Neural Vector Representations beyond Words: Sentence and Document Embeddings

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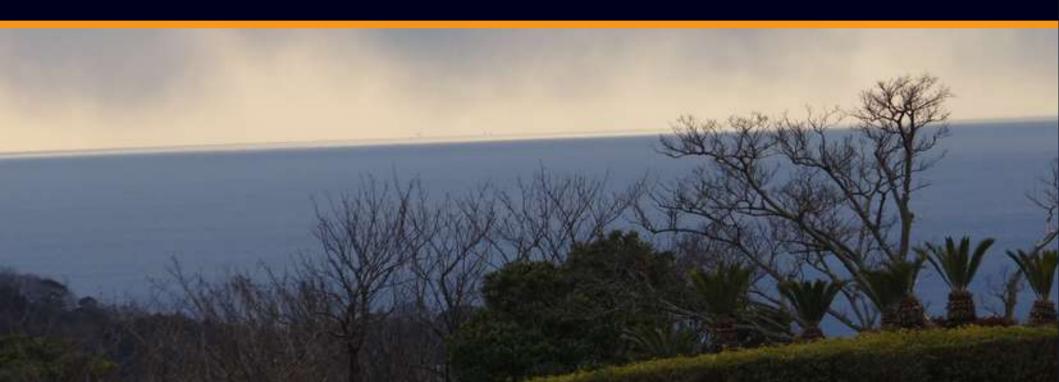
Outline

- Word Representations
- Phrase Representations
- Sentence Representations
- Document Representations
- Applications and Outlook

Phrases/Multiword Expressions

Kind	Example	
Compound Noun	dog park	
Adjective Noun	fresh food	
Verb Object	win money	
Verb Particle Phrase	walk up the stairs	
Named Entities	East London	
•••	•••	

Compositional Models



Models for Composition

Composition Function

$$\mathbf{v}_p = f(\mathbf{v}_{w_1}, \dots, \mathbf{v}_{w_n})$$

Vector for phrase, e.g. "mobile phone"

Vectors for parts of phrase e.g. "mobile" and "phone"

Models for Composition: Elementwise Composition

$$f(\mathbf{v}_{w_1},\ldots,\mathbf{v}_{w_n})=\mathbf{v}_{w_1}+\cdots+\mathbf{v}_{w_n}$$

Vector 1		Vector 2	Result Vector
0.0		0.0	0.0
0.3		0.1	0.4
0.4	+	0.2	0.6
0.0		0.1	0.1
0.3		0.0	0.3
0.2		0.0	0.2

Models for Composition: Elementwise Composition

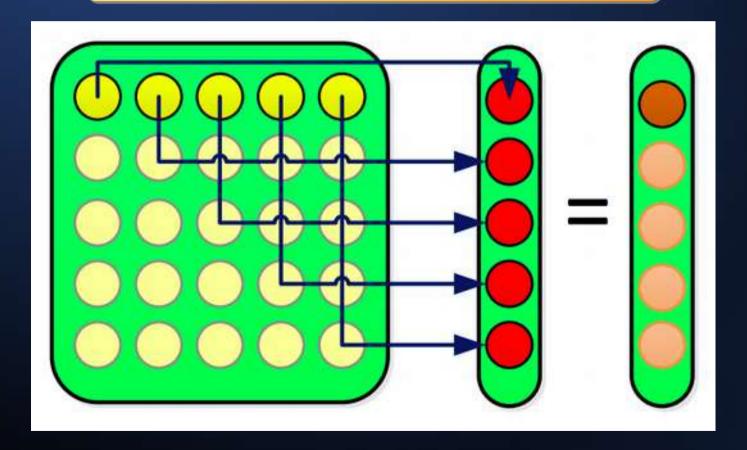
$$f(\mathbf{v}_{w_1},\ldots,\mathbf{v}_{w_n})=\mathbf{v}_{w_1}\odot\cdots\odot\mathbf{v}_{w_n}$$

Elementwise multiplication

Vector 1		Vector 2	Result Vector
0.0		0.0	0.00
0.3		0.1	0.03
0.4	+	0.2	 0.08
0.0		0.1	0.00
0.3		0.0	0.00
0.2		0.0	0.00

Models for Composition: Tensor Models

Tensors that can be applied to one or more vectors for arguments



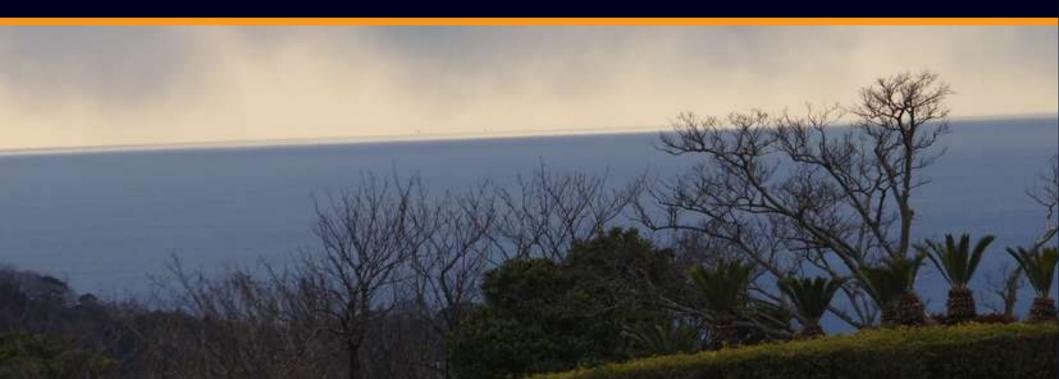
Phrases/Multiword Expressions

Kind	Example	
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•••	•••	

Phrases/Multiword Expressions

Kind	Compositional Example	Non-Compositional Example	
Compound Noun	dog park	zebra crossing	
Adjective Noun	fresh food	hot dog	
Verb Object	win money	kick the bucket	
Verb Particle Phrase	walk up the stairs	wrap up the session	
Named Entities	East London	Los Angeles	
•••	•••	•••	

Learning from Text



word2vec Implementation

1. PMI-like scores to find frequent MWEs

Bigram Count

$$score(w_i, w_j) = \frac{count(w_i w_j) - \delta}{count(w_i) \times count(w_j)}$$

Unigram Counts

- 2. Select MWEs above threshold, then repeat to find even longer MWEs
- 3. Finally, simply treat MWEs as unigrams

Tomas Mikolov, Ilya Sutskever, Kai Chen. Distributed Representations of Words and Phrases and their Compositionality. NIPS 2013

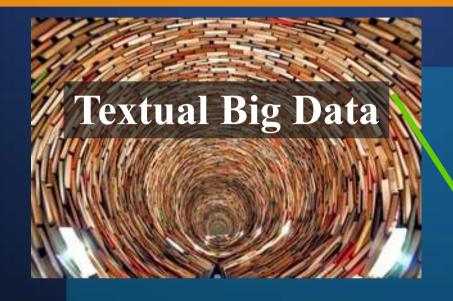
word2vec Implementation

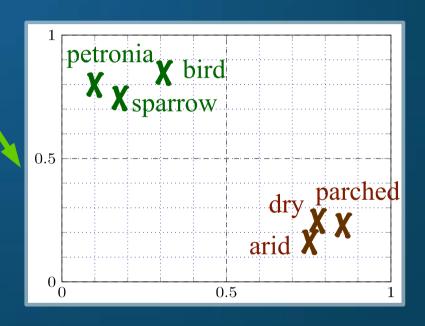
Czech + currency	Vietnam + capital	German + airlines	Russian + river	French + actress
koruna	Hanoi	airline Lufthansa	Moscow	Juliette Binoche
Check crown	Ho Chi Minh City	carrier Lufthansa	Volga River	Vanessa Paradis
Polish zolty	Viet Nam	flag carrier Lufthansa	upriver	Charlotte Gainsbourg
CTK	Vietnamese	Lufthansa	Russia	Cecile De

Nearest neighbours of Component-wise sums are meaningful

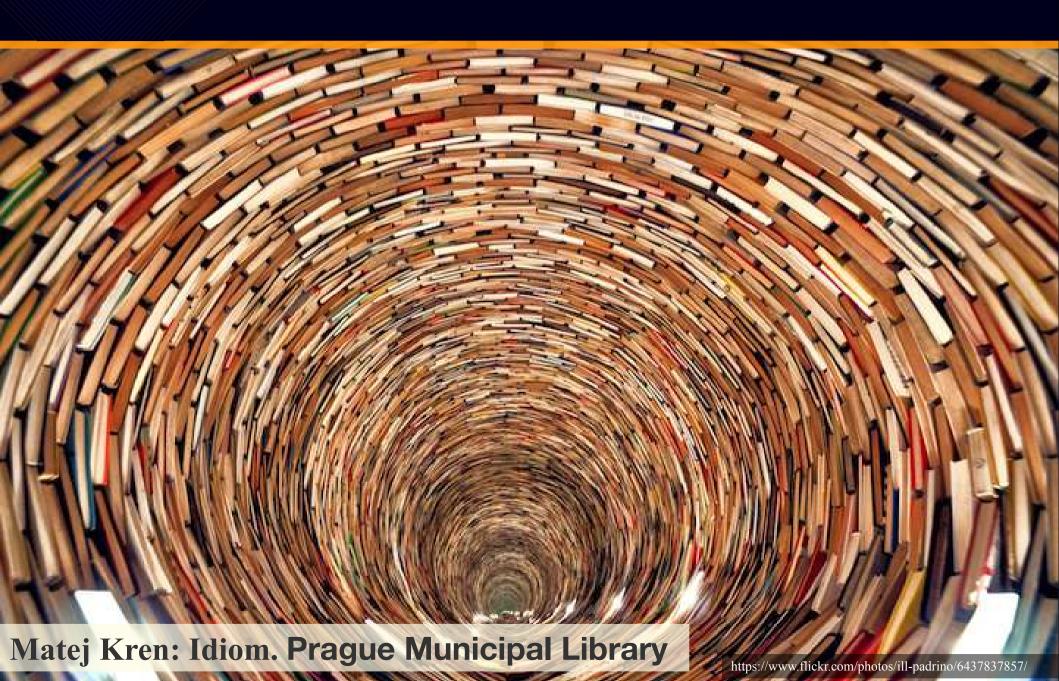
Tomas Mikolov, Ilya Sutskever, Kai Chen. Distributed Representations of Words and Phrases and their Compositionality. NIPS 2013

Learning from Heterogeneous Data

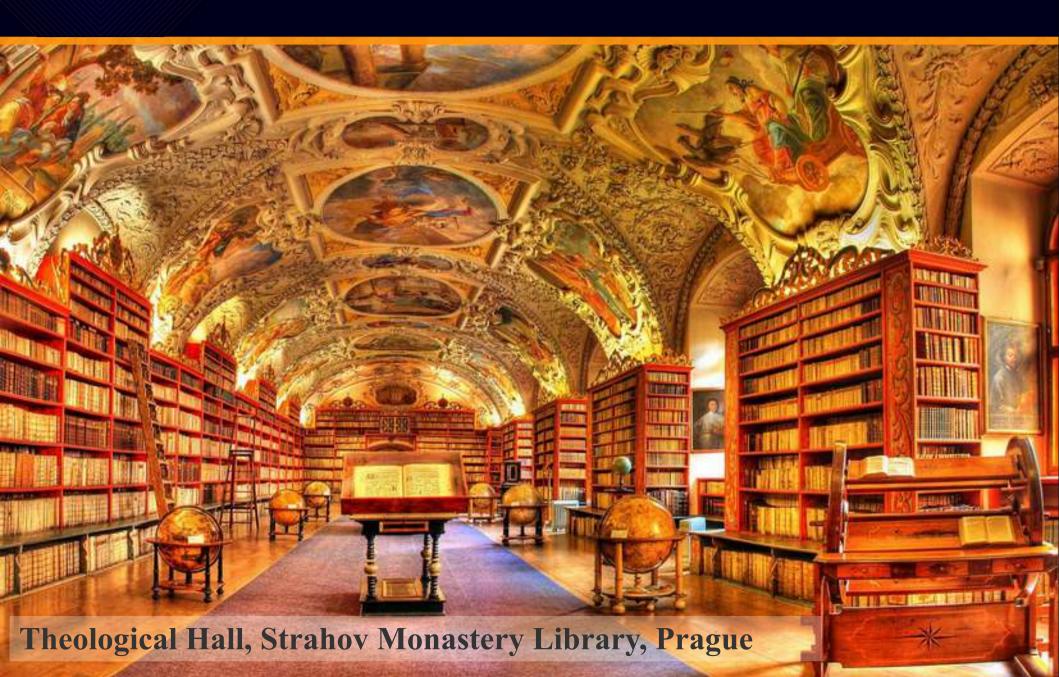




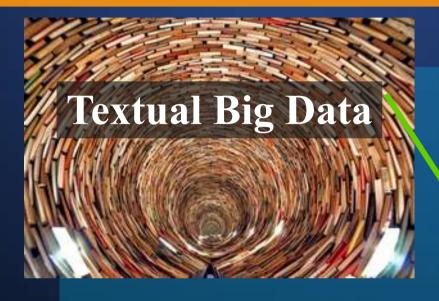
Textual Big Data



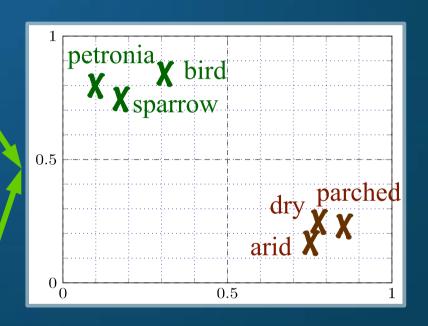
High-Quality Knowledge



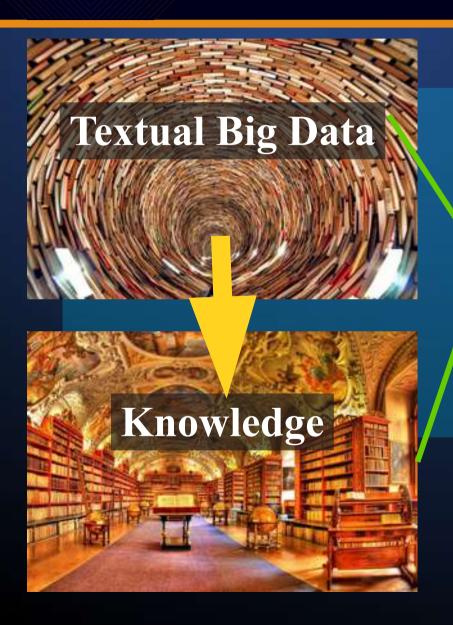
Learning from Heterogeneous Data

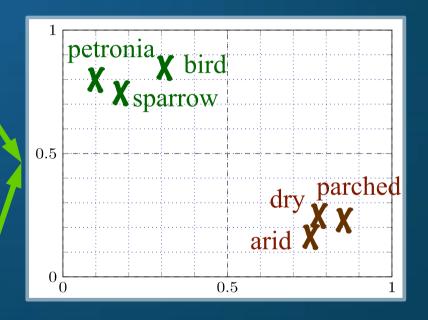






Information Extraction Approach





Information Extraction Approach



semantic!

...Greek and Roman mythology...

look for semantically salient contexts in text!

Information Extraction Approach: Joint Training

Given an extracted pair of semantically related words, the intuition is that the embeddings for the two words should be pulled together

$$\max \frac{1}{T} \sum_{t=1}^{T} \sum_{w_r} \log p(w_r | w_t)$$

 w_r : related words of w_t

Information Extraction Approach: Joint Training

$$\max \frac{1}{T} \sum_{t=1}^{T} \sum_{w_r} \log p(w_r | w_t)$$

softmax function
$$p(w_r|w_t) = \frac{\exp(v_{w_r}^{\prime} v_{w_t})}{\sum_{w=1}^{W} \exp(v_{w}^{\prime} v_{w_t})}$$

To compute its gradient is impractical. It is proportional to T, which is often large $(10^5 - 10^7 \text{ terms})$

Case Study: Information Extraction

List Extraction

- Look for repeated occurrences of commas
- Short units of roughly equal length
- noun phrases, adjectives

Case Study: Information Extraction

List Extraction

- Look for repeated occurrences of commas
- Short units of roughly equal length
- noun phrases, adjectives
- Also: Hearst patterns, e.g.
 - "cities such as New York, London, ..."

Case Study: Information Extraction

Extracted Lists

player captain manager director vice-chairman

group race culture religion organisation person

Italian Mexican Chinese Creole French

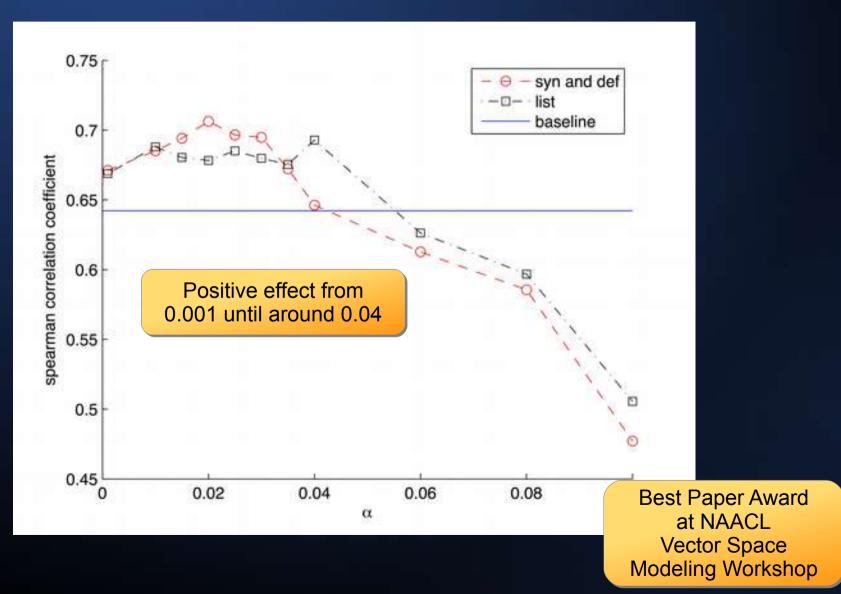
Self-Portraits Portraits iris Still-Lives with Sunflowers view from the Asylum Works after Millet Vineyards

ballscrews leadscrews worm gear screwjacks linear actuator

Cleveland Essex Lincolnshire Northamptonshire Nottinghamshire Thames Valley South Wales

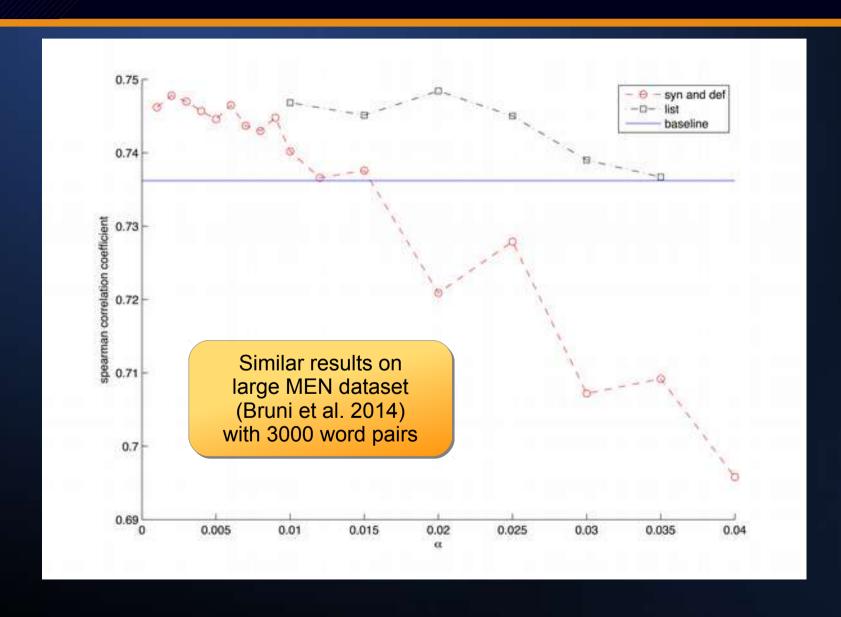
ant.py dimdriver.py dimdriverdatafile.py dimdriverdatasetdef.py dimexception.py dimmaker.py dimoperators.py dimparser.py dimrex.py dimension.py

Case Study: Results on WS353

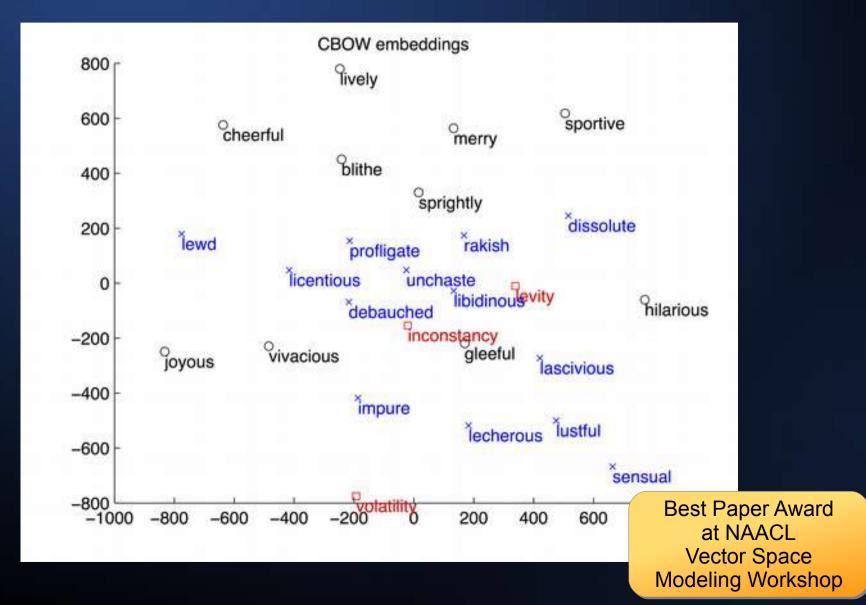


Jiaqiang Chen and Gerard de Melo. Semantic Information Extraction for Improved Word Embeddings

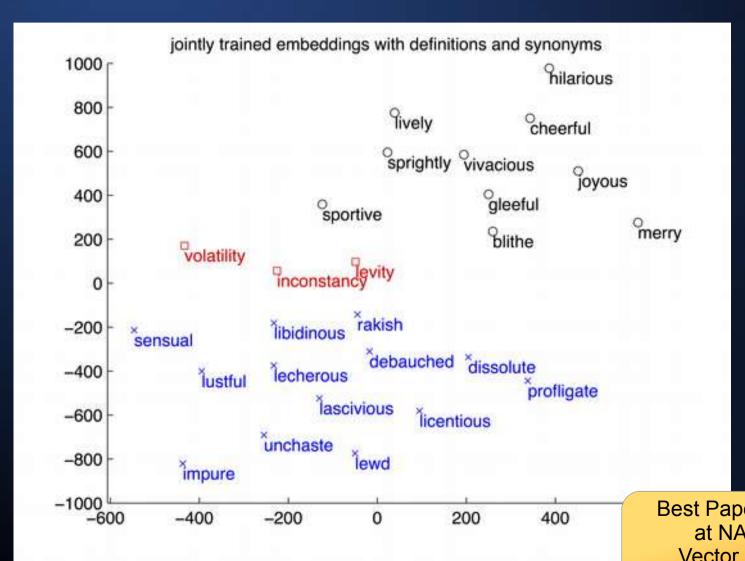
Case Study: Results on MEN



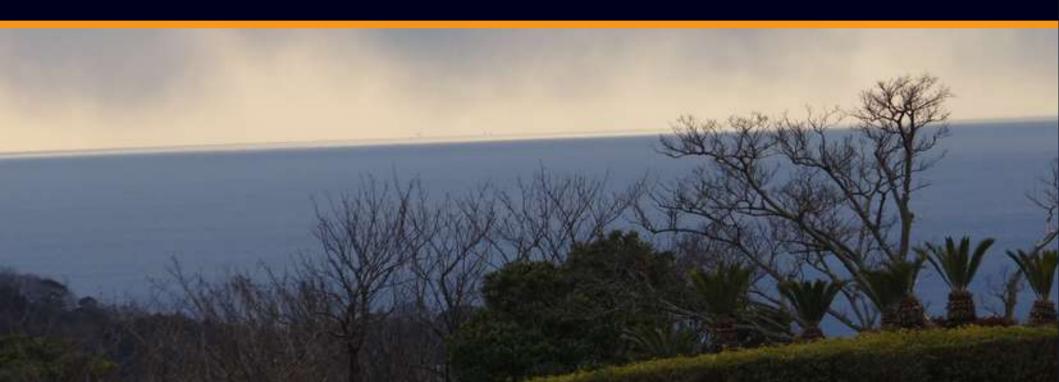
Case Study: Example



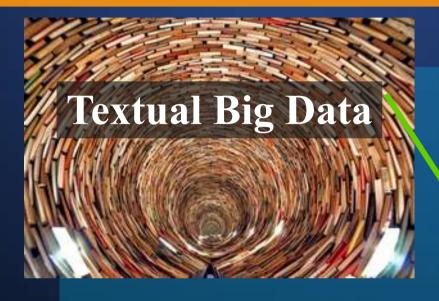
Case Study: Example



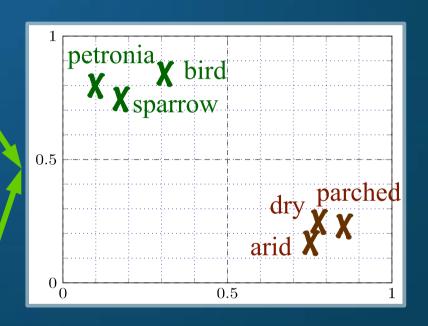
Learning from Text and Structured Data



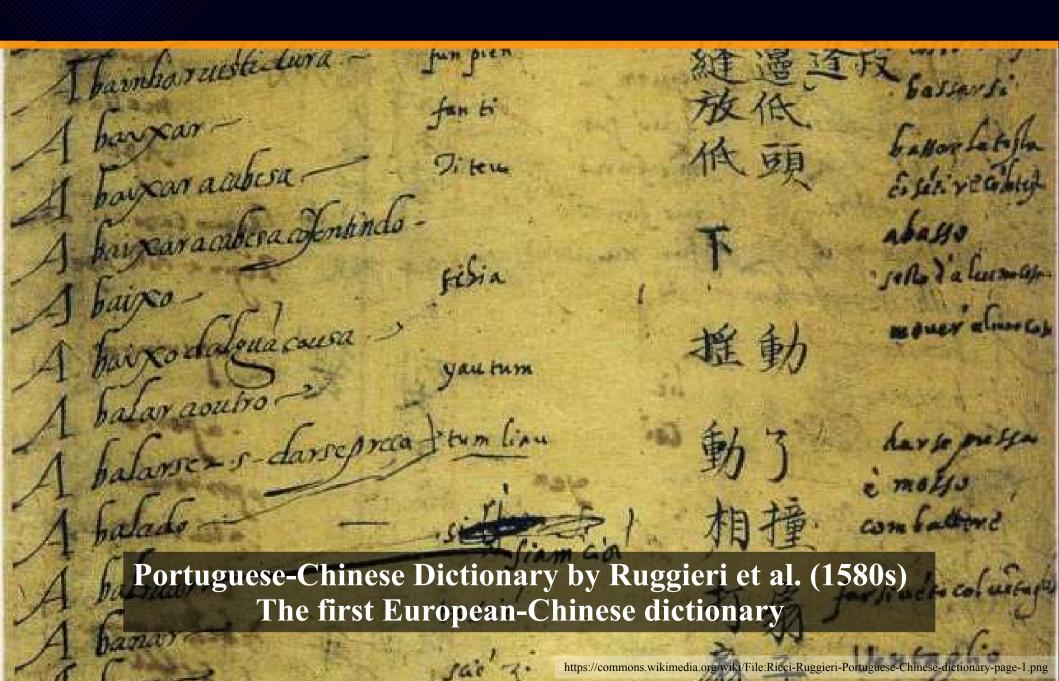
Learning from Heterogeneous Data







Lexical Knowledge



Lexical Knowledge: Wiktionary

Wiktionary



Provides translations, antonyms, etc.

Find a language: →

\$

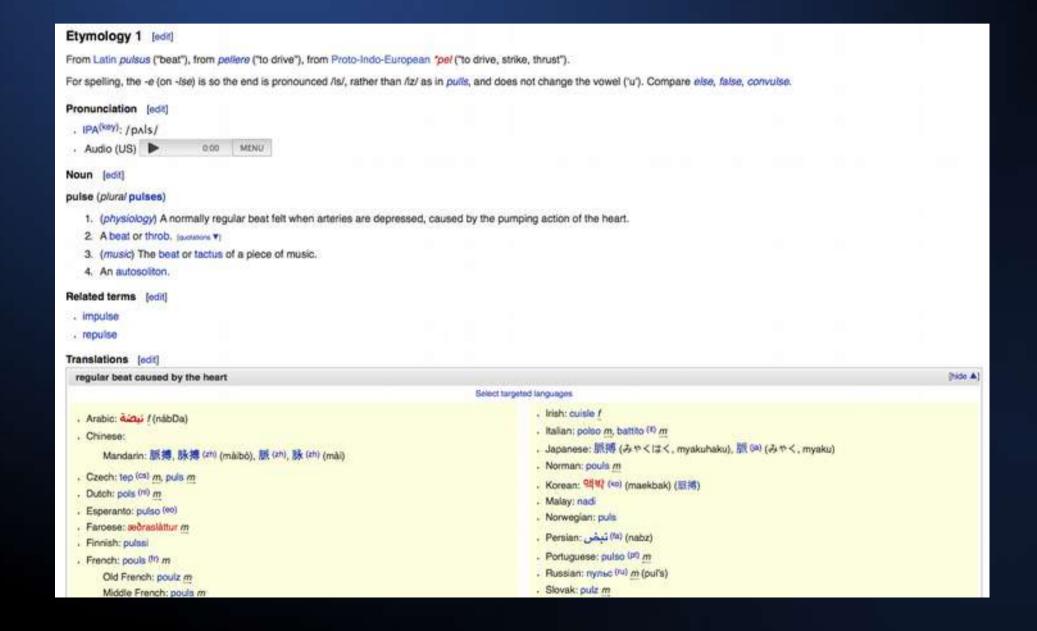
Q

English

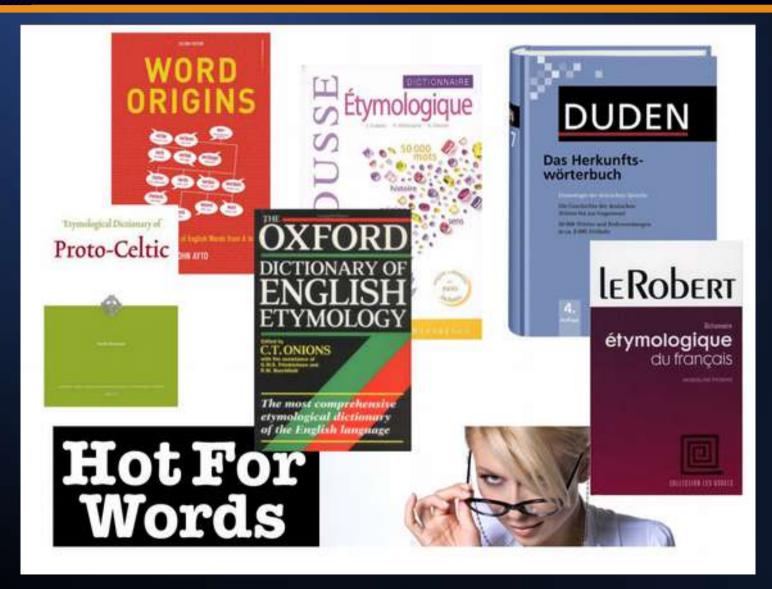
Lexical Knowledge: Wiktionary

a muttilingual free encyclopedia Discussion Citations Wiktionary ['wikfənri] n., déjeûna a wiki-based Open Content dictionary Wilen I'wrl kartl French [edit] Main Page Pronunciation [edit] Community portal Homophones: déjeûnas, déjeûnât Preferences Requested entries Verb [edit] Recent changes Random entry déjeûna Help third-person singular past historic of déjeûner Donations Contact us Categories: French verb forms French non-lemma forms Tools What links here Related changes

Lexical Knowledge: Wiktionary

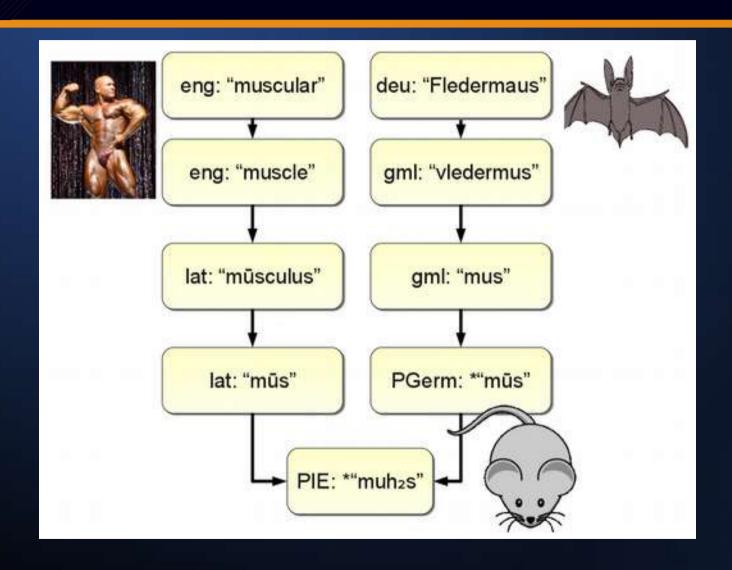


Etymological Wordnet

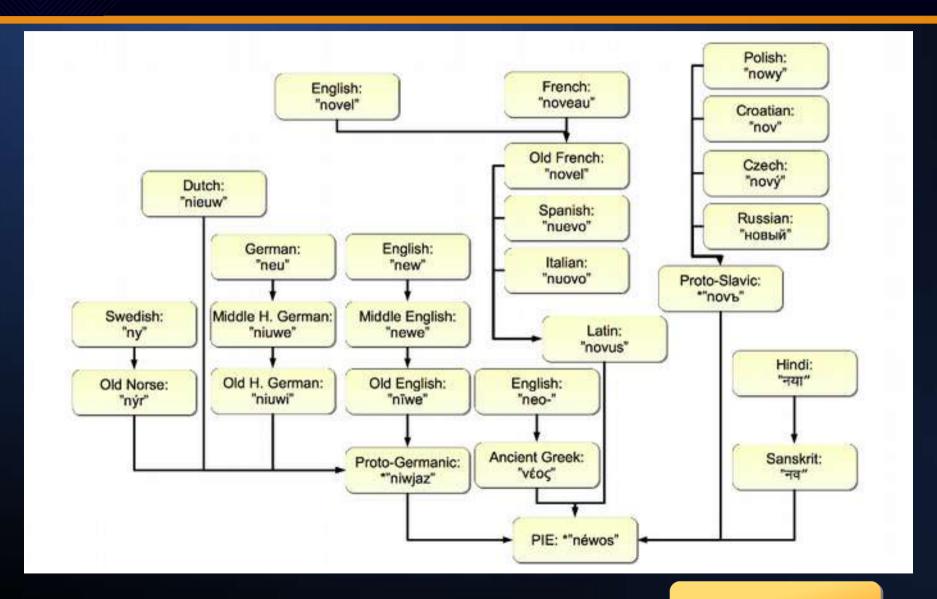


e.g. "salary" < Lat. "salarius" < Lat. "sal" (salt)

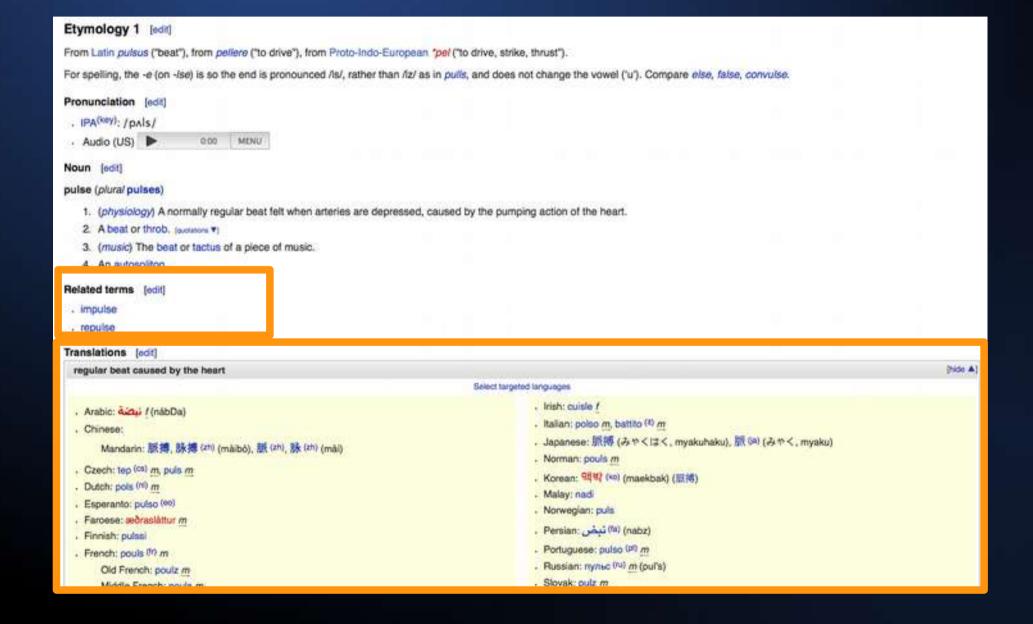
Etymological Wordnet



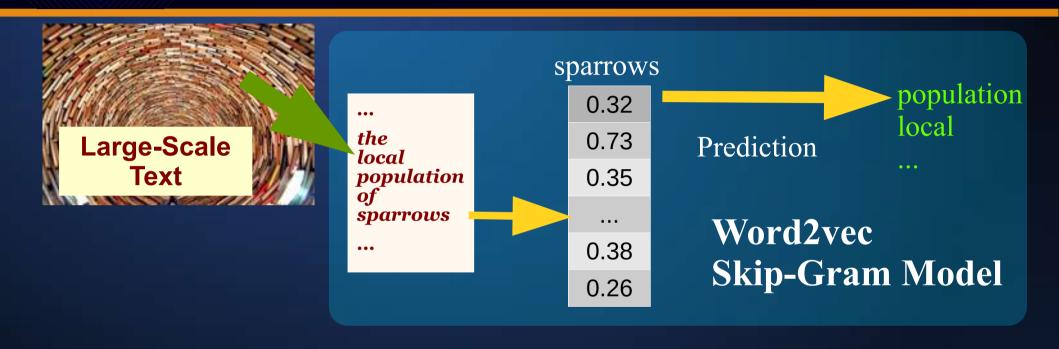
Etymological Wordnet



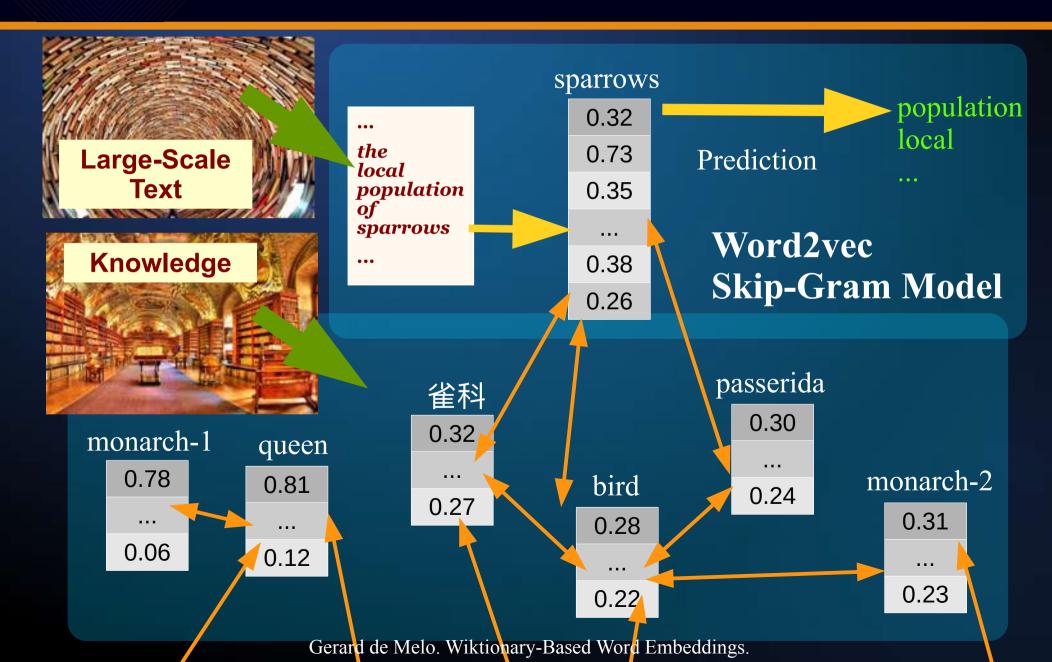
Lexical Knowledge: Wiktionary

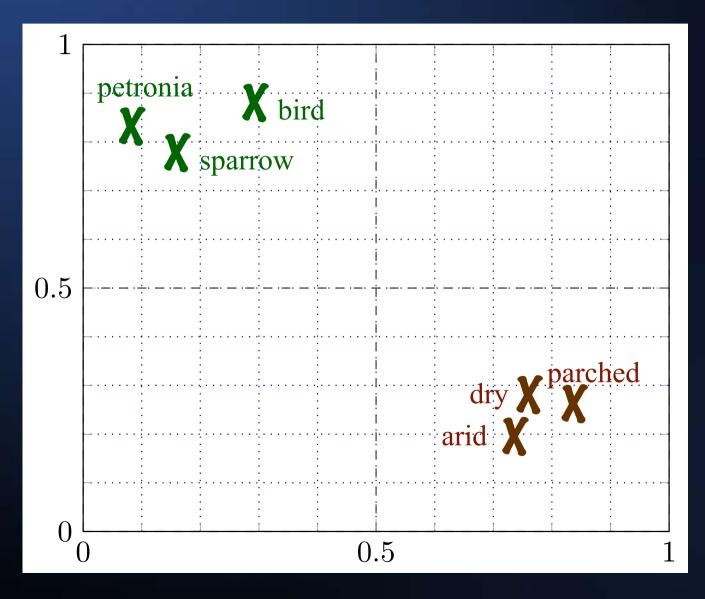


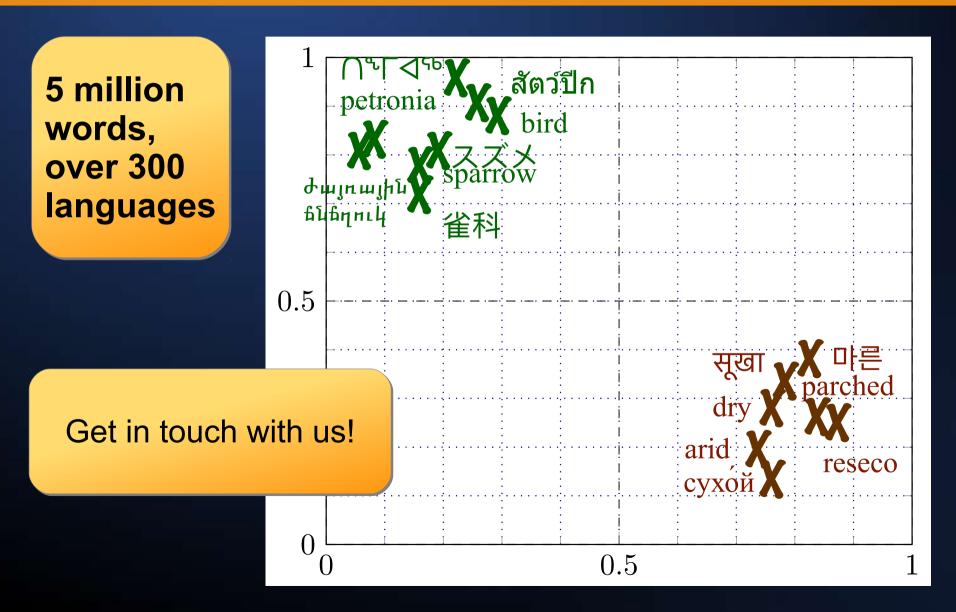
Word Vector Representations: word2vec



Word Vector Representations: word2vec







Combine word2vec/GloVe Vectors with multilingual lexical data from Wiktionary

Example: German language datasets

RG65	Chandar A P et al. (2014) En-Es Vectors	0.629 @ 55.4%
	Ours (word2vec)	0.834 @ 100.0%
	Ours (Glove)	0.809 @ 100.0%
MC30	Chandar A P et al. (2014) En-Es Vectors	0.430 @ 60.0%
	Faruqui et al. (2015)	0.591 @ N/A
	Ours (word2vec)	0.811 @ 76.7%
	Ours (Glove)	0.848 @ 76.7%
WS353	Chandar A P et al. (2014) En-Es Vectors	0.256 @ 65.1%
	Ours (word2vec)	0.548 @ 65.6%
	Ours (Glove)	0.591 @ 65.6%

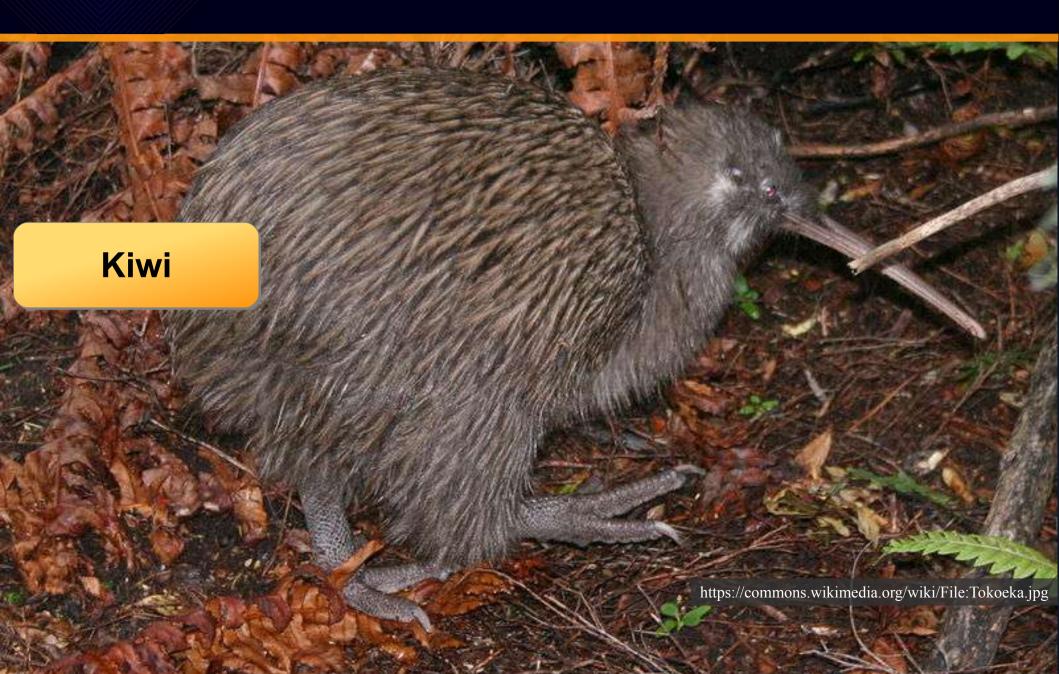
English-German RG65	Chandar A P et al. (2014) En-De Vectors	0.441 @ 38.4%
	Ours (word2vec)	0.812 @ 97.6%
	Ours (GloVe)	0.828 @ 97.6%
English-Spanish RG65	Chandar A P et al. (2014) En-Es Vectors	0.588 @ 59.5%
	Ours (word2vec)	0.869@100.0%
	Ours (GloVe)	0.863 @ 100.0%
English-French RG65	Chandar A P et al. (2014) En-Fr Vectors	0.598 @ 52.0%
ALL WHILE THE CONTROL OF THE CONTROL	Ours (word2vec)	0.864 @ 100.0%
	Ours (GloVe)	0.855@ 100.0%
English-Spanish MC30	Chandar A P et al. (2014) En-Es Vectors	0.351 @ 70.0%
5	Ours (word2vec)	0.745 @ 90.0%
	Ours (GloVe)	0.797 @ 90.0%
Spanish-English MC30	Chandar A P et al. (2014) En-Es Vectors	0.645 @ 56.7%
	Ours (word2vec)	0.713 @ 83.3%
	Ours (GloVe)	0.721 @ 83.3%
English-Spanish WS353	Chandar A P et al. (2014) En-Es Vectors	0.303 @ 75.9%
	Ours (word2vec)	0.582 @ 79.8%
	Ours (GloVe)	0.641 @ 79.8%
Spanish-English WS353	Chandar A P et al. (2014) En-Es Vectors	0.299 @ 73.3%
	Ours (word2vec)	0.550 @ 78.7%
	Ours (GloVe)	0.612 @ 78.7%

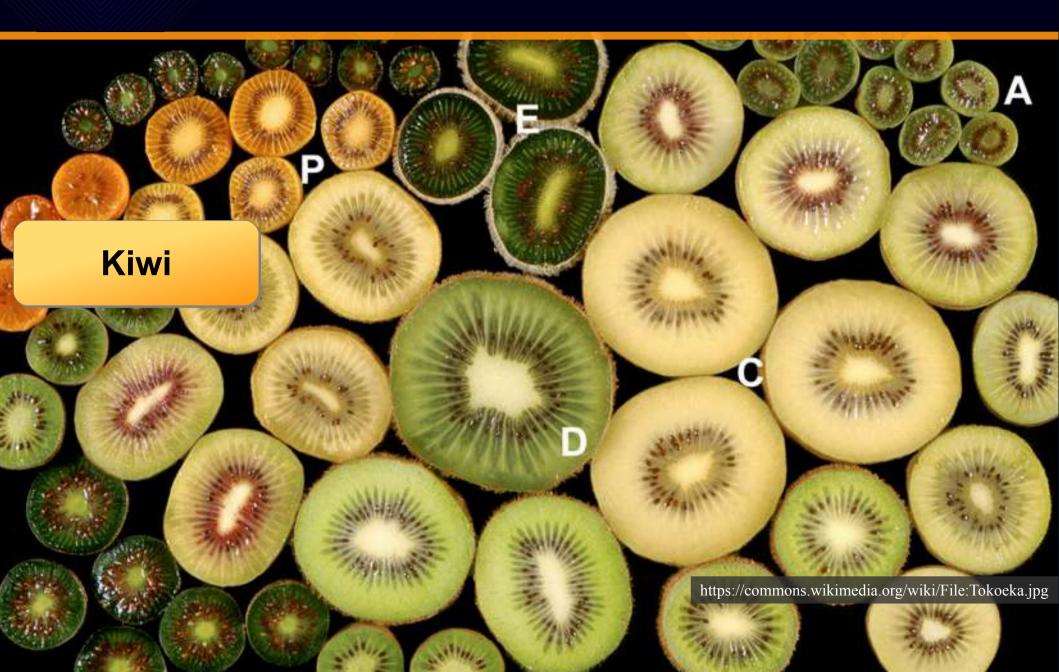
Multilingual Word Choice Quizzes

gourmetdalebracea) enjoys cookinga) plaina) to screamb) has indigestionb) retreatb) prepare for dangerc) has an expert appreciation of foodc) shelterc) hold your breathd) is hungryd) valleyd) close your eyes

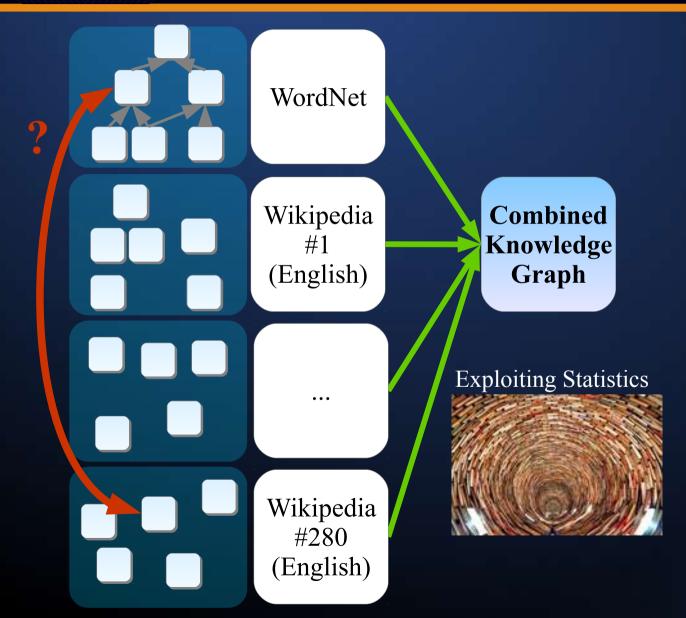








Connecting Multiple Sources



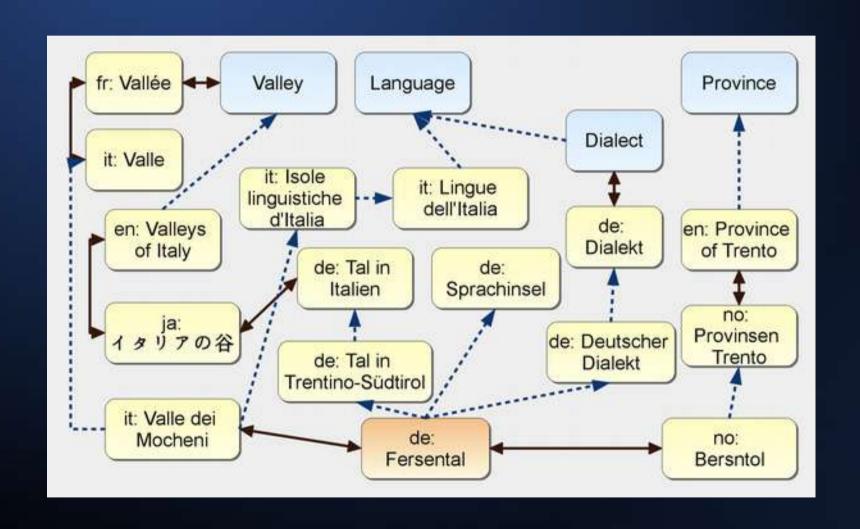
Gerard de Melo, Gerhard Weikum. Taxonomic Data Integration from Multilingual Wikipedia Editions

Extraction from Wikipedia

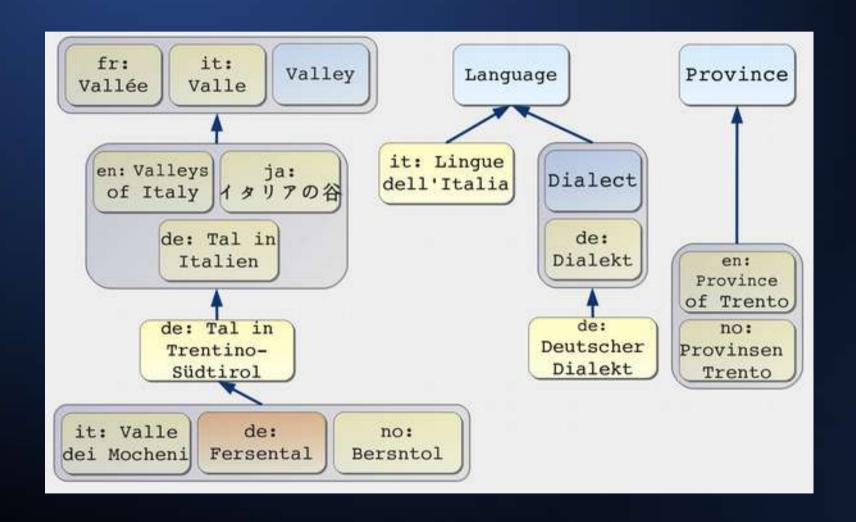




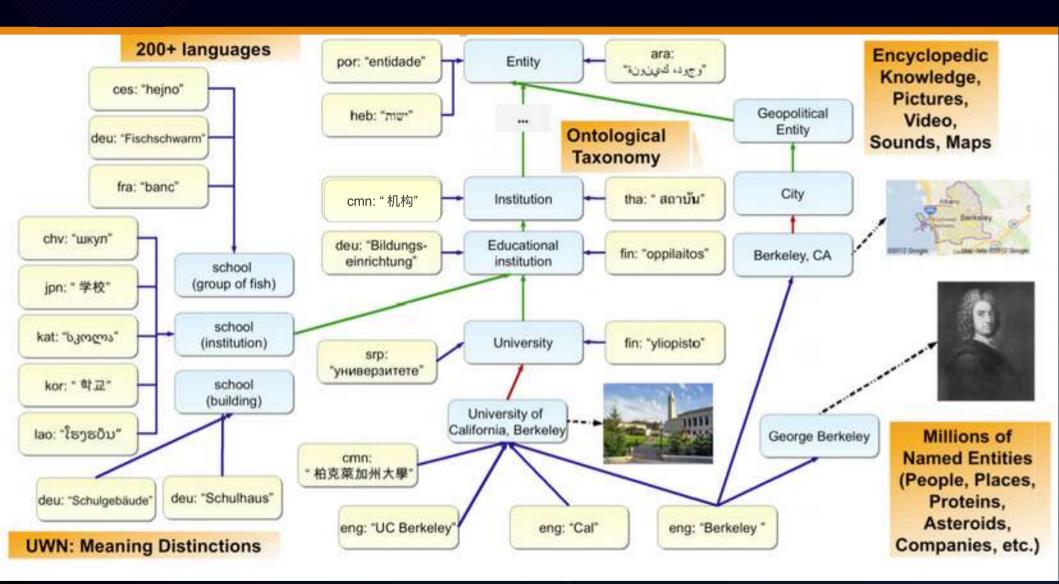
MENTA Integration Approach



MENTA Integration Approach

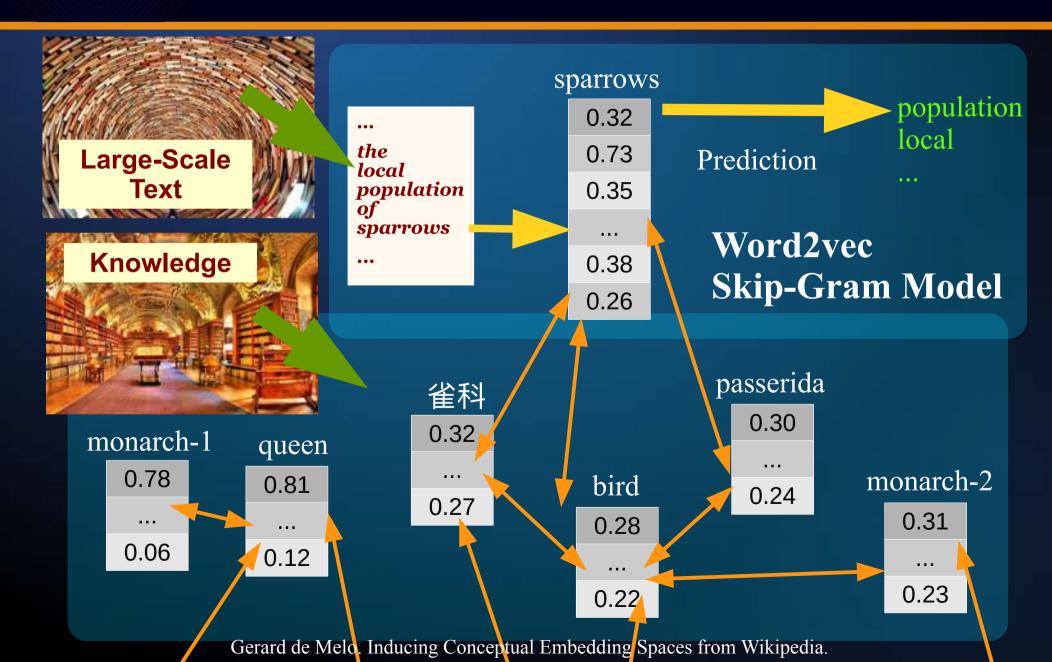


Universal Wordnet

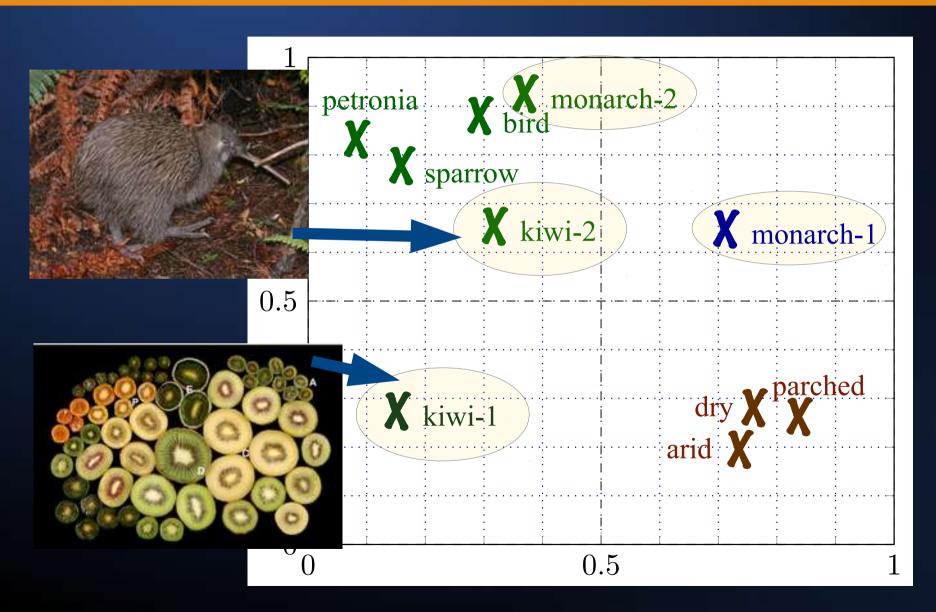


http://lexvo.org/uwn/

Word Vector Representations: word2vec



Sense Representations



Application: Verbal Questions in IQ Tests

Identify two words (one from each set of brackets) that form a connection (analogy) when paired with the words in capitals.

CHEMISTRY (laboratory, reaction, substances) FAUNA (plants, animals, countryside)

Answer: substances, animals

Multilingual Analogical Reasoning



Coffee is to Starbucks as ... is to Lipton?

System: Tea

Source vectors: GLOVE

Ongoing Research: Multilingual Analogical Reasoning



Apple is to Macbook as ... is to Thinkpad?

System: 1. IBM 2. Compaq 3. Lenovo

Source vectors: GLOVE

Ongoing Research: Multilingual Analogical Reasoning



m is to meters as ... is to kilograms?

System: 1. kilos 2. kg 3. kilogrammes

Source vectors: GLOVE

Ongoing Research: Multilingual Analogical Reasoning

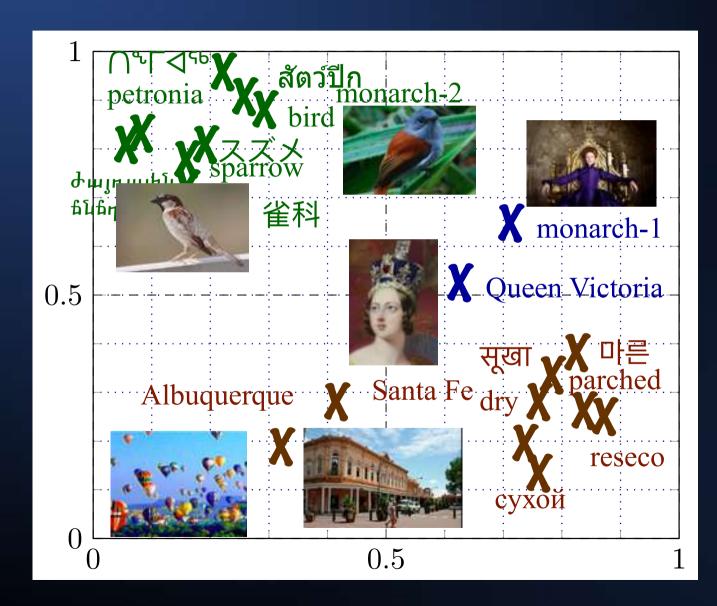


Germany is to Merkel as ... is to Putin?

System: 1. Russia 2. Moscow 3. Europe

Source vectors: GLOVE

Multilingual and Multimodal Word Vectors



Questions?

