0 I-LOC 0 I-ORG  
 SENT: <unk> government newspapers have <unk> Britain for allowing Islamists , whom they <unk> as " <unk> " , to hold their conference , saying the meeting will be a chance for dangerous Moslem <unk> to <unk> against their countries of <unk> .  
 TRUE: I-MISC 0 0 0 0 I-LOC 0 0 I-MISC 0 I-MISC  
 0 0 0 0 0 0 0 0 0 0  
 PRED: 0 0 0 0 0 I-LOC 0 0 I-MISC 0 I-MISC 0 0  
 0 0 0 0 0 0 0 0  
 SENT: Scottish Cup first round  
 TRUE: I-MISC I-MISC 0 0  
 PRED: I-MISC I-MISC 0 0  
 --- EPOCH 11 ---  
 Avg loss over last 500 updates: 0.9937420989043426  
 Avg loss over last 500 updates: 1.085926796061788  
 Avg loss over last 500 updates: 1.0147756261950014  
 Avg loss over last 500 updates: 0.9733271421422574  
 Avg loss over last 500 updates: 0.913839882302878  
 Avg loss over last 500 updates: 1.1085896791702925  
 Avg evaluation loss: 3.3456211852904274  
 processed 11170 tokens with 1231 phrases; found: 1130 phrases; correct: 832.  
 accuracy: 73.51%; (non-O)  
 accuracy: 94.25%; precision: 73.63%; recall: 67.59%; FB1: 70.48  
           LOC: precision: 85.98%; recall: 76.03%; FB1: 80.70 321  
           MISC: precision: 73.24%; recall: 54.17%; FB1: 62.28 142  
           ORG: precision: 63.96%; recall: 58.96%; FB1: 61.36 283  
           PER: precision: 70.57%; recall: 73.44%; FB1: 71.98 384  
 (73.6283185840708, 67.58732737611697, 70.47861075815331)

5 random evaluation samples:

SENT: Hapoel <unk> 0000 Maccabi Tel Aviv 0000  
 TRUE: I-ORG I-ORG 0 0 I-ORG I-ORG 0  
 PRED: I-ORG I-ORG 0 I-ORG I-ORG I-ORG 0  
 SENT: - Pakistan <unk> <unk> tonnes of <unk> <unk> yellow <unk> from <unk> Inc for \$ <unk> per tonne , <unk> U.S. Gulf , agents for the <unk> said .  
 TRUE: 0 I-LOC 0 0 0 0 0 0 0 0 0 I-ORG I-ORG 0 0 0 0 0 0 0 I-LOC I-LOC 0 0 0 0 0 0 0  
 PRED: 0 I-LOC 0 0 0 0 I-ORG 0 0 0 0 I-ORG I-ORG 0 0 0 0 0 0 0 I-LOC I-LOC 0 0 0 0 0 0 0  
 SENT: A human rights <unk> said on Wednesday he had been released after more than two weeks in <unk> that followed his call for an <unk> into the death of a Gaza man <unk> by Palestinian police .  
 TRUE: 0 I-LOC 0 0 0 I-MISC 0 0  
 PRED: 0 I-LOC 0 0 0 I-MISC 0 0  
 SENT: A <unk> <unk> in U.S. <unk> after a <unk> rise in the Chicago <unk> pulled <unk> lower , but traders said the market was <unk> <unk> ahead of August <unk> data and the <unk> <unk> due on Monday .  
 TRUE: 0 0 0 0 I-ORG I-ORG 0 0 0 0 0 0 I-MISC I-MISC 0  
 0 0 0 0 0 0 0  
 PRED: 0 0 0 0 I-LOC 0 0 0 0 0 0 0 I-LOC 0  
 0  
 SENT: No arrests had been made , a police spokesman said .  
 TRUE: 0 0 0 0 0 0 0 0 0 0 0 0  
 PRED: 0 0 0 0 0 0 0 0 0 0 0 0  
 --- EPOCH 12 ---

Avg loss over last 500 updates: 0.891786853779171  
 Avg loss over last 500 updates: 1.015059345187378  
 Avg loss over last 500 updates: 1.0023076614066495  
 Avg loss over last 500 updates: 0.931654472417199  
 Avg loss over last 500 updates: 0.787670547499122  
 Avg loss over last 500 updates: 0.9972805048931024  
 Avg evaluation loss: 3.4089158575289127  
 processed 11170 tokens with 1231 phrases; found: 1212 phrases; correct: 842.  
 accuracy: 74.78%; (non-O)

accuracy: 93.85%; precision: 69.47%; recall: 68.40%; FB1: 68.93  
LOC: precision: 85.71%; recall: 77.69%; FB1: 81.50 329  
MISC: precision: 67.72%; recall: 55.73%; FB1: 61.14 158  
ORG: precision: 56.48%; recall: 59.61%; FB1: 58.00 324  
PER: precision: 67.33%; recall: 73.17%; FB1: 70.13 401  
(69.47194719471948, 68.39967506092609, 68.9316414244781)

5 random evaluation samples:

SENT: 1. <unk> <unk> ( U.S. ) 0000 minutes <unk> seconds

TRUE: O I-PER I-PER O I-LOC O O O O O

PRED: O I-PER I-PER O I-LOC O O O O O

SENT: Bank of New Zealand said on Thursday it was <unk> its <unk> home lending rates .

TRUE: I-ORG I-ORG I-ORG I-ORG O O O O O O O O O O O

PRED: I-ORG I-ORG I-LOC I-LOC O O O O O O O O O O O

SENT: A government statement , <unk> <unk> by state radio , said the two days of <unk> were " for the dead , for peace and <unk> in Guinea , the victory of the new government and the health of the head of state " .

TRUE: O I-LOC O O O O O O O O O O O O O O O O O O O

PRED: O I-LOC O O O O O O O O O O O O O O O O O O O

SENT: When we <unk> the shares we <unk> ...

TRUE: O O O O O O O O

PRED: O O O O O O O O

SENT: 6. Michael <unk> ( U.S. ) <unk>

TRUE: O I-PER I-PER O I-LOC O O

PRED: O I-PER I-PER O I-LOC O O

--- EPOCH 13 ---

Avg loss over last 500 updates: 0.8148250419716885

Avg loss over last 500 updates: 1.009307216465378

Avg loss over last 500 updates: 0.867149907768798

Avg loss over last 500 updates: 0.918188081821459

Avg loss over last 500 updates: 0.761379256395828

Avg loss over last 500 updates: 0.9401957673084848

Avg evaluation loss: 3.6750318801613546

processed 11170 tokens with 1231 phrases; found: 1178 phrases; correct: 833.

accuracy: 73.90%; (non-O)

accuracy: 94.02%; precision: 70.71%; recall: 67.67%; FB1: 69.16

LOC: precision: 87.46%; recall: 76.86%; FB1: 81.82 319

MISC: precision: 73.68%; recall: 58.33%; FB1: 65.12 152

ORG: precision: 58.36%; recall: 57.98%; FB1: 58.17 305

PER: precision: 65.67%; recall: 71.54%; FB1: 68.48 402

(70.71307300509338, 67.66856214459789, 69.15732669157326)

5 random evaluation samples:

SENT: Bank of New Zealand said on Thursday it was <unk> its <unk> home lending rates .

TRUE: I-ORG I-ORG I-ORG I-ORG O O O O O O O O O O O

PRED: I-ORG I-ORG I-LOC I-LOC O O O O O O O O O O O

SENT: Officials said the <unk> vote removed all existing <unk> hurdles in the way of <unk>'s <unk> .

TRUE: O O O I-ORG O O O O O O O O O I-ORG O O O

PRED: O O O O O O O O O O O O O O O O O

SENT: <unk> Bremen 0000 <unk> <unk> 0000

TRUE: I-ORG I-ORG O I-ORG I-ORG O

PRED: I-ORG I-ORG O I-ORG I-ORG O

SENT: Pace <unk> three senior finalists -- <unk> <unk> defensive end <unk> Brown , <unk> State <unk> tackle Juan <unk> and defensive end <unk> <unk> of <unk> .

TRUE: I-PER O O O O O I-ORG I-ORG O O I-PER I-PER O I-ORG I-ORG O O I-PER I-PER O O O I-PER I-PER O I-ORG O

PRED: I-PER O O O O O I-PER I-PER O O O I-PER O I-ORG O O O I-PER I-PER O O O O O O O O

SENT: <unk> made <unk> in the <unk> minute when he headed in a <unk> to score the <unk> .

TRUE: I-PER O O O O O O O O O O O O O O O O

PRED: I-PER O O O O O O O O O O O O O O O O

--- EPOCH 14 ---

Avg loss over last 500 updates: 0.7740641272167711

Avg loss over last 500 updates: 0.8967057252129684



Avg loss over last 500 updates: 0.8234615896720595  
Avg loss over last 500 updates: 0.8462402475484294  
Avg loss over last 500 updates: 0.8342506089115492  
Avg loss over last 500 updates: 0.8577411838049119  
Avg evaluation loss: 3.5461925919802244  
processed 11170 tokens with 1231 phrases; found: 1192 phrases; correct: 853.  
accuracy: 74.17%; (non-O)  
accuracy: 94.13%; precision: 71.56%; recall: 69.29%; FB1: 70.41  
LOC: precision: 85.84%; recall: 78.51%; FB1: 82.01 332  
MISC: precision: 74.67%; recall: 58.33%; FB1: 65.50 150  
ORG: precision: 63.19%; recall: 59.28%; FB1: 61.18 288  
PER: precision: 64.93%; recall: 74.25%; FB1: 69.28 422  
(71.56040268456377, 69.2932575142161, 70.40858439950475)

5 random evaluation samples:

SENT: <unk> Sudan plane expected at London 's Stansted .

TRUE: O I-LOC O O O I-LOC O I-LOC O

PRED: O I-LOC O O O I-LOC O I-LOC O

SENT: Net foreign currency - <unk> - <unk>

TRUE: O O O O O O O

PRED: O O O O O O I-PER

SENT: <unk> <unk> 0000 <unk> <unk> 0000

TRUE: I-ORG I-ORG O I-ORG I-ORG O

PRED: I-ORG I-ORG O I-ORG I-ORG O

SENT: <unk> AT SAN FRANCISCO

TRUE: I-ORG O I-LOC I-LOC

PRED: I-ORG O I-LOC I-LOC

SENT: They said they wanted to <unk> independent unions on university <unk> and <unk> that details of the punishment of <unk> who allegedly <unk> some students at the October <unk> be published in newspapers .

TRUE: O

PRED: O O O O O O O O O O O O O O O O O O I-LOC O O O O O O O O O O O O O O O O

--- EPOCH 15 ---

Avg loss over last 500 updates: 0.7322419075766545

Avg loss over last 500 updates: 0.9132976816976268

Avg loss over last 500 updates: 0.8170230439607609

Avg loss over last 500 updates: 0.8095421005745819

Avg loss over last 500 updates: 0.7308510470163437

Avg loss over last 500 updates: 0.9245831879022764

Avg evaluation loss: 3.634887895364175

processed 11170 tokens with 1231 phrases; found: 1181 phrases; correct: 859.

accuracy: 74.67%; (non-O)

accuracy: 94.23%; precision: 72.73%; recall: 69.78%; FB1: 71.23

LOC: precision: 83.81%; recall: 81.27%; FB1: 82.52 352

MISC: precision: 76.55%; recall: 57.81%; FB1: 65.88 145

ORG: precision: 61.89%; recall: 61.89%; FB1: 61.89 307

PER: precision: 69.76%; recall: 71.27%; FB1: 70.51 377

(72.73497036409822, 69.78066612510155, 71.22719734660033)

5 random evaluation samples:

SENT: German <unk> <unk> of motor <unk> jumped <unk> percent in July this year from the <unk> period , the Federal office for motor <unk> said on Thursday .

TRUE: I-MISC O O O O O O O O O O O O O O O O O I-ORG I-ORG I-ORG I-ORG I-ORG O O O O

PRED: I-MISC I-MISC O O O O O O O O O O O O O O O O O I-ORG O O O I-ORG O O O O

SENT: <unk> 0000 0000 0000 0000 0000 0000 0000

TRUE: I-ORG O O O O O O O

PRED: I-ORG O O O O O O O

SENT: -DOCSTART-

TRUE: O

PRED: O

SENT: From Gencor 's <unk> we are taking the position that it is not on , " <unk> said .

TRUE: O I-ORG O O O O O O O O O O O O O O I-PER O O

PRED: O I-ORG O O O O O O O O O O O O O O I-PER O O

SENT: <unk> director <unk> Jordan says he never lost more <unk> over a film than over " Michael <unk> " , his <unk> <unk> about the <unk> which has its <unk> on Saturday at the <unk> <unk> <unk> .

TRUE: O O I-PER I-PER O O O O O O O O I-MISC I-MISC O O O O O O I-ORG O O O O O  
O O O I-MISC I-MISC I-MISC O  
PRED: I-ORG O O I-PER O O O O O O O O O O O I-PER I-PER O O O O O O O I-ORG O O O O O O  
O O O O O O  
--- EPOCH 16 ---  
Avg loss over last 500 updates: 0.6532472014020982  
Avg loss over last 500 updates: 0.9010892660501117  
Avg loss over last 500 updates: 0.8033524641626472  
Avg loss over last 500 updates: 0.6415689004928716  
Avg loss over last 500 updates: 0.615256977588911  
Avg loss over last 500 updates: 0.7365913449302555  
Avg evaluation loss: 3.8705170074968653  
processed 11170 tokens with 1231 phrases; found: 1194 phrases; correct: 862.  
accuracy: 75.61%; (non-O)  
accuracy: 94.29%; precision: 72.19%; recall: 70.02%; FB1: 71.09  
LOC: precision: 88.79%; recall: 78.51%; FB1: 83.33 321  
MISC: precision: 77.93%; recall: 58.85%; FB1: 67.06 145  
ORG: precision: 62.09%; recall: 61.89%; FB1: 61.99 306  
PER: precision: 64.93%; recall: 74.25%; FB1: 69.28 422  
(72.19430485762143, 70.02437043054427, 71.09278350515464)

5 random evaluation samples:

SENT: They said they wanted to <unk> independent unions on university <unk> and <unk> that details of the punishment of <unk> who allegedly <unk> some students at the October <unk> be published in newspapers .

TRUE: O

PRED: O O O O O O O O O O O O O O O O O O I-PER O O O O O O O O O O O O O O O

SENT: James is a <unk> for a <unk> act of <unk> , while those who have done nothing for the cause are free , " she <unk> .

TRUE: I-PER O

PRED: I-ORG O

SENT: But <unk> <unk> , one of the refugees who signed the letter of <unk> , told Reuters :

TRUE: O I-PER I-PER O O O O O O O O O O O O O I-ORG O

PRED: O I-PER I-PER O O O O O O O O O O O O O I-ORG O

SENT: 2-2 ( halftime 0-0 ) in a friendly soccer international on

TRUE: O O O O O O O O O O O

PRED: O O O O O O O O O O O

SENT: Last season 's league and Cup winners Manchester United host 0000 champions Blackburn on Sunday .

TRUE: O O O O O I-MISC O I-ORG I-ORG O O O I-ORG O O O

PRED: O O O O O I-MISC O I-ORG I-ORG O O O I-ORG O O O

--- EPOCH 17 ---

Avg loss over last 500 updates: 0.6165716926998883

Avg loss over last 500 updates: 0.7082875396478351

Avg loss over last 500 updates: 0.7745582393392559

Avg loss over last 500 updates: 0.7264612795272467

Avg loss over last 500 updates: 0.5709444740643335

Avg loss over last 500 updates: 0.7498370851717168

Avg evaluation loss: 3.906349148949287

processed 11170 tokens with 1231 phrases; found: 1187 phrases; correct: 847.

accuracy: 74.39%; (non-O)

accuracy: 94.14%; precision: 71.36%; recall: 68.81%; FB1: 70.06

LOC: precision: 84.82%; recall: 78.51%; FB1: 81.55 336

MISC: precision: 71.92%; recall: 54.69%; FB1: 62.13 146

ORG: precision: 61.67%; recall: 60.26%; FB1: 60.96 300

PER: precision: 67.16%; recall: 73.71%; FB1: 70.28 405

(71.35636057287279, 68.80584890333063, 70.05789909015715)

5 random evaluation samples:

SENT: <unk> 0000 0000 0000 0000 0000 0000 0000

TRUE: I-ORG O O O O O O O

PRED: I-ORG O O O O O O O

SENT: \* President Clinton <unk> <unk> plan to <unk> up toxic waste <unk> .

TRUE: O O I-PER O O O O O O O O O

PRED: O O I-PER I-PER O O O O O O O O O

SENT: <unk> <unk>  
 TRUE: I-PER I-PER  
 PRED: I-PER I-PER  
 SENT: <unk> <unk> ISS <unk> <unk> PAY DATE <unk>  
 TRUE: O O O O O O O O  
 PRED: O O O O O O O O  
 SENT: Russian and rebel military <unk> finally met in Chechnya on Tuesday for delayed talk  
 s aimed at <unk> a ceasefire <unk> last week by President <unk> Yeltsin 's <unk> Alexander  
 Lebed .  
 TRUE: I-MISC O O O O O O O I-LOC O O O O O O O O O O O O O I-PER I-PER O O I-PER I-PER  
 O  
 PRED: I-MISC O O O O O O O I-LOC O O O O O O O O O O O O O I-PER I-PER O O I-PER I-PER  
 O  
 --- EPOCH 18 ---  
 Avg loss over last 500 updates: 0.7942087516420665  
 Avg loss over last 500 updates: 0.8223073366666718  
 Avg loss over last 500 updates: 0.7427986781571476  
 Avg loss over last 500 updates: 0.7233215832193992  
 Avg loss over last 500 updates: 0.6209400304548369  
 Avg loss over last 500 updates: 0.7522316498110118  
 Avg evaluation loss: 3.7720433978722823  
 processed 11170 tokens with 1231 phrases; found: 1189 phrases; correct: 859.  
 accuracy: 74.83%; (non-O)  
 accuracy: 94.20%; precision: 72.25%; recall: 69.78%; FB1: 70.99  
     LOC: precision: 84.41%; recall: 79.06%; FB1: 81.65 340  
     MISC: precision: 73.83%; recall: 57.29%; FB1: 64.52 149  
     ORG: precision: 62.33%; recall: 59.28%; FB1: 60.77 292  
     PER: precision: 68.63%; recall: 75.88%; FB1: 72.07 408  
 (72.24558452481077, 69.78066612510155, 70.99173553719007)  
  
 5 random evaluation samples:  
 SENT: <unk> <unk> 0000 0000 0000 0000 0000 0000 0000  
 TRUE: I-ORG I-ORG O O O O O O O  
 PRED: I-ORG I-ORG O O O O O O O  
 SENT: <unk> had been working for the <unk> which provides food to civilians for only a few  
 weeks before he was <unk> .  
 TRUE: I-PER O  
 PRED: O  
 SENT: -DOCSTART-  
 TRUE: O  
 PRED: O  
 SENT: -DOCSTART-  
 TRUE: O  
 PRED: O  
 SENT: <unk> :  
 TRUE: O O  
 PRED: O O  
 --- EPOCH 19 ---  
 Avg loss over last 500 updates: 0.7102352405928112  
 Avg loss over last 500 updates: 0.650632812975827  
 Avg loss over last 500 updates: 0.692608732817354  
 Avg loss over last 500 updates: 0.6503745693749318  
 Avg loss over last 500 updates: 0.5121360552306327  
 Avg loss over last 500 updates: 0.697548881384634  
 Avg evaluation loss: 4.16100994757011  
 processed 11170 tokens with 1231 phrases; found: 1201 phrases; correct: 871.  
 accuracy: 75.33%; (non-O)  
 accuracy: 94.28%; precision: 72.52%; recall: 70.76%; FB1: 71.63  
     LOC: precision: 83.57%; recall: 81.27%; FB1: 82.40 353  
     MISC: precision: 74.83%; recall: 58.85%; FB1: 65.89 151  
     ORG: precision: 63.70%; recall: 58.31%; FB1: 60.88 281  
     PER: precision: 68.27%; recall: 76.96%; FB1: 72.36 416  
 (72.52289758534555, 70.75548334687247, 71.6282894736842)  
  
 5 random evaluation samples:  
 SENT: 3. <unk> <unk> ( Italy ) <unk>

TRUE: O I-PER I-PER O I-LOC O O  
PRED: O I-PER I-PER O I-LOC O O  
SENT: <unk> <unk> ( Belarus ) beat <unk> <unk> ( Spain ) 0000  
TRUE: I-PER I-PER O I-LOC O O I-PER I-PER O I-LOC O O  
PRED: I-PER I-PER O I-LOC O O I-PER I-PER O I-LOC O O  
SENT: Sri Lanka  
TRUE: I-LOC I-LOC  
PRED: I-LOC I-LOC  
SENT: The Civil War <unk> <unk> is mostly <unk> joined by students during the school year  
.

TRUE: O I-ORG I-ORG I-ORG I-ORG O O O O O O O O O O  
PRED: O I-MISC I-MISC O I-PER O O O O O O O O O O  
SENT: <unk> <unk> 0000 <unk> <unk> 0000  
TRUE: I-ORG I-ORG O I-ORG I-ORG O  
PRED: I-ORG I-ORG O I-ORG I-ORG O

--- EPOCH 20 ---

Avg loss over last 500 updates: 0.6154825951090147  
Avg loss over last 500 updates: 0.684232204180006  
Avg loss over last 500 updates: 0.694574514479792  
Avg loss over last 500 updates: 0.640440738757681  
Avg loss over last 500 updates: 0.5266944110689162  
Avg loss over last 500 updates: 0.686997306616179  
Avg evaluation loss: 4.066602269197315  
processed 11170 tokens with 1231 phrases; found: 1186 phrases; correct: 861.  
accuracy: 75.22%; (non-O)  
accuracy: 94.23%; precision: 72.60%; recall: 69.94%; FB1: 71.25  
LOC: precision: 86.49%; recall: 79.34%; FB1: 82.76 333  
MISC: precision: 73.51%; recall: 57.81%; FB1: 64.72 151  
ORG: precision: 58.13%; recall: 60.59%; FB1: 59.33 320  
PER: precision: 72.25%; recall: 74.80%; FB1: 73.50 382  
(72.59696458684655, 69.94313566206336, 71.2453454695904)

5 random evaluation samples:

SENT: He is not as <unk> as he used to be be but was too good for me in the end .  
TRUE: O  
PRED: O  
SENT: 7. <unk> 0000  
TRUE: O I-ORG O  
PRED: O I-ORG O  
SENT: Cologne 0000 0000 0000 0000 0000 0000 0000  
TRUE: I-ORG O O O O O O O  
PRED: I-ORG O O O O O O O  
SENT: <unk> sources said feed <unk> demand was keeping <unk> with <unk> production and driving prices higher .  
TRUE: I-LOC O O O O O O O O O O O O O O O O  
PRED: O O O O O O O O O O O O O O O O O  
SENT: <unk> - <unk> <unk> figures <unk> to value of orders on books at end of period .  
TRUE: O O O O O O O O O O O O O O O O O  
PRED: O O O O O O O O O O O O O O O O O

--- EPOCH 21 ---

Avg loss over last 500 updates: 0.6009327363215686  
Avg loss over last 500 updates: 0.697571519225759  
Avg loss over last 500 updates: 0.6478157823512293  
Avg loss over last 500 updates: 0.5654472256586893  
Avg loss over last 500 updates: 0.5337016331360191  
Avg loss over last 500 updates: 0.6954160323206039  
Avg evaluation loss: 4.221641649038902  
processed 11170 tokens with 1231 phrases; found: 1214 phrases; correct: 858.  
accuracy: 75.28%; (non-O)  
accuracy: 94.09%; precision: 70.68%; recall: 69.70%; FB1: 70.18  
LOC: precision: 85.76%; recall: 77.96%; FB1: 81.67 330  
MISC: precision: 76.60%; recall: 56.25%; FB1: 64.86 141  
ORG: precision: 57.91%; recall: 59.61%; FB1: 58.75 316  
PER: precision: 66.51%; recall: 76.96%; FB1: 71.36 427  
(70.67545304777595, 69.69943135662064, 70.1840490797546)

5 random evaluation samples:

SENT: " The Foreign Ministry is trying to find out from the Greek embassy why Albanian refugees have been <unk> from Greece , " <unk> told Reuters .

TRUE: O O I-ORG I-ORG O O O O O O I-MISC O O I-MISC O O O O O I-LOC O O I-PER O I-ORG O

PRED: O O O I-ORG O O O O O O I-MISC O O I-MISC O O O O O I-LOC O O I-PER O I-ORG O

SENT: <unk> <unk> <unk> ( Netherlands ) <unk> <unk>

TRUE: O I-PER I-PER O I-LOC O I-ORG O

PRED: I-PER I-PER I-PER O I-LOC O O O

SENT: <unk> 1996-12-07

TRUE: I-LOC O

PRED: I-LOC O

SENT: <unk> Mushtaq b Harris 0000

TRUE: I-PER I-PER O I-PER O

PRED: I-PER I-PER O I-PER O

SENT: <unk> <unk> 1996-08-25

TRUE: I-LOC I-LOC O

PRED: I-LOC I-LOC O

--- EPOCH 22 ---

Avg loss over last 500 updates: 0.6030482251726085

Avg loss over last 500 updates: 0.5843819178212584

Avg loss over last 500 updates: 0.5746028549436517

Avg loss over last 500 updates: 0.575509608385968

Avg loss over last 500 updates: 0.4392929700463437

Avg loss over last 500 updates: 0.6482446090732723

Avg evaluation loss: 4.1000374059156055

processed 11170 tokens with 1231 phrases; found: 1203 phrases; correct: 866.

accuracy: 75.33%; (non-O)

accuracy: 94.26%; precision: 71.99%; recall: 70.35%; FB1: 71.16

LOC: precision: 83.43%; recall: 80.44%; FB1: 81.91 350

MISC: precision: 74.48%; recall: 56.25%; FB1: 64.09 145

ORG: precision: 66.06%; recall: 58.96%; FB1: 62.31 274

PER: precision: 65.67%; recall: 77.24%; FB1: 70.98 434

(71.98669991687449, 70.34930950446791, 71.15858668857847)

5 random evaluation samples:

SENT: 6. <unk> <unk> ( Netherlands ) Rabobank 0000

TRUE: O I-PER I-PER O I-LOC O I-ORG O

PRED: O I-PER I-PER O I-LOC O I-ORG O

SENT: <unk> 's autonomy was <unk> in 0000 and Serb police forces <unk> down on Albanian protests .

TRUE: I-LOC O O O O O O O I-MISC O O O O O I-MISC O O

PRED: I-ORG O O O O O O O I-MISC O O O O O I-MISC O O

SENT: <unk> <unk> ( Sweden ) 0000 0000 , <unk> <unk> 0000 0000 , <unk>

TRUE: I-PER I-PER O I-LOC O O O O I-PER I-PER O O O I-PER

PRED: I-PER I-PER O I-LOC O O O O I-PER I-PER O O O I-PER

SENT: 0000 Robert <unk> 0000 0000 , David Williams 0000 0000 , Thomas <unk>

TRUE: O I-PER I-PER O O O I-PER I-PER O O O I-PER I-PER

PRED: O I-PER I-PER O O O I-PER I-PER O O O I-PER I-PER

SENT: <unk> said he knew of no plans to return the man to Cuba .

TRUE: I-PER O O O O O O O O O O I-LOC O

PRED: I-PER O O O O O O O O O O I-LOC O

--- EPOCH 23 ---

Avg loss over last 500 updates: 0.5599351446596423

Avg loss over last 500 updates: 0.6122765303015385

Avg loss over last 500 updates: 0.6597101653421901

Avg loss over last 500 updates: 0.5065431149324071

Avg loss over last 500 updates: 0.4721722274444788

Avg loss over last 500 updates: 0.577534871560387

Avg evaluation loss: 4.098952841927502

processed 11170 tokens with 1231 phrases; found: 1220 phrases; correct: 865.

accuracy: 75.77%; (non-O)

accuracy: 94.21%; precision: 70.90%; recall: 70.27%; FB1: 70.58

LOC: precision: 83.43%; recall: 80.44%; FB1: 81.91 350

MISC: precision: 77.86%; recall: 56.77%; FB1: 65.66 140

ORG: precision: 57.72%; recall: 60.91%; FB1: 59.27 324

PER: precision: 68.23%; recall: 75.07%; FB1: 71.48 406

(70.90163934426229, 70.26807473598701, 70.58343533251734)

5 random evaluation samples:

SENT: 0000 - <unk> <unk>

TRUE: O O O O

PRED: O O I-PER I-PER

SENT: England

TRUE: I-LOC

PRED: I-LOC

SENT: As Glenn <unk> , a <unk> Florida minister who is the victim 's father , looked on ,  
<unk> was <unk> dead at <unk> a.m. <unk> ( 0000 GMT ) for the murder of <unk> <unk> .

TRUE: O I-PER I-PER O O O I-LOC O O O O O O O O O O I-PER O O O O O O O O O I-MISC O O O  
O O I-PER I-PER O

PRED: O I-PER I-PER O O O I-ORG O O O O O O O O O O O I-PER O O O O O O O O O I-MISC O O O  
O O O O O

SENT: <unk> Munich 0000 0000 0000 0000 0000 0000 0000

TRUE: I-ORG I-ORG O O O O O O O

PRED: I-ORG I-ORG O O O O O O O

SENT: <unk> <unk> ( U.S. ) beat <unk> <unk> ( Netherlands ) 5-7 6-3 6-3

TRUE: I-PER I-PER O I-LOC O O I-PER I-PER O I-LOC O O O O

PRED: I-PER I-PER O I-LOC O O I-PER I-PER O I-LOC O O O O

--- EPOCH 24 ---

Avg loss over last 500 updates: 0.5085958704439554

Avg loss over last 500 updates: 0.6501610889473707

Avg loss over last 500 updates: 0.5304056844841569

Avg loss over last 500 updates: 0.5681731101949625

Avg loss over last 500 updates: 0.4932107595173675

Avg loss over last 500 updates: 0.6053295722414498

Avg evaluation loss: 4.554911585001087

processed 11170 tokens with 1231 phrases; found: 1185 phrases; correct: 855.

accuracy: 74.17%; (non-O)

accuracy: 94.20%; precision: 72.15%; recall: 69.46%; FB1: 70.78

LOC: precision: 83.14%; recall: 80.17%; FB1: 81.63 350

MISC: precision: 77.86%; recall: 56.77%; FB1: 65.66 140

ORG: precision: 64.06%; recall: 58.63%; FB1: 61.22 281

PER: precision: 66.43%; recall: 74.53%; FB1: 70.24 414

(72.15189873417721, 69.4557270511779, 70.77814569536423)

5 random evaluation samples:

SENT: ATLANTA AT PITTSBURGH

TRUE: I-ORG O I-LOC

PRED: I-ORG O I-LOC

SENT: Pires scored first with a <unk> shot in the 35th minute before <unk> again from close range just before the break .

TRUE: I-PER O

PRED: I-PER O

SENT: <unk> , Belgium 1996-08-25

TRUE: I-LOC O I-LOC O

PRED: I-LOC O I-LOC O

SENT: Australia at South Africa

TRUE: I-LOC O I-LOC I-LOC

PRED: I-LOC O I-LOC I-LOC

SENT: -DOCSTART-

TRUE: O

PRED: O

--- EPOCH 25 ---

Avg loss over last 500 updates: 0.5236864984488501

Avg loss over last 500 updates: 0.655418227541318

Avg loss over last 500 updates: 0.5824074144754928

Avg loss over last 500 updates: 0.5544339723955486

Avg loss over last 500 updates: 0.4802982270438341

Avg loss over last 500 updates: 0.6096444674673303

Avg evaluation loss: 4.349667527265353

processed 11170 tokens with 1231 phrases; found: 1196 phrases; correct: 856.

accuracy: 74.28%; (non-O)

accuracy: 94.17%; precision: 71.57%; recall: 69.54%; FB1: 70.54

LOC: precision: 83.57%; recall: 79.89%; FB1: 81.69 347  
MISC: precision: 69.43%; recall: 56.77%; FB1: 62.46 157  
ORG: precision: 60.07%; recall: 58.31%; FB1: 59.17 298  
PER: precision: 70.56%; recall: 75.34%; FB1: 72.87 394  
(71.57190635451505, 69.53696181965881, 70.53976102183766)

5 random evaluation samples:

SENT: 0000 - <unk> Khan ( Pakistan ) beat Simon <unk> ( Germany ) 15-12 15-7 <unk> 15-10  
TRUE: O O I-PER I-PER O I-LOC O O I-PER I-PER O I-LOC O O O O O  
PRED: O O I-PER I-PER O I-LOC O O I-PER I-PER O I-LOC O O O O O  
SENT: <unk> profit <unk> vs <unk>  
TRUE: O O O O O  
PRED: O O O O O  
SENT: " There was no <unk> today to make a <unk> run , " said <unk> <unk> , the Canadian m  
en 's national coach , <unk> too much new <unk> and poor <unk> .  
TRUE: O O O O O O O O O O O O O O I-PER I-PER O O I-MISC O O O O O O O O O O O O O O  
PRED: O O O O O O O O O O O O O O I-PER I-PER O O I-MISC O O O O O O O O O O O O O O  
SENT: 4. <unk> <unk> ( Kenya ) <unk>  
TRUE: O I-PER I-PER O I-LOC O O  
PRED: O I-PER I-PER O I-LOC O O  
SENT: " <unk> is getting stronger and stronger , and it already has <unk> of 0000 <unk> ( 0000 kph ) , " said <unk> <unk> <unk> <unk> .  
TRUE: O I-MISC O I-PER I-PER O  
PRED: O I-PER I-PER I-PER I-PER O  
--- EPOCH 26 ---

Avg loss over last 500 updates: 0.4892712708635235  
Avg loss over last 500 updates: 0.5606451400599992  
Avg loss over last 500 updates: 0.49115067909560084  
Avg loss over last 500 updates: 0.567455058201582  
Avg loss over last 500 updates: 0.45613947528275833  
Avg loss over last 500 updates: 0.6365499658510251  
Avg evaluation loss: 4.34903436519975  
processed 11170 tokens with 1231 phrases; found: 1184 phrases; correct: 857.  
accuracy: 74.56%; (non-O)  
accuracy: 94.31%; precision: 72.38%; recall: 69.62%; FB1: 70.97  
LOC: precision: 80.49%; recall: 80.72%; FB1: 80.61 364  
MISC: precision: 76.09%; recall: 54.69%; FB1: 63.64 138  
ORG: precision: 63.67%; recall: 59.93%; FB1: 61.74 289  
PER: precision: 69.97%; recall: 74.53%; FB1: 72.18 393  
(72.38175675675676, 69.61819658813972, 70.97308488612836)

5 random evaluation samples:

SENT: 2. <unk> Sang ( Kenya ) <unk>  
TRUE: O I-PER I-PER O I-LOC O O  
PRED: O I-PER I-PER O I-LOC O O  
SENT: Zimbabwe on Monday :  
TRUE: I-LOC O O O  
PRED: I-LOC O O O  
SENT: <unk> <unk> 0000 <unk> Munich 0000 ( <unk> <unk> , <unk> <unk> and  
TRUE: I-ORG I-ORG O I-ORG I-ORG O O I-PER O O I-PER O O  
PRED: I-ORG I-ORG O I-ORG I-ORG O O I-PER I-PER O I-PER I-PER O  
SENT: The teams meet each other once in each  
TRUE: O O O O O O O O  
PRED: O O O O O O O O  
SENT: The defeat put the <unk> out of the <unk> Cup .  
TRUE: O O O O I-MISC O O O I-MISC I-MISC O  
PRED: O O O O O O O O I-MISC I-MISC O  
--- EPOCH 27 ---

Avg loss over last 500 updates: 0.4986109310818142  
Avg loss over last 500 updates: 0.5406353076365065  
Avg loss over last 500 updates: 0.5493270318661887  
Avg loss over last 500 updates: 0.5004222199366561  
Avg loss over last 500 updates: 0.433571810602062  
Avg loss over last 500 updates: 0.6027956119507611  
Avg evaluation loss: 4.683567622896375  
processed 11170 tokens with 1231 phrases; found: 1178 phrases; correct: 848.

accuracy: 73.90%; (non-O)  
accuracy: 94.14%; precision: 71.99%; recall: 68.89%; FB1: 70.40  
LOC: precision: 85.29%; recall: 79.89%; FB1: 82.50 340  
MISC: precision: 78.99%; recall: 56.77%; FB1: 66.06 138  
ORG: precision: 61.72%; recall: 58.31%; FB1: 59.97 290  
PER: precision: 65.85%; recall: 73.17%; FB1: 69.32 410  
(71.98641765704585, 68.88708367181154, 70.40265670402657)

5 random evaluation samples:

SENT: <unk> 1996-08-26

TRUE: I-LOC O

PRED: I-LOC O

SENT: - Pakistan <unk> <unk> tonnes of <unk> <unk> yellow <unk> from <unk> Inc for \$ <unk> per tonne , <unk> U.S. Gulf , agents for the <unk> said .

TRUE: O I-LOC O O O O O O O O I-ORG I-ORG O O O O O O O I-LOC I-LOC O O O O O O O

PRED: O I-LOC O O O O O O O O I-ORG I-ORG O O O O O O O I-LOC I-LOC O O O O O O O

SENT: <unk> 0000 0000 0000 0000 0000 0000 0000

TRUE: I-ORG O O O O O O O

PRED: I-ORG O O O O O O O

SENT: India fishermen say forced to carry Tamil refugees .

TRUE: I-LOC O O O O O I-MISC O O

PRED: I-LOC O O O O O I-MISC O O

SENT: -DOCSTART-

TRUE: O

PRED: O

--- EPOCH 28 ---

Avg loss over last 500 updates: 0.5034467078847457

Avg loss over last 500 updates: 0.546407786855606

Avg loss over last 500 updates: 0.5520131686133827

Avg loss over last 500 updates: 0.5029821045477086

Avg loss over last 500 updates: 0.43543156519198895

Avg loss over last 500 updates: 0.5134126868891331

Avg evaluation loss: 4.6581245195716825

processed 11170 tokens with 1231 phrases; found: 1201 phrases; correct: 855.

accuracy: 75.06%; (non-O)

accuracy: 94.21%; precision: 71.19%; recall: 69.46%; FB1: 70.31

LOC: precision: 85.38%; recall: 80.44%; FB1: 82.84 342

MISC: precision: 78.99%; recall: 56.77%; FB1: 66.06 138

ORG: precision: 59.93%; recall: 59.93%; FB1: 59.93 307

PER: precision: 65.22%; recall: 73.17%; FB1: 68.97 414

(71.19067443796835, 69.4557270511779, 70.3125)

5 random evaluation samples:

SENT: Extras ( <unk> <unk> <unk> ) 0000

TRUE: O O O O O O O

PRED: O O O O O O O

SENT: 4. <unk> <unk> ( Kenya ) <unk>

TRUE: O I-PER I-PER O I-LOC O O

PRED: O I-PER I-PER O I-LOC O O

SENT: <unk> is <unk> by the level of competition in the <unk> .

TRUE: I-PER O O O O O O O O O O

PRED: O O O O O O O O O O O

SENT: 3. <unk> <unk> ( Germany ) <unk>

TRUE: O I-PER I-PER O I-LOC O O

PRED: O I-PER I-PER O I-LOC O O

SENT: France on Friday expelled another African man seized in a police <unk> on a Paris church as about 0000 Air France workers <unk> " <unk> of <unk> " used to fly illegal <unk> home .

TRUE: I-LOC O O O O I-MISC O O O O O O O O I-LOC O O O O I-ORG I-ORG O O O O O O O O O O O O O

PRED: I-LOC O O O O I-MISC O O O O O O O O I-LOC O O O O O I-LOC O I-MISC O I-PER O O O O O O O O O O

--- EPOCH 29 ---

Avg loss over last 500 updates: 0.42709097764811577

Avg loss over last 500 updates: 0.5115384472019388

Avg loss over last 500 updates: 0.5003525798341107



```

Avg loss over last 500 updates: 0.47634904861663413
Avg loss over last 500 updates: 0.4095727051005166
Avg loss over last 500 updates: 0.45489802008140456
Avg evaluation loss: 4.690180216010472
processed 11170 tokens with 1231 phrases; found: 1224 phrases; correct: 869.
accuracy: 75.11%; (non-O)
accuracy: 94.25%; precision: 71.00%; recall: 70.59%; FB1: 70.79
          LOC: precision: 85.22%; recall: 80.99%; FB1: 83.05 345
          MISC: precision: 67.07%; recall: 58.33%; FB1: 62.40 167
          ORG: precision: 62.50%; recall: 58.63%; FB1: 60.50 288
          PER: precision: 66.75%; recall: 76.69%; FB1: 71.37 424
(70.99673202614379, 70.59301380991064, 70.79429735234216)

```

5 random evaluation samples:

```

SENT: A <unk> <unk> in U.S. <unk> after a <unk> rise in the Chicago <unk> pulled <unk> low
er , but traders said the market was <unk> <unk> ahead of August <unk> data and the <unk>
<unk> due on Monday .
TRUE: O O O O I-ORG I-ORG O O O O O O I-MISC I-MISC O O O O O O O O O O O O O O O O O O
O O O O O O
PRED: O O O O I-LOC O O O O O O O I-LOC O O O O O O O O O O O O O O O O O O O O O O O
O
SENT: The <unk> <unk> of Nigeria ( <unk> ) quoted police spokesman <unk> <unk> as saying t
he six were killed on Wednesday .
TRUE: O I-ORG I-ORG I-ORG I-ORG O I-ORG O O O O I-PER I-PER O O O O O O O O O
PRED: O I-ORG O O I-LOC O O O O O O I-PER I-PER O O O O O O O O O
SENT: <unk> health began to <unk> in 0000 when she was <unk> with a heart <unk> .
TRUE: O O O O O O O O O O O O O O O O
PRED: O O O O O O O O O O O O O O O O
SENT: <unk> 1996-12-07
TRUE: I-LOC O
PRED: I-LOC O
SENT: <unk> times set on Friday
TRUE: O O O O O
PRED: O O O O O
Wall time: 4min 33s

```

```
In [61]: df = df.drop(columns = ['ORG'])
```

```
In [1]: crf = {'0': 50.12, '1': 62.19, '2': 67.02, '3': 69.45, '4': 69.15, '5': 69.22, '6': 70.49,
              '10': 71.76, '11': 71.36, '12': 71.29, '13': 70.69, '14': 70.02, '15': 71.41, '16':
              '20': 70.76, '21': 71.00, '22': 71.06, '23': 72.02, '24': 70.27, '25': 72.10, '26':
```

```
In [2]: original = {'0': 47.89, '1': 58.97, '2': 63.05, '3': 65.77, '4': 67.88, '5': 67.84, '6': 69.85,
                   '10': 69.70, '11': 70.48, '12': 68.93, '13': 69.16, '14': 70.41, '15': 71.23, '16':
                   '20': 71.25, '21': 70.18, '22': 71.16, '23': 70.58, '24': 70.78, '25': 70.54, '26':
```

```
In [3]: import pandas as pd
```

```
In [4]: table1 = pd.DataFrame.from_dict(crf, orient='index', columns = ['crf_FB1'])
        table2 = pd.DataFrame.from_dict(original, orient='index', columns = ['original_FB1'])
```

```
In [5]: table1['original_FB1'] = table2['original_FB1']
```

```
In [6]: table1
```

```
Out[6]: crf_FB1  original_FB1
```

	crf_FB1	original_FB1
<b>0</b>	50.12	47.89
<b>1</b>	62.19	58.97
<b>2</b>	67.02	63.05
<b>3</b>	69.45	65.77
<b>4</b>	69.15	67.88
<b>5</b>	69.22	67.84
<b>6</b>	70.49	69.85
<b>7</b>	71.97	69.20
<b>8</b>	70.97	70.02
<b>9</b>	70.64	69.86
<b>10</b>	71.76	69.70
<b>11</b>	71.36	70.48
<b>12</b>	71.29	68.93
<b>13</b>	70.69	69.16
<b>14</b>	70.02	70.41
<b>15</b>	71.41	71.23
<b>16</b>	72.16	71.09
<b>17</b>	71.20	70.06
<b>18</b>	71.14	70.99
<b>19</b>	71.05	71.63
<b>20</b>	70.76	71.25
<b>21</b>	71.00	70.18
<b>22</b>	71.06	71.16
<b>23</b>	72.02	70.58
<b>24</b>	70.27	70.78
<b>25</b>	72.10	70.54
<b>26</b>	69.52	70.97
<b>27</b>	71.35	70.40
<b>28</b>	70.53	70.31
<b>29</b>	72.04	70.79

In [7]: `table1.sort_values('crf_FB1', ascending = False)`

Out[7]:

	crf_FB1	original_FB1
<b>16</b>	72.16	71.09
<b>25</b>	72.10	70.54
<b>29</b>	72.04	70.79

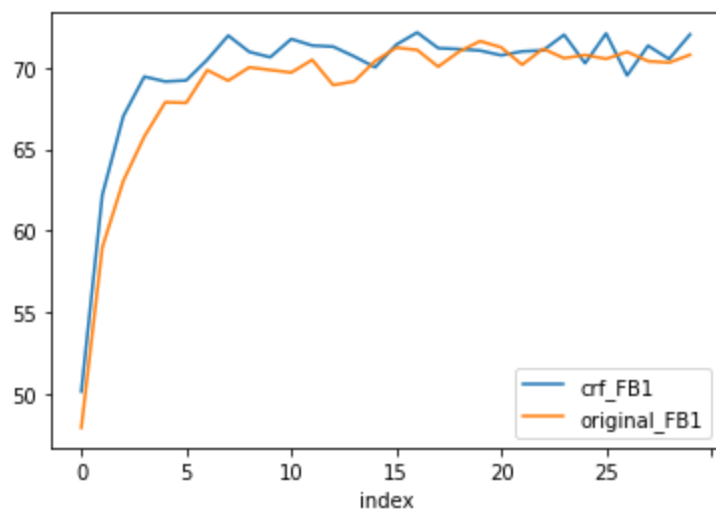
	crf_FB1	original_FB1
23	72.02	70.58
7	71.97	69.20
10	71.76	69.70
15	71.41	71.23
11	71.36	70.48
27	71.35	70.40
12	71.29	68.93
17	71.20	70.06
18	71.14	70.99
22	71.06	71.16
19	71.05	71.63
21	71.00	70.18
8	70.97	70.02
20	70.76	71.25
13	70.69	69.16
9	70.64	69.86
28	70.53	70.31
6	70.49	69.85
24	70.27	70.78
14	70.02	70.41
26	69.52	70.97
3	69.45	65.77
5	69.22	67.84
4	69.15	67.88
2	67.02	63.05
1	62.19	58.97
0	50.12	47.89

```
In [8]: import matplotlib.pyplot as plt
```

```
In [9]: table1 = table1.reset_index()
```

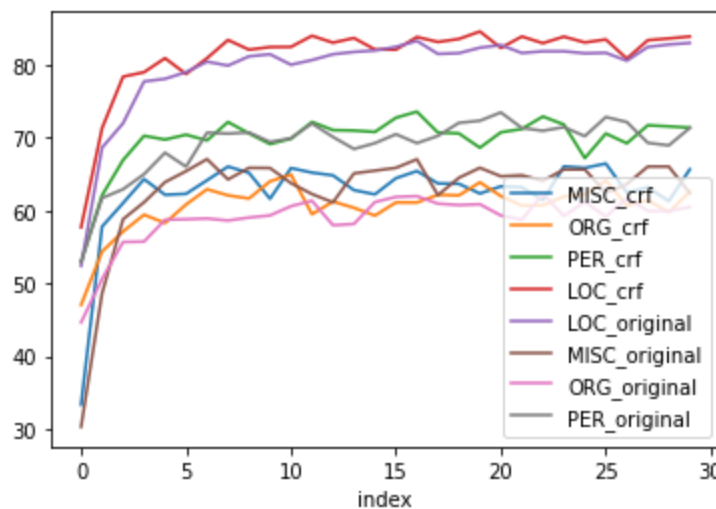
```
In [10]: table1.plot(x = 'index', y = ['crf_FB1', 'original_FB1'])
```

```
Out[10]: <AxesSubplot:xlabel='index'>
```



```
In [65]: df.plot(x = 'index', y = ['MISC_crf', 'ORG_crf', 'PER_crf', 'LOC_crf', 'LOC_original', 'MISC_original', 'ORG_original', 'PER_original'])
```

```
Out[65]: <AxesSubplot:xlabel='index'>
```



```
In [64]: df
```

```
Out[64]:
```

	index	MISC_crf	ORG_crf	PER_crf	LOC_crf	LOC_original	MISC_original	ORG_original	PER_original
0	0	33.33	47.04	53.00	57.71	52.40	30.28	44.63	52.93
1	1	57.81	54.38	62.11	71.34	68.66	48.63	50.61	61.73
2	2	61.04	57.14	66.95	78.42	72.01	58.82	55.69	62.94
3	3	64.33	59.44	70.29	79.03	77.76	61.15	55.74	65.01
4	4	62.18	58.30	69.77	80.96	78.12	63.92	58.75	67.96
5	5	62.31	60.84	70.44	78.79	79.04	65.43	58.82	66.04
6	6	64.17	62.94	69.65	80.96	80.48	67.08	58.92	70.72
7	7	66.06	62.10	72.18	83.46	79.94	64.29	58.64	70.59
8	8	65.20	61.67	70.62	82.13	81.21	65.88	59.05	70.75
9	9	61.63	64.03	69.15	82.49	81.50	65.86	59.34	69.44
10	10	65.85	64.95	69.89	82.51	80.06	63.78	60.61	69.96
11	11	65.23	59.51	72.19	84.04	80.70	62.28	61.36	71.98

	index	MISC_crf	ORG_crf	PER_crf	LOC_crf	LOC_original	MISC_original	ORG_original	PER_original
<b>12</b>	12	64.85	61.25	71.07	83.09	81.50	61.14	58.00	70.13
<b>13</b>	13	62.82	60.39	71.01	83.73	81.82	65.12	58.17	68.48
<b>14</b>	14	62.24	59.32	70.82	82.15	82.01	65.50	61.18	69.28
<b>15</b>	15	64.46	61.13	72.77	82.13	82.52	65.88	61.89	70.51
<b>16</b>	16	65.44	61.12	73.61	83.87	83.33	67.06	61.99	69.28
<b>17</b>	17	63.74	62.17	70.73	83.19	81.55	62.13	60.96	70.28
<b>18</b>	18	63.69	62.10	70.62	83.60	81.65	64.52	60.77	72.07
<b>19</b>	19	62.35	63.89	68.65	84.63	82.40	65.89	60.88	72.36
<b>20</b>	20	63.34	62.00	70.77	82.37	82.76	64.72	59.33	73.50
<b>21</b>	21	63.22	60.69	71.23	83.94	81.67	64.86	58.75	71.36
<b>22</b>	22	61.45	60.72	72.94	83.02	81.91	64.09	62.31	70.98
<b>23</b>	23	66.08	61.95	71.84	83.92	81.91	65.66	59.27	71.48
<b>24</b>	24	65.88	62.23	67.22	83.12	81.63	65.66	61.22	70.24
<b>25</b>	25	66.47	64.13	70.60	83.53	81.69	62.46	59.17	72.87
<b>26</b>	26	62.50	60.69	69.26	80.90	80.61	63.64	61.74	72.18
<b>27</b>	27	63.19	61.44	71.74	83.43	82.50	66.06	59.97	69.32
<b>28</b>	28	61.32	59.78	71.58	83.67	82.84	66.06	59.93	68.97
<b>29</b>	29	65.68	62.61	71.41	83.94	83.05	62.40	60.50	71.37

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