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Natural Language Processing

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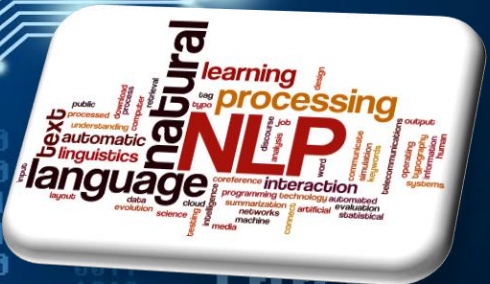


Conditional Random Field (CRF)

- While the HMM is a useful and powerful model, it turns out that HMMs need a number of augmentations to achieve high accuracy.
  - For example, in POS tagging as in other tasks, we often run into **unknown words**.
  - It would be great to have ways to add **arbitrary features** to help:
    - Capitalization or morphology (words starting with capital letters are likely to be proper nouns, words ending with -ed tend to be past tense)
    - Knowing the previous or following words might be a useful feature (if the previous word is *the*, the current tag is unlikely to be a verb).

- In general, it's hard for generative models like HMMs to add arbitrary features directly into the model in a clean way.
  - Logistic regression is a log-linear model for combining arbitrary features,

  →But logistic regression isn't a sequence model; it assigns a class to a single observation.

- There is a **discriminative sequence** model based on **log-linear** models: the conditional random field (CRF)→ we will describe **linear chain CRF**, the version of the CRF most commonly used for language processing, and the one whose conditioning closely matches the HMM.

Conditional Random Field (CRF)

We have a sequence of input words X = x1…xn and want to compute a sequence of output tags Y = y1…yn.

- In HMM:

$$\begin{aligned}\hat{Y} &= \operatorname*{argmax}_{Y} p(Y|X)\\ &= \operatorname*{argmax}_{Y} p(X|Y)p(Y)\\ &= \operatorname*{argmax}_{Y} \prod_i p(x_i|y_i) \prod_i p(y_i|y_{i-1})\end{aligned}$$

mkan el Pi msh hyfr2

- In CRF: we compute the **posterior p(Y|X)** directly:

$$\hat{Y} = \operatorname*{argmax}_{Y \in \mathcal{Y}} P(Y|X)$$

The CRF does not compute a probability for each tag at each time step.
Instead, at each time step the CRF computes log-linear functions over a set of relevant features.

?

$$p(Y|X) = \frac{\exp\left(\sum_{k=1}^{K} w_k F_k(X,Y)\right)}{\sum_{Y' \in \mathcal{Y}} \exp\left(\sum_{k=1}^{K} w_k F_k(X,Y')\right)}$$

The function F maps an entire input sequence X and an entire output sequence Y to a feature vector.

Let's assume we have K features, with a weight w_k for each feature F_k

Conditional Random Field (CRF)

<s> NLP Couse Lec </s>
what will be the value of the global feature
given that we use the template in the next slide?

Fk=1 (X,Y) =
since our first featue is <yi,xi> = <Noun, NLP>
so we will look for that template, so the result will be
(1 + 0 + 0)
as NLP is the only one which satisfies the current
feature.
if we had another NLP, the global will be 2.

- Re-write as:

$$p(Y|X) = \frac{1}{Z(X)}\exp\left(\sum_{k=1}^{K} w_k F_k(X,Y)\right)$$

$$Z(X) = \sum_{Y' \in \mathcal{Y}} \exp\left(\sum_{k=1}^{K} w_k F_k(X,Y')\right)$$

- These K functions $F_k(X,Y)$ are called **global features** ?

→since each one is a property of the entire input sequence X and output sequence Y.

- Computed by decomposing into a sum of **local features** for each position i in Y:

number of global featues =
number of local features.

n => 3dd el kalemat (timestep)

$$F_k(X,Y) = \sum_{i=1}^{n} f_k(\underbrace{y_{i-1}}_{\text{prev tag}}, \underbrace{y_i}_{\text{curr tag}}, \underbrace{X}_{\text{inp seq}}, \underbrace{i}_{\text{curr timestep}})$$

Each of these local features fk in a linear-chain CRF is allowed to make use of:
- current output token yi, you must use Markov assumption.
- previous output token yi-1, lw m3mltsh dol, hyb2a genral CRF, w sa3tha 34an ast5dm vetrbi aw keda hyb2a feh shwyt modifications lazm ne3mlhom.
- entire input string X (or any subpart of it),
- current position i.

what characterizes a linear chain CRF: this limitation makes it possible to use versions of the efficient Viterbi and Forward-Backwards algorithms from the HMM.

A general CRF, by contrast, allows a feature to make use of any output token.

Features in a CRF POS Tagger

- Some legal features representing common situations might be the following:

$$\mathbb{1}\{x_i = the,\ y_i = \text{DET}\}$$
$$\mathbb{1}\{y_i = \text{PROPN},\ x_{i+1} = Street,\ y_{i-1} = \text{NUM}\}$$
$$\mathbb{1}\{y_i = \text{VERB},\ y_{i-1} = \text{AUX}\}$$

f1 =

For simplicity, we'll assume all CRF features take on the value 1 or 0.

Proper noun: name of a person, organization, place, etc.

- Specific features can be automatically populated by using **feature templates:**
  - These templates automatically populate the set of features from every instance in the training and test set.

number of generated features = number of local features * number of words.

$$\langle y_i, x_i \rangle, \langle y_i, y_{i-1} \rangle, \langle y_i, x_{i-1}, x_{i+2} \rangle$$

el xi+2 da example, bs enta keda keda m3ak el input kolo fkhud meno el enta 3auzo.

example: Janet/NNP will/MD back/VB the/DT bill/NN, when xi is the word back, the following features would be generated and have the value 1 (we've assigned them arbitrary feature numbers):

f_{3743}: y_i = VB and x_i = back

bn3ml el klam da 3la kol el inputs.

f_{156}: y_i = VB and y_{i-1} = MD

f_{99732}: y_i = VB and x_{i-1} = will and x_{i+2} = bill

Features in a CRF POS Tagger

- It's also important to have features that help with **unknown words**:
  - **word shape features**:
    - which represent the abstract letter pattern of the word by mapping: lower-case letters to 'x', upper-case to 'X', numbers to 'd', retaining punctuation.
    - Examples: I.M.F would map to X.X.X. and DC10-30 would map to XXdd-dd.
  - **short word shape features:**
    - consecutive character types are removed, so words in all caps map to X, words with initial-caps map to Xx,
    - Examples: DC10-30 would be mapped to Xd-d but I.M.F would still map to X.X.X.
  - Example features:

x_i contains a particular prefix (perhaps from all prefixes of length ≤ 2)
x_i contains a particular suffix (perhaps from all suffixes of length ≤ 2)
x_i's word shape
x_i's short word shape

The word: *well-dressed*

$\text{prefix}(x_i) = \texttt{w}$
$\text{prefix}(x_i) = \texttt{we}$
$\text{suffix}(x_i) = \texttt{ed}$
$\text{suffix}(x_i) = \texttt{d}$
$\text{word-shape}(x_i) = \texttt{xxxx-xxxxxxx}$
$\text{short-word-shape}(x_i) = \texttt{x-x}$

hena khadna 2 34an hwa 3aml define en el prefix kol el shapes elly a2l or = mn 2

fa 3la 7asab enta m3rfha ezay

prefix mmkn brdo yfedak -> replay -> (re)

el suffix momken yfedny eny a3rf hwa verb msln wla a -> ed

Features in a CRF POS Tagger

- The known-word templates are computed for every word seen in the training set.
- The unknown word features can also be computed for all words in training, or only on training words whose frequency is below some threshold.

→The result is a very large set of features:

Generally, a **feature cutoff** is used in which features are thrown out if they have count < 5 in the training set.

- In a CRF we don’t learn weights for each of these local features fk.
- Instead, we first sum the values of each local feature (for example feature f3743) over the entire sentence, to create each global feature (for example F3743).
- It is those global features that will then be multiplied by weight w3743.
- Thus, for training and inference there is always a **fixed set of K features with K weights**, even though the length of each sentence is different.

Features for CRF Named Entity Recognizers

- A CRF for NER makes use of very similar features to a POS tagger:

identity of w_i, identity of neighboring words
embeddings for w_i, embeddings for neighboring words
part of speech of w_i, part of speech of neighboring words
presence of w_i in a **gazetteer**
w_i contains a particular prefix (from all prefixes of length ≤ 4)
w_i contains a particular suffix (from all suffixes of length ≤ 4)
word shape of w_i, word shape of neighboring words
short word shape of w_i, short word shape of neighboring words
gazetteer features

  - **gazetteer:** list of place names, often providing millions of entries for locations with detailed geographical and political information.
  - name-lists, lists of corporations or products, …etc.

- Some NER features for a sample sentence:

Words	POS	Short shape	Gazetteer	BIO Label
Jane	NNP	Xx	0	B-PER
Villanueva	NNP	Xx	1	I-PER
of	IN	x	0	O
United	NNP	Xx	0	B-ORG
Airlines	NNP	Xx	0	I-ORG
Holding	NNP	Xx	0	I-ORG
discussed	VBD	x	0	O
the	DT	x	0	O
Chicago	NNP	Xx	1	B-LOC
route	NN	x	0	O
.	.	.	0	O

Inference and Training for CRFs

$$\begin{aligned}
\hat{Y} &= \underset{Y \in \mathcal{Y}}{\operatorname{argmax}}\, P(Y|X) \\
&= \underset{Y \in \mathcal{Y}}{\operatorname{argmax}}\, \frac{1}{Z(X)} \exp\left(\sum_{k=1}^{K} w_k F_k(X,Y)\right) \\
&= \underset{Y \in \mathcal{Y}}{\operatorname{argmax}}\, \exp\left(\sum_{k=1}^{K} w_k \sum_{i=1}^{n} f_k(y_{i-1}, y_i, X, i)\right) \\
&= \underset{Y \in \mathcal{Y}}{\operatorname{argmax}} \sum_{k=1}^{K} w_k \sum_{i=1}^{n} f_k(y_{i-1}, y_i, X, i) \\
&= \underset{Y \in \mathcal{Y}}{\operatorname{argmax}} \sum_{i=1}^{n} \sum_{k=1}^{K} w_k f_k(y_{i-1}, y_i, X, i)
\end{aligned}$$

Inference: How do we find the best tag sequence $\hat{Y}$ for a given input X?

we can ignore the exp function and the denominator Z(X) because this doesn't change the argmax, and the denominator Z(X) is constant for a given observation sequence X.

replacing transition and emission probabilities with the CRF features

- Using Viterbi Algorithm:

$$v_t(j) = \max_{i=1}^{N} v_{t-1}(i) \sum_{k=1}^{K} w_k f_k(y_{t-1}, y_t, X, t) \quad 1 \leq j \leq N, 1 < t \leq T$$

Training: given a sequence of observations, feature functions, and corresponding outputs, we use stochastic gradient descent to train the weights to maximize the log-likelihood of the training corpus.

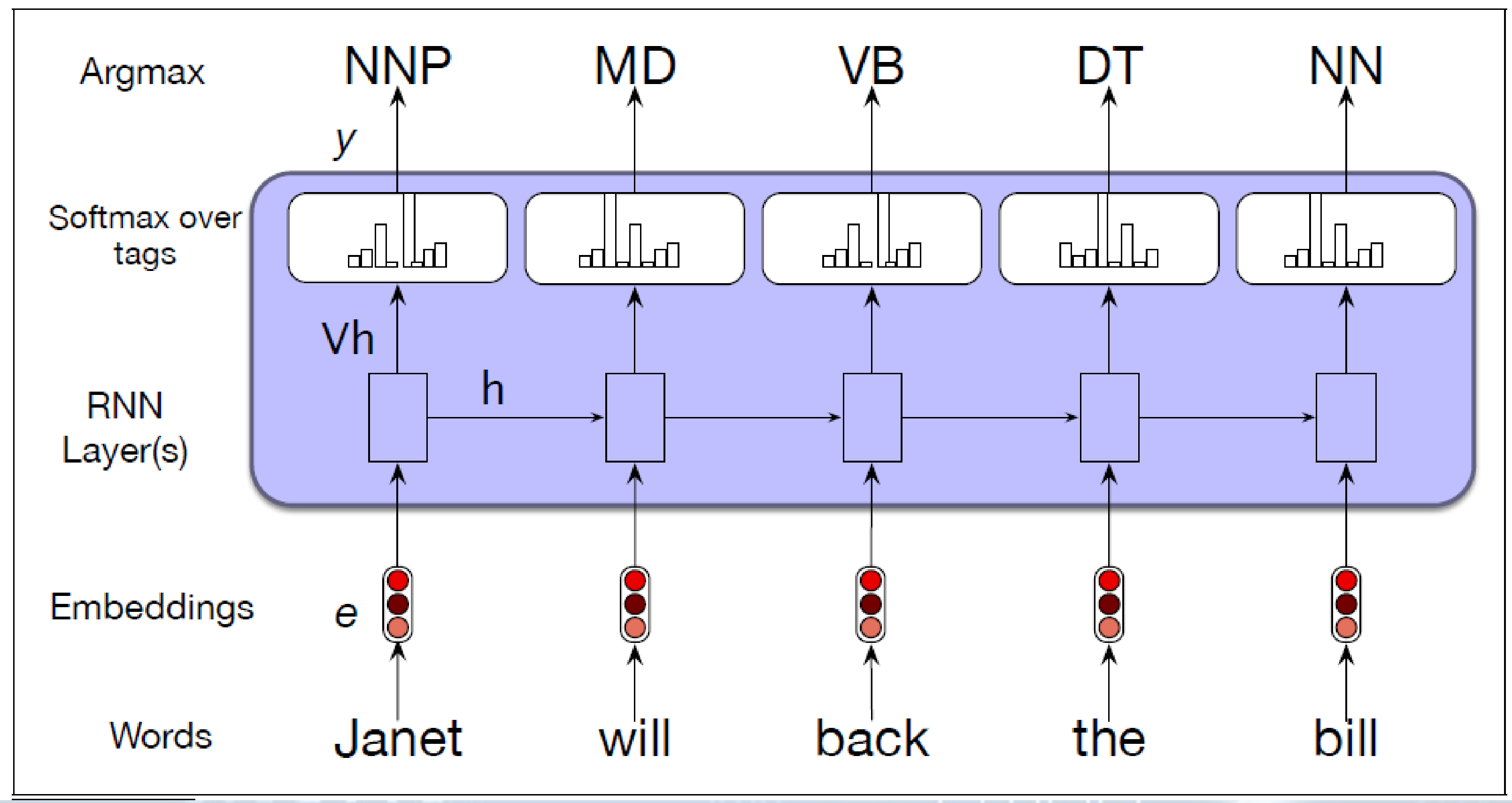
Evaluation

- Part-of-speech taggers are evaluated by the standard metric of **accuracy**.

- Named entity recognizers are evaluated by **recall**, **precision**, and **F1 measure**.
  - The fact that named entity tagging has a segmentation component which is not present in tasks like text categorization or part-of-speech tagging causes some problems with evaluation.
  - For example, a system that labeled *Jane* but not *Jane Villanueva* as a person would cause two errors:
    - a false positive for O
    - a false negative for I-PER

RNN Sequence Labeling

- Inputs: are word embeddings
- Outputs: are tag probabilities generated by a softmax layer over the given tagset.




Thank You