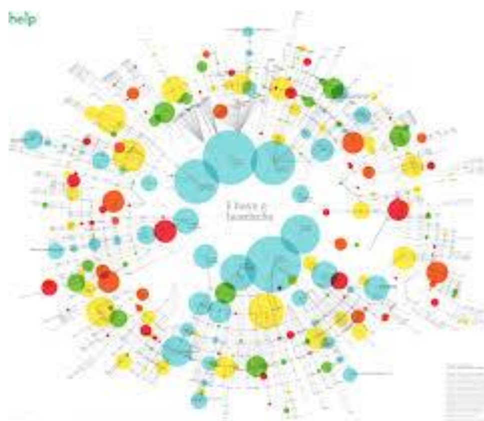
Pinpointing Ambiguity and Incompleteness in Requirements Engineering via Information Visualization and NLP



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1. Context and Motivation

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- Requirements defects are still present in practice
  - Ambiguity, vagueness, incompleteness, etc.

The system shall send a message to the receiver, and it provides an acknowledge message within some seconds

[Rosadini 2017] [Vogelsang 2016]

1. Context and Motivation

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  - Ambiguity, vagueness, incompleteness, etc.

The system shall send a message to the receiver, and <u>it</u> provides an acknowledge message within <u>some</u> seconds

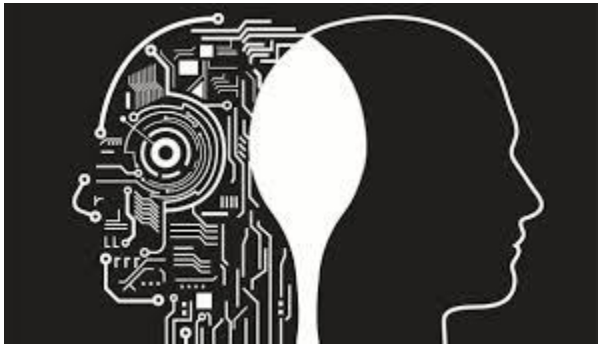
Referential pronoun ambiguity

Vague term

[Rosadini 2017] [Vogelsang 2016]

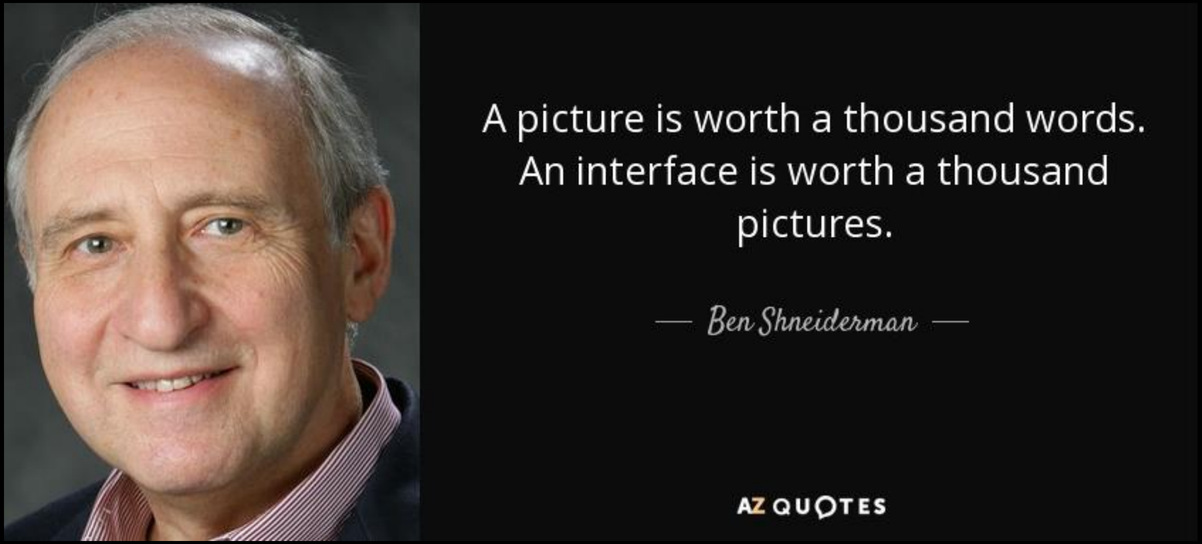
1. Context and Motivation

- Identifying requirements defects is still hard!
  - Natural language processing (NLP) tools do not deliver perfect accuracy in automated defect identification
  - Human analysts are effective, but how do they scale?



[Rosadini 2017] [Tjong 2013] [Vogelsang 2016]

2. Conceptual Solution



2. Conceptual solution

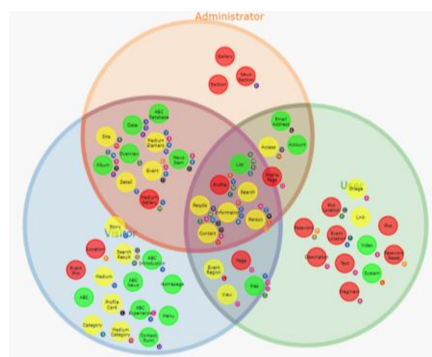
- Requirements artifact: user stories

  As a student,
  I want to receive my grades via e-mail,
  so that I can quickly check them.

Highly popular in agile dev! [Lucassen 2016]

- Idea: combine NLP with information visualization (InfoVis)
  → automation to help humans!

NLP



InfoVis

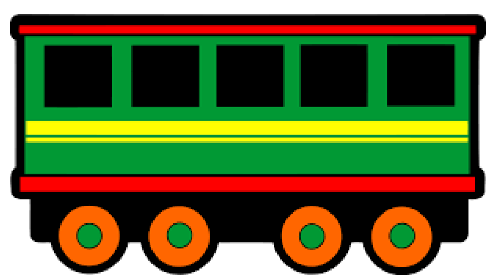
Human analyst

2. Conceptual solution

- Different stakeholders have their own viewpoints

- We focus on differences in their terminology!
  - For example, do *car* and *automobile* have the same meaning?
  - $[\![t]\!]^{V_1}$ is the denotation of term t according to viewpoint V_1

$[\![car]\!]^{V_{Fabiano}}$ $[\![car]\!]^{V_{train\,engineer}}$

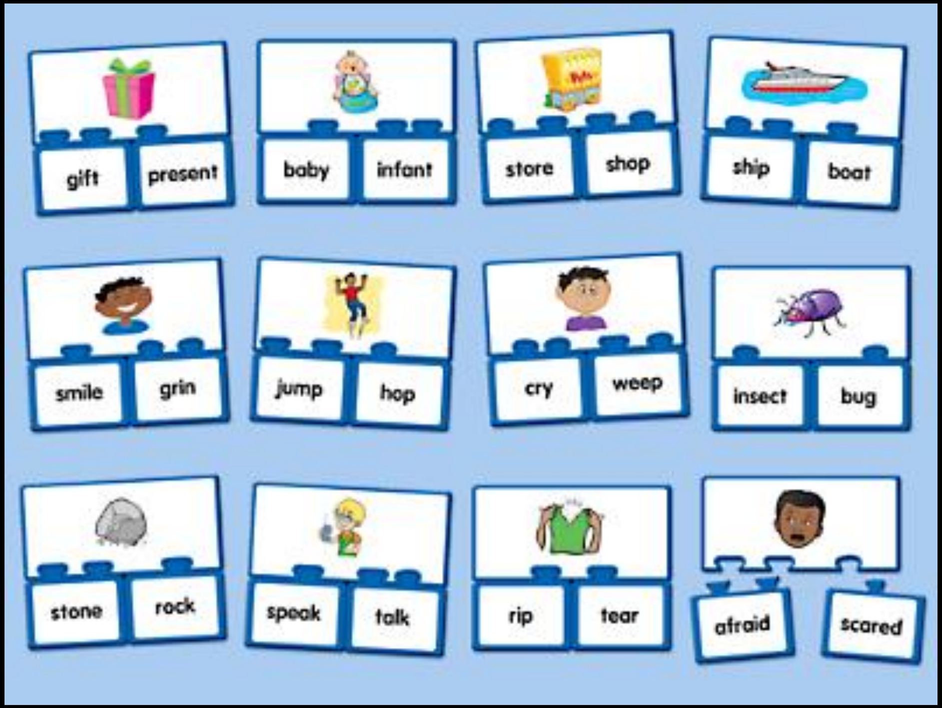


2. Conceptual solution

- We identify possible defects depending on the denotations that the viewpoints associate with a term

Relation [12]	Possible defect	Defect formalization	Example
Consensus	-	$[\![t_1]\!]^{V_1} = [\![t_1]\!]^{V_2}$	$[\![\text{bank}]\!]^{V_1} = \text{financial institution}$ $[\![\text{bank}]\!]^{V_2} = \text{financial institution}$
Correspondence	(Near-)synonymy leading to ambiguity	$[\![t_1]\!]^{V_1} = [\![t_2]\!]^{V_2}$	$[\![\text{car}]\!]^{V_1} = \text{road vehicle}$ $[\![\text{automobile}]\!]^{V_2} = \text{road vehicle}$
Conflict	Homonymy leading to ambiguity	$[\![t_1]\!]^{V_1} \neq [\![t_1]\!]^{V_2}$	$[\![\text{bank}]\!]^{V_1} = \text{financial institution}$ $[\![\text{bank}]\!]^{V_2} = \text{land alongside river}$
Contrast	Incompleteness	$[\![t_1]\!]^{V_1} \neq \bot \wedge [\![t_1]\!]^{V_2} = \bot$	$[\![\text{bank}]\!]^{V_1} = \text{financial institution}$ $[\![\text{bank}]\!]^{V_2} = \bot$

3. (Near-)Synonymy Detection

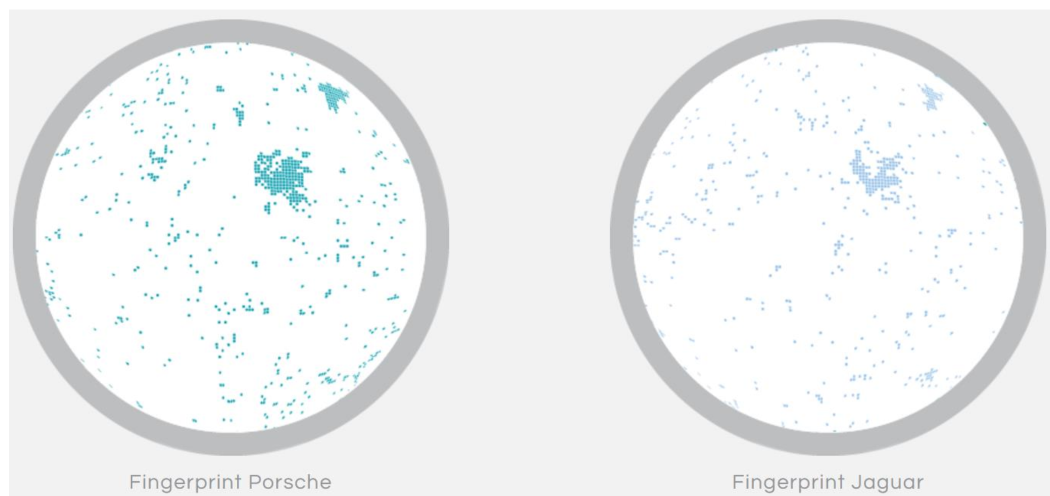


3. (Near-)Synonymy Detection

- Goal: identifying possible inter-view ambiguity

(Near-)synonymy leading to ambiguity	$[\![t_1]\!]^{V_1} = [\![t_2]\!]^{V_2}$	$[\![\text{car}]\!]^{V_1} = \text{road vehicle}$ $[\![\text{automobile}]\!]^{V_2} = \text{road vehicle}$

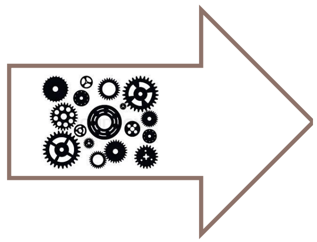
- How? We use Semantic Folding Theory (SFT)
  - Every term is associated a semantic fingerprint
  - Such fingerprints are created by analyzing huge amounts of text
  - Similar fingerprints indicate similar terms



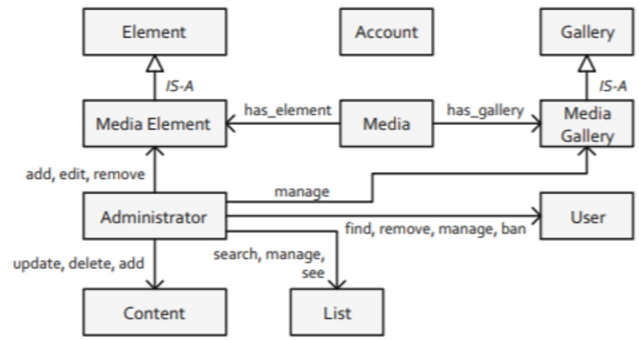
3. (Near-)Synonymy Detection

- How do we apply SFT to requirements engineering?

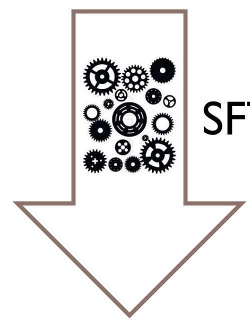
User Story Set
US1
US2
…
USn



Visual Narrator (Robeer 2015)



Conceptual model of the terms



SFT

Near-synonyms, a source of ambiguity

3. (Near-)Synonymy Detection

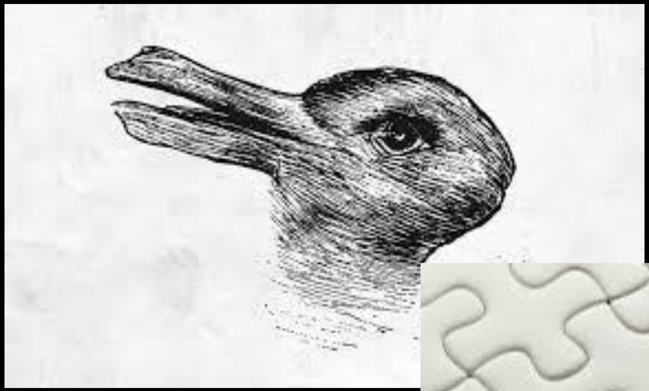
- **(Near-)synonymity between two terms t_1 and t_2**

$$ambig_{t1,t2} = \frac{2 \cdot sim_{t1,t2} + simc_{t1,t2}}{3}$$

  - A combination of term similarity and context similarity
  - 2/3 term similarity (car-automobile, etc.)
  - 1/3 context similarity: user stories where the terms appear
    - As a user, I want to make a bid for a car, so that …
    - As a visitor, I want to see the automobiles on the market, so that…

  - Weights assessed via a correlation study with humans

4. InfoVis for Ambiguity and Incompleteness



4. InfoVis for Ambiguity and Incompleteness

- NLP cannot (yet?) replace humans!
- Use InfoVis using Schneiderman's mantra

**Overview first, zoom and filter,
then details-on-demand**

- Focus mostly on ambiguity and incompleteness

(Near-)synonymy leading to ambiguity	$[\![t_1]\!]^{V_1} = [\![t_2]\!]^{V_2}$	$[\![\text{car}]\!]^{V_1} = \text{road vehicle}$ $[\![\text{automobile}]\!]^{V_2} = \text{road vehicle}$

Incompleteness	$[\![t_1]\!]^{V_1} \neq \perp \wedge [\![t_1]\!]^{V_2} = \perp$	$[\![\text{bank}]\!]^{V_1} = \text{financial institution}$ $[\![\text{bank}]\!]^{V_2} = \perp$

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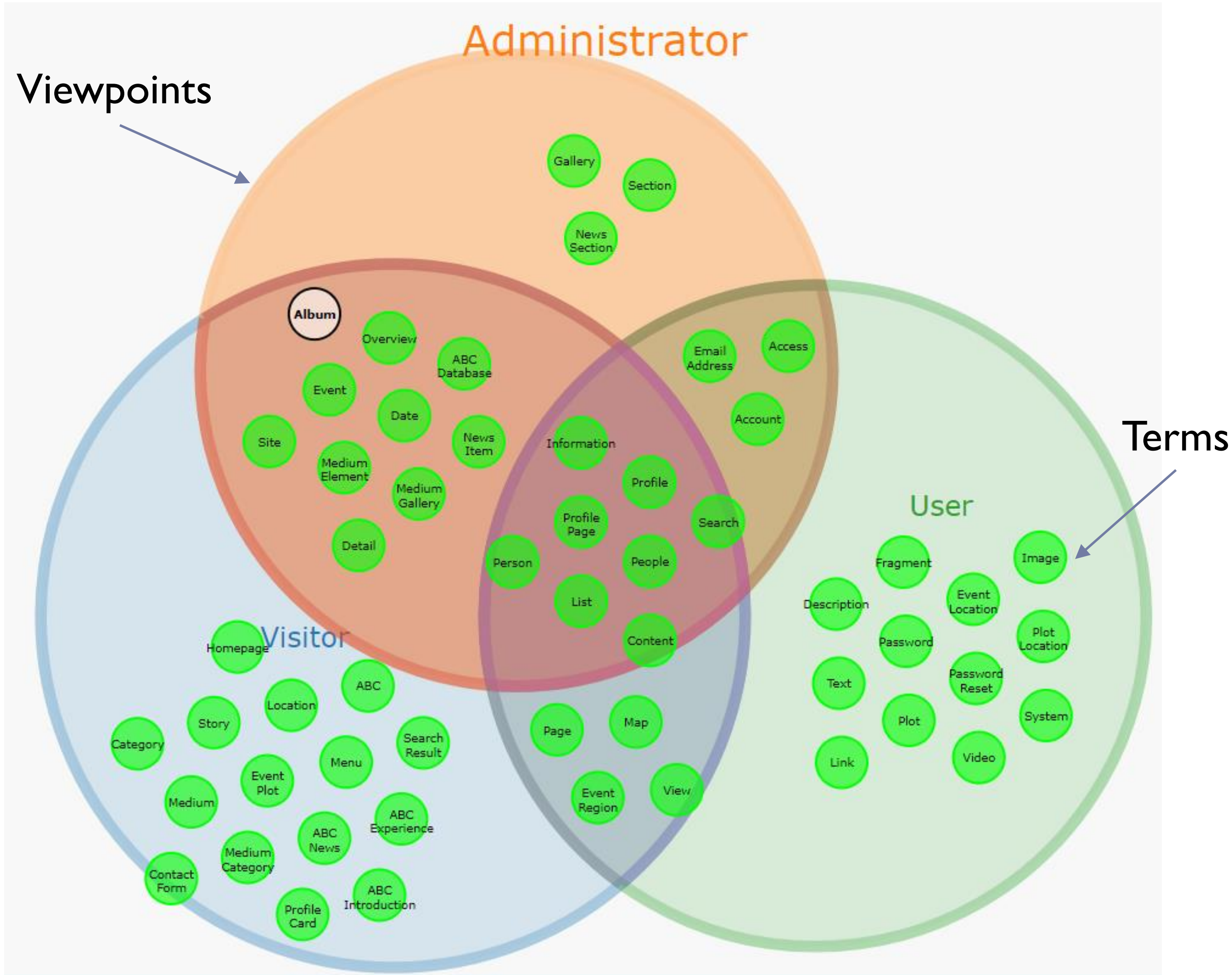

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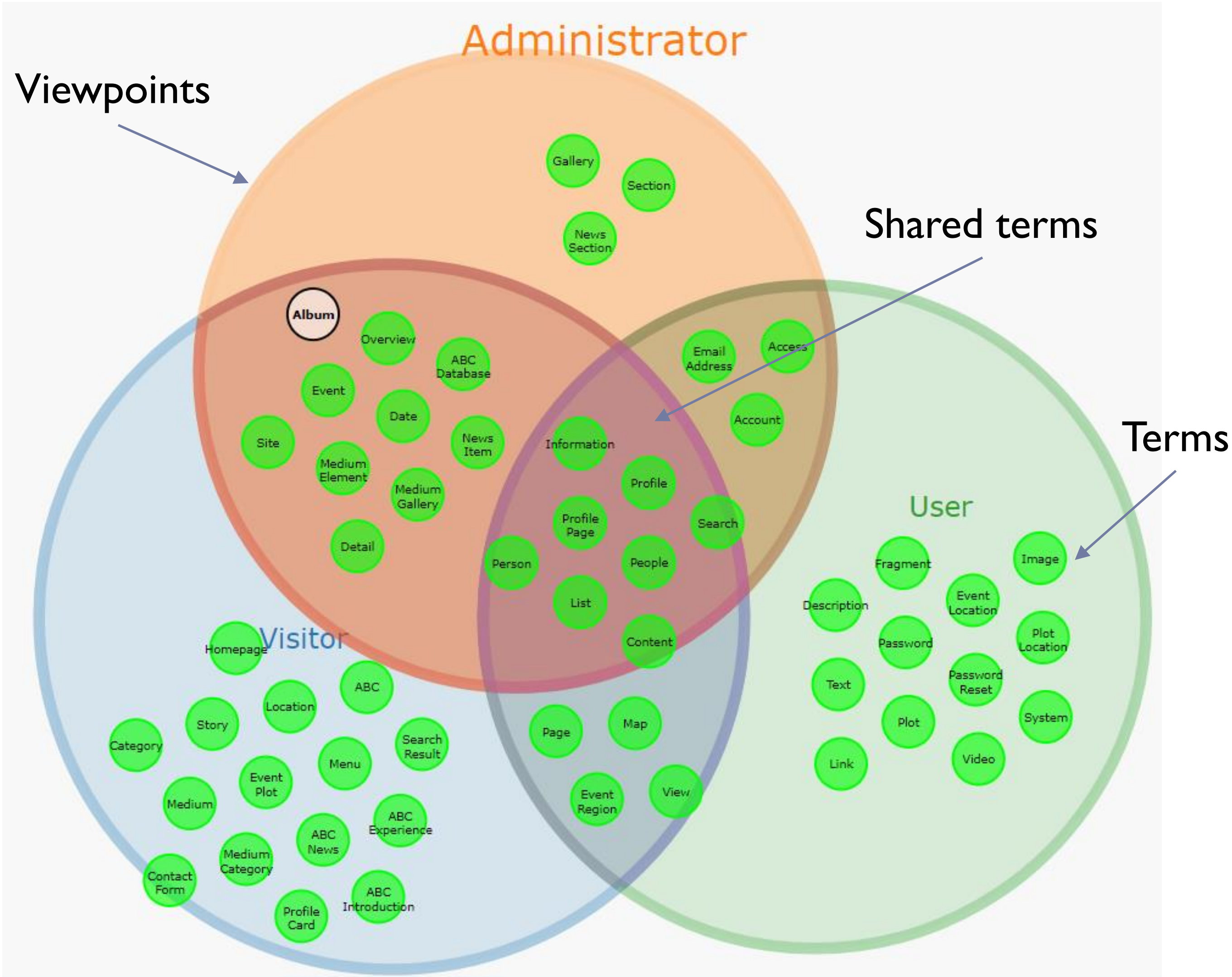

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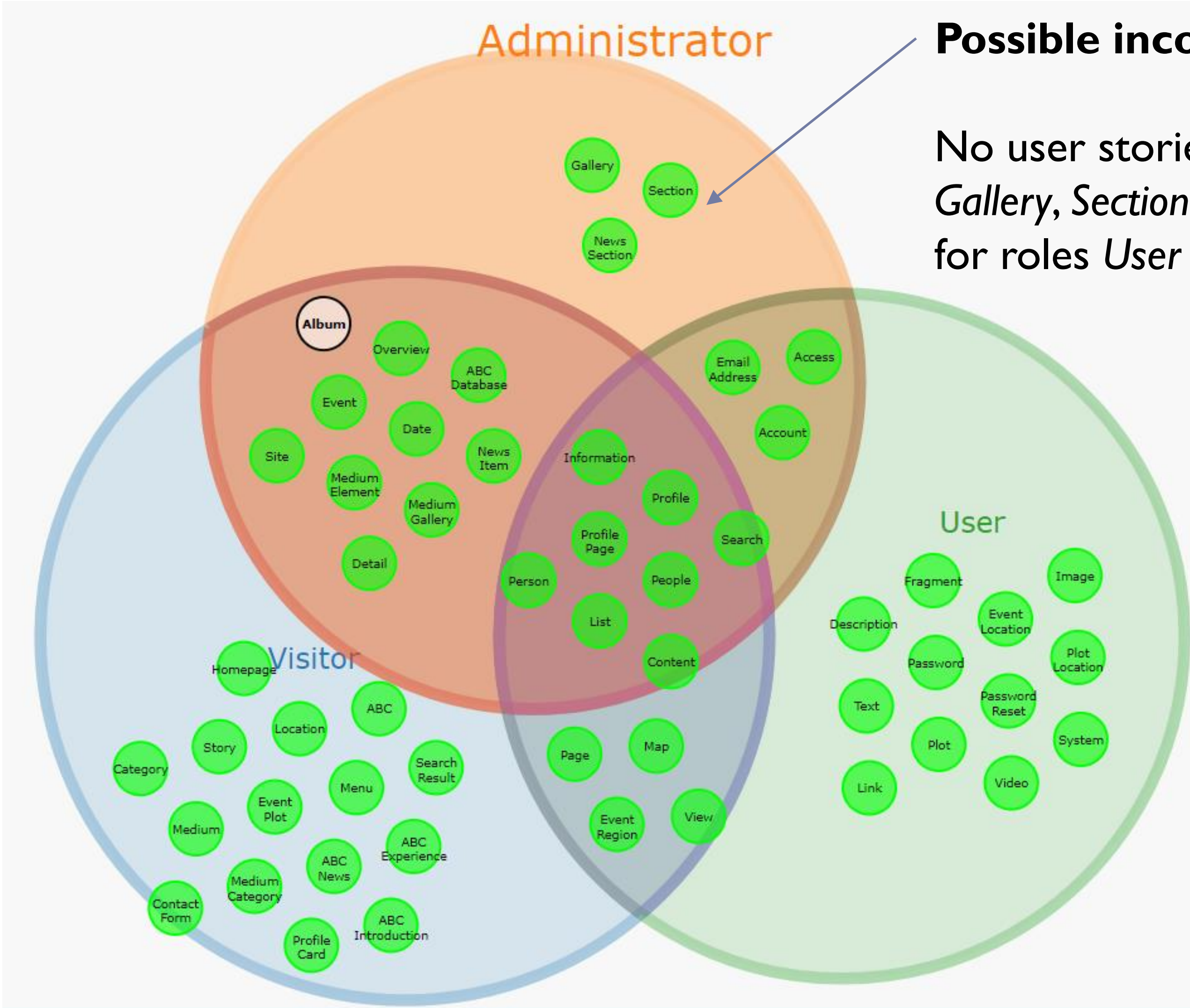
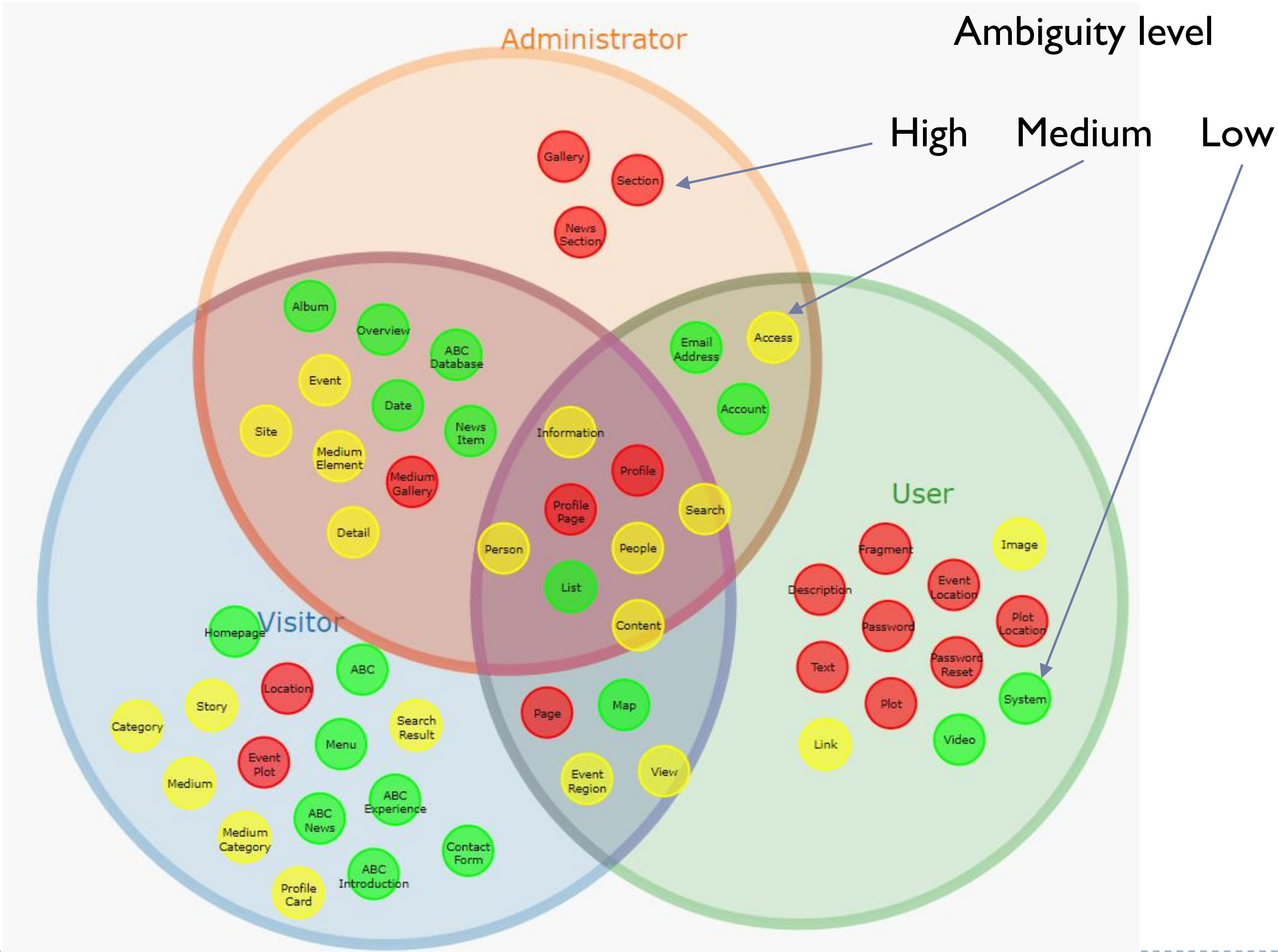


Possible incompleteness

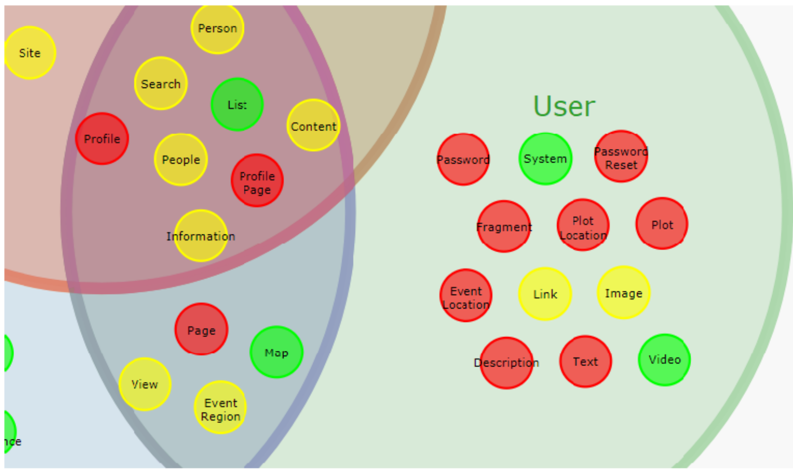
No user stories about *Gallery*, *Section*, *News Section* for roles *User* and *Visitor*?

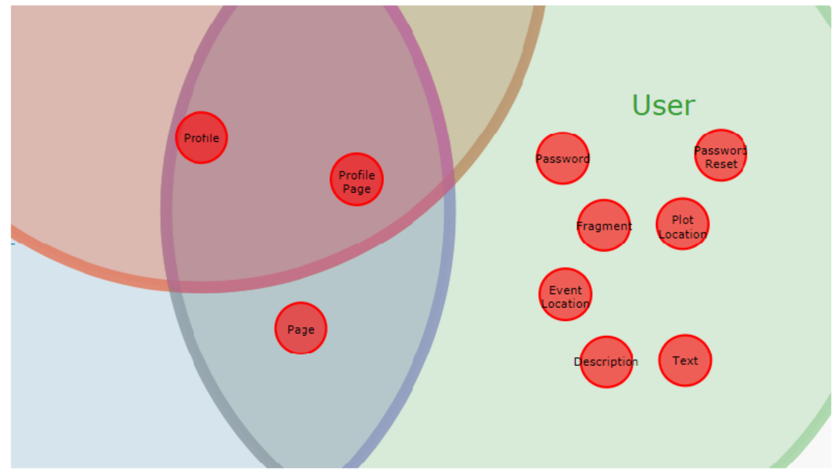
4. InfoVis for Ambiguity and Incompleteness



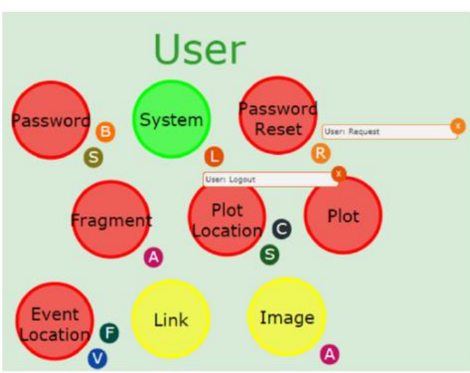
4. InfoVis for Ambiguity and Incompleteness

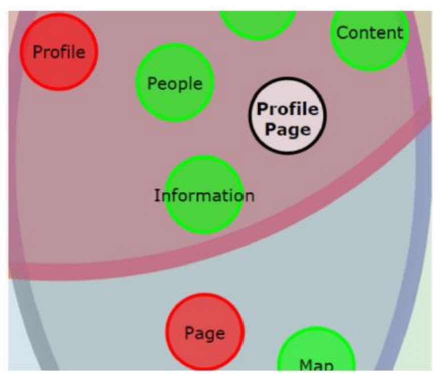
- Filter

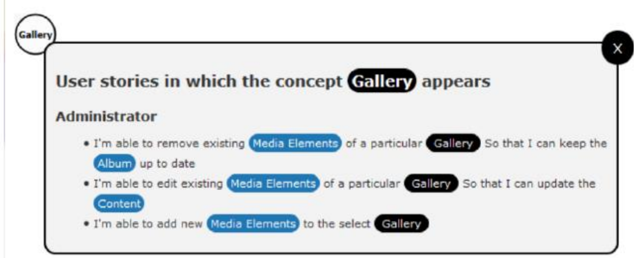




- Zooming







5. Quasi-Experiment

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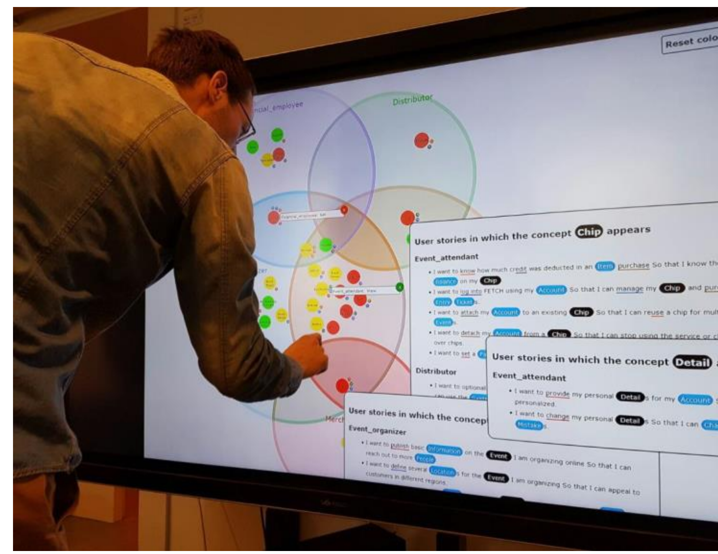
- Hypothesis: analysts who use our approach obtain a significantly higher…
  - precision in finding ambiguities (H1);
  - recall in finding ambiguities (H2);
  - precision in finding missing requirements (H3);
  - recall in finding missing requirements (H4);
- …compared to analysts using a pen-and-paper inspection.

5. Quasi-Experiment

- Study purpose/object: compare the relative effectiveness of
  - Our approach (REVV tool) supported by an 84” touch screen
  - A manual, pen-and-paper inspection of the requirements



- With voluntary MSc students in information science (n=8)
- 2 groups of 2 students with REVV
- 2 groups of 2 students pen&paper

5. Quasi-Experiment

- Constructs were defined through brainstorming among the authors, a pilot test, and the existing literature

- A **missing user story** is one whose absence inhibits the realization of at least another user story
- An **ambiguity** occurs when two user stories contain distinct terms that shares the same denotations

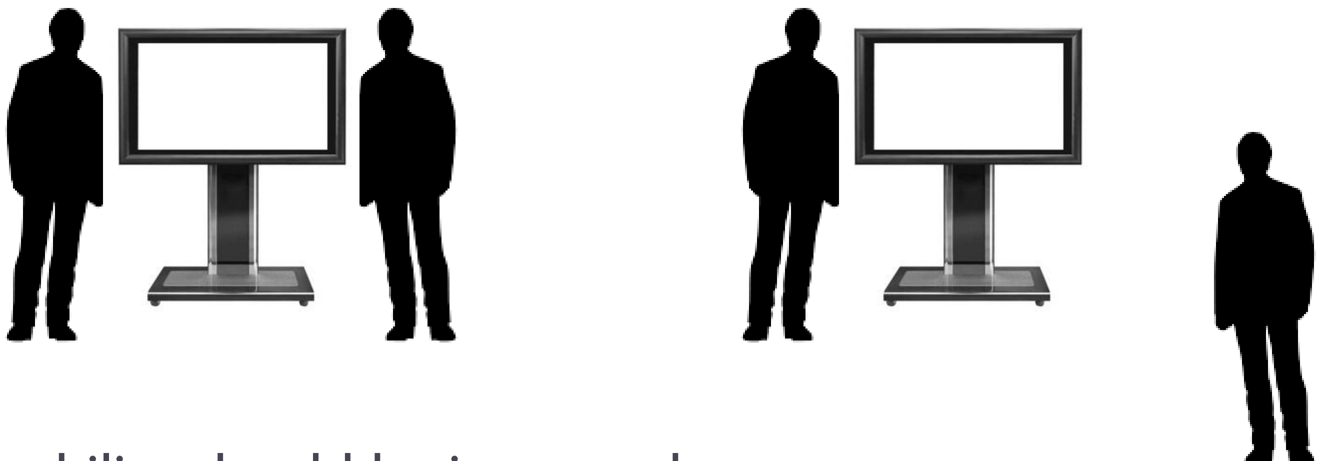
5. Quasi-Experiment

- Quantitative results
  - Reject H1 and H3 (precision)
  - Retain H2 and H4 (recall)

	Total TP	#TP	#FP	Precision	Recall
Session 1 – ambiguity					
Pen & paper	28	8	1	0.888	0.285
Tool		23	4	0.851	0.821
Session 2 – ambiguity					
Pen & paper	12	3	4	0.428	0.25
Tool		9	0	1	0.75
Session 1 – incompleteness					
Pen & paper	9	4	1	0.8	0.444
Tool		5	2	0.714	0.555
Session 2 – incompleteness					
Pen & paper	5	2	2	0.5	0.4
Tool		3	2	0.6	0.6

5. Quasi-Experiment

- Qualitative findings
  - Different types of interaction with the screen



  - Tool usability should be improved
  - The tool can lead to time savings

6. Discussion and Outlook

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- A first attempt to combine NLP and InfoVis
- Focus on ambiguity (near-synonymity) and missing reqs
- Inspiration by Venn diagrams

- Future directions
  - Algorithm can be further tuned (risk of overfitting?)
  - Evaluation, evaluation, evaluation!
  - Using domain ontologies for better results?

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