# A Cross-Lingual Dictionary for English Wikipedia Concepts 

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 with Angel X. ChangStanford University / Google Inc.


## From Words to Concepts and Back:

## From Words to Concepts and Back:

Dictionaries for Linking Text, Entities and Ideas

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Yet in each word some concept there must be...

- from Goethe's Faust


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## Example:

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## Example:

- word sense disambiguation


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- words:


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- words: raw, unstructured natural language representation


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- or coarse categories
- high-level (low-dimensional) representation
- e.g., aggregation via Wikipedia's hierarchical structure


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Leech's main academic interests are: English grammar; ... Corpus-based natural language processing by computer

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Matt eats very well. He is also a computational linguist who takes time off from the research he usually does for culinary road trips and other adventures.

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## Computational_linguistics

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http://wikipapers.referata.com/wiki/List_of_datasets

## Football: Forward

## Football: Forward

- 44,984 - Association football


## Football: Forward

- 44,984 - Association football
- 23,373 - American football


## Football: Back

## Football: Back

- Association football


## Football: Back

- Association football
- soccer


## Football: Back

- Association football
- soccer
- association football


## Football: Back

- Association football
- soccer
- association football
- fútbol
- futbol
- Fußball
- futebol


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## Named Entities: Highly Ambiguous

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- people named after other people


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- organizations named after people or places
- organizations become places...


## Named Entities: Example <br> - Stanford

# Named Entities: Example <br> 1. Stanford University 

## - Stanford 50.3 ORG

## Named Entities: Example <br> 1. Stanford University <br> 2. Stanford (disambiguation)

## - Stanford 50.3 ORG <br> 7.7

## Named Entities: Example

1. Stanford University
2. Stanford (disambiguation)
3. Stanford, California

- Stanford 50.3 ORG
7.7
7.5 LOC


## Named Entities: Example

1. Stanford University
2. Stanford (disambiguation)
3. Stanford, California
4. Stanford Cardinal football

## - Stanford

50.3 ORG
7.7
7.5 LOC 5.7 ORG

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1. Stanford University
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3. Stanford, California
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5. Stanford Cardinal

## - Stanford

50.3 ORG
7.7
7.5 LOC
5.7 ORG
4.1

## Named Entities: Example

1. Stanford University
2. Stanford (disambiguation)
3. Stanford, California
4. Stanford Cardinal football
5. Stanford Cardinal
6. Stanford Cardinal men's basketball

- Stanford
50.3 ORG
7.7
7.5 LOC
5.7 ORG
4.1
2.0 ORG


## Named Entities: Example

1. Stanford University
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7. Stanford prison experiment

## - Stanford

50.3 ORG
7.7
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4.1
2.0 ORG
2.0

## Named Entities: Example

 - Stanford1. Stanford University
2. Stanford (disambiguation)
3. Stanford, California
4. Stanford Cardinal football
5. Stanford Cardinal
6. Stanford Cardinal men's basketball
7. Stanford prison experiment
8. Stanford, Kentucky

| 50.3 | ORG |
| :---: | :---: |
| 7.7 | - |
| 7.5 | LOC |
| 5.7 | ORG |
| 4.1 | - |
| 2.0 | ORG |
| 2.0 | - |
| 1.7 | LOC |

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 - Stanford1. Stanford University
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4. Stanford Cardinal football
5. Stanford Cardinal
6. Stanford Cardinal men's basketball
7. Stanford prison experiment
8. Stanford, Kentucky
9. Stanford, Norfolk
50.3 ORG
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8. Stanford, Kentucky
9. Stanford, Norfolk
10. Bank of the West Classic
50.3 ORG
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5. Stanford Cardinal
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8. Stanford, Kentucky
9. Stanford, Norfolk
10. Bank of the West Classic
11. Stanford, Illinois

| 50.3 | ORG |
| :---: | :---: |
| 7.7 | - |
| 7.5 | LOC |
| 5.7 | ORG |
| 4.1 | - |
| 2.0 | ORG |
| 2.0 | - |
| 1.7 | LOC |
| 1.0 | LOC |
| 1.0 | - |
| 0.9 | LOC |

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50.3 ORG
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13. Charles Villiers Stanford
0.8 PER
14. Stanford, New York
0.8 LOC
15. Stanford, Bedfordshire

## Named Entities: Objective Evaluation

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## - entity linking

(TAC-KBP)

## Named Entities: Objective Evaluation

- entity linking
(TAC-KBP)
- task: disambiguate entity mentions in text


## Named Entities: Objective Evaluation

- entity linking
- task: disambiguate entity mentions in text, by linking to appropriate Wikipedia article


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- abstract away sheer engineering effort
- let research focus on context-sensitive techniques
- machine learning, linguistic features, etc.


## From Words to Concepts and Back:

## Examples:

- word sense disambiguation
- named entity recognition


## From Words to Concepts and Back:

## Examples:

- word sense disambiguation
- named entity recognition
- entity linking


## From Words to Concepts and Back:

## Examples:

- word sense disambiguation
- named entity recognition
- entity linking
- coreference resolution


## From Words to Concepts and Back:

## Examples:

- word sense disambiguation
- named entity recognition
- entity linking
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- web search


## From Words to Concepts and Back:

## Examples (Recognition):

- word sense disambiguation
- named entity recognition
- entity linking
- coreference resolution
- web search


## From Words to Concepts and Back:

- inverse problem


## Examples (Generation):

## From Words to Concepts and Back:

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## Examples (Generation): <br> - word synonyms

## From Words to Concepts and Back:

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## Examples (Generation):

- word synonyms
- paraphrasing


## From Words to Concepts and Back:

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## Examples (Generation):

- word synonyms
- paraphrasing
- summarization


## From Words to Concepts and Back:

- inverse problem -


## Examples (Generation):

- word synonyms
- paraphrasing
- summarization
- translation


## From Words to Concepts and Back:

- inverse problem -


## Examples (Generation):

- word synonyms
- paraphrasing
- summarization
- translation
- keyword targeting


## From Words to Concepts and Back:

## Comes up in IR and NLP all the time!

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- Interface is conditional probabilities:
$-\mathbb{P}$ (concept $\mid$ words $)$; and $\mathbb{P}$ (words $\mid$ concept $)$.
Conceptually trivial platform (hides engineering/systems details).


## Another Example:

## - Soft_drink

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1. soft drink ..... 28.62. soda3. soda pop
2. fizzy drinks ..... 0.65.50.9
3. carbonated beverages ..... 0.36. non-alcoholic7. soft0.20.18. pop0.1
4. carbonated soft drink ..... 0.1
5. aerated water

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- Normalized (for capitalization, pluralization and punctuation differences).

1. soft drink ..... 28.62. soda
2. fizzy drinks5.5
3. soda pop ..... 0.9
4. carbonated beverages ..... 0.3
5. non-alcoholic ..... 0.2
6. soft ..... 0.1
7. pop ..... 0.1
8. carbonated soft drink ..... 0.1
9. aerated water ..... 0.1

- Restricted to English Wikipedia (and hence missing 2/3 of the data).


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| :---: | :---: | :---: |
| 0.966102 | Galago D w:11 | W08 W09 WDB w:2/5 w':2/2 |
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- README file has (much) more about the features;


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- More than half the paper is detailed examples...


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We hope you will find creative uses for these! :)

## Thanks!

## Yet in each word some concept there must be...

Quite true! But don't torment yourself too anxiously; For at the point where concepts fail, At the right time a word is thrust in there.

- Mephistopheles, in Goethe's Faust (Part I, Scene III, as translated by G.M. Priest)
http://www.levity.com/alchemy/faust05.html


## Thanks!

## Any questions?

