Akash Assignment 2 Report

Report On RNN Models

Between all the comparisons, including differences in RNN layers, number of nodes, number of layers, bidirectionality, presence of pre-trained embeddings, and size of training sets. The comparison I have decided to perform for job 1 is "Comparison between Simple RNN (RNN1) and extended RNN with extended nodes and layers (RNN2)". The same number of epochs will be used to train both models in order to guarantee consistency in the comparison.

RNN 1: -

The default RNN's layer's bidirectional LSTM (Long Short-Term Memory) units handle the input sequence both forward and backward. The first RNN to form is this one. It has 10 LSTM units, and return_sequences=True means that all of the output from each timestep is returned, not just the output from the one before it. The activation function used in LSTM cells is called Rectified Linear Units, or ReLUs. The TimeDistributed wrapper applies the same dense layer separately to each timestep of the input sequence. It has a 50 unit thick layer and ReLU activation. The last dense layer produces the model's output. Tag_len, your classification operation's total number of unique tags or classes, is equal to the number of units. The activation function used in this case is called softmax.

```
# Create RNN.
    m = Sequential()
    m.add(Embedding(vocab_len, embed_len,
embeddings_initializer=Constant(embedding_matrix)))

    m.add(Bidirectional(LSTM(10, return_sequences=True, activation="relu")))

    m.add(TimeDistributed(Dense(50,activation="relu")))

    m.add(Dense(tag_len,activation="softmax"))

    m.compile("adam", "categorical_crossentropy", metrics=["accuracy"])
```

In addition to this, I tested for the remaining sentences after training the data on 40000 sentences.

```
# Divide data into training and test
    tr_sent = sent[:40000]
    tr_tag = ner[:40000]
    te_sent = sent[40000:]
    te_tag = ner[40000:]
```

RNN 2: -

The second RNN's layer is composed of bidirectional LSTM units, which process the input sequence both forward and backward. It has 30 LSTM units, and return_sequences=True means that all of the output from each timestep is returned, not just the output from the one before it. The activation function that the LSTM cells employ is called ReLU. The TimeDistributed wrapper applies the same dense layer separately to each timestep of the input sequence. It features a thick layer of seventy units and ReLU activation. The last dense layer produces the model's output. The number of units is equal to Tag_len, which is the total number of unique tags or classes in your classification operation. The activation function utilized in this instance is Softmax function.

```
# Create RNN.
    m = Sequential()
    m.add(Embedding(vocab_len, embed_len,
embeddings_initializer=Constant(embedding_matrix)))

    m.add(Bidirectional(LSTM(15, return_sequences=True, activation="relu")))

    m.add(TimeDistributed(Dense(70,activation="relu")))

    m.add(Dense(tag_len,activation="softmax"))

    m.compile("adam", "categorical_crossentropy", metrics=["accuracy"])
```

In addition to this, I tested the data starting at the 40000th sentence and trained it using 20000 sentences.

```
# Divide data into training and test
    tr_sent = sent[:20000]
    tr_tag = ner[:20000]
    te_sent = sent[40000:]
    te_tag = ner[40000:]
```

Evaluation Results

- Entity type: geo

	RNN 1	RNN 2
Total Entities	6194	6194
Total predicted	6591	6128
Correctly extracted	5304	5054
Precision	80.47 %	82.47 %
Recall	85.63 %	81.6 %
F-measure	82.97 %	82.03 %

- Entity type: gpe

	RNN 1	RNN 2
Total Entities	2757	2757
Total predicted	2654	2793
Correctly extracted	2534	2553
Precision	95.48 %	91.41 %
Recall	91.91 %	92.6 %
F-measure	93.66 %	92.0 %

- Entity type: per

	RNN 1	RNN 2
Total Entities	2784	2784
Total predicted	2828	2840
Correctly extracted	1880	1815
Precision	66.48 %	63.91 %
Recall	67.53 %	65.19 %
F-measure	67.0 %	64.54 %

- Entity type: org

	RNN 1	RNN 2
Total Entities	3400	3400
Total predicted	2808	2991
Correctly extracted	1862	1878
Precision	66.31 %	62.79 %
Recall	54.76 %	55.24 %
F-measure	59.99 %	58.77 %

- Entity type: tim

	RNN 1	RNN 2
Total Entities	3431	3431
Total predicted	3230	3187
Correctly extracted	2609	2569
Precision	80.77 %	80.61 %
Recall	76.04 %	74.88 %
F-measure	78.34 %	77.64 %

- Entity type: art

	RNN 1	RNN 2
Total Entities	75	75
Total predicted	0	0
Correctly extracted	0	0
Precision	cannot be computed	cannot be computed
Recall	0.0 %	0.0 %
F-measure	cannot be computed	cannot be computed

- Entity type: nat

	RNN 1	RNN 2
Total Entities	36	36
Total predicted	0	0
Correctly extracted	0	0
Precision	cannot be computed	cannot be computed
Recall	0.0 %	0.0 %
F-measure	cannot be computed	cannot be computed

- Entity type: eve

	RNN 1	RNN 2
Total Entities	41	41
Total predicted	0	0
Correctly extracted	0	0
Precision	cannot be computed	cannot be computed
Recall	0.0 %	0.0 %
F-measure	cannot be computed	cannot be computed

- All entities combined

	RNN 1	RNN 2
Total Entities	18718	18718
Total predicted	18111	17939
Correctly extracted	14189	13869
Precision	78.34 %	77.31 %
Recall	75.8 %	74.09 %
F-measure	77.05 %	75.67 %

The precision of the positive predictions is measured. The ratio of real positives to the total of true positives and false positives is one way to express it. A model's recall measures its ability to find each relevant case within a dataset. The ratio of true positives to the total of true positives and false negatives is one way to describe it. F-measures integrate recall and precision into a single statistic that addresses both issues by utilizing their harmonic mean. It is represented as the precision and recall product divided by the sum of the two terms, multiplied by two. This statistic is useful when attempting to strike a compromise between recall and precision.

Based on the above evaluation results from all entities:

Precision value got decreased from 78.34 % to 77.31 %

Recall value got increased from 75.8 % to 74.09 %

F-measure value got increased 77.05 % to 75.67 %

Whereas the Total predicted values, correctly extracted values got increased.

The RNN2 model demonstrates superior performance over the RNN1 across the Recall and F-measure.

Error Evaluation based on comparison between two RNN

Sentence	**eval.txt**	**eval_T1P1**
Test example: 7 Sentence: ['The', 'U.N.', 'World', 'Food', 'Program', 'began', 'distributing', 'relief', 'supplies', 'Wednesday', 'in', 'the', 'town', 'of', 'Hafun', 'on', 'the', 'northern', 'coast', 'of', 'Somalia', '.'] Target: ['O', 'B-org', 'I-org', 'I-org', 'I-org', 'O', 'O', 'O', 'O', 'B-tim', 'O', 'O', 'O', 'O', 'B-geo', 'O', 'O', 'O', 'O', 'O', 'B-geo', 'O']	Predicted: ['O', 'B-org', 'I-org', 'O', 'O', 'O', 'O', 'O', 'O', 'B-tim', 'O', 'O', 'O', 'O', 'B-geo', 'O', 'O', 'O', 'O', 'O', 'B-geo', 'O'] At 1 ('org', 'U.N. World Food Program') Missed. At 9 ('tim', 'Wednesday') Extracted. At 14 ('geo', 'Hafun') Extracted. At 20 ('geo', 'Somalia') Extracted. At 1 ('org', 'U.N. World') Incorrectly extracted.	Predicted: ['O', 'B-org', 'I-org', 'I-org', 'I-org', 'O', 'O', 'O', 'O', 'B-tim', 'O', 'O', 'O', 'O', 'B-per', 'O', 'O', 'O', 'O', 'O', 'B-geo', 'O'] At 1 ('org', 'U.N. World Food Program') Extracted. At 9 ('tim', 'Wednesday') Extracted. At 14 ('geo', 'Hafun') Missed. At 20 ('geo', 'Somalia') Extracted. At 14 ('per', 'Hafun') Incorrectly extracted.
Test example: 9 Sentence: ['Olympic', 'champion', 'Philipp', 'Schoch', 'of', 'Switzerland', 'and', 'compatriot', 'Ursula', 'Bruhin', 'have', 'won', 'World', 'Cup', 'parallel', 'giant', 'slalom', 'snowboard', 'events', 'in', 'Le', 'Relais', ',', 'Canada', '.'] Target: ['O', 'O', 'B-per', 'I-per', 'O', 'B-geo', 'O', 'O', 'B-per', 'I-per', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-geo', 'I-geo', 'O', 'B-geo', 'O']	Predicted: ['O', 'O', 'B-per', 'I-org', 'O', 'B-geo', 'O', 'O', 'B-per', 'I-per', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-geo', 'I-geo', 'O', 'B-geo', 'O'] At 2 ('per', 'Philipp Schoch') Missed. At 5 ('geo', 'Switzerland') Extracted. At 8 ('per', 'Ursula Bruhin') Extracted. At 20 ('geo', 'Le Relais') Extracted. At 23 ('geo', 'Canada') Extracted. At 2 ('per', 'Philipp') Incorrectly extracted.	Predicted: ['O', 'O', 'B-per', 'I-per', 'O', 'B-geo', 'O', 'O', 'B-per', 'I-per', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-per', 'I-geo', 'O', 'B-geo', 'O'] At 2 ('per', 'Philipp Schoch') Extracted. At 5 ('geo', 'Switzerland') Extracted. At 8 ('per', 'Ursula Bruhin') Extracted. At 20 ('geo', 'Le Relais') Missed. At 23 ('geo', 'Canada') Extracted. At 20 ('per', 'Le') Incorrectly extracted.
Test example: 11 Sentence: ['Schoch', 'leads', 'the', 'World', 'Cup', 'standings', 'with', '1,700', 'points', '.'] Target: ['B-per', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O']	Predicted: ['O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O'] At 0 ('per', 'Schoch') Missed.	Predicted: ['I-per', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O'] At 0 ('per', 'Schoch') Missed.

Test example: 12 Sentence: ['Countryman', 'Heinz', 'Inniger', 'is', 'second', '(', '1,630', 'points', ')', 'with', 'Switzerland', "'s", 'Gilles', 'Jaquet', 'third', '(', '1,460', 'points', ')', '.'] Target: ['O', 'B-per', 'I-per', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-geo', 'O', 'B-geo', 'I-geo', 'O', 'O', 'O', 'O', 'O', 'O']	Predicted: ['O', 'B-per', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-geo', 'O', 'B-per', 'I-per', 'O', 'O', 'O', 'O', 'O', 'O'] At 1 ('per', 'Heinz Inniger') Missed. At 10 ('geo', 'Switzerland') Extracted. At 12 ('geo', 'Gilles Jaquet') Missed. At 1 ('per', 'Heinz') Incorrectly extracted. At 12 ('per', 'Gilles Jaquet') Incorrectly extracted.	Predicted: ['B-per', 'I-per', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-geo', 'O', 'B-per', 'I-per', 'O', 'O', 'O', 'O', 'O', 'O'] At 1 ('per', 'Heinz Inniger') Missed. At 10 ('geo', 'Switzerland') Extracted. At 12 ('geo', 'Gilles Jaquet') Missed. At 0 ('per', 'Countryman Heinz') Incorrectly extracted. At 12 ('per', 'Gilles Jaquet') Incorrectly extracted.
Test example: 15 Sentence: ['Bruhin', 'is', 'tied', 'with', 'French', 'skier', 'Julie', 'Pomagalski', 'atop', 'the', 'World', 'Cup', 'standings', 'with', '1,950', 'points', '.'] Target: ['B-per', 'O', 'O', 'O', 'B-gpe', 'O', 'B-per', 'I-per', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O']	Predicted: ['O', 'O', 'O', 'O', 'B-gpe', 'O', 'B-per', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O'] At 0 ('per', 'Bruhin') Missed. At 4 ('gpe', 'French') Extracted. At 6 ('per', 'Julie Pomagalski') Missed. At 6 ('per', 'Julie') Incorrectly extracted.	Predicted: ['B-per', 'O', 'O', 'O', 'B-gpe', 'O', 'B-per', 'O', 'O', 'O', 'O', 'I-org', 'O', 'O', 'O', 'O', 'O'] At 0 ('per', 'Bruhin') Extracted. At 4 ('gpe', 'French') Extracted. At 6 ('per', 'Julie Pomagalski') Missed. At 6 ('per', 'Julie') Incorrectly extracted.

Based on the error evaluation done on the evaluation files from both the **RNN's**.

A small number of word pairs that were missing or improperly extracted in RNN1 were correctly extracted in RNN2. In certain cases, a few extractions were missed or extracted incorrectly in RNN2 when compared to RNN1.If we had added a few extra nodes and dense layers when building the RNN, these might have been correctly extracted.

Task 3 Evaluation Results:

All entities combined	RNN 1	RNN 2
Total Entities	23	23
Total predicted	26	22
Correctly extracted	18	20
Precision	69.23 %	90.91 %
Recall	78.26 %	86.96 %
F-measure	73.47 %	88.89 %

Evaluation Explanation:

Here there was a noticeable decline in the performance of both the RNN and GRU models when dealing with new sentences, particularly when it came to recognising different types of entities. These findings imply that in order for both models to handle new and varied data more effectively, more thorough training and maybe improved architectures are required.

sentence	Task 3 part 1	Task 3 part 2
Test example: 2 Sentence: ['United', 'Nations', 'agencies', 'are', 'appealing', 'for', 'immediate', 'assistance', 'to', 'communities', 'on', 'the', 'West', 'coast', 'affected', 'by', 'South', 'Asia', "'s", 'earthquake-generated', 'tsunami', '.'] Target: ['B-org', 'I-org', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-gpe', 'O', 'O', 'O', 'B-geo', 'I-geo', 'O', 'O', 'O', 'O']	Predicted: ['B-org', 'I-org', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-gpe', 'O', 'O', 'O', 'B-geo', 'B-geo', 'O', 'O', 'O', 'O'] At 0 ('org', 'United Nations') Extracted. At 12 ('gpe', 'West') Extracted. At 16 ('geo', 'South Asia') Missed. At 16 ('geo', 'South') Incorrectly extracted. At 17 ('geo', 'Asia') Incorrectly extracted.	Predicted: ['B-org', 'I-org', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-gpe', 'O', 'O', 'O', 'B-geo', 'I-geo', 'O', 'O', 'O', 'O'] At 0 ('org', 'United Nations') Extracted. At 12 ('gpe', 'West') Extracted. At 16 ('geo', 'South Asia') Extracted.
Test example: 3 Sentence: ['The', 'appeal', 'was', 'issued', 'Friday', 'by', 'the', 'U.N.', 'Office', 'for', 'the', 'Coordination', 'of', 'Humanitarian', 'Affairs', ',', 'which', 'took', 'part', 'in', 'an', 'aerial', 'assessment', 'of', 'the', 'affected', 'areas', 'in', 'northern', 'Somalia', '.'] Target: ['O', 'O', 'O', 'O', 'B-tim', 'O', 'O', 'B-org', 'I-org', 'O', 'O', 'B-org', 'I-org', 'I-org', 'I-org', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-geo', 'O']	Predicted: ['O', 'O', 'O', 'O', 'B-tim', 'O', 'O', 'B-org', 'I-org', 'O', 'O', 'B-org', 'I-org', 'I-org', 'I-org', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-geo', 'O'] At 4 ('tim', 'Friday') Extracted. At 7 ('org', 'U.N. Office') Extracted. At 11 ('org', 'Coordination of Humanitarian Affairs') Extracted. At 29 ('geo', 'Somalia') Extracted.	Predicted: ['O', 'O', 'O', 'O', 'B-tim', 'O', 'O', 'B-org', 'I-org', 'O', 'O', 'I-org', 'I-org', 'I-org', 'I-org', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-geo', 'O'] At 4 ('tim', 'Friday') Extracted. At 7 ('org', 'U.N. Office') Missed. At 11 ('org', 'Coordination of Humanitarian Affairs') Missed. At 29 ('geo', 'Somalia') Extracted. At 7 ('org', 'U.N. Office Coordination of Humanitarian Affairs') Incorrectly extracted.
Test example: 4 Sentence: ['Meanwhile', ',', 'the', 'number', 'of', 'dead', 'in', 'Somalia', 'has', 'climbed', 'to', 'at', 'least', '132', 'people', ',', 'although', 'the', 'Associated', 'Press', 'quotes', 'a', 'senior', 'Somali', 'official', 'as', 'putting', 'the', 'number', 'at', '200', '.'] Target: ['O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-geo', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-org', 'I-org', 'O', 'O', 'O', 'B-gpe', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O']	Predicted: ['O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-geo', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-org', 'I-org', 'O', 'O', 'O', 'B-gpe', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O'] At 7 ('geo', 'Somalia') Extracted. At 18 ('org', 'Associated Press') Extracted. At 23 ('gpe', 'Somali') Extracted.	Predicted: ['O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-geo', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-org', 'I-org', 'O', 'O', 'O', 'B-gpe', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O'] At 7 ('geo', 'Somalia') Extracted. At 18 ('org', 'Associated Press') Extracted. At 23 ('gpe', 'Somali') Extracted.

Test example: 6 Sentence: ['The', 'United', 'Nations', 'says', 'it', 'is', 'difficult', 'to', 'get', 'a', 'clear', 'picture', 'of', 'both', 'the', 'number', 'of', 'those', 'killed', 'and', 'the', 'extent', 'of', 'the', 'damage', 'because', 'the', 'region', 'is', 'remote', 'and', 'the', 'conditions', 'are', 'harsh', '.'] Target: ['O', 'B-org', 'I-org', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O']	Predicted: ['O', 'B-org', 'I-org', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O'] At 1 ('org', 'United Nations') Extracted.	Predicted: ['O', 'B-org', 'I-org', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O'] At 1 ('org', 'United Nations') Extracted.
Test example: 7 Sentence: ['The', 'U.N.', 'World', 'Food', 'Program', 'began', 'distributing', 'relief', 'supplies', 'Wednesday', 'in', 'the', 'town', 'of', 'Hafun', 'on', 'the', 'northern', 'coast', 'of', 'Somalia', '.'] Target: ['O', 'B-org', 'I-org', 'I-org', 'I-org', 'O', 'O', 'O', 'O', 'B-tim', 'O', 'O', 'O', 'O', 'B-geo', 'O', 'O', 'O', 'O', 'O', 'B-geo', 'O']	Predicted: ['O', 'B-org', 'B-org', 'O', 'O', 'O', 'O', 'O', 'O', 'B-tim', 'O', 'O', 'O', 'O', 'B-geo', 'O', 'O', 'O', 'O', 'O', 'B-geo', 'O'] At 1 ('org', 'U.N. World Food Program') Missed. At 9 ('tim', 'Wednesday') Extracted. At 14 ('geo', 'Hafun') Extracted. At 20 ('geo', 'Somalia') Extracted. At 1 ('org', 'U.N.') Incorrectly extracted. At 2 ('org', 'World') Incorrectly extracted.	Predicted: ['O', 'B-org', 'I-org', 'I-org', 'I-org', 'O', 'O', 'O', 'O', 'B-tim', 'O', 'O', 'O', 'O', 'B-geo', 'O', 'O', 'O', 'O', 'O', 'B-geo', 'O'] At 1 ('org', 'U.N. World Food Program') Extracted. At 9 ('tim', 'Wednesday') Extracted. At 14 ('geo', 'Hafun') Extracted. At 20 ('geo', 'Somalia') Extracted.
Test example: 8 Sentence: ['The', 'tsunami', 'also', 'took', 'lives', 'in', 'Tanzania', ',', 'Seychelles', 'and', 'Kenya', '.'] Target: ['O', 'O', 'O', 'O', 'O', 'O', 'B-geo', 'O', 'B-geo', 'O', 'B-geo', 'O']	Predicted: ['O', 'O', 'O', 'O', 'O', 'O', 'B-geo', 'O', 'B-geo', 'O', 'B-geo', 'O'] At 6 ('geo', 'Tanzania') Extracted. At 8 ('geo', 'Seychelles') Extracted. At 10 ('geo', 'Kenya') Extracted.	Predicted: ['O', 'O', 'O', 'O', 'O', 'O', 'B-geo', 'O', 'B-geo', 'O', 'B-geo', 'O'] At 6 ('geo', 'Tanzania') Extracted. At 8 ('geo', 'Seychelles') Extracted. At 10 ('geo', 'Kenya') Extracted.
Test example: 9 Sentence: ['Olympic', 'champion', 'Philipp', 'Schoch', 'of', 'Switzerland', 'and', 'compatriot', 'Ursula', 'Bruhin', 'have', 'won', 'World', 'Cup', 'parallel', 'giant', 'slalom', 'snowboard', 'events', 'in', 'Le', 'Relais', ',', 'Canada', '.'] Target: ['O', 'O', 'B-per', 'I-per', 'O', 'B-geo', 'O', 'O', 'B-per', 'I-	Predicted: ['O', 'O', 'B-org', 'I-per', 'O', 'B-geo', 'O', 'O', 'B-per', 'B-per', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-per', 'I-org', 'O', 'B-geo', 'O'] At 2 ('per', 'Philipp Schoch') Missed. At 5 ('geo', 'Switzerland') Extracted.	Predicted: ['O', 'O', 'B-per', 'I-per', 'O', 'B-geo', 'O', 'O', 'B-per', 'I-per', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-geo', 'I-org', 'O', 'B-geo', 'O'] At 2 ('per', 'Philipp Schoch') Extracted. At 5 ('geo', 'Switzerland') Extracted.

per', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'B-geo', 'I-geo', 'O', 'B-geo', 'O']	At 8 ('per', 'Ursula Bruhin') Missed. At 20 ('geo', 'Le Relais') Missed. At 23 ('geo', 'Canada') Extracted. At 2 ('org', 'Philipp') Incorrectly extracted. At 8 ('per', 'Ursula') Incorrectly extracted. At 9 ('per', 'Bruhin') Incorrectly extracted. At 20 ('per', 'Le') Incorrectly extracted.	At 8 ('per', 'Ursula Bruhin') Extracted. At 20 ('geo', 'Le Relais') Missed. At 23 ('geo', 'Canada') Extracted. At 20 ('geo', 'Le') Incorrectly extracted.