NLP Programming Tutorial 3 - The Perceptron Algorithm

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Prediction Problems

Given x, predict y

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Given x, predict y

A book review
Oh, man I love this book!
This book is so boring...

Is it positive?
yes
no

Binary Prediction (2 choices)

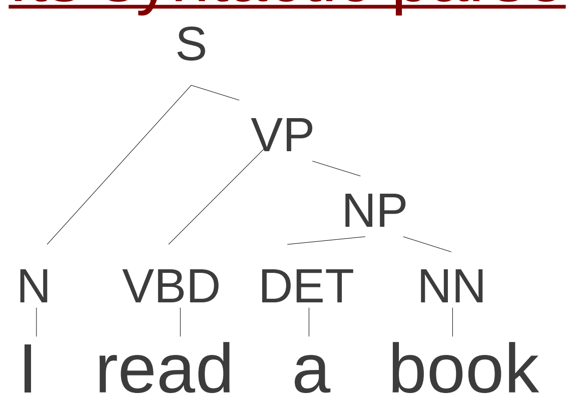
A tweet
On the way to the park!
公園に行くなう！

Its language
English
Japanese

Multi-class Prediction (several choices)

A sentence
I read a book

Its syntactic parse



Structured Prediction (millions of choices)

Example we will use:

- Given an introductory sentence from Wikipedia
- Predict whether the article is about a person

Given		Predict
Gonso was a Sanron sect priest (754-827) in the late Nara and early Heian periods.	→	Yes!
Shichikuzan Chigogataki Fudomyoo is a historical site located at Magura, Maizuru City, Kyoto Prefecture.	→	No!

- This is binary classification (of course!)

Performing Prediction

How do We Predict?

Gonso was a Sanron sect priest (754 – 827)
in the late Nara and early Heian periods .

Shichikuzan Chigogataki Fudomyoo is
a historical site located at Magura , Maizuru
City , Kyoto Prefecture .

How do We Predict?

Contains “priest” → probably person!

Contains “(<#>-<#>)” → probably person!

Gonso was a Sanron sect priest (754 – 827) in the late Nara and early Heian periods .

Contains “site” → probably not person!

Shichikuzan Chigogataki Fudomyoo is a historical site located at Magura , Maizuru City , Kyoto Prefecture .

Contains “Kyoto Prefecture” → probably not person!

Combining Pieces of Information

- Each element that helps us predict is a *feature*

contains “priest” contains “(<#>-<#>)”
contains “site” contains “Kyoto Prefecture”

- Each feature has a weight, *positive* if it indicates “yes”, and *negative* if it indicates “no”

$w_{\text{contains “priest”}} = 2$ $w_{\text{contains “(<\#>-<\#>)”}} = 1$
$w_{\text{contains “site”}} = -3$ $w_{\text{contains “Kyoto Prefecture”}} = -1$

- For a new example, sum the weights

Kuya (903-972) was a priest born in Kyoto Prefecture. → 2 + -1 + 1 = 2

- If the sum is at least 0: “yes”, otherwise: “no”

Let me Say that in Math!

$$
\begin{aligned}
y &= \operatorname{sign}(\mathbf{w} \cdot \boldsymbol{\varphi}(x)) \\
&= \operatorname{sign}\left(\sum_{i=1}^{I} w_i \cdot \varphi_i(x)\right)
\end{aligned}
$$

- x: the input
- **φ(x)**: vector of feature functions $\{\varphi_1(x), \varphi_2(x), \ldots, \varphi_I(x)\}$
- **w**: the weight vector $\{w_1, w_2, \ldots, w_I\}$
- y: the prediction, +1 if “yes”, -1 if “no”
  - (sign(v) is +1 if v >= 0, -1 otherwise)

Example Feature Functions: Unigram Features

- Equal to “number of times a particular word appears”

x = A site , located in Maizuru , Kyoto

$\varphi_{\text{unigram “A”}}(x) = 1$ $\varphi_{\text{unigram “site”}}(x) = 1$ $\varphi_{\text{unigram “,”}}(x) = 2$

$\varphi_{\text{unigram “located”}}(x) = 1$ $\varphi_{\text{unigram “in”}}(x) = 1$

$\varphi_{\text{unigram “Maizuru”}}(x) = 1$ $\varphi_{\text{unigram “Kyoto”}}(x) = 1$

$\varphi_{\text{unigram “the”}}(x) = 0$ $\varphi_{\text{unigram “temple”}}(x) = 0$

…

} The rest are all 0

- For convenience, we use feature names ($\varphi_{\text{unigram “A”}}$) instead of feature indexes (φ_1)

Calculating the Weighted Sum

x = A site , located in Maizuru , Kyoto

$\varphi_{\text{unigram “A”}}(x)$	= 1		$w_{\text{unigram “a”}}$	= 0		0 +
$\varphi_{\text{unigram “site”}}(x)$	= 1		$w_{\text{unigram “site”}}$	= -3		-3 +
$\varphi_{\text{unigram “located”}}(x)$	= 1		$w_{\text{unigram “located”}}$	= 0		0 +
$\varphi_{\text{unigram “Maizuru”}}(x)$	= 1		$w_{\text{unigram “Maizuru”}}$	= 0		0 +
$\varphi_{\text{unigram “,”}}(x)$	= 2	*	$w_{\text{unigram “,”}}$	= 0	=	0 +
$\varphi_{\text{unigram “in”}}(x)$	= 1		$w_{\text{unigram “in”}}$	= 0		0 +
$\varphi_{\text{unigram “Kyoto”}}(x)$	= 1		$w_{\text{unigram “Kyoto”}}$	= 0		0 +
$\varphi_{\text{unigram “priest”}}(x)$	= 0		$w_{\text{unigram “priest”}}$	= 2		0 +
$\varphi_{\text{unigram “black”}}(x)$	= 0		$w_{\text{unigram “black”}}$	= 0		0 +

…

…

=

-3 → No!

Pseudo Code for Prediction

```
PREDICT_ALL(model_file, input_file):
    load w from model_file   # so w[name] = w_name
    for each x in input_file
        phi = CREATE_FEATURES(x)    # so phi[name] = φ_name(x)
        y' = PREDICT_ONE(w, phi)    # calculate sign(w*φ(x))
        print y'
```

Pseudo Code for Predicting a Single Example

```
PREDICT_ONE(w, phi)
    score = 0
    for each name, value in phi          # score = w*φ(x)
        if name exists in w
            score += value * w[name]
    if score >= 0
        return 1
    else
        return -1
```

Pseudo Code for Feature Creation (Example: Unigram Features)

```
CREATE_FEATURES(x):
    create map phi
    split x into words
    for word in words
        phi["UNI:"+word] += 1    # We add "UNI:" to indicate unigrams
    return phi
```

- You can modify this function to use other features!
  - Bigrams?
  - Other features?

Learning Weights Using the Perceptron Algorithm

Learning Weights

- Manually creating weights is hard
  - Many many possible useful features
  - Changing weights changes results in unexpected ways
- Instead, we can learn from labeled data

y	x
1	FUJIWARA no Chikamori (year of birth and death unknown) was a samurai and poet who lived at the end of the Heian period .
1	Ryonen (1646 - October 29 , 1711) was a Buddhist nun of the Obaku Sect who lived from the early Edo period to the mid-Edo period .
-1	A moat settlement is a village surrounded by a moat .
-1	Fushimi Momoyama Athletic Park is located in Momoyama-cho , Kyoto City , Kyoto Prefecture .

Online Learning

```
create map w
for I iterations
    for each labeled pair x, y in the data
        phi = CREATE_FEATURES(x)
        y' = PREDICT_ONE(w, phi)
        if y' != y
            UPDATE_WEIGHTS(w, phi, y)
```

- In other words
  - Try to classify each training example
  - Every time we make a mistake, update the weights
- Many different online learning algorithms
  - The most simple is the perceptron

Perceptron Weight Update

$$w \leftarrow w + y\,\varphi(x)$$

- In other words:
  - If y=1, increase the weights for features in φ(x)
    - Features for positive examples get a higher weight
  - If y=-1, decrease the weights for features in φ(x)
    - Features for negative examples get a lower weight

→ Every time we update, our predictions get better!

```
UPDATE_WEIGHTS(w, phi, y)
  for name, value in phi:
    w[name] += value * y
```

Example: Initial Update

- Initialize **w**=**0**

x = A site , located in Maizuru , Kyoto   y = -1

$$\boldsymbol{w}\cdot\varphi(x)=0 \qquad y' = \text{sign}(\boldsymbol{w}\cdot\varphi(x)) = 1$$

↓

$$y' \neq y$$

↓

$$\boldsymbol{w} \leftarrow \boldsymbol{w} + y\,\varphi(x)$$

↓

$w_{\text{unigram “Maizuru”}} = -1$

$w_{\text{unigram “,”}} = -2$

$w_{\text{unigram “in”}} = -1$

$w_{\text{unigram “Kyoto”}} = -1$

$w_{\text{unigram “A”}} = -1$

$w_{\text{unigram “site”}} = -1$

$w_{\text{unigram “located”}} = -1$

Example: Second Update

x = Shoken , monk born in Kyoto   y = 1

-2 -1 -1

$$w\cdot\varphi(x) = -4 \qquad y' = \text{sign}(w\cdot\varphi(x)) = -1$$

$$y' \neq y$$

$$w \leftarrow w + y\,\varphi(x)$$

$w_{\text{unigram “Maizuru”}}$ = -1	$w_{\text{unigram “A”}}$ = -1	$w_{\text{unigram “Shoken”}}$ = 1
$w_{\text{unigram “,”}}$ = -1	$w_{\text{unigram “site”}}$ = -1	$w_{\text{unigram “monk”}}$ = 1
$w_{\text{unigram “in”}}$ = 0	$w_{\text{unigram “located”}}$ = -1	$w_{\text{unigram “born”}}$ = 1
$w_{\text{unigram “Kyoto”}}$ = 0		

Exercise

Exercise (1)

- Write two programs
  - train-perceptron: Creates a perceptron model
  - test-perceptron: Reads a perceptron model and outputs one prediction per line
- Test train-perceptron
  - Input: test/03-train-input.txt
  - Answer: test/03-train-answer.txt

Exercise (2)

- Train a model on data-en/titles-en-train.labeled
- Predict the labels of data-en/titles-en-test.word
- Grade your answers and report next week
  - script/grade-prediction.py data-en/titles-en-test.labeled your_answer
- Extra challenge:
  - Find places where the model makes a mistake and analyze why
  - Devise new features that could increase accuracy

Thank You!