

Lecture3 Neural Networks

CS224N第三章前面主要介绍了神经网络方面的知识，这里就不做整理了。这章后面部分主要以**命名实体识别** Named Entity Recognition 来讲DNN在NLP领域内的应用。

Named Entity Recognition (NER)

命名实体识别是什么

学完这部分后回过来，我认为首先我们要理解实体是什么。

简单的理解，**实体可以被认为是一个概念的实例**。例如“人名”是一个概念，或者说是实体类型，那么“吴天鹤”就是一种“人名”的实体。“时间”是一种实体类型，那么“国庆节”就是一种“时间”实体了。而**所谓实体识别，就是将你想要获取到的实体类型，从一句话里挑出来的过程**。

这里可以举个例子：

小明 在 北京大学 的 燕园 看了 中国男篮 的一场比赛

PER ORG LOC ORG

对于上面的例子，句子“小明在北京大学的燕园看了中国男篮 的一场比赛”，通过NER模型，将“小明”以PER，“北京大学”以ORG，“燕园”以LOC，“中国男篮”以ORG为类别分别挑了出来。

命名实体识别的数据标注方式

NER是一种序列标注问题，因此他们的数据标注方式也遵照序列标注问题的方式，主要是BIO和BIOES两种。这里直接介绍BIOES，明白了BIOES，BIO也就掌握了。

先列出来BIOES分别代表什么意思：

B，即Begin，表示开始

I，即Intermediate，表示中间

E，即End，表示结尾

S，即Single，表示单个字符

O，即Other，表示其他，用于标记无关字符

将“小明在北京大学的燕园看了中国男篮的一场比赛”这句话，进行标注，结果就是：

[B-PER, E-PER, O, B-ORG, I-ORG, I-ORG, E-ORG, O, B-LOC, E-LOC, O, O, B-ORG, I-ORG, I-ORG, E-ORG, O, O, O, O]

那么，换句话说，**NER的过程，就是根据输入的句子，预测出其标注序列的过程**。

命名实体识别的任务

- The task: **find** and **classify** names in text, for example:

The **European Commission** [ORG] said on Thursday it disagreed with **German** [MISC] advice.

Only **France** [LOC] and **Britain** [LOC] backed **Fischler** [PER] 's proposal .

“What we have to be extremely careful of is how other countries are going to take Germany 's lead”, **Welsh National Farmers ' Union** [ORG] (**NFU** [ORG]) chairman **John Lloyd Jones** [PER] said on **BBC** [ORG] radio .

其实对于NER问题的定义就是找到文本中的名字并对其进行分类。如上图中标黄色的字眼。

找到地点类的名词France，Britain以及人名Fischler。

- **Possible purposes**
 - Tracking mentions of particular entities in documents
 - For question answering, answers are usually named entities
 - A lot of wanted information is really associations between named entities
 - The same techniques can be extended to other slot-filling classifications

Named Entity Recognition on word sequences

We predict entities by classifying words in context and then extracting entities as word subsequences.

Why might NER be hard

- **Hard to work out boundaries of entity**
 - 这里有一个简单的例子说明NER有时候很难区分Named Entity的边界



Is the first entity "First National Bank" or "National Bank"

- **Hard to know if something is an entity**

Is there a school called "Future School" or is it a future school?

- **Hard to know class of unknown/novel entity**

To find out more about Zig Ziglar and read features by other Creators Syndicate writers and

What class is "Zig Ziglar"? (A person.)

- **Entity class is ambiguous and depends on context**

where Larry Ellison and Charles Schwab can
live discreetly amongst wooded estates. And

"Charles Schwab" is PER not ORG here

Binary word window classification

鉴于同一个词在不同上下文可能是不同的Named Entity，一个思路是通过对该词在某一窗口内附近的词来对其进行分类（这里的类别是人名，地点，机构名等等）。

Window classification

Idea

Classify a word in its context window of neighboring words.

A simple way to classify a word in context might be to **average** the word vectors in a window and to classify the average vector.

- Problem: **that would loss position information.**

Named Entity Classification

Person, Location, Organization, None

Window classification: Softmax

Train softmax classifier to classify a center word by taking **concatenation of word vectors surrounding it** in a window.

Example

Classify "Paris" in the context of this sentence with window length 2:

... museums in Paris are amazing ...

● ● ● ● ● ● ● ● ● ● ● ● ● ● ● ●

$$X_{\text{window}} = \begin{bmatrix} x_{\text{museums}} & x_{\text{in}} & x_{\text{Paris}} & x_{\text{are}} & x_{\text{amazing}} \end{bmatrix}^T$$

Resulting vector $x_{\text{window}} = x \in R^{5d}$, a column vectoe!

Simplest window classifier: Softmax

predicted model
output probability

$$\hat{y}_y = p(y|x) = \frac{\exp(W_y \cdot x)}{\sum_{c=1}^C \exp(W_c \cdot x)}$$

- With cross entropy error as before:

$$J(\theta) = \frac{1}{N} \sum_{i=1}^N -\log \left(\frac{e^{f_{y_i}}}{\sum_{c=1}^C e^{f_c}} \right)$$

same

Binary classification with unnormalized scores

- For our previous example:

`X_window = [x_museums x_in x_Paris x_are x_amazing]`

- Assume we want to **classify whether the center word is a Location**
- Similar to word2vec, we will go over all positions in a corpus. But this time, it will be supervised and **only some positions should get a high score**.
- E.g., **the positions that have an actual NER Location in their center are "true" positions and get a high score**

Binary classification for NER Location

Example

Not all museums in Paris are amazing.

这里只有一个真实的window就是Paris在中心,而其余的windows我们称它们为"corrupt".

正确的window是: [museums in Paris are amazing]

- "Corrupt" windows are easy to find and there are many: Any window whose center word isn't specifically labeled as NER location in our corpus

Neural Network Feed-forward Computation

Use neural activation a simply to give an unnormalized score

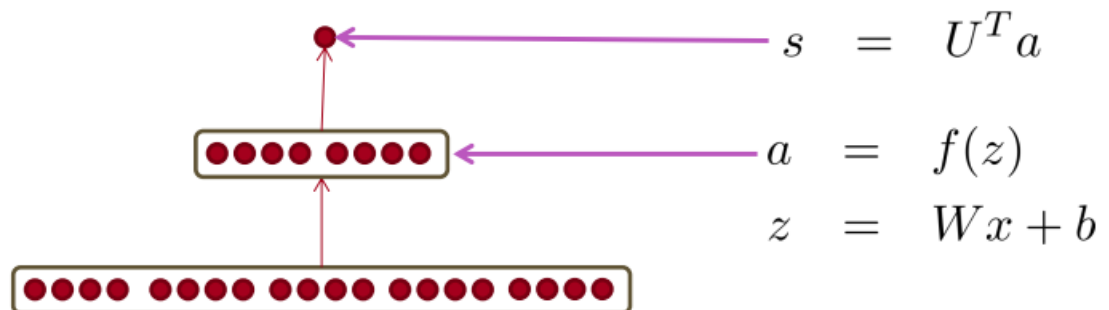
$$score(x) = U^T a$$

We compute a window's score with a **3-layer neural net**:

- $s = \text{score}(\text{"museums in Paris are amazing"})$

$$s = U^T f(Wx + b)$$

$$x \in \mathbb{R}^{20 \times 1}, W \in \mathbb{R}^{8 \times 20}, U \in \mathbb{R}^{8 \times 1}$$



34 $x_{\text{window}} = [x_{\text{museums}} \quad x_{\text{in}} \quad x_{\text{Paris}} \quad x_{\text{are}} \quad x_{\text{amazing}}]$

The middle layer learns **non-linear interactions** between the input word vectors.

The max-margin loss

Idea for training objective

Make true window's score larger and corrupt window's score lower (until they're good enough)

- $s = \text{score}(\text{museums}, \text{in}, \text{Pairs}, \text{are}, \text{amazing})$
- $s_c = \text{score}(\text{Not}, \text{all}, \text{museums}, \text{in}, \text{Pairs})$
- Minimize

$$J = \max(0, 1 - s + s_c)$$

- This is not differentiable but it is continuous: we can use SGD
- Each window with an NER location at its center should have a score +1 higher than any window without a location at its center

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