Lexical Knowledge Structures

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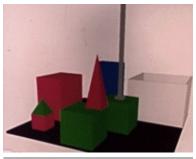
July 10, 2012



Overview

- Need of Lexical resources.
 - Making computers smarter.
 - From AI-NLP perspective.
 - Providing information.
- Lexical Knowledge Structures.

SHRDLU (1971)



READY How many blocks and pyramids are there.	_
I DON'T UNDERSTAND.	
READY	
What does the box contain? THE BLUE PYRAMID .	
READY	
1	<u> </u>
Send Clear Exit	

SHRDLU, Demo by Terry Winograd at the MIT AI Lab (1971)

The dialog that was used as a SHRDLU demo (in 1971):1

Person: PICK UP A BIG RED BLOCK.

Computer: OK. (does it)
Person: GRASP THE PYRAMID.

Computer: I DON'T UNDERSTAND WHICH PYRAMID YOU MEAN.

Person: FIND A BLOCK WHICH IS TALLER THAN THE ONE YOU ARE HOLDING AND PUT IT INTO THE BOX.

COMPUTER: BY "IT". I ASSUME YOU MEAN THE BLOCK WHICH IS TALLER THAN THE ONE I AM HOLDING.

Computer: OK. (does it)

Person: WHAT DOES THE BOX CONTAIN?

Computer: THE BLUE PYRAMID AND THE BLUE BLOCK.
Person: WHAT IS THE PYRAMID SUPPORTED BY?
Computer: THE BOX.

Person: HOW MANY BLOCKS ARE NOT IN THE BOX?

Computer: FOUR OF THEM.

Person: IS AT LEAST ONE OF THEM NARROWER THAN THE ONE WHICH I TOLD YOU TO PICK UP?

Computer: YES, THE RED CUBE.
Person: IS IT SUPPORTED?
Computer: YES, BY THE TABLE.

¹taken from : http://hci.stanford.edu/winograd/shrdlu/index.html 📳 📜 🔊 🤉

SHRDLU: a success story.

- Considered a significant step forward in NLP, as it combines
 - models of human linguistic
 - reasoning methods in the language understanding process.
- But so far has not been extended further.
 - Works in simple, logical, and closed domain.
 - Can-not handle hypothesis.
 - Things are totaly abstracted.

Lexical Knowledge Networks

- Cyc project, started 1984 by Doug Lenat
 - Goal is to capture all facts that the average person knows.
 - 350 man-years of effort estimated
- ConceptNet, started 1999, by MIT Media Lab
 - In 2000 become a World Wide Web collaborative project.
 - By 2004 had 300 000 concepts and 1.6 million relations.
- English WordNet, started 1985, by direction of George A. Miller
 - Lexical database that could be searched conceptually.
- YAGO ontologies 2007
 - Combines WordNet and Wikipedia.
 - Made by crawling Wikipedia in January 2007.
- VerbOcean
 - Contains relations between verbs.
 - Relations captured semi-automatically.



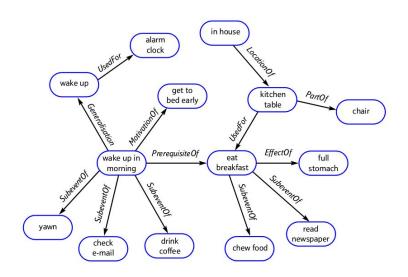
ConceptNet

ConceptNet

ConceptNet [4]

- A common sense knowledge base from MIT Media Lab.
- Aims to capture facts,
 -which enables humans in day to day activity.
 - by cpaturing relations between concepts
- Started in 1999,
- Contributed by 1000s of people.
 - via OMCS web interface. (Till ConceptNet 4.orc4)
 - in ConceptNet 5, English Wikipedia, WordNet and many other.

Typical relations in concept net



Relations in ConceptNet, K-Lines

• There are 20 different relations (as in ConceptNet2.1)

K lines² (1.25 million assertion)

ConceptuallyRelatedTo	'bad breath''mint''f=4;i=0;'
ThematicKLine	'wedding dress''veil''f=9;i=0;'
SuperThematicKLine	'western civilisation' civilisation'
	'f=0;i=12;'

²[5]: Marvin Minsky: A Theory of Memory



Relations in ConceptNet Agents, Things

AGENTS (104 000 assertions)

CapableOf dentist pull tooth $f=4; i=0;$	oleOf 'dentist''pull tooth''f=4;i=0	apableOf 'der
------------------------------------------	-------------------------------------	---------------

THINGS (52 000 assertions)

IsA (Hyponym)	'horse''mammal''f=17;i=3;'
PartOf (Meronym)	'butterfly''wing''f=5;i=1;'
DefinedAs (Gloss)	'meat''flesh of animal''f=2;i=1;'
MadeOf	'bacon''pig''f=3;i=0;'
PropertyOf	'fire''dangerous''f=17;i=1;'

Relations in ConceptNet Events, Spatial, Causal

EVENTS (38 000 assertions)

— — — — — — — — — — — — — — — — — — —	
PrerequisiteEventOf	'eat breakfast''wake up in morning'
	'f=2;i=0;'
FirstSubeventOf	'start fire''light match''f=2;i=3;'
SubeventOf	'eat breakfast''chew food''f=2;i=0;'
LastSubeventOf	'attend classical concert''applaud''f=2;i=1;'

SPATIAL (36 000 assertions)

LocationOf	'army''in war''f=3;i=0;'

CAUSAL (17 000 assertions)

EffectOf	'view video''entertainment''f=2;i=0;'
DesirousEffectOf	'sweat''take shower''f=3;i=1;'



Relations in ConceptNet Functional, Affective

FUNCTIONAL (115 000 assertions)

1 011011	12 (110 000 0000110110)
UsedFor	'alarm clock''wake up''f=1;i =2;'
CapableOfReceivingAction	'drink''serve''f =0;i =14;'

AFFECTIVE (34 000 assertions)

MotivationOf	'go to bed early''wake up in morning' 'f =3;i=0;'
DesireOf	'person''not be depressed' 'f=2;i=0;'

ConceptNet

Development Process of ConceptNet

Development Process of ConceptNet via OMCS

- Knowledge acquisition from the general public[7].
- Extraction & Normalisation phase.
- Relaxation phase.

Knowledge acquisition from the general public, OMCS1

- People not having special training in NLP or AI.
 - CycL like Cyc can not be used
- So a context is given, like:-Bob had a cold. Bob went to a doctor knowledge helpful to understand it was collected.
 - Bob was feeling sick.
 - The doctor made Bob feel better.
 - The doctor might have worn a white coat.

Extraction phase

Relations are extracted by matching patterns like

- [a | an | the] N1 (is | are) [a | an | the] [A1] N2
 - ightarrow Dogs are mammals
 - → Hurricanes are powerful storms

gives

Dog IsA mammal Hurricane IsA powerful storm

- N1 requires [a | an] [A1] N2
 - \rightarrow Writing requires a pen
 - → Bathing requires water

gives:-

pen UsedFor writing Water UsedFor bathing



Relaxation phase

- Duplicate assertions are merged and count is maintained.
- IsA relation is used to lift the concepts

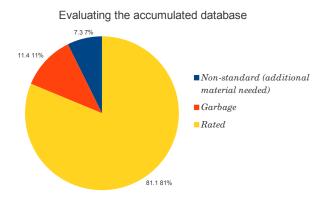
```
(IsA 'apple' 'fruit')
(IsA 'banana' 'fruit')
(IsA 'peach' 'fruit')
AND
(PropertyOf 'apple' 'sweet')
(PropertyOf 'banana' 'sweet')
(PropertyOf 'peach' 'sweet')
IMPLIES
(PropertyOf 'fruit' 'sweet')
```

Relaxation phase (contd.)

- SuperThematicKLine relations capturing generalization are produced.
 - WordNet and FrameNet's verb synonym sets and class-hierarchies are used. (SuperThematicKLine 'buy food' 'buy') (SuperThematicKLine 'purchase food' 'buy')
- If noun phrase have adjectival modifier and is repeated then PropertyOf relation is inferd.
 - [(IsA 'apple' 'red round object');
 (IsA 'apple' 'red fruit');]
 It implies (PropertyOf 'apple' 'red');

Evaluation of accumulated data

1% of the OMCS-1 corpus was manually evaluated.



Evaluation of accumulated data

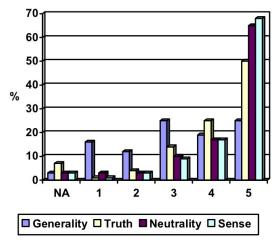
- 8 judges rated items on 4 attributes
- Scored on 1 to 5
 where score 5 means total agreement with the attribute.
 - Generality : is item too specific?
 - score 5 : Dew is wet
 - score 1 : Eritrea is part of Africa
 - Truth
 - Score 1 : Someone can be at infinity
 - Neutrality: is it personal opinion?
 - Score 1: Idiots are obsessed with star trek.
 - **Sense**: does the item makes sens?
 - Score 1 : Cows can low quietly.!!

Manual Rating

• Rating, with increasing relevance [7].

Avg Score

Generality : 3.26 Truth : 4.28 Neutrality : 4.42 Sense : 4.55



Knowledge acquisition from the general public, OMCS2

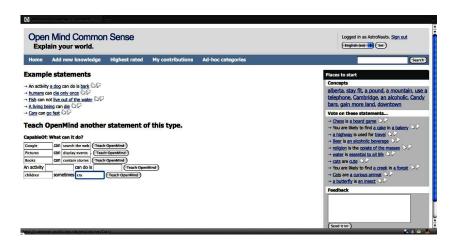
- Following observations were made
 - Templates are efficient.
 - Participants want to enter what is in there mind.
 - Participants wished interaction, access and modification to data.

Workflow model for acquisition

- User browse database
 - Finds item, assoc with a template, of interest.
- On click on template a form is presented to user.
 - Examples are also shown
 - User fills the form and submit.
- System display the inferred relations.
- User can accept or reject them.

OMCS web interface

• A sample web interface ³.



Feedback and Inference

- Method 1: Analogies over concept
 - Slots filled in the template are searched for other templates.
 - A mother can have a baby gives
 - A mother can hold her baby
 - Then other relations matching this newly found template are searched
 - A small girl can hold her small dog
 - For each match, slots values are replaced with the found one.
 - A small girl can have a small dog
 - If user finds it correct he may confirm this.

Feedback and Inference (contd.)

- Method 2 : Analogies over Relations
 - Template are searched for other concepts.
 - A mother can have a baby gives
 - A child can have a goldfish
 - Then for new slots values other Template are searched.
 - A child can take care of goldfish
 - For each match, slots values are replaced with entered one.
 - A mother can take care of a child
 - If user finds it correct he may confirm this.

Feedback and Inference (contd.)

- Method 3: Analogies as Inference Rules
 - It first generates a list of inference rules.
 - For this programs first tries to find a cycle.



- Rules are automatically extracted using OMCS-1 database.
- More matches ⇒ better rules.
- If two links for rules are discovered program can infer third
 - User enters : Bats like darkness
 - If db has: You might find bats near cave interiors
 - and the corresponding rule, then it will infer
 - Cave interior is a darkness

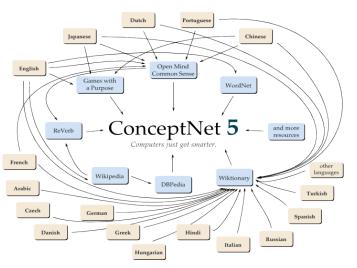


More user inputs

- Clarification by suggesting common words as replacement.
 - common words extracted as frequency from OMCS-1 corpus.
 - Replacement using synonym dictionaries.
- Users are prompted for WSD.
 - Automated methods suggest sense tags.
 - User only need to provide one or two senses.
- Concepts are linked to topic.
 - Linking maintained as topic vectors.
 - Facilitates wide knowledge retrieval.

ConceptNet5

ConceptNet5 contains concepts from a no of sources.⁴



⁴taken from : http://conceptnet5.media.mit.edu/<□> <♂> <≥> <≥> ≥ <>><○

ConceptNet5

- ConceptNet5 released on 2011 October 28
- ConceptNet5.1 released on 2012 April 30
- Multiple sources.
- Concepts in other languages.

```
本 — MadeOf → 紙
本は紙でできている。(A book is made of paper.)
ईसाई धर्म — TranslationOf → christianity
ईसाई धर्म is Hindi for Christianity
```

 Available as full download and Core download without relations from other resources.

Graphical structure of ConceptNet5

- Available in multiple formats.
- Hypergraph, edges about relations.
 - justified by other assertions, knowledge sources or processes.
 - each justification have positive or negative weight.
 - Negative means not true.
- Relations could be interlingual or automatically extracted relations, specific to a language.

URI hierarchy

Uniform Resource Identifier.

eg: http://conceptnet5.media.mit.edu/web/c/en/gandhi

- every object has URI.
- standard place to look it up.
- meaningful
- for edges it is hash for uniqueness.

URI hierarchy (contd)

Different kinds distinguished from first element.

- /a/ assertions.
- /c/ concepts (words, phrases from a language).
- /ctx/ context in which assertion is true.
- /d/ datasets.
- /e/ unique id for edges.
- /I/ license for redistributing information in an edge.
 - /I/CC/By Creative Commons.
 - /I/CC/By-SA Attribution-ShareAlike.
- /r/ language independent relation like /r/lsA
- /s/ knowledge sources
 - human contributors, Web sites or automated processes.



Concept URIs

- Each concept has minimum three components /c/hi/बेटा/
 - /c/ to indicate it is a concept.
 - language part, ISO abbreviated.
 - concept text.
- Optional fourth component for POS /c/en/read/v
- Optional fifth component for a particular sense.
 /c/en/read/v/interpret_something_that_is_written_or_printed

Fields in ConceptNet5.1

```
"endLemmas": "fruit".
"rel": "/r/IsA".
"end": "/c/en/fruit".
"features": [
 "/c/en/apple /r/IsA -".
 "/c/en/apple - /c/en/fruit".
 "- /r/IsA /c/en/fruit"
"license": "/l/CC/By",
"sources": [
 "/s/rule/sum edges"
"startLemmas": "apple",
"text": [
 "fruit".
 "apple"
"uri": "/a/[/r/IsA/./c/en/apple/./c/en/fruit/]".
"dataset": "/d/conceptnet/5/combined-core",
"start": "/c/en/apple".
"context": "/ctx/all".
"timestamp": "2012-05-25T03:41:00.346Z".
"nodes": [
 "/c/en/fruit",
 "/c/en/apple",
 "/r/TsA"
"id": "/e/3221407ec935683f2b7079b0495f164e1e321cd4"
```

ConceptNet5.1 WEB API

Lookup: When URI is known.
 Example
 http://conceptnet5.media.mit.edu/data/5.1/c/en/apple

- Search: when URI is not known
 - Performed with base URL + criteria (in GET)
 BASE URL:
 http://conceptnet5.media.mit.edu/data/5.1/search
 WITH criteria:
 http://conceptnet5.media.mit.edu/data/5.1/search?text=apple
- Association : for finding similar concepts.

Arguments for Search

Passed as GET parameter

- {id, uri, rel, start, end, context, dataset, license} : matches start of the field.
- nodes: if start of any node matches.
- text, {startLemmas, endLemmas, relLemmas}: matches anywhere.
- surfaceText matches surface text but is case sensitive
- minWeight, limit, offset
- features : needs exact match.
- filter:
 - core : no ShareAlike resources included
 - core-assertions : one result per assertion



API for Association

- BASE URL:
 - http://conceptnet5.media.mit.edu/data/5.1/assoc
- SOURCE CONCEPT : /list/<language><term list>
 - multiple terms are ','separated.
 - @ specifies a weight (relative to other elements)
- GET PARAMETERS
 - limit=n
 - filter=URI

http://conceptnet5.media.mit.edu/data/5.1/assoc/list/en/cat,food@0.5?limit=1&filter=/c/en/dog

ConceptNet

Applications Developed using ConceptNet

GOOSE 2004

Goal-Oriented Search Engine With Commonsense ⁵



GOOSE: working [3]

- Parses the query into semantic frame.
- Classify into common sense sub-domain.
- Reformulation
 - Apply reasoning using inference chain.
 - Heuristically guided.
 - Termination on application-level rule.
 - extract the reformulated search term.
 - Search on commercial search engine.
- Re-ranking
 - Based on weighted concepts.

GOOSE: a scenario [3]

- Goal: I want help solving this problem and query, my golden retriever has a cough
- Parsing gives
 Problem Attribute [cough]
 Problem Object [golden retriever]
- commonsense sub-domain classified : animals with the chain
 - A golden retriever is a kind of dog.
 - A dog may be a kind of pet.
 - Something that coughs indicates it is sick.
 - Veterinarians can solve problems with pets that are sick.
 - Veterinarians are locally located.
- The reformulated search is Veterinarians, Cambridge MA
 Location obtained from user profile. Page containing concepts closer to veterinarians is ranked high

GOOSE Results [3]

Search Task	no of successful inferences	Avg. score GOOSE	Avg. score Google
Solve household problem	7/8	6.1	3.5
Find someone online	4/8	4.0	3.6
Research a product	1/8	5.9	6.1
Learn more about	5/8	5.3	5.0

Other applications [4]

- Commonsense ARIA
 - Suggests photos while writing email or Web pages.
 - Uses manually marked tags.
 - Add tags when photo is used.
 - Use common sense for better search [7]
 - Given: Susan is Jane's sister
 - Commonsense: in a wedding, the bridesmaid is often the sister of the bride
 - Jain's photo can be retrieved if tag is Susan and her bridesmaids
- MAKEBELIEVE : interactively invents a story.
 - Uses causal projection chains to create storyline.
- GloBuddy: dynamic foreign language phrasebook.
 - Translates related concepts.
 - eg: I am at a restaurant generates
 people, waiter, chair, eat with translations.
- Suggesting words in mobile text-messages by inferring context



YAGO: Yet Another Great Ontology

YAGO : A Large Ontology from Wikipedia and WordNet⁶

⁶[9]: Fabian M.Suchanek, Gjergji Kasneci, Gerhard-Weiktum ← ≥ → ← ≥ → ∞ ∞ ∞

Information Extraction

Google searches web pages.



YAGO ontology

- Combines high coverage with high quality.
 - Uses infoboxes and category of Wikipedia.
 - Overall precision of 95%
 - decidable.
- YAGO model uses extension to RDFS.
- Expresses entities, facts, relation between facts and properties of relation.

YAGO data model, few examples

- Elvis won a Grammy Award
 - (Elvis Presley, HASWONPRIZE, Grammy Award)
- words are entities as well.
 - Quotes to distinguish from other entities.
 - ("Elvis", MEANS, Elvis Presley)
 - Allows to deal with synonyms and ambiguity
 - ("Elvis", MEANS, Elvis Costello)
- Similar entities are grouped into classes.
 - (Elvis Presley, TYPE, singer)
- Classes & relations are entities as well.
 - (singer, SUBCLASSOF, person)
 - (subclassOf, TYPE, atr)

n-ary relations

- Expressing multiple relations⁷
 - Every edge is given an edge identifier.



YAGO Model: Formal view

- common entities: which are neither facts nor relations.
 E.g.#: singer, person, Elvis Presley
- **individuals** : common entities which are not classes. E.g.# : Elvis Presley
- Its a reification graph. defined over
 - set of common entities nodes C,
 - set of edge identifiers I
 - set of relation names R
 - reification graph is an injective total function $G_{C \mid I \mid R} : I \to (C \cup I) \times R \times (C \cup I)$

Semantics

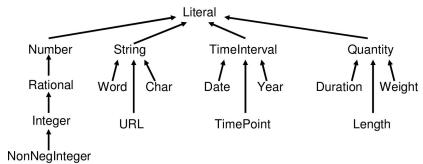
Any YAGO ontologies must have following relations (R)

```
type : (Elvis Presley, TYPE, singer)
subClassOf : (singer, SUBCLASSOF, person)
domain : (subClassOf, DOMAIN, class)
range : (subRelationOf, RANGE, relation)
subRelationOf : (fatherOf, SUBRELATIONOF, parentOf)
```

- Common entities (C) must contain the classes
 - entity
 - class
 - relation
 - atr : acyclic transitive relation

Classes for all literals

Classes for all literals⁸.



⁸Graph from [10]: YAGO report 2007

Semantics: Rewrite rule

$$\{f_1, ..., f_n\} \hookrightarrow f$$

i.e., given facts f_1 to f_n , fact f is infered.

- $\Phi \hookrightarrow$ (domain, RANGE, class) $\Phi \hookrightarrow$ (domain, DOMAIN, relation)
 - i.e., range for domain (which is a relation) will be a class.
 - But, "domain" relation can only be applied to a relation.
 - So, any relation's domain will always be some class.
 - E.g.# (isCitizenOf, domain, person)
- $\Phi \hookrightarrow$ (range, RANGE, class)
 - $\Phi \hookrightarrow (range, DOMAIN, relation)$
 - E.g.# (isCitizenOf, range, country)

Semantics : Rewrite rule (contd.)

```
• \Phi \hookrightarrow (subClassOf, DOMAIN, class)
• \Phi \hookrightarrow (subClassOf, RANGE, class)
• \Phi \hookrightarrow (subClassOf, TYPE, atr)
     • E.g1. #
       (NonNegInteger, SUBCLASSOF, Integer) &
       (Integer, SUBCLASSOF, Number)
       So: (NonNegInteger, SUBCLASSOF, Number)
     • E.g2. #
       (wordnet_carnival_100511555, SUBCLASSOF,
       wordnet_festival_100517728) &
       (wordnet_festival_100517728, SUBCLASSOF,
       wordnet_celebration_100428000)
       So: (wordnet_carnival_100511555, SUBCLASSOF,
       wordnet_celebration_100428000)
```

Semantics : Rewrite rule (contd.)

- Φ → (type, RANGE, class)
 Φ → (subRelationOf, DOMAIN, relation)
 Φ → (subRelationOf, RANGE, relation)
 Φ → (subRelationOf, TYPE, atr)
 E.g. #

 (happenedOnDate, SUBRELATIONOF, startedOnDate) &
 (startedOnDate, SUBRELATIONOF, startsExistingOnDate)
 So:
 (happenedOnDate, SUBRELATIONOF, startsExistingOnDate)
 - For literal class for each edge $X \longrightarrow Y$ $\Phi \hookrightarrow (X, subClassOf, Y)$

Semantics : Rewrite rule (contd)

Given

- $r, r_1, r_2 \in R$, where
 - $r, r_1 \neq \text{type}$, and
 - $r, r_2 \neq subRelationOf$
- $x, y, c, c_1, c_2 \in I \cup C \cup R$, where
 - $c, c_2 \neq atr$

Then,

- $\{(r_1 \text{ , subRelationOf, } r_2), (x, r_1, y)\} \hookrightarrow (x, r_2, y)$
 - E.g.#: {(motherOf, SUBRELATIONOF, parentOf), (Kunti, MOTHEROF, Arjun)} ↔
 (Kunti, PARENTOF, Arjun)
- $\{(r, \text{ type, atr}), (x, r, y), (y, r, z)\} \hookrightarrow (x, r, z)$
 - E.g1. #
 {(NonNegInteger, SUBCLASSOF, Integer),
 (Integer, SUBCLASSOF, Number)}
 So: (NonNegInteger, SUBCLASSOF, Number)

Semantics : Rewrite rule (contd)

```
• \{(r, domain, c), (x, r, y)\} \hookrightarrow (x, type, c)
      • E.g.#
         {(Sonia_Gandhi, ISCITIZENOF, India),
         (isCitizenOf, DOMAIN, person)} \hookrightarrow
         (Sonia_Gandhi, TYPE, person)
• \{(r, \text{ range}, c), (x, r, y)\} \hookrightarrow (y, \text{ type}, c)
      • E.g.#
         {(Sonia_Gandhi, ISCITIZENOF, India),
         (isCitizenOf, RANGE, country)} \hookrightarrow
         (India, TYPE, country)
• \{(x, \text{type}, c_1), (c_1, \text{subClassOf}, c_2)\} \hookrightarrow (x, \text{type}, c_2)
      E.g.#
         { (Elvis Presley, TYPE, singer),
         (singer, SUBCLASSOF, person)} \hookrightarrow
         (Elvis Presley, TYPE, person)
```

Theorems & Corollary

Given
$$\mathbf{F} = (I \cup C \cup R) \times R \times (I \cup C \cup R)$$

• Theorem 1

[Convergence of \longrightarrow] Given a set of facts $F \subset \mathbf{F}$, the largest set S with $F \longrightarrow S$ is finite and unique.

- Corollary 1
 [Decidability]
 The consistency of a YAGO ontology is decidable.
- Theorem 2

[Uniqueness of the Canonical Base]

The canonical base of a consistent YAGO ontology is unique.

• Can be computed by greedily removing derivable facts.



Restrictions

- Can't state : f is FALSE
- Primary relation of n-ary relation is always true.
 - E.g Elvis was a singer from 1950 to 1977 #1: (Elvis, TYPE, singer)

```
#2: (#1, DURING, 1950-1977)
```

• Intentional predicates (like BELIEVESTHAT) NOT POSSIBLE

Sources for YAGO

Sources and Information Extraction

Sources for YAGO

- WordNet
 - Uses hypernyms/hyponyms relation
 - Conceptually it is DAG in WordNet
- Wikipedia
 - XML dump of Wikipedia
 - categories.
 - infobox.
 - 2,000,000 articles in english wikipedia (Nov 2007) YAGO.
 - 3,867,050 articles in english wikipedia (Feb. 2012) YAGO2.
- YAGO29: geo-location information from Geonames¹⁰



⁹YAGO2: Exploring and Querying World Knowledge in Time, Space, Context, and Many Languages

¹⁰from http://www.geonames.org/

Information Extraction

Two steps (YAGO 1)

- Extraction from Wikipedia
- Quality Control.

Extraction from Wikipedia

- Page title is a candidate for individual.
- Infoboxes
- Each row has attribute value.
- manual rules designed for 170 (200 for YAGO2) frequent attributes E.g:

relation : BIRTHDATE

domain : person

range : timeInterval



Albert Einstein in 1921

Born 14 March 1879

Ulm, Kingdom of Württemberg, German Empire

Died 18 April 1955 (aged 76) Princeton, New Jersey, United

Infoboxes

- Infobox type establishes the article entity class.
 E.g.# city infobox or person infobox.
 - however, for *Economy of a country*, type is country.
- Each row can generate fact. (Arg₁, RELATION, Arg₂)
 Usually
 - Arg₁ is article entity.
 - RELATION determined by attribute.
 - Arg₂ value of the attribute.
- Inverse attribute : entity becomes Arg₂
 E.g.#
 - if attribute is official namee
 (entity HASOFFICIALNAME officialname)
 (officialname MEANS entity)
 is not generated
 is generated instead

Infoboxes (contd)

- Infobox type may disambiguate meaning of attribute E.g.#
 - length of car is in space
 - length of song is in duration
- Value is parsed¹¹ as an instance of the range of target relation.
 - Regular expression is uesd to parse numbers, dates and quantities
 - Units of measurement normalized to ISO units.
- If range is not a literal class
 - Wikipedia link is searched for entity.
 - If search fails corresponding attribute is ignored.



¹¹[8] LEILA, A link type parser is used

Types of facts

- Category system of Wikipedia is exploited
- Broadly categories could be
 - conceptual categories, like Naturalized citizens of a country
 - category for administrative purposes, like Articles with unsourced statements
 - categories giving relational information like 1879 births
 - categories indicating thematic vicinity like Physics
- Only conceptual category can be class for individual.

Identifying Conceptual Category

- Administrative and relation categories are very low.
 - less than a dozen
 - manually excluded
- Shallow linguistic parsing splits category name Naturalized citizens of Japan is split as pre-modifier Naturalized

head citizens post-modifier of Japan

Plural head usually means conceptual category



Defining hierarchy of classes using WordNet

- Wikipedia categories are organized as DAG
 - reflects only thematic structure of Wikipedia Elvis is in the category Grammy Awards
 - So WordNet is used to define hierarchy over leaf category of Wikipedia.
- Each synset of WordNet becomes a class.
 - Proper nouns are removed.
 - Identified If WordNet sysnset has a common noun with Wikipedia page.
 - Some information is lost only common nouns become class.
- subClassOf relation taken from hyponyms relation of WordNet
 - A is subClassOf of B in YAGO, if synset A is hyponyms of synset B in WordNet



Defining hierarchy of classes using WordNet

- Lower classes of Wikipedia are connected to higher class of WordNet
 - E.g.# American people in Japan is a subclass of person
 - First category name is split in pre, head and post.
 pre American head people post in Japan
 - head is stemmed to its singular form people → person
 - If pre + head is in WordNet, desired class is achieved *American person*
 - else, only head compound is searched
 - The match with highest frequency sysnset is used.
 - Exception like capital whose predominant sense in WordNet (financial asset) and Wikipedia (capital city) differed were manually corrected

Word heuristics

- A means relation is established between each word of WordNet synset
 - E.g.# (metropolis, means, city)
- Wikipedia redirects are used to give means relation
 E.g.# (Einstein, Albert, means, Albert Einstein)
- givenNameOf and familyNameOf relations are used using person names

```
E.g.# (Albert, givenNameOf, Albert Einstein)
E.g.# (Einstein, familyNameOf, Albert Einstein)
```

Category heuristics

- Relational category pages gives info about article
 - E.g.# category Rivers in Germany ensures article entity has locatedIn relation with Germany.
 - Regular expressions heuristics are used to get category names like Mountains | Rivers in (.*)
- Exploiting Language Category
 - Categories like fr:Londers, and articles in them like the city of London gives relation
 London isCalled "Londres" inLanguage French

Quality Control & Type Checking

Canonicalization

- Redirect Resolution:
 - facts are obtained from infobox.
 - Some links might be to the Wikipedia redirect pages.
 - Such incorrect arguments are corrected.
- Duplicate facts are removed.
 - more precise facts are kept
 E.g.# out of birthDate 1935-01-08 and 1935 only 1935-01-08 is kept.

Type Checking

- Reductive : facts are dropped if
 - class for an entity can not be detected.
 - first argument is not in the domain of the relation.
- Inductive : class for an entity is inferred
 - Works well with person E.g.# if entity has birthDate then person is infered.



Storage

- Meta relations are stored like normal relation.
 - URL for each individual is stored with describes
 - foundIn relation are stored as witness.
 - using relation stores technique of extraction.
 - during relation stores the time of extraction.
- File format : model is independent of storage.
 - simple text files are used as internal format
 - Estimated accuracy between 1 and 0 is stored as well.
 - XML version of text file and RDFS version are available.
 - database schema is simply FACTS(faactId, arg1, relation, arg2, accuracy)
 - Software to load in Oracle, Postgres or MySQL is provided.



Evaluating YAGO

- Randomly selected facts were presented to judges along with Wiki pages.
- pages were rated correct, incorrect or don't know
- Only facts that stem from heuristics were evaluated
 - Portion stems from WordNet is not evaluated.
 - Non-heuristics relations like describes, foundIn are not evaluated.
- 13 judges evaluated 5200 facts.

Precision of heuristics

	Heuristic	#Eval	Precision
1	hasExpenses	46	$100.0\% \pm 0.0\%$
2	hasInflation	25	$100.0\% \pm 0.0\%$
3	hasLaborForce	43	$97.67441\% \pm 0.0\%$
4	during	232	$97.48950\% \pm 1.838\%$
5	ConceptualCategory	59	$96.94342\% \pm 3.056\%$
6	participatedIn	59	$96.94342\% \pm 3.056\%$
7	plays	59	$96.94342\% \pm 3.056\%$
8	establishedInYear	57	$96.84294\% \pm 3.157\%$
9	createdOn	57	$96.84294\% \pm 3.157\%$
10	originatesFrom	57	$96.84294\% \pm 3.157\%$
72	WordNetLinker	56	$95.11911\% \pm 4.564\%$
74	InfoboxType	76	$95.08927\% \pm 4.186\%$
75	hasSuccessor	53	$94.86150\% \pm 4.804\%$
88	hasGDPPPP	75	$91.22189\% \pm 5.897\%$
89	hasGini	62	$91.00750\% \pm 6.455\%$
90	discovered	84	$90.98286 \pm 5.702\%$

YAGO 2: Extensible Extraction Architecture

- Rules are interpreted no longer hard coded.
- Becomes Addition YAGO2 facts.
- Factual rules
 - Declarative translations of
 - all the manually defined *exceptions* and *facts* (total 60) in the code of YAGO1
 - "capital" hasPreferredMeaning wordnet_capital_108518505
 - Litral types come with regular expression to match them.

YAGO 2: Extensible Extraction Architecture

- Implication rules stored as
 - "\$1 \$2 \$3; \$2 subpropertyOf \$4;" implies "\$1 \$4 \$3"
- Replacement rules for cleaning HTML tags, normalizing units etc
 - "\{\{USA\}\}" replace "[[United States]]"
- Extraction rules stores regular expression rules¹². for deriving fact.

¹²the *regex* is as defined for : regular expression syntax of java.util.regex

Information Extraction from different dimension

- Temporal Dimension: Assign begin and/or end of time spans to all entries, facts, events, etc.
- Geo-Spatial Dimension: assign location in space to all entities having a permanent location.
 - GeoNames¹³ is taped.
- Textual Dimension:
 - relation like hasWikipediaAnchorText, hasCitationTitle, etc, are extracted from Wikipedia
 - multi-lingual data from Universal Wordnet is added.



¹³from http://www.geonames.org/

Application

YAGO: Application

YAGO in development of ontologies

YAGO in development of ontologies 14



¹⁴ picture taken from presentation of Besnik fetahu () () () () () () ()

Application of YAGO

- Querying
- Semantic Search : Basis for search engines like NAGA and ESTER
 - NAGA uses YAGO KB for graph-based information retrieval.
 - ESTER combines ontological search with text search.

Downloading YAGO

 Freely available at http://www.mpi-inf.mpg.de/yago-naga/yago/downloads.html

VerbOcean

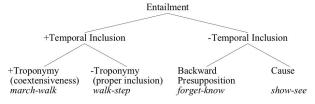
VerbOcean

VerbOcean

- Developed at University of Southern California.
- Captures semantic relation between 29,165 verb pairs [1].
 - by mining the Web for Fine-Grained Semantic Verb Relation

Why VerbOcean

- WordNet provide relations between verbs
 - but at a coarser level.



- No entailment of buy by sell.
- VerbOcean relates verbs
 - doesn't group them in classes.

Relations captured by VerbOcean

Similarity

produce :: createreduce :: restrict

 Strength: Subclass of Similarity intensity or completeness of change produced.

taint :: poisonpermit :: authorizesurprise :: startlestartle :: shock

Relations captured by VerbOcean

Antonymy

- Switching thematic roles of the verb
 - buy :: selllend :: borrow
- Between stative verbs
 - live :: diediffer :: equal
- Between siblings sharing a parent
 - walk :: run
- Entailed by common verb
 - fail :: succeed both entailed by try
- In happens-before relation
 - damage :: repairwrap :: unwrap

Relations captured by VerbOcean

• **Enablement** between V_1 and V_2 if V_1 is accomplished by V_2 .

```
• assess :: review
```

- accomplish :: complete
- Happens-before: Related verbs refer to temporally disjoint intervals.

```
detain :: prosecuteenroll :: graduate
```

• schedule :: reschedule



Approach

- Associated verb pairs are extracted.
- Scored on Lexico-syntactic patterns.
- Semantic relation extracted on score of the patterns.
- Pruning.

Extracting Associated verb pairs

- 1.5GB¹⁵ newspaper corpus is considered.
- Verbs are associated if they link same sets of words.
 - Corpus is searched¹⁶ for verbs, relating same words.
 - The path considered is : *subject-verb-object*.

```
• E.g.# Verbs associated with X solves Y (top 20)
   Y is solved by X
                                X resolves Y
   X finds a solution to Y
                               X tries to solve Y
   X deals with Y
                               Y is resolved by X
   X addresses Y
                               X seeks a solution to Y
   X does something about Y X solution to Y
   Y is resolved in X
                                Y is solved through X
   X rectifies Y
                                X copes with Y
   X overcomes Y
                                X eases Y
   X tackles Y
                                X alleviates Y
   X corrects Y
                               X is a solution to Y
   X makes Y worse
                                X irons out Y
```

 $^{^{15}}$ corpus consists of San Jose Mercury, Wall Street Journal and AP Newswire articles from the TREC-9 collection.

¹⁶using DIRT (Discovery of Inference Rules from Text) algorithm Lin and Pantel (2001)[2]

Lexico-syntactic patterns

- 35 Lexico-syntactic pattern are used.
- Different Lexico-syntactic patterns indicate different relation.
 - Manually selected,
 - by examining, known semantic relation, verb pairs.
 - Tense variations are accounted.
 - Xed instantiates on sing and dance as sung and danced.
- Web is googled for each associated verb pair with these pattern.
- Patterns indicating narrow similarity
 - X ie Y
 - Xed ie Yed
 - Kile, the software, has **produced** ie **created** this presentation.



Lexico-syntactic patterns (contd.)

- Patterns indicating broad similarity
 - Xed and Yed
 - to X and Y
 - The enemy camp was bombarded and destroyed
- Patterns indicating strength
 - X even Y
 - Xed even Yed
 - X and even Y
 - Xed and even Yed
 - Y or at least X
 - Yed or at least Xed
 - not only Xed but Yed
 - not just Xed but Yed
 - Better purchase or at least borrow this book

Lexico-syntactic patterns (contd.)

- Patterns indicating enablement
 - Xed * by Ying the
 - Xed * by Ying or
 - to X * by Ying the
 - to X * by Ying or
 - You have an option to choose by selecting the values from a drop down.
- Patterns indicating antonymy
 - either X or Y
 - either Xs or Ys
 - either Xed or Yed
 - either Xing or Ying
 - whether to X or Y
 - Xed * but Yed
 - to X * but Y
 - People either hate or adore movies like Prometheus



Lexico-syntactic patterns (contd.)

- Patterns indicating happens-before
 - to X and then Y
 - to X * and then Y
 - Xed and then Yed
 - Xed * and then Yed
 - to X and later Y
 - Xed and later Yed
 - to X and subsequently Y
 - Xed and subsequently Yed
 - to X and eventually Y
 - Xed and eventually Yed
 - The enemy forces were crushed immediately and later annihilateed completely



Scoring the verb pair on the pattern

- Strength of association is computed between
 - ullet verb pair V_1 and V_2 and
 - A lexico-syntactic pattern p
- An approach inspired by mutual information

$$S_p(V_1, V_2) = \frac{P(V_1, p, V_2)}{P(p) \times P(V_1) \times P(V_2)}$$

Scoring the verb pair on the pattern

- Expanding & approximating the formula
 - For symmetric relations (similarity, antonymy)

$$S_{p}(V_{1},V_{2}) \approx \frac{\frac{hits(V_{1},p,V_{2})}{N} + \frac{hits(V_{2},p,V_{1})}{N}}{\frac{N}{N}} \times \frac{hits("to~V_{1}") \times C_{v}}{N} \times \frac{hits("to~V_{2}") \times C_{v}}{N}$$

 For asymmetric relations (strength, enablement, happens-before)

$$S_{p}(V_{1}, V_{2}) \approx \frac{\frac{hits(V_{1}, p, V_{2})}{N}}{\frac{hits_{ear}(p)}{N} \times \frac{hits("to V_{1}") \times C_{v}}{N} \times \frac{hits("to V_{2}") \times C_{v}}{N}}$$

- Where,
 - ullet N : No of words indexed by the search engine $pprox 7.2 imes 10^{11})$
 - hits(S): of documents containing S, as returned by Google
 - C_v: Correction factor to account for count of all tenses of verb from "to V"
 - hits_{est}(p): pattern counted as estimated from a 500M POS tagged corpus.



Extracting semantic relation

- if $S_p(V_1, V_2) > C_1 (= 8.5)$
 - then semantic relation, S_p , as indicated by the pattern p is inferred between (V_1, V_2)
- Also for asymmetric relations
 - $S_p(V_1, V_2)/S_p(V_2, V_1) > C_2$ (taken as 5)

Pruning

- ullet If the pattern matching was low (< 10)
 - mark unrelated.
- happens-before
 - If not-detected
 - Un-mark enablement, if it is detected.
- strength
 - if detected
 - Un-mark similarity, if it is detected.
- Out of strength, similarity, opposition and enablement
 - Output the one with highest score.
 - and still marked.
- If no relation detected so far.
 - mark unrelated.



Quality of VerbOcean

- Overall accuracy : 65.5%
- Human also agree on only 73% cases.
- Overall accuracy

SEMANTIC RELATION	System Tags	Tags Correct	Preferred Tags Correct
similarity	41	63.4%	40.2%
strength	14	75.0%	75.0%
antonymy	8	50.0%	43.8%
enablement	2	100%	100%
no relation	35	72.9%	72.9%
happens before	17	67.6%	55.9%

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