Making Sense of English Nominal Compounds

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Nominal Compounds

- [Li, 1971]: “the simple concatenation of any two or more nouns functioning as a third nominal”

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- Frequent:
  - 3% of all words in the British National Corpus [Ó Séaghdha, 2008]
  - 3.9% of all words in Reuters corpus [Baldwin and Tanaka, 2004]
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FIGURE 3.

Figure: [Downing, 1977]

Background: Three Tasks

Three NLP tasks related to noun compounds [Lauer and Dras, 1994]

- Detection or identification of noun compounds
- Syntactic analysis of the internal structure, i.e. left vs. right bracketing of compounds with more than two constituents
- *Interpretation of the semantic relation holding between the constituents of the compound*

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Two Main Approaches

Two main approaches to semantic interpretation of nominal compounds:

- Taxonomy-based [Girju et al., 2005, Tratz and Hovy, 2010, Ó Séaghdha and Copestake, 2013]
- Paraphrase-based [Nakov, 2013]

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Background: Datasets

Dataset	Size	Relations
Nastase & Szpakowicz (2003)	600	30
Girju et al. (2005)	4,500	21
Ó Séaghdha & Copestake (2007)	1,443	6
Kim & Baldwin (2008)	2,169	20
Tratz & Hovy (2010)	17,509	43
Nombank (Fares 2016)	10,596	20
Functor (Fares 2016)	10,596	35

Table: Overview of noun compound datasets. Size: type count

Background: Datasets – Examples

- *cancer death*
  - Tratz: `CREATOR-PROVIDER-CAUSE_OF`
  - Ó Séaghdha: `INST`
  - Nombank: `ARGM-CAU`
  - Functor: `CAUS`
- *world opinion*
  - Tratz: `EXPERIENCER-OF-EXPERIENCE`
  - Ó Séaghdha: `HAVE`
  - Nombank: `ARG0`
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- *research team*
  - Tratz: `PERFORM&ENGAGE_IN`
  - Ó Séaghdha: `ACTOR`
  - Nombank: `ARG1`
  - Functor: `RSTR`
- *aid package*
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Background: Classification Approaches

- Maximum Entropy [Tratz and Hovy, 2010]
- Support Vector Machines [Ó Séaghdha and Copestake, 2009]
- Deep Neural Networks [Dima and Hinrichs, 2015]
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The Big Questions

Do *word embeddings* capture the semantic relations holding between the constituents of nominal compounds?

Can we predict the compound semantic relations using the *vector arithmetic* typically used to solve word analogy tasks?

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Vector Space Models

- Vector space representations of words (meaning) based on the distributional hypothesis
- Words are represented as vectors of real numbers in $\mathbb{R}^d$
  - Corresponding to number of times w_j occur in the *context* of w_i
  - The vectors are referred to as the *co-occurrence matrix*
- Similarity measures: Euclidean distance, cosine similarity, etc.
- Typically very high-dimensional sparse models

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GloVe: Global Vectors for Word Representation

- Let X be a word-word co-occurrence matrix
- X_{ij}: the number of times word j occurs in the context of word i
- $P_{ij} = P(j|i) = \frac{X_{ij}}{X_i}$

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GloVe: Ratios

GloVe relies on ratio of co-occurrence probabilities instead of just co-occurrence probabilities

Prob. & ratio	$k = solid$	$k = gas$	$k = water$	$k = fashion$
$P(k\|ice)$	1.9×10^{-4}	6.6×10^{-5}	3.0×10^{-3}	1.7×10^{-5}
$P(k\|steam)$	2.2×10^{-5}	7.8×10^{-4}	2.2×10^{-3}	1.8×10^{-5}
$P(k\|ice)/P(k\|steam)$	8.9	8.5×10^{-2}	1.36	0.96

Table: Based on Table 1 in [Pennington et al., 2014]

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GloVe: Vector Learning

Given the observation about ratio of co-occurrence probabilities

$$F(w_i, w_j, \tilde{w}_k) = \frac{P_{ik}}{P_{jk}}$$

. . . fast forward seven steps

$$J = \sum_{i,j=1}^{V} f(X_{ij})\left(w_j^T \tilde{w}_j + b_i + \tilde{b}_j - log X_{ij}\right)^2$$

See [Pennington et al., 2014]

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GloVe: Training

Given a training corpus and a set of parameters (to be discussed later):

1. Construct a vocabulary dictionary
2. Construct a co-occurrence matrix
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GloVe: Parameters and Hyperparameters

- Text pre-processing:
  - sentence segmentation
  - tokenization
  - lemmatization
- Vocabulary:
  - frequency cutoff
- Co-occurrence matrix:
  - context window size
  - (a)symmetric window
- Training:
  - vector dimensions
  - number of iterations
  - learning rate
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Vector Arithmetic

Can we predict the compound semantic relations using the vector arithmetic typically used to solve word analogy tasks?

King is to queen as man is to ?

$$\text{3COSADD:} \quad \arg\max_{b^* \in V}(cos(b^*, b - a + a^*))$$

$$\text{PAIRDIRECTION:} \quad \arg\max_{b^* \in V}(cos(b^* - b, a^* - a))$$

[Levy and Goldberg, 2014] report that [Mikolov et al., 2013] used 3COSADD to solve the syntactic analogies task and PAIRDIRECTION to solve the semantic one.

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Vector Arithmetic for Nominal Compounds

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Experimental Setup: Datasets

Dataset	Size	Relations
Ó Séaghdha	1,443	6
Tratz (2011)	19,027	37
Nombank	7,850	17
Functors	7,850	33

Table: Overview of noun compound datasets.

- 5-fold cross validation: Ó Séaghdha
- 10-fold cross validation: Tratz, Nombank, Functor
- Numbers reported are accuracy, unless otherwise said

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Five Sets of Experiments

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1. Text Pre-processing: Lemma vs. Full Form

	Tratz	Ó Séaghdha	Nombank	Functor
Full form	57.24	45.14	66.43	42.46
Lemma	56.08	45.21	67.03	42.54

Table: Lemma vs. full form. Wiki+Giga, $300d$, PAIRDIRECTION

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Aside: Lemma vs. Full Form

Model	SimLex	Analogy
GloVe wiki lemmas	0.36	0.81
GloVe wiki forms	0.31	0.81
GloVe giga lemmas	0.38	0.72
GloVe giga forms	0.32	0.71
GloVe comb lemmas	0.40	0.77
GloVe comb forms	0.35	0.76

Table: Benchmarking against SimLex-999 and the Google Analogies Dataset

2. Size of Training Data

	Corpus	Tratz	Ó Séaghdha	Nombank	Functor
PAIRDIRECTION	Wikipeida	55.99	**45.56**	65.36	41.57
	Gigaword	**56.34**	43.75	**67.17**	**43.29**
	Wiki+Giga	56.08	45.21	67.03	42.54
3COSADD	Wikipeida	54.57	**40.14**	64.05	41.45
	Gigaword	**55.25**	37.92	**67.49**	**44.09**
	Wiki+Giga	55.22	39.65	66.91	43.72

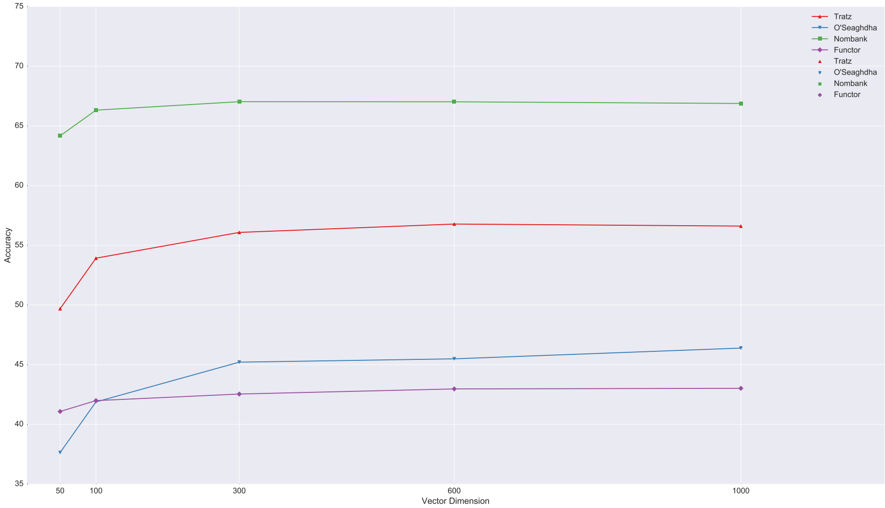
Table: The impact of the size of training data on accuracy. Other parameters: lemma, $300d$

Wikipedia: 1.08 billion tokens

Gigaword: 2.47 billion tokens

Wiki+Giga: 3.56 billion tokens

3. Vector Dimensionality



Other model parameters: lemma, Wiki+Giga, PAIRDIRECTION

4. Vector Arithmetics: PairDirection vs. 3CosAdd

Reminder:

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5. 1-NN vs. k-NN

	Tratz	Ó Séaghdha	Nombank	Functor
$n = 1$	56.08	45.21	67.03	42.54
$n = 3$	58.58	46.39	71.03	45.71
$n = 5$	60.28	45.7	72.06	47.8
$n = 7$	60.84	44.24	72.38	49.8
$n = 9$	*61.12*	*45.69*	*72.21*	*51.08*
$n = 11$	61.35	44.72	72.18	51.7

Table: 1-NN vs. k-NN. Other parameters: lemma, $300d$, Wiki+Giga, PAIRDIRECTION

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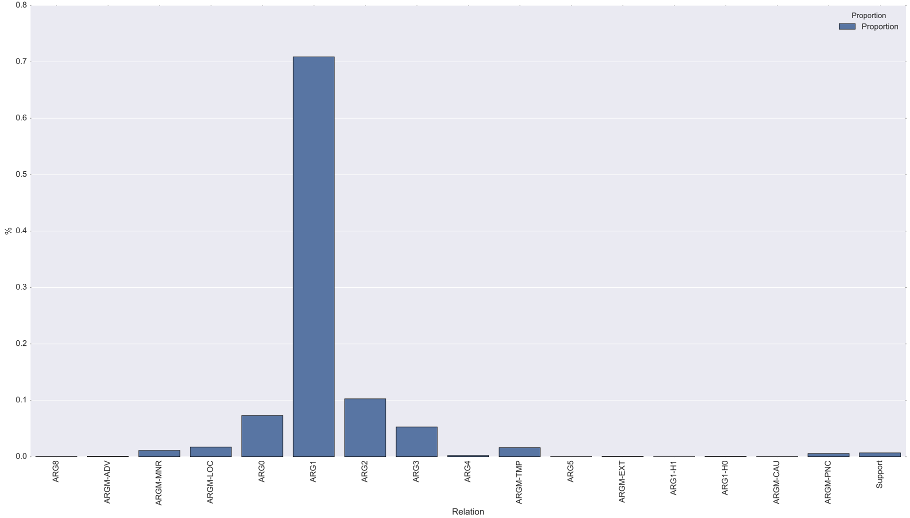
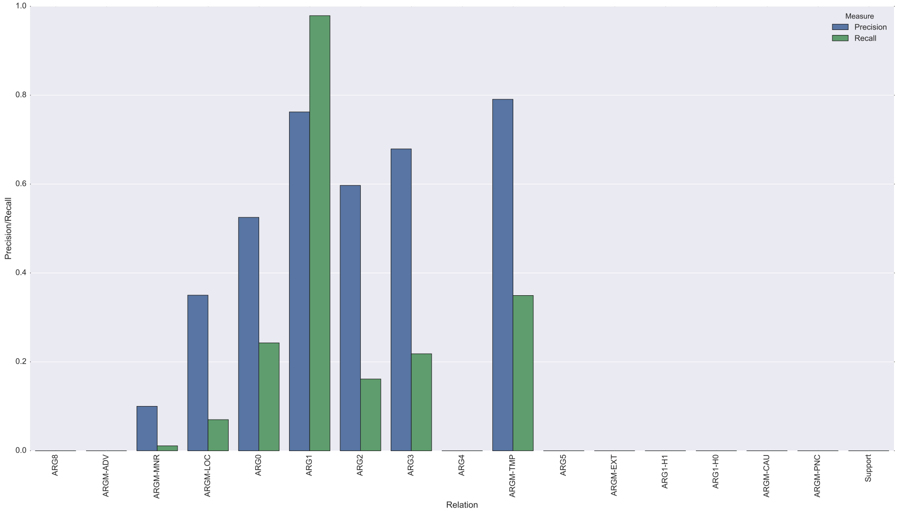
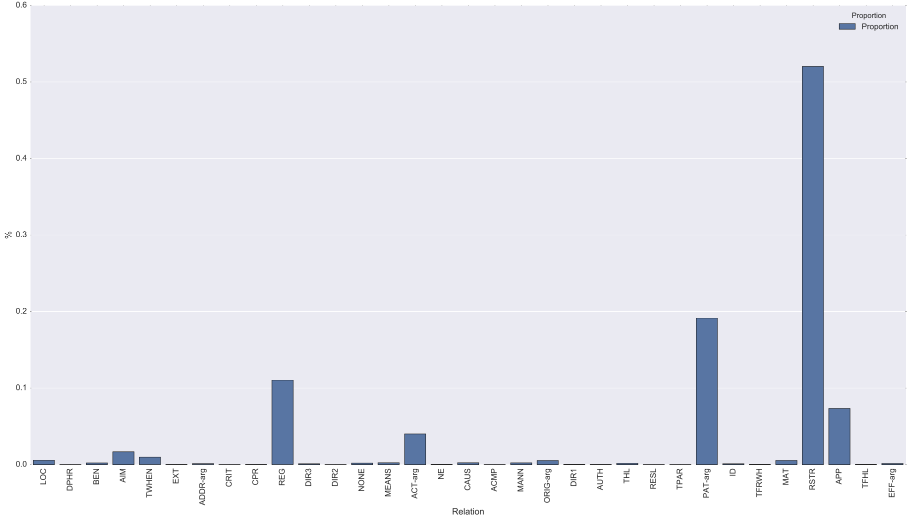


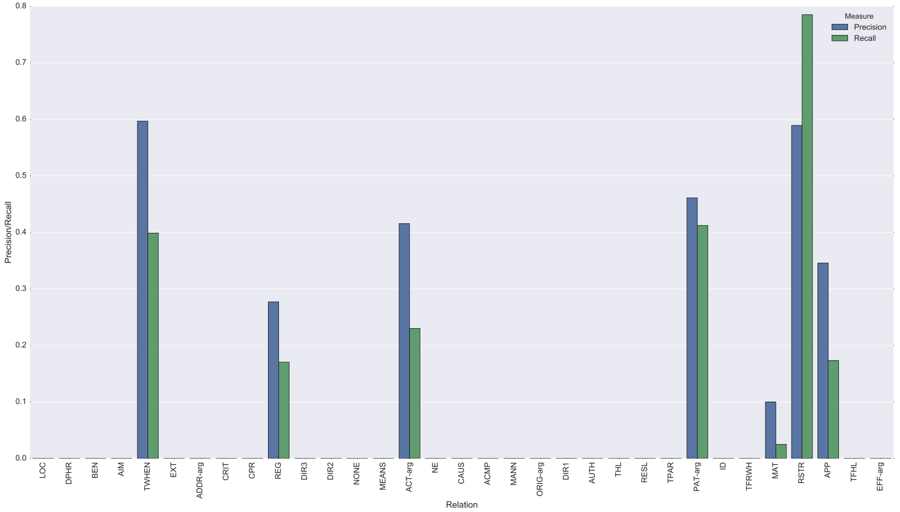
Per Relation Precision & Recall - Nombank



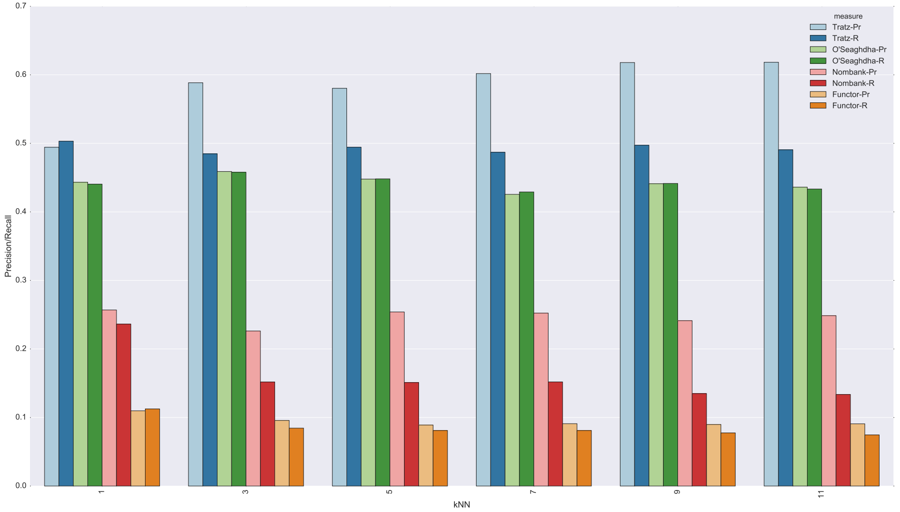
Functor: Distribution of Relations



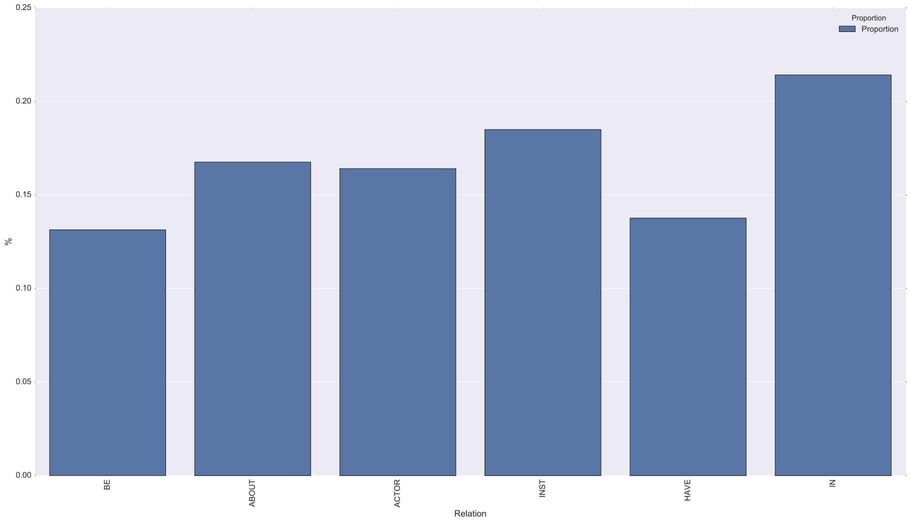
Per Relation Precision & Recall - Functor



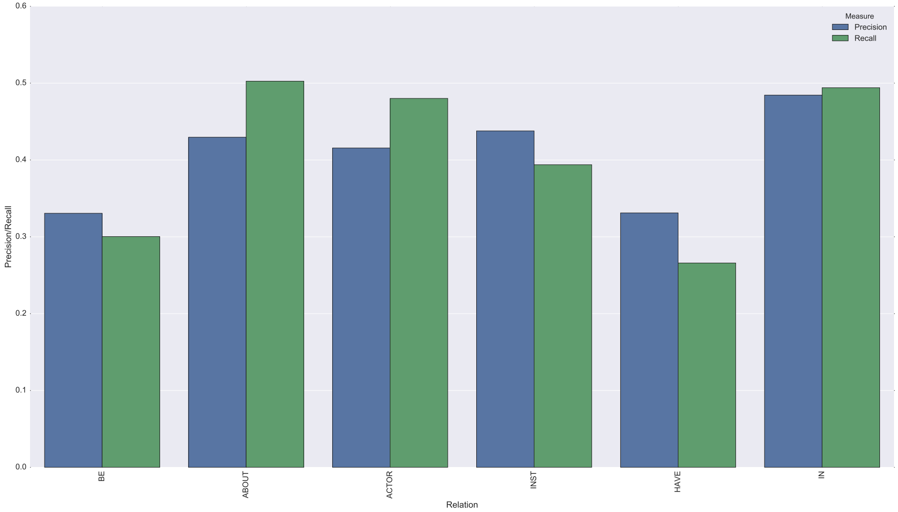
Macro-average: Precision & Recall



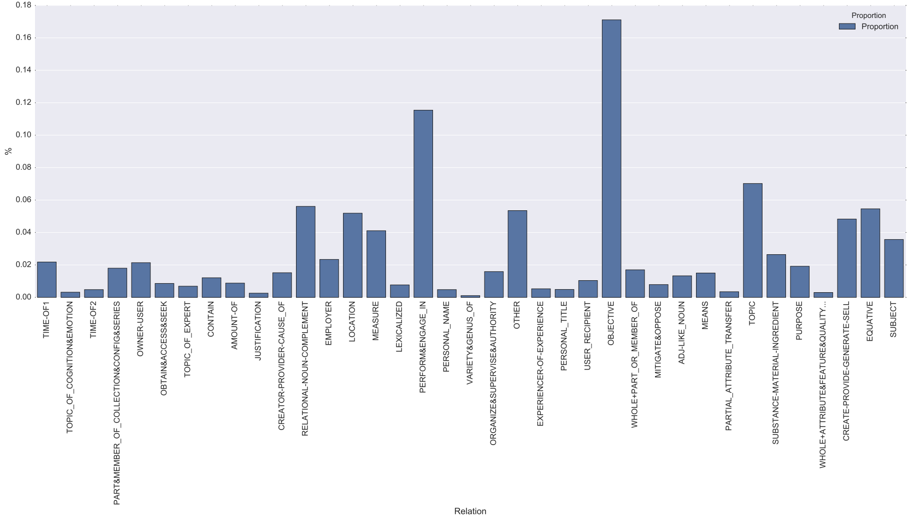
Ó Séaghdha: Distribution of Relations



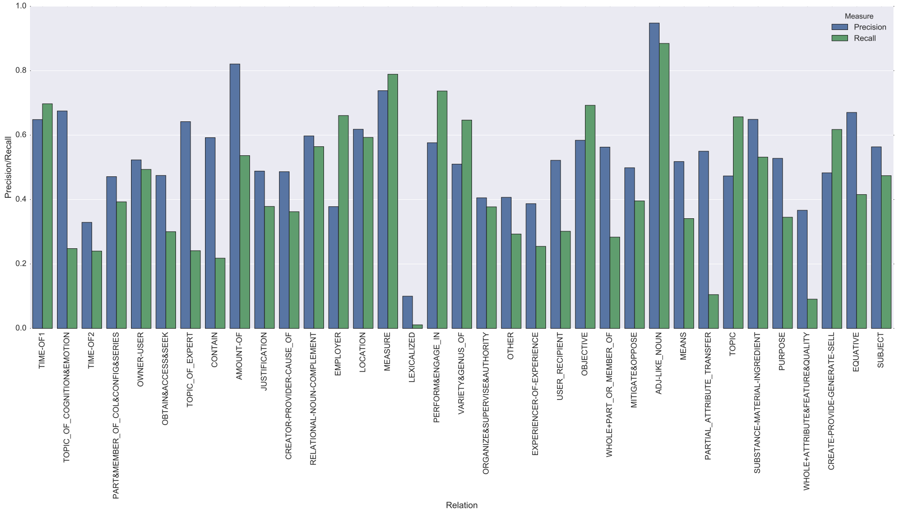
Per Relation Precision & Recall - Ó Séaghdha



Tratz: Distribution of Relations



Per Relation Precision & Recall - Tratz



Closer Look into Tratz's Dataset

- ADJ-LIKE_NOUN has only 7 distinct modifiers for 254 compounds [Dima, 2016]
- AMOUNT_OF has only 15 distinct heads for 168 compounds [Dima, 2016]
- which means . . .

Lexical memorization not relation learning :-(

"Lexical Memorization is the phenomenon in which the classifier learns that a specific word in a specific slot is a strong indicator of the label." [Levy et al., 2015]

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Recap: Putting the Results in Perspective

	Tratz	Ó Séaghdha	Nombank	Functor
Majority-class baseline	17	15.4	71	51.7
State-of-the-art	79.3	63.1	n/a	n/a
$n = 11$	61.35	44.72	72.18	51.7

Recommendations to Train GloVe Models

- Use lemmas (if possible)
- Use the original C implementation of GloVe
- Start with 300d vectors
- More training data is not necessarily better
- Pre-shuffle the training data to make your experiments 'more' deterministic

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