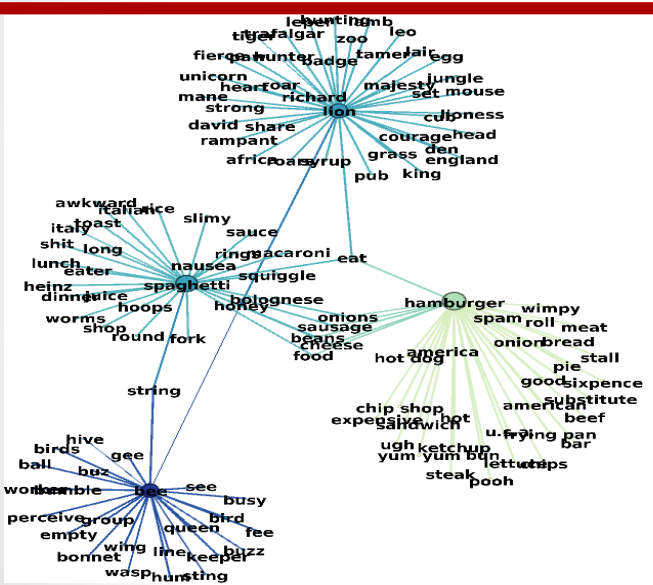


Designing an Electronic Reverse Dictionary Based on Two Word Association Norms of English Language

Jorge Reyes-Magaña , Gemma Bel-Enguix, Gerardo Sierra, Helena Gómez-Adorno
jorge.reyes@correo.uady.mx

ELEX 2019: SMART LEXICOGRAPHY. October 1 to 3, 2019, Sintra, Portugal.

Content

- Introduction.
- Word Asssociaton Words.
- Graph.
  - Algorithms. Betweenness Centrality.
  - Algorithms. Page Rank.
- Search Model.
- Evaluation corpus.
- Experiments.
- Results
- Evaluation
- Conclusion

Introduction

Two types of dictionaries

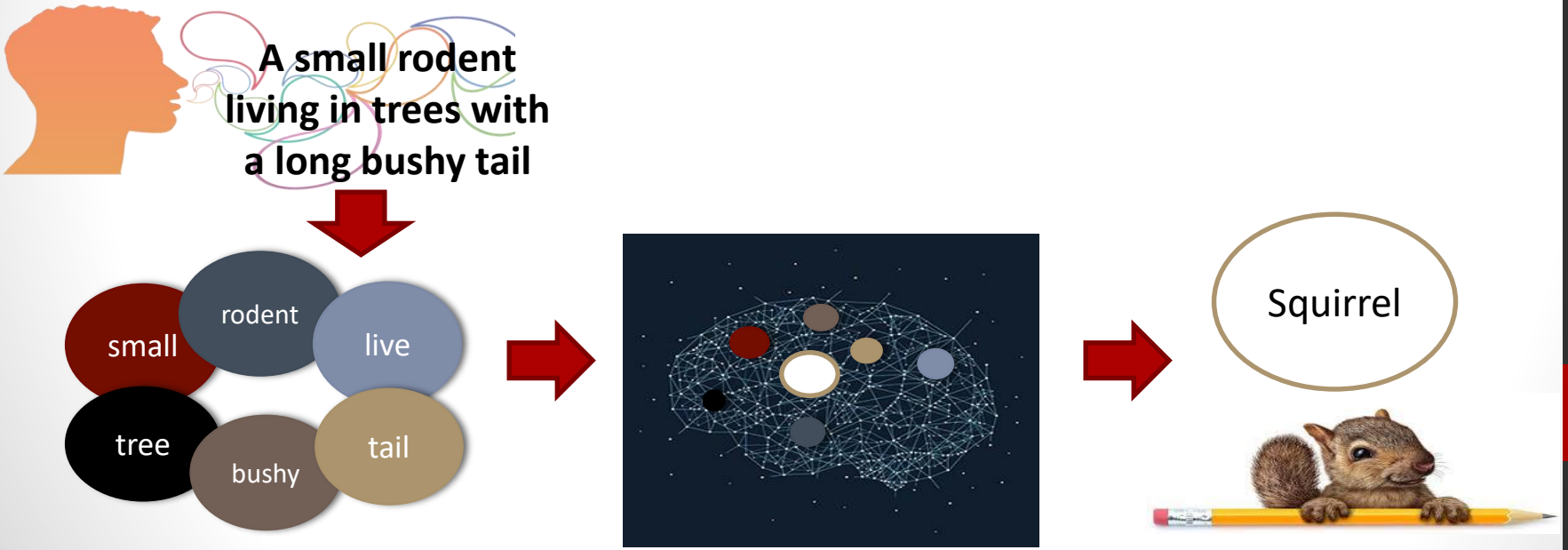
- Semasiological. Provides meanings, ie. given a word, the user obtains the meaning of such word.
- Onomasiological. Works in the opposite way, given the description of a word, the user obtains the related concept (Baldinger, 1970)

Introduction

- Onomasiological search nowadays

Introduction

- This work perform a lexical search over a knowledge graph in a similar way onomasiological dictionaries.



Word Asssociaton Words

- Free word associations (WA) are commonly collected by presenting a stimulus word (SW) to the participant and asking him to produce in a verbal or written form the first word that comes to his mind. The answer generated by the participant is called response word (RW).
- Compilations of WA are called Word Association Norms

BEE	
hive	0.793814433
honey	0.793814433
sting	0.8865979381
buzz	0.9175257732
wasp	0.9175257732
line	0.9587628866
busy	0.9690721649
bonnet	0.9793814433
bumble	0.9793814433
buz	0.9793814433
gee	0.9793814433
queen	0.9793814433
ball	0.9896907216
bird	0.9896907216

Graph


honey
pollen
hive
busy
yellow
flower
bumble
worker
bee
bumblebee
summer
spelling
buzz
sting
stripes
fear
wasp
wings
insect
fly
bug


drink
bottle
thirsty
thirst
glass
liquid
fluid
life
wet
fall
pure
aqua
water
cold
fresh
rain
clean
ice
cool
clear
pool
ocean
river
swim
sea
blue
stream
lake

Word Asssociaton Norms

- Edinburgh Associative Thesaurus (EAT) (Kiss et al., 1973a)
  - 8,211 stimulus words, and 20,445 different words including both, stimuli and responses.

- Collection of the University of South Florida (USF) (Nelson et al., 1998)
  - 6,000 participants that produced nearly three-quarters of a million responses to 5,019 stimulus words.

Graph

- The graph representing the WAN has been elaborated with lemmatized lexical items.
- The graph is undirected, so that every stimulus is connected to every associated word without any precedence order.
- For the weight of the edges there are two different functions:
  - Frequency. Counts the number of occurrences of every associated to its stimulus in the whole dataset.
  - Association Strength. Establishes a relation between the frequency (F) and the number of associations for every stimulus.
- For the system to work in the **shortest paths**, we need to calculate the IF and the IAS.

Algorithms. Betweenness centrality

- Given a definition, we search in the graph the word that better match with it.
- For this purpose, we used a variation of the **betweenness centrality** (BT) algorithm (Freeman, 1977)
- The traditional betweenness algorithm assumes that important nodes connect other nodes.

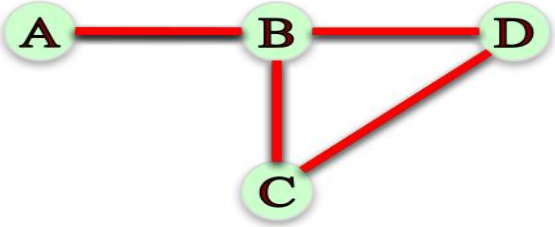
Algorithms. Betweenness centrality

- For a given node (v) in a graph (G), the BT is calculated as the relation between the number of shortest paths between nodes i and j that pass through node v and the number of shortest paths between nodes i and j

$$C_{btw}(v) = \sum_{i,j \in N} \frac{\sigma_{i,j}(v)}{\sigma_{i,j}}$$

- N = the total number of nodes in the graph.

Algorithms. Betweenness centrality



All the edges have a weight of 1

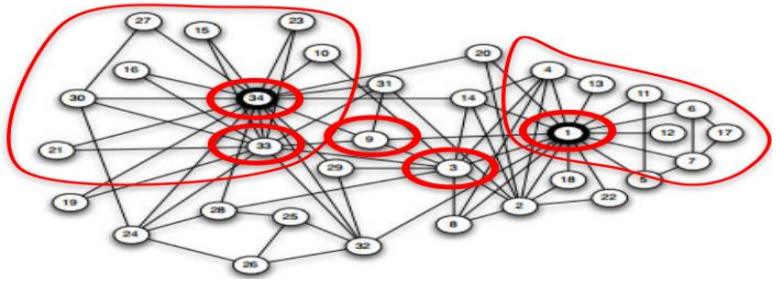
$$C_{BT}(B) = \frac{\sigma_{A,B}(B)}{\sigma_{A,B}} + \frac{\sigma_{A,C}(B)}{\sigma_{A,C}} + \frac{\sigma_{A,D}(B)}{\sigma_{A,D}} + \frac{\sigma_{B,C}(B)}{\sigma_{B,C}} + \frac{\sigma_{B,D}(B)}{\sigma_{B,D}} + \frac{\sigma_{C,D}(B)}{\sigma_{C,D}}$$

$$= \frac{1}{1} + \frac{1}{1} + \frac{1}{1} + \frac{1}{1} + \frac{1}{1} + \frac{0}{1}$$

$$= 5$$

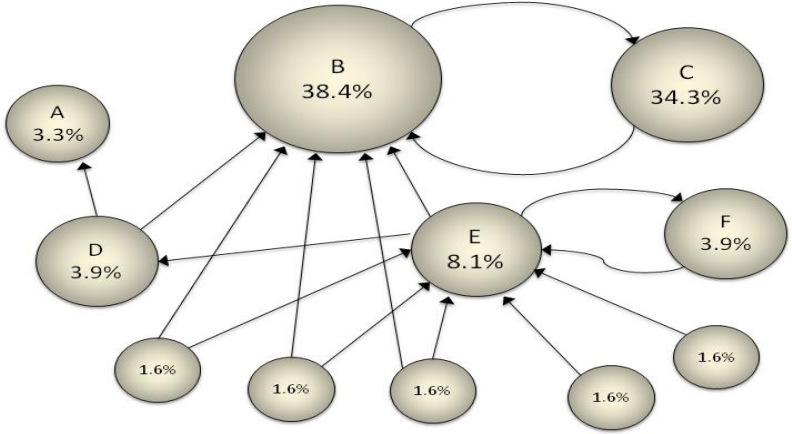
Algorithms. Betweenness centrality.

- Our hypothesis is that, if we use a subset, the nodes of the WAN graph (WG) that represent the words of a definition as initial and final nodes in the BT algorithm, and calculate the centrality of the other nodes in WN taking these nodes as pairs, then the more central nodes will be the concept of such definition



Algorithms. Page Rank.

- PageRank computes a ranking nodes in a graph G based on the structure of the incoming links. It was originally designed as an algorithm to rank web pages. It was developed by Page et al. (1999).



Algorithms. Page Rank.

- In our case, the pages described above are the words in the WAN datasets, the web page links correspond to all the relations given by the stimuli-response between words.
- The hypothesis driven here is that the target word tested with a definition to be searched corresponds to the higher scores returned by the PageRank algorithm.

Search Model

Algorithm 1: Reverse dictionary

```
Data: WAN datasets, definitions to search
Result: list of ranked concepts
pre-process(WAN datasets);
pre-process(definitions to search);
GraphWAN = build-graph(WAN datasets);
GraphWAN = prune-graph(GraphWAN);
for each definition do
    definition = remove-StopWords(definition);
    definition = filter-WordsInWAN(definition);
    build_subgraph(definition);
    ranking_nodes_BT = BT(GraphWAN,subgraph);
    ranking_nodes_PR = PR(GraphWAN);
    ascending_order(ranking_nodes_BT);
    ascending_order(ranking_nodes_PR);
```

Evaluation corpus

- We used an evaluation corpus consisting of 7 concepts.
  - 10 definitions were provided.
  - Human native speakers. In most cases, the definitions are very different from the ones found in dictionaries; they lack specialized terms and include cultural references and connotations.
  - Selected words: *water, squirrel, bench, hurricane, lemon, bucket and clothes.*

Evaluation corpus

Definitions of squirrel given by the students.

It's a little rodent and can be red or grey, it has a big bushy tail
A small rodent living in trees with a long bushy tail
A small rodent which lives in trees, collects nuts and has a bushy tail
Animal, grey/red, bushy tail, lives in trees, buries nuts
Small animal, lives in trees, eats acorns, has a bushy tail
Animal, bushy tail, eats nuts, builds nests in trees called dreys
Small funny animal with big, bushy tail, likes nuts, likes trees
Animal that lives in trees and collects acorns, has a long tail
A small-sized animal, habitat in trees
Small grey mammal, relative to the rodent, found in both countryside and town

Experiments

- For the evaluation of the inference process, we used the technique of precision at k p(k) (Manning et al. , 2009).
- P(1) stands that the concept associated to a definition given was ranked correctly in the first place, in p(3) the concept was in the first three results, and the same applies to p(5).

Results

Results in terms of precision of our model with EAT dataset

Weighting function	Graph Algorithm	p@1	p@3	p@5	p@10
Inverse Frequency (IF)	Betweenness Centrality (BT)	**0.152**	0.186	0.220	0.237
Inverse Association Strength (IAS)	Betweenness Centrality (BT)	**0.152**	**0.220**	**0.237**	**0.254**
Inverse Frequency (IF)	PageRank (PR)	0.000	0.074	0.129	0.129
Inverse Association Strength (IAS)	PageRank (PR)	0.000	0.0740	0.129	0.129

Results in terms of precision of our model with USF dataset

Weighting function	Graph Algorithm	p@1	p@3	p@5	p@10
Inverse Frequency (IF)	Betweenness Centrality (BT)	0.236	0.309	**0.418**	0.436
Inverse Association Strength (IAS)	Betweenness Centrality (BT)	**0.290**	**0.363**	**0.418**	**0.5272**
Inverse Frequency (IF)	PageRank (PR)	0.037	0.074	0.129	0.222
Inverse Association Strength (IAS)	PageRank (PR)	0.037	0.074	0.148	0.222

Evaluation

- Comparison to other IR models
  - **OneLook Thesaurus**. Allows to describe a concept and returns a list of words and phrases related to that concept.
  - **Okapi BM25**. Based on probabilistic models with a bag of words implementation (Robertson & Zaragoza ,2009).

Evaluation

Method	P@1	P@3	P@5	P@10
OneLook	0.202	0.347	0.376	0.434
Reverse Dictionary with USF (IAS)	**0.290**	0.363	0.418	**0.5272**
BM25 with EAT	0.257	0.357	0.414	0.471
BM25 with USF	0.257	**0.400**	**0.457**	0.514

- The BM25 algorithm showed better performance than the Onelook reverse dictionary when the search is performed over the WAN datasets.
- The higher results are consistent with the ones seen in the reverse dictionary, USF norms show the best performance

Conclusions

- This paper introduces a model for onomasiological searches that has some novelties, among them the simplicity, the use of graph-based techniques.

- We observed that the graph built with all the nodes and edges contained in the datasets tends to be not so good due to the number of paths that outcome on wrong results.

Conclusions

- We have shown how descriptions of concepts that are made by common people with nonscientific specifications can retrieve accurate results using our method.
- The success of the system with non-scientific input can drive new lines of applied research, and the implementation of different assistant writing systems especially oriented to people with a range of aphasias, like dysnomia and Alzheimer's disease.

References

- Baldinger, K. (1970). Teoría semántica: hacia una semántica moderna, volume 12. Alcalá.
- Freeman, L.C. (1977). A set of measures of centrality based on betweenness. Sociometry, pp. 35–41.
- Kiss, G., Armstrong, C., Milroy, R. & Piper, J. (1973a). An associative thesaurus of English and its computer analysis. Edinburgh.: Edinburgh University Press.
- Manning, C., Raghavan, P. & Schutze, H. (2009). Introduction to Information Retrieval. Cambridge University Press.
- Nelson, D.L., McEvoy, C.L. & Schreiber, T.A. (1998). Word association rhyme and word fragment norms. The University of South Florida.
- Page, L., Brin, S., Motwani, R. & Winograd, T. (1999). The PageRank citation ranking: Bringing order to the web. Technical report, Stanford InfoLab.
- Robertson, S. & Zaragoza, H. (2009). The Probabilistic Relevance Framework: BM25 and Beyond. Foundations and Trends in Information Retrieval, 3(4), pp. 333–389.

Thank you!