Computational approaches to pun detection and interpretation

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Transilvania University of Brașov
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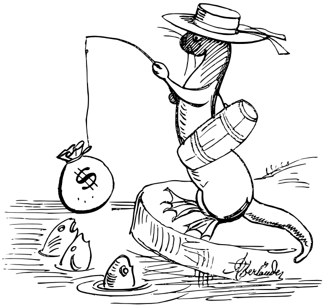
Introduction

- Pun: a form of (humorous) wordplay in which a term suggests two meanings by exploiting a similarity in form



*Where do otters keep their money? At the **bank**!*

Scholarly study of puns

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- Computational humour and puns
  - Pun generation
  - Phonological analysis of puns

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  - Phonological analysis of puns
  - Detection and interpretation of puns

Overview of this talk

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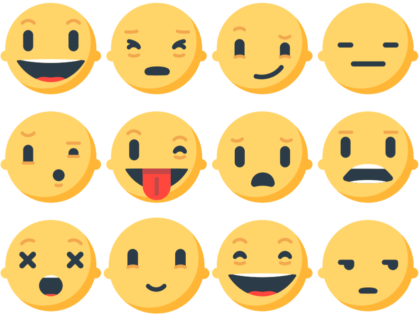
1. Motivation
2. Tasks in computational pun processing
   2.1 Pun detection
   2.2 Pun location
   2.3 Pun interpretation (including recovery of the target form)
3. Conclusions and future directions

Motivation: Human–computer interaction (HCI)

- “Humanization” of natural language interfaces
- Humorous interfaces increase user satisfaction without adversely affecting user efficiency
- Interfaces implementing wordplay and punning benefit augmentative and alternative communication
- Natural language understanding needed to move beyond canned and generated humour

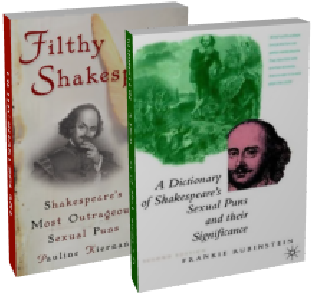
Motivation: Sentiment analysis

- Sentiment analysis: automatically identify subjective information in text
- Useful in social research to track popular opinions and attitudes, and those of influencers
- Puns are particularly common in advertising



Motivation: Digital humanities

- Wordplay is a perennial topic in literary criticism and analysis
- Shakespeare's puns among the most intensively studied aspects of his rhetoric
- Puns in historical literature often non-obvious due to diachronic shifts in semantics and pronunciation, obscure cultural references, etc.
- Digital humanities: computer-assisted analysis of literature



Motivation: Machine-assisted translation

- Comedic movies and TV shows among today's most widely translated popular discourses
- Puns a recurrent, expected feature
- Challenges to translators:
    - Recognition of pun
    - Comprehension of pun
    - Selection and implementation of translation strategy
- MT systems could flag puns and propose ambiguity-preserving alternatives

Puns: Definition and classification

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- Puns are a form of wordplay where a signifier suggests two meanings by exploiting a formal similarity
- Signifier can be any meaning-bearing phonological or orthographic sequence
- Relationship between the surface pun and the latent target:

	homophonic	**heterophonic**
homographic	A political prisoner is one who stands behind her *con-victions*.	A lumberjack's world revolves on its *axes*.
heterographic	She fell through the window but felt no *pane*.	The sign at the nudist camp read, "*Clothed* until April."

Puns: Definition and classification

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- **Homographic:** same spelling
- **Heterographic:** different spelling
- **Homophonic:** same pronunciation
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- **Homographic:** same spelling
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- **Homophonic:** same pronunciation
- **Heterophonic:** different pronunciation
- **Homonymic, perfect:** synonyms for “homophonic” or “homographic” (or sometimes “homophonic and homographic”)
- **Heteronymic, paronymic, paronomasic, imperfect:** synonyms for “non-homonymic”

Computational processing of puns

- **Pun detection:** Given some text, does it contain a pun?

Computational processing of puns

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Computational processing of puns

- **Pun detection:** Given some text, does it contain a pun?
- **Pun location:** Given some text known to contain a pun, which part is the pun?
- **Pun interpretation:** Given some text known to contain a pun, and the location of the pun, what are the meanings of the pun and its target?

Pun detection

- Task: Given some text, does it contain a pun?
- A special case of humour detection

Pun detection

- Task: Given some text, does it contain a pun?
- A special case of humour detection
- General semantic incongruity detection (Mihalcea & Strapparava, 2005, 2006; Mihalcea & Pulman, 2007)
- Detecting a specific class of ambiguity-exploiting joke (Kiddon & Brun, 2011)
- Both of the above approaches rely on machine learning

Machine learning for joke detection

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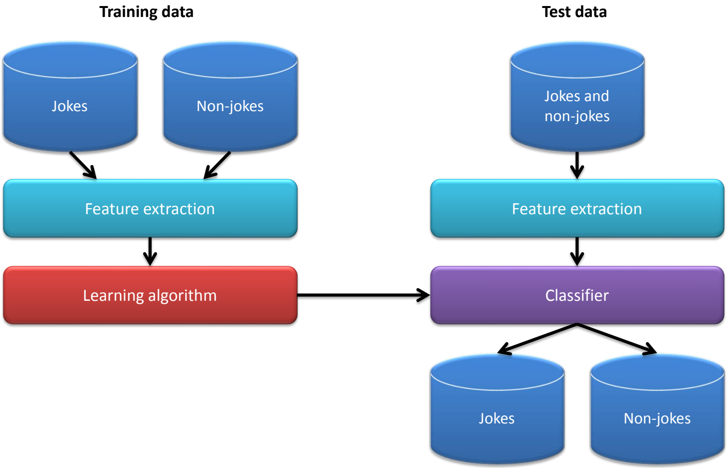

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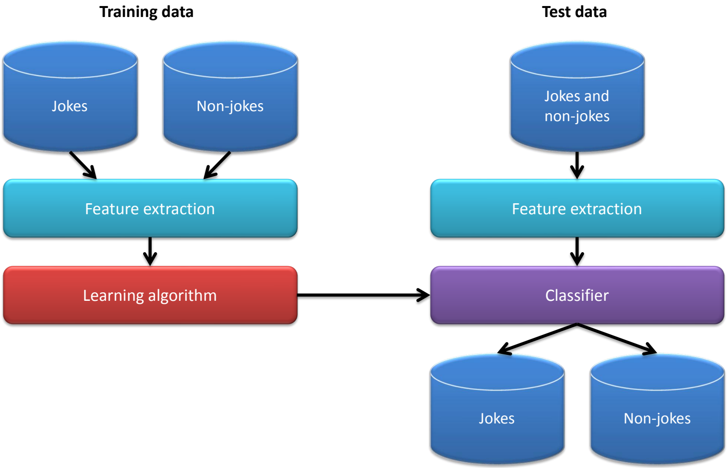

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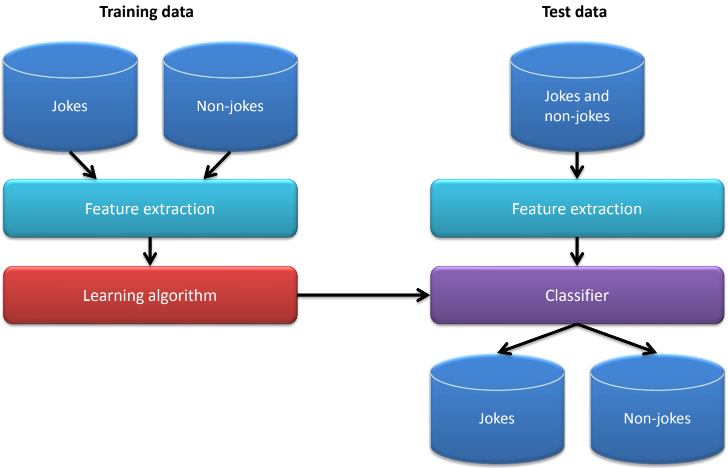

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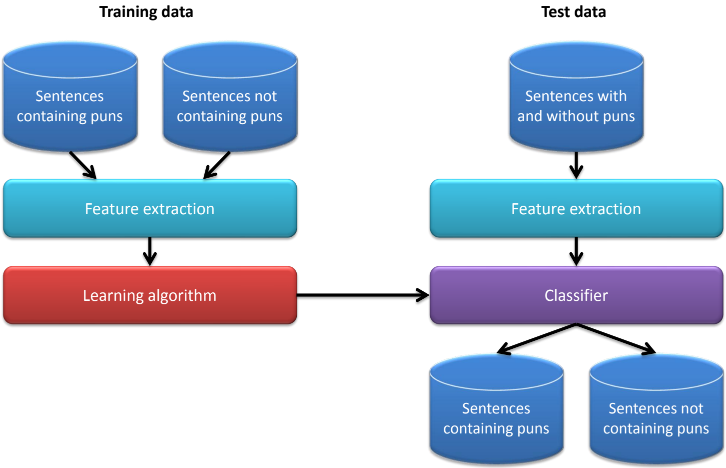

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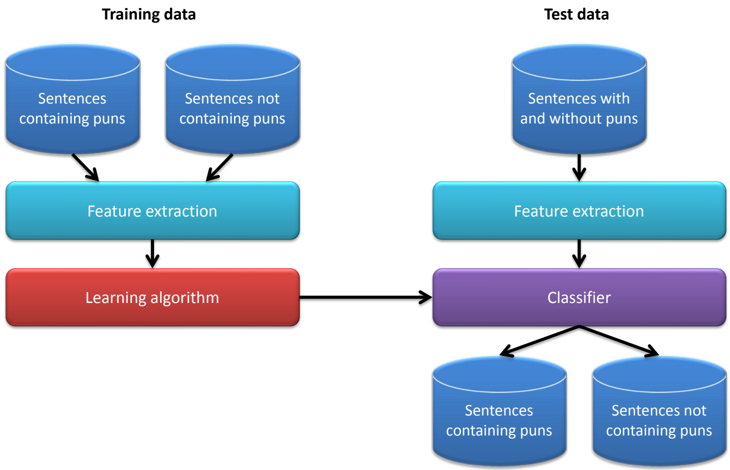

Pun location

- Task: Given some text known to contain a pun, which part is the pun?
- So far only very cursory investigations
- "Highest polysemy" baseline achieves 18% accuracy, compared to 14% for random guessing (Miller, 2016)
- Machine learning approaches might also work here

Pun interpretation

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- Task: Given a context containing a pun, and the location of the pun, identify the meaning of the pun and its target
- Prerequisite for imperfect puns: Determine the form of the target

Background: Interpretation of unambiguous expressions

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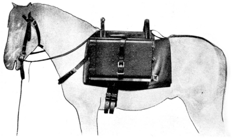

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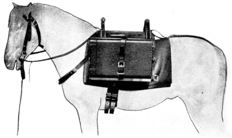
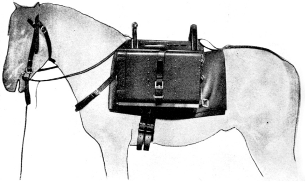


Word sense disambiguation (WSD) is the task of determining which of a word’s senses is intended in a given context.

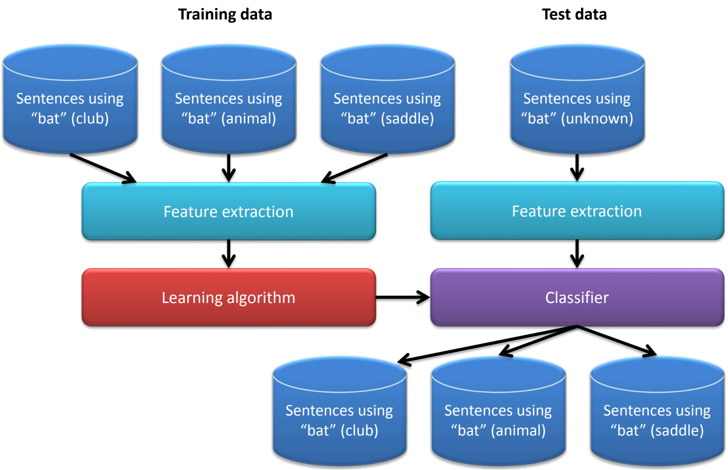
Motivation for WSD

Machine translation does not work unless word senses can be disambiguated:



English:	bat	bat	bat
Romanian:	bâtă	liliac	șa

Supervised word sense disambiguation



Knowledge-based word sense disambiguation

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- No manually annotated training data is required
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"He **hit** the **ball** with the bat."

bat
1. A small, nocturnal flying mammal of order *Chiroptera*.
2. A wooden club used to **hit** a **ball** in various sports.
3. A pack saddle.

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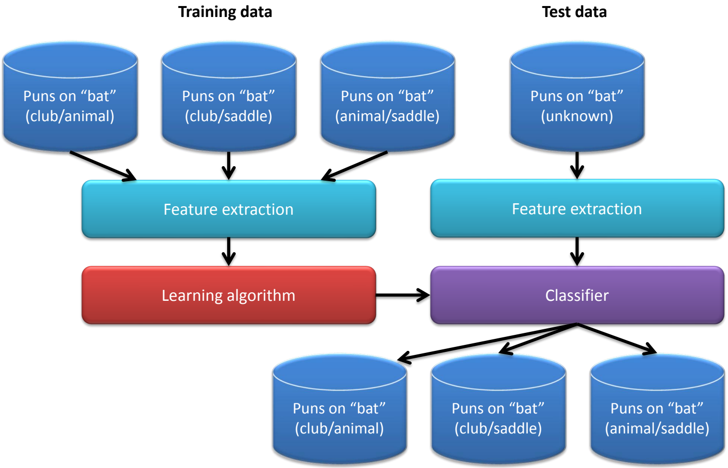
Adapting WSD to (perfect) pun interpretation: Supervised pun interpretation (naïve)



Challenges to supervised pun interpretation

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Knowledge acquisition bottleneck:

- Supervised WSD generally requires a large number of training examples per word sense
- Unrealistic to find large numbers of training examples for each pun

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Knowledge acquisition bottleneck:

- Supervised WSD generally requires a large number of training examples per word sense
- Unrealistic to find large numbers of training examples for each pun
- Combinatorial explosion in number of sense combinations:
  - Assuming a perfect pun on a word with n senses, there are $\binom{n}{2} = \frac{n!}{2(n-2)!}$ classes to distinguish
  - Number of classes practically limitless for imperfect puns

Adapting WSD for perfect pun interpretation: A slightly less naïve way

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- Basic adaptation of WSD systems to pun interpretation:
  - select the *two* top-scoring senses
- Advantages:
  - straightforward
  - works with both supervised and knowledge-based approaches

Adapting WSD for perfect pun interpretation: A slightly less naïve way

- Basic adaptation of WSD systems to pun interpretation:
  - select the *two* top-scoring senses
- Advantages:
  - straightforward
  - works with both supervised and knowledge-based approaches
- Disadvantages:
  - works only for homographic puns
  - works only for monolexemic puns

Adapting WSD for perfect pun interpretation: Further refinements

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- Problem Dictionary sense distinctions often too fine-grained

Adapting WSD for perfect pun interpretation: Further refinements

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- Problem Dictionary sense distinctions often too fine-grained
- Work-around: Cluster senses by similarity; ensure that the system does not choose two senses in the same cluster

Example: Using sense clustering to break ties

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Senses

sloping land (especially the slope beside a body of water)

a long ridge or pile

an arrangement of similar objects in a row or in tiers

a financial institution that accepts deposits…

a building in which the business of banking transacted

a flight maneuver; aircraft tips laterally about its longitudinal axis

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Results

System	Accuracy (%)
Basic Lesk-like disambiguator	11.90
. . . with sense cluster filter	16.77
Random baseline	9.31

Adapting WSD for imperfect pun interpretation: Sound similarity

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Adapting WSD for imperfect pun interpretation: Sound similarity

- Any pair of words can be characterized by their (perceived) similarity in terms of sound or pronunciation.
- Studying pairs with a phonologically constrained relationship can help us model that relationship.
- Conversely, a model that quantifies perceived sound differences between words can assess the probability of a given relationship.
- In particular, a model of sound similarity could help detect and interpret puns.

Early similarity models

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- "Predicted phonetic distance" or "PPD" (Vitz & Winkler, 1973)
  1. Optimally align two phonemic sequences
  2. Compute the relative Hamming distance (i.e., the proportion of non-matching phoneme positions)

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#	ʌ	n	d	ə	ɹ	ɹ	ɪ	∅	∅	t	n	#	*underwritten*

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- Method works better when it is applied separately to the syllable onset, nucleus, and coda.
- Aligning the sequences is a nontrivial task.

Sound similarity based on phonemic features

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  Trying to preserve his savoir faire in a new restaurant, the guest looked down at the eggs the waiter had spilled in his lap and said brightly, "Well, I guess the yolk's on me!"

- Variously mitigated by the use of multivalued features (Ladefoged, 1995), feature salience coefficients (Kondrak, 2002), and Optimality Theory (Lutz & Greene, 2003).

Similarity models based on puns

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- Sobkowiak (1991): pun understandability is maximized when the consonantal skeleton is kept largely intact

Computational pun target recovery

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- Past phonological analyses tend to agree

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	Accuracy (%)		
Model	**Perfect**	**Imperfect**	**Overall**
Hempelmann	47.8	7.7	29.3
Jaech et al.	73.9	65.4	68.0

Conclusions and future directions

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- Pun interpretation is a hard problem
- Machine learning can aid in target recovery for imperfect puns
- Little or no prior work in pun detection and location
- Existing work not deeply based on theories of humour

SemEval-2017 Shared Task on Detection and Interpretation of English Puns

- SemEval: An organized evaluation competition for tasks in computational semantics, since 1998
- Basic shared task setup:
  1. Organizers provide data (annotations withheld)
  2. Participants build annotation systems, submit results
  3. Organizers evaluate, tabulate, and analyze results
  4. Participants write papers describing their systems
- SemEval-2017 to include tasks in pun detection, location, and interpretation
- Two tracks for each task: homographic and heterographic
- Organizers: Iryna Gurevych, Christian F. Hempelmann, Tristan Miller

References and further reading I

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References and further reading IV

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