Context Dependent Fine Grained Entity Typing

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Reading Group Presentation

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Entity Type Classification

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- They have also increased the performance of several downstream applications such as Question Answering (Lin et al., 2012) and Knowledge Base Completion (Carlson et al., 2010; Das et al., 2016)

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- Today I will discuss few recent paper about context dependent fine grained entity types…

Context-Dependent Fine-Grained Entity Type Tagging

Dan Gillick, Nevena Lazic, Kuzman Ganchev, Jesse Kirchner, David Huynh
Google

Why context dependent types?

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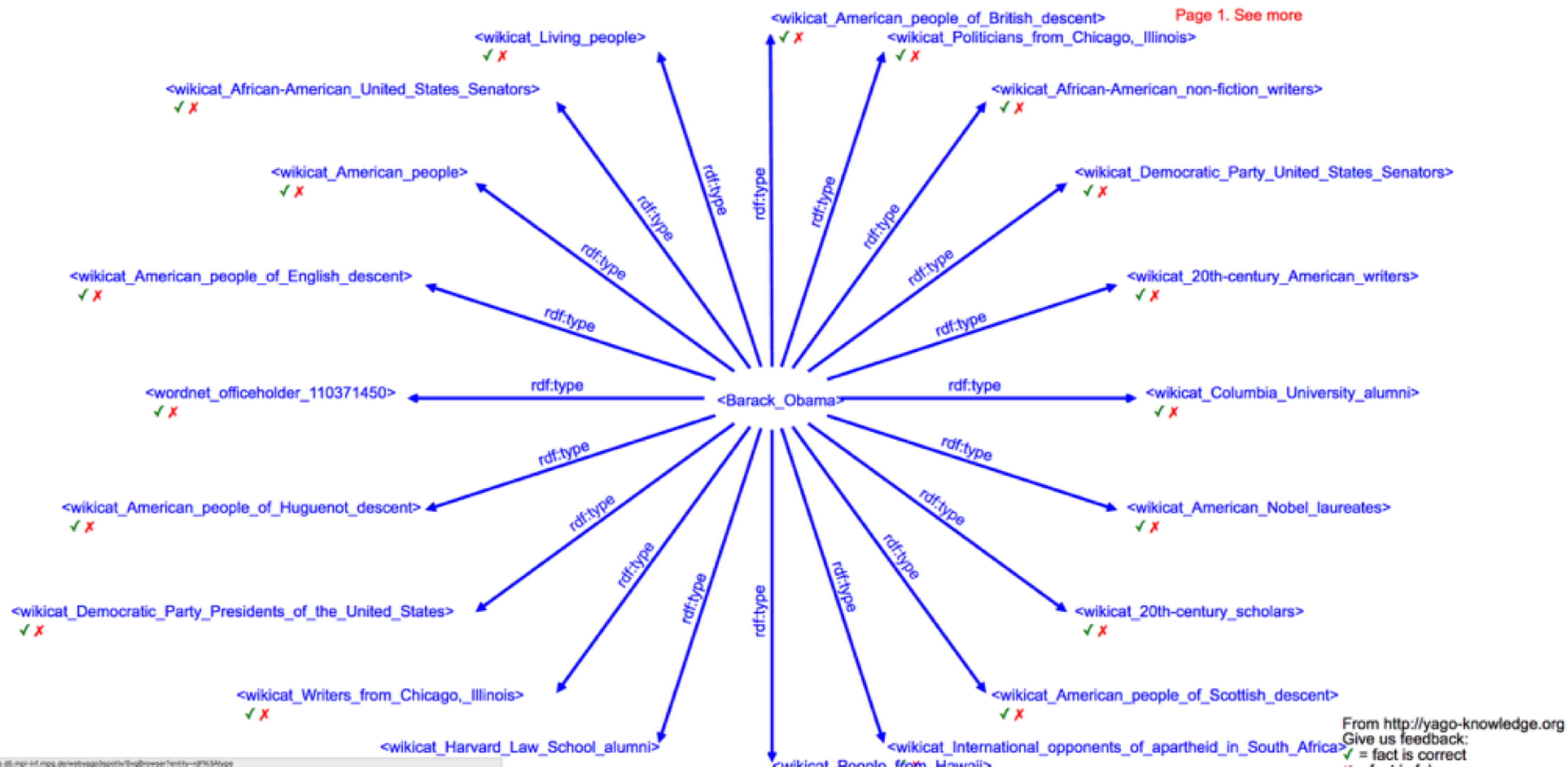
Why context dependent types?

Types in YAGO



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Relevant Types:
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Fine Types:
predator, Saatchi & Saatchi Co. : ***organization/company***
Charles and Maurice Saatchi : ***person/business***

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Note: Without the context "predator" would not be identified as an "organization"

Type Labels and Manual Annotation

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PERSON

- **artist**
  - actor
  - author
  - director
  - music
- **education**
  - student
  - teacher
- **athlete**
- **business**
- **coach**
- **doctor**
- **legal**
- **military**
- **political figure**
- **religious leader**
- **title**

LOCATION

- **structure**
  - airport
  - government
  - hospital
  - hotel
  - restaurant
  - sports facility
  - theatre
- **geography**
  - body of water
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ORGANIZATION

- **company**
  - broadcast
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Type Labels and Manual Annotation

PERSON	LOCATION	ORGANIZATION	OTHER	
artist actor author director music	**structure** airport government hospital hotel restaurant sports facility theatre	**company** broadcast news	**art** broadcast film music stage writing	**language** programming language
education student teacher	**geography** body of water island mountain	**education**	**event** accident election holiday natural disaster protest sports event violent conflict	**living thing** animal
athlete	**transit** bridge railway road	**government**	**health** malady treatment	**product** camera car computer mobile phone software weapon
business	**celestial**	**military**	**award**	**food**
coach	**city**	**music**	**body part**	**heritage**
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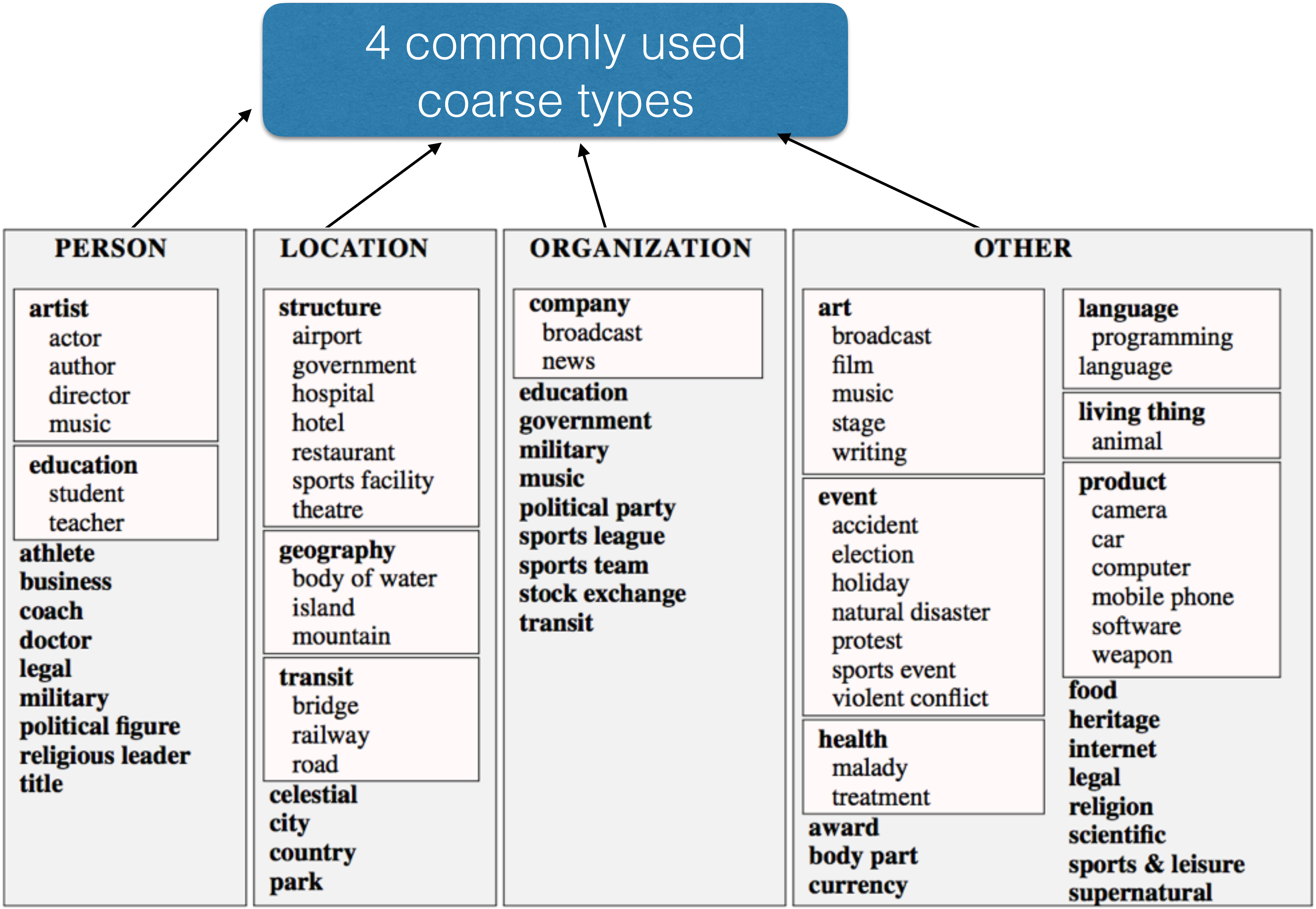

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Level II types -
person/athlete
organiztion/company

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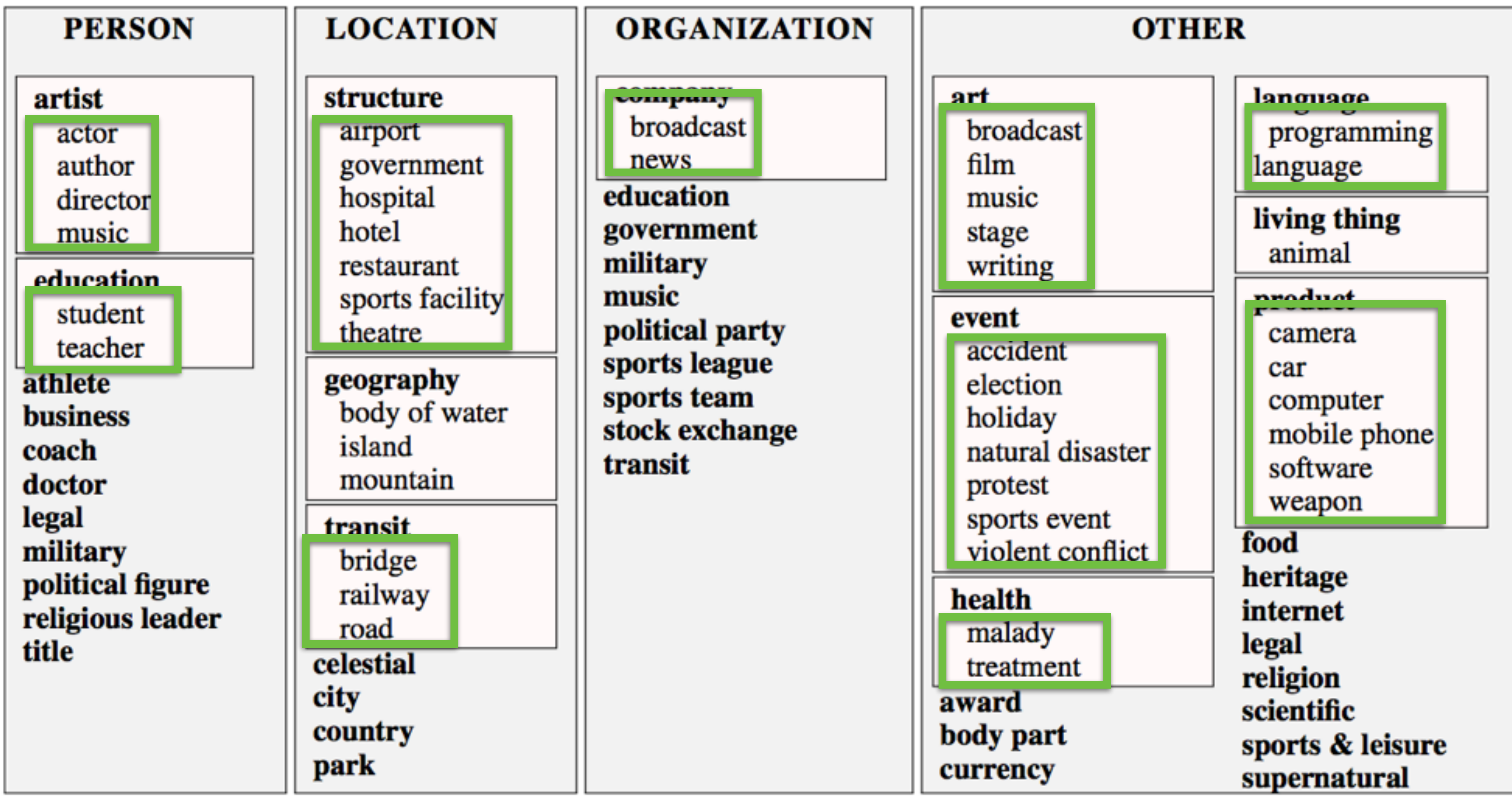
Level III types -
person/artist/actor
other/event/election



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Documents	77
Entity mentions	11304
Labels	17704
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- Each document annotated by 6 annotators
- More annotations at the top level
- More disagreement at the bottom level (Specificity)
- Some disagreements at type level too (Type)

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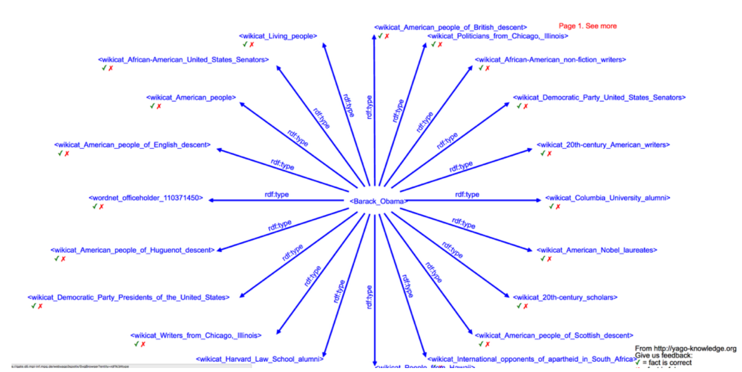

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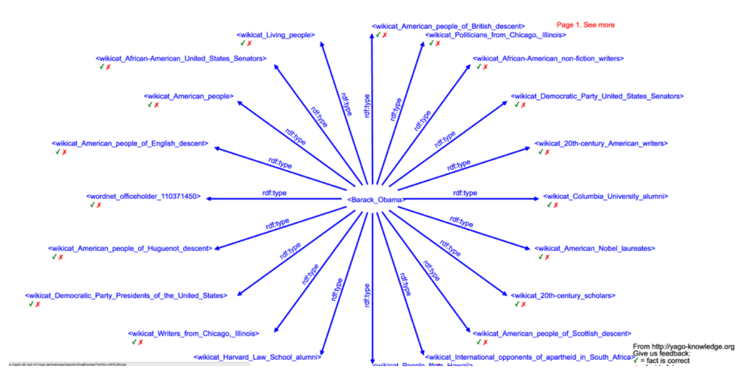

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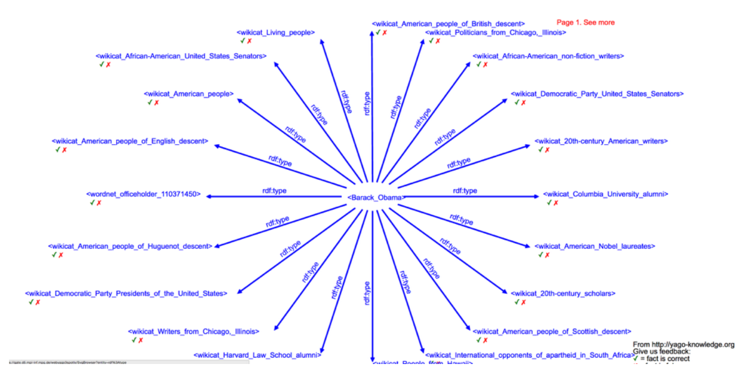

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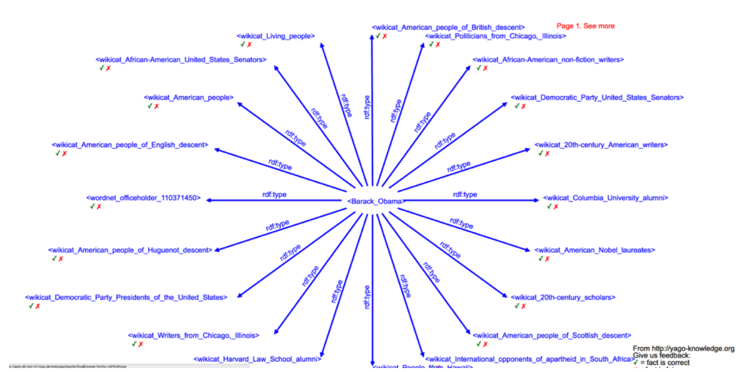

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- <u>Minimum Count Pruning</u>: Remove types which appear less then 'k' times.

Features, Model & Inference

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x

Feature	Description	Example
Head	The syntactic head of the mention phrase	"Obama"
Non-head	Each non-head word in the mention phrase	"Barack", "H."
Cluster	Word cluster id for the head word	"59"
Characters	Each character trigram in the mention head	":ob", "oba", "bam", "ama", "ma:"
Shape	The word shape of the words in the mention phrase	"Aa A. Aa"
Role	Dependency label on the mention head	"nsubj"
Context	Words before and after the mention phrase	"B:who", "A:first"
Parent	The head's lexical parent in the dependency tree	"picked"
Topic	The most likely topic label for the document	"politics"

Table 4: List of features used in type tagging. Features are extracted from each mention. Context used for example features: "... who [Barack H. Obama] first picked ..."

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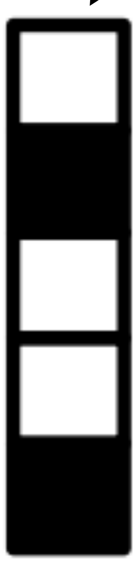

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$\mathbf{y}_t \in \mathbb{R}^{\mathsf{T}}$

T equals the total number of types.

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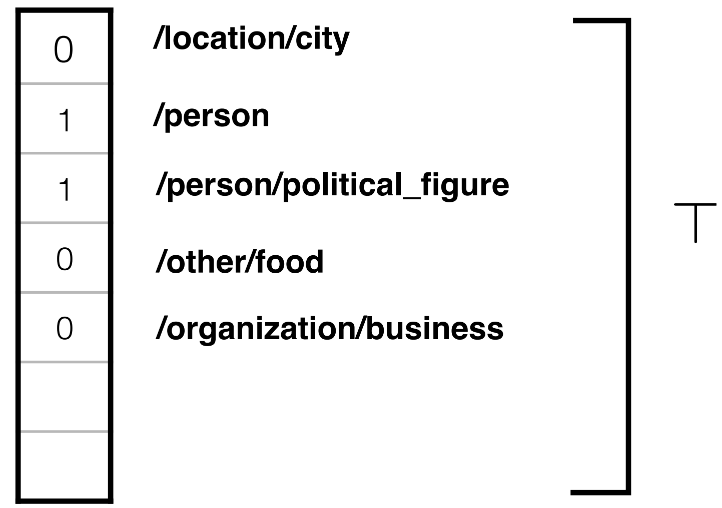

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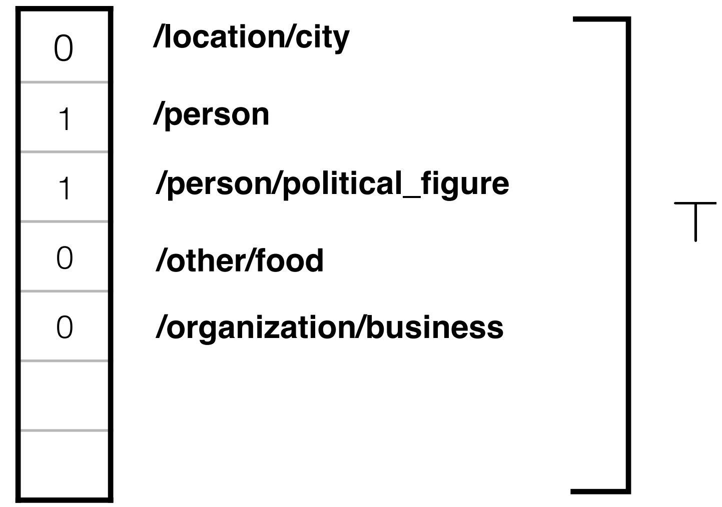

Training Data

- +ve examples: For a type, +ve examples are all mentions marked as itself and also its descendants i.e. a mention labeled '*person/artist*' is a +ve example for '*person*'
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  3. all other types

Models & Inference
Local Model

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- Local classifiers: A binary logistic regression classifier is trained for each label (i.e. there are T classifiers) and label consistency is enforced at inference time
- During inference:
    - Independent: Assign all types that exceeds some decision threshold
    - Conditional: Multiply each label with the probability of its parent. This strategy ensures that if a label is selected then its parent would also be selected
    - Marginalization: (if I understand correctly) Probability of a label is the sum of configurations in which it appears.

Models & Inference
Global/Flat Model

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- Inference time: assign all labels whose probability exceeds a threshold; not just the max.

Results

Results

Different -ve example strategies:

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Negatives	Prec	Rec	F1	AUC
All	77.98	59.55	67.53	66.56
Sibling	79.93	58.94	67.85	66.50
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Different inference schemes:

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Conditional	77.89	**63.30**	69.84	**70.04**
Marginals	**80.05**	62.20	**70.01**	69.29

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Classifier	Precision	Recall	F1
Level 1 Flat	84.39	79.01	81.61
Level 1 Local	87.12	78.84	**82.80**
Level 2 Flat	46.61	25.99	33.37
Level 2 Local	56.76	30.88	**40.00**
Level 3 Flat	75.00	1.78	3.47
Level 3 Local	24.00	8.28	**12.32**

Table 6: Precision, recall, and F-Score given by the flat and local classifiers at each level of the type taxonomy. We use all heuristics and Depth negative examples for the local classifiers. Level 1 are the labels immediately below the root of our tree: *person*, *location*, *organization*, and *other*. Level 2 are the labels below them such as *person/artist* while Level 3 are one level lower such as *person/artist/actor*.

Conclusions

- Strives to make fine grained typing meaningful by requiring context dependence
- Introduce several distant supervision heuristics aimed at pruning irrelevant labels from the training data and match the gold data.
- Introduce new dataset 11,304 manually annotated mentions in 77 OntoNotes news documents.

Embedding Methods for Fine Grained Entity Type Classification

-Dani Yogatama, Dan Gillick, Nevena Lazic
CMU, Google

Key Contribution

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If a hostile predator emerges for Saatchi & Saatchi Co., cofounders

Charles and Maurice Saatchi will lead…..

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Head	The syntactic head of the mention phrase	"Obama"
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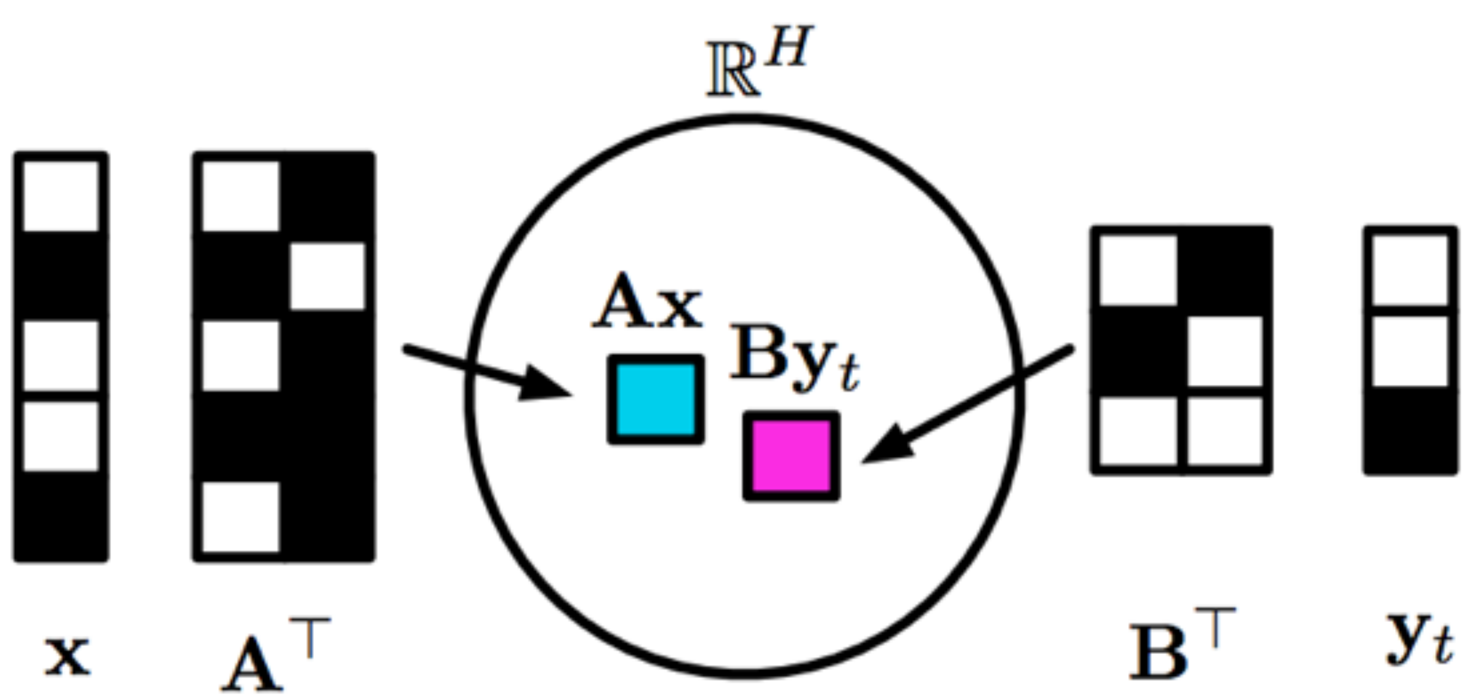

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- Motivation: Learning low dimensional embeddings allows information sharing among related labels. For example: person/author would be more closer to person/artist than location/city.

Model

Model

Interested in learning mapping function f and g

$$f(x) : \mathbb{R}^D \rightarrow \mathbb{R}^H$$

$$\forall t \in \{1, 2, \ldots, \top\}, g(y_t) : \{0, 1\}^\top \rightarrow \mathbb{R}^H$$

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Score of a label t (represented as one hot vector y_t) and a feature vector x

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$$\mathbf{A} \in \mathbb{R}^{\mathbf{H} \times \mathbf{D}}, \mathbf{B} \in \mathbb{R}^{\mathbf{H} \times \top}$$

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$$\mathbf{A} \in \mathbb{R}^{\mathbf{H} \times \mathbf{D}}, \mathbf{B} \in \mathbb{R}^{\mathbf{H} \times \top}$$

f and g are linear mappings and score is calculated as dot product

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- It is also a way of introducing non-linearity!

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BINARY	80.05	62.20	70.01
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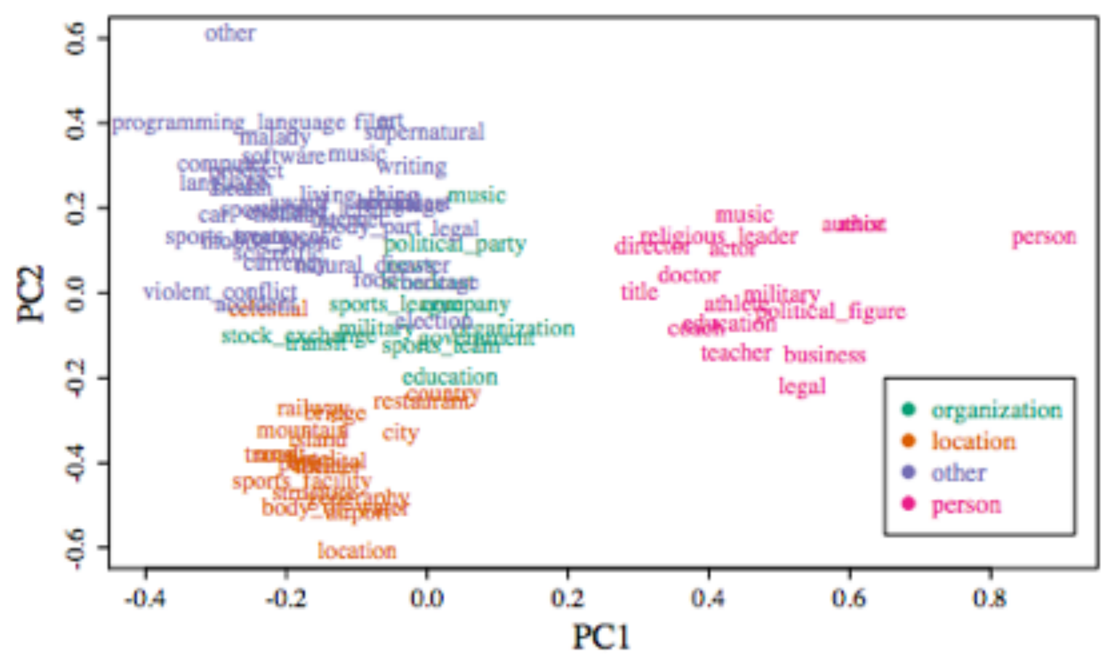

Figure 3: Two-dimensional projections of label embeddings for GFT dataset. See text for details.

An Attentive Neural Architecture for Fine-grained Entity Type Classification

Sonse Shimaoka, Pontus Stenetorp, Kentaro Inui, Sebastian Riedel
Tohoku University, University College London

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River Monongahela <u>flows through</u> Pittsburgh

Pittsburgh has 3 rivers Allegheny, Monongahela, Ohio <u>running through</u> it

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- Side Note: They averaged the mention embeddings to get one vector

$$v_m = \frac{\sum_{i=1}^{M} u(m_i)}{M}$$

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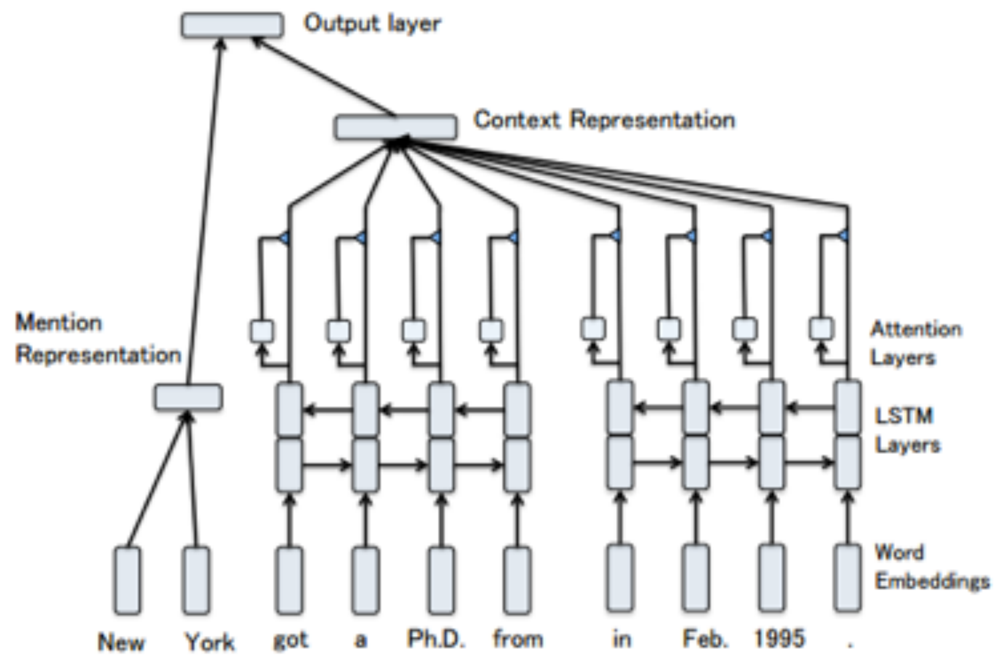

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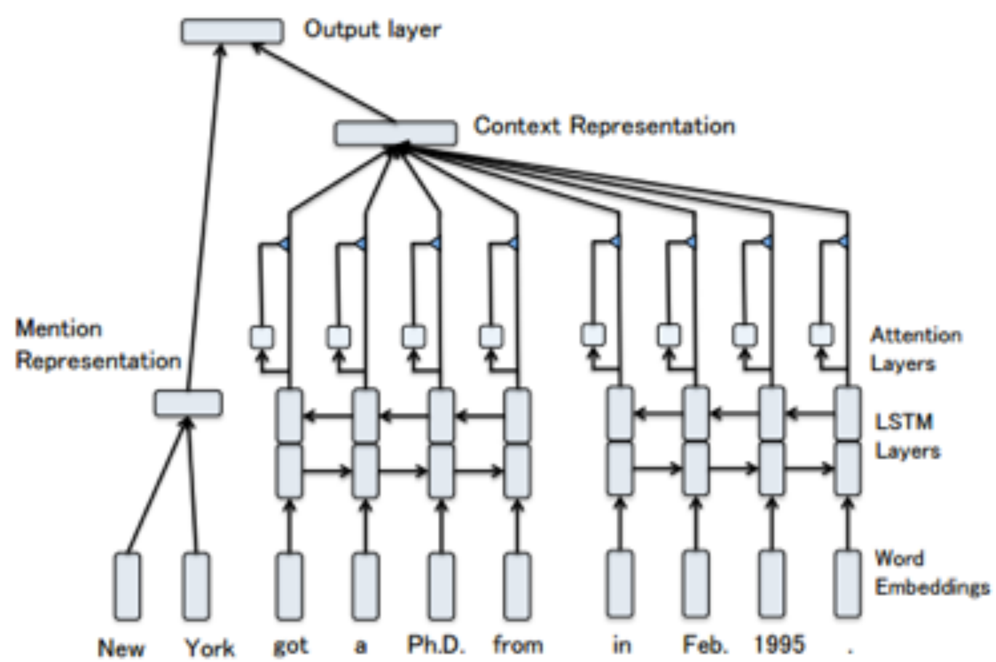

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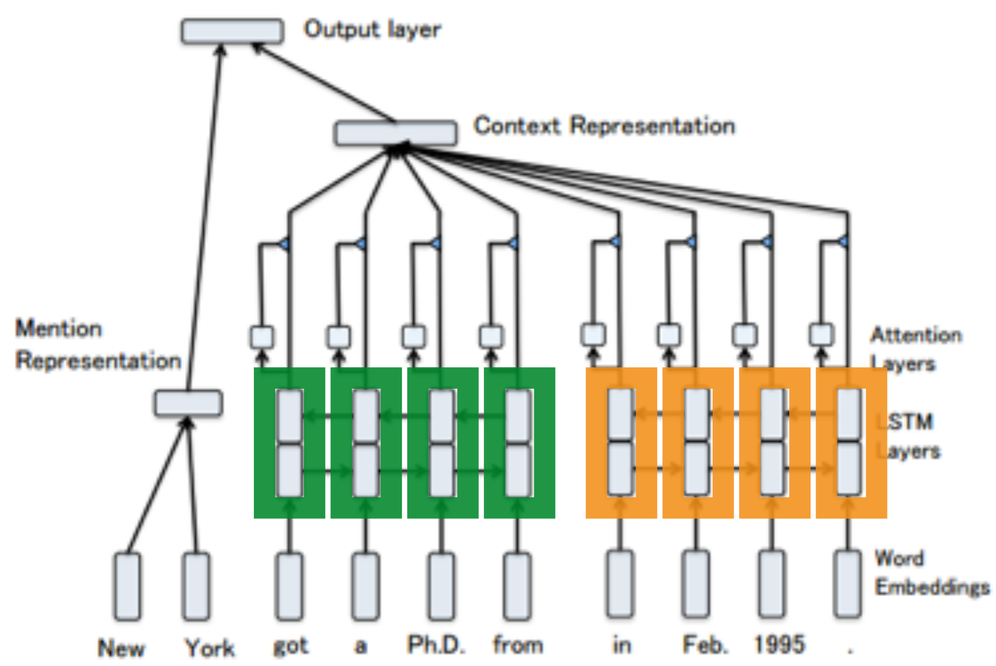

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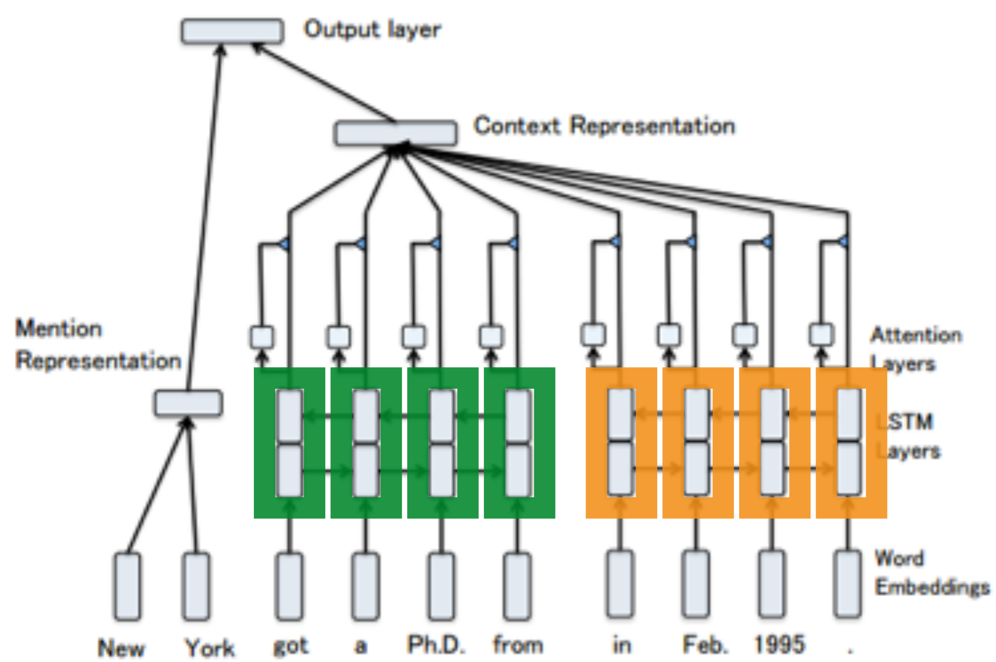

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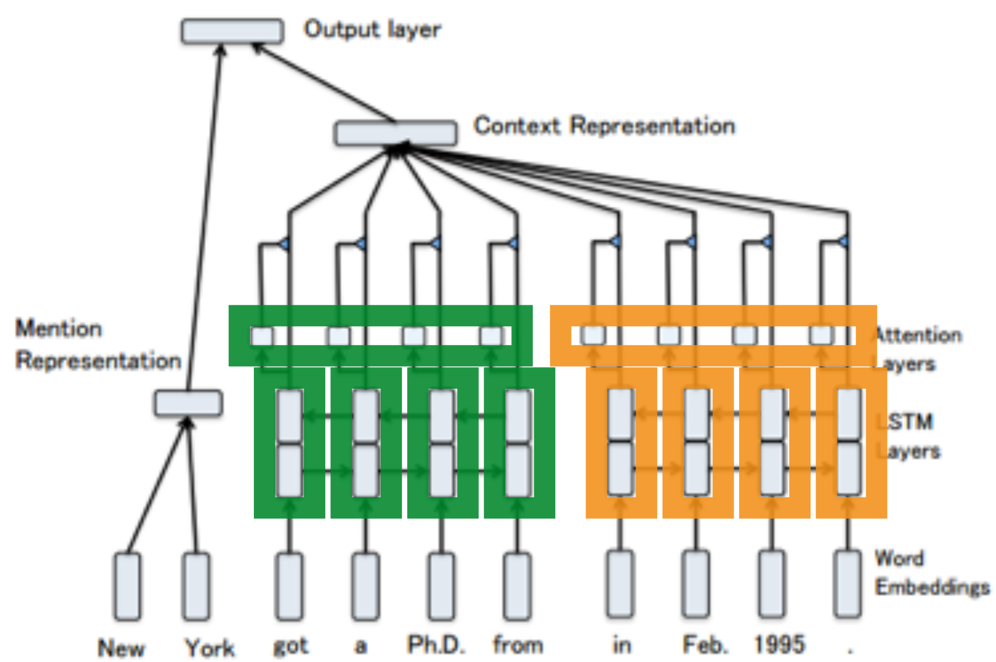

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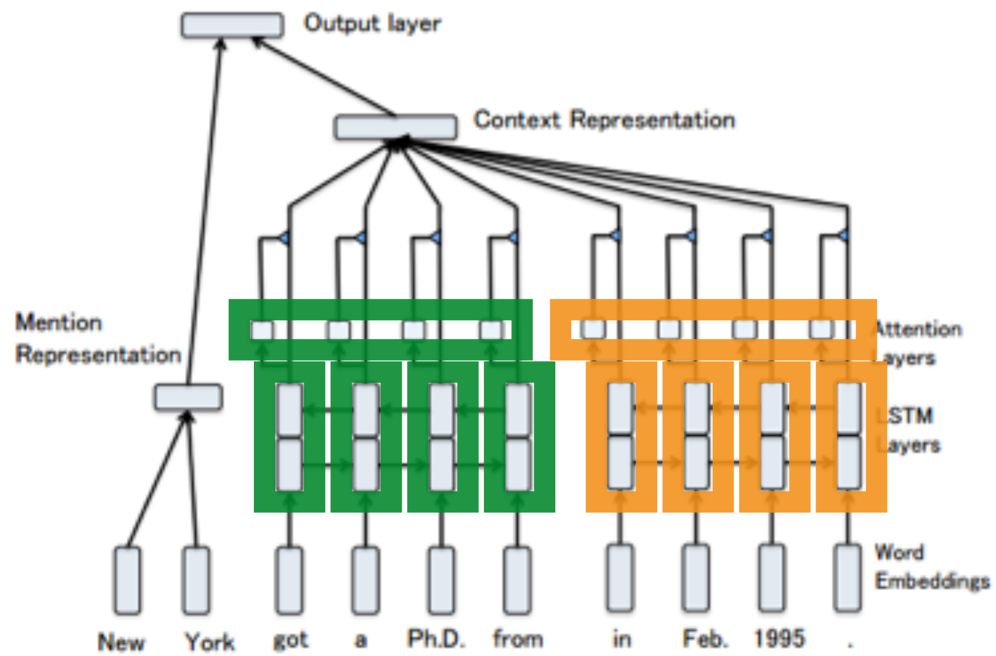

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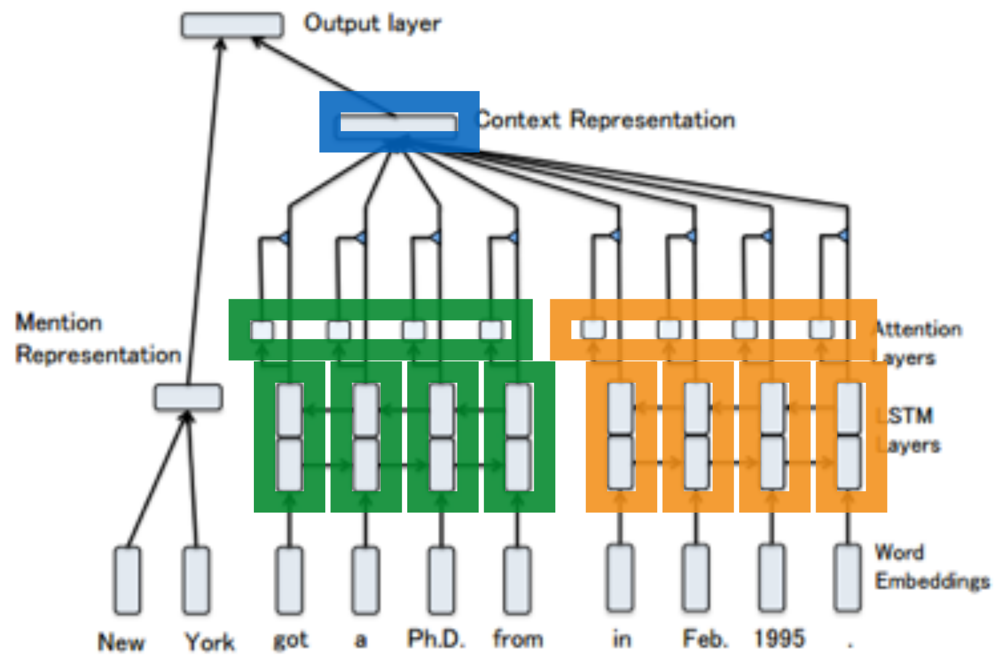

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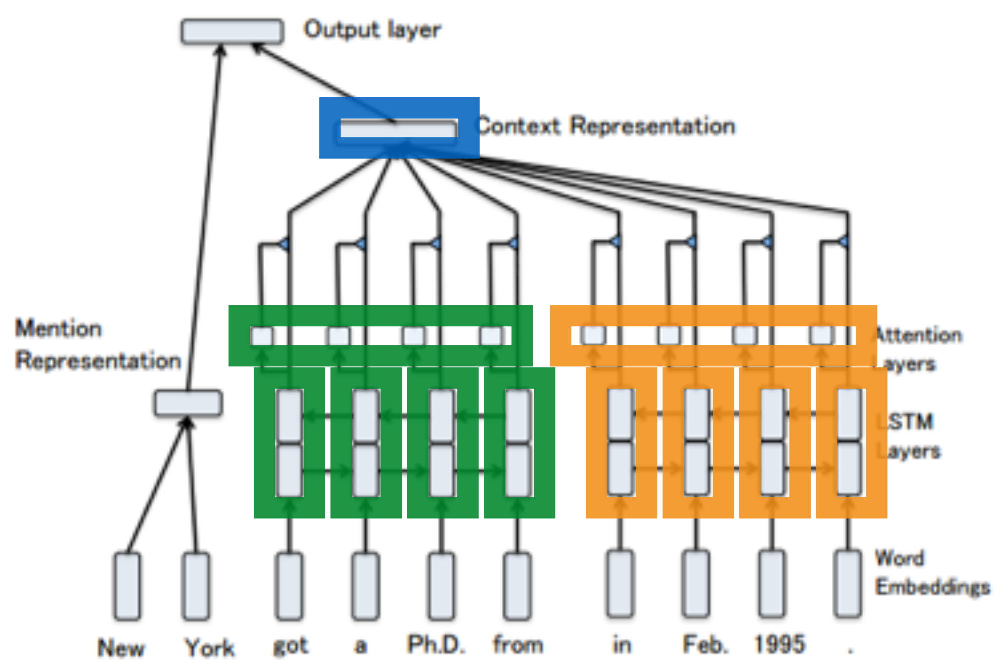

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- For each of the intermediate context vector, compute an attention weight.
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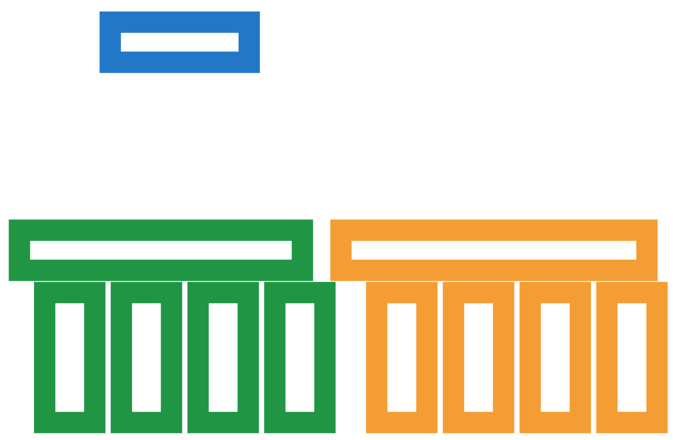

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$$
\begin{aligned}
e_i^l &= \tanh\left(W_e \begin{bmatrix} \overrightarrow{h_i^l} \\ \overleftarrow{h_i^l} \end{bmatrix}\right) && (7) \\
\tilde{a}_i^l &= \exp(W_a e_i^l) && (8) \\
a_i^l &= \frac{\tilde{a}_i^l}{\sum_{i=1}^{C} \tilde{a}_i^l + \tilde{a}_i^r} && (9) \\
v_c &= \sum_{i=1}^{C} a_i^l \begin{bmatrix} \overrightarrow{h_i^l} \\ \overleftarrow{h_i^l} \end{bmatrix} + a_i^r \begin{bmatrix} \overrightarrow{h_i^r} \\ \overleftarrow{h_i^r} \end{bmatrix} && (10)
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Attentive Encoder

- The extend their LSTM model to incorporate attention over the context words.

$$e_i^l = \tanh\left(W_e \begin{bmatrix} \overrightarrow{h}_i^l \\ \overleftarrow{h}_i^l \end{bmatrix}\right) \quad (7)$$

$$\tilde{a}_i^l = \exp(W_a e_i^l) \quad (8)$$

$$a_i^l = \frac{\tilde{a}_i^l}{\sum_{i=1}^{C} \tilde{a}_i^l + \tilde{a}_i^r} \quad (9)$$

$$v_c = \sum_{i=1}^{C} a_i^l \begin{bmatrix} \overrightarrow{h}_i^l \\ \overleftarrow{h}_i^l \end{bmatrix} + a_i^r \begin{bmatrix} \overrightarrow{h}_i^r \\ \overleftarrow{h}_i^r \end{bmatrix} \quad (10)$$

Side Note: I am not
sure
why don't they
condition on the
mention embedding

- For each of the intermediate context vector, compute an attention weight.
- The context representation is the weighted sum of the intermediate representations.
- The attention weights are computed using a 2 layer feed forward network.

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- Loss is the usual cross entropy loss to maximize the likelihood of the training set.

$$L(y,t) = \sum_{k=1}^{K} -t_k \log(y_k) - (1-t_k)\log(1-y_k)$$

$$t \in \{0,1\}^K$$

Results

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Sentence	Prediction
... ... The film is a remake of [Secrets (1924)] , a silent film starring Norma Talmadge	/film 0.986 /art 0.982
The film is a remake of Secrets (1924) , a silent film starring [Norma Talmadge]	/person 0.999 /actor 0.987
... ... The festival brought together the foremost filmmakers , including Francois Truffaut , [Roman Polanski] , Robert Enrico , and others	/person 1.00 /director 0.963 /author 0.958 /artist 0.950 /actor 0.871
... ... Jim Hodges , the Democratic nominee , handily defeated Republican Governor [David Beasley] to become the 114th governor of South Carolina	/person 1.00 /politician 0.983
She is best known for roles in various TV Dramas and tokusatsu shows such as [Ultraseven X] and Kamen Rider Kiva	/broadcats_program 0.892

Figure 2: Examples of our model attending over contexts for a given mention.

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Models	Strict	Loose Macro	Loose Micro
Ling and Weld (2012)	52.30	69.90	69.30
Yogatama et al. (2015)	-	-	72.25
Averaging Encoder	51.89	72.24	68.65
LSTM Encoder	55.60	73.95	71.34
Attentive Encoder	**58.97**	**77.96**	**74.94**

Table 2: Strict, Loose Macro and Loose Micro F1-scores

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  - Any other way of representing context?

References

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