

Homeworks presentation

Natural Language Processing course

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Homework 1

Named Entity Recognition (NER)



Task description

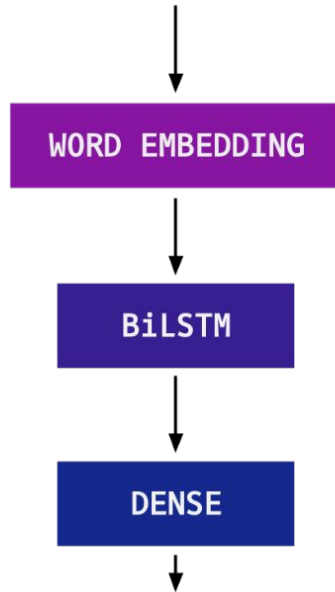
In Named Entity Recognition (NER) we are interested in locate and classify **named entities** mentioned in a text.

A **named entity** is a real-world object that can be denoted with a proper name.
We consider six types of entities:

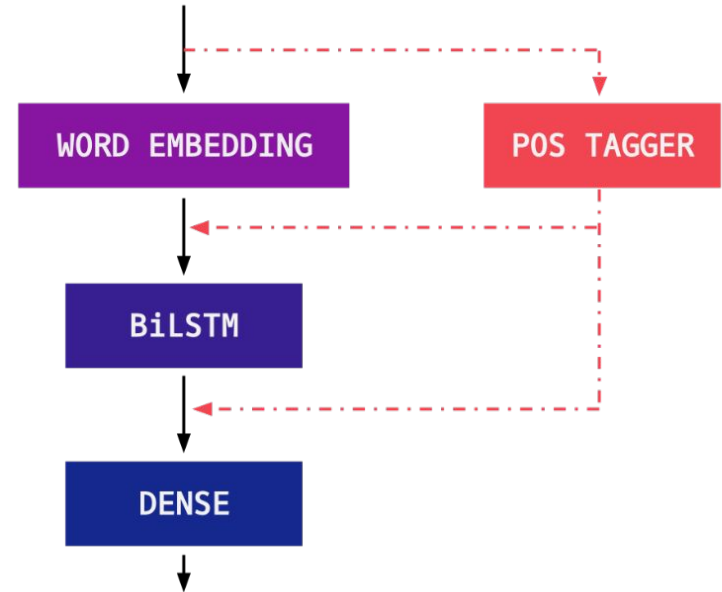
person, corporation, location, product, group and creative work

Obama	went to	Italy
PERSON		LOCATION

Model architectures



BASELINE



BASELINE + POS TAGGER

Model architectures: **Baseline parameters**

Word embedding tested:

word2vec-google-news-300

(17% unknown words)

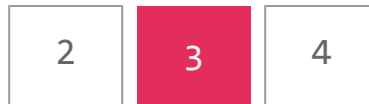
glove.6B.100d

(2% unknown words)

BiLSTM - Hidden size:



BiLSTM - Number of layers:



Model architectures: **Baseline + POS Tagger parameters**

POS Tagging:

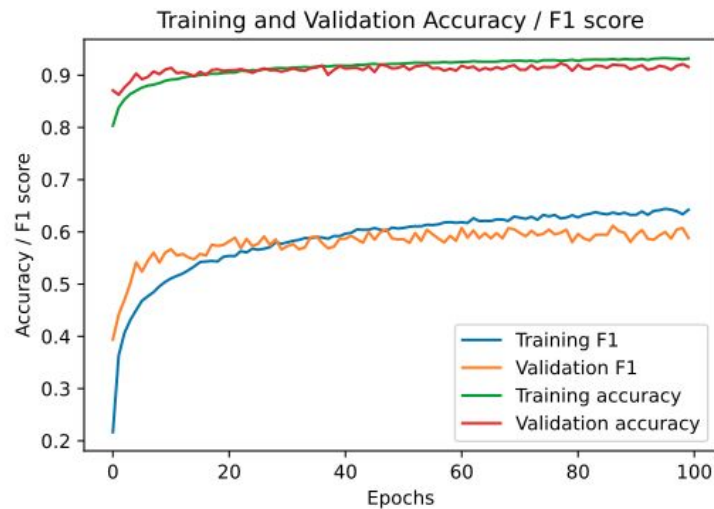
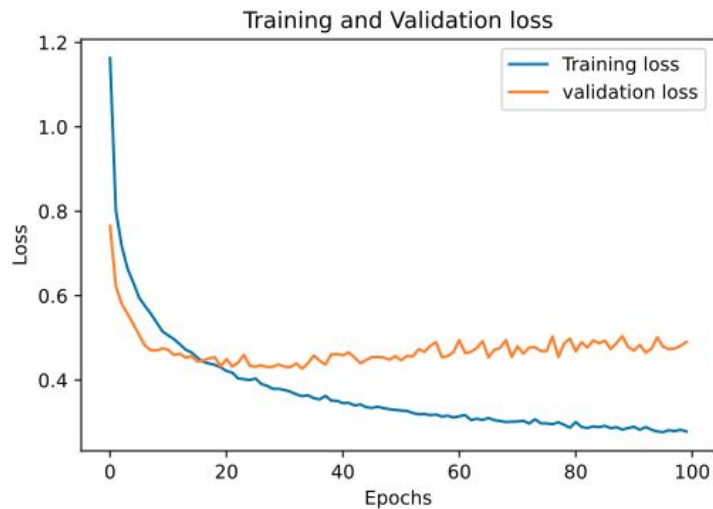
- Performed with nltk library
- Penn Treebank tagset
- POS Tags with one-hot encoding

Dense layer changes w.r.t. baseline:

- BiLSTM output + POS Tags as input
- Increased the number of dense layers from 1 to 3
 - Hidden layer of size (300 x 300)
 - ReLU activation function

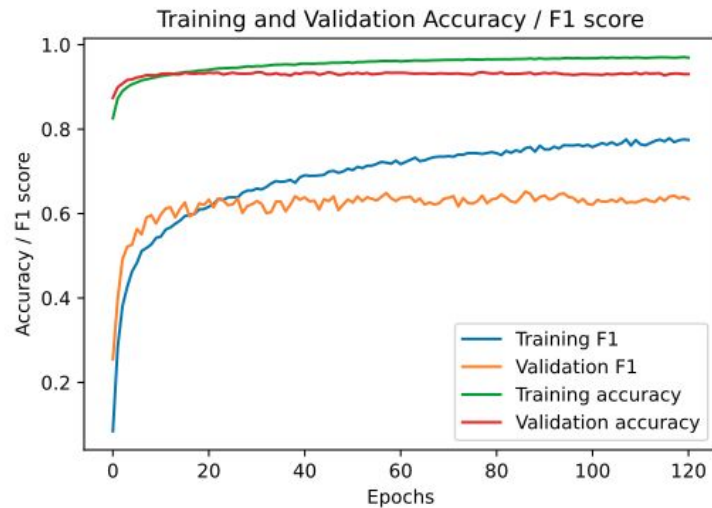
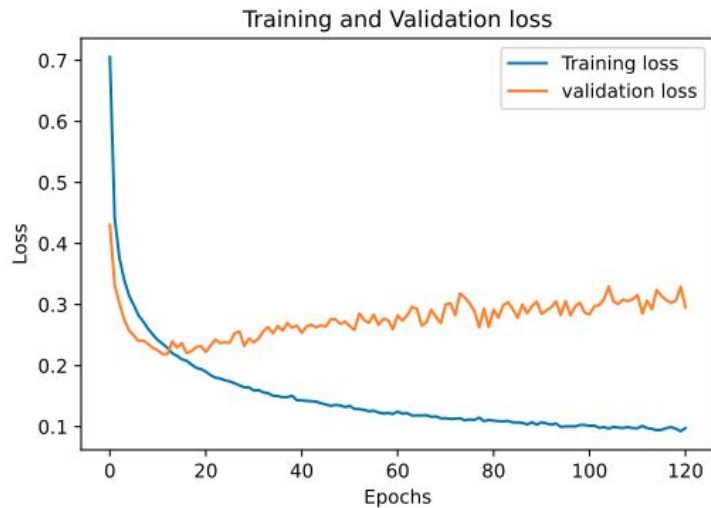
Training: Baseline

Cross entropy weighted loss, Adam optimizer $lr=0.001$, dropout 50%, $l_2=5e-05$



Training: **Baseline + POS Tagger**

Cross entropy weighted loss, Adam optimizer $\text{lr}=0.001$, dropout 50%, $\text{l2}=1\text{e-}05$



Results: Baseline

Baseline

	precision	recall	f1-score	support
CORP	0.51	0.61	0.56	133
CW	0.40	0.59	0.48	170
GRP	0.64	0.67	0.65	190
LOC	0.67	0.81	0.74	243
PER	0.82	0.86	0.84	300
PROD	0.35	0.56	0.43	149
micro avg	0.58	0.71	0.64	1185
macro avg	0.57	0.68	0.62	1185
weighted avg	0.61	0.71	0.65	1185

Results: **Baseline + POS Tagger**

POS Tagger increases macro F1-score by 3%

Baseline + POS Tagger

	precision	recall	f1-score	support
CORP	0.56	0.59	0.58	133
CW	0.55	0.49	0.52	170
GRP	0.69	0.69	0.69	190
LOC	0.81	0.80	0.81	243
PER	0.78	0.87	0.82	300
PROD	0.51	0.52	0.51	149
micro avg	0.68	0.70	0.69	1185
macro avg	0.65	0.66	0.65	1185
weighted avg	0.68	0.70	0.69	1185

Homework 2

Semantic Role Labeling (SRL)

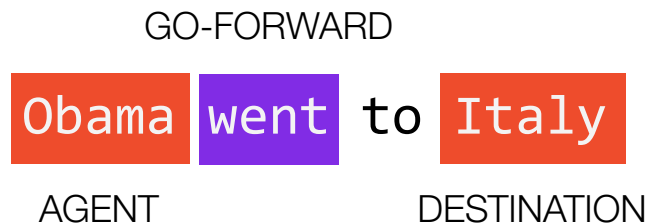


Task description

In Semantic Role Labeling (SRL) we are interested in analyzing the **predicate-argument structures** within a sentence.

PREDICATE: Word or a multi-word expression denoting an event or an action

ARGUMENT: Part of the text linked in some way to the predicate



Task description: **Pipeline**

SRL can be seen as a pipeline of four subtasks:

1) Predicate identification

Obama **went** to Italy

2) Predicate disambiguation

GO-FORWARD
Obama **went** to Italy

3) Argument identification

GO-FORWARD
Obama **went** to **Italy**

4) Argument classification

GO-FORWARD
Obama **went** to **Italy**
AGENT DESTINATION

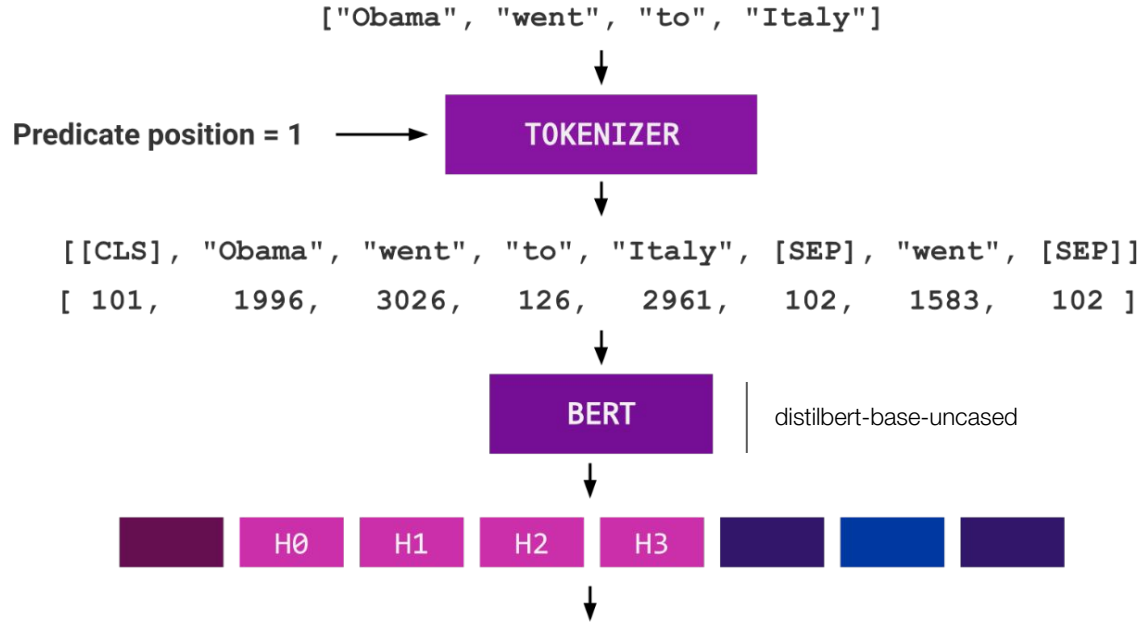
SRL scenarios

We consider two different scenarios

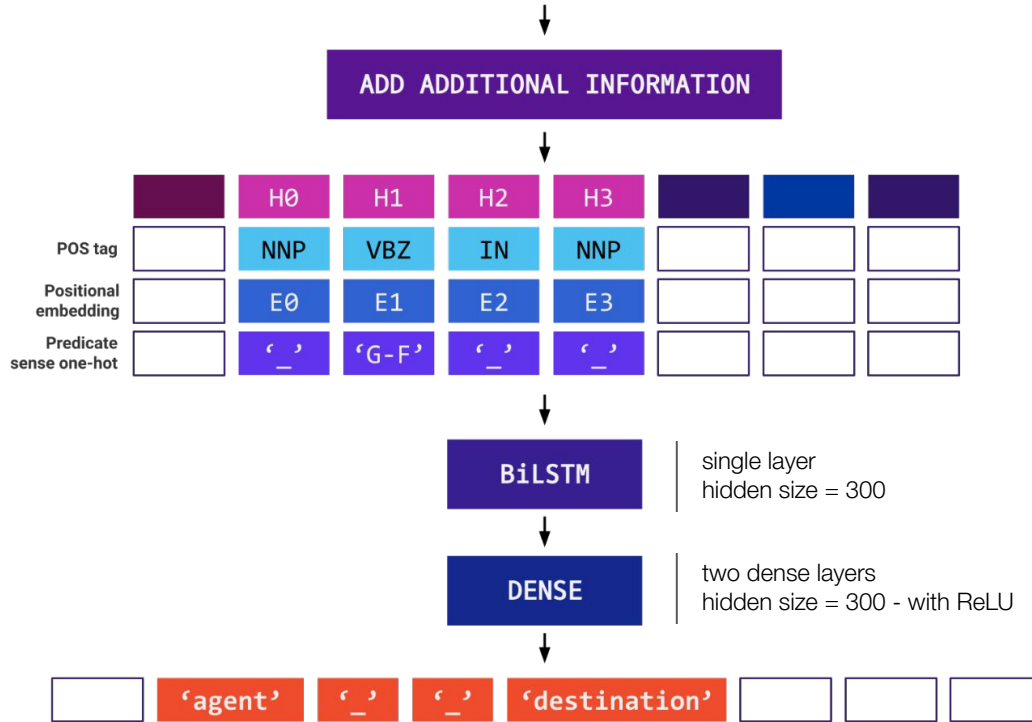
SRL_34: *Predicate identification* and *disambiguation* have already been done

SRL_234: Only *predicate identification* has already been done

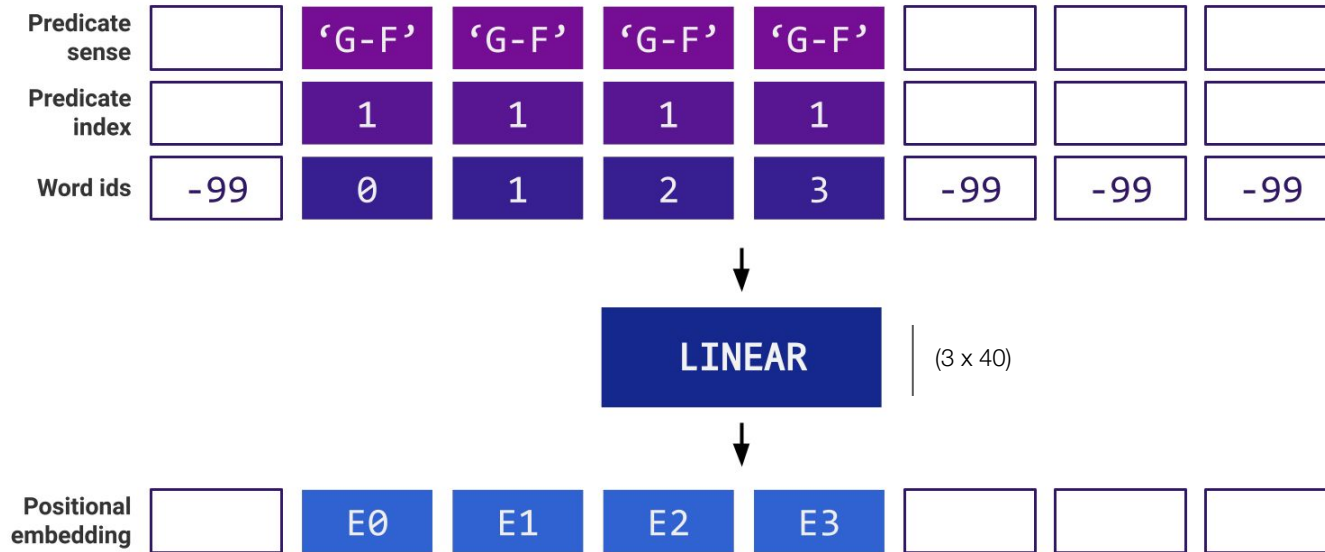
SRL_34 Model: Sentence encoding



SRL_34 Model: **Add additional information**

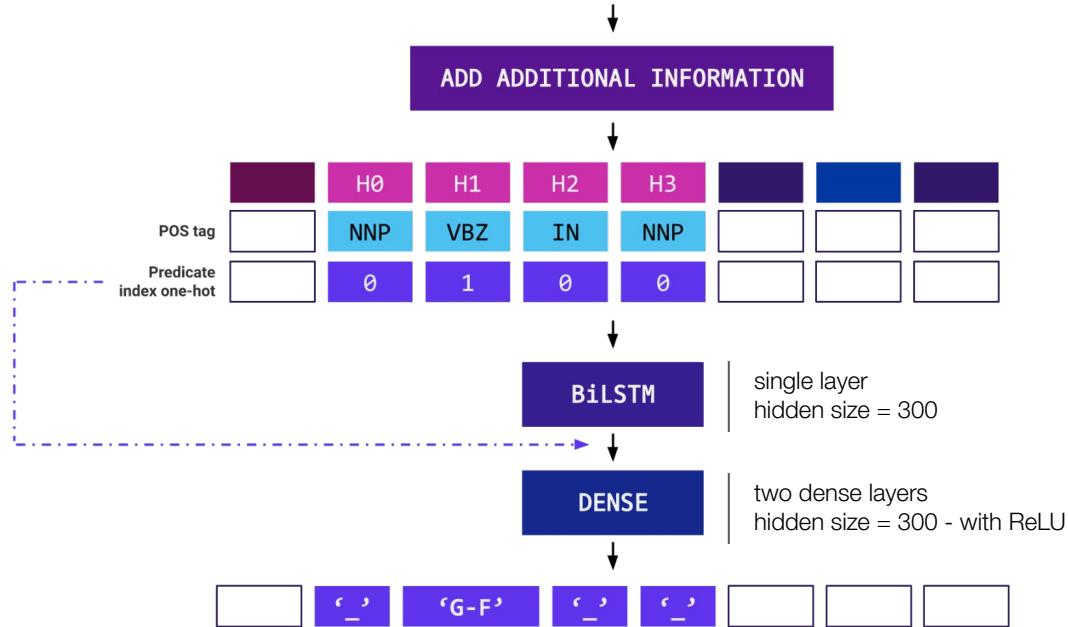


Add additional information: **Positional embedding**

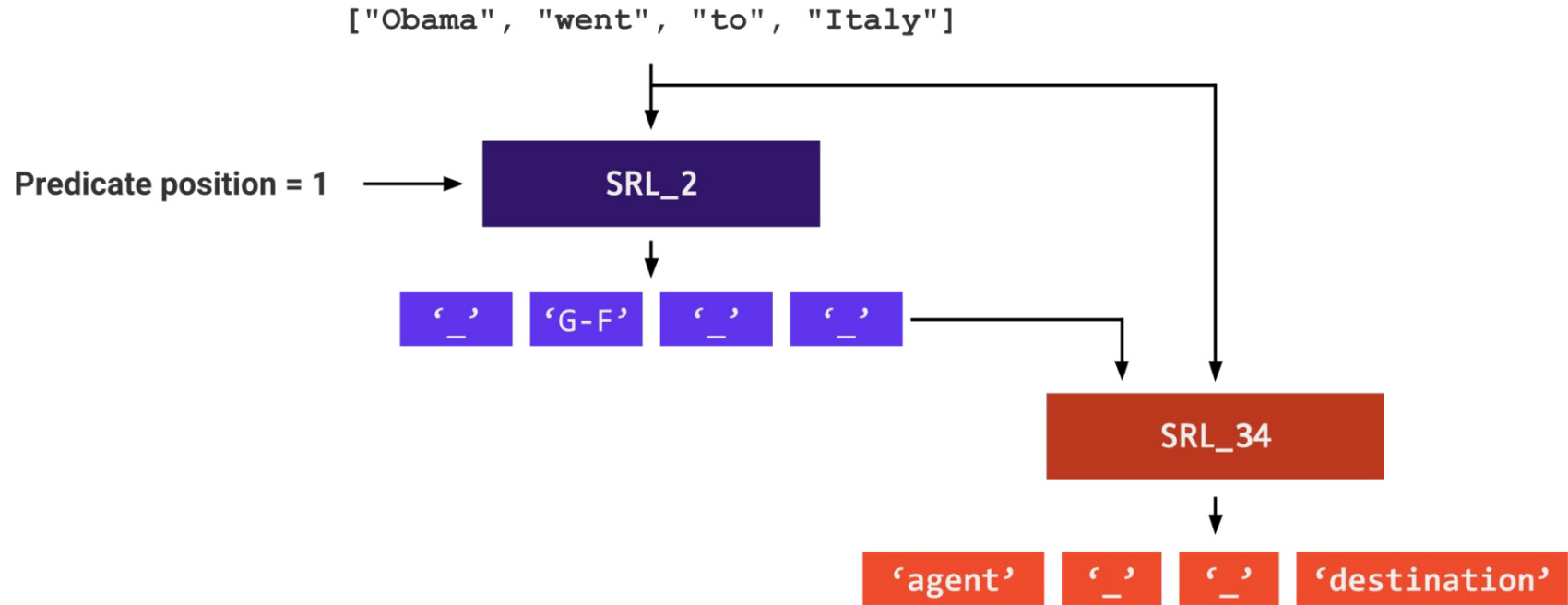


SRL_234: Predicate disambiguation

To perform step 2, SRL_234 uses a sub-model SRL_2 similar to SRL_34



SRL_234: Overall model

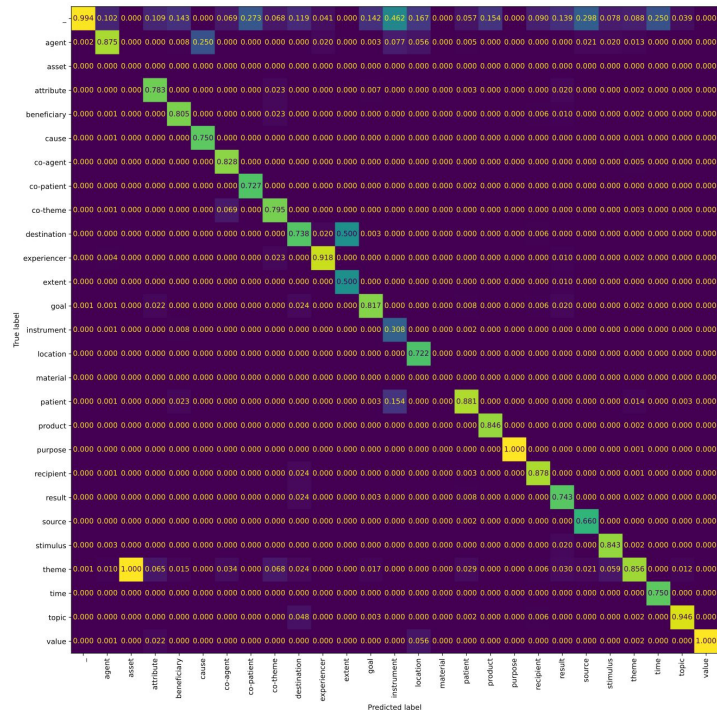


Results: Performance comparison

SRL_34 Tasks	P	R	F1
arg_ident	90.57	88.69	89.62
arg_class	85.96	84.18	85.06

SRL_234 Tasks	P	R	F1
pred_disamb	88.37	88.09	88.23
arg_ident	91.26	88.37	89.79
arg_class	85.04	82.35	83.67

Results: Confusion matrix SRL_34



Best accuracy argument classification on:

- EXPERIENCER

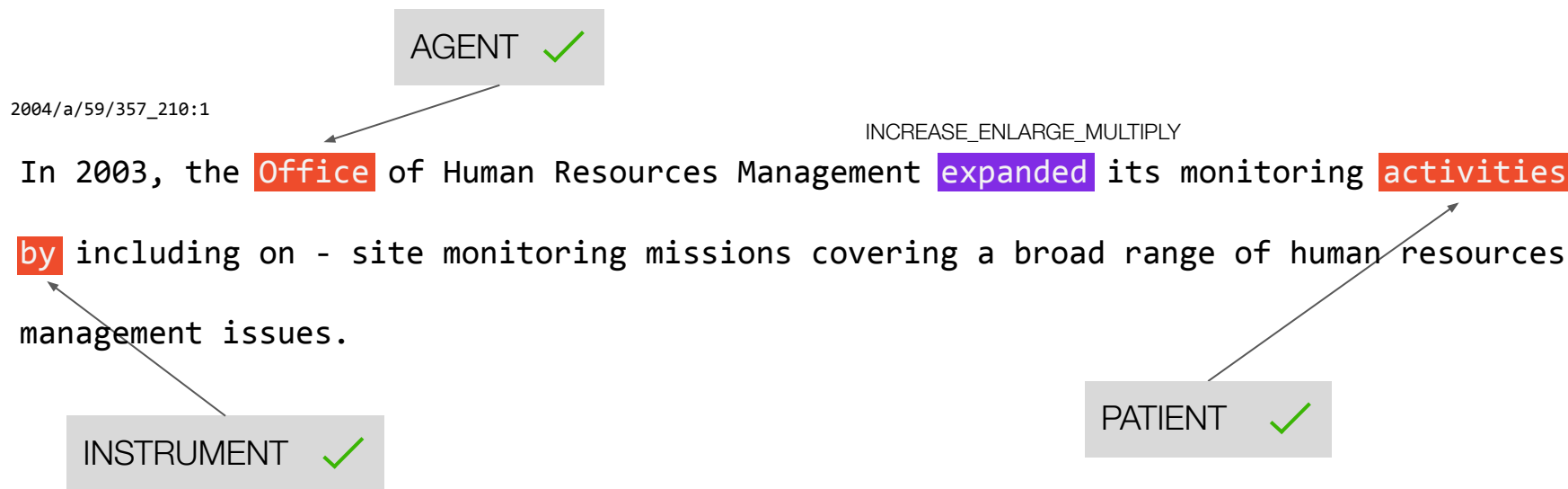
Worst accuracy argument classification on:

- INSTRUMENT

(46% of the time is a false positive)

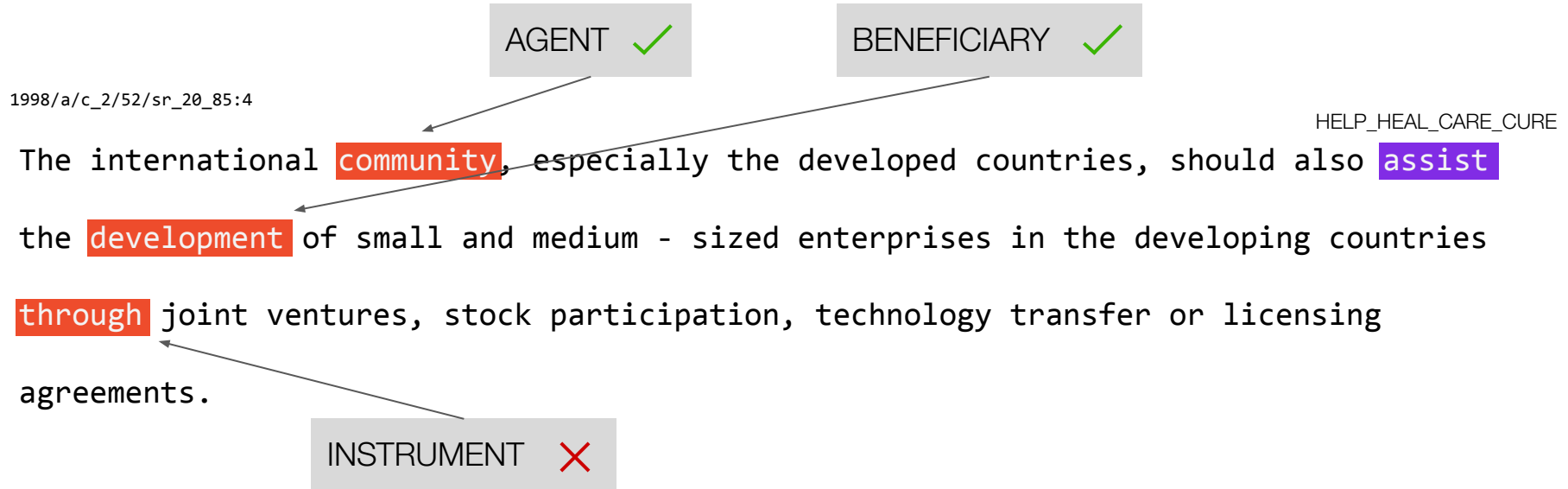
Confusion matrix SRL_34: **True positive INSTRUMENT**

Example of true positive INSTRUMENT argument class

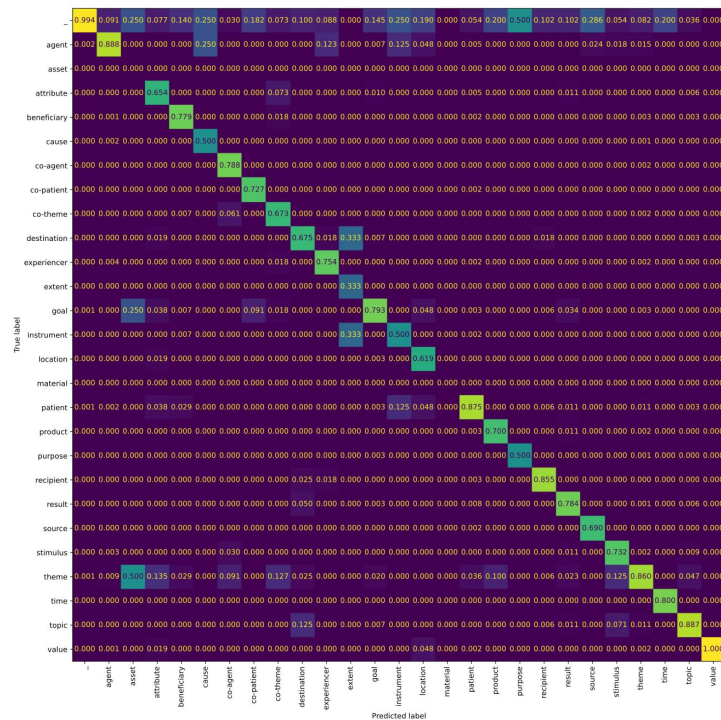


Confusion matrix SRL_34: **False positive INSTRUMENT**

Example of false positive argument identification.



Results: Confusion matrix SRL_234 drop



Drop accuracy argument classification on:

- EXPERIENCER
(12% of the time assigned to AGENT)

Confusion matrix SRL_234 drop: **EXPERIENCER**

SRL_234 performs worse due to wrong predictions of SRL_2.

1999/a/c_2/54/sr_29_21:1

SRL_2: BELIEVE ✗
INTERPRET ✓

Ms. Critchlow (Guyana), introducing the draft resolution on behalf of the Group of 77 and China, said that the use of solar energy was viewed by the Group of 77 and China as another step in the implementation of Agenda 21.

ATTRIBUTE

SRL_234: STIMULUS ✗
SRL_34: THEME ✓

SRL_234: EXPERIENCER ✗
SRL_34: AGENT ✓



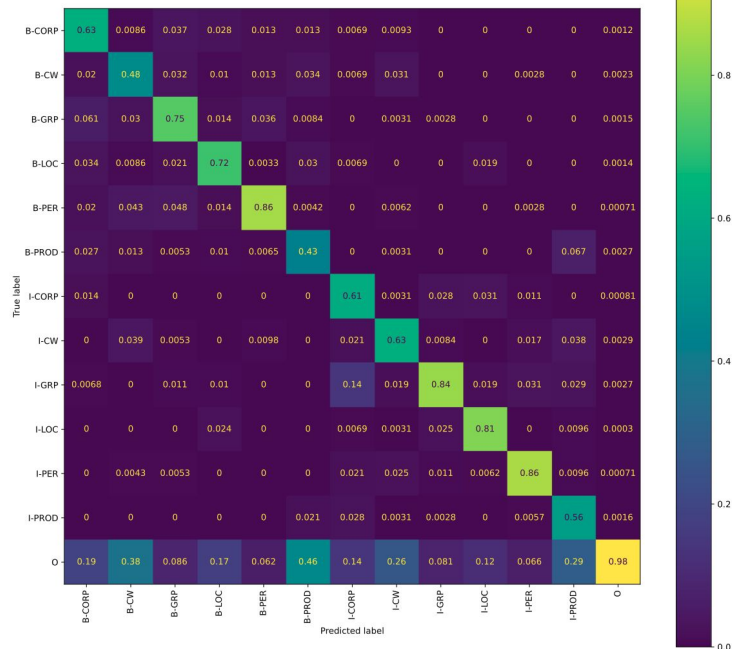
Thanks for your attention



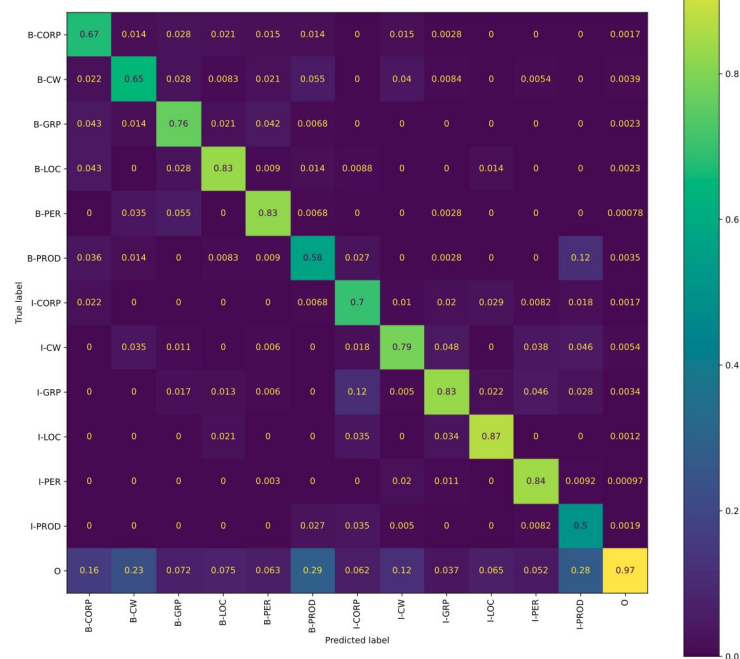
End of the presentation

Results: Confusion Matrices

Baseline

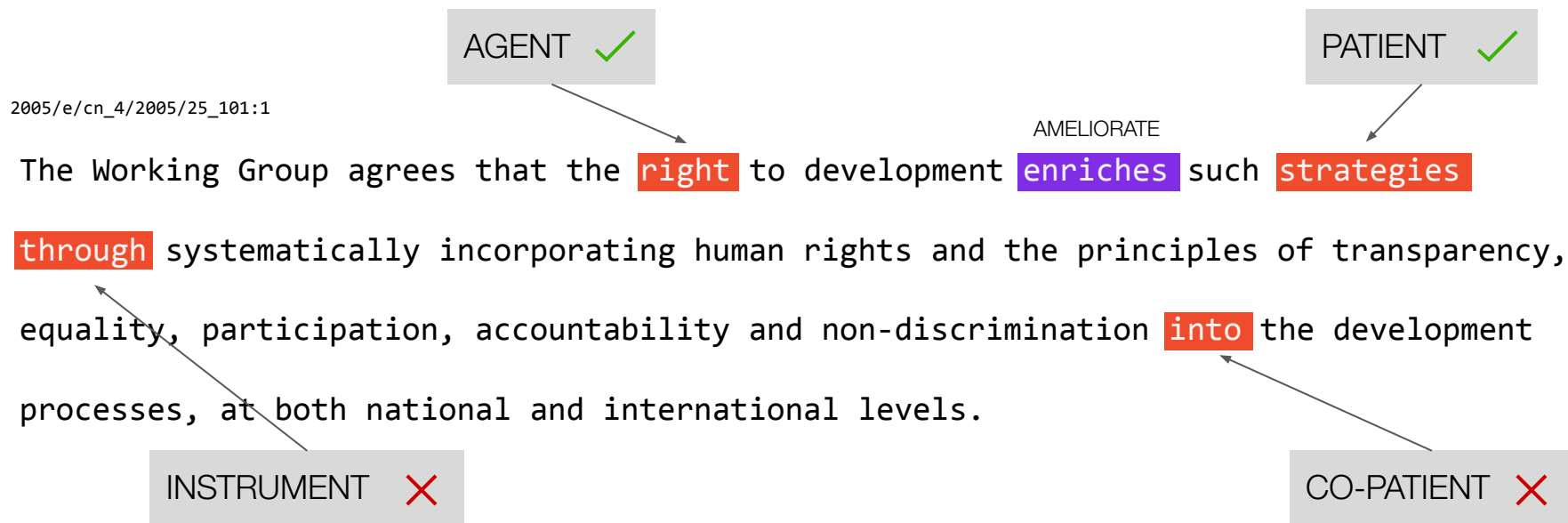


BiLSTM+POS Tagger

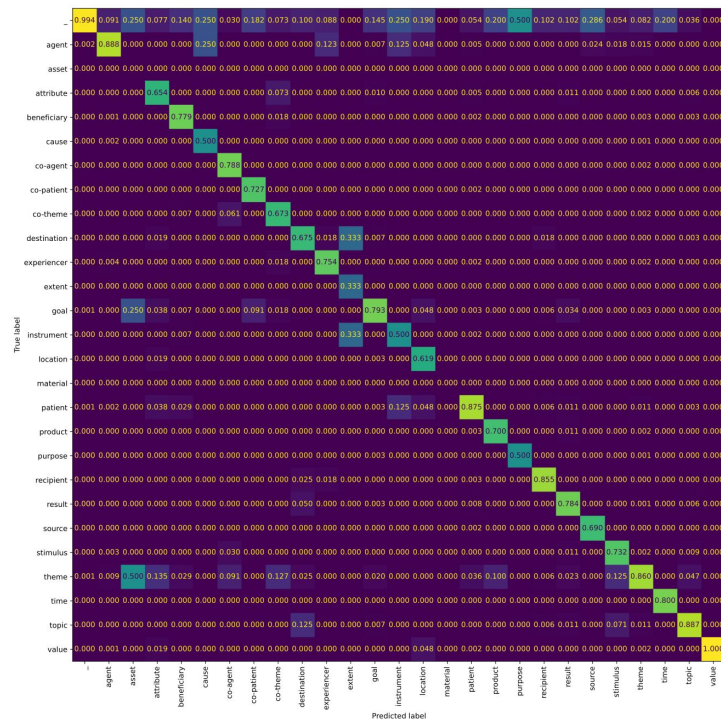


Confusion matrix SRL_34: **False positive INSTRUMENT** - 2

Second example of false positive argument identification.



Results: Confusion matrix SRL_234 drop



Drop accuracy argument classification on:

- EXPERIENCER (12% of the time assigned to AGENT)
- CAUSE (25% of the time assigned to AGENT)*

*only 4 samples in validation set

Confusion matrix SRL_234 drop: **EXPERIENCER**

SRL_234 performs worse due to wrong predictions of SRL_2.

1999/a/c_2/54/sr_29_21:1

SRL_2:	BELIEVE	✗
	INTERPRET	✓

Ms. Critchlow (Guyana), introducing the draft resolution on behalf of the Group of 77 and China, said that the **use** of solar energy was **viewed** **by** the Group of 77 and China **as** another step in the implementation of Agenda 21.

ATTRIBUTE

SRL_34:	THEME	✓
SRL_234:	STIMULUS	✗

SRL_34:	AGENT	✓
SRL_234:	EXPERIENCER	✗

Confusion matrix SRL_234 drop: **CAUSE**

SRL_234 performs worse due to wrong predictions of SRL_2

1998/a/cn_9/sr_620_123:1

SRL_34: INCITE_INDUCE ✓
SRL_234: IMPLY ✗

Mr. MARKUS (Observer for Switzerland) said that, although he agreed with the substance of the text, **it** could **lead** **to** misunderstandings.

SRL_34: AGENT ✓
SRL_234: CAUSE ✗

SRL_34: RESULT ✓
SRL_234: TOPIC ✗