Measuring Semantic Distance

using Distributional Profiles of Concepts

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Semantic Distance

SALSA DANCE

CLOWN BRIDGE

A measure of how close or distant two units of language are in terms of their meaning

Why measure semantic distance?

- Natural language processing is teeming with semantic-distance problems:
  - Machine translation

bag of hypotheses

You know a person by the company they keep

Das Wesen eines Menschen erkennt man an der Gesellschaft, mitder er sich umgibt

Why measure semantic distance?

- Natural language processing is teeming with semantic-distance problems:
  - Word sense disambiguation

Hermione cast a bewitching spell

CHARM OR INCANTATION

bag of hypotheses

Why measure semantic distance?

- Natural language processing is teeming with semantic-distance problems:
  - Speech recognition, real-word spelling correction

... *interest* ... *money* ... *band* ... *loan* ...

bank or *bond*

bag of hypotheses

Knowledge source–based semantic measures

- Structure of a network or resource
  - The nodes represent senses or concepts
  - Examples: Resnik (1995), Jiang and Conrath (1997)
- Drawbacks
  - Resource bottleneck
  - Not easily domain-adaptable
  - Accuracy on pairs other than noun–noun is poor
  - Relatedness estimation is poor

Corpus-based distributional measures

- Words in similar contexts are close.
  - **Distributional profile (DP)** of a word: strength of association of the word with co-occurring words in text

DP of a word

DP of *fusion*

heat 0.16

hydrogen 0.16

energy 0.13

hot 0.09

light 0.09

space 0.04

gravity 0.03

pressure 0.03

DPs of words

DP of *star*

space 0.21
movie 0.16
famous 0.15
light 0.12
rich 0.11
heat 0.08
planet 0.07
hydrogen 0.07

DP of *fusion*

heat 0.16
hydrogen 0.16
energy 0.13
hot 0.09
light 0.09
space 0.04
gravity 0.03
pressure 0.03

Distance between two words

DP of *star*	**DP of *fusion***
space 0.21	*heat* 0.16
movie 0.16	*hydrogen* 0.16
famous 0.15	*energy* 0.13
light 0.12	*hot* 0.09
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Distributional measures of word-distance

- Words in similar contexts are close.
  - Distributional profile (DP) of a word: strength of association of the word with co-occurring words (text)
  - Distributional measure: distance between DPs

    Cosine, Lin, α-skew divergence
- Drawback
  - Poor accuracy (albeit higher coverage)
    - Conflation of word senses

Problem with distributional word-distance measures

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Word sense ambiguity reduces accuracy of distance measures

Shared limitations

- Precomputing all distances is computationally expensive
  - WordNet-based measures:

    $117,000 \times 117,000$ sense–sense distance matrix
  - Distributional measures:

    $100,000 \times 100,000$ word–word distance matrix

- Monolingual

A new hybrid approach

- Combines a knowledge source with text
  - Thesaurus categories: concepts/coarse senses
  - Most published thesauri: around 1000 categories

- Profiles concepts (rather than words)
  - Uses sets of words to represent each concept
  - Creates profiles using bootstrapping

Features

- Can be used in real-time applications
  - Concept–concept distance matrix: only 1000×1000
- Accurate for all pos–pos pairs
  - Not just noun–noun
- Capable of giving both similarity and relatedness values
- Easily domain adaptable
- Cross-lingual

Problem with distributional word-distance measures

DP of *star*

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movie 0.16

famous 0.15

light 0.12

rich 0.11

heat 0.08

planet 0.07

hydrogen 0.07

Word sense ambiguity reduces accuracy of distance measures

Solution:
tease out the senses

star

space

movie

famous

light

rich

heat

planet

hydrogen

Solution:
tease out the senses

star

space

movie

famous

light

rich

heat

planet

hydrogen

Profile the senses separately.

Distributional profiles of concepts

DPs of the concepts referred to by *star*:

DP of CELESTIAL BODY	**DP of CELEBRITY**
space 0.36	*famous* 0.24
light 0.27	*movie* 0.14
heat 0.11	*rich* 0.14
planet 0.07	*fan* 0.10
hydrogen 0.06	*hot* 0.04
hot 0.01	*fashion* 0.01

Distributional profiles of concepts

DPs of the concepts referred to by *star* :

DP of CELESTIAL BODY	**DP of** CELEBRITY
(celestial body, star, sun,...)	*(celebrity, hero, star,...)*
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planet 0.07	*fan* 0.10
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hot 0.01	*fashion* 0.01

Distance: *star* and *fusion*

DP of FUSION

(atomic reaction, fusion, thermonuclear reaction,...)

heat 0.16

hydrogen 0.16

energy 0.13

hot 0.09

light 0.09

space 0.04

Distance: *star* and *fusion*

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(celebrity, hero, star,...)	*(atomic reaction, fusion, thermonuclear reaction,...)*
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fashion 0.01	*space* 0.04

First, consider the CELEBRITY sense of *star*.

Distance: *star* and *fusion*

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(celebrity, hero, star,...)	*(atomic reaction, fusion, thermonuclear reaction,...)*
famous 0.24	*heat* 0.16
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hot 0.04	*light* 0.09
fashion 0.01	*space* 0.04

First, consider the CELEBRITY sense of *star*.

- Distributionally NOT close

Distance: *star* and *fusion*

DP of FUSION

(atomic reaction, fusion, thermonuclear reaction,...)

heat 0.16

hydrogen 0.16

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Then, consider the CELESTIAL BODY sense of *star*.

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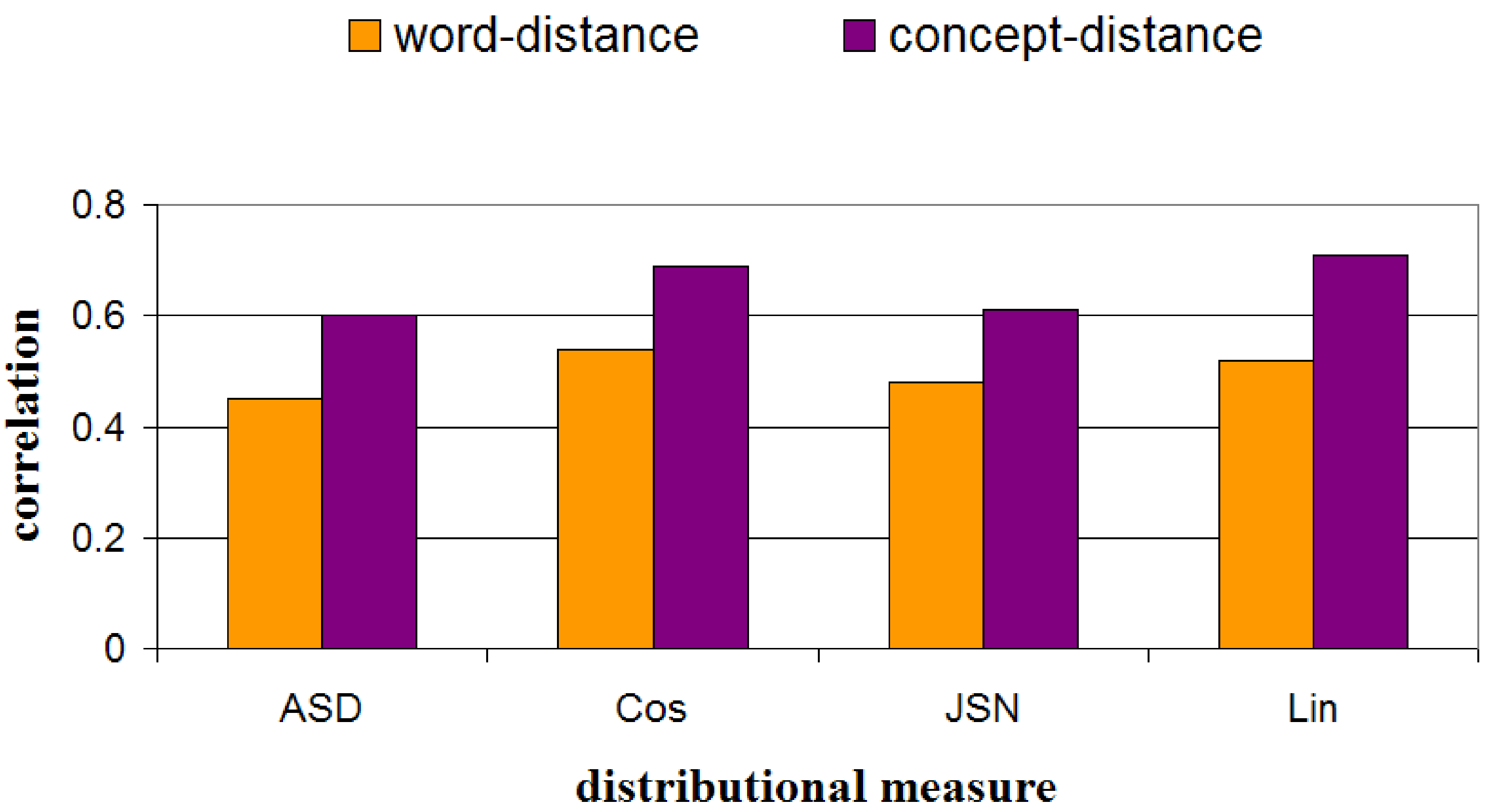
hydrogen 0.07	*light* 0.09
hot 0.07	*space* 0.04

Then, consider the CELESTIAL BODY sense of *star*.

- Distributionally close
- Word sense ambiguity NOT a problem

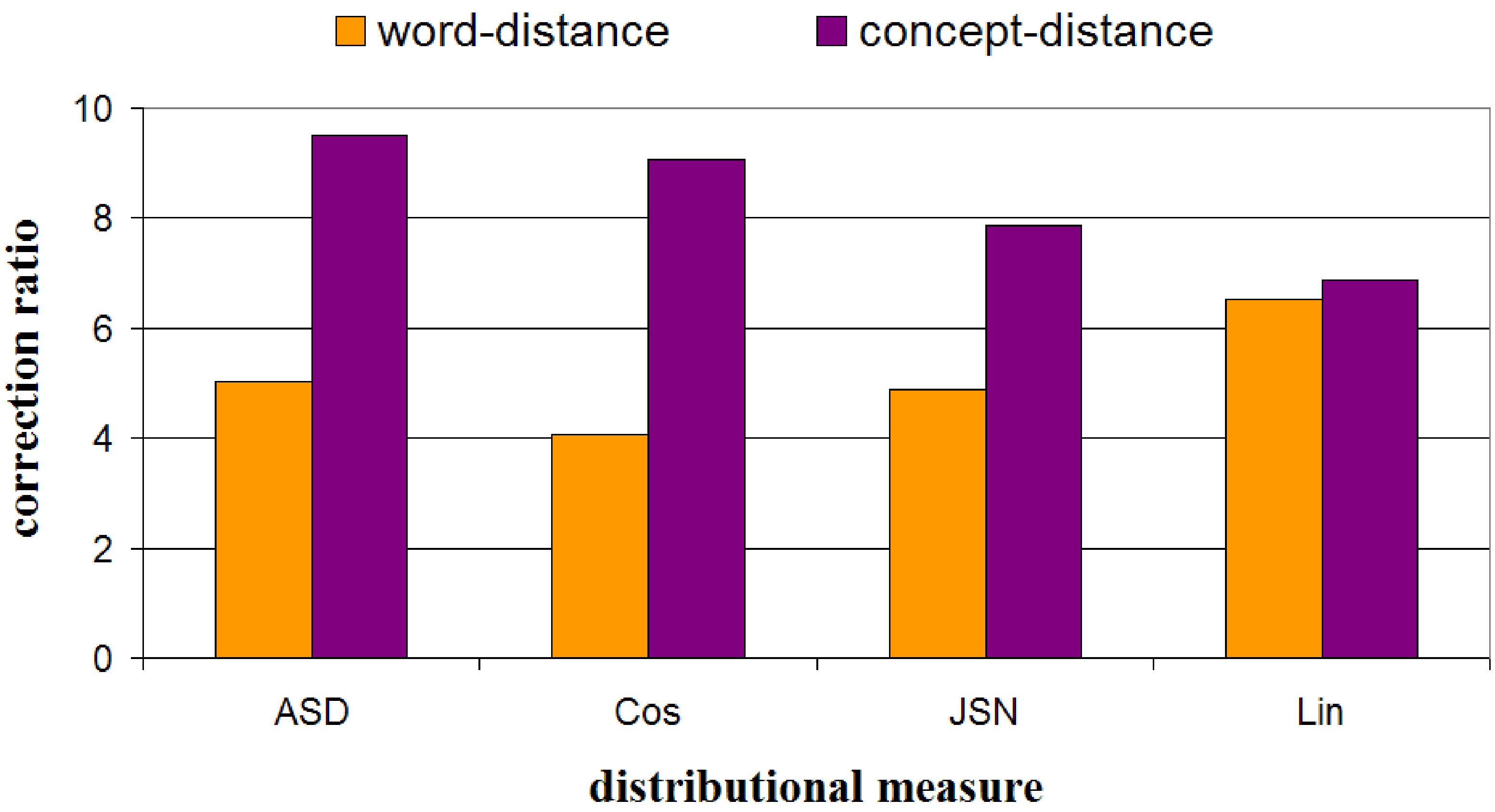
Ranking word pairs

(Monolingual)



Correcting spelling errors

(Monolingual)



But. . .

Application of distance algorithms in most languages is hindered by a lack of high-quality linguistic resources.

So: Make it cross-lingual

- Determining distance in a resource-poor language
  - Combine its text with a thesaurus from a (possibly resource-rich) language
    - Largely alleviates the knowledge-source bottleneck
  - Use a bilingual lexicon
  - Without parallel corpora or sense-annotated data

- Experiments: German as a “resource-poor” language

Cross-lingual links

Stern *Bank* $\mapsto w^{de}$

German words w^{de}

Cross-lingual links

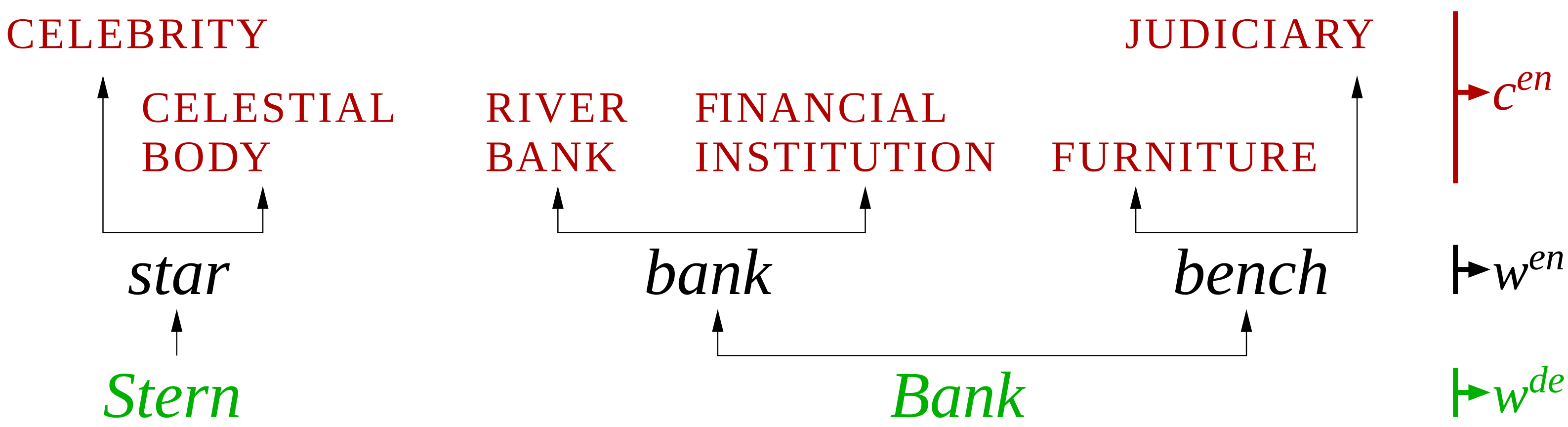
star   *bank*   *bench* $\mapsto w^{en}$

Stern   *Bank* $\mapsto w^{de}$

German words w^{de}

English translations w^{en} (German–English lexicon)

Cross-lingual links

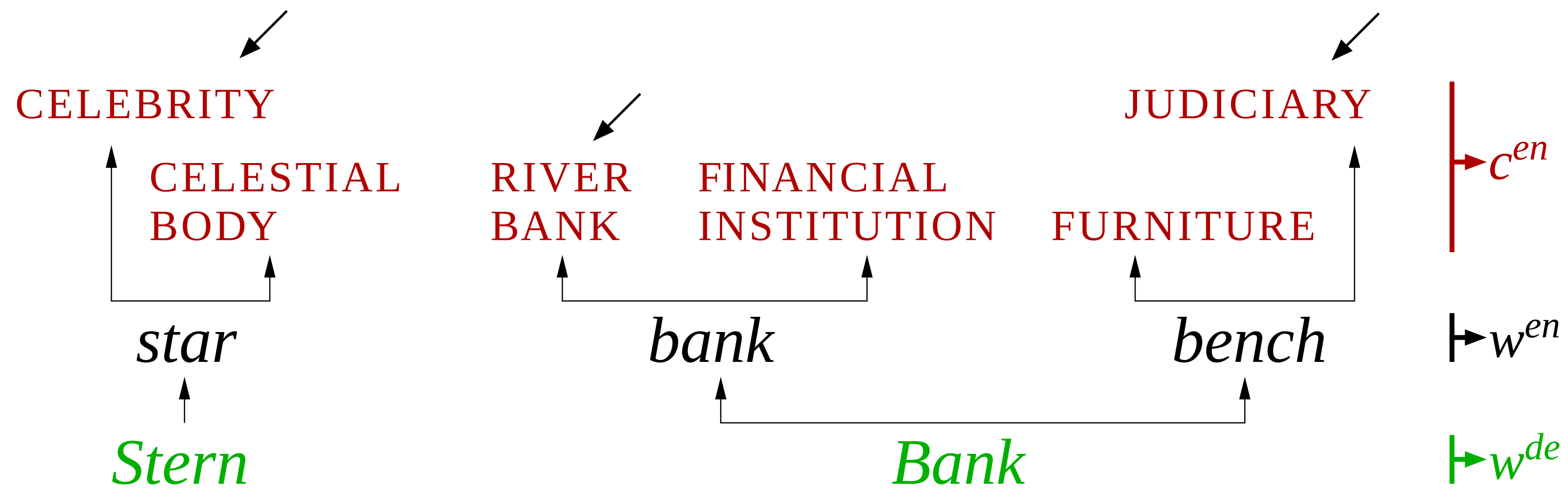


German words w^{de}

English translations w^{en} (German–English lexicon)

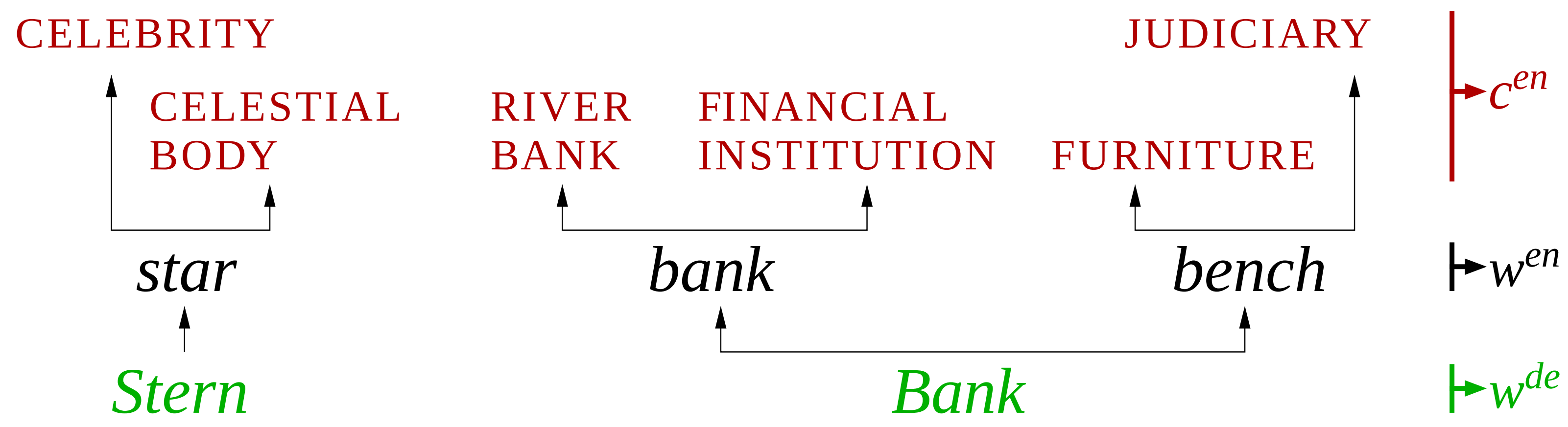
English concepts c^{en} (English thesaurus)

Dealing with ambiguity

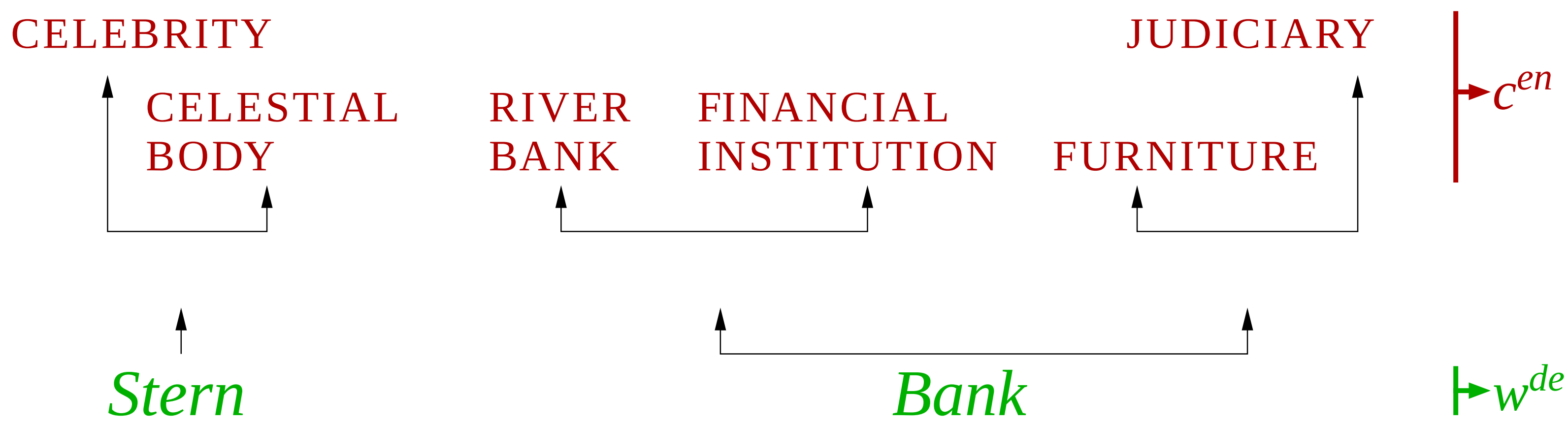


The concepts of CELEBRITY, RIVER BANK and JUDICIARY are semantically unrelated to *Stern* and *Bank*.

Losing the English words



Losing the English words



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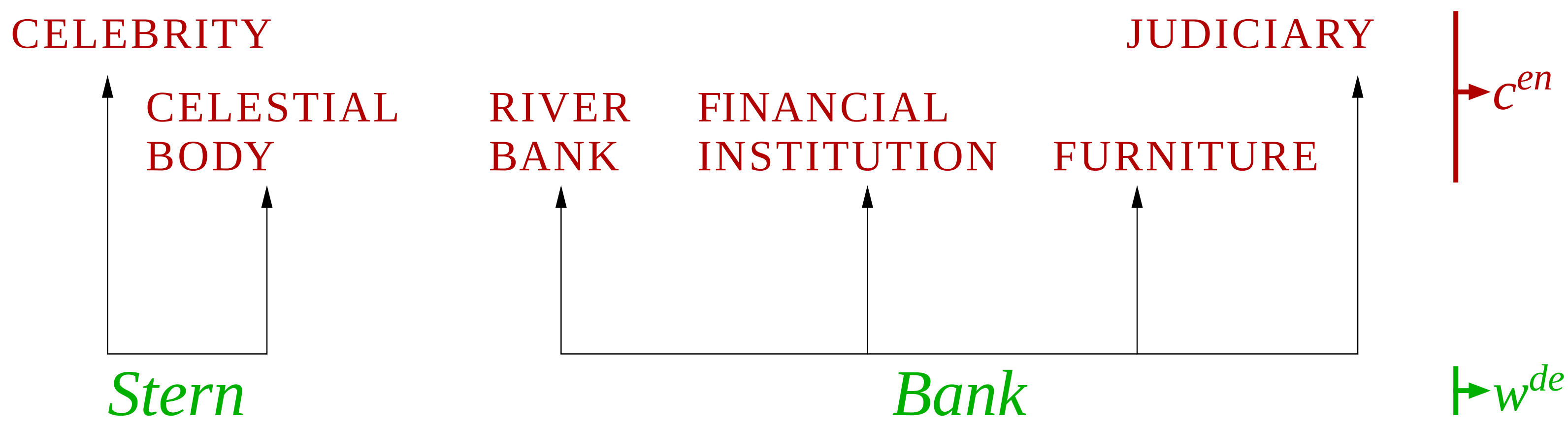


Cross-lingual candidate senses of German words *Stern* and *Bank*

Cross-lingual DPCs

Cross-lingual DPs of the concepts referred to by *star* :

DP of **CELESTIAL BODY**
(celestial body, star, sun,...)

DP of **CELEBRITY**
(celebrity, hero, star,...)

English

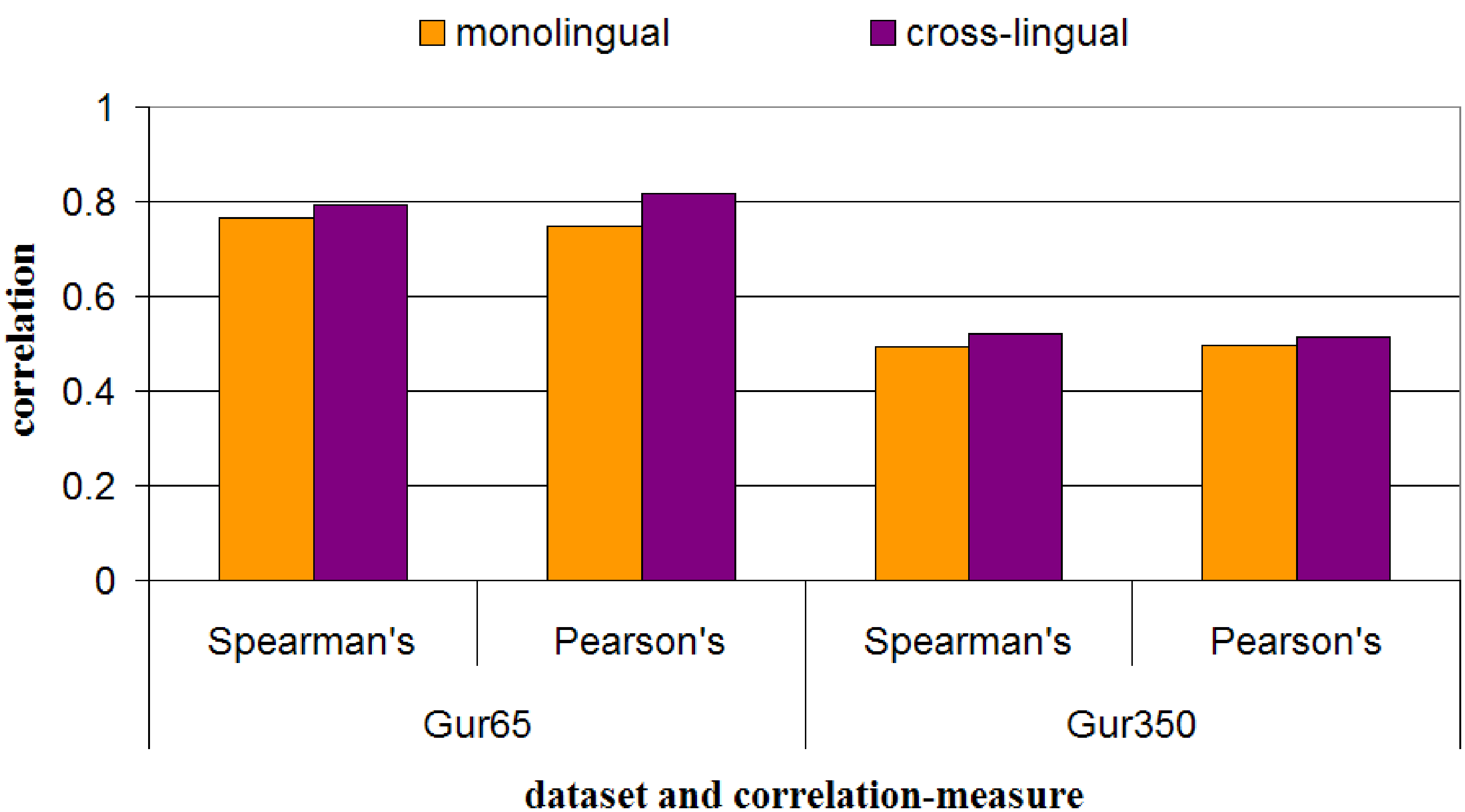
Cross-lingual DPCs

Cross-lingual DPs of the concepts referred to by *star* :

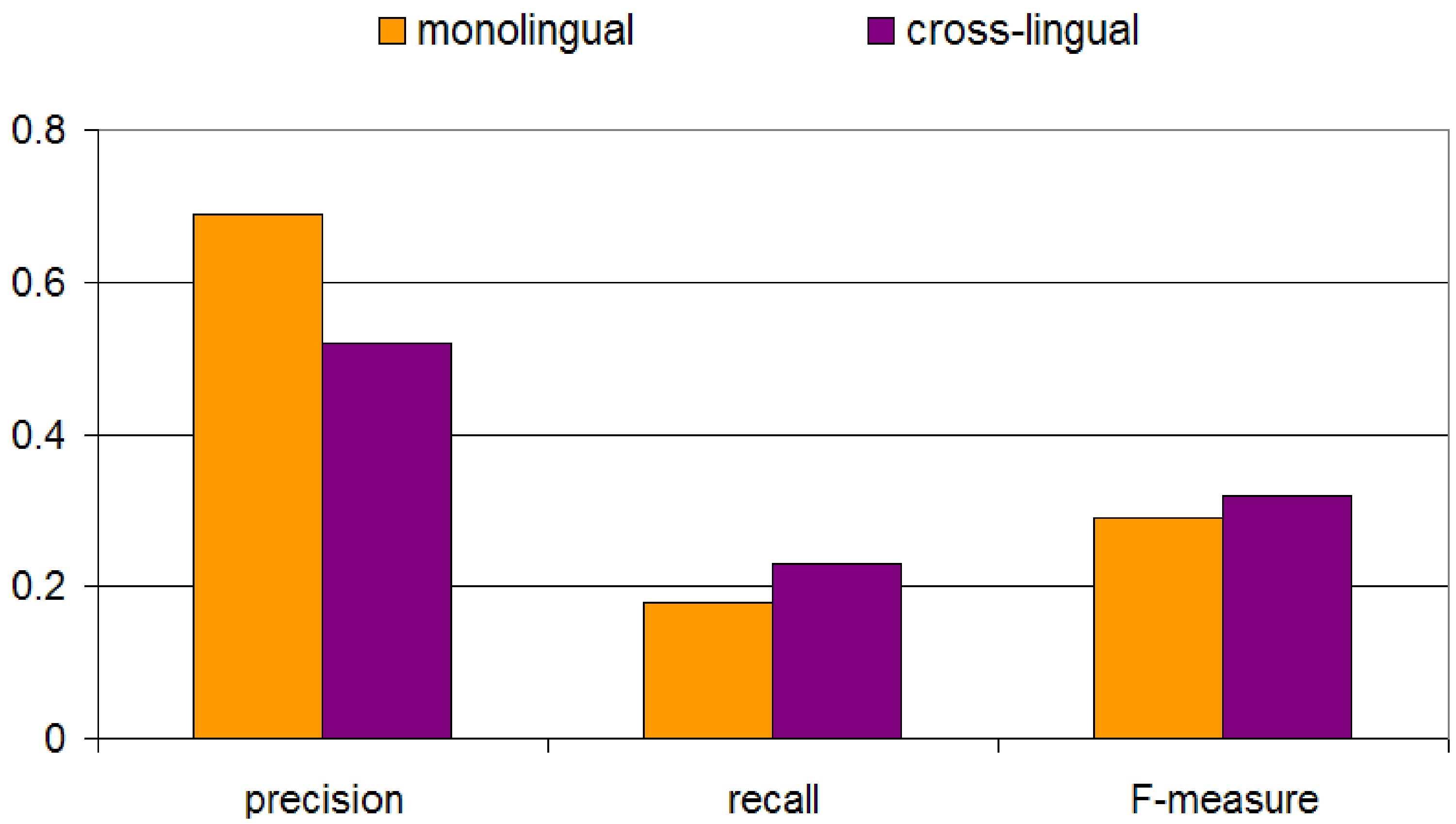
DP of CELESTIAL BODY	**DP of** CELEBRITY	
(celestial body, star, sun,...)	*(celebrity, hero, star,...)*	English
Raum 0.36	*berühmt* 0.24	German
Licht 0.27	*Film* 0.14	
Hitze 0.11	*reich* 0.14	
Planet 0.07	*Fan* 0.10	
Wasserstoff 0.06	*heiß* 0.04	
heiß 0.01	*Mode* 0.01	

Ranking word pairs

(Cross-lingual)



Solving word choice problems
(Cross-lingual)



Distance between a concept and its context

word ... word ... target word ... word ... word

Distance between a concept and its context

CONCEPT2

CONCEPT1

word ... word ... target word ... word ... word

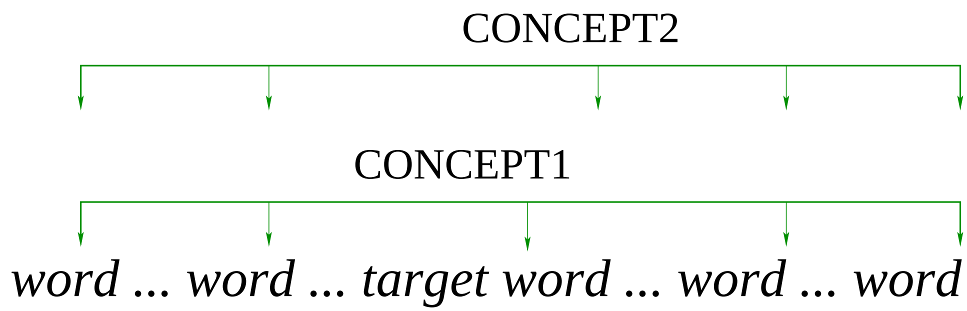
Distance between a concept and its context

CONCEPT2

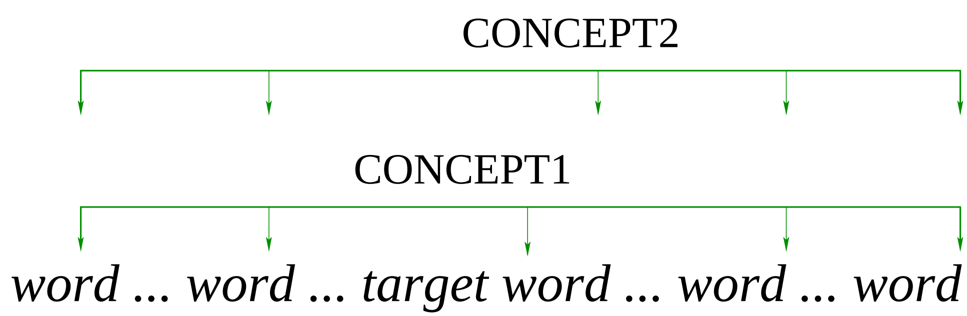
CONCEPT1

word ... word ... target word ... word ... word

Distance between a concept and its context



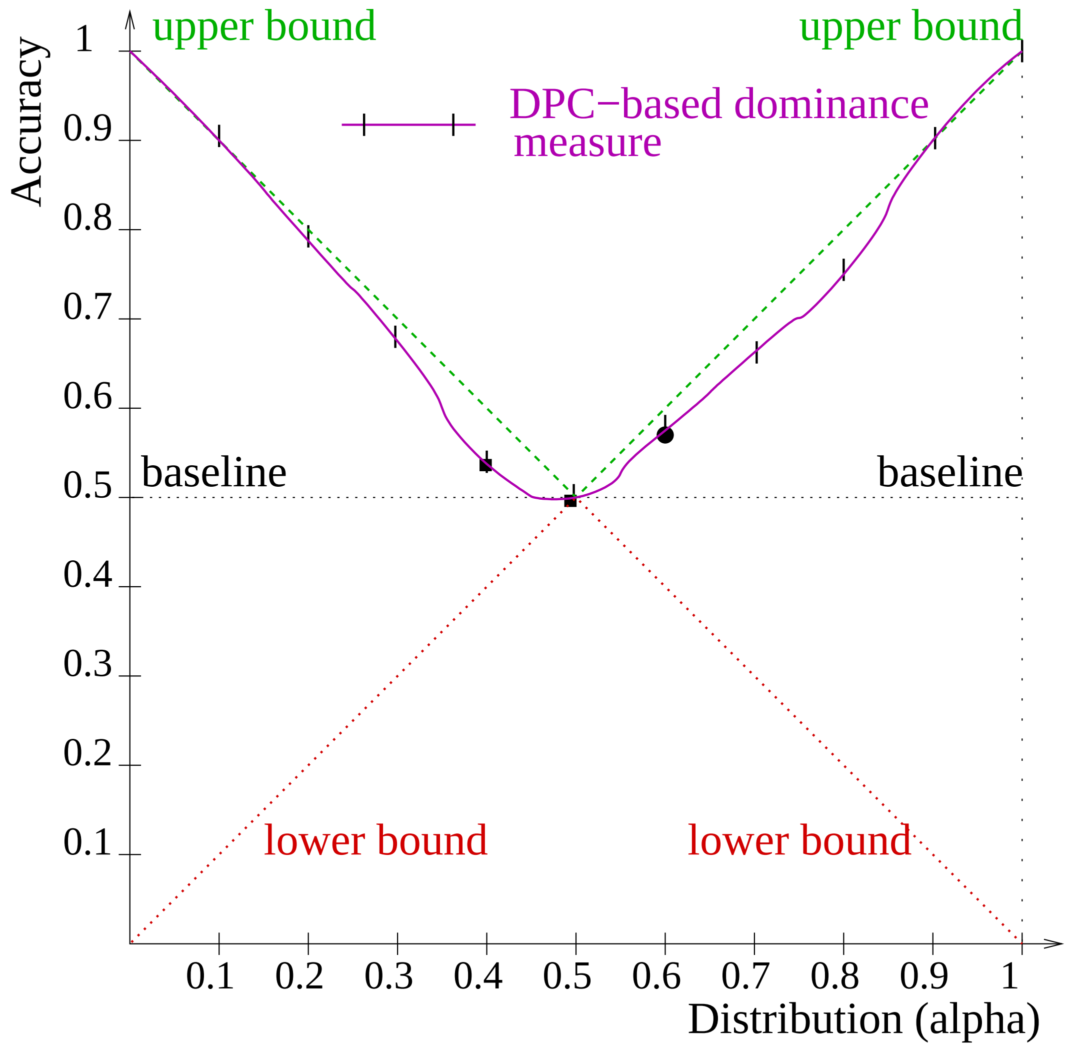
Distance between a concept and its context



Word sense dominance and word sense disambiguation:

- Obviate the need of sense-annotated data

Word sense dominance



Mean distance below upper bound = 0.02

Unsupervised Naïve Bayes word sense classifier

- Estimated probabilities from the DPC
- Took part in SemEval-07's:
  - English Lexical Sample Task
    - Only one percentage point behind the best unsupervised system
  - Multilingual Chinese–English Lexical Sample Task
    - Placed clear first among unsupervised systems

Accomplishments (1)

- Performed a qualitative and quantitative comparison of WordNet-based and distributional measures

- Identified significant limitations of state-of-the-art approaches to measuring semantic distance
  - Word sense ambiguity
    - A hurdle for distributional measures

Accomplishments (2)

- Proposed a new hybrid approach to semantic distance
  - Combines text with a thesaurus
  - Models concepts (rather than words)
  - Uses thesaurus categories as very coarse senses

Accomplishments (3)

- Extensive evaluation
  - Monolingual
    - By combining English text with an English thesaurus
      - Ranked word pairs
      - Corrected real-word spelling errors
      - Determined word sense dominance
      - Did word sense disambiguation

Accomplishments (4)

- Extensive evaluation (continued)
  - Cross-lingual
    - By combining German text with an English thesaurus
      - Ranked word pairs and solving word-choice problems in German
    - By combining Chinese text with an English thesaurus
      - Identified the English translations of Chinese words from their contexts

Future work

- Adding cross-lingual semantic distance as a feature to a state-of-the-art MT system (with Philip Resnik)
- Cross-lingual document clustering
- Cross-lingual information retrieval
- Cross-lingual summarization (with Bonnie Dorr)
- Determining paraphrases, lexical entailment, and contradictions (with Bonnie Dorr)
- Determining cognates using semantic distance between words in different languages (with Greg Kondrak)
- Porting the approach to Wikipedia (with Torsten Zesch and Iryna Gurevych)

Conclusions (1)

- Distributional profiles of concepts can be used to infer their semantic properties, and indeed estimate semantic distance.
- Cross-lingual DPCs allow for a seamless transition from words in one language to concepts in another.

Conclusions (2)

- Distributional measures of concept-distance are markedly superior to previous approaches.

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  - Gives both relatedness and similarity
  - Domain adaptable
  - Can be used in real-time systems
  - Cross-lingual
    - Solve problems in a one language using a knowledge source from another
    - Solve problems that involve multiple languages