Building a default knowledge base of objects (and other stories of robots)

Valerio Basile
16/11/2016

Dipartimento di Informatica
Università di Torino

Outline

Introduction: Granny Annie and the Robot

Part I: Where are my things?

Part II: Default Knowledge by frames

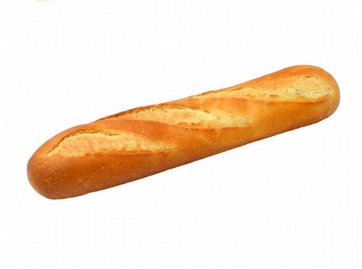
Epilogue: What are objects, anyway?

Granny Annie and the Robot

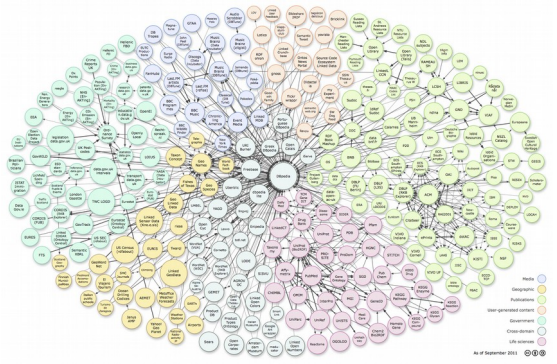
Granny Annie

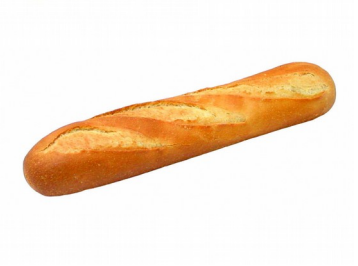
Bob

Granny Annie and the Robot

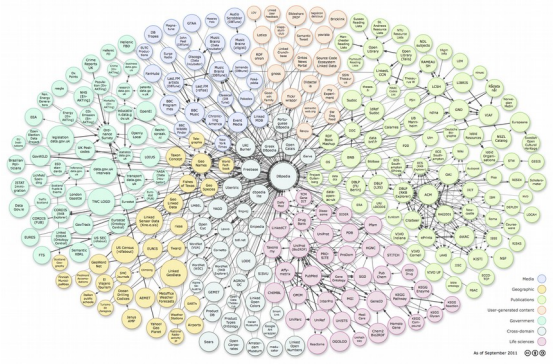


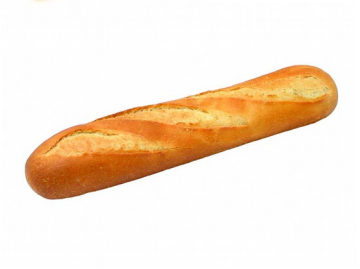
Granny Annie and the Robot





Granny Annie and the Robot





Part I: Where are my things?

Goal: Learn Semantic Relations

Ingredients: Natural Language

Distributional Semantics
(Word Space Models)

Linked Open Data
(DBpedia)

Vector Space Model

QUESTION

Is it legal to fit a washing machine in the bathroom?

Hi all, I would like to fit a washing machine in the the bathroom. The power cable will be fed through a small hole in the wall with the outlet socket on the outside of the bathroom and the machine will be +1200mm from the edge of the bath and 500mm from the toilet. My question is, is this legal?

Asked by: edward_88 29th Dec, 2012 Electrical

Vector Space Model

QUESTION

Is it legal to fit a washing machine in the bathroom?

Hi all, I would like to fit a washing machine in the the bathroom. The power cable will be fed through a small hole in the wall with the outlet socket on the outside of the bathroom and the machine will be +1200mm from the edge of the bath and 500mm from the toilet. My question is, is this legal?

Asked by: edward_88 29th Dec, 2012 Electrical AddThis

washing machine, washer, automatic washer

A home appliance for washing clothes and linens automatically

ID: 00007365n | Concept

bathroom, bath, full bathroom

A room (as in a residence) containing a bathtub or shower and usually a washbasin and toilet

ID: 00008995n | Concept

Vector Space Model

Co-occurrence matrix

	Washing_machine	Ashtray
Bathroom	5	2
Bedroom	0	1
Living_room	1	6

Vector Space Model

Co-occurrence matrix

	Washing_machine	Ashtray
Bathroom	5	2
Bedroom	0	1
Living_room	1	6

Singular value decomposition

$$M = U \Sigma V^*$$

Low-rank approximation

$$U_k \Sigma_k V_k^* = M_k$$

Vector Space Model

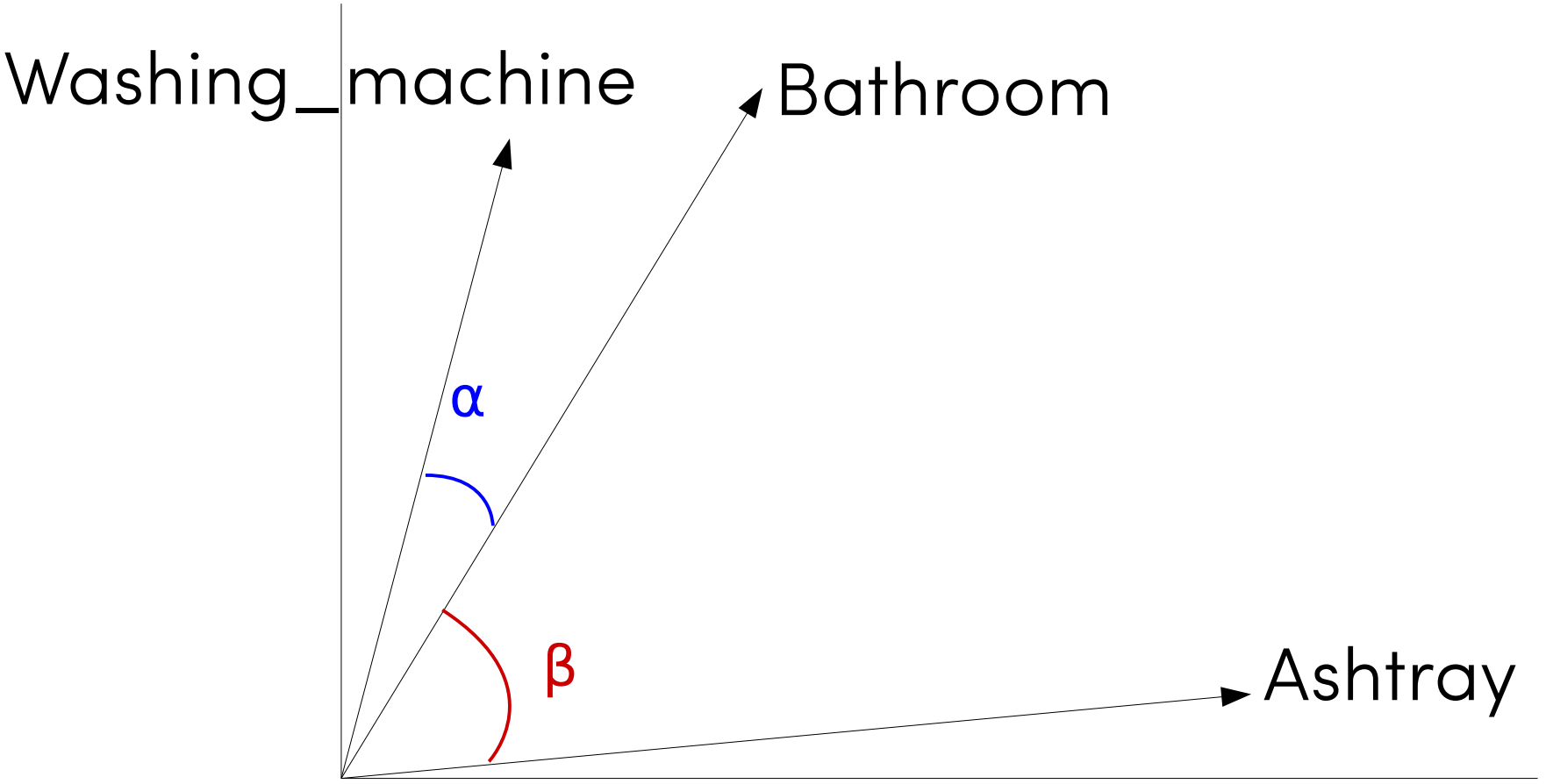
bn:00008995n Bathroom -0.03750793 0.06731935 -0.02334246 -0.02009913
0.02251291 0.07689607 0.01527985 -0.10780967 0.18232885 0.1234034
-0.0520944 -0.25805958 0.12200121 -0.04875973 -0.03544397 -0.03841146
0.00970973 …

bn:00007365n Washing_machine -0.00911299 0.11549547 -0.04274256 0.03672424
-0.06627292 0.13761881 0.01171631 -0.08721243 0.08270955 0.13095092
-0.00137408 -0.16226186 0.0422162 0.0545828 -0.01007292 0.10094466
-0.05663372 0.09864459 0.10167608 7.534e-05 0.08067719 0.05527394

Cosine similarity:

$$\frac{A \cdot B}{\|A\|\|B\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

Vector Space Model



sim(Bathroom, Washing_machine) = cos(α) ≈ 0.71

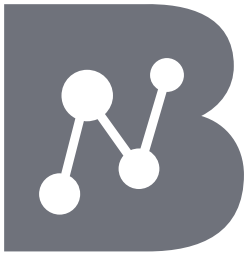
sim(Bathroom, Ashtray) = cos(β) ≈ 0.37

Vector Space Model

José Camacho-Collados, Mohammad Taher Pilehvar and Roberto Navigli.

Nasari: Integrating explicit knowledge and corpus statistics for a multilingual representation of concepts and entities.

Artificial Intelligence 240, Elsevier, 2016, pp.567-57



BabelNet

Object Detection

Object Detection

$q_1, \ldots, q_n$ observed objects in the query

$o_1, \ldots, o_m$ candidate object

$$likelihood(o_i) = \prod_{j=i}^{n} relatedness(o_i, q_j)$$

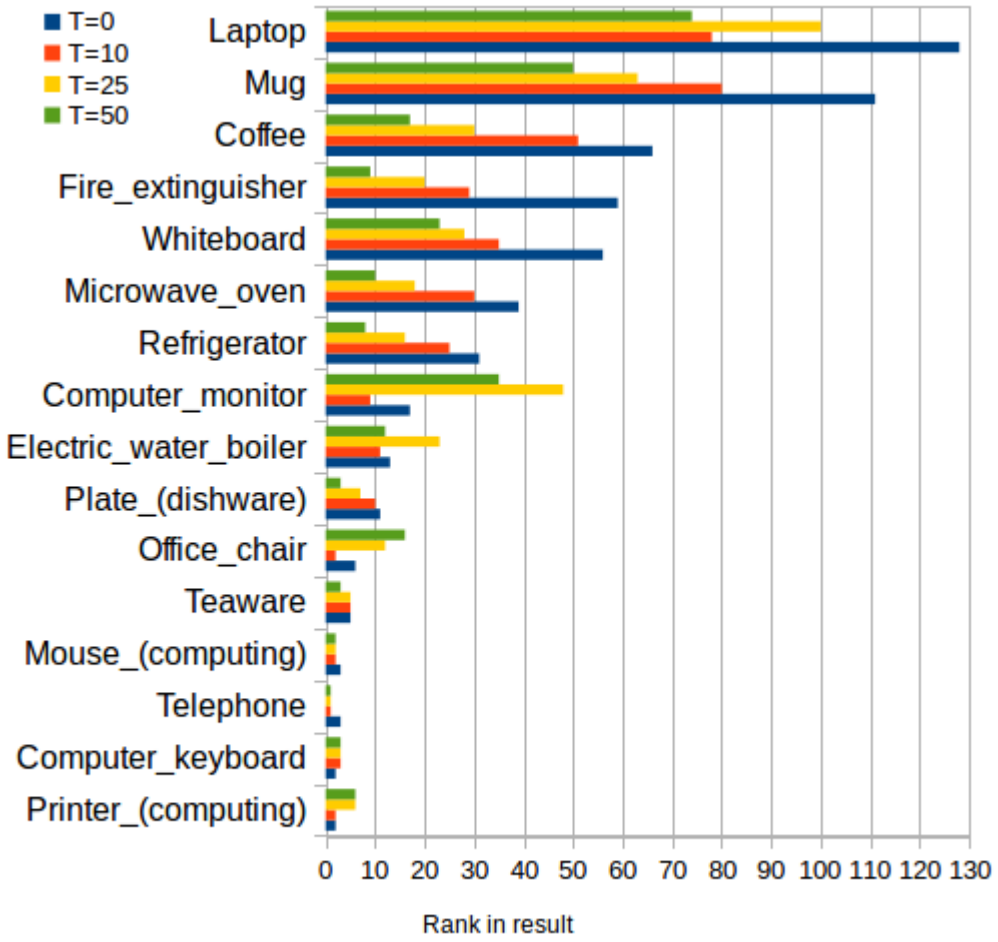
Objects Detection

Candidate objects

Query objects

	Tea_cosy	Pitcher_(container)	Mug
Refrigerator	.473	.544	.522
Sink	.565	.693	.621
Sugar_bowl_(dishware)	.555	.600	.627
Teabox	.781	.466	.602
Instant_coffee	.821	.575	.796
Electric_water_boiler	.503	.559	.488
product	**.048**	**.034**	**.047**

Objects Detection



First results
at **ECAI 2016**

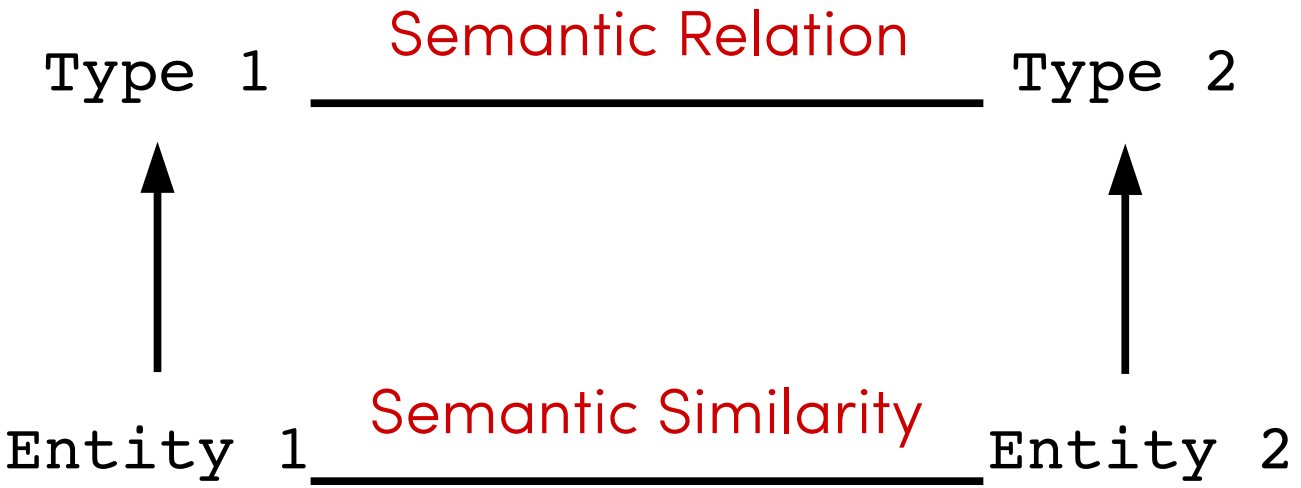
Application-driven
evaluation at **ICRA 2016**

Funded by **ALOOF**
and **STRANDS**

Objects and Rooms

Distributional Relational Hypothesis

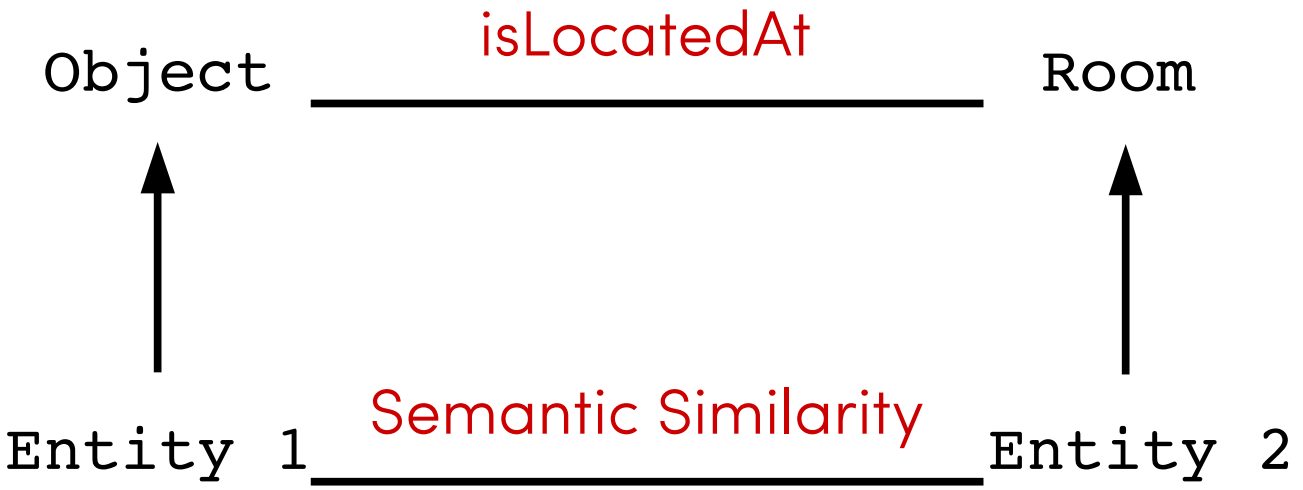
If two entities are semantically related, the natural relation that comes from their respective types is highly likely to occur.



Objects and Rooms

Distributional Relational Hypothesis

For example, the location relation that holds between an object and a room is represented in a distributional space if the entities representing the object and the room are highly associated



Objects and Rooms

Distributional representation of **entities** from NASARI, aligned to DBpedia

Similarity to `Dishwasher`

Location	Cosine Similarity
Kitchen	.803
Air_shower_(room)	.788
Utility_room	.763
Bathroom	.758
Furnace_room	.749

Objects and Rooms

A word space model of entity lexicalizations

Skip-gram NN-based model from Amazon reviews (83M)

vector(public toilet) = vector(public) + vector(toilet)

public_toilet	paper_towel
restrooms	towels
toilets	paper
restroom	dishtowel
toilet	papertowel
public	napkin

Best Neighbors

	Cosine Similarity
Kitchen	.636
Laundry_room	.531
Pantry	.525
Wine_cellar	.519
Cabinet_(room)	.505

Similarity to Dishwasher

Objects and Rooms

www.CrowdFlower.com

20 rooms (Category:Rooms)

100 objects (Category:Domestic_Implement*)

2.000 pairs annotated:

- -2: unexpected
- -1: unusual
- 1: plausible
- 2: expected

Objects and Rooms

www.CrowdFlower.com

object:
Toothbrush

The toothbrush is an oral hygiene instrument used to clean the teeth and gums that consists of a head of tightly clustered bristles mounted on a handle, which facilitates the cleansing of hard-to-reach areas of the mouth.

room:
Classroom

A classroom or schoolroom is a room in which classes are held.

How likely is it to find this object in this room?

- ○ unexpected
- ○ unusual
- ○ plausible
- ○ usual

Objects and Rooms

Data collected:
`https://project.inria.fr/aloof/data/`

12,767 valid judgments

455 untrusted

At least 5 judgment per pair

Average agreement 64.74%

Distribution 37%/30%/24%/9%

86 USD

Objects and Rooms

Evaluation

Method	Precision at 1	Precision at 3
Location Frequency	.000	.008
Link Frequency	.280	.260
NASARI-sim	.390	.380
SkipGram-sim	.350	.400

Objects and Rooms

Automatically built knowledge base

336 `dbc:Domestic_implements`

199 `dbc:Rooms`

Similarity > 0.570 corresponding to best precision

931 object-location pairs (879 new ones!)

Objects and Rooms

Results at **EKAW 2016**

Submission to **Semantic Web Journal**

Data at:

`https://project.inria.fr/aloof/data/`

Part II: Default Knowledge by Frames

Goal: Learn Typical Situations

Ingredients: Natural Language

Frame Semantics
(FrameNet)

Linked Open Data
(DBpedia, WordNet, FrameBase)

Default Knowledge

Loose operational definition

Knowledge that Bob can use when it doesn't know about its current environment.

Example:

`dbr:Spoon deko:locatedAt dbr:Kitchen`

Frame Semantics

Cutting

Definition:

An Agent cuts a Item into Pieces using an Instrument (which may or may not be expressed).
At the ceremony, The CEO CUT the red ribbon hanging across the main entrance into a glorious confetti.

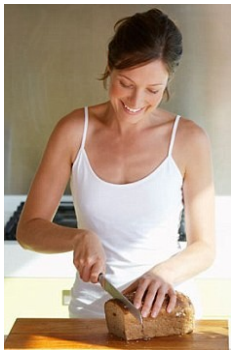
FEs:

Core:

Agent [Agt] **Semantic Type:** Sentient	The Agent is the person cutting the Item into Pieces.
Item [Item]	The item which is being cut into Pieces. People back then had to CHOP firewood all day long.
Pieces [Pie]	The Pieces are the parts of the original Item which are the result of the slicing.

Non-Core:

Instrument [Ins] **Semantic Type:** Physical_entity	The Instrument with which the Item is being cut into Pieces.
Manner [Manr] **Semantic Type:** Manner	Manner in which the Item is being cut into Pieces.
Means [Mns] **Semantic Type:** State_of_affairs	An act of the Agent that accomplishes the slicing. I SLICED the cucumber in 1/8th inch slices by marking intervals with a ruler.
Place [Place] **Semantic Type:** Locative_relation	Where the slicing takes place.
Purpose [Purp] **Semantic Type:** State_of_affairs	The purpose for which the Item is being sliced into Pieces.
Result [Result]	The Result of the Item being sliced into Pieces.
Time [Time] **Semantic Type:** Time	When the slicing occurs.



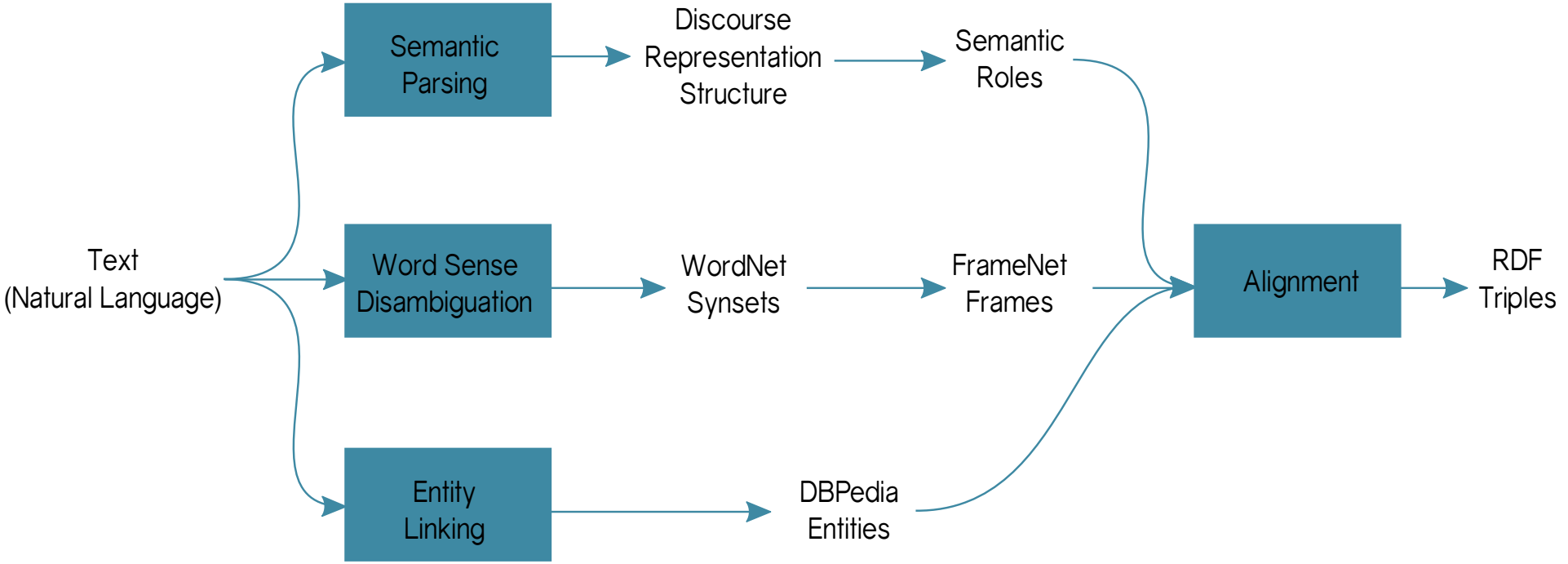
Agent

Instrument

Item

KNEWS

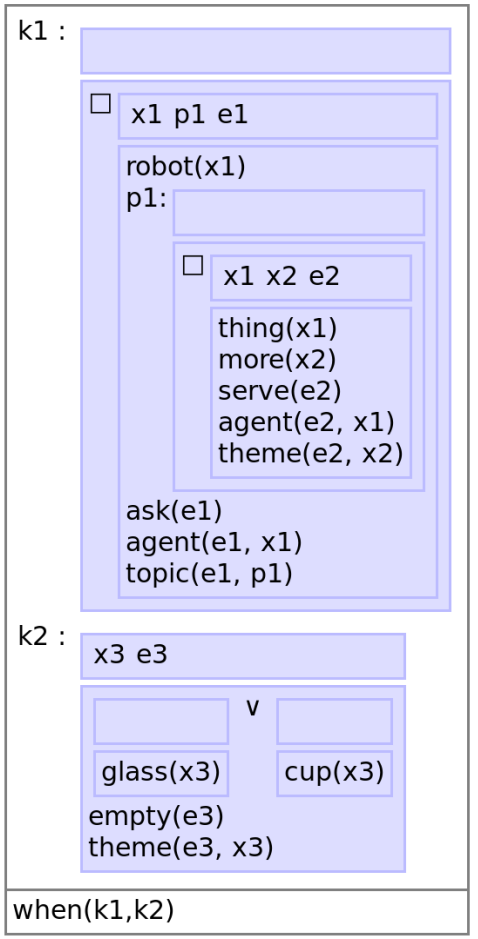
Knowledge Extraction with Semantics



NLP pipeline to extract frame instances from text

KNEWS

"The robot should ask if it should serve more."



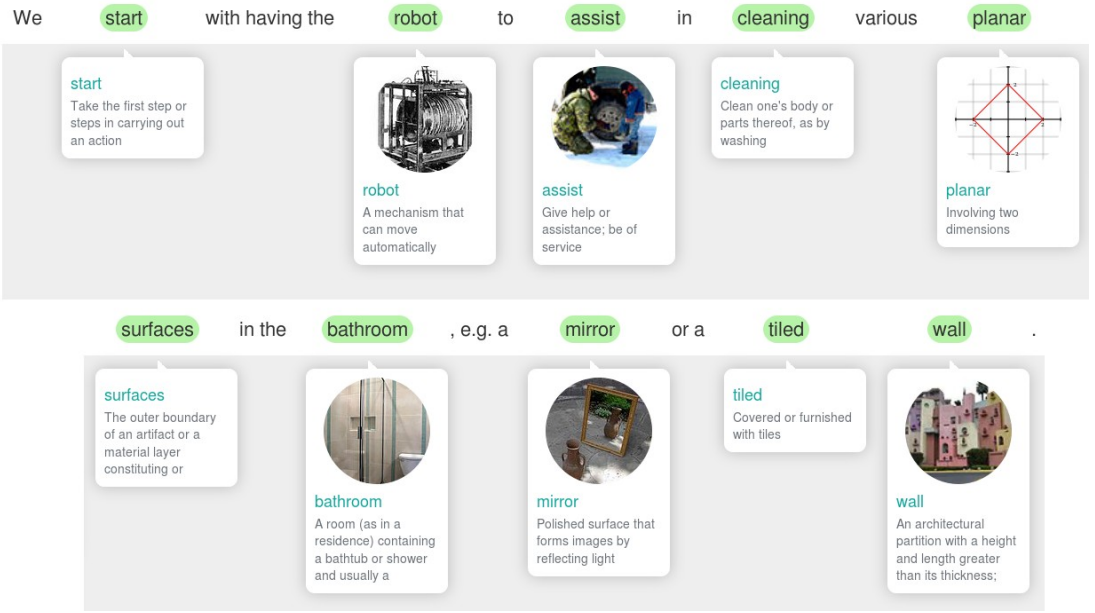
(Curran, Clark and Bos 2007)

`http://babelnet.org/`

KNEWS

Link words to entities in Babelnet

(Navigli and Ponzetto, 2012)



`http://babelfy.org`

KNEWS

"The robot is driving the car."

```
<http://framebase.org/ns/fi-Operate_vehicle_1ba93ab3-6136-4f83-9299-152685ba35da>
  <http://www.w3.org/1999/02/22-rdf-syntax-ns#type>
  <http://framebase.org/ns/frame-Operate_vehicle-drive.v>

<http://framebase.org/ns/fi-Operate_vehicle_1ba93ab3-6136-4f83-9299-152685ba35da>
  <http://framebase.org/ns/fe-Driver>
  <http://wordnet-rdf.princeton.edu/wn31/02764397-n>

<http://framebase.org/ns/fi-Operate_vehicle_1ba93ab3-6136-4f83-9299-152685ba35da>
  <http://framebase.org/ns/fe-Vehicle>
  <http://wordnet-rdf.princeton.edu/wn31/02961779-n>
```

```
  <frameinstance id="Operate_vehicle_ce746f21-2d8d-4fe8-8981-
df95c9b0eb07" type="Operate_vehicle-drive.v" internalvariable="e1">
    <framelexicalization>k3:x1 is driving k3:x2</framelexicalization>
    <instancelexicalization>
      The robot is driving the car .
    </instancelexicalization>
    <frameelements>
      <frameelement role="Driver" internalvariable="x1">
        <concept>
           http://dbpedia.org/resource/Robot
        </concept>
        <rolelexicalization>
           The robot is driving x2
        </rolelexicalization>
        <conceptlexicalization>The robot</conceptlexicalization>
      </frameelement>
      <frameelement role="Vehicle" internalvariable="x2">
        <concept>
          http://wordnet-rdf.princeton.edu/wn31/02961779-n
        </concept>
        <rolelexicalization>
          x1 is driving the car .
        </rolelexicalization>
        <conceptlexicalization>the car .</conceptlexicalization>
      </frameelement>
    </frameelements>
  </frameinstance>
```

KNEWS

Demo: `http://gingerbeard.alwaysdata.net/knews/`

Source code:
`https://github.com/valeriobasile/learningbyreading`

Demo at **ECAI 2016**

Paper at **INLG 2016**

DeKO KB

Default **K**nowledge about **O**bjects

First version: collection of
frame instances

1) Collect text
2) Extract frame instances
3) ???
4) Infer default knowledge

Poster at **ESWC 2016**

Avijit

DeKO Corpus

Intermediate Stories : 1.198
Beginner Stories : 426
UVCS Stories : 29
Total Stories : 1.653
Total Sentences : 34.384
Total Tokens: 282.664
Average Sentence length: 8 words

http://web2.uvcs.uvic.ca/elc/studyzone/
http://www.eslfast.com/
http://www.rong-chang.com/customs/

DeKO RDF

268.958 RDF triples

114.536 Frame instances

666 Frame types
(from 4.215 Wordnet synsets)

222 roles

3830 entities

DeKO Clusters

Hard clustering of frame instances

```
deko:fi-Ingestion_dac1675d
  a fb:frame-Ingestion-eat.v
  fb:fe-Ingestibles dbr:Apple
  fb:fe-Ingestor wn:09890332-n
```

A boy is eating an apple

```
deko:fi-Ingestion_12f561d7
  a fb:frame-Ingestion-eat.v
  fb:fe-Ingestibles dbr:Pear
  fb:fe-Ingestor wn:10149362-n
```

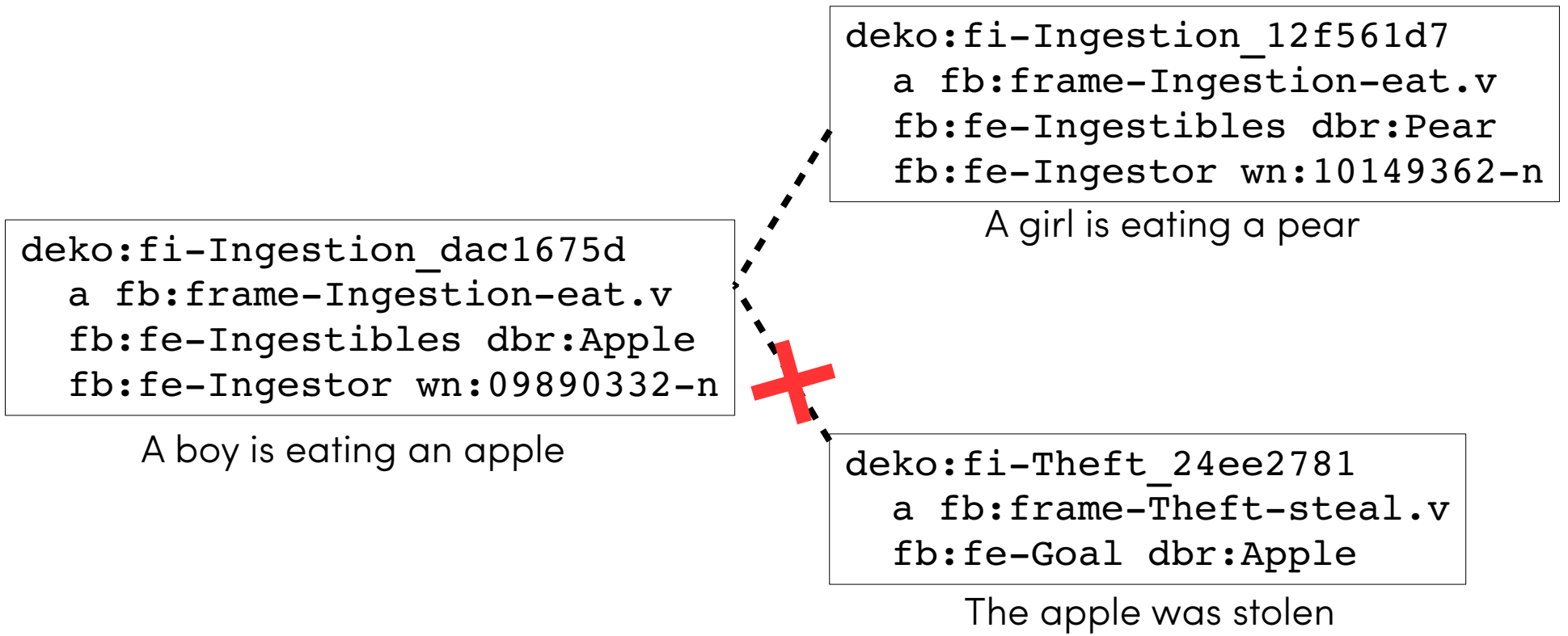
A girl is eating a pear

```
deko:fi-Theft_24ee2781
  a fb:frame-Theft-steal.v
  fb:fe-Goal dbr:Apple
```

The apple was stolen

DeKO Clusters

Hard clustering of frame instances



Epilogue: What are objects anyway?

Goal: Identify objects in DBpedia

Ingredients: DBpedia

Generic Entities

Wikipedia

Linguistic features

Extra-linguistic features

?

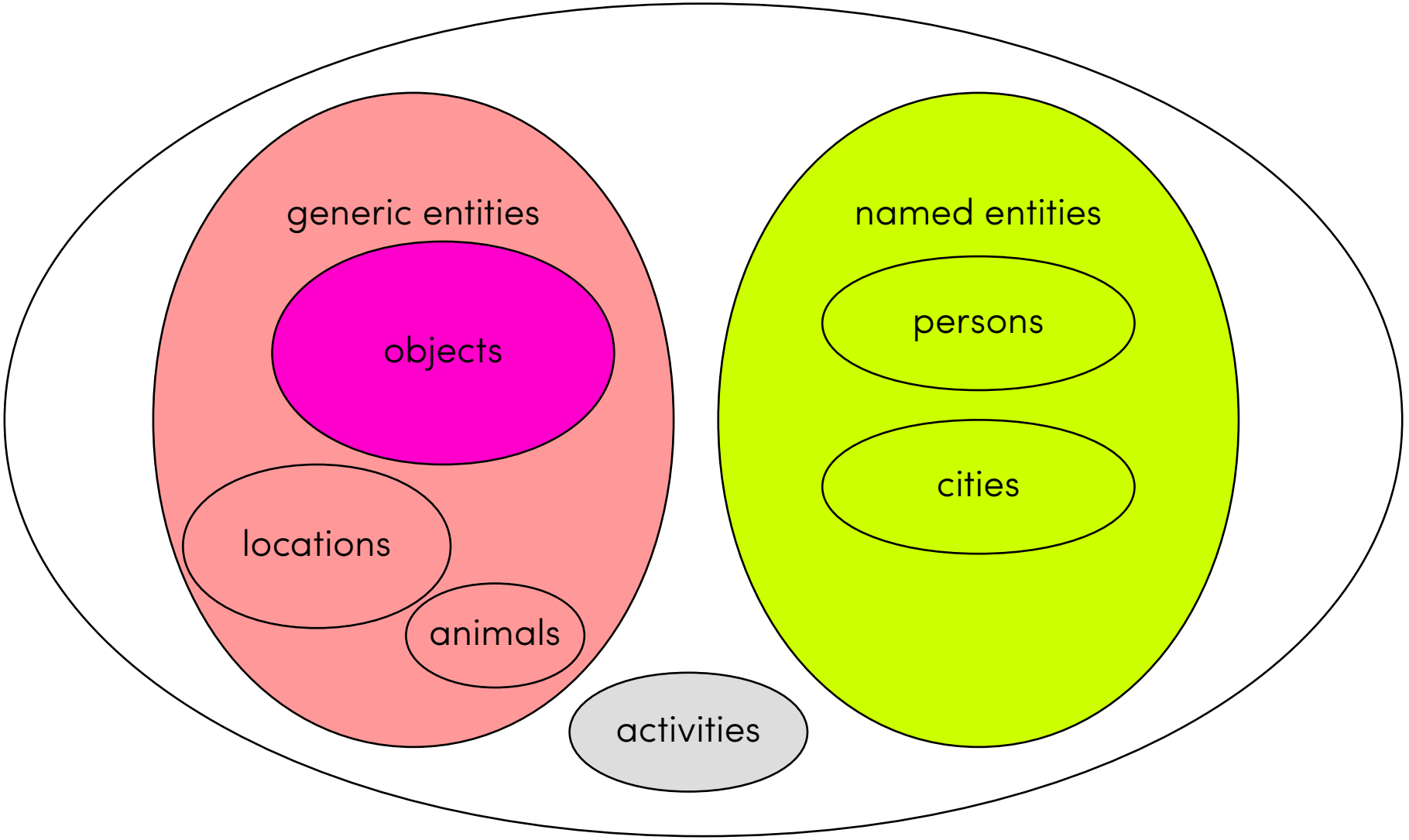
Epilogue: What are objects anyway?

`dbr:Frying_pan`
A frying pan, frypan, or skillet is a flat-bottomed pan used for frying, searing, and browning foods.

Is fundamentally different from

`dbr:Turin`
Turin is a city and an important business and cultural centre in northern Italy, capital of the Piedmont region, located mainly on the left bank of the Po River, in front of Susa Valley and surrounded by the western Alpine arch and by the Superga Hill.

Epilogue: What are objects anyway?



Epilogue: What are objects anyway?

`dbr:Frying_pan` vs `dbr:Turin`

Syntax (determiner?)
Word form (plural?)
WordNet synsets
Word embeddings
Category in SKOS
Class in OpenCyC
...

Problem related to facts vs beliefs

THE END

References

- Jay Young, Valerio Basile, Lars Kunze, Elena Cabrio, Nick Hawes: *Towards Lifelong Object Learning by Integrating Situated Robot Perception and Semantic Web Mining* ECAI 2016
- Jay Young, Lars Kunze, Valerio Basile, Elena Cabrio, Nick Hawes and Barbara Caputo: *Semantic Web-Mining and Deep Vision for Lifelong Object Discovery* ICRA 2016 (under review)
- Valerio Basile, Soufian Jebbara, Elena Cabrio, Philipp Cimiano: *Populating a Knowledge Base with Object-Location Relations using Distributional Semantics* EKAW 2016
- Valerio Basile, Elena Cabrio, Claudia Schon: *KNEWS: Using Logical and Lexical Semantics to Extract Knowledge from Natural Language* ECAI 2016
- Valerio Basile: *A Repository of Frame Instance Lexicalizations for Generation* WebNLG 2016
- Valerio Basile, Elena Cabrio, Fabien Gandon: *Building a General Knowledge Base of Physical Objects for Robots*, ESWC 2016