



Machine learning for sequential data:

A comparative study with applications to natural language processing

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Predicting label sequences

input	a	b	c	d	e
output	$oxed{A}$	В	$oxed{C}$	$ \mathbf{D} $	$oxed{E}$





Sequences in NLP

Olympic champion Agassi meets Karim Alami of Morocco in the first round.

```
NN
                                    NNP
                                          NNP IN
JJ
                    NNP
                            VBZ
                                                      NNP
                                                                         NN
          I-NP
                   I-NP
                                         I-NP I-PP I-NP
                                                           I-PP I-NP I-NP I-NP
I-NP
                            I-VP
                                   I-NP
[NP
                           [VP
                                   [NP
                                               ] [PP] [NP
                                                          ][PP][NP
                                    I-PER I-PER O I-LOC
I-MISC
                    I-PER
 [MISC
                   [PER
                                   [PER
                                                   [LOC
```





Sequences in NLP

```
      p
      r
      e
      e
      x
      i
      s
      t
      i
      n
      g

      p
      r
      i
      I
      G
      I
      s
      t
      I
      N

      c
      0
      0
      c
      0
      0
      0
      0
      i
      0
      0

      [c
      ]
      [i
      ]
      [i
      ]
      ]
      [i
      ]
```





Machine learning methods

Conditional Random Fields

Hidden Markov SVM, Label Sequence AdaBoost

Cycling Dependency Networks

Max-margin Markov Networks

Conditional Markov Models

Maximum-entropy Markov Models

Discriminatively trained Hidden Markov Models

Stacked Sequential Learning

Constraint Satisfaction Inference

(Lafferty et al., 2001)

(Altun & Hofmann, 2003)

(Toutanova et al., 2003)

(Taskar et al., 2003)

(Ratnaparkhi, 1996)

(McCallum et al., 2000)

(Collins, 2002)

(Cohen, 2004)

(Canisius et al., 2006)

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Benchmark data sets

Natural language processing

- Word-level
 - CELEX Morphological segmentation / parsing
 - CELEX Grapheme-phoneme conversion
- Sentence-level
 - CoNLL-2000 Syntactic chunking
 - CoNLL-2002/3 Named-entity recognition
 - GENIA Named-entity recognition
- Document level
 - FAQ segmentation





Benchmark data sets

Bioinformatics

- Protein secondary structure prediction
- Gene prediction

Suggestions?

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Case study: (bio)medical named-entity recognition

Named-entity recognition in Medline abstracts

[DNA_part li kappa B-1] is a [DNA positive regulatory element] in [cell_line B-cell lines] and in the [cell_line li-expressing T-cell line], [cell_line H9], but acts as a [DNA negative regulatory element] in [cell_line myelomonocytic] and [cell_line glia cell lines].





Case study: (bio)medical named-entity recognition

Named-entity recognition in Dutch medical encyclopedias

[duration Tussen het vierde en tiende jaar] kunnen [symptom vetophopingen] ([symptom xanthoma 's]) in de [body_part huid] ontstaan .





Learning method

- Maximum-entropy models
 - a.k.a log-linear models

$$P(c|d,\lambda) = \frac{\exp(\sum_{i} \lambda_{i} f_{i}(c,d))}{\sum_{c'} \exp(\sum_{i} \lambda_{i} f_{i}(c',d))}$$





Sequence prediction methods

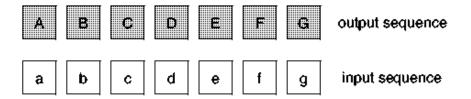
- Sliding window
- Recurrent sliding window
- Stacking
- Constraint satisfaction inference
- Conditional markov models
- Maximum-entropy markov models
- Conditional random fields

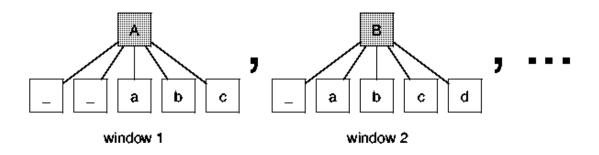




Features

- Simple features only
 - 3-1-3 sliding window of words and POS tags









Results GENIA

Ν	И	e	tl	h	0	d
		$\overline{}$	•		$\overline{}$	_

Sliding window

Rec. sliding window

Stacking

CSI

CMM

MEMM

CRF

Precision Recall		F _{β=1}	
54.9 ±1.16	54.1 ±1.23	54.5 ±1.02	
67.3 ±1.04	57.6 ±1.25	62.1 ±1.11	
57.8 ±1.21	55.3 ±1.07	56.5 ±1.11	
64.1 ±1.06	56.6 ±1.10	60.1 ±1.03	
67.7 ±0.96	57.9 ±1.07	62.4 ±1.01	
67.1 ±1.14	57.7 ±1.13	62.1 ±1.15	
66.8 ±1.10	59.2 ±1.14	62.8 ±1.08	





Results

Dutch medical encyclopedia

Method
Sliding window
Rec. sliding window
Stacking
CSI
CMM
MEMM
CRF

	Precision	Recall	F _{β=1}	
_	62.3 ±1.12	60.8 ±1.06	61.5 ±0.98	
	68.5 ±1.16	60.0 ±1.13	63.9 ±0.89	
_	63.2 ±1.23	60.8 ±1.13	62.0 ±1.10	
_	68.6 ±1.15	59.9 ±1.11	63.9 ±1.02	
	68.8 ±1.26	59.6 ±1.09	63.9 ±0.99	
	68.8 ±1.09	59.3 ±1.26	63.7 ±1.09	
	66.8 ±1.14	60.2 ±1.14	63.4 ±0.99	





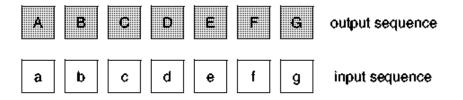
Observations

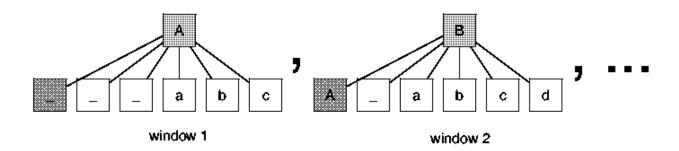
- Sequence methods tend to favour precision over recall
 - In named-entity recognition tasks, entities are predicted more conservatively
- Very similar performance with many sequence methods
- Recurrent sliding window and its probabilistic version CMM have almost exactly the same performance
 - Doesn't the extra inference step add anything?





Recurrent sliding window









Ratnaparkhi's conditional markov models

Label sequence conditional probability

$$P(y_1, y_2, ..., y_n | x_1, x_2, ..., x_n) = \sum_i p(y_i | h_i, x_i)$$

h_i corresponds to the history features in the recurrent sliding window method

Beam search is used to select to most likely label sequence





FAQ segmentation

McCallum et al., 2000

<prolog> <prolog> <prolog></prolog></prolog></prolog>	This section of the FAQ is about the electronic support network that exists for 386bsd and its off-spring.
<question>1.0 <question> <answer></answer></question></question>	I just downloaded all of 386bsd version 0.1 and I can't get [some feature] to work? Do you have any suggestions?
<answer> <answer> <answer></answer></answer></answer>	Yes. Get FreeBSD, OpenBSD, or NetBSD.
<question>1.1 <answer></answer></question>	Minimum hardware configuration recommended
<answer> <answer></answer></answer>	There has been considerable debate about what the REAL minimum configuration for *BSD is. Some would claim that it is the





Features for FAQ segmentation

McCallum et al., 2000

begins-with-number
begins-with-ordinal
begins-with-punctuation
begins-with-question-word
begins-with-subject
blank
contains-alphanum
contains-bracketed-number
contains-http
contains-non-space
contains-number
contains-pipe

contains-question-mark contains-question-word ends-with-question-mark first-alpha-is-capitalized indented indented-1-to-4 indented-5-to-10 more-than-one-third-space only-punctuation prev-is-blank prev-begins-with-ordinal shorter-than-30





Results

FAQ segmentation

Method	Precision	Recall F	
Default maxent	21.3	46.6	27.7
Rec. sliding window	70.8	73.6	70.7
CMM	74.2	78.0	74.9





Discussion

- Recurrent sliding window (CMM, beam size: 1) vs. CMM
 - Hardly any difference on two domain-specific entity recognition tasks
 - CMM outperforms recurrent sliding window on FAQ segmentation
 - What causes these differences?
 - Do the properties that favour CMMs actually occur in real-world NLP tasks?
 - So far, various potential explanations have been explored, none proved to be true





Summary

- Presented plans and preliminary results for a large-scale empirical evaluation of sequence prediction methods in the context of natural language processing
- Suggestions for relevant/informative data sets are welcome
- Small case study on domain-specific entity recognition
 - Sequence prediction methods tend to improve F-score mainly by improving precision, not recall
 - Inference methods on top of probabilistic (maxent) classifiers did not prove to have a large advantage over simpler methods
 - However, there may be data sets where this advantage does exist (e.g. FAQ segmentation)