Constrained Decoding for Computationally Efficient Named Entity Recognition Taggers

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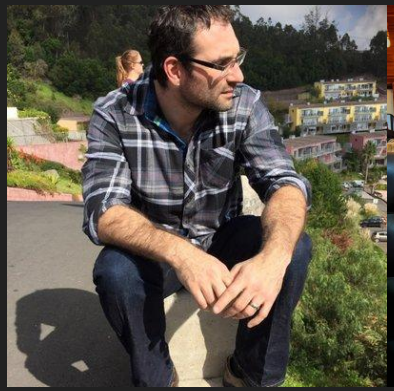
Collaborators





What are Taggers?

- A Sequence Transduction task

  $X = (x_1, x_2, \ldots, x_n)$

  $Y = (y_1, y_2, \ldots, y_n)$

- Additional constraint that the input and output sequences have the same length.

Tagger Tasks

- Token Level
  - Part of Speech Tagging
- Span Level
  - Named Entity Recognition
  - Slot Filling for Dialogue Systems

Why do we Want to Train Efficient Taggers?

We train a lot of taggers, in 3 months:

- CoNLL 2003: 342
- Ontonotes: 56
- Snips: 49
- WNUT: 34
- Internal: 788

Tagger Models

- Windowed Classifiers
- MEMMs
- BiLSTM-CRF
- Transformers

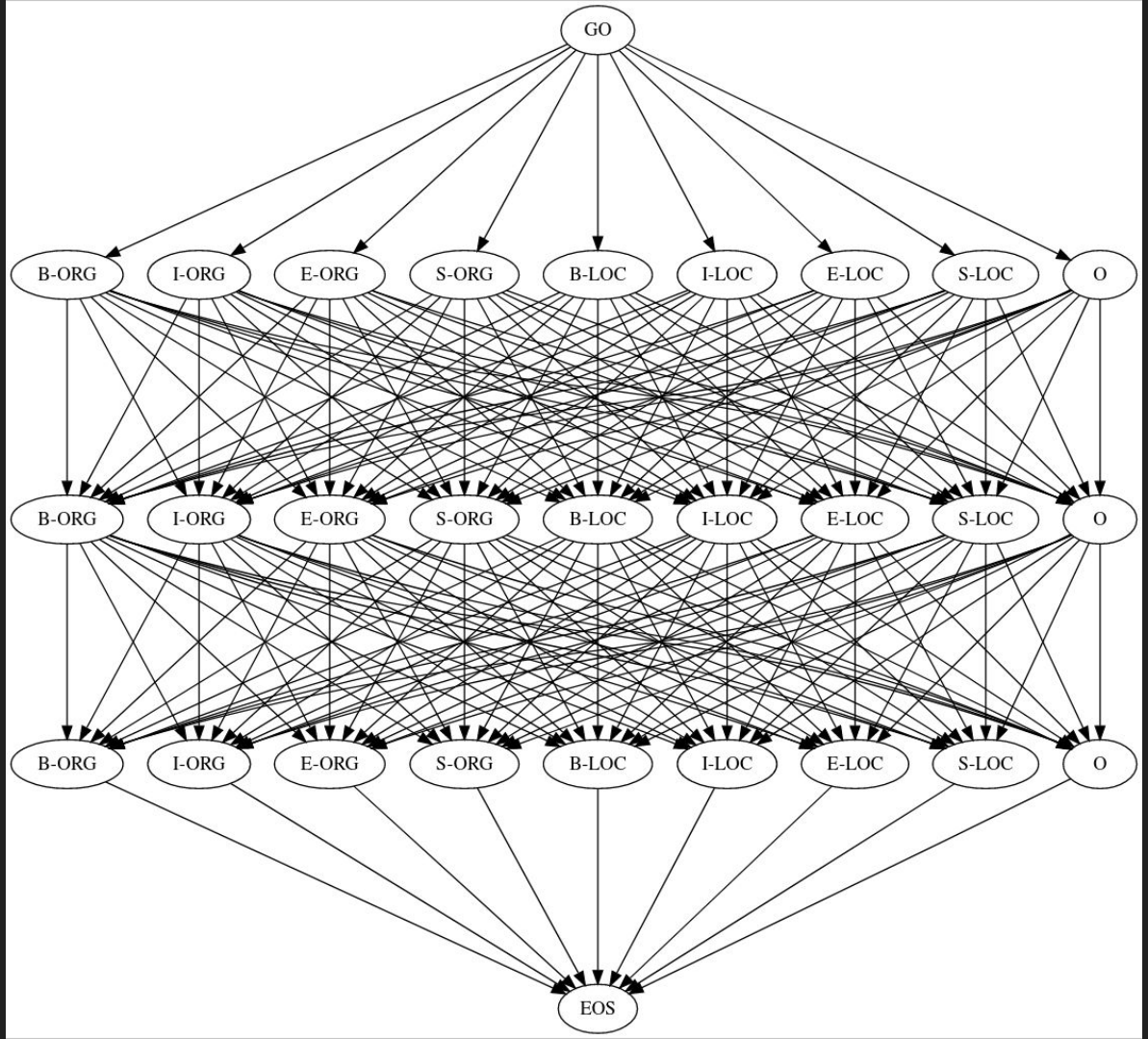
Greedy Taggers

- Make an independent decision at each timestep
- Your choice at t-1 doesn’t factor into your choice at t
- These taggers often have difficulty with global coherence
  - They change the types of entities in the middle of spans

Structured Tagger Inference

- We want to find the best over all tag sequence
- Not just the best tag for each token
- Enumerating and scoring each sequence would be intractable
- We use dynamic programming with the Viterbi Algorithm
- This generally involves emission scores, a distribution over labels for a given token, and transition scores, a distribution of transitions from one label to another.

Viterbi Decoding



Span Encoding

- For some tasks we need more than just a token label
- We want the whole phrase “Jack White” to be labeled as a single person, not each token to be labeled separately
- We keep the labels types like in tokens
- We add special prefixes to group tokens into spans

Span Encoding

B-PER

Each tag is made from two parts

- The second part is the type of entity it is. A person, location, etc.
- The first part is the function of this token in the span
  - B is the beginning of the span
  - I is inside of a span
  - E is the end of a span
  - S is a token that makes up the whole span
  - O is outside of a span

Span Encoding

```
Jack     B-PER
White    E-PER
was      O
born     O
in       O
Detroit  S-LOC
On       O
July     B-DATE
9th      I-DATE
1975     E-DATE
```

“Jack White” is a person

“Detroit” is a location

“July 9th 1975” is a date

Span Encoding Constraints

- The span encoding scheme imposes some rules
  - I and E must follow a token of the same type
  - B can only follow an O, E, or S
  - S cannot follow B or I

Constraints as Transition Parameters

What if instead of learning these transition scores we use these constraints to stop illegal moves?

Constraints as Transition Parameters

Our Method

- Train a Tagger with Cross Entropy Loss
- Create a mask based on the transition rules
  - A mapping from one label to another
  - Zero if the transition is legal
  - Negative infinity if it is illegal
- Use this mask as transition parameters in our CRF implementation

Results

Dataset	CRF Score	CD Score	Difference
CoNLL 2003	91.61	91.44	-0.03
WNUT-17	40.33	40.59	0.65
Snips	96.04	96.07	0.03
Ontonotes	87.43	86.13	-1.48
Internal Customer Service			0.21
Internal Automotive			-0.68
Internal Cyber Security			0.84
Internal NER			0.80

Analysis

Why did we only see this drop in Ontonotes?

Strictly Dominated Tokens

- Within a dataset a type can often have different labels assigned to different tokens
  - Kurdistan can be a `B-ORG`, `E-ORG`, or `E-LOC`

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  - Kurdistan can be a `B-ORG`, `E-ORG`, or `E-LOC`
- Previous tokens (and their labels) and our transition rules can help use make a decision
- What if the last token was `I-ORG`?
- What if the last token was `B-LOC`?

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- Once you decide a token in `B-ORG` you know your next token is either `I-ORG` or `E-ORG`.
- What about entities where the first token is always a `B-ORG`?
- Because of how Viterbi works the same ideas apply to entities where the last token always has a single label.

Efficiency

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- 65% of the Carbon Emissions during training
    - It does draw 1.3 times the power

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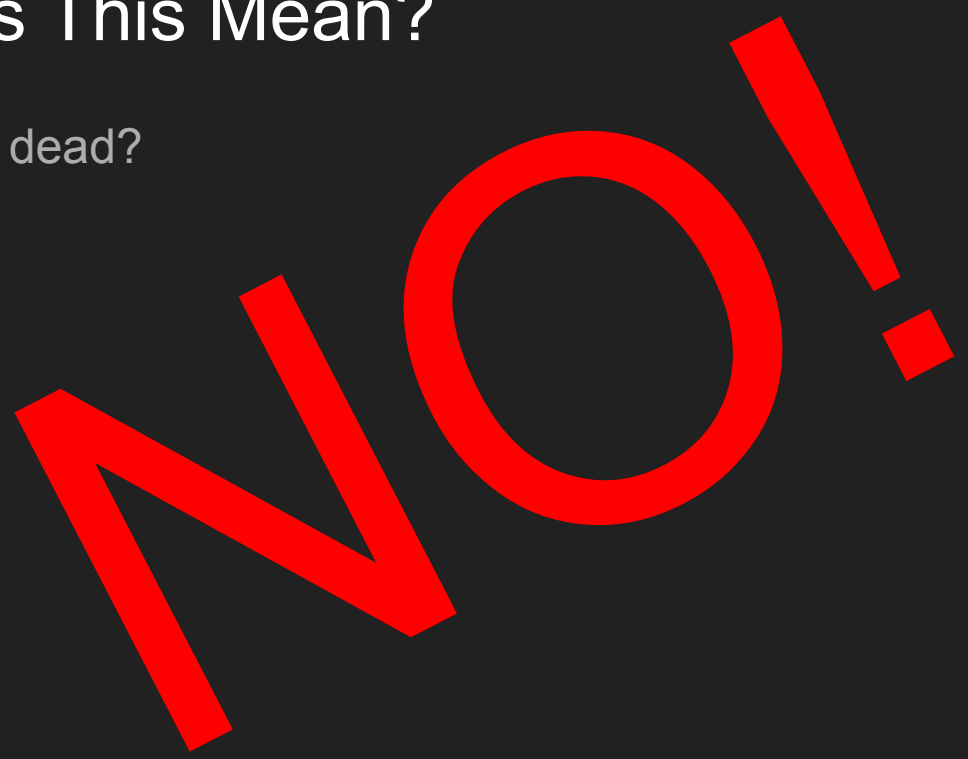

What Does This Mean?

- Structure is dead?
- Structure needs to evolve

Contact

- The work: https://github.com/blester125/constrained-decoding
- Me
  - Twitter: https://twitter.com/blester125
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