



# Hypernym Detection

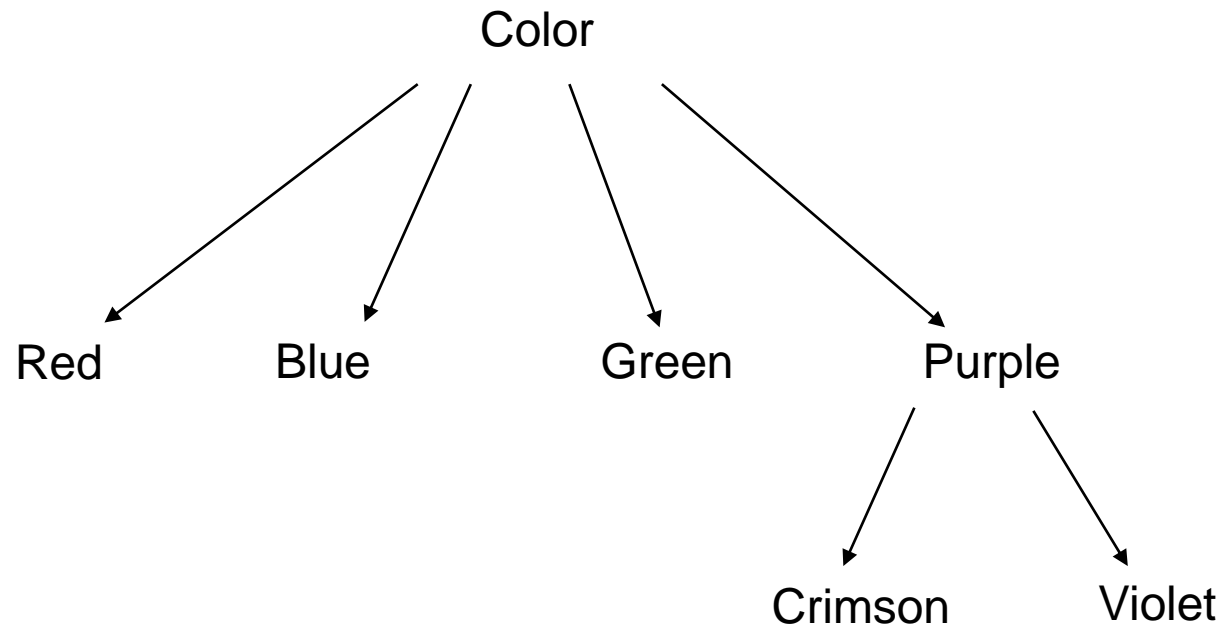
**Shaurya Rawat**

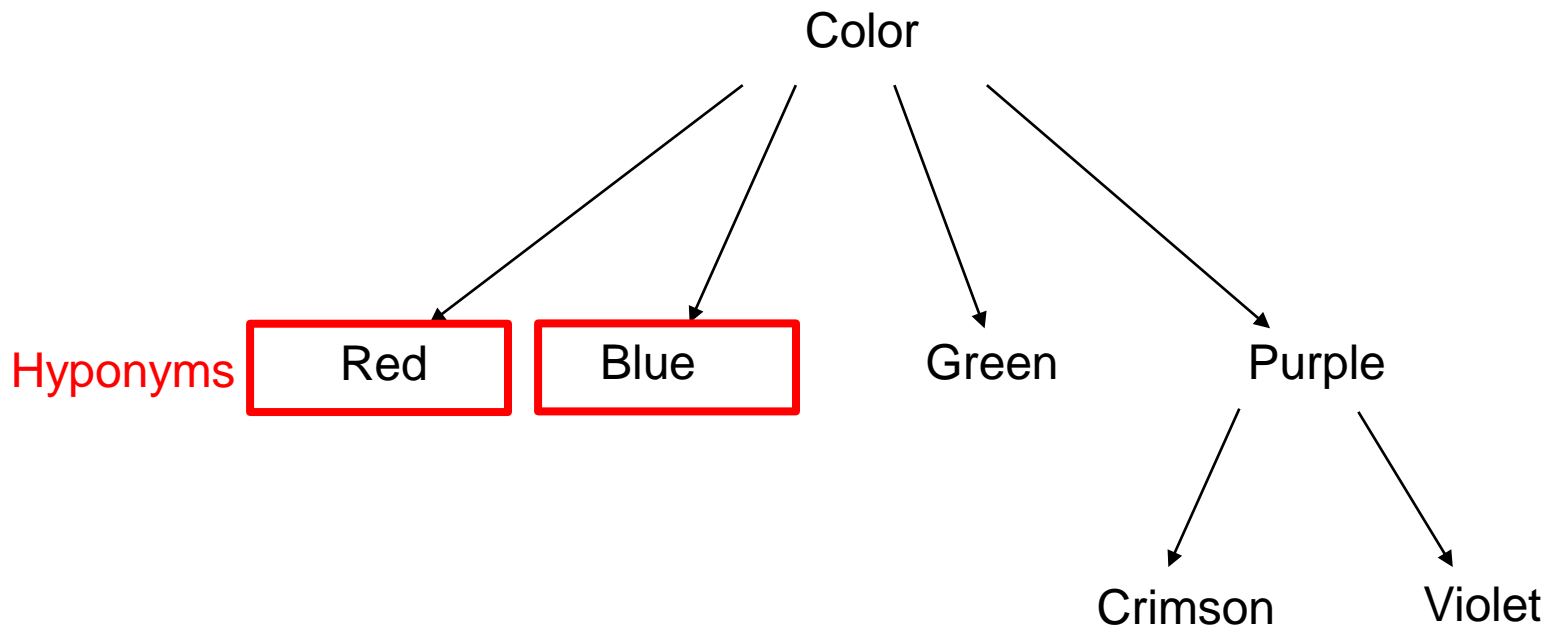
Ontology Engineering Group  
Universidad Politécnica de Madrid, Spain

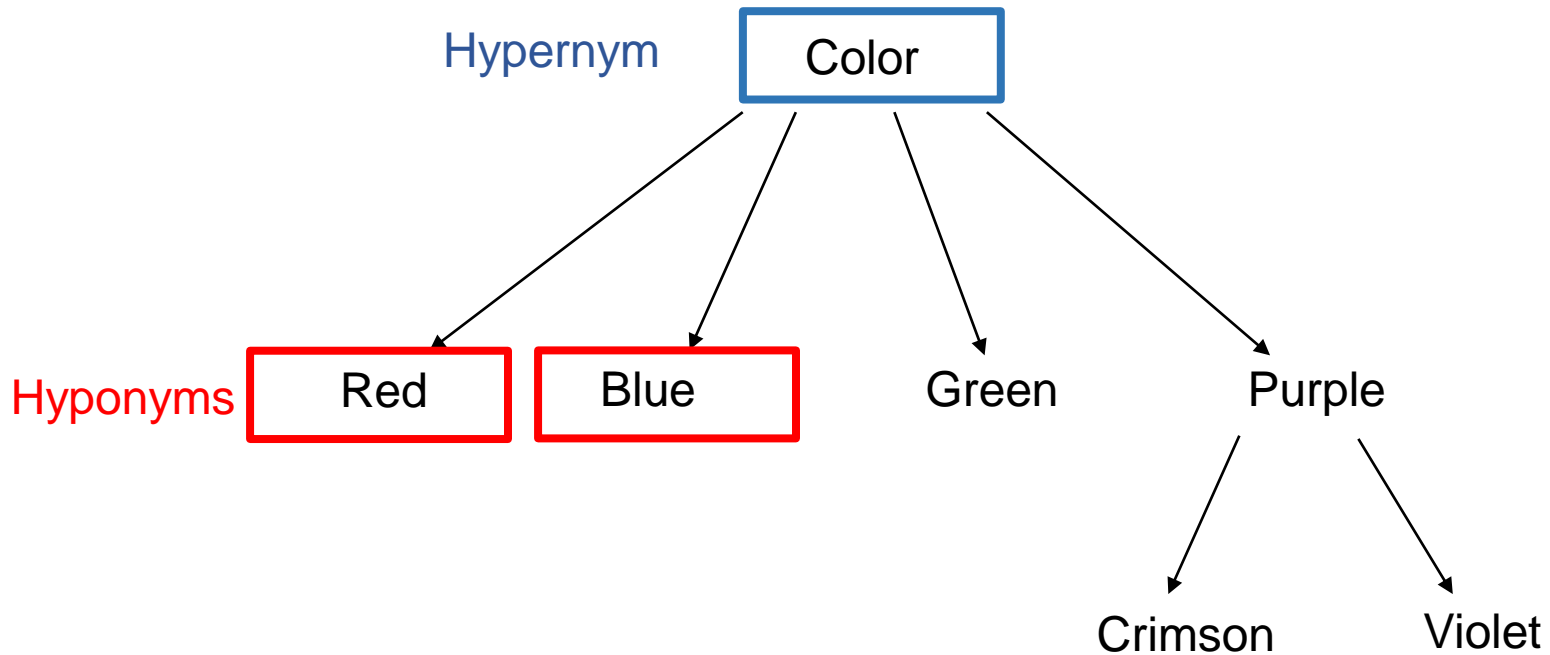
- What are Hypernyms?

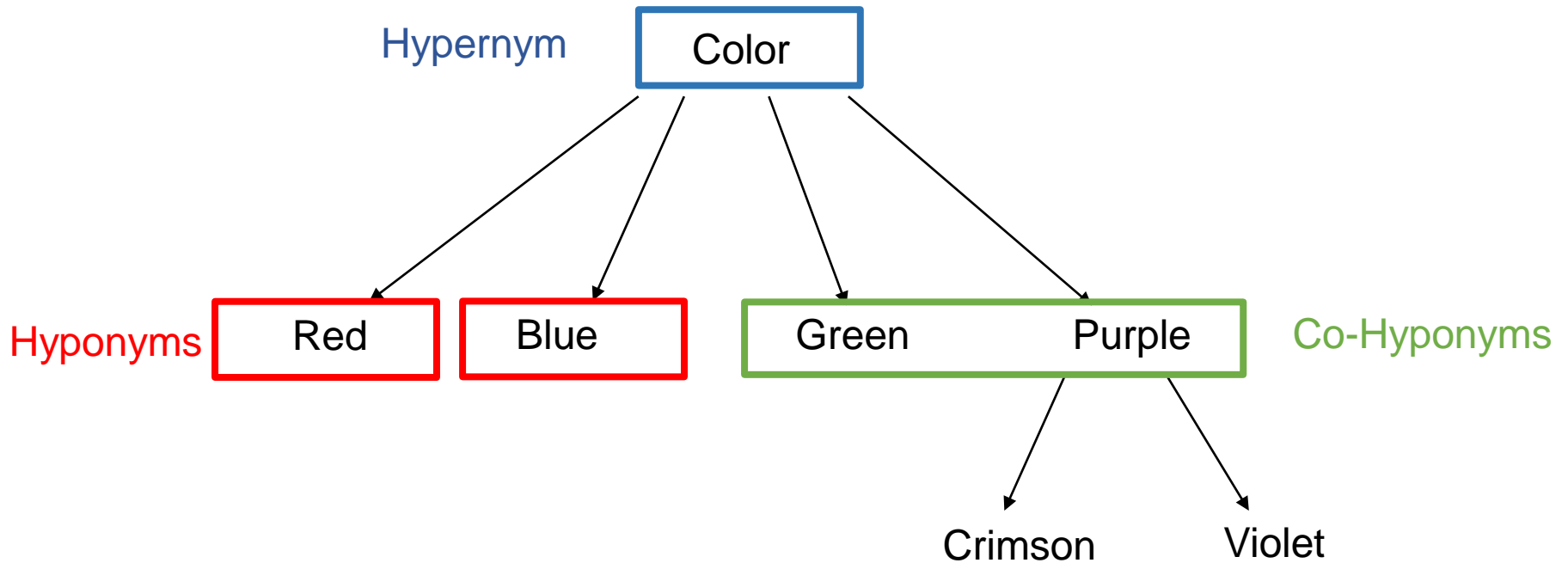
A *hyponym* is a word or phrase whose semantic field is included within that of another term, which is called its *hypernym*

It generally covers the ***type-of*** or ***is-a*** relationship between 2 words.









Approaches for Hypernym detection from text:

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## 1) Pattern Based Approaches



Approaches for Hypernym detection from text:

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Using lexico-syntactic patterns (LSPs) to extract Hypernyms from text

Most popular: Hearst Patterns by Marti Hearst

Example:

“NPx such as NPy” or “NPx and other NPy”

Countries such as Spain, France and Germany are ...

Matches with Pattern

(NP\_\\w+ (,)?)such as (NP\_\\w+ ? (,)?)?(and |or )?)+

Hypernym

Country

Hyponyms

Spain  
France  
Germany

Approaches for Hypernym detection from text:

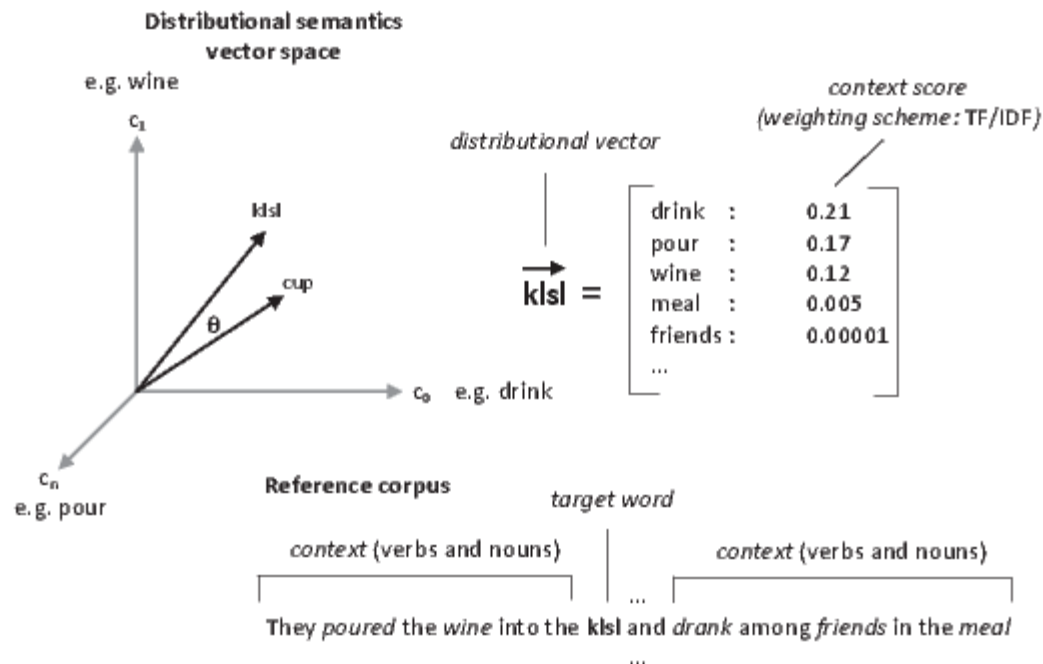
- 1) Pattern Based Approaches

- 1) Unsupervised Distributional Approaches

## Approaches for Hypernym detection from text:

### 2) Unsupervised Distributional Approaches

Creating distributional semantic spaces based on target and context of different words



Approaches for Hypernym detection from text:

## 2) Unsupervised Distributional Approaches

Most approaches based on ***DIH(Distributional Inclusion Hypothesis)***

Measures:

📁 WeedsPrec (Weeds et al. 2004)

📁 invCL (Lenci and Benotto 2012)

📁 SLQS (Santus et al. 2014, Shwartz et al. 2017)

Approaches for Hypernym detection from text:

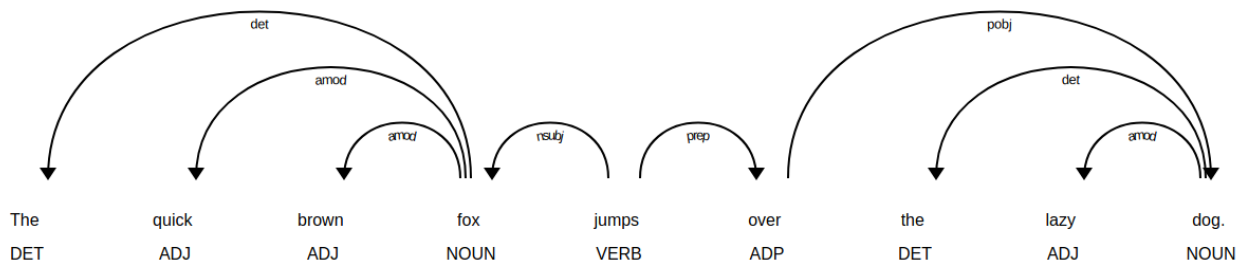
- 1) Pattern Based Approaches
- 1) Unsupervised Distributional Approaches
- 1) Machine Learning Based Approaches

## Approaches for Hypernym detection from text:

### 3) Machine Learning Based Approaches

Using Dependency Paths between known known hypernym pairs to train a classifier (Snow et al. 2005, Sheena et al. 2016)

Hyponymy shows the relationship between a generic term (hypernym) and a specific term (hyponym). A hypernym, also known as a superordinate, is broader than that of a hyponym. It is difficult with abstract words such as *imagine*, *understand* and *knowledge* to find a broad category of actions. For example, verbs such as *stare*, *gaze*, *view* are all instances of the hypernym *look*. Hyponyms and hyponyms are asymmetric. Hyponymy can be tested by asking 'A tool is a kind of screwdriver'.



Train

**Hypernym Classifier**

Takes dependency path between two words as input and classifies it as Hypernym or not

## State of the Art

Paper: **Roller et al.2018 (Facebook AI)**

**Hearst Patterns Revisited:  
Automatic Hypernym Detection from Large Text Corpora**

**Stephen Roller, Douwe Kiela, and Maximilian Nickel**  
Facebook AI Research  
`{roller, dkiela, maxn}@fb.com`

Pattern based and Distributional models were evaluated against each other on various datasets, using Average Precision.

→ Conclusions from the Paper:

**Pattern based methods outperform Distributional methods.**



## State of the Art (Results from Paper):

	Detection (AP)				
	BLESS	EVAL	LEDS	SHWARTZ	WBLESS
Cosine	.12	.29	.71	.31	.53
WeedsPrec	.19	.39	.87	.43	.68
invCL	.18	.37	<b>.89</b>	.38	.66
SLQS	.15	.35	.60	.38	.69
p(x, y)	.49	.38	.71	.29	.74
ppmi(x, y)	.45	.36	.70	.28	.72
sp(x, y)	.66	.45	.81	.41	.91
spmi(x, y)	<b>.76</b>	<b>.48</b>	.84	<b>.44</b>	<b>.96</b>

## Datasets Used

(For extraction of Hypernyms using Pattern based Approaches)

In the SOTA paper, Dataset used:

***Gigaword (4 Billion words) + Wikipedia***

We used:

***UMBC Corpus (3 Billion Words) + Wikipedia***

***Link to UMBc Corpus:***

***<https://ebiquity.umbc.edu/resource/html/id/351>***

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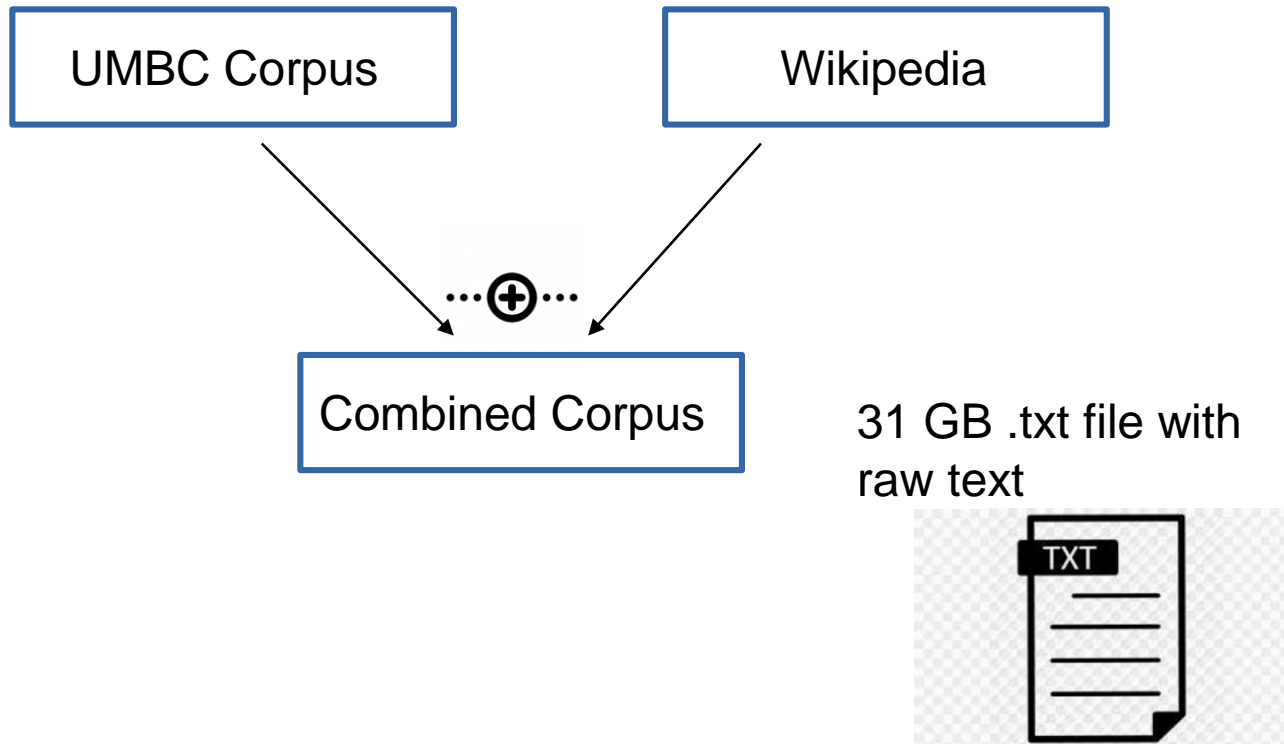
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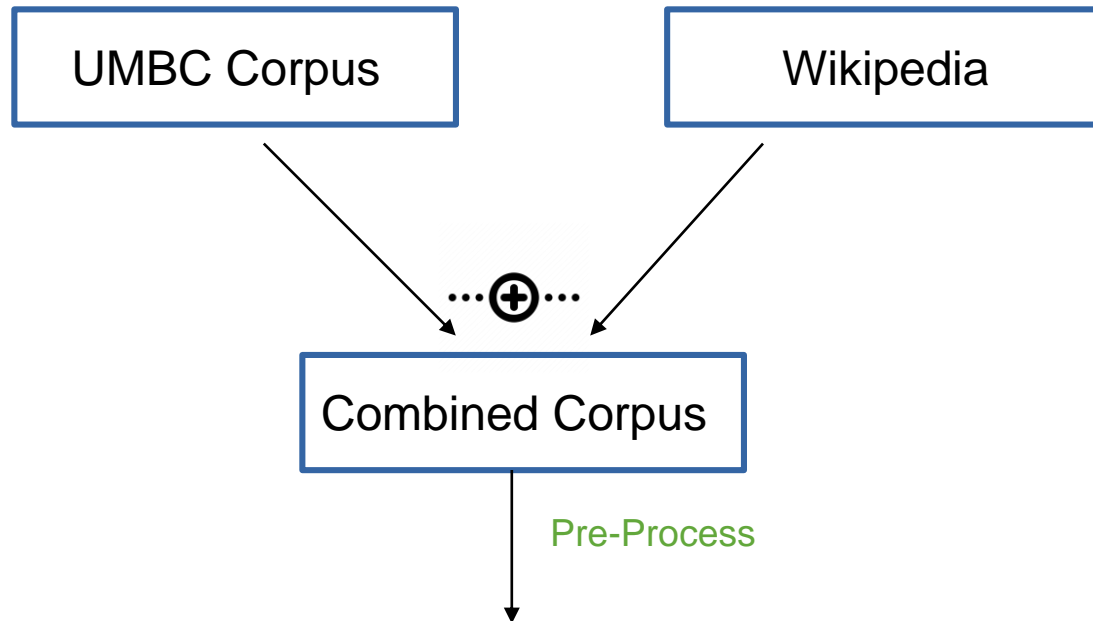
We used:

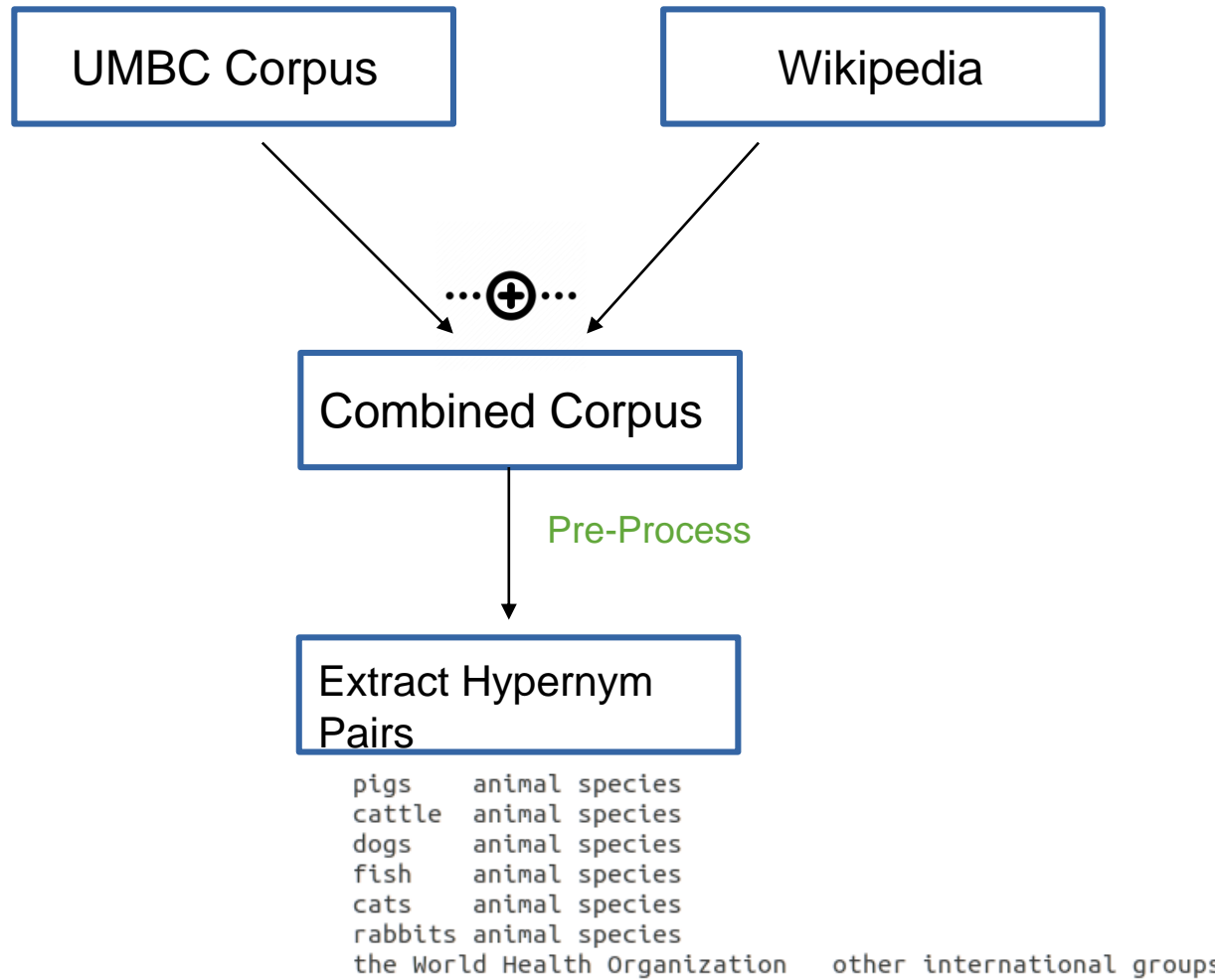
***UMBC Corpus (3 Billion Words) + Wikipedia***

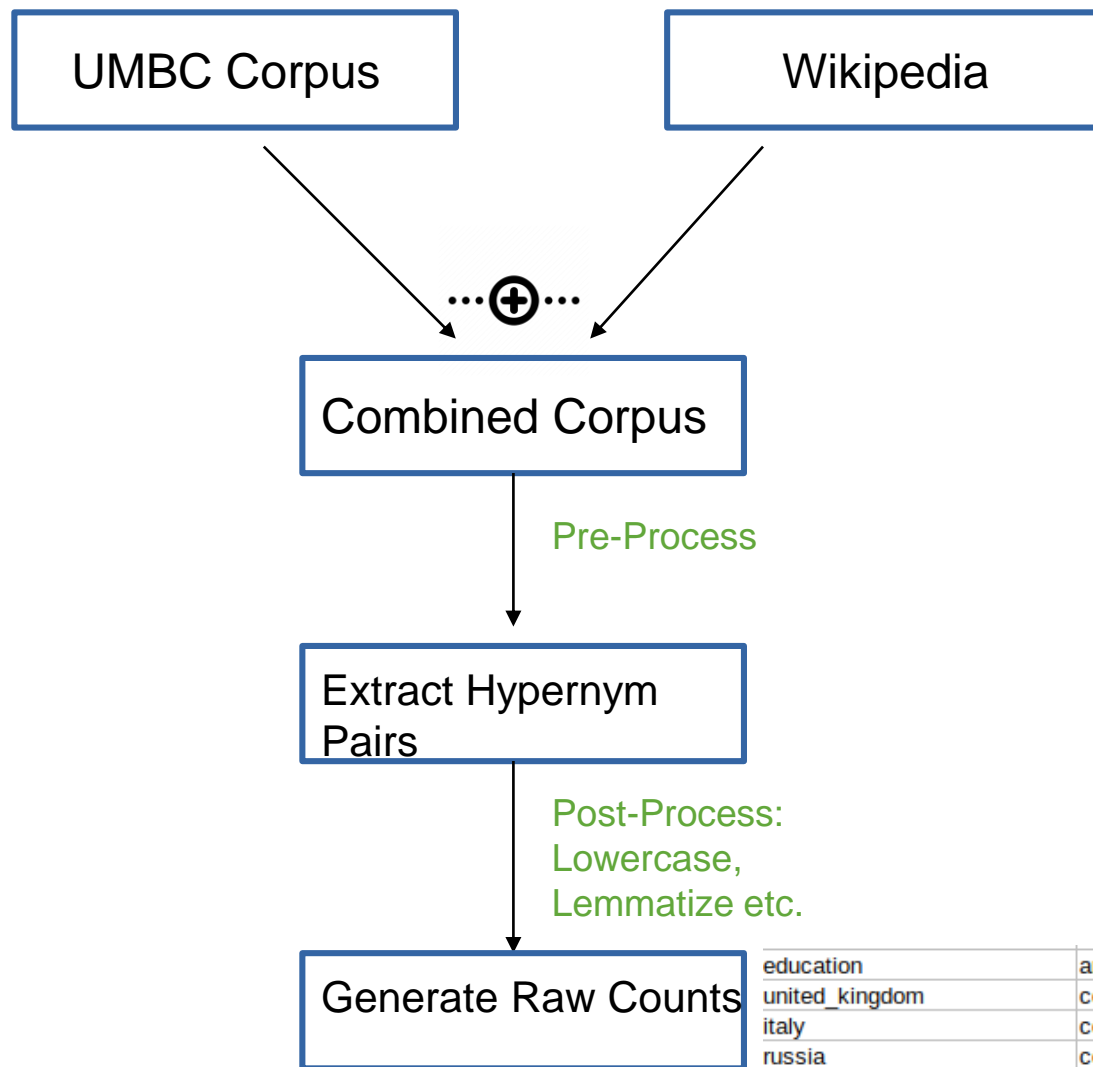
***Link to UMBC Corpus(Freely available from  
University of Maryland Baltimore):***

***<https://ebiquity.umbc.edu/resource/html/id/351>***



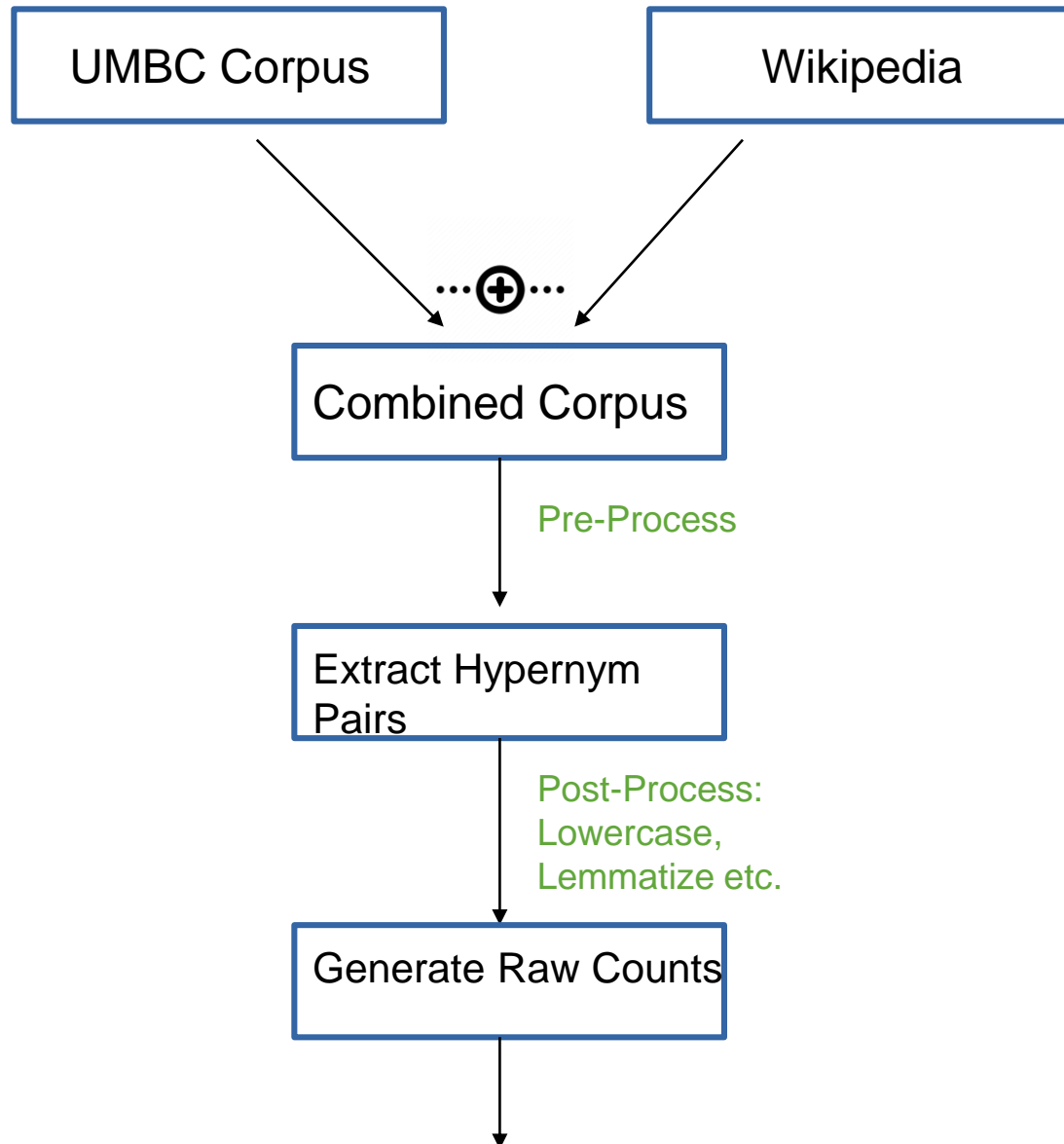






education	area	1339
united_kingdom	country	1304
italy	country	1234
russia	country	1228
cancer	disease	1142







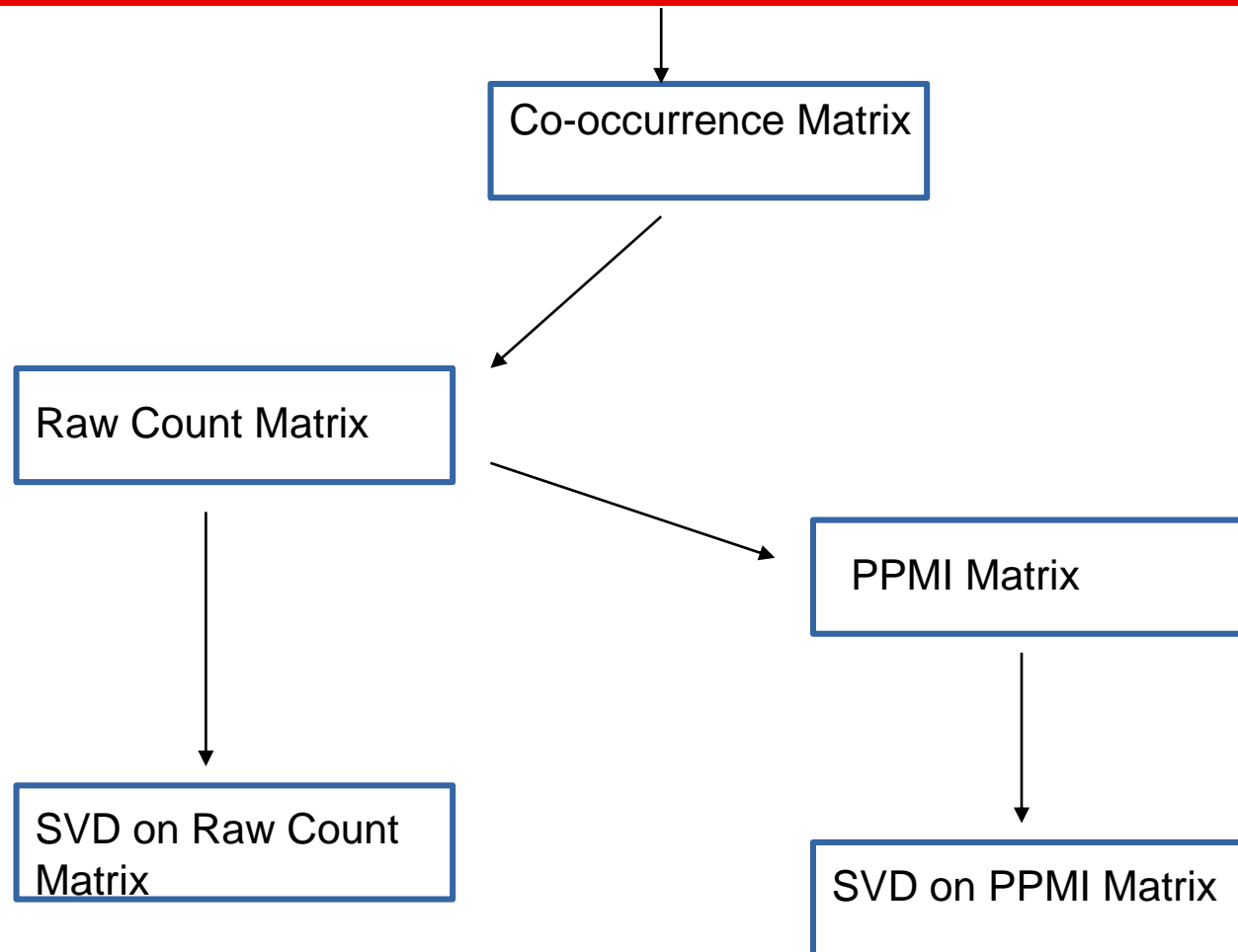
Co-occurrence Matrix

$w$  = words

$c$  = contexts

$f_{ij}$  = frequency of cooccurrence

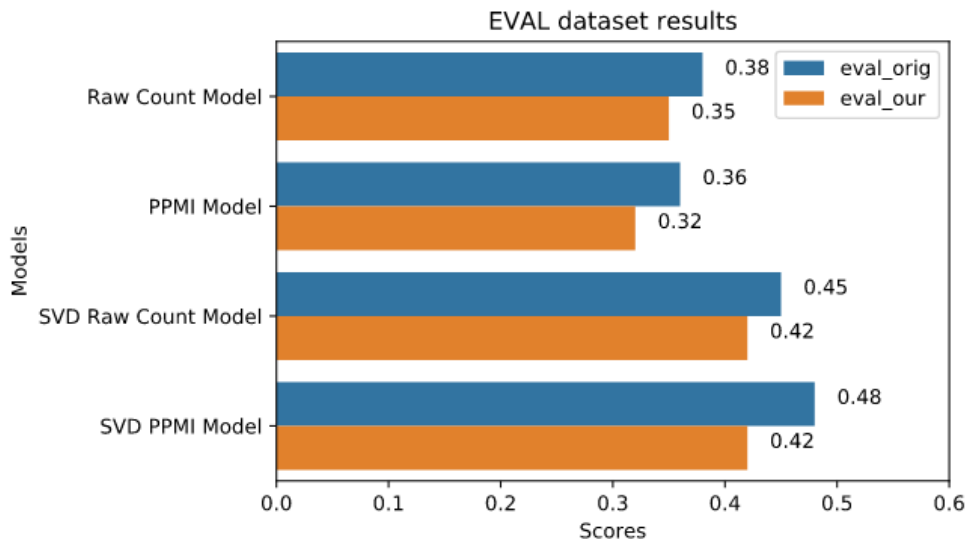
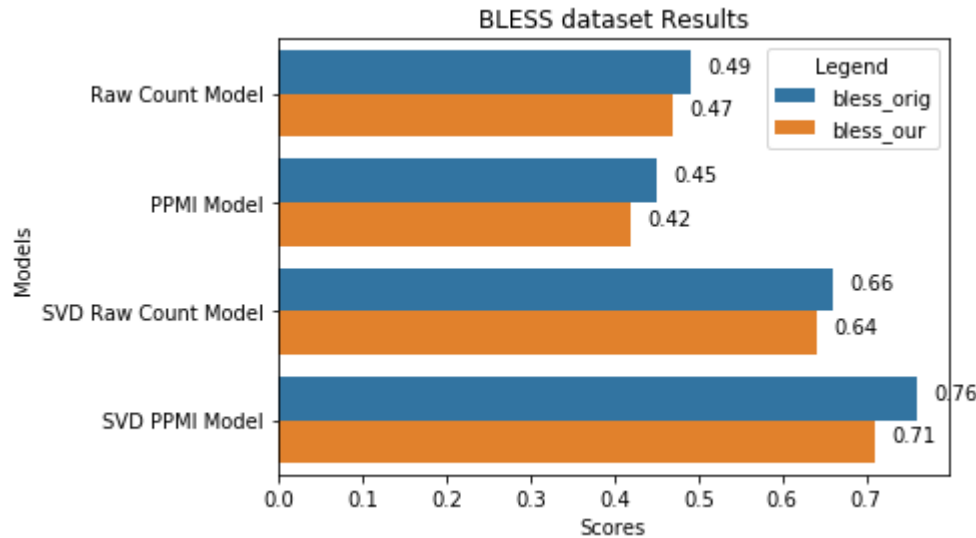
	C1	C2	C3	C4	C5
W1	1	0	0	2	0
W2	0	4	1	0	0
W3	2	0	0	1	0



- BLESS (Baroni and Lenci 2011)**

- 14 572 pairs
- 1337 positive examples

alligator	crocodile	False
alligator	frog	False
alligator	lizard	False
alligator	snake	False
alligator	toad	False
alligator	turtle	False
alligator	animal	True
alligator	beast	True
alligator	carnivore	True
alligator	chordate	True
alligator	creature	True
alligator	predator	True
alligator	reptile	True
alligator	vertebrate	True
alligator	eye	False
alligator	foot	False

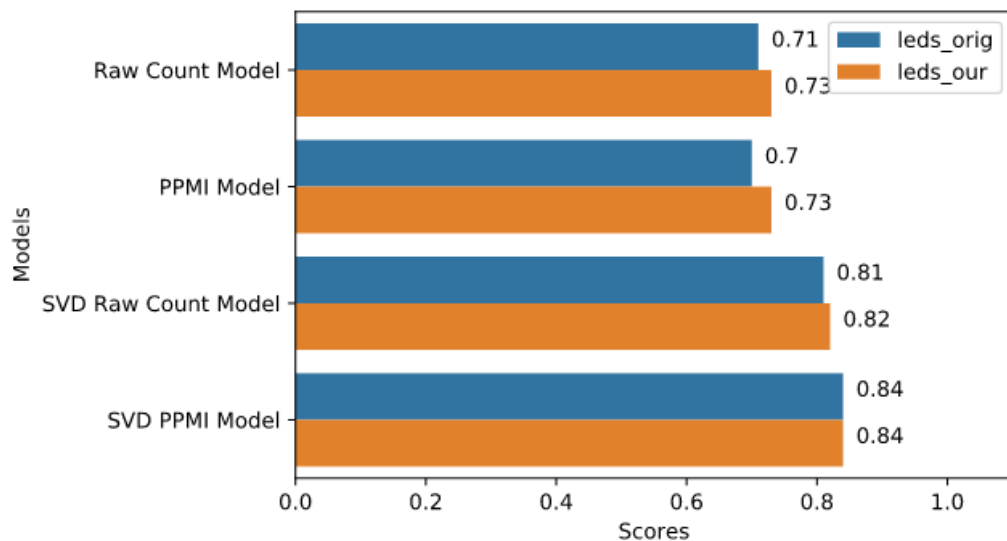


- EVAL (Santus et al. 2015 )**

- 7 378 pairs

hate	dislike	True	hyper	val
hate	dislike	True	hyper	val
hate	dislike	True	hyper	val
heart	courage	False	hyper	val
black	color	False	hyper	val
black	color	False	hyper	val
black	color	False	hyper	val
want	demand	True	hyper	val
want	demand	True	hyper	val
queen	insect	True	hyper	val

LEDS dataset results

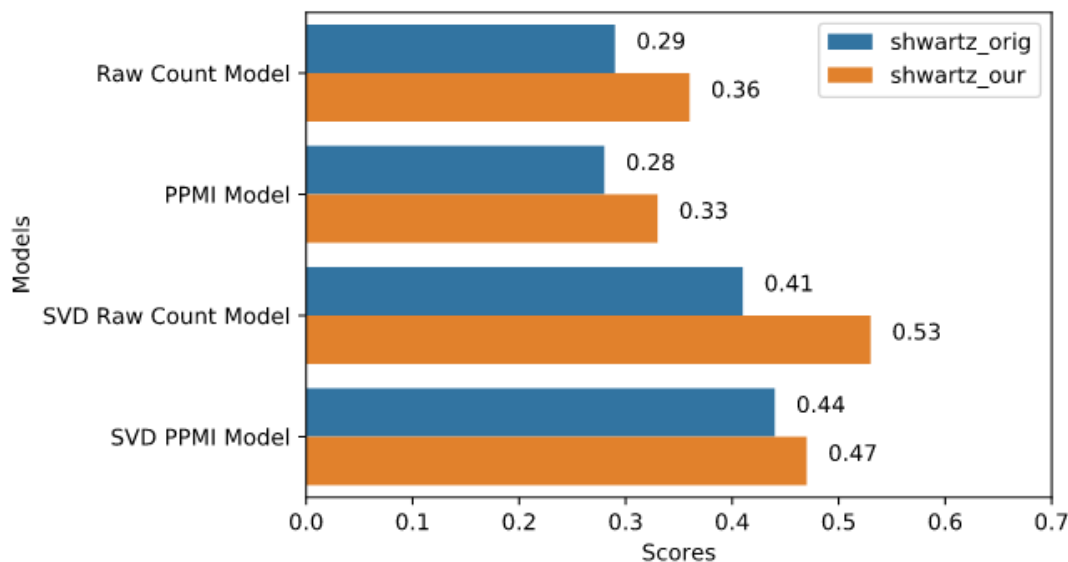


- LEDS (Baroni et al. 2012)

- 2 770 pairs
- balanced randomly shuffled pairs

meal	sport	False	val
poet	writer	True	val
garment	jean	False	val
worker	traveler	False	val
hamlet	community	True	val
velocity	rate	True	val
berry	diplomat	False	val
integer	eleven	False	val

SHWARTZ dataset results

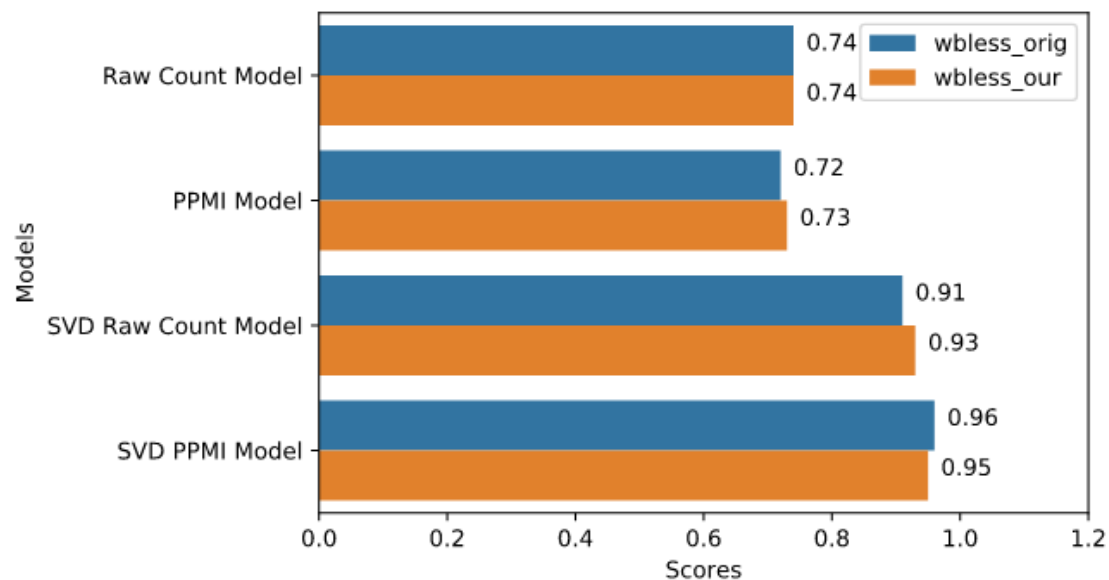


- SHWARTZ (Shwartz et al. 2016)

- 52 578 pairs

<u>icomb</u>	<u>gloucestershire</u>	False	val
<u>cumhuriyet</u>	<u>turkey</u>	False	val
<u>lomonosov</u>	<u>ruusia</u>	False	val
<u>personality</u>	<u>soul</u>	False	val
<u>beyer</u>	<u>garratt</u>	False	val
<u>kimberley</u>	<u>australia</u>	False	val
<u>nesiotica</u>	<u>genus</u>	False	val
<u>oppland</u>	<u>norway</u>	False	val
<u>anglet</u>	<u>bayonne</u>	False	val
<u>nicholas</u>	<u>ruusia</u>	False	val

WBLESS dataset results



- WBLESS (Weeds et al. 2014)**

- 1 668 pairs

cloth	table	False	other	val
butt	gun	False	other	val
cow	cattle	True	hyper	val
whale	mammal	True	hyper	val
radio	device	True	hyper	val
cod	food	True	hyper	val
blouse	clothes	True	hyper	val
peel	banana	False	other	val
good	stove	False	other	val
cucumber	garlic	False	other	val
giraffe	violin	False	other	val
cloak	covering	True	hyper	val

Reasons for slight deviation in Results from SOTA:

On some datasets, we perform better and on some we are slightly below the SOTA.

- 1) Slight variations in datasets used
- 2) Difference in Pre and post processing methodologies

Results difference is negligible and our pattern based methods still outperform

Future work from here:

- 1) Extract dependency paths between known hypernym pairs from large text corpora and form new patterns
- 2) Explore Distributional methods that form space through linguistic features. Trying to encode patterns in DSMs
- 3) ML/DL approaches





# Thank You!