Identifying and Connecting Salient Information via Semantic Text Representations

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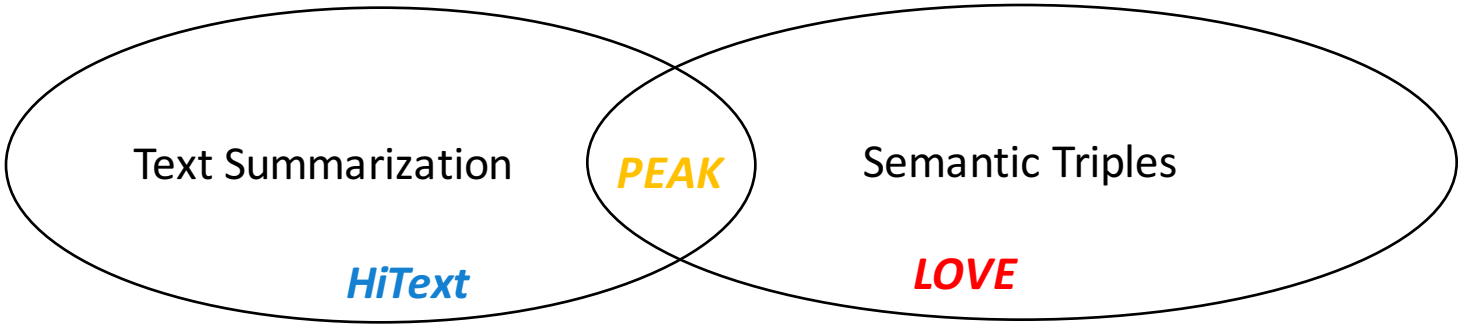
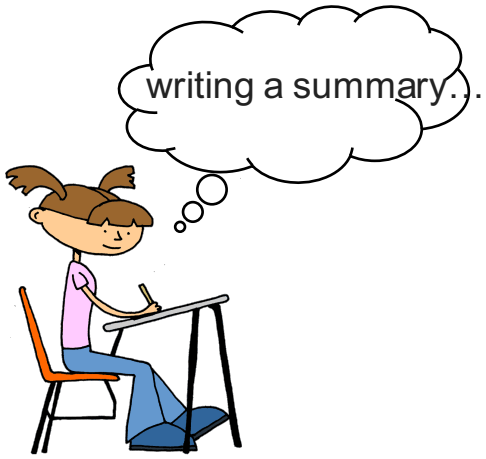
Outline



Text Summarization



d30001.txt

```
1  Cambodian leader Hun Sen on Friday rejected opposition parties'
   demands for talks outside the country, accusing them of trying to
   "internationalize" the political crisis. Government and opposition
   parties have asked King Norodom Sihanouk to host a summit meeting
   after a series of post-election negotiations between the two
   opposition groups and Hun Sen's party to form a new government
   failed. Opposition leaders Prince Norodom Ranariddh and Sam
   Rainsy, citing Hun Sen's threats to arrest opposition figures
   after two alleged attempts on his life, said they could not
   negotiate freely in Cambodia and called for talks at Sihanouk's
   residence in Beijing. Hun Sen, however, rejected that. "I would
   like to make it clear that all meetings related to Cambodian
   affairs must be conducted in the Kingdom of Cambodia," Hun Sen
   told reporters after a Cabinet meeting on Friday. "No-one should
   internationalize Cambodian affairs. It is detrimental to the
   sovereignty of Cambodia," he said. Hun Sen's Cambodian People's
   Party won 64 of the 122 parliamentary seats in July's elections,
   short of the two-thirds majority needed to form a government on
   its own. Ranariddh and Sam Rainsy have charged that Hun Sen's
   victory in the elections was achieved through widespread fraud.
   They have demanded a thorough investigation into their election
   complaints as a precondition for their cooperation in getting the
   national assembly moving and a new government formed. Hun Sen said
   on Friday that the opposition concerns over their safety in the
   country was "just an excuse for them to stay abroad." Both
```

Line 1, Column 1 | Tab Size: 4 | Plain Text

d30001.m.100.t.a.sum

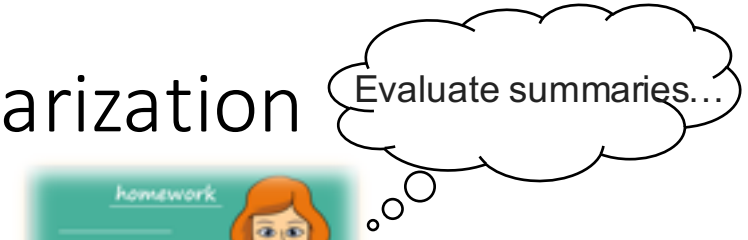
```
1  Prospects were dim for resolution of the political crisis in
   Cambodia in October 1998.
2  Prime Minister Hun Sen insisted that talks take place in Cambodia
   while opposition leaders Ranariddh and Sam Rainsy, fearing arrest
   at home, wanted them abroad.
3  King Sihanouk declined to chair talks in either place.
4  A U.S. House resolution criticized Hun Sen's regime while the
   opposition tried to cut off his access to loans.
5  But in November the King announced a coalition government with Hun
   Sen heading the executive and Ranariddh leading the parliament.
6  Left out, Sam Rainsy sought the King's assurance of Hun Sen's
   promise of safety and freedom for all politicians.
7
```

Line 1, Column 1 | Tab Size: 4 | Plain Text

- Automatically creating a compressed version of a given text that provides useful information for the user.

The picture of a student is from
https://clipartfest.com/download/7dfea091507a6a63de033859b26e880cecbbd49e.html

Evaluation of Text Summarization



d30001.txt

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```

Line 1, Column 1 | Tab Size: 4 | Plain Text

d30001.m.100.t.a.sum

```
1  Prospects were dim for resolution of the political crisis in
   Cambodia in October 1998.
2  Prime Minister Hun Sen insisted that talks take place in Cambodia
```

d30001.m.100.t.b.sum

```
1  Cambodian prime minister Hun Sen rejects demands of 2 opposition
   parties for talks in Beijing after failing to win a 2/3 majority
```

d30001.m.100.t.c.sum

```
1  Cambodia King Norodom Sihanouk praised formation of a coalition of
   the Countries top two political parties, leaving strongman Hun Sen
   as Prime Minister and opposition leader Prince Norodom Ranariddh
   president of the National Assembly.
2  The announcement comes after months of bitter argument following
   the failure of any party to attain the required quota to form a
   government.
3  Opposition leader Sam Rainey was seeking assurances that he and
   his party members would not be arrested if they return to Cambodia.
4  Rainey had been accused by Hun Sen of being behind an
   assassination attempt against him during massive street
   demonstrations in September.
5
```

Line 1, Column 1 | Tab Size: 4 | Plain Text

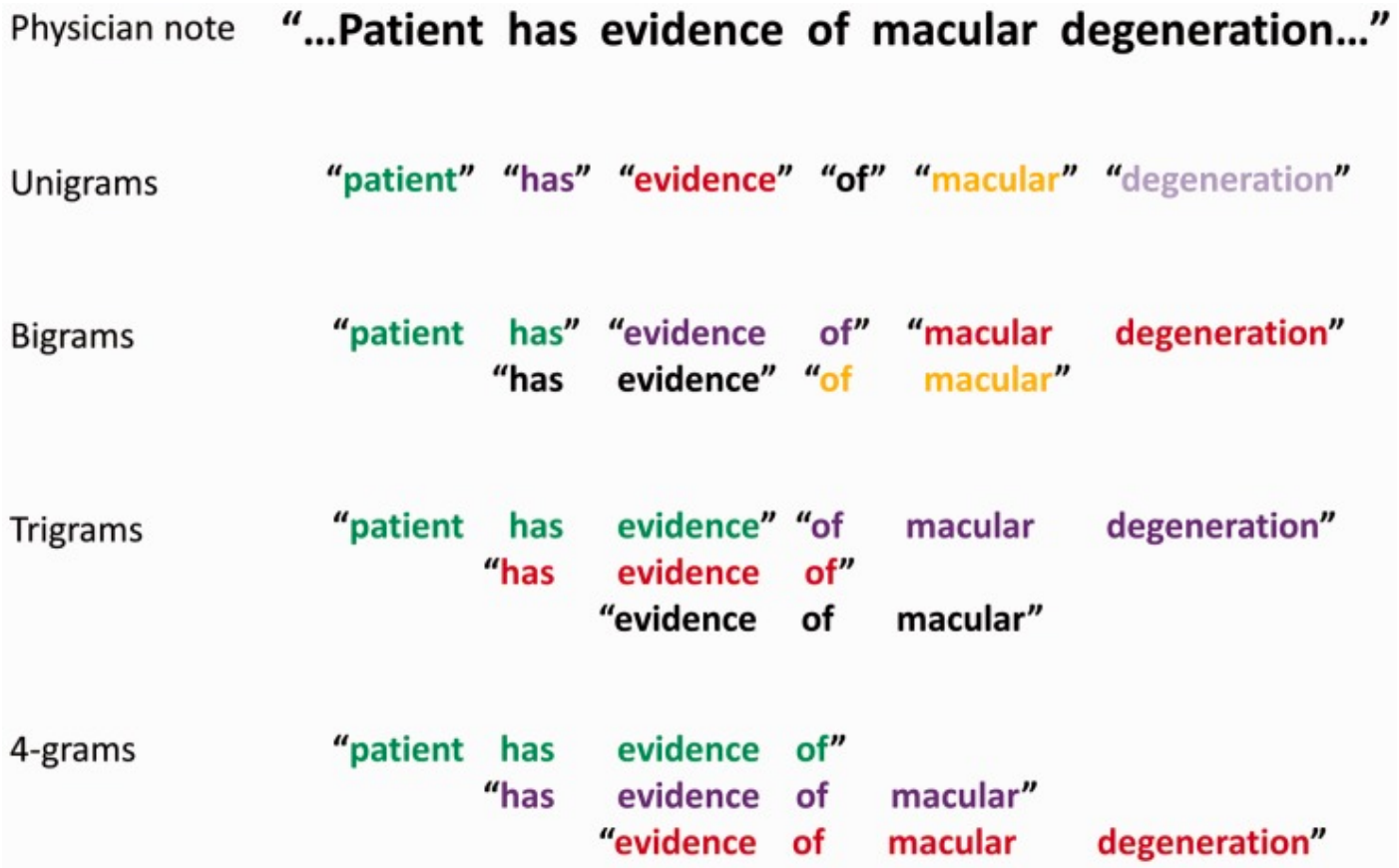
The picture of a teacher is from http://www.clipartpanda.com/categories/teacher-clip-art.

Evaluating Summary Content

- **Human assessors**
  - Judge each summary individually
  - Very time-consuming and does not scale well

- **ROUGE** (Lin 2004)
  - Automatically compares n-grams from target summaries to reference summaries (model summaries) and can be applied to a large number of summaries.
  - Recall-based measure
    - ROUGE-1: $\frac{\text{count of unigrams in reference that appear in system}}{\text{count of unigrams in reference summary}}$

N-grams



From: https://www.researchgate.net/figure/271910222_fig1_Fig-1-An-example-of-unigrams-bigrams-trigrams-and-4-grams-extracted-from-the-clinical

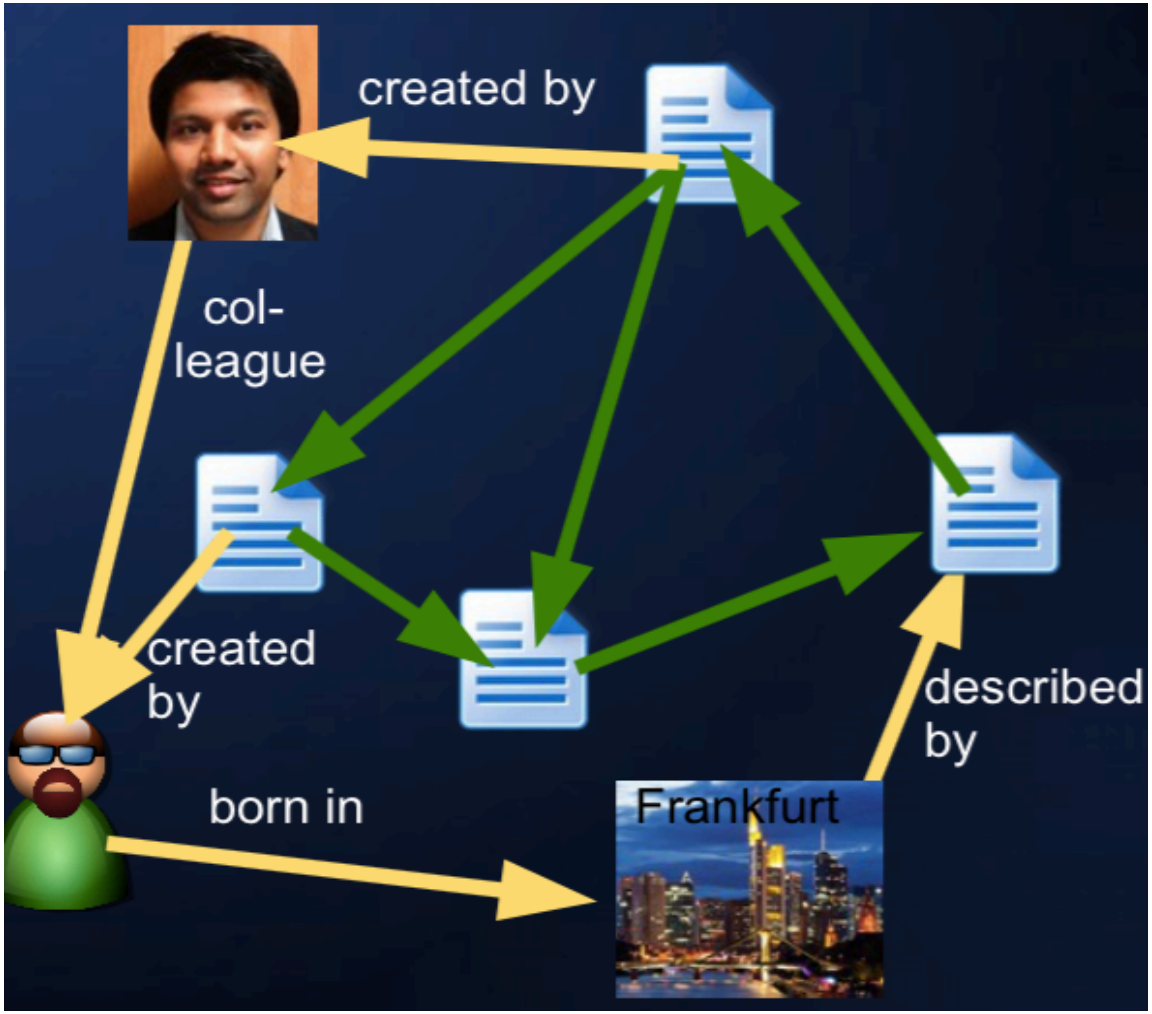
Problem

- N-grams can be quite different between the reference summary and the target summary
  - "Benz developed a new kind of motor"
    vs. "This new engine type was designed by Karl Benz”
- Our idea: Use semantic triples to evaluate summary content automatically

Semantic Triples

- A semantic triple consists of (head entity, relation, tail entity)
  - Example: (City:Beijing, CityCapitalOfCountry, Country:China)

Example: Semantic Web

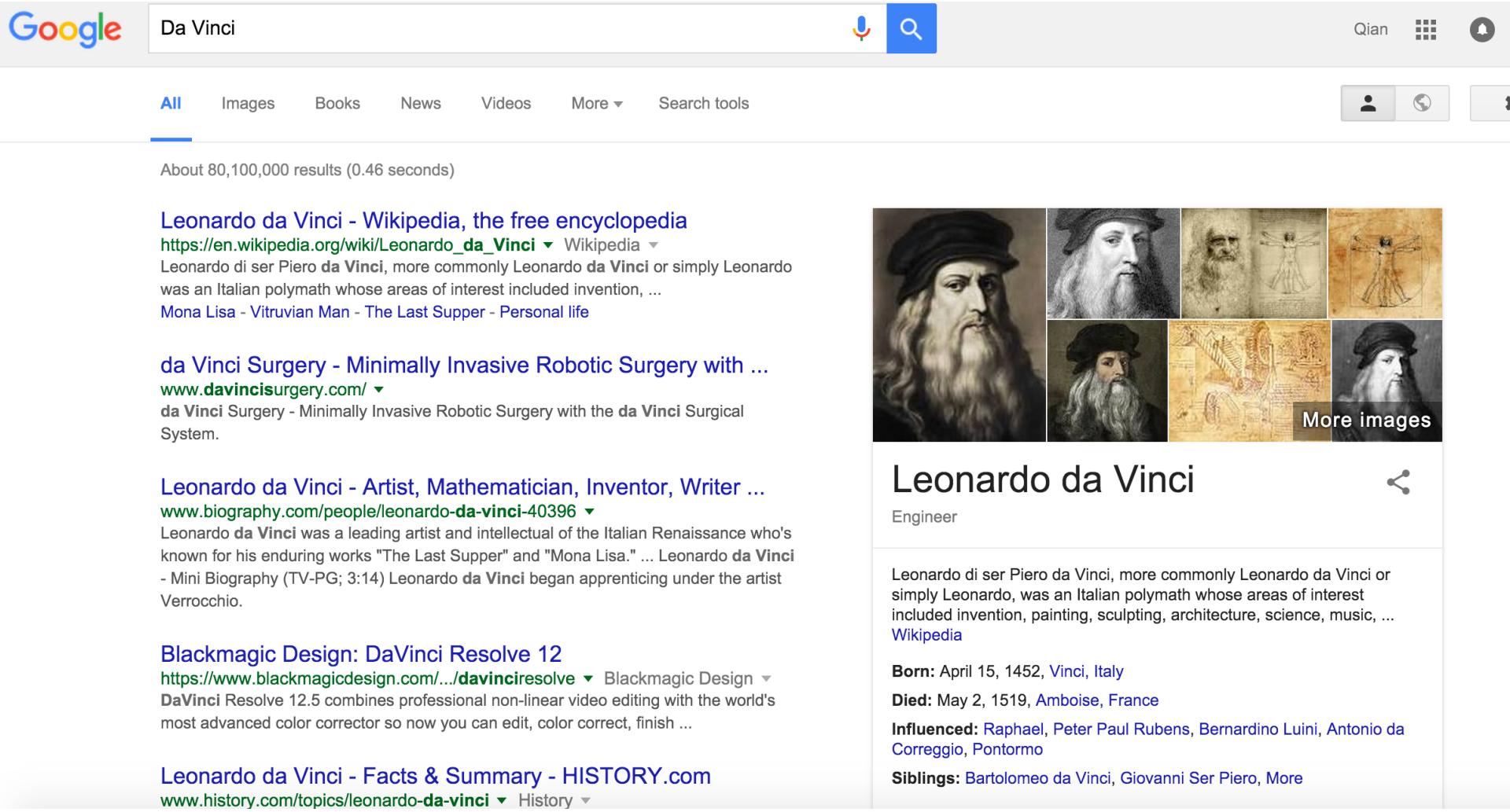


From: Tutorial of Gerard de Melo

Example: Google Knowledge Graph

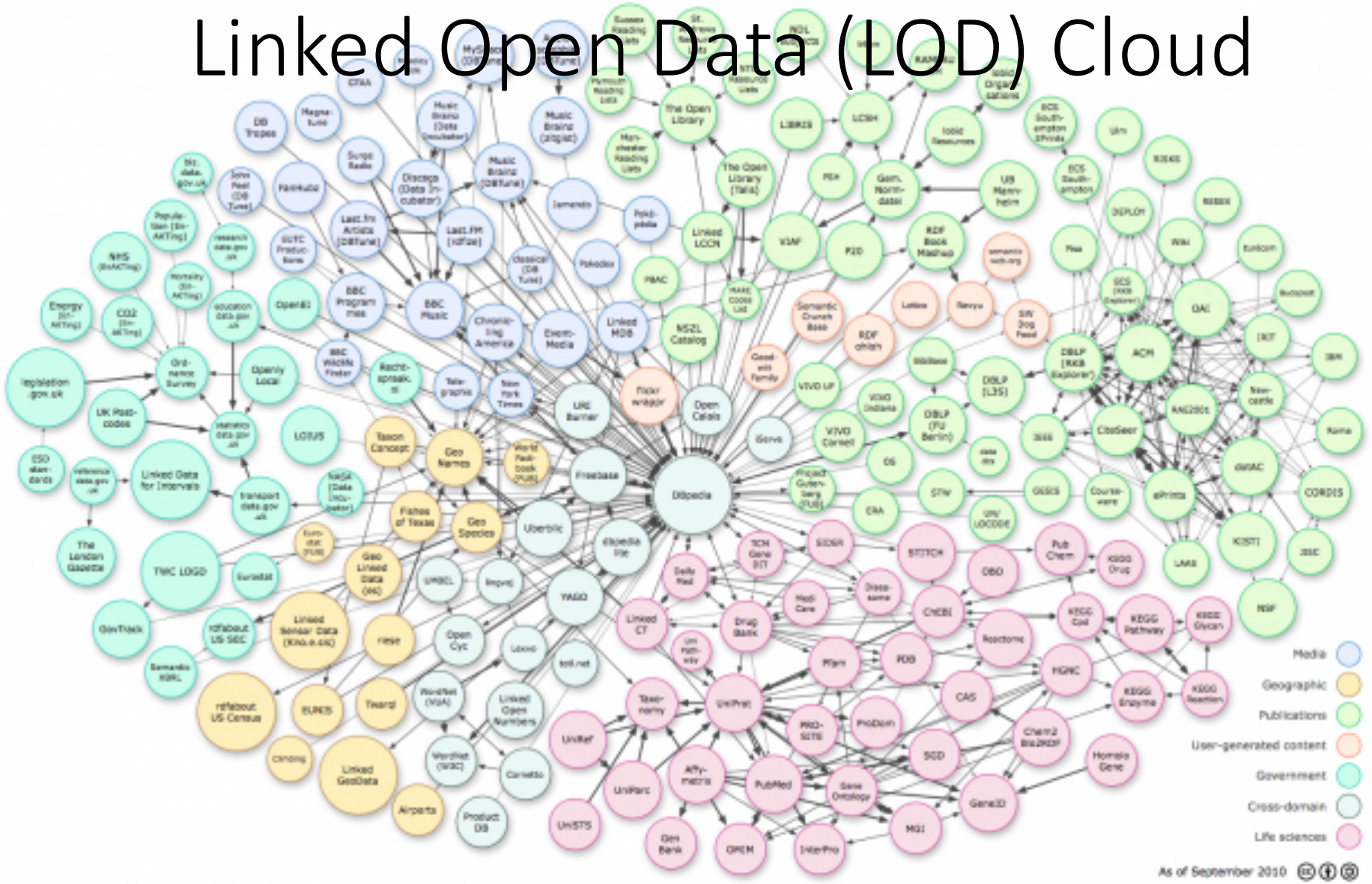
From: https://www.google.com/intl/es419/insidesearch/features/search/knowledge.html

Example: Google Knowledge Graph

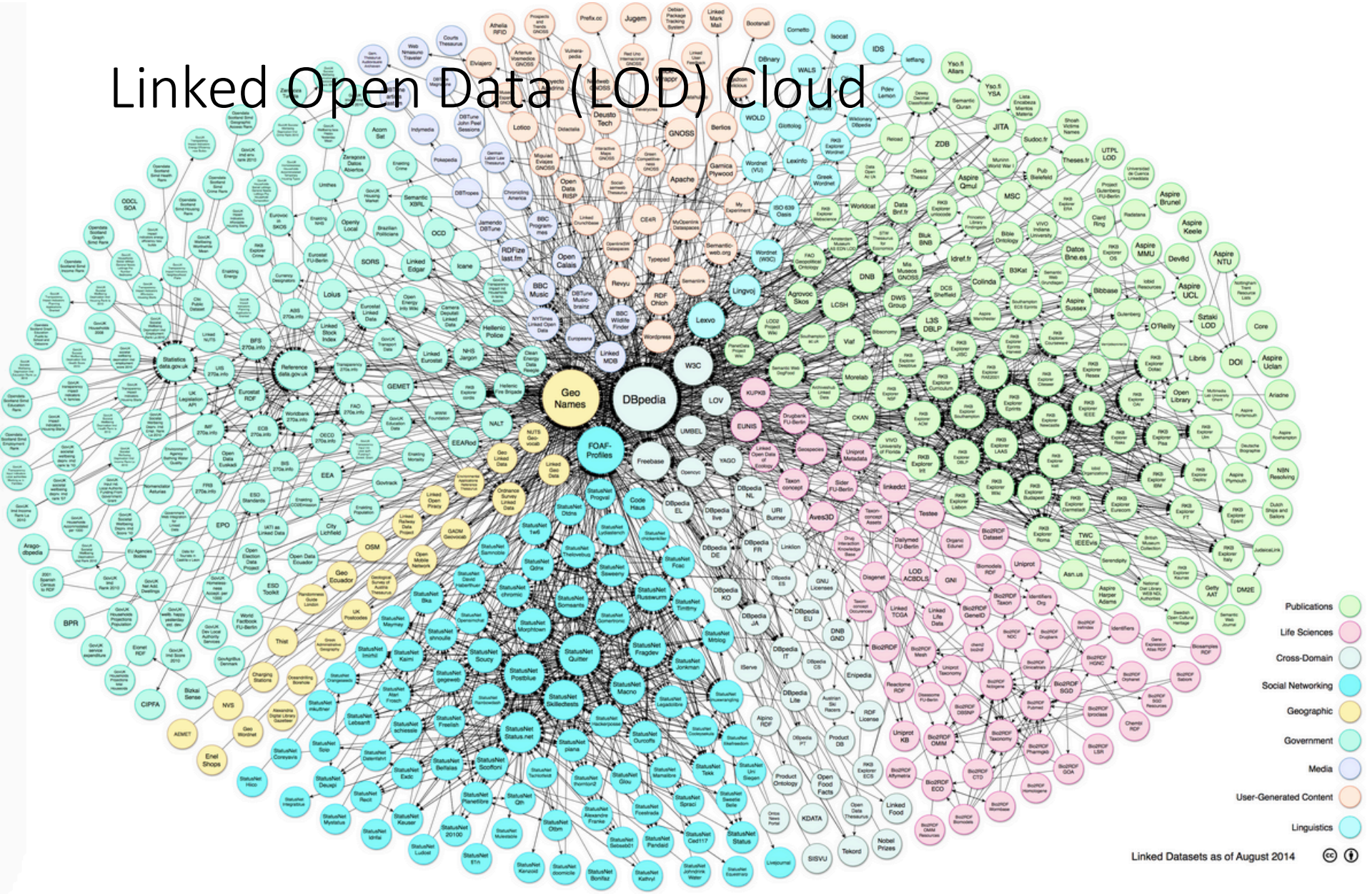


From: https://www.google.com

Linked Open Data (LOD) Cloud

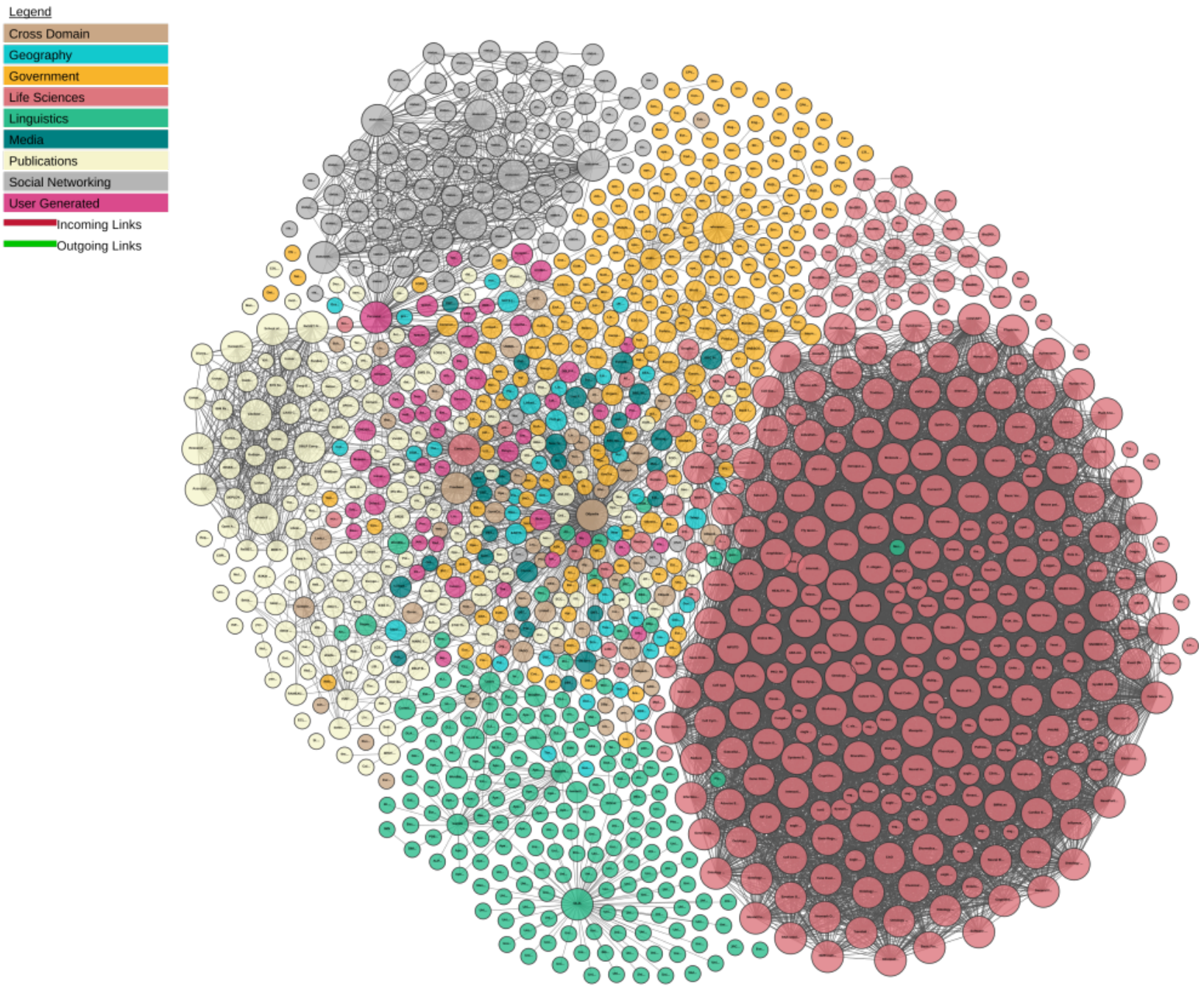


Linked Open Data (LOD) Cloud



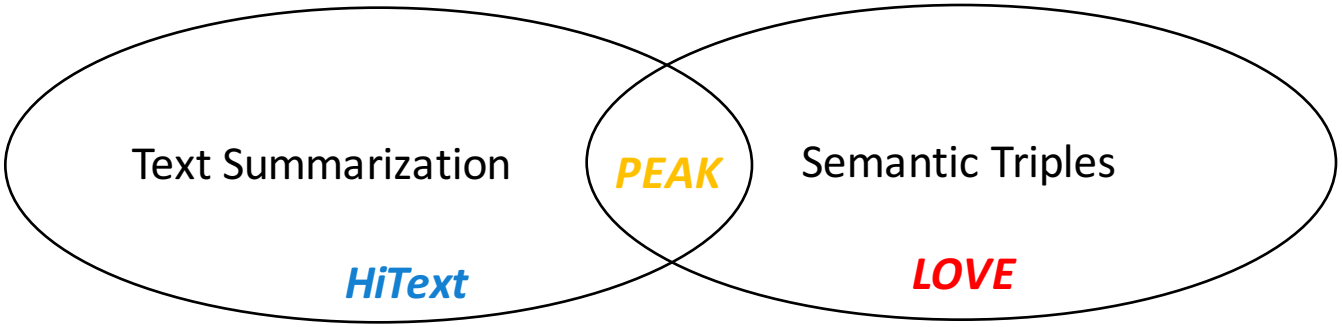
570 datasets and 2909 linkage relationships

Linking Open Data cloud diagram 2014, by Max Schmachtenberg, Christian Bizer, Anja Jentzsch and Richard Cyganiak. http://lod-cloud.net/



"Linking Open Data cloud diagram 2017, by Andrejs Abele, John P. McCrae, Paul Buitelaar, Anja Jentzsch and Richard Cyganiak. http://lod-cloud.net/"

Outline



PEAK: Pyramid Evaluation via Automated Knowledge Extraction

1. PEAK: Pyramid Evaluation via Automated Knowledge Extraction.
Qian Yang, Rebecca J. Passonneau, Gerard de Melo.
In: *Proc. AAAI 2016.* AAAI Press.

2. Wise Crowd Content Assessment and Educational Rubrics.
Rebecca J. Passonneau, Ananya Poddar, Gaurav Gite, Alisa Krivokapic, **Qian Yang**, Dolores Perin.
International Journal of Artificial Intelligence in Education, 10.1007/s40593-016-0128-6, 2016.

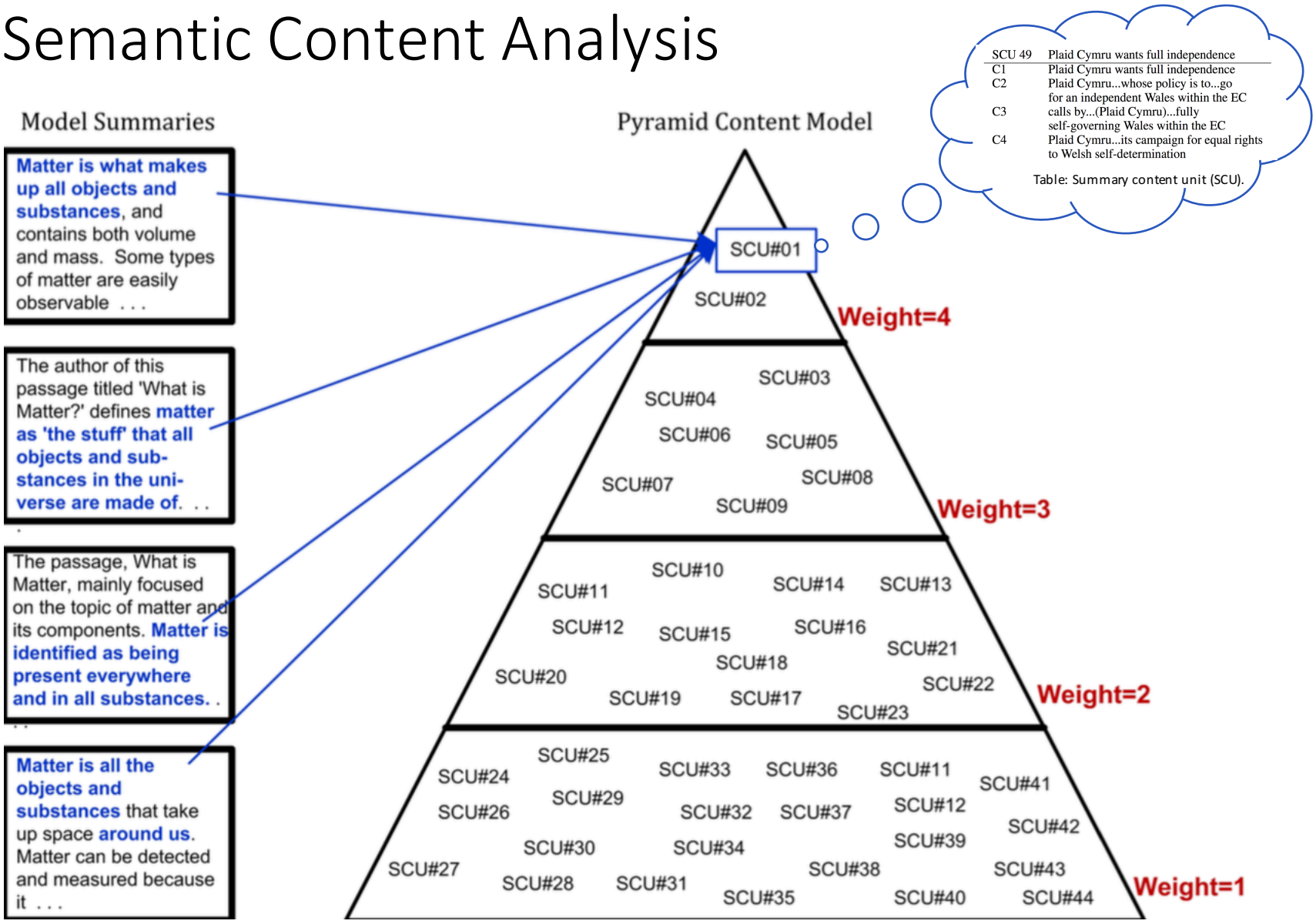
Related Work

- **ROUGE** (Lin 2004)
  - Cannot capture similarity of meaning when little lexical overlap
- **Pyramid Method** (Nenkova and Passonneau, 2004)
  - Semantic comparison, reliable for individual summaries
  - Has required manual annotation
- **Our Method**
  - No need for manually created pyramids
  - Also good results on automatic assessment given a manually created pyramid

Overview

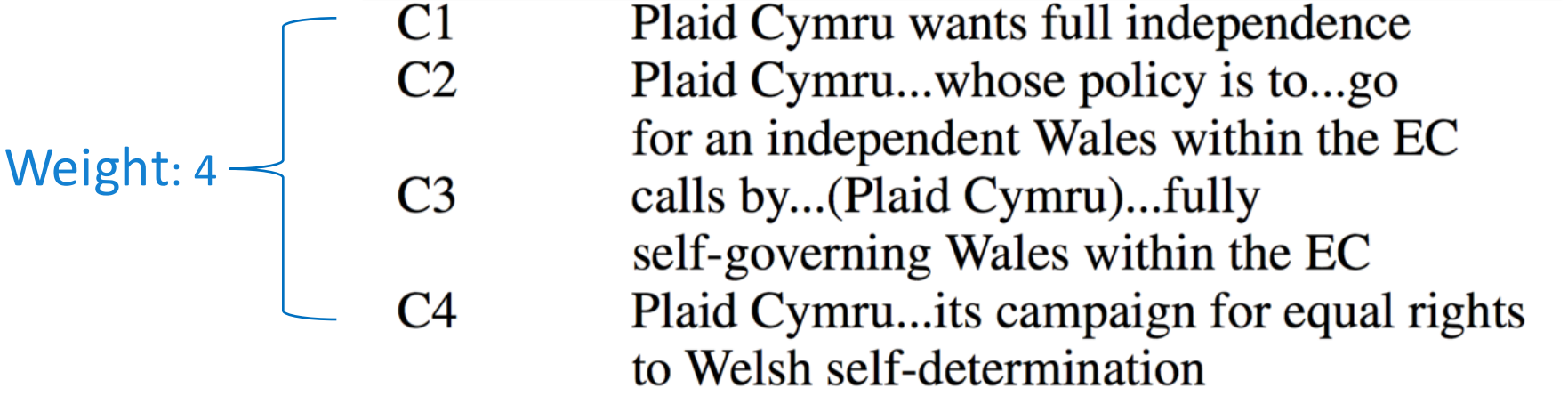
- Semantic Content Analysis
- Pyramid Induction
- Automated Scoring of Summaries

Semantic Content Analysis



Source: http://www1.ccls.columbia.edu/~beck/pubs/2458_PassonneauEtAl.pdf

Semantic Content Analysis



SCU	Plaid Cymru wants full independence
C1	Plaid Cymru wants full independence
C2	Plaid Cymru...whose policy is to...go for an independent Wales within the EC
C3	calls by...(Plaid Cymru)...fully self-governing Wales within the EC
C4	Plaid Cymru...its campaign for equal rights to Welsh self-determination

Figure 1: Sample SCU from *Pyramid Annotation Guide: DUC 2006*.

Semantic Content Analysis -PEAK

- "*The law of conservation of energy is the notion that energy can be transferred between objects but cannot be created or destroyed.*"
- Open information extraction (Open IE) methods split them and extract <subject,predicate,object> triples
- Example:

"*These characteristics determine the properties of matter*"

yields the triple

⟨*These characteristics*, *determine*, *the properties of matter*⟩

- We use ClausIE (Del Corro and Gemulla 2013)

Semantic Content Analysis-PEAK

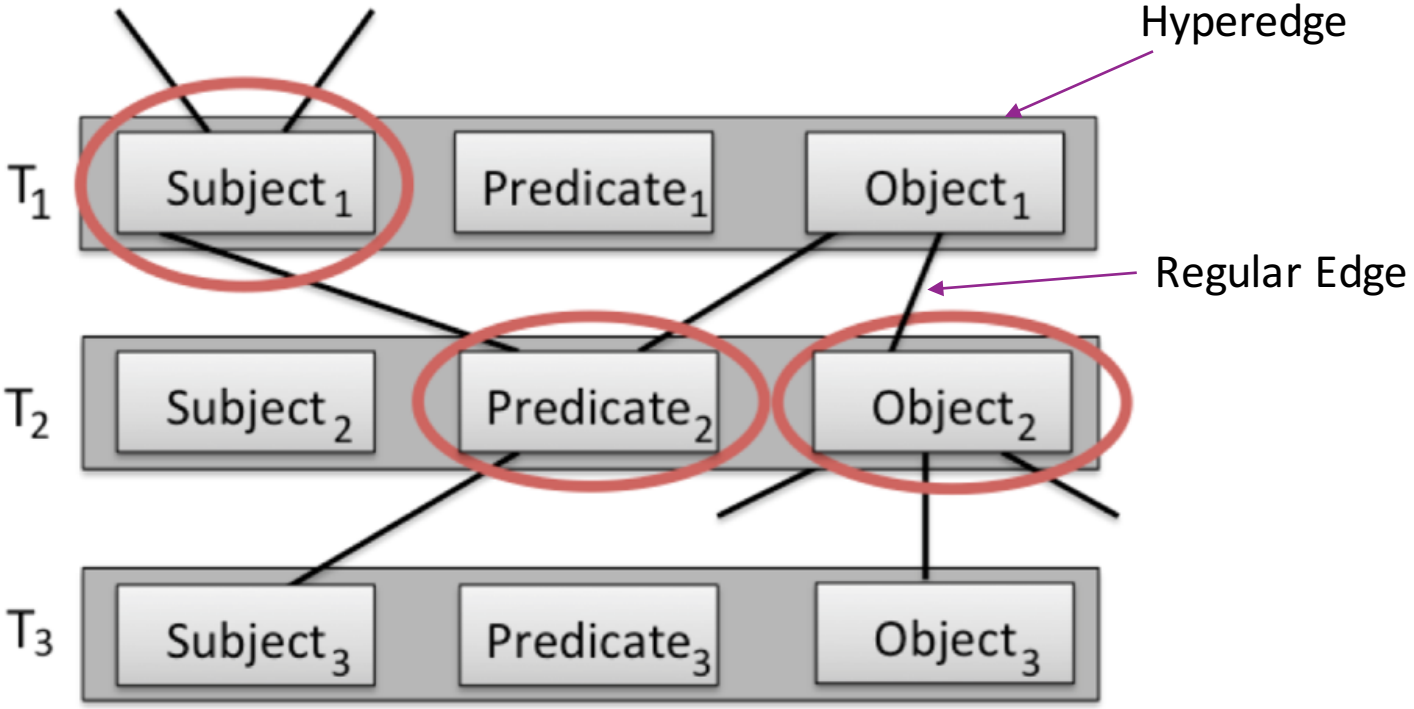


Figure 2: Hypergraph to capture similarites between elements of triples, with salient nodes circled in red

Similarity Score: *Align, Disambiguate and Walk* (ADW) (Pilehvar, Jurgens, and Navigli 2013)

Pyramid Induction

ANCHOR: "Matter" "is" "all the objects and substances"

Similarity Class E1 for "Matter"	Similarity Class E2 for "all the objects and substances"
"Matter", "All matter", "matter", "the matter itself", "a different matter", "the matter itself systematically", ...	"all the objects and substances", "the substance", "all objects and substances in the universe", "what makes up all objects or substances and contains both volume and mass", "as being present everywhere and in all substances", ...

Pyramid Induction

WEIGHT: 4
ANCHOR: "Matter" "is" "all the objects and substances"

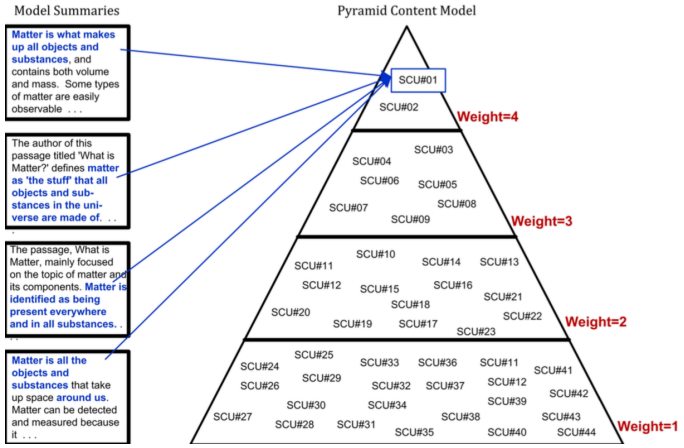
FROM SENTENCE1 of CONTRIBUTOR1: Matter is all the objects and substances that take up space around us.
SALIENT NODES: "Matter" "all the objects and substances"

CONTRIBUTOR1: "Matter" "is" "all the objects and substances"
CONTRIBUTOR2: "Matter" "is identified" "as being present everywhere and in all substances"
CONTRIBUTOR3: "The author of this passage titled What is Matter" "defines" "matter as the stuff that all objects and substances in the universe are made of"
CONTRIBUTOR4: "Matter" "is" "what makes up all objects or substances and contains both volume and mass"

Pyramid Induction

Algorithm 1 Merge similar SCUs

```
1:  procedure MERGE(SCU anchors, weights)
2:      set a graph G whose nodes are all SCU anchors
3:      set threshold T_1
4:      for each node anchor_m do
5:          for each node anchor_n do
6:              calculate similarityScore_{m,n}
7:              if similarityScore_{m,n} ≥ T_1 then
8:                  add edge between anchor_m and anchor_n
9:      mergedSCU ← the connected component in G
10:     mergedWeight ← max. weight of connected component
11:     Return mergedAnchor, mergedWeight
```



SCU 49	Plaid Cymru wants full independence
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SCU created by the original Pyramid method

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SCU created by PEAK

Scoring – Pyramid Method

- Score a target summary against a pyramid
  - Annotators mark spans of text in the target summary that express an SCU
  - The SCU weights increment the raw score for the target summary

- Example:
  - SCU Label: Plaid Cymru wants full independence
  - Target Summary: **Plaid Cymru demands an independent Wales**

Automated Scoring – PEAK

Algorithm 2 Computing scores for target summaries

```
1:  procedure SCORE(target summary sum)
2:      for each sentence s in sum do
3:          T_s ← triples extracted from s
4:      for each triple t ∈ ⋃ T_s do
5:          for each SCU s with weight w do
6:              m ← similarity score between t and s
7:              if m ≥ T then
8:                  W[t][s] ← w                          ▷ store weight
9:      S ← Munkres-Kuhn (Hungarian) Algorithm(W)
10:     Return S
```

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Results: Student Summaries

- Dataset:
  - Twenty target summaries written by students from Perin et al. (2013).
  - Five reference model summaries from Passonneau et al. (2013).
- Metric: Pearson's correlation
- P: PEAK's pyramid v.s. P1 and P2: two human pyramids
- A: Our automatic method v.s. M: Manual method

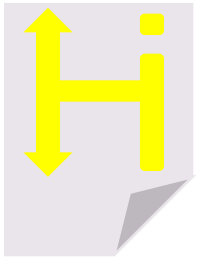
	P1 + M. Scoring	P2 + M. Scoring
P + A.Scoring	0.8263	0.7769
P2 +A. Scoring	0.8538	0.8112
P1 + M. Scoring	1	0.8857

Results

- Machine-Generated Summaries
  - Dataset: the 2006 Document Understanding Conference (DUC) administered by NIST (“DUC06”)
  - The Pearson’s correlation score between PEAK’s scores and the manual ones is 0.7094.

Conclusion

- The first fully automatic version of the pyramid method
- Not only evaluates target summaries but also generates the pyramids automatically
- Experiments show that
  - Our SCUs are similar to those created by humans
  - The method for assessing target summaries automatically has a high correlation with human assessors



HiText: Text Reading with Dynamic Salience Marking

HiText: Text Reading with Dynamic Salience Marking
Qian Yang, Yong Cheng, Sen Wang, Gerard de Melo.
In: *Proc. WWW 2017 (Digital Learning Track).* ACM.

Content

- Chanllenge and Related Work
- The HiText Method
- Interface Evaluation
- General Discussion and Conclusion

Challenge

- Information Overload
  - Massive, non-stop 24/7 stream of new information
- Human ability
  - People can't peruse all information

- Current solution
  - Macro-level content selection
    - Aggregators (Google News), Recommendation engines
    - Helpful but insufficient

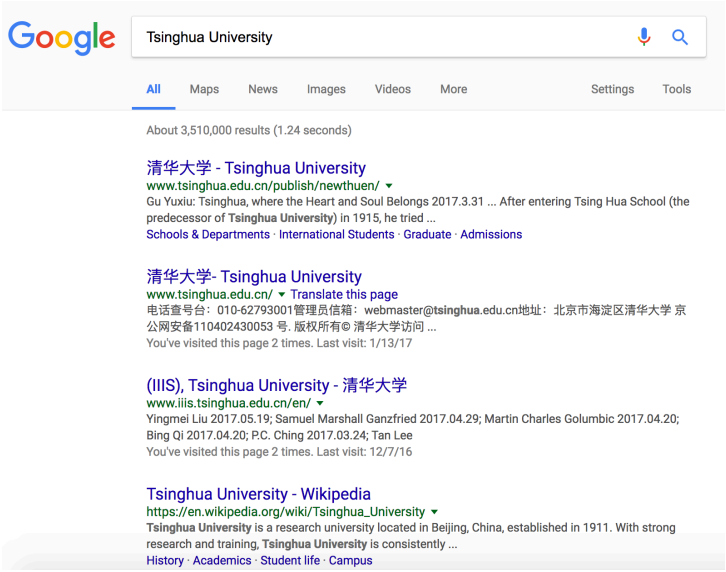
The figure above is from http://chiefexecutive.net/ceos-can-reduce-information-overload/
The figure below is from google news.

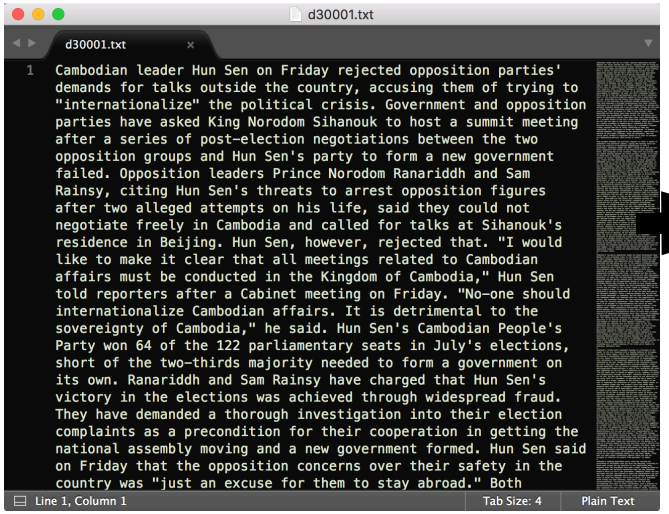
Our Focus

- Micro-level selection *within* a given document to help people reading text more efficient
  - Typical: hit-or-miss form of skimming
    - Glancing at somewhat randomly selected parts of the text
    - More efficient but not perfect
  - Our HiText Approach: Help the readers by specially marking on the screen those parts of the text that are likely to be salient.

Related Work

- Short Excerpts/Snippets
  - Problem: missing context.
- Summaries
  - Problem: Too many details missing, hard to see the rest of document





Related Work

- Receiving a summary is unsatisfactory
  - Automatic summarization systems are known to make mistakes [Gillick 2011]
  - Different readers may exhibit different interests [Rapp 2005]
  - Certain elements are vital for comprehension, such as
    - text structure [Carrell 1985]
    - formatting
    - figures and tables [Yi 2014]

Related Work

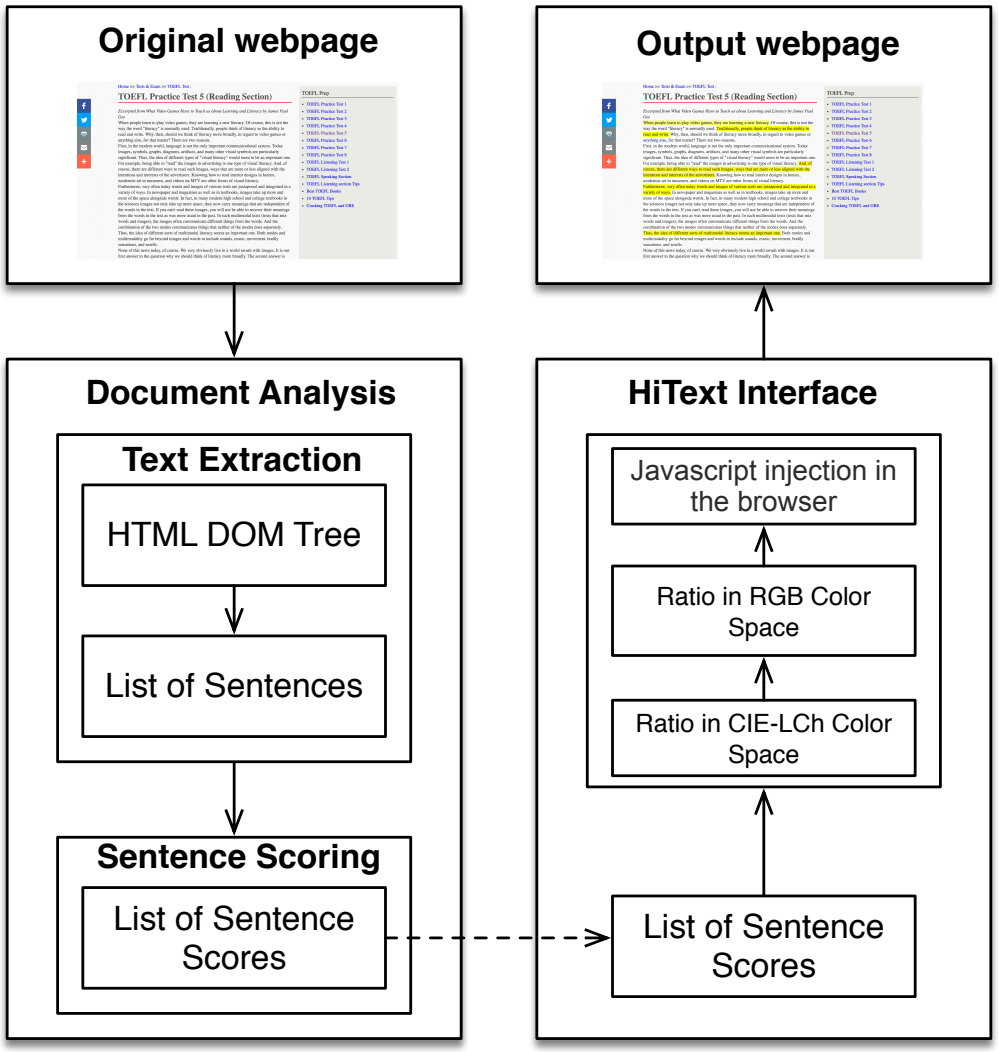
- Reading and comprehension
  - Three forms of behavior that readers seem to combine when skimming under time pressure
    - (1) scanning
    - (2) satisficing, i.e., skipping ahead, possibly to the next paragraph, once the information gain drops below a threshold
    - (3) sampling
  - Salience-based marking could lead to gains in efficiency

Related Work

- The approach we follow is to highlight the key sentences in a text.
- Reading Assistance
  - The Semantize system [Wecker 2014]
  - A study in [Paiva 2014]
  - The ScentHighlights system [Chi 2005]
  - The Nestor Highlighter Extension

The HiText Method

- 1. Document Analysis
  - Text Extraction
  - Sentence Scoring
- 2. HiText Interface
  - Document Rendering
  - Top phrase highlighting
  - Dynamic graded highlighting



System Overview

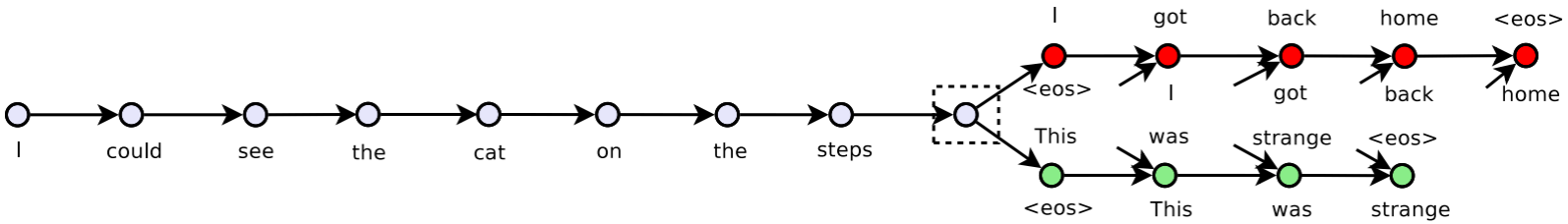
1. Document Analysis

- **Text Extraction**
  - Parse the input HTML, get HTML DOM tree
  - Identify the main text using a stop word ratio-based heuristic
  - Split each paragraph
    - Ignore abbreviations, such as U.K.

- **Sentence Scoring**
  - Each extracted sentence s is analysed and assessed using a deep learning-based scoring technique to produce a salience score $\sigma(s)$

Skip-Thought Vector Approach [Kiros, 2015]

Given a tuple (s_{i-1}, s_i, s_{i+1}) of contiguous sentences, with s_i the i-th sentence of a book, the sentence s_i is encoded and tries to reconstruct the previous sentence s_{i-1} and next sentence s_{i+1}.



In this example, the input is the sentence triplet *I got back home*. *I could see the cat on the steps.* *This was strange*. Unattached arrows are connected to the encoder output. Colors indicate which components share parameters. <eos> is the end of sentence token.

Our Method

- We use a pre-trained model for this architecture to produce a 4,800-dimensional real-valued vector representation v_s of every sentence s in the document
- Compute initial sentence scores
  - $\sigma_o(s) = \sum_{s'} \frac{v_s^t v_{s'}}{\|v_s\|\|v_{s'}\|}$
- Final scores
  - $\sigma(s) = \max\{0, 1 - 2\frac{r(\sigma_0(s))-1}{n}\}$

2. The HiText Interface

- Document rendering
  - Inject additional JavaScript code
- Top phrase highlighting
  - Highlights the top-k sentences
- Dynamic graded highlighting
  - Capture the location of the pointing device
  - $\sigma_{\min} = min_s\sigma(s),\ \sigma_{max} = max_s\sigma(s)$
  - Assign two background colors C_{max}, C_{min} to σ_{max}, σ_{min}
  - $\frac{\sigma(s)-\sigma_{min}}{\sigma_{max}-\sigma_{min}}(C_{max} - C_{min})+C_{min}$

TOEFL Practice Test 5 (Reading Section)

Excerpted from What Video Games Have to Teach us about Learning and Literacy by James Paul Gee

When people learn to play video games, they are learning a new literacy. Of course, this is not the way the word "literacy" is normally used. Traditionally, people think of literacy as the ability to read and write. Why, then, should we think of literacy more broadly, in regard to video games or anything else, for that matter? There are two reasons.

First, in the modern world, language is not the only important communicational system. Today images, symbols, graphs, diagrams, artifacts, and many other visual symbols are particularly significant. Thus, the idea of different types of "visual literacy" would seem to be an important one. For example, being able to "read" the images in advertising is one type of visual literacy. And, of course, there are different ways to read such images, ways that are more or less aligned with the intentions and interests of the advertisers. Knowing how to read interior designs in homes, modernist art in museums, and videos on MTV are other forms of visual literacy.

Furthermore, very often today words and images of various sorts are juxtaposed and integrated in a variety of ways. In newspaper and magazines as well as in textbooks, images take up more and more of the space alongside words. In fact, in many modern high school and college textbooks in the sciences images not only take up more space, they now carry meanings that are independent of the words in the text. If you can't read these images, you will not be able to recover their meanings from the words in the text as was more usual in the past. In such multimodal texts (texts that mix words and images), the images often communicate different things from the words. And the combination of the two modes communicates things that neither of the modes does separately. Thus, the idea of different sorts of multimodal literacy seems an important one. Both modes and multimodality go far beyond images and words to include sounds, music, movement, bodily sensations, and smells.

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Interface Evaluation

- Experiment 1: Comprehension Survey
- Experiment 2: Comprehension Tests
  - Experiment 2-A: Response Time
  - Experiment 2-B: Time-Restricted Case
- Experiment 3: Salience Scoring

Experiment 1: Comprehension Survey

- Evaluating comprehension is non-trival
  - Impossible to repeat a given task with different methods under equal conditions
- One way is by finding two participants with comparable reading abilities.
- In our experiment: more robust by relying on two groups (with counterbalancing)

Experiment 1: Comprehension Survey

- Participants
  - A pool of 10 participants
- Materials
  - Two articles from popular online journals
    - one 543 words, the other 1260 words
- Procedure and Measures
  - Randomly divided into two groups
  - Read a given text under two different conditions in a counterbalanced order
    - Top5, Top5+Graded

Experiment 1: Comprehension Survey

	Article 1	Article 2
HiText Group	86 (40.37, 18.06)	187 (183.15, 81.91)
Control Group	127 (66.86, 29.90)	234 (121.57, 54.37)
Time saved	32.28%	20.09%

Table 1: Efficiency analysis (Experiment 1), given as means (std. deviation, std. error) in seconds.

	Strongly Agree	Agree	Not Sure	Disagree	Strongly Disagree
Q1	1.00	0.00	0.00	0.00	0.00
Q2	0.90	0.10	0.00	0.00	0.00
Q3	0.90	0.10	0.00	0.00	0.00

Table 2: Qualitative feedback from participants.

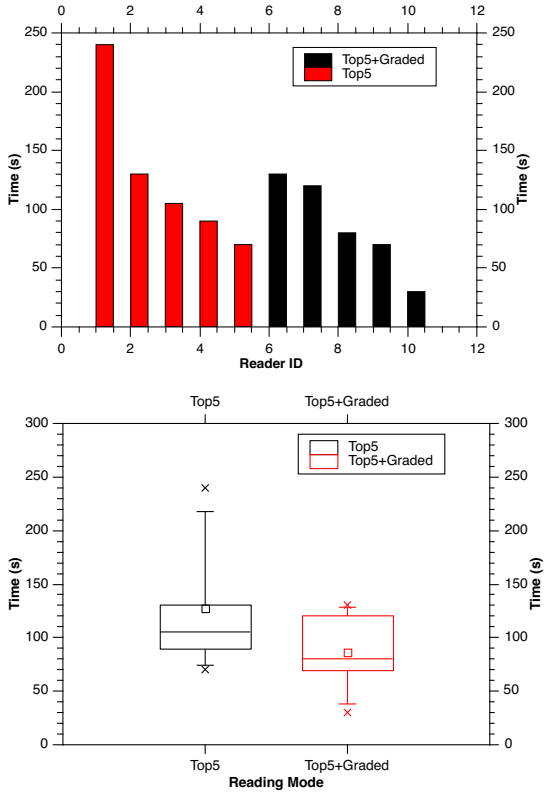


Figure 4: Analysis of reading times for article 1 (Experiment 1) as a bar chart and box plot. Top5 refers to the control group and serves as the baseline.

Experiment 2: Comprehension Tests

- Experiment 2-A: Response Time
  - Materials (from TOEFL exams)
    - Text 1 (Plain Text) 649 words; Text 2 (Top5) 974 words; Text 3 (Top5+Graded) 818 words
    - One question to evaluate the reader's global understanding
  - Participants, Procedure, and Measure
    - Only participants that answered all three questions correctly were considered.
    - Until we had 10 participants with correct answers
    - Measure the time

Experiment 2: Comprehension Tests

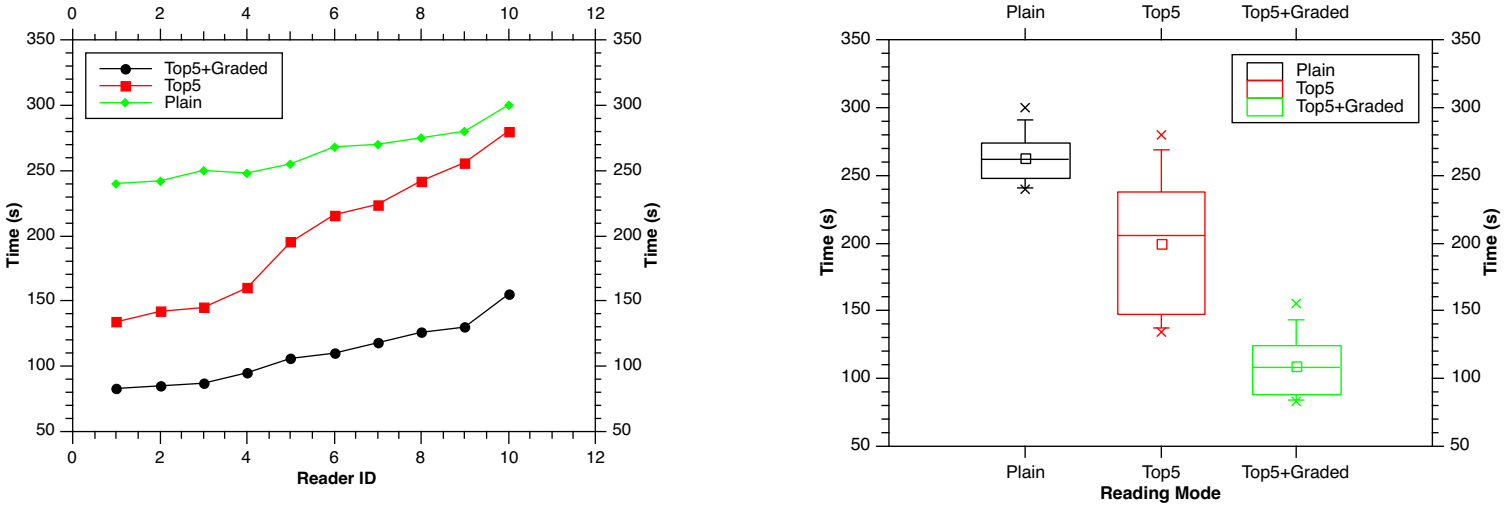


Figure 5: Response time for correctly answering reading comprehension questions (Experiment 2-A)

	Plain	**Top5**	**Top5+Graded**
Average Time (SD, SE)	262.8 (19.16, 6.06)	199.4 (52.17, 16.50)	109.5 (23.25, 7.35)
T-test (paired)	w/ Top5 t = 5.928, p-value = 0.0002213	w/ Top5+Graded t = 9.5539, p-value = 5.225e-06	w/ Plain t = 89.832, p-value = 1.331e-14

Table 3: Efficiency analysis (Experiment 2-A), given as means (std. deviation, std. error) in seconds.

Experiment 2: Comprehension Tests

- Experiment 2-B: Time-Restricted Case
  - Participants and Materials
    - A different set of 10 participants
    - The same materials as in Experiment 2-A.
  - Procedure
    - First read the texts and then answer the question within 2 minutes.
    - Respond to Question, irrespective of whether the given time is enough or not

Experiment 2: Comprehension Tests

- Results and Discussion
- The resulting ratios of correct results for the three settings
  - For plain text, only 40% of participants answered the question correctly
  - For Top5 highlighting, 70% answered correctly
  - While for Top5 + Graded highlighting, in fact 100% made the right choice

Experiment 3: Salience Scoring

- Materials
  - One of the texts from our pool of texts from Experiment 1.
- Participants and Procedure
  - Two independent annotators
    - The 7-point Likert-style importance scale given by Vagias [Vagias 2006]
  - For LexRank [Erkan 2004], SumBasic [Nenkova 2005], and Luhn [Luhn 1958]
    - Gradually increases the length of the expected summaries
    - Ultimately rank the salience of every sentence
  - For HiText
    - Obtain the rank directly from its salience scores.

Experiment 3: Salience Scoring

	Annotator 1	**Annotator 2**
Annotator 2	0.91	1.00
Our method	0.75	0.83
LexRank	0.53	0.52
SumBasic	-0.06	-0.05
Luhn	-0.15	-0.06

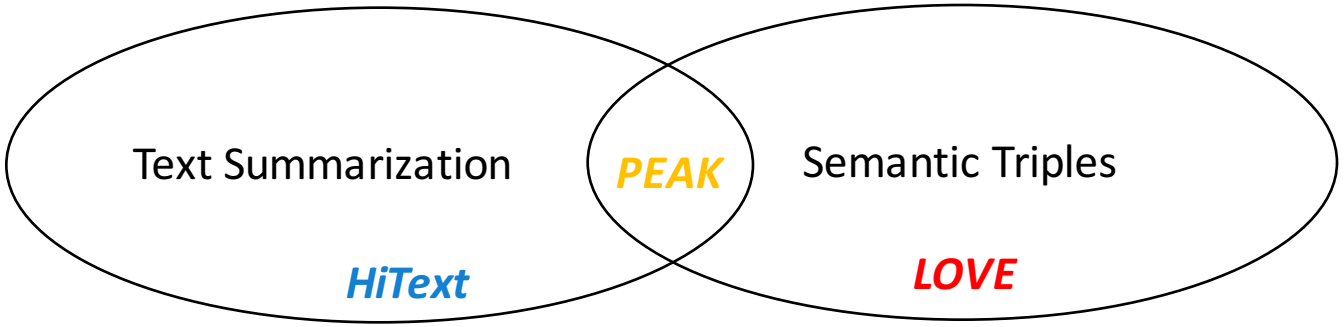
Table 4: Spearman correlations with human salience assessments.

- Deep learning-based representations
  - Learn to map different sentences to similar representations
- Word-based comparisons (✔ large document clusters, ✘ short text units)
  - Example: car and automobile

CONCLUSION

- A simple but effective new method for guiding the reader towards salient content units in text
- Enables faster and better reading comprehension.

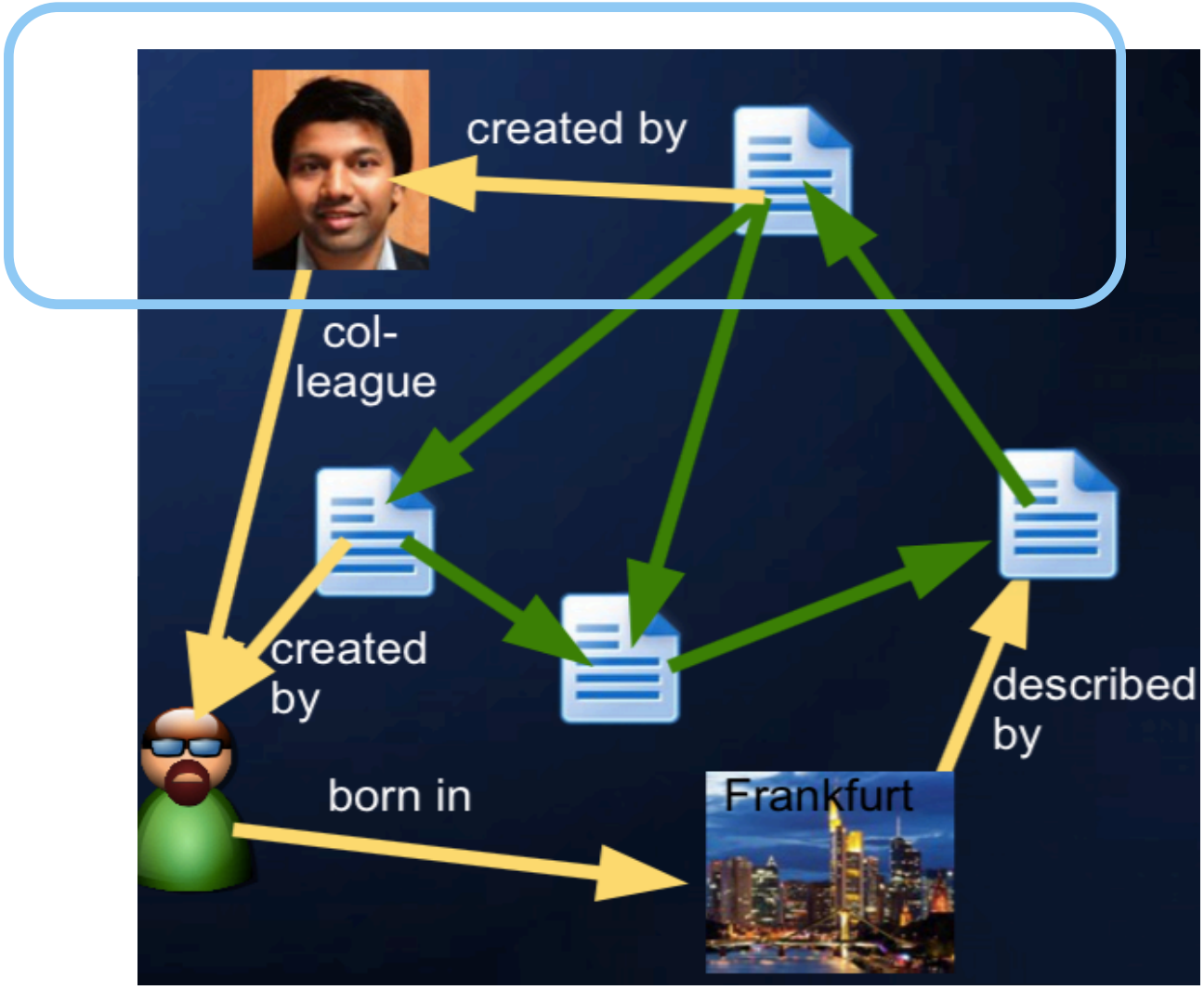
Outline



- Example
  - "The book's author is Kafka."
    "Kafka wrote the book."
    "Kafka created the book."

LOVE: Disambiguation and Alignment of Properties via Linked Open Vocabularies Enrichment

Example: Semantic Web



From: Tutorial of Gerard de Melo

Problem

METADATA
Dublin Core® Metadata Initiative
INNOVATION

join us!

Term Name: creator	
URI:	http://purl.org/dc/elements/1.1/creator
Label:	Creator
Definition:	An entity primarily responsible for making the resource.
Comment:	Examples of a Creator include a person, an organization, or a service. Typically, the name of a Creator should be used to indicate the entity.

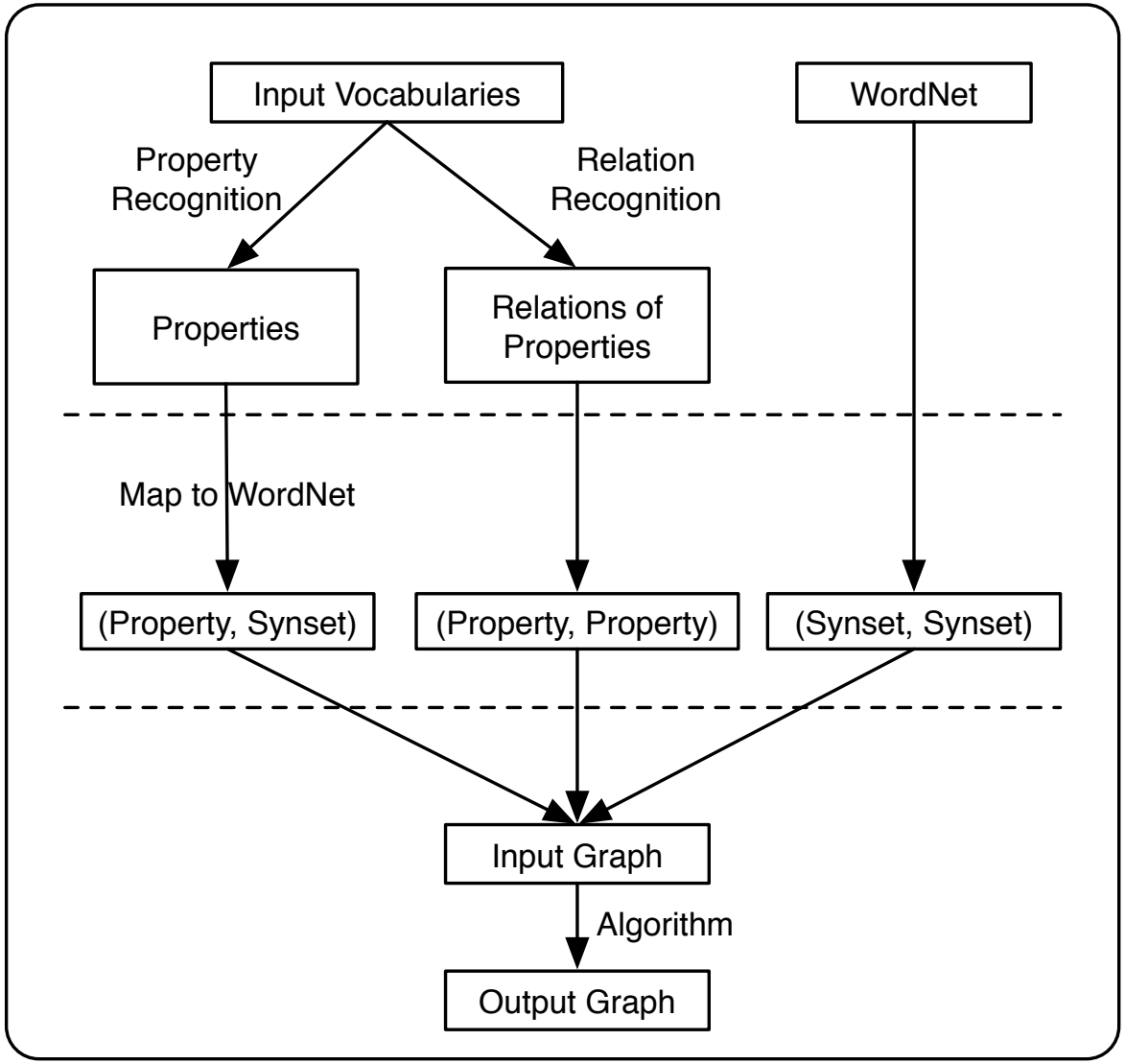
Problem


schema.org
Search
Thing > Property > author
The author of this content Please note that author is special in that HTML 5 provides a special mechanism for indicating authorship via the rel tag. That is equivalent to this and may be used interchangeably.
Values expected to be one of these types
Organization
Person
Used on these types
CreativeWork

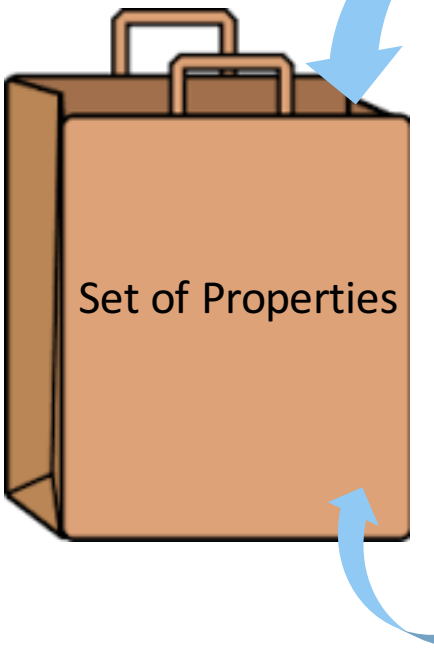
Our goal is more ambitious

- PEAK: if triples are similar
- LOVE: if one is more specific than the other (subProperty) or inverse of the other

Overview of our approach



Collect all the properties



Property	Relation
http://www.w3.org/2002/07/owl#equivalentProperty	equivalent
http://www.w3.org/2002/07/owl#propertyDisjointWith	nonEquivalent
http://www.w3.org/2002/07/owl#inverseOf	inverse
http://www.w3.org/2000/01/rdf-schema#subPropertyOf	subProperty

Table 1: Predicates for four relations.

Property
owl:Property[1]
owl:ObjectProperty
owl:DatatypeProperty
owl:AnnotationProperty

Table 2: Types of Properties.

The picture of bag is from http://cn.clipartlogo.com/free/brown-paper-bag-lunch.html

Algorithm 1 Collect all the properties

procedure COLLECT(input vocabularies in $\mathcal{V}$)
  $T \leftarrow \bigcup_{V \in \mathcal{V}} V$ ▷ input triples
  $P \leftarrow \{\}$ ▷ empty set
  for each triple $t_i = \langle s_i, p_i, o_i \rangle \in T$ **do**
    if its predicate p_i is listed in Table 1 **then**
      $P \leftarrow P \cup \{s_i, o_i\}$
    if o_i is in Table 2 (with appropriate predicate) **then**
      $P \leftarrow P \cup \{s_i\}$
  $P \leftarrow P \cup$ items in Table 1
  $P \leftarrow P \cup$ items in Table 2
  $A \leftarrow \{t \in T \mid t$ describes attribute of $p \in P\}$ ▷ attributes
  $L \leftarrow \{t \in T \mid$ property in Table 1$\}$ ▷ links
  return P, A, L

Mapping to Wordnet: Example

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Dublin Core® Metadata Initiative

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Term Name: creator	
URI:	http://purl.org/dc/elements/1.1/creator
Label:	Creator
Definition:	An entity primarily responsible for making the resource.
Comment:	Examples of a Creator include a person, an organization, or a service. Typically, the name of a Creator should be used to indicate the entity.

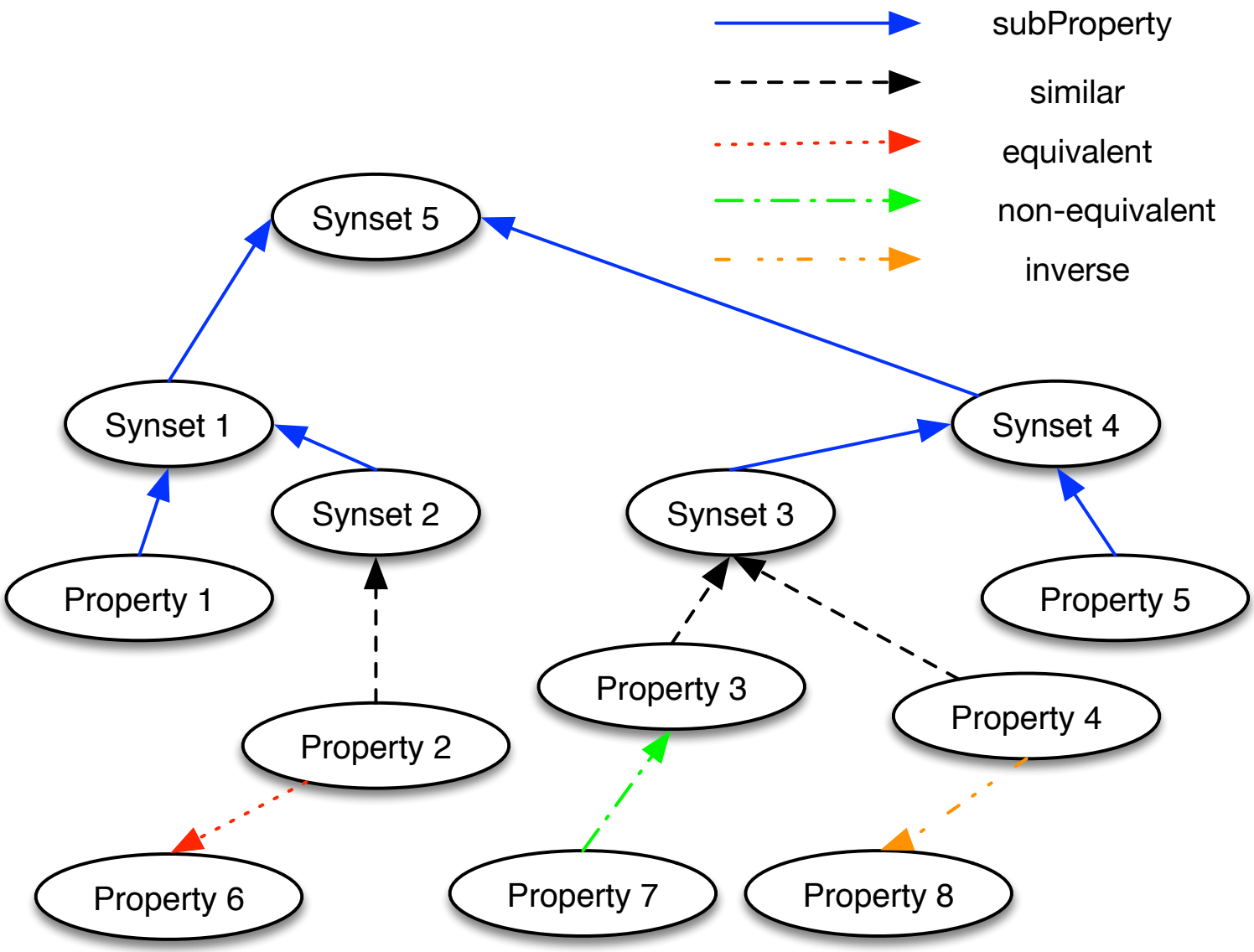
[Synset: [Offset: 9637345] [POS: noun] Words: creator -- (a person who grows or makes or invents things)] [PointerType: [Label: hypernym] [Key: @] Applies To: noun, verb]]

[Synset: [Offset: 9559474] [POS: noun] Words: Godhead, Lord, Creator, Maker, Divine, God Almighty, Almighty, Jehovah -- (terms referring to the Judeo-Christian God)]

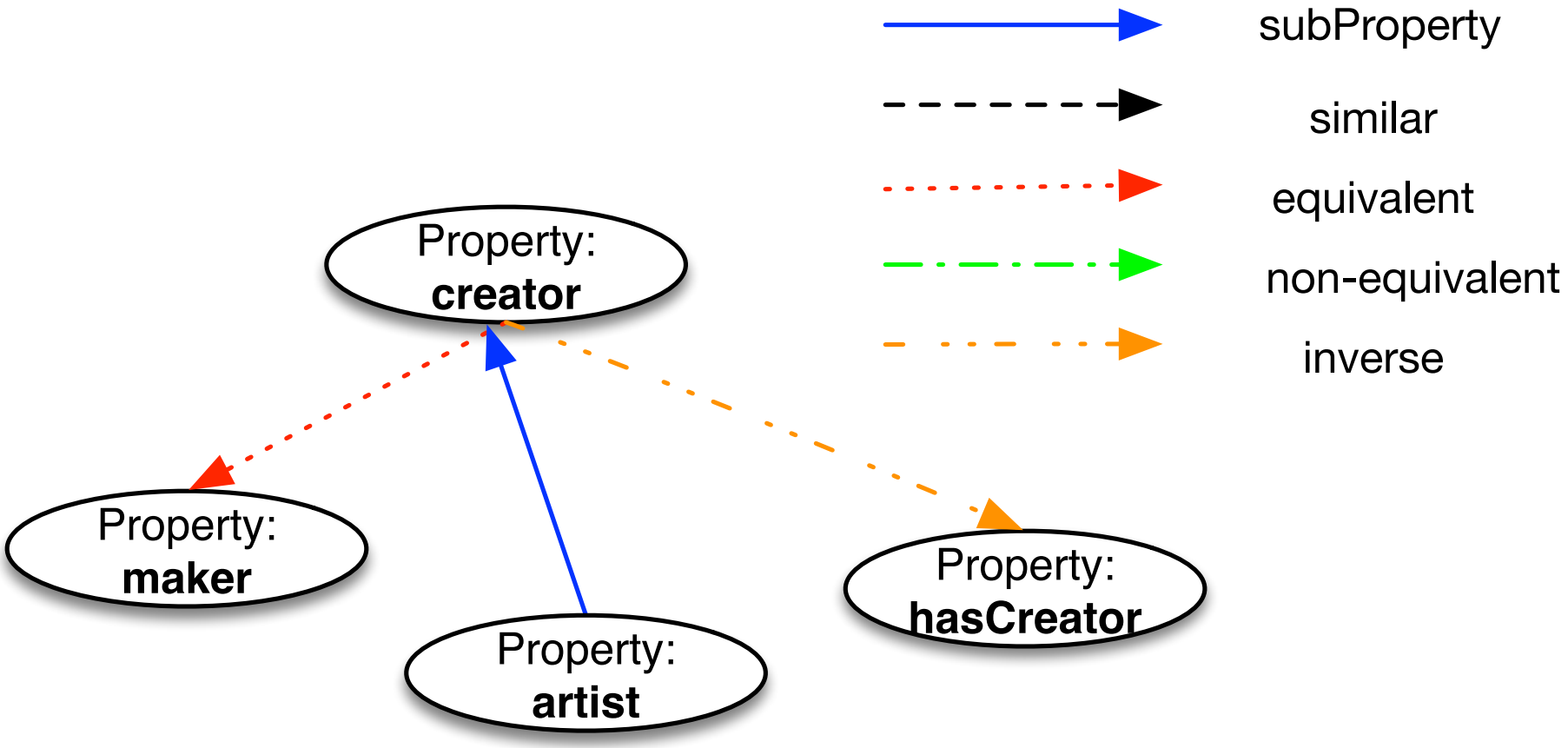
Algorithm 2 Mapping to Wordnet

procedure MAP(set of properties P, WordNet synsets S)
  $V \leftarrow P \cup S$, $E \leftarrow \emptyset$ ▷ Graph
  for each property $p \in P$ **do**
    extract *keyword* k_p from p ▷ Cf. definition in text
    obtain POS tag pos_p of k_p ▷ Stanford CoreNLP
    $S_p \leftarrow$ synsets of k_p with pos_p in WordNet
    for every synset $s_p \in S_p$ **do**
      $E \leftarrow E \cup \{$weighted edge between p, s_p with weight $score_{(c_p, s_p)}\}$
  return $G = (V, E)$

Conceptual-graph of the Input Graph



Example: Input Graph



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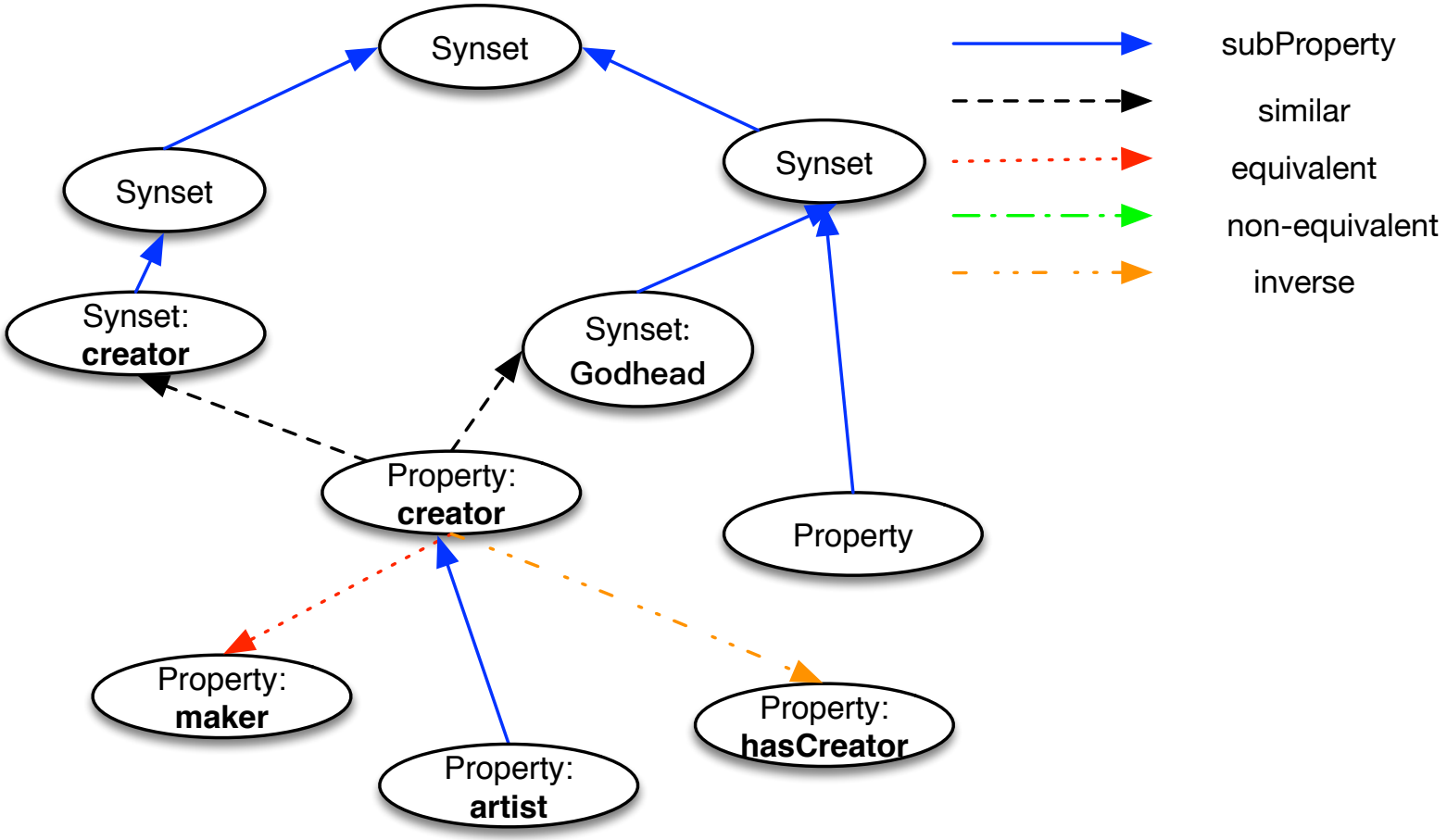


LP Problem

$$\underset{x}{\text{maximize}} \quad \sum_{p\in\Phi,m,n} x^p_{mn} + \sum_{p\in\phi,m} x^p_{mm} - \sum_{p\in\phi,m,n} \alpha_p * C * \epsilon^p_{mn} \tag{2a}$$

subject to

$$x^p_{mn} \leq x^p_{nm} \qquad \forall m,n,p \in \{eq, frameEq, nonEq, inverseOf, hasE0P1, hasE0P3, hasE0P5\} \tag{2b}$$

$$x^p_{mn} \leq x^q_{mn} \qquad \forall m,n,p \in \{eq, inverseOf, synFrameEq\}, q \in \{frameEq\} \tag{2c}$$

$$x^p_{mn} + x^p_{nl} - 1 \leq x^p_{ml} \qquad \forall m,n,l,p \in \{eq, frameEq, subOf\} \tag{2d}$$

$$x^p_{mn} \leq 1 - x^p_{nm} \qquad \forall m,n,p \in \{subOf\} \tag{2e}$$

$$x^p_{mn} + x^p_{nl} - 1 \leq x^q_{ml} + x^r_{ml} + x^r_{lm} \qquad \forall m,n,l,p \in \{inverseOf\}, q \in \{eq\}, r \in \{subOf\} \tag{2f}$$

$$x^p_{mn} \leq 1 - x^q_{mn} \qquad \forall m,n,p \in \{subOf\}, q \in \{eq, inverseOf\}$$
$$\text{and } \forall m,n,p \in \{nonEq\}, q \in \{eq\}$$
$$\text{and } \forall m,n,p \in \{eq\}, q \in \{inverseOf\} \tag{2g}$$

$$x^p_{mn} + x^q_{ml} - 1 \leq x^q_{nl} \qquad \forall m,n,l,p \in \{eq\}, q \in \{nonEq, subOf, inverseOf\} \tag{2h}$$

$$x^p_{mn} - \epsilon^p_{mn} \leq x^q_{mn} \qquad \forall m,n,p \in \{hasE0P1, hasE0P3, hasE0P5\}, q \in \{eq\} \tag{2i}$$

$$x^p_{mn} \in [0,1] \qquad \forall p \in \Phi, m, n \tag{2j}$$

$$x^p_{mm} \in [0,1] \qquad \forall p \in \Phi, m \tag{2k}$$

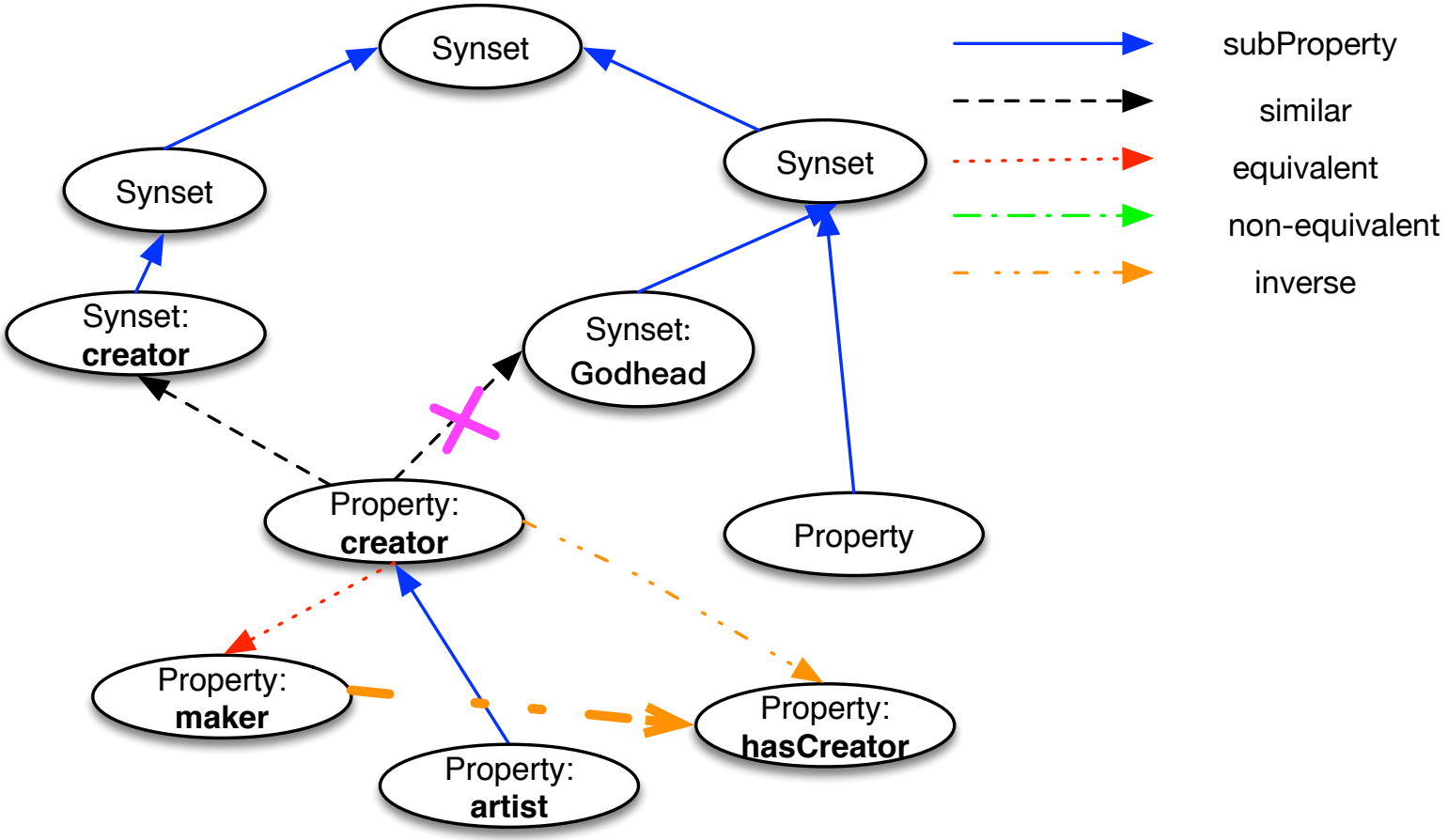
$$\epsilon^p_{mn} \in [0,1] \qquad \forall p \in \{hasE0P1, hasE0P3, hasE0P5\}, m, n \tag{2l}$$

$$\alpha, C \in \mathbb{R} \tag{2m}$$

$$\Phi \in \{eq, frameEq, nonEq, inverseOf, hasE0P1, hasE0P3, hasE0P5, synFrameEq, subOf\} \tag{2n}$$

$$\Phi \in \{eSyn\} \tag{2o}$$

Example: Output Graph



Precision of New Relations

- 8,564 equivalent relations, 1,138 inverse relations, and 2,237 subProperty relations, denoted as Dataset R1, R2, and R3 respectively.

	Precision of R1S	Precision of R2S	Precision of R3S
Annotator 1	0.92	0.77	0.93
Annotator 2	0.89	0.77	0.93

Table 5.9: Precision of output.

- Non-equivalent

```
Property: http://purl.org/ontology/daia/availableFor
   http://purl.org/ontology/daia/unavailableFor
Property: http://purl.org/spar/fabio/isDisciplineOf
   http://www.w3.org/2004/02/skos/core#inScheme
Property: http://purl.org/spar/fabio/hasDiscipline
   http://purl.org/spar/fabio/isSchemeOf
```

- Inverse

```
Property: http://d-nb.info/standards/elementset/agrelon.owl#hasMuse
   http://d-nb.info/standards/elementset/agrelon.owl#isMuseOf
Property: http://d-nb.info/standards/elementset/agrelon.owl#hasParent
   http://d-nb.info/standards/elementset/agrelon.owl#hasChild
Property: http://d-nb.info/standards/elementset/agrelon.owl#hasMurderer
   http://d-nb.info/standards/elementset/agrelon.owl#hasMurderee
Property: http://d-nb.info/standards/elementset/agrelon.owl#hasStudent
   http://d-nb.info/standards/elementset/agrelon.owl#hasTeacher
Property: http://d-nb.info/standards/elementset/agrelon.owl#hasEmployer
```

Our Contribution

- Overcoming the heterogeneity of vocabularies on the Web of Data.
- Enabling new knowledge-driven applications such as question answering across large numbers of datasets.

Overall Contributions and Significances

- PEAK: The first method to automatically assess summary content using the pyramid method that also generates the pyramid content models.

- HiText: A novel approach for supporting the reading process.

- LOVE: A novel approach to disambiguate and align properties across vocabularies from the Web of Data.

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The data and code are available at
http://www.larayang.com.

Thank you!

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