# Mining Unstructured Data Exercises on features for learning CRF models to classify word sequences 

## Features for bigram-factored sequence annotation models

Recall the linear CRF models for sequence prediction, and think of a named entity task. A bigram CRF model computes:

$$
\begin{equation*}
\operatorname{tags}\left(x_{1: n}\right)=\underset{y_{1: n} \in \mathcal{Y}^{n}}{\operatorname{argmax}} \sum_{i=1}^{n} \mathbf{w} \cdot \mathbf{f}\left(x, i, y_{i-1}, y_{i}\right) \tag{1}
\end{equation*}
$$

where $x_{1: n}$ is an input sentence of $n$ tokens ( $x_{i}$ is the $i$-th token), $y_{1: n}$ is an output sequence of $n$ tags ( $\mathcal{Y}$ is the set of valid tags). $\mathbf{f}\left(x, i, y_{i-1}, y_{i}\right)$ is a function returning a feature vector of the bigram $y_{i-1}, y_{i}$ at position $i$ of the sentence (assume that $y_{0}$ is a special tag START that indicates the start of the sequence). $\mathbf{w}$ is a vector of parameters of the same dimensionality of the feature vectors.

## Exercise 1.

We specify features using templates. For example, the following template captures the current word and the current tag:

$$
\mathbf{f}_{1, l, a}\left(x, i, y_{i-1}, y_{i}\right)= \begin{cases}1 & \text { if } x_{i}=a \text { and } y_{i}=l \\ 0 & \text { otherwise }\end{cases}
$$

Write feature templates that capture the following patterns. Justify your answers if necessary.

- $\mathbf{f}_{2, a}$ : the current word is the first of the sentence, it is capitalized, and its tag is $a$
- $\mathbf{f}_{3, s, a}$ : 3-letter prefix of the current word, together with the current tag
- $\mathbf{f}_{4, w, a, b}$ : the current word, the current tag, and the previous tag
- $\mathbf{f}_{5, w, v, a}$ : the two previous words and the current tag
- $\mathbf{f}_{6, a, b, c}$ : the two previous tags and the current tag


## SOLUTION

$$
\begin{aligned}
& \mathbf{f}_{2, a}\left(x_{1: n}, i, y_{i-1}, y_{i}\right)= \begin{cases}1 & \text { if } i=1 \text { and capitalized }\left(x_{i}\right) \text { and } y_{i}=a \\
0 & \text { otherwise }\end{cases} \\
& \mathbf{f}_{3, s, a}\left(x_{1: n}, i, y_{i-1}, y_{i}\right)= \begin{cases}1 & \text { if prefix }\left(w_{i}\right)=s \text { and } y_{i}=a \\
0 & \text { otherwise }\end{cases} \\
& \mathbf{f}_{4, w, a, b}\left(x_{1: n}, i, y_{i-1}, y_{i}\right)= \begin{cases}1 & \text { if } w_{i}=w \text { and } y_{i-1}=a \text { and } y_{i}=b \\
0 & \text { otherwise }\end{cases}
\end{aligned}
$$

$$
\begin{aligned}
\mathbf{f}_{5, w, v, a}\left(x_{1: n}, i, y_{i-1}, y_{i}\right) & = \begin{cases}1 & \text { if } w_{i-2}=w \text { and } w_{i-1}=v \text { and } y_{i}=a \\
0 & \text { otherwise }\end{cases} \\
\mathbf{f}_{5, a, b, c}\left(x_{1: n}, i, y_{i-1}, y_{i}\right) & = \begin{cases}1 & \text { if } y_{i-2}=a \\
0 & \text { otherwise }\end{cases}
\end{aligned}
$$

## Exercise 2.

1. Given the training example the/DT dog/NN saw/VBD the/DT man/nN, if we convert it to pairs $(x, y)$ pairs, where $x=\left(y_{i-2}, y_{i-1}, O, i\right)$ for training a trigram-based CRF model for PoS tagging, which of the following pairs are in the training set?
(a) $x=(\mathrm{DT}, \mathrm{NN}$, the dog saw the man, 3$) ; y=\mathrm{NN}$
(b) $x=(\mathrm{VBD}, \mathrm{DT}$, the dog saw the man, 3$) ; y=\mathrm{VBD}$
(c) $x=(\mathrm{DT}, \mathrm{NN}$, the dog saw the man, 3$) ; y=\mathrm{VBD}$
(d) $x=(\mathrm{DT}, \mathrm{NN}$, the dog saw the man, 4$) ; y=\mathrm{NN}$
2. List all $(x, y)$ pairs that can be generated from this training set. Assume phantom tags $y_{-2}=y_{-1}=$ START.

## SOLUTION

1. (a) does not match because position 3 is has $y=$ VBD and not NN. Similarly, (d) is discarded because position 4 has $y=$ DT and not NN. Pattern (b) is not matched because previous tags $y_{i-2}, y_{i-1}$ for position 3 are DT and NN respectively, and not VBD and DT. The only pair matching the trainig set is (c), since the tag for word 3 is $y=$ VBD, and the previous tags $y_{i-2}, y_{i-1}$ are DT and NN respectively.
2. Pairs generated by this training set are:

$$
\begin{aligned}
& x=(\mathrm{START}, \mathrm{START}, \text { the dog saw the man, } 1) ; y=\mathrm{DT} \\
& x=(\mathrm{START}, \mathrm{DT}, \text { the dog saw the man, } 2) ; y=\mathrm{NN} \\
& x=(\mathrm{DT}, \mathrm{NN}, \text { the dog saw the man, } 3) ; y=\mathrm{VBD} \\
& x=(\mathrm{NN}, \mathrm{VBD}, \text { the dog saw the man, } 4) ; y=\mathrm{DT} \\
& x=(\mathrm{VBD}, \mathrm{DT}, \text { the dog saw the man, } 5) ; y=\mathrm{NN}
\end{aligned}
$$

## Exercise 3.

We want to approach a PoS tagging task with a bigram-based CRF model that will compute the tag for each word as:

$$
\operatorname{tag}\left(x_{1: n}, i\right)=\underset{y_{i} \in \mathcal{Y}}{\operatorname{argmax}} w \cdot f\left(x_{1: n}, i, y_{i-1}, y_{i}\right)
$$

We have defined the following feature function types:

- Type 1: Current tag is $a$ :

$$
f_{1, a}\left(x_{1: n}, i, y_{i-1}, y_{i}\right)= \begin{cases}1 & \text { if } y_{i}=a \\ 0 & \text { otherwise }\end{cases}
$$

- Type 2: Current word is capitalized and current tag is $a$ :

$$
f_{2, a}\left(x_{1: n}, i, y_{i-1}, y_{i}\right)= \begin{cases}1 & \text { if } x_{i} \text { is capitalized and } y_{i}=a \\ 0 & \text { otherwise }\end{cases}
$$

- Type 3: Previous tag is $a$ and current tag is $b$ :

$$
f_{3, a, b}\left(x_{1: n}, i, y_{i-1}, y_{i}\right)= \begin{cases}1 & \text { if } y_{i-1}=a \text { and } y_{i}=b \\ 0 & \text { otherwise }\end{cases}
$$

1. Propose values for appropriate features in vector $w$ that will correctly classify all words in the following sentences. Try to set the minimum number of non-zero weights. Proof or justification of the chosen values is required.


## SOLUTION

- $w_{1, \mathrm{v}}=1$ will score +1 for any word to be tagged as a verb. This will solve correctly all verbs, and introduce a wrong biass in the other words.
- $w_{3, V, N}=2$ will score +2 in favor of tag N for any word after a V . This will overcome the first feature and correctly solve the noun results in the last sentence.
- $w_{3, S T A R T, N}=3$ will score +3 in favor of tag N for any word at the begining of the sentence. This will overcome the first feature and solve correctly the noun programs in the last sentence. If we used +2 here, we would get a tie between combinations V-N and $\mathrm{N}-\mathrm{V}$ at sentence begining, so we use +3 .
- $w_{2, \mathrm{E}}=4$ will score +4 for all capitalized words to be tagged E . This will overcome the previous features and solve properly all occurrences of John and Mary.
Let's apply Viterbi algorithm to check these weights work for all given sentences:

|  | John | programs | bugs |
| :---: | :---: | :---: | :---: |
|  | Mary | runs | programs |
| E | E:4 | E-E: $4+0=4$ | E-E-E: $4+0=4$ |
|  |  | N-E: $3+0=3$ | E-N-E: $4+0=4$ |
|  |  | V-E $1+0=1$ | E-V-E: $5+0=5$ |
| N | $\mathrm{N}: 3$ | E-N: 4+0=4 | E-E-N: $4+0=0$ |
|  |  | N-N: $3+0=3$ | E-N-N: 4+0 $=0$ |
|  |  | V-N: $1+2=3$ | E-V-N: 5+2=7 |
| V | V: 1 | E-V: $4+1=5$ | E-E-V: $4+1=5$ |
|  |  | $\mathrm{N}-\mathrm{V}: 3+1=4$ | E-N-V: $4+1=5$ |
|  |  | V-V: $1+1=2$ | E-V-V: $5+1=6$ |

For sentences John programs bugs and Mary runs programs, the best sequence is $\mathrm{E}-\mathrm{V}-\mathrm{N}$ with a score of 7 , higher than any other combination.

|  | Mary | bugs | John |
| :---: | :---: | :---: | :---: |
| E | E: 4 | E-E: $4+0=4$ <br> N-E: $3+0=3$ <br> V-E $1+0=1$ | E-E-E: 4+4=8 |
|  |  | E-N-E: $4+4=8$ |  |
| E-V-E: $\mathbf{5 + 4}=\mathbf{4}$ |  |  |  |$| \leftarrow$ Best

For sentence Mary bugs John, the best sequence is E-V-E with a score of 9 , higher than any other combination.

|  | programs | print | results |
| :---: | :---: | :---: | :---: |
| E | E: 0 | $\begin{aligned} & \text { E-E: } 0+0=0 \\ & \text { N-E: } 3+\mathbf{0}=\mathbf{3} \\ & \text { V-E } 1+0=1 \end{aligned}$ | N-E-E: $3+0=3$ N-N-E: $3+0=3$ N-V-E: $4+0=4$ |
| N | N: 3 | $\begin{aligned} & \text { E-N: } 0+0=0 \\ & \text { N-N: } \mathbf{3 + 0}=\mathbf{3} \\ & \text { V-N: } \mathbf{1 + 2}=\mathbf{3} \end{aligned}$ | N-E-N: $3+0=3$ $\mathrm{N}-\mathrm{N}-\mathrm{N}: 3+0=0$ N-V-N: 4+2=6 |
| V | V: 1 | $\begin{aligned} & \text { E-V: } 0+1=1 \\ & \mathrm{~N}-\mathrm{V}: \mathbf{3 + 1}=\mathbf{4} \\ & \text { V-V: } 1+1=2 \end{aligned}$ | $\begin{aligned} & \text { N-E-V: } 3+1=4 \\ & \mathrm{~N}-\mathrm{N}-\mathrm{V}: 3+1=4 \\ & \mathrm{~N}-\mathrm{V}-\mathrm{V}: 4+1=5 \end{aligned}$ |

For sentence programs print results, the best sequence is $\mathrm{N}-\mathrm{V}$ N with a score of 6 , higher than any other combination.

## Exercise 4.

We are performing PoS tagging with a trigram-factored CRF, using tagset $\mathcal{T}=\{\mathrm{DT}, \mathrm{V}, \mathrm{NN}, \mathrm{ADV}, \mathrm{PREP}\}$, and we defined a history as $h=\left\langle t_{i-2}, t_{i-1}, w_{[1: n]}, i\right\rangle$.

1. How many possible histories are there for a given input sequence $\mathcal{X}$ and a fixed value of $i$ ?
2. Which of the following are valid features?

$$
\begin{aligned}
& \mathbf{f}_{1}(h, t)= \begin{cases}1 & \text { if } t=\mathrm{V} \text { and } t_{i-1}=\mathrm{PREP} \\
0 & \text { otherwise }\end{cases} \\
& \mathbf{f}_{2}(h, t)= \begin{cases}1 & \text { if } t=\mathrm{V} \text { and } w_{i-2}=\mathrm{dog} \\
0 & \text { otherwise }\end{cases} \\
& \mathbf{f}_{3}(h, t)= \begin{cases}1 & \text { if } t=\mathrm{V} \text { and } t_{i-3}=\mathrm{NN} \\
0 & \text { otherwise }\end{cases} \\
& \mathbf{f}_{4}(h, t)= \begin{cases}1 & \text { if } t=\mathrm{V} \text { and } t_{i+1}=\operatorname{PREP} \text { and } w_{2}=\mathrm{cow} \\
0 & \text { otherwise }\end{cases}
\end{aligned}
$$

3. Compute the global feature vector $\mathbf{f}(\mathcal{X}, \mathcal{Y})$ for the input sequence is $\mathcal{X}=$ the dog walked to a park and the tag sequence $\mathcal{Y}=\mathrm{DT}$ NN V PREP DT NN, when using the following features:

$$
\begin{aligned}
& \mathbf{f}_{1}(h, t)= \begin{cases}1 & \text { if } t=\text { NN and } w_{i}=\operatorname{dog} \\
0 & \text { otherwise }\end{cases} \\
& \mathbf{f}_{2}(h, t)= \begin{cases}1 & \text { if } t=\text { NN and } t_{i-1}=\mathrm{DT} \\
0 & \text { otherwise }\end{cases} \\
& \mathbf{f}_{3}(h, t)
\end{aligned}= \begin{cases}1 & \text { if } t=\text { NN and } t_{i-1}=\mathrm{DT} \text { and } w_{i-1}=\text { the } \\
0 & \text { otherwise }\end{cases}
$$

4. Given the history $h=\left(t_{i-2}, t_{i-1}, w_{[1: n]}, 5\right)=(\mathrm{V}, \mathrm{DT}$, the man saw the dog in the park, 5$)$, which of the following features yield $\mathbf{f}(h, \mathrm{NN})=1$ ?

$$
\begin{aligned}
& \mathbf{f}_{1}(h, t)= \begin{cases}1 & \text { if } t=\text { NN and } w_{i}=\operatorname{dog} \\
0 & \text { otherwise }\end{cases} \\
& \mathbf{f}_{2}(h, t)= \begin{cases}1 & \text { if } t=\mathrm{DT} \text { and } w_{i}=\operatorname{dog} \\
0 & \text { otherwise }\end{cases} \\
& \mathbf{f}_{3}(h, t)= \begin{cases}1 & \text { if } t=\text { NN and } w_{i+1}=\operatorname{dog} \\
0 & \text { otherwise }\end{cases} \\
& \mathbf{f}_{4}(h, t)= \begin{cases}1 & \text { if } t=\text { NN and } t_{i-1}=\mathrm{DT} \\
0 & \text { otherwise }\end{cases}
\end{aligned}
$$

## SOLUTION

1. Each history has the form $h=\left\langle t_{i-2}, t_{i-1}, w_{[1: n]}, i\right\rangle$. If we fix $\mathcal{X}=w_{[1: n]}$ and the position $i$, there are only two parameters left: $t_{i-2}$ and $t_{i-1}$. Since each of them can take any of the possible five PoS tag values $\{\mathrm{DT}, \mathrm{V}, \mathrm{NN}, \operatorname{ADV}, \mathrm{PREP}\}$, the number of posible combinations is $5 \times 5=25$.
2. Features $f_{1}$ and $f_{2}$ are valid beacuse they use elements in $h$ (i.e. $t_{i-1}$ and $w_{i-2}$, respectively). Feature $f_{3}$ is invalid because $t_{i-3}$ is not included in $h$. Feature $f_{4}$ is not valid beacuse $t_{i+1}$ is not included in $h$
3. Given the values of $\mathcal{X}$ and $\mathcal{Y}$, for each word we obtain the following features:

| $\mathcal{X}$ | the | dog | walked | to | a | park |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| $\mathcal{Y}$ | DT | NN | V | PREP | DT | NN |
| Features |  | $f_{1}$ |  |  |  |  |
|  | - | $f_{2}$ | - | - | - | $f_{2}$ |
|  |  | $f_{3}$ |  |  |  |  |

Thus, the vector resulting of applying given features is: $\left(f_{1}, f_{2}, f_{3}\right)=(1,2,1)$
4. Position $i=5$ corresponds to word dog in the sentence. Thus, when evaluating each feature for $t=$ nN, we get that:

$$
\begin{aligned}
& f_{1}(h, \mathrm{NN})=1, \text { since } t=\mathrm{NN} \text { and } w_{5}=\operatorname{dog} \\
& f_{2}(h, \mathrm{NN})=0, \text { since } t \neq \mathrm{DT} \\
& f_{3}(h, \mathrm{NN})=0, \text { since } w_{6} \neq \text { dog } \\
& f_{4}(h, \mathrm{NN})=1, \text { since } t=\text { NN and } t_{i-1}=\mathrm{DT}
\end{aligned}
$$

## Exercise 5.

We want to address a Named Entity Recognition task consisting in identifying diseases in medical texts. For this, we want to train a sequence classifier such as a CRF using bigram factorization (i.e. only previous and current tag hypothesis are considered). Thus, the used context is $h=\left(t_{i-1}, w_{[1: n]}, \operatorname{pos}_{[1: n]}, i\right)$.

We use the following feature templates:

$$
\begin{aligned}
\mathbf{f}_{1, a}(h, t) & = \begin{cases}1 & \text { if } \text { pos }_{i-1}=\mathrm{N} \text { and } t_{i-1}=\mathrm{O} \text { and } t=a \\
0 & \text { otherwise }\end{cases} \\
\mathbf{f}_{2}(h, t) & = \begin{cases}1 & \text { if } \text { suf }\left(w_{i-1}\right)=^{\prime} \mathrm{ing}^{\prime} \text { and } t=\mathrm{B} \\
0 & \text { otherwise }\end{cases} \\
\mathbf{f}_{3, a, b}(h, t) & = \begin{cases}1 & \text { if } w_{i-1}=a \text { and } t=b \\
0 & \text { otherwise }\end{cases} \\
\mathbf{f}_{4, a, b, c}(h, t) & = \begin{cases}1 & \text { if } w_{i-1}=a \text { and } t=b \text { and } \operatorname{pos}_{i}=c \\
0 & \text { otherwise }\end{cases} \\
\mathbf{f}_{5, a, b}(h, t) & = \begin{cases}1 & \text { if } w_{i}=a \text { and capitalized }\left(w_{i-1}\right) \text { and } t=b \\
0 & \text { otherwise }\end{cases}
\end{aligned}
$$

Given the above templates, and the training sentence:

| $i$ | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $w$ | Fragile-X | syndrome | is | an | inherited | form | of | mental | retardation | involving | mitral | valve | prolapse |
| $p o s$ | N | N | V | D | JJ | N | P | JJ | N | V | JJ | N | N |
| $t$ | B | I | O | 0 | 0 | 0 | 0 | O | O | O | B | I | I |

List which feature instances would be generated for words:
a) $i=2$ (syndrome)
b) $i=10$ (involving)
c) $i=11$ (mitral)

## SOLUTION

a) Features for $i=2$ (syndrome): $\left(f_{3, \text { Fragile-X,I }}, f_{4, \text { Fragile-X,I,N }}, f_{5, \text { syndrome }, I}\right)$
b) Features for $i=10$ (involving): $\left(f_{1, O}, f_{3, \text { retardation, } 0}, f_{4, \text { retardation, } O, \mathrm{v}}\right)$
c) Features for $i=11$ (mitral): $\left(f_{2}, f_{3, \text { involving, } \mathrm{B}}, f_{4, \text { involving }, B, \mathrm{JJ}}\right)$

## Exercise 6. Features for log linear sequence annotation models

We are performing PoS tagging for a recently discovered alien language, using a trigram-factored CRF, using tagset $\mathcal{T}=\{\mathrm{D}, \mathrm{V}, \mathrm{N}, \mathrm{A}, \mathrm{P}\}$, and we defined a history as $h=\left\langle t_{i-2}, t_{i-1}, w_{[1: n]}, i\right\rangle$.

1. How many possible histories are there for a given input sequence $\mathcal{X}$ and a fixed value of $i$ ? Justify your answer.
2. Which of the following are valid features and which are not? Justify your answer.

$$
\begin{aligned}
& \mathbf{f}_{1}(h, t)= \begin{cases}1 & \text { if } t=\mathrm{V} \text { and } t_{i-1}=\mathrm{N} \\
0 & \text { otherwise }\end{cases} \\
& \mathbf{f}_{2}(h, t)= \begin{cases}1 & \text { if } t=\mathrm{K} \text { and } w_{i-2}=\mathrm{skjkeg} \\
0 & \text { otherwise }\end{cases} \\
& \mathbf{f}_{3}(h, t)= \begin{cases}1 & \text { if } t=\mathrm{N} \text { and } t_{i-3}=\mathrm{P} \\
0 & \text { otherwise }\end{cases} \\
& \mathbf{f}_{4}(h, t)= \begin{cases}1 & \text { if } t=\mathrm{V} \text { and } t_{i+1}=\mathrm{A} \text { and } w_{2}=\text { wuakla } \\
0 & \text { otherwise }\end{cases}
\end{aligned}
$$

3. Compute the feature vectors $\mathbf{f}(h, t)$ for each position $i$, and the global feature vector $\mathbf{f}(\mathcal{X}, \mathcal{Y})$ for the input sequence $\mathcal{X}=$ grufp umdk wuakla du blha skjkeg and the tag sequence $\mathcal{Y}=$ $\mathrm{P} V \mathrm{~N} D \mathrm{~N} \mathrm{~A}$, when using the following features:

$$
\begin{aligned}
& \mathbf{f}_{1}(h, t)= \begin{cases}1 & \text { if } t=\mathrm{N} \text { and } w_{i}=\text { wuakla } \\
0 & \text { otherwise }\end{cases} \\
& \mathbf{f}_{2}(h, t)= \begin{cases}1 & \text { if } t=\mathrm{N} \text { and } t_{i-1} \neq \mathrm{A} \\
0 & \text { otherwise }\end{cases} \\
& \mathbf{f}_{3}(h, t)= \begin{cases}1 & \text { if } t=\mathrm{N} \text { and } t_{i-1}=\mathrm{V} \text { and } w_{i-1}=\mathrm{umdk} \\
0 & \text { otherwise }\end{cases}
\end{aligned}
$$

## SOLUTION

1. For fixed $\mathcal{X}$ and $i$, the only varible elements of the history are $t_{i-2}$ and $t_{i-1}$. Since each of them may have any value in $\mathcal{T}$, the number of different possible histories is $|\mathcal{T}|^{2}=5^{2}=25$
2. $f_{1}$ is valid, since it depends only on $t$ and $t_{i-1}$, which is included in $h$.
$f_{2}$ is not valid, since $\mathrm{K} \notin \mathcal{T}$.
$f_{3}$ is not valid, since $t_{i-3}$ is not included in $h$.
$f_{4}$ is not valid, since $t_{i+1}$ is not included in $h$.
3. for $i=1$, we have $h=\langle\operatorname{START}, \operatorname{START}, \mathcal{X}, 1\rangle$, and $\mathbf{f}(h, t)=\left(\mathbf{f}_{1}(h, \mathrm{P}), \mathbf{f}_{2}(h, \mathrm{P}), \mathbf{f}_{3}(h, \mathrm{P})\right)=(0,0,0)$
for $i=2$, we have $h=\langle\operatorname{START}, \mathrm{P}, \mathcal{X}, 2\rangle$, and $\mathbf{f}(h, t)=\left(\mathbf{f}_{1}(h, \mathrm{~V}), \mathbf{f}_{2}(h, \mathrm{~V}), \mathbf{f}_{3}(h, \mathrm{~V})\right)=(0,0,0)$
for $i=3$, we have $h=\langle\mathrm{P}, \mathrm{V}, \mathcal{X}, 3\rangle$, and $\mathbf{f}(h, t)=\left(\mathbf{f}_{1}(h, \mathrm{~N}), \mathbf{f}_{2}(h, \mathrm{~N}), \mathbf{f}_{3}(h, \mathrm{~N})\right)=(1,1,1)$
for $i=4$, we have $h=\langle\mathrm{V}, \mathrm{N}, \mathcal{X}, 4\rangle$, and $\mathbf{f}(h, t)=\left(\mathbf{f}_{1}(h, \mathrm{D}), \mathbf{f}_{2}(h, \mathrm{D}), \mathbf{f}_{3}(h, \mathrm{D})\right)=(0,0,0)$
for $i=5$, we have $h=\langle\mathrm{N}, \mathrm{D}, \mathcal{X}, 5\rangle$, and $\mathbf{f}(h, t)=\left(\mathbf{f}_{1}(h, \mathrm{~N}), \mathbf{f}_{2}(h, \mathrm{~N}), \mathbf{f}_{3}(h, \mathrm{~N})\right)=(0,1,0)$
for $i=6$, we have $h=\langle\mathrm{D}, \mathrm{N}, \mathcal{X}, 6\rangle$, and $\mathbf{f}(h, t)=\left(\mathbf{f}_{1}(h, \mathrm{~A}), \mathbf{f}_{2}(h, \mathrm{~A}), \mathbf{f}_{3}(h, \mathrm{~A})\right)=(0,0,0)$
Thus the global feature vector is the sum of the factored vectors: $\mathbf{f}(\mathcal{X}, \mathcal{Y})=(1,2,1)$

## Exercise 7.

Negation detection is a task consisting in identifying which phrases in a sentence are affected by a negation. It is a vital task e.g. in applications related to the processing of medical documents.

The task is often modeled as a B-I-O labeling task, and solved using sequence-labeling algorithms such as CRFs.
We have the following training data:

| $\mathcal{X}$ | The | patient | does | not | show | any | lung | symptoms | . |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| $\mathcal{Y}$ | 0 | 0 | 0 | B | I | I | I | I | 0 |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |
| $\mathcal{X}$ | Dark | spots | were | observed | in | lung | X-ray | imaging | . |  |  |
| $\mathcal{Y}$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |
| $\mathcal{X}$ | Exhoglovifin | never | caused | adverse | reactions | and | should | not | be | banned |  |
| $\mathcal{Y}$ | 0 | B | I | I | I | 0 | 0 | B | I | I | 0 |

And the following feature templates:

$$
\begin{aligned}
\mathbf{f}_{1, a, l}(\mathcal{X}, i, t) & = \begin{cases}1 & \text { if } w_{i}=a \wedge t=l \\
0 & \text { otherwise }\end{cases} \\
\mathbf{f}_{2, l}(\mathcal{X}, i, t) & = \begin{cases}1 & \text { if } w_{i-1} \in\{\text { no, not, never, any }\} \wedge t=l \\
0 & \text { otherwise }\end{cases} \\
\mathbf{f}_{3, l}(\mathcal{X}, i, t) & = \begin{cases}1 & \text { if punctuation }\left(w_{i}\right) \wedge t=l \\
0 & \text { otherwise }\end{cases} \\
\mathbf{f}_{4, l}(\mathcal{X}, i, t) & = \begin{cases}1 & \text { if } w_{i-1}=\text { dark } \wedge w_{i}=\text { spots } \wedge t=l \\
0 & \text { otherwise }\end{cases}
\end{aligned}
$$

1. Which is the dimension of the feature space instantiated by this dataset? Justify your answer.
2. Given the following test sentence $\mathcal{X}$ and hypothesis tag sequence $\mathcal{Y}$ :

| $\mathcal{X}$ | X-Ray | results | do | not | show | any | dark | spots | . |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| $\mathcal{Y}$ | 0 | 0 | 0 | B | I | I | I | I | 0 |

compute the feature vectors $\mathbf{f}(\mathcal{X}, i, t)$ for each position $i$, and the global feature vector $\mathbf{f}(\mathcal{X}, \mathcal{Y})$. Highlight which features in the global vector that are present in the vector space instantiated by the three training sentences above.

## SOLUTION

1. Feature $f_{1}$ is instantiated for each combination word-label seen in the training data. Sentence 1 contains 9 combinations. Sentence 2 contains 8 new combinations -combination (.,0) is repeated. Sentence 3 contains 9 new combinations -combinations (not,B) and (.,0) are repeated. Total $9+8+9=26$ feature instances for template $f_{1}$.
Feature $f_{2}$ is instantiated for each occurrence of not, never, or any combined with a label. Sentence 1 contains one occurrence (with label B), sentence 2 does not contain any, and sentence 3 contains two more occurrences, also with label B , so they generate the same feature $f_{2, B}$. Total, 1 feature instances for template $f_{2}$.
Feature $f_{3}$ is instantiated for each occurrence of a punctuation sign combined with a label. Each sentence has one occurrence of the combination (.,0), thus only one instance is generated for $f_{3}$.

Feature $f_{4}$ is instantiated for each occurrence of dark spots combined with a label. This only happens once in sentence 2 (with label 0), thus only one instance is generated for $f_{4}$.
So, the total number of generated features (i.e. our feature space dimension) is $26+1+1+1=29$.
2. Feature vectors for each position are:

$$
\begin{aligned}
& \mathbf{f}(\mathcal{X}, 1,0)=\left\{f_{1, \text { X Ray }, O}\right\} \\
& \mathbf{f}(\mathcal{X}, 2,0)=\left\{f_{1, \text { results }, O}\right\} \\
& \mathbf{f}(\mathcal{X}, 3,0)=\left\{f_{1, \text { do }, O}\right\} \\
& \mathbf{f}(\mathcal{X}, 4, \mathrm{~B})=\left\{f_{1, \text { not }, B}\right\} \\
& \mathbf{f}(\mathcal{X}, 5, \mathrm{I})=\left\{f_{1, \text { show }, I}, f_{2 . I}\right\} \\
& \mathbf{f}(\mathcal{X}, 6, \mathrm{I})=\left\{f_{1, \text { any }, I}\right\} \\
& \mathbf{f}(\mathcal{X}, 7, \mathrm{I})=\left\{f_{1, \text { dark }, I}, f_{2, I}\right\} \\
& \mathbf{f}(\mathcal{X}, 8, \mathrm{I})=\left\{f_{1, \text { spots }, I}, f_{4, I}\right\} \\
& \mathbf{f}(\mathcal{X}, 9, \mathrm{O})=\left\{f_{\left.1, ., O, f_{3, O}\right\}}\right.
\end{aligned}
$$

Thus, the global feature vector $\mathbf{f}(\mathcal{X}, \mathcal{Y})=\sum_{i} \mathbf{f}\left(\mathcal{X}, i, \mathcal{Y}_{i}\right)$ is:

| feature | value | in training feature space? |
| :--- | :---: | :--- |
| $f_{1, X \text { Ray }, O}$ | 1 | $\checkmark$ |
| $f_{1, \text { results }, I}$ | 1 | $\times$ (word results is not in training) |
| $f_{1, \text { do }, O}$ | 1 | $\times$ (word do is not in training) |
| $f_{1, \text { not }, B}$ | 1 | $\checkmark$ |
| $f_{1, \text { show }, I}$ | 1 | $\checkmark$ |
| $f_{2, I}$ | 2 | $\checkmark$ |
| $f_{1, \text { any }, I}$ | 1 | $\checkmark$ |
| $f_{1, \text { dark }, I}$ | 1 | $\times\left(f_{1, \text { dark }, O}\right.$ appears in training, but $f_{1, \text { dark }, I}$ does not) |
| $f_{1, \text { spots }, I}$ | 1 | $\times\left(f_{1, \text { spots, } O}\right.$ appears in training, but $f_{1, \text { spots, } I}$ does not) |
| $f_{4, I}$ | 1 | $\times\left(f_{4, O}\right.$ appears in training, but $f_{4, I}$ does not) |
| $f_{1, ., O}$ | 1 | $\checkmark$ |
| $f_{3, O}$ | 1 | $\checkmark$ |

