Graph Clustering for Natural Language Processing

Invited Lecture at Skoltech NLP

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About Me

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Outline

Section 1

Introduction

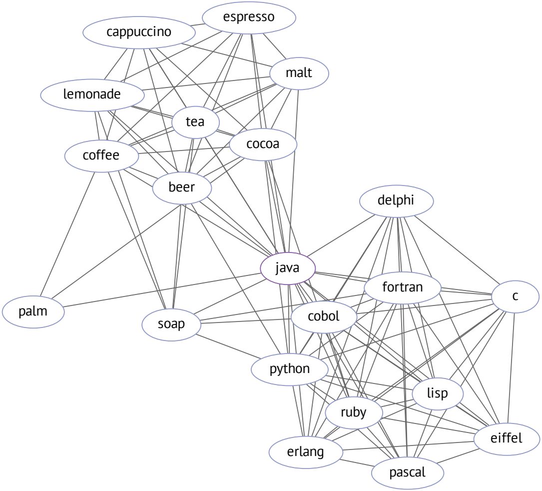
Introduction

- Natural Language Processing (NLP) focuses on *analysis* and synthesis of natural language
- Linguistic phenomena instantinate in linguistic data, showing interconnections and relationships
- **Graph clustering**, as an *unsupervised learning* technique, captures the *implicit structure* of the data
- Today, we will learn how to do it!

Core Idea: Graphs are a Representation

After constructing it explicitly, we can extract useful knowledge from it.

Motivation I



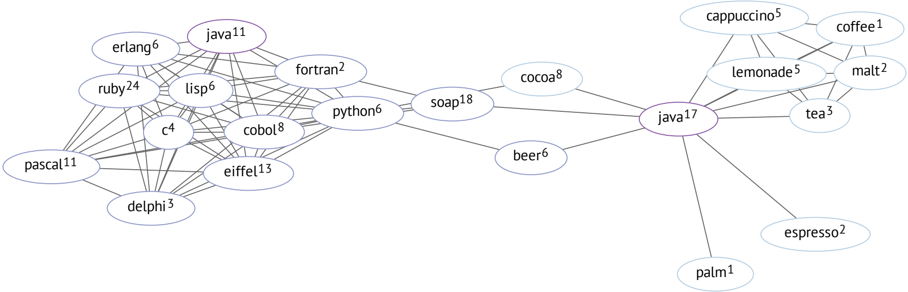
Source: Ustalov et al. (2019)

Look at this *distributional thesaurus*!

- It represents words and their connections
- Can we learn word meanings from its structure?
- Can we infer linguistic knowledge computationally?

Motivation II

Yes, as soon as we employ its structure and observe linguistic regularities.



Source: Ustalov et al. (2019)

This graph is a *disambiguated* distributional thesaurus.

Successful Applications

Graph clustering helps in addressing very challenging NLP problems:

- word sense induction (Biemann, 2006)
- cross-lingual semantic relationship induction (Lewis et al., 2013)
- unsupervised term discovery (Lyzinski et al., 2015)
- making sense of word embeddings (Pelevina et al., 2016)
- text summarization (Azadani et al., 2018)
- entity resolution from multiple sources (Tauer et al., 2019)

Other well-known applications of graph-based methods (not clustering):

- **PageRank**, a citation-based ranking algorithm (Page et al., 1999)
- **BabelNet**, a multilingual semantic network (Navigli et al., 2012)

Section 2

Graph Theory Recap

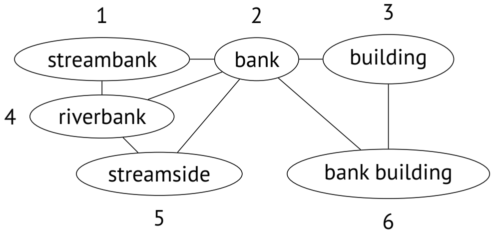
Graph Theory Recap I

- A graph is a tuple $G = (V, E)$, where V is a set of objects called *nodes* and $E \subseteq V^2$ is a set of pairs called *edges*
- Graphs can be undirected (edges are unordered) or directed (edges are called *arcs*)
  - The maximal number of edges in an *undirected* graph is $\frac{|V|(|V|-1)}{2}$
  - The maximal number of arcs in a *directed* graph is $|V|(|V|-1)$
- Graphs can be *weighted*, i.e., there is $w : (u, v) \to \mathbb{R}, \forall (u, v) \in E$
- A neighborhood $G_u = (V_u, E_u)$ is a subgraph induced from G containing the nodes *incident* to $u \in V$ without u

Graph Theory Recap II

- There is a lot of ways to represent a graph, the most common is *adjacency matrix* $A_{i,j} = \mathbb{1}_E(V_i, V_j)$:

$$A = \begin{pmatrix} 0 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 0 \end{pmatrix}$$



- Sparse matrices can be efficiently represented in such formats as CSC (Duff et al., 1989), CSR (Buluç et al., 2009), etc.
- A node *degree* is the number of nodes incident to this node, e.g., $\deg(\text{riverbank}) = 3$; the maximal degree Δ in this graph is 5
- In a directed graph, $\operatorname{succ}(u) \subset V$ is a set of *successors*, which are the nodes reachable from $u \in V$

Graph Clustering: Problem Formulation

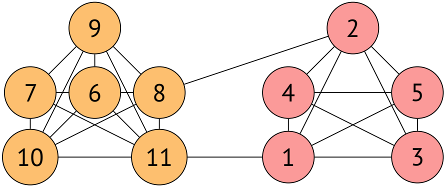
- Given an *undirected* graph $G = (V, E)$, we are interested in obtaining a set cover for V called *clustering* C of this graph:

$$V = \bigcup_{C^i \in C} C^i$$

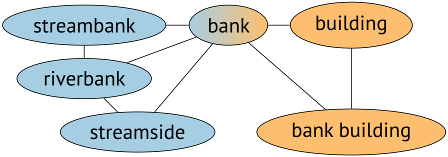
- **Hard clustering** algorithms (partitionings) produce non-overlapping clusters: $C^i \cap C^j = \emptyset \iff i \neq j, \forall C^i, C^j \in C$
- **Soft clustering** algorithms permit cluster overlapping, i.e., a node can be a member of several clusters: $\exists u \in V : |C^i \in C : u \in C^i| > 1$
- Like in other *unsupervised learning* tasks, similar objects are expected to be close, while non-similar are not
- Every algorithm defines what good clustering is

Graph Clustering: Example

Hard Clustering



Soft Clustering



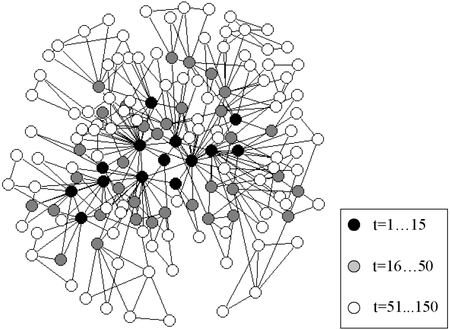
Can We Trust Graphs?

Graphs representing languistic phenomena exhibit **small world** properties (Biemann, 2012):

- *co-occurrence networks* tend to follow the Dorogovtsev-Mendes distribution (2001),
- *semantic networks* tend to follow the scale-free properties (Steyvers et al., 2005), etc.

Yes We Can

These properties do not depend on a language w.r.t. the parameters.



Source: Steyvers et al. (2005)

Section 3

Clustering Algorithms

Clustering Algorithms

We will focus on four different clustering algorithms:

- Chinese Whispers (CW)
- Markov Clustering (MCL)
- MaxMax
- Watset

There are *a lot* of other clustering algorithms!

Chinese Whispers (CW)

- **Chinese Whispers** (CW) is a *randomized* hard clustering algorithm for both weighted and unweighted graphs (Biemann, 2006)
- Named after a famous children's game, it uses random shuffling to induce clusters
- Originally designed for such NLP tasks as word sense induction, language separation, etc.

Source: Adamovich (2015)

Chinese Whispers: Algorithm

Input: graph $G = (V, E), \text{weight} : (G_u, i) \to \mathbb{R}, \forall u \in V, 1 \leq i \leq |V|$
Output: clustering C

1: $\text{label}(V_i) \leftarrow i$ **for all** $1 \leq i \leq |V|$ ▷ Initialization
2: **while** labels change **do** ▷ $\text{labels}(G_u)$ is a set of node labels in G_u
3: **for all** $u \in V$ in random order **do**
4: $\text{label}(u) \leftarrow \arg\max_{i \in \text{labels}(G_u)} \text{weight}(G_u, i)$
▷ Pick the most weighted label in G_u
5: $C \leftarrow \{\{u \in V : \text{label}(u) = i\} : i \in \text{labels}(G)\}$
6: **return** C

Chinese Whispers: Label Weighting

Typical strategies to weigh the labels in the neighborhood G_u of u in G:

- Sum of the edge weights corresponding to the label i (`top`):

$$\text{weight}(G_u, i) = \sum_{\{u,v\} \in E_u : \text{label}(v) = i} w(u, v)$$

- Use the node degree $\deg(v)$ to amortize highly-weighted edges (`linear`):

$$\text{weight}(G_u, i) = \sum_{\{u,v\} \in E_u : \text{label}(v) = i} \frac{w(u,v)}{\deg(v)}$$

- Use log-degree for amortization (`log`):

$$\text{weight}(G_u, i) = \sum_{\{u,v\} \in E_u : \text{label}(v) = i} \frac{w(u,v)}{\log(1 + \deg(v))}$$

Chinese Whispers: Example

- We consider an example on a graph from Biemann (2006, Figure 2)

Chinese Whispers: Discussion

Pros:

- Very simple and non-parametric
- Very fast, the running time is $O(|E|)$
- Works well for a lot of NLP tasks

Cons:

- Every run yields different results
- Node oscillation is possible
- No convergence guarantee

Implementations:

- https://github.com/uhh-lt/chinese-whispers
- https://github.com/nlpub/chinese-whispers-python

Markov Clustering (MCL)

- **Markov Clustering** (MCL) is a *stochastic* hard clustering algorithm that simulates *flows* in a graph using **random walks** (van Dongen, 2000)
- The algorithm makes a series of adjacency matrix transformations to obtain the partitioning: *expansion* and *inflation*
- MCL has been applied in a number of different domains, mostly in bioinformatics (Vlasblom et al., 2009)
- Similar to Affinity Propagation (Frey et al., 2007)

Source: Merrill (2014)

Markov Clustering: Algorithm

Input: graph $G = (V, E)$, adjacency matrix A,
expansion parameter $e \in \mathbb{N}$, inflation parameter $r \in \mathbb{R}^+$

Output: clustering C

1: $A_{i,i} \leftarrow 1$ **for all** $1 \leq i \leq |V|$ ▷ Add self-loops
2: $A_{i,j} \leftarrow \frac{A_{i,j}}{\sum_{1 \leq k \leq |V|} A_{k,j}}$ **for all** $1 \leq i \leq |V|, 1 \leq j \leq |V|$ ▷ Normalize
3: **while** A changes **do**
4: $A \leftarrow A^e$ ▷ Expand
5: $A_{i,j} \leftarrow A^r_{i,j}$ **for all** $1 \leq i \leq |V|, 1 \leq j \leq |V|$ ▷ Inflate
6: $A_{i,j} \leftarrow \frac{A_{i,j}}{\sum_{1 \leq k \leq |V|} A_{k,j}}$ **for all** $1 \leq i \leq |V|, 1 \leq j \leq |V|$ ▷ Normalize
7: $C \leftarrow \{\{V_j \in V : A_{i,j} \neq 0\} : 1 \leq i \leq |V|, 1 \leq j \leq |V|\}$
8: **return** C

Markov Clustering: Example

- We consider an example on a graph from Biemann (2006, Figure 2)

Markov Clustering: Discussion

Pros:

- \+ Eventually, the algorithm converges (but there is no formal proof)
- \+ Works well for a lot of NLP tasks

Cons:

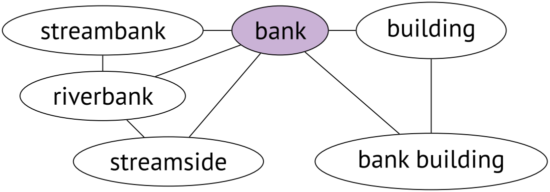
- − Relatively slow, the worst-case running time is $O(|V|^3)$
- − An efficient implementation requires sparse matrices

Implementations:

- https://micans.org/mcl/

This Clustering is Very Hard!

- OK, but how about the fact that the word "bank" is polysemeous?
- Hard clustering algorithms will treat this word incorrectly



Source: McGuire (2015)

MaxMax

- **MaxMax** is a *soft* clustering algorithm designed for *weighted* graphs, such as co-occurrence graphs (Hope et al., 2013a)
- MaxMax transforms the input undirected weighted graph G into an unweighted directed graph G'
- Then, it extracts *quasi-strongly connected* subgraphs from G', which are overlapping clusters

Source: Rahman Rony (2016)

MaxMax: Algorithm

Input: graph $G = (V, E)$, weigthing function $w : E \to \mathbb{R}$
Output: clustering C

$E' \leftarrow \emptyset$
for all $\{u, v\} \in E$ **do**
    if $w(u, v) = \max_{v' \in V_u} w(u, v')$ **then**
        $E' \leftarrow E' \cup \{(v, u)\}$
$G' = (V, E')$
$\mathrm{root}(u) \leftarrow \mathrm{true}$ **for all** $u \in V$
for all $u \in V$ **do** $\triangleright$ Can be done using BFS
    if $\mathrm{root}(u)$ **then**
        for all $v \in \mathrm{succ}(u)$ **do** $\triangleright$ Successors of u in G'
            $\mathrm{root}(u) \leftarrow \mathrm{false}$
$C \leftarrow \{\{u\} \cup \mathrm{succ}(u) : u \in V, \mathrm{root}(u)\}$
return C

MaxMax: Example

- We consider an example from Hope et al. (2013a, Figure 3)

MaxMax: Discussion

Pros:

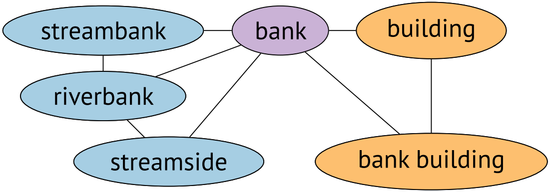
+ The algorithm is non-parametric
+ Very fast, the running time is $O(|E|)$, like CW
+ Works well for word sense induction (Hope et al., 2013b)

Cons:

- Assumptions are not clear
- Applicability seems to be limited (Ustalov et al., 2019)
- No implementation offered by the authors

Graph-Based Word Sense Induction (WSI)

- Dorow et al. (2003) proposed a nice approach for **word sense induction** (WSI) using graphs
- Extract the *node neighborhood*, remove the node, and cluster the remaining graph
- Every cluster C^i corresponds to the *context* of the i-th sense of the node



Source: Kittner (2015)

Watset

- **Watset** is not a clustering algorithm
- However, it is a *meta-algorithm* for turning *hard* clustering algorithms into *soft* clustering algorithms
- Watset **transforms** the input graph by replacing each node with one or more *senses* of this node using *word sense induction* (Dorow et al., 2003) and *context disambiguation* (Faralli et al., 2016)
- We will focus on the better variation called **Simplified Watset** (or Watset§) as described in Ustalov et al. (2019, Section 3.4)

Source: FreePhotosART (2016)

Watset: Algorithm

Input: graph $G = (V, E)$, algorithms $\mathrm{Cluster}_{\mathsf{Local}}$ and $\mathrm{Cluster}_{\mathsf{Global}}$
Output: clusters C

for all $u \in V$ **do** ▷ Local Step
    $V_u \leftarrow \{v \in V : \{u, v\} \in E\}$ ▷ Note that $u \notin V_u$
    $E_u \leftarrow \{\{v, w\} \in E : v, w \in V_u\}$
    $G_u \leftarrow (V_u, E_u)$
    $C_u \leftarrow \mathrm{Cluster}_{\mathsf{Local}}(G_u)$ ▷ Cluster the open neighborhood of u
    for all $C_u^i \in C_u$ **do**
        for all $v \in C_u^i$ **do**
            $\mathrm{senses}[u][v] \leftarrow i$ ▷ Node v is connected to the i-th sense of u
        $\mathcal{V} \leftarrow \mathcal{V} \cup \{u^i\}$
$\mathcal{E} \leftarrow \{\{u^{\mathrm{senses}[u][v]}, v^{\mathrm{senses}[v][u]}\} \in \mathcal{V}^2 : \{u, v\} \in E\}$ ▷ Global Step
$\mathcal{G} \leftarrow (\mathcal{V}, \mathcal{E})$
$\mathcal{C} \leftarrow \mathrm{Cluster}_{\mathsf{Global}}(\mathcal{G})$ ▷ Prepare to remove node labels
return $\{\{u \in V : \hat{u} \in \mathcal{C}^i\} \subseteq V : \mathcal{C}^i \in \mathcal{C}\}$

Watset: Example

- We consider an example from Ustalov et al. (2019)

Watset: Discussion

Pros:

- \+ Conceptually, very simple
- \+ Scales very well
- \+ Shows very good results on very different tasks (Ustalov et al., 2019)

Cons:

- − Adds overhead for local clustering of $O(|V|^2\Delta^2)$ for CW and $O(|V|^3\Delta^3)$ for MCL
- − As good as the underlying clustering algorithms are good

Implementations:

- https://github.com/dustalov/watset
- https://github.com/nlpub/watset-java

  The Java implementation of Watset also contains CW, MCL, and MaxMax. **Feel free to play with them!**

Section 4

Evaluation

Evaluation

- Clustering is an *unsupervised* task, so evaluation is not easy
  - For evaluating *hard* clustering algorithms, it is possible to use the evaluation techniques for flat clustering, see Manning et al. (2008, Chapter 16)
  - Evaluation of *soft* clustering is an even more challenging task, we will focus on *paired F-score* and *normalized modified purity*
- There are a lot of others, such as generalized conventional mutual information (Viamontes Esquivel et al., 2012), etc.
- Also, apparently, NLP researchers do not pay enough attention to statistical significance of their results (Dror et al., 2018)

Paired Precision, Recall, and F_1-score

- Every cluster C^i can be represented as a complete graph of $\frac{|C^i|(|C^i|-1)}{2}$ undirected edges (pairs) P^i
- A clustering C can be then compared to a gold clustering C_G using *paired F-score* between pair unions P and P_G (Manandhar et al., 2010):

$$\mathrm{TP} = |P \cup P_G|, \quad \mathrm{FP} = |P \setminus P_G|, \quad \mathrm{FN} = |P_G \setminus P|$$
$$\mathrm{Pr} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}, \quad \mathrm{Re} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}, \quad \mathrm{F}_1 = 2\frac{\mathrm{Pr} \times \mathrm{Re}}{\mathrm{Pr} + \mathrm{Re}}$$

- This is a very straightforward and interpretable approach, but it does not explicitly assess the quality of overlapping clusters

Normalized Modified Purity

- **Purity** is a measure of the extent to which clusters contain a single class (Manning et al., 2008), which is useful for evaluating *hard* clusterings:

$$\mathrm{PU} = \frac{1}{|C|} \sum_{i}^{|C|} \max_{j} |C^i \cap C_G^j|$$

- Kawahara et al. (2014) proposed *normalized modified purity* for *soft* clustering that considers weighted overlaps $\delta_{C^i}(C^i \cap C_G^j)$:

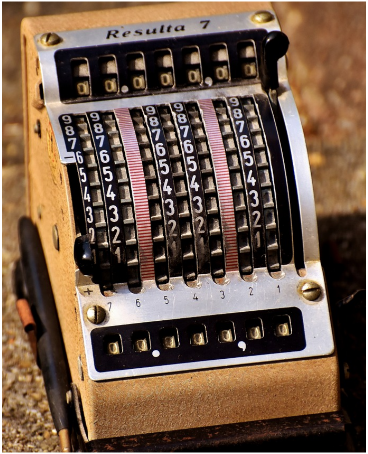
$$\mathrm{nmPU} = \frac{1}{|C|} \sum_{i \text{ s.t. } |C^i|>1}^{|C|} \max_{1 \leq j \leq |C_G|} \delta_{C^i}(C^i \cap C_G^j)$$

$$\mathrm{niPU} = \frac{1}{|C_G|} \sum_{j=1}^{|G|} \max_{1 \leq i \leq |C|} \delta_{C_G^j}(C^i \cap C_G^j)$$

$$\mathrm{F}_1 = 2\frac{\mathrm{nmPU} \times \mathrm{niPU}}{\mathrm{nmPU} + \mathrm{niPU}}$$

Statistical Significance

- It is not enough just to measure the clustering quality, it is necessary to evaluate the statistical significance!
- However, the use of statistical tests is not yet widespread in NLP experiments (Dror et al., 2018)
- Use computationally-intensive **randomization tests** for precision, recall and F-score (Yeh, 2000)
  - "No difference in means after *shuffling*"
- Consider the `sigf` toolkit (Padó, 2006) that implements these tests in Java



Source: Alexas_Fotos (2017)

Randomization Test for Average Values

Input: vectors $\vec{A}$ and $\vec{B}$, number of trials $N \in \mathbb{N}$
Output: two-tailed p-value

$\text{uncommon} \leftarrow \{1 \leq i \leq |\vec{A}| : A_i \neq B_i\}$
$s \leftarrow 0$
for all $1 \leq n \leq N$ **do**
  $\vec{A}' \leftarrow \vec{A}$ ▷ Copy $\vec{A}$
  $\vec{B}' \leftarrow \vec{B}$ ▷ Copy $\vec{B}$
  for all $i \in \text{uncommon}$ **do**
    if $\texttt{rand}(1) = 0$ **then** ▷ Flip a coin
      $A'_i, B'_i \leftarrow B_i, A_i$ ▷ Shuffle by swapping the values if tails
  if $|\text{mean}(\vec{A}') - \text{mean}(\vec{B}')| \geq |\text{mean}(\vec{A}) - \text{mean}(\vec{B})|$ **then**
    $\text{s} \leftarrow \text{s} + 1$ ▷ The test is two-tailed
return $\frac{s}{N}$ ▷ This value can be compared to a significance level

Randomization Test for Average Values: Example

Example from Padó (2006):

- $\vec{A} = (1, 2, 1, 2, 2, \mathbf{2}, 0), \quad \mathrm{mean}(\vec{A}) \approx 1.4286$
- $\vec{B} = (4, 5, 5, 4, 3, \mathbf{2}, 1), \quad \mathrm{mean}(\vec{B}) \approx 3.4286$
- $\mathrm{uncommon} = \{1, 2, 3, 4, 5, 7\}$
- $|\mathrm{mean}(\vec{A}) - \mathrm{mean}(\vec{B})| = 2$
- $N = 10^6$
- $p \approx 0.0313$
- Given the significance level of 0.05, the difference is significant

This technique can be generalized to F-score and others (Yeh, 2000).

Section 5

Case Studies

Case Studies

We describe two case studies from our COLI paper (Ustalov et al., 2019):

- **Synset Induction** from Synonymy Dictionaries
- Unsupervised Semantic **Frame Induction**

Source: Finnsson (2017)

- Ontologies and thesauri are crucial to many NLP applications that require common sense reasoning
- The building blocks of WordNet (Fellbaum, 1998) are **synsets**, sets of mutual synonyms

  {*broadcast*, *program*, *programme*}
- Can we build synsets from scratch using just *synonymy dictionaries* like Wiktionary?

Source: Buissinne (2016)

Synset Induction: WordNet

WordNet Search - 3.1
- WordNet home page - Glossary - Help

Word to search for: cat [Search WordNet]

Display Options: (Select option to change) [Change]

Key: "S:" = Show Synset (semantic) relations, "W:" = Show Word (lexical) relations

Display options for sense: (gloss) "an example sentence"

Noun

- S: (n) **cat**, true cat (feline mammal usually having thick soft fur and no ability to roar: domestic cats; wildcats)
  - ***direct hyponym*** / *full hyponym*
    - S: (n) domestic cat, house cat, Felis domesticus, Felis catus (any domesticated member of the genus Felis)
    - S: (n) wildcat (any small or medium-sized cat resembling the domestic cat and living in the wild)
  - *direct hypernym* / *inherited hypernym* / *sister term*
    - S: (n) feline, felid (any of various lithe-bodied roundheaded fissiped mammals, many with retractile claws)
      - S: (n) carnivore (a terrestrial or aquatic flesh-eating mammal) *"terrestrial carnivores have four or five clawed digits on each limb"*
        - S: (n) placental, placental mammal, eutherian, eutherian mammal (mammals having a placenta; all mammals except monotremes and marsupials)
          - S: (n) mammal, mammalian (any warm-blooded vertebrate having the skin more or less covered with hair; young are born alive except for the small subclass of monotremes and nourished with milk)
            - S: (n) vertebrate, craniate (animals having a bony or cartilaginous skeleton with a segmented spinal column and a large brain enclosed in a skull or cranium)
              - S: (n) chordate (any animal of the phylum Chordata having a notochord or spinal column)
                - S: (n) animal, animate being, beast, brute, creature, fauna (a living organism characterized by voluntary movement)
                  - S: (n) organism, being (a living thing that has (or can develop) the ability to act or function independently)
                    - S: (n) living thing, animate thing (a living (or once living) entity)
                      - S: (n) whole, unit (an assemblage of parts that is regarded as a single entity) *"how big is that part compared to the whole?"; "the team is a unit"*
                        - S: (n) object, physical object (a tangible and visible entity; an entity that can cast a shadow) *"it was full of rackets, balls and other objects"*
                          - S: (n) physical entity (an entity that has physical existence)
                            - S: (n) entity (that which is perceived or known or inferred to have its own distinct existence (living or nonliving))

Source: `http://wordnetweb.princeton.edu/perl/webwn`

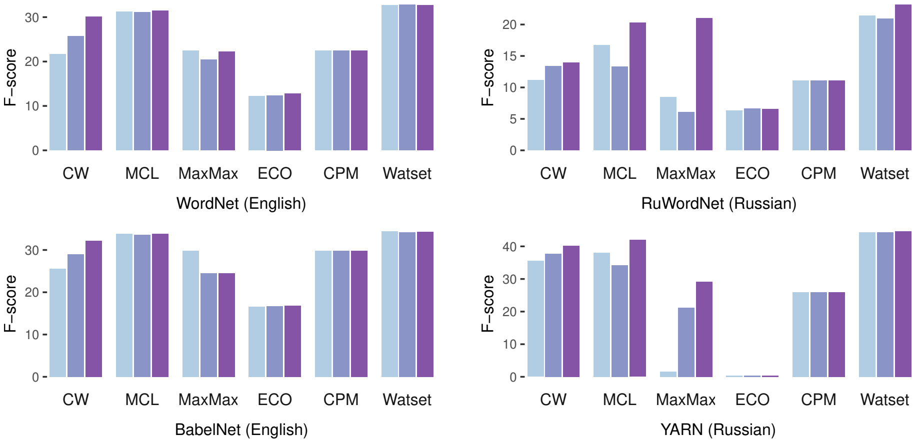
Synset Induction: Approach

1. Construct a weighted undirected graph using synonymy pairs from Wiktionary as edges
2. Weight them using cosine similarity between the corresponding word embeddings
3. Cluster this graph and treat the clusters as the synsets

Code and Data: `https://github.com/dustalov/watset`

Synset Induction: Results

- Watset showed the best results as according to paired F_1-score



Weighting: ones, count, sim

Synset Induction: Example

Size	Synset
2	decimal point, dot
2	wall socket, power point
3	gullet, throat, food pipe
3	CAT, computed axial tomography, CT
4	microwave meal, ready meal, TV dinner, frozen dinner
4	mock strawberry, false strawberry, gurbir, Indian strawberry
5	objective case, accusative case, oblique case, object case, accusative
5	discipline, sphere, area, domain, sector
6	radio theater, dramatized audiobook, audio theater, radio play, radio drama, audio play
6	integrator, reconciler, consolidator, mediator, harmonizer, uniter
7	invite, motivate, entreat, ask for, incentify, ask out, encourage
7	curtail, craw, yield, riding crop, harvest, crop, hunting crop

Frame Induction

- A **semantic frame** is a collection of facts that specify features, attributes, and functions (Fillmore, 1982)

FrameNet	**Role**	**Lexical Units (LU)**
Perpetrator	Subject	kidnapper, alien, militant
FEE	Verb	snatch, kidnap, abduct
Victim	Object	son, people, soldier, child

- Used in question answering, textual entailment, event-based predictions of stock markets, etc.
- Can we build frames from scratch using just *subject-verb-object* (SVO) triples like DepCC (Panchenko et al., 2018)?

Source: rawpixel (2017)

Kidnapping

Definition:

The words in this frame describe situations in which a Perpetrator carries off and holds the Victim against his or her will by force.

> Two men KIDNAPPED a Millwall soccer club employee, police said last night.
>
> Not even the ABDUCTION of his children by Captain Hook and his scurvy sidekick, Smee, can shake Peter's scepticism.

FEs:

Core:

Perpetrator [Perp] **Semantic Type:** Sentient	The Perpetrator is the person (or other agent) who carries off and holds the Victim against his or her will.
Victim [Vict] **Semantic Type:** Sentient	The Victim is the person who is carried off and held against his/her will.

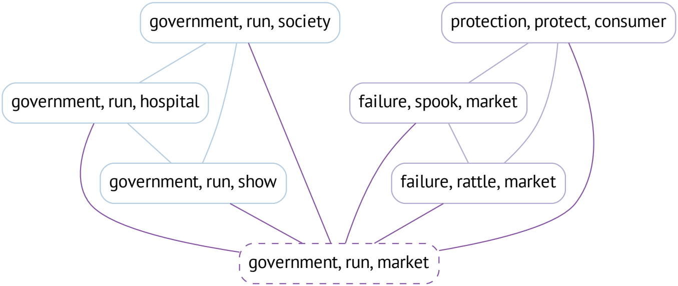
Lexical Units:

abduct.v, abducted.a, abduction.n, abductor.n, kidnap.v, kidnapped.a, kidnapper.n, kidnapping.n, nab.v, shanghai.v, snatch.v, snatcher.n

Source: https://framenet.icsi.berkeley.edu/fndrupal/luIndex

Frame Induction: Approach

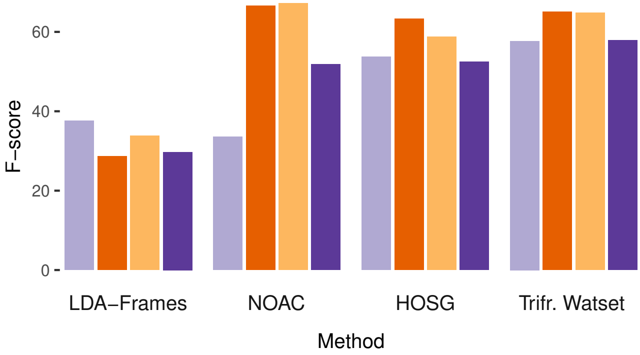
1. Use word embeddings to embed each triple $t = (s, v, o)$ in a low-dimensional *vector space* as $\vec{t} = \vec{s} \oplus \vec{v} \oplus \vec{o}$
2. Construct a weighted undirected graph using $k \in \mathbb{N}$ nearest neighbors of each triple vector
3. Cluster this graph and extract *triframes* by aggregating the corresponding roles



Code and Data: https://github.com/uhh-lt/triframes

Frame Induction: Results

- *Triframes* outperformed state-of-the-art frame induction approaches, including Higher-Order Skip-Gram (HOSG) and LDA-Frames, on the FrameNet corpus (Baker et al., 1998) as according to F_1 $(\mathrm{nmPU}/\mathrm{niPU})$



Element: verb, subject, object, frame

Frame Induction: Good Example

Subjects: expert, scientist, lecturer, engineer, analyst
Verbs: study, examine, tell, detect, investigate, do, observe, hold, find, have, predict, claim, notice, give, discover, explore, learn, monitor, check, recognize, demand, look, call, engage, spot, inspect, ask
Objects: view, problem, gas, area, change, market

Subjects: leader, officer, khan, president, government, member, minister, chief, chairman
Verbs: belong, run, head, spearhead, lead
Objects: party, people

Subjects: evidence, research, report, survey
Verbs: prove, reveal, tell, show, suggest, confirm, indicate, demonstrate
Objects: method, evidence

Frame Induction: Bad Example

Subjects: wine, act, power
Verbs: hearten, bring, discourage, encumber, ...*432 more verbs*..., build, chew, unsettle, snap
Objects: right, good, school, there, thousand

Subjects: parent, scientist, officer, event
Verbs: promise, pledge
Objects: parent, be, good, government, client, minister, people, coach

Subjects: people, doctor
Verbs: spell, steal, tell, say, know
Objects: egg, food, potato

Section 6

Miscellaneous

Which Algorithm to Choose?

? Is your graph relatively small and you need *hard* clustering?

! Markov Clustering

? Is your graph big and you still need *hard* clustering?

! Chinese Whispers

? Do you need *soft* clustering?

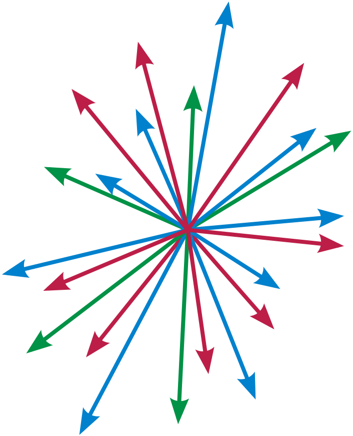
! Watset

…but My Objects are Just Vectors!

It is possible to represent the objects in a vector space as a graph (von Luxburg, 2007):

- use the k nearest neighbors,
- use all the neighbors within the ε-radius,
- use a fully-connected *weighted* graph

Think of a graph as a *discretized* vector space.



Source: Wikipedia (2007)

Resources

Events:

- **TextGraphs**, the Workshop on Graph-Based Algorithms for NLP, http://www.textgraphs.org/

Books:

- Graph-Based NLP & IR (Mihalcea et al., 2011)
- Structure Discovery in Natural Language (Biemann, 2012)

Datasets:

- Stanford Network Analysis Project, https://snap.stanford.edu/data/
- Leipzig Corpora Collection (Goldhahn et al., 2012)
- Wiktionary (Zesch et al., 2008; Krizhanovsky et al., 2013)

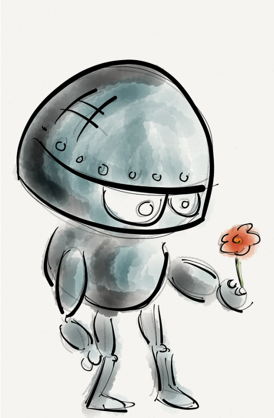
NLPub, https://nlpub.ru/ (in Russian)

Section 7

Conclusion

Conclusion

- A graph is a meaningful representation; clustering captures its implicit structure as exhibited by data
- The algorithms are well-developed and ready to use as soon as a graph is constructed
- Not covered here:
  - spectral graph theory, see a great tutorial by von Luxburg (2007)
  - community detection algorithms from network science, see Fortunato (2010)
- A few promising research directions:
  - graph convolutional networks (Marcheggiani et al., 2017),
  - graph embeddings (Goyal et al., 2018)



Source: bamenny (2016)

Questions?

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