General sequence tagging: NER and Chunking

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Quick review

Review: with your groups

1. For a trigram model, how do we refactor $p(w_1, w_2, \ldots, w_n)$?
2. For a bigram HMM, how do we refactor $p(x, y)$?
3. What parameters does an HMM have?
4. Annotate the following sentences with UD POS tags
    - The dog jumped on my back.
    - The politicians backed the proposal.
    - I want my book back.

Review: with your groups: answers

1. For a trigram model, how do we refactor $p(w_1, w_2, \ldots, w_n)$?
   - $p(w_1, w_2, \ldots, w_3) = \prod_{i=1}^{n} p(w_i | w_{i-2}, w_{i-1})$
2. For a bigram HMM, how do we refactor $p(x, y)$?
   - $p(x, y) = p(y)p(x|y) = \prod_{i=1}^{n} p(y_i | y_{i-1}) \prod_{i=1}^{n} p(x_i | y_i)$
3. What parameters does an HMM have?
   - initialization probabilities: π
   - transition probabilities: A
   - emission probabilities: B
4. Annotate the following sentences with UD POS tags
   - The/DET dog/NOUN jumped/VERB on/ADP my/PRON back/NOUN.
   - The/DET politicians/NOUN backed/VERB the/DET proposal/NOUN.
   - I/PRON want/VERB my/PRON book/NOUN back/ADV.

Tagging sequences

Until now

- Language modeling: $p(w_1, w_2, \ldots, w_n) = \prod_{i=1}^{n} p(w_i | w_{i-1})$
- POS tagging: $p(x, y) = p(y)p(x|y) = \prod_{i=1}^{n} p(y_i | y_{i-1}) \prod_{i=1}^{n} p(x_i | y_i)$
- Notice that we don't really have any constraints on what y is.
- So far, we have seen how to parameterize the model when y is part of speech tags.
- Today we'll see how to apply the same model to other tasks.

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- Not easy to retrieve most information in a useful form.
- Instead, we could process this information and keep it in another format:
  - Should be easily machine readable:
  - Relational database
  - XML markup

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2. Perform co-reference resolution.
3. Determine what relationship they have.
4. Use this information to populate the database

Information extraction

Uses

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- News paper articles

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- News paper articles
- Web pages

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Information extraction

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- Medical notes

Knowledge Base Population

Penner is survived by his brother, John, a copy editor at the Times, and his former wife, Times sportswriter Lisa Dillman.

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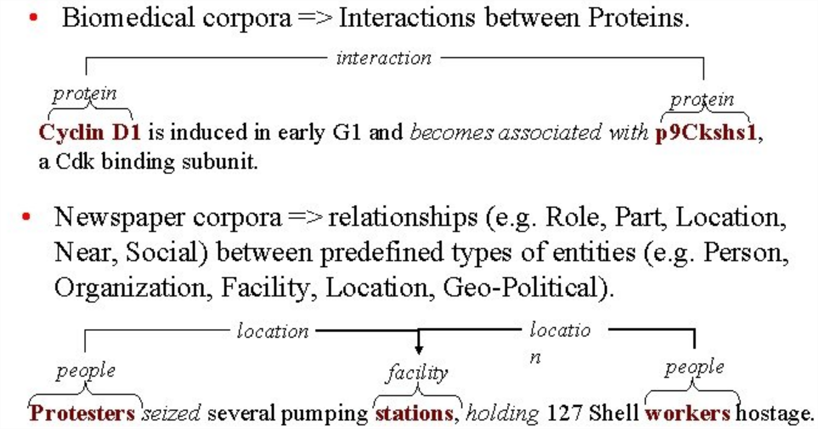
Subject	Relation/Slot	Object
Mike Penner	per:spouse	Lisa Dillman
Lisa Dillman	per:title	Sportswriter
Lisa Dillman	per:employee_of	Los Angeles Times
…	…	…

Information extraction



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- The actual tags depend highly on the final use case.
- In research, we often use data from CONLL shared task:
  - PER: person
  - LOC: location
  - ORG: organization
  - MISC: miscellaneous

Named Entity Recognition

[PER Wolff] , currently a journalist in [LOC Argentina] , played with [PER Del Bosque] in the final years of the seventies in [ORG Real Madrid] .

Differences

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[PER Wolff] , currently a journalist in [LOC Argentina] , played with [PER Del Bosque] in the final years of the seventies in [ORG Real Madrid] .

Differences

- There are two major differences between NER and POS tagging that we need to deal with before we can apply the HMM from last class.
- Can you see the two main differences?

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  - Labels can span across several tokens.
  - A token doesn't have to have a label.

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- There are two major differences between NER and POS tagging that we need to deal with before we can apply the HMM from last class.
- Can you see the two main differences?
  - Labels can span across several tokens.
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Any ideas on how we could deal with these?

(With partners for 5 minutes)

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Named Entity Recognition

Options

- Since we already have a model we really like, we can change the label structure
- "If all you have is a hammer, everything looks like a nail" - Abraham Maslow
- Alternatively, "If you have a good hammer, why make a new hammer for every problem?" - Unknown author

Named Entity Recognition

[PER Wolff] , currently a journalist in [LOC Argentina] , played with [PER Del Bosque] in the final years of the seventies in [ORG Real Madrid] .

Options

- 1. Let's make a small change and give all tokens a tag.

Named Entity Recognition

Wolff/PER , currently/O a/O journalist/O in/O Argentina/LOC ,/O played/O with/O Del/PER Bosque/PER in/O the/O final/O years/O of/O the/O seventies/O in/O Real/ORG Madrid/ORG ./O

Options

- 1. Let's make a small change and give all tokens a tag.
- Give the tokens not in a label the O tag: outside of label.
- But now it is not possible to ensure that tags that span over 2 or more tokens are retrievable.

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Wolff/B-PER , currently/O a/O journalist/O in/O Argentina/B-LOC ,/O played/O with/O Del/B-PER Bosque/I-PER in/O the/O final/O years/O of/O the/O seventies/O in/O Real/B-ORG Madrid/I-ORG ./O

Options

- 1. Let's make a small change and give all tokens a tag.
- Give the tokens not in a label the O tag: outside of label.
- But now it is not possible to ensure that tags that span over 2 or more tokens are retrievable.
- Add beginning and inside to labels, i.e., B-ORG, I-ORG
- This tagging scheme is known as IOB or BIO.
- There are a few variants that propose improvements.

Chunking

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Robust, efficient approach to syntax

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  - Non-recursive text spans
  - Includes a head and its modifiers

Wolff/PROPN ,/PUNCT currently/ADV a/DET journalist/NOUN in/ADP Argentina/NOUN ,/PUNCT played/VERB with/ADP Del/PROPN Bosque/PROPN in/ADP the/DET final/ADJ years/NOUN of/ADP the/DET seventies/NOUN in/ADP Real/PROPN Madrid/PROPN ./PUNCT

Chunking

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[NP Wolff/PROPN] ,/PUNCT currently/ADV [NP a/DET journalist/NOUN in/ADP Argentina/NOUN] ,/PUNCT [VP played/VERB] with/ADP [NP Del/PROPN Bosque/PROPN] in/ADP [NP the/DET final/ADJ years/NOUN] of/ADP [NP the/DET seventies/NOUN] in/ADP [NP Real/PROPN Madrid/PROPN] ./PUNCT

Chunking

Quick exercise: Use IOB tagging for this chunking example

[NP Wolff] , currently [NP a journalist] in [NP Argentina] ,
[VP played] with [NP Del Bosque] in [NP the final years]
of [NP the seventies] in [NP Real Madrid] .

Chunking

Wolff	B-NP
,	O
currently	O
a	B-NP
journalist	I-NP
in	O
Argentina	B-NP
,	O
played	B-VP
with	O
Del	B-NP
Bosque	I-NP
in	O
the	B-NP
final	I-NP
years	I-NP
of	O
the	B-NP
seventies	I-NP
in	O
Real	B-NP
Madrid	I-NP
.	PUNCT

Evaluation of sequence tagging

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Let's go back to our NER example and think of how to evaluate this sentence.

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gold =['B-PER', 'O', 'O', 'O', 'O', 'B-LOC', 'O', 'O', 'O', 'O']

pred =['B-PER', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O', 'O']

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What is the accuracy?

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What is the accuracy?

Acc = 0.90

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What is the accuracy?

Acc $= 0.80$

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Acc = 0.80

So, if you just always predict 'O', you could easily achieve 80-90% accuracy.

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What is the accuracy?

Acc = 0.80

So, if you just always predict 'O', you could easily achieve 80-90% accuracy. Our artificially adding labels to all tokens means we can't really use accuracy anymore.

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Precision = 1.0 (Only one prediction, which was correct)

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$F_1 = \frac{2*1*0.5}{1+0.5} = 0.66$

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