Dynamic Extraction of Topic Descriptors and Discriminators: Towards Automatic Context-Based Topic Search

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Joint project with IHMC

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Alternative Views of Knowledge Management

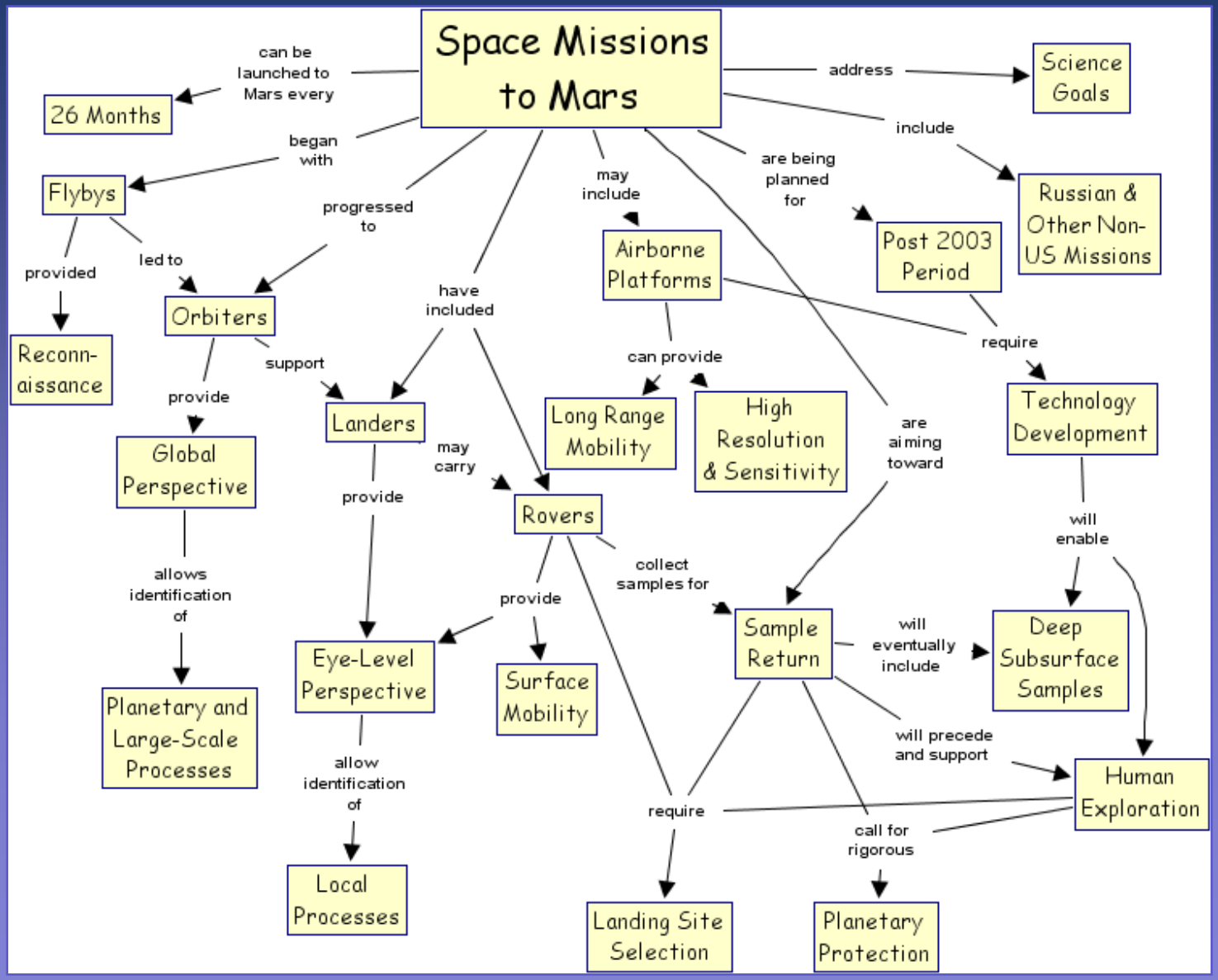
- Knowledge acquisition:

  Capture knowledge that is already within the expert.

- Knowledge extension:

  Knowledge models evolve from coordinated processes of knowledge acquisition and knowledge construction.

Concept Maps [Novak,1977]



IHMC CmapTools - Concept Mapping Software Toolkit - Microsoft Internet ...

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Welcome to the Web Site of

IHMC – A University Affiliated Research Institute

CmapTools knowledge modeling kit

The IHMC CmapTools software empowers users to construct, navigate, share, and criticize knowledge models represented as Concept Maps

IHMC CmapTools

was developed at

facilitates the manipulation of

is a

was used to build

Institute for Human and Machine Cognition (IHMC)

Concept Maps

Software Toolkit

The Knowledge Model in this Web Site

is

Documented

provides

Support

are built using the

CmapTools Program

is composed of

CmapServers

runs on

can be

Downloaded

is navigated by

1. Clicking on one of the icons under a Concept

for example

IHMC CmapTools

and then

2. Selecting one of the choices that is Displayed

for example

IHMC CmapTools

CmapTools

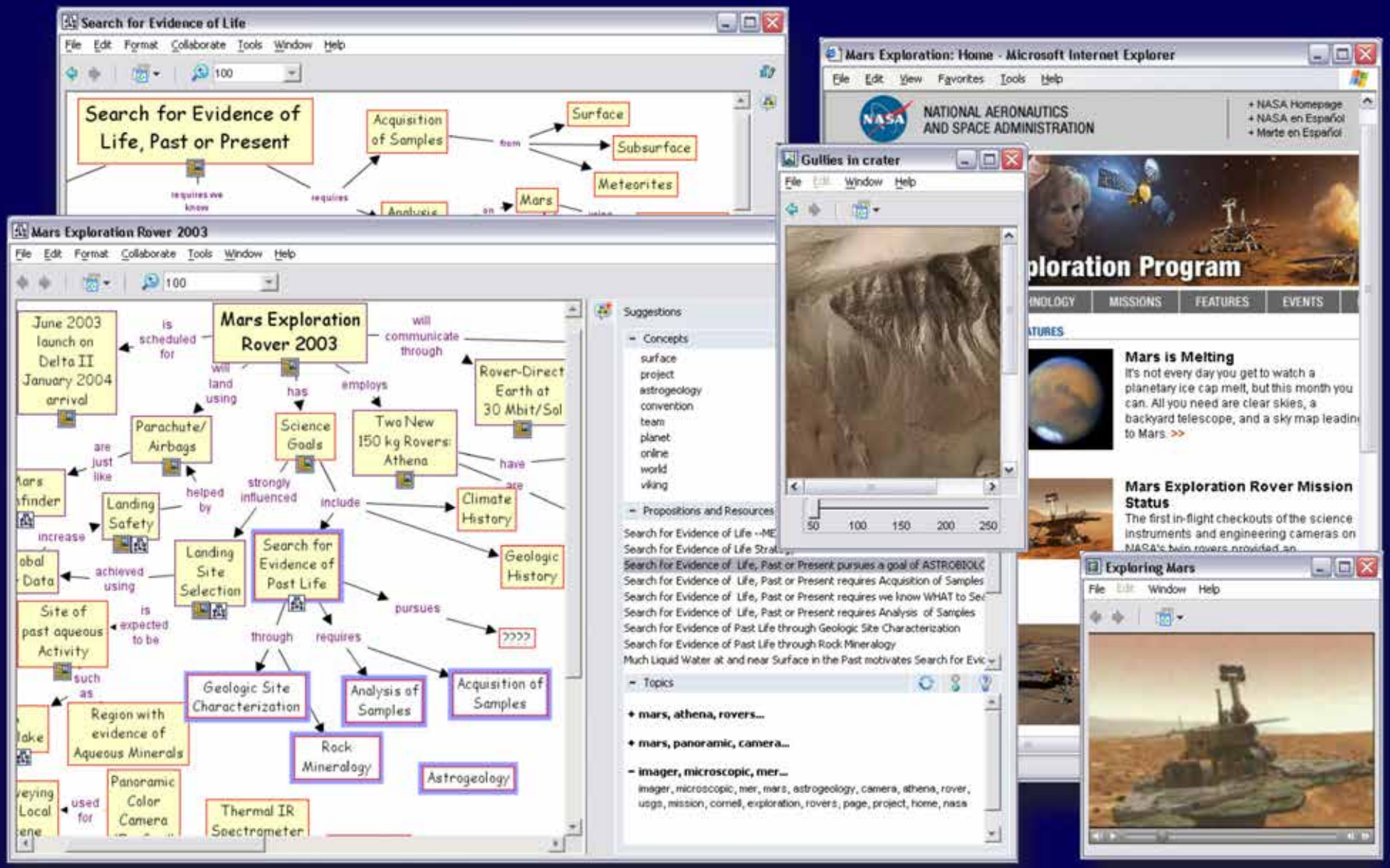
will

3. Open the Selected Concept Map, Image, Video, Web Page, etc

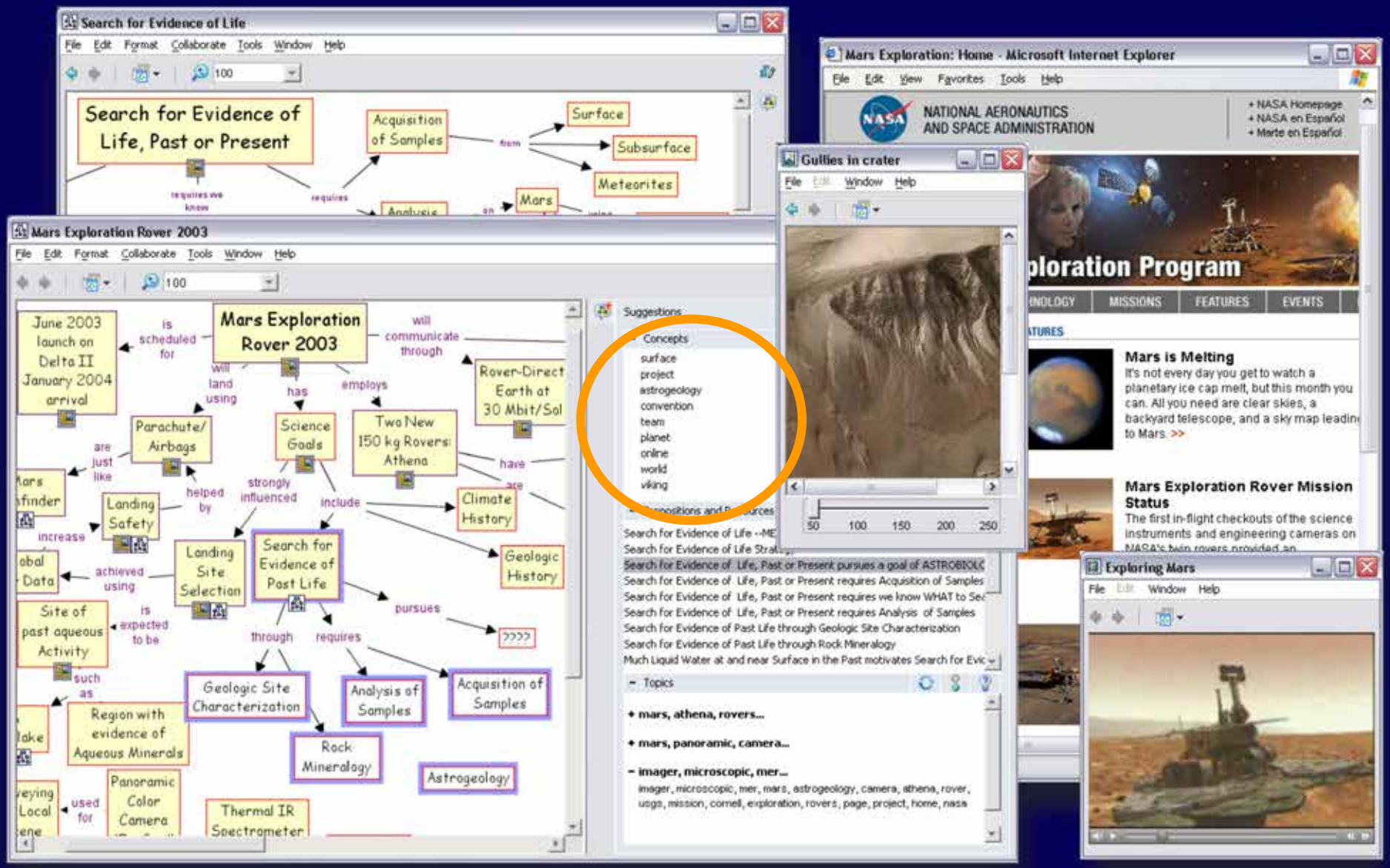
Plan to Participate in the 1st International Conference on Concept Mapping Sept. 14-17, 2004 Pamplona, Spain

Done Internet

A Family of Suggesters for CmapTools



A Family of Suggesters for CmapTools



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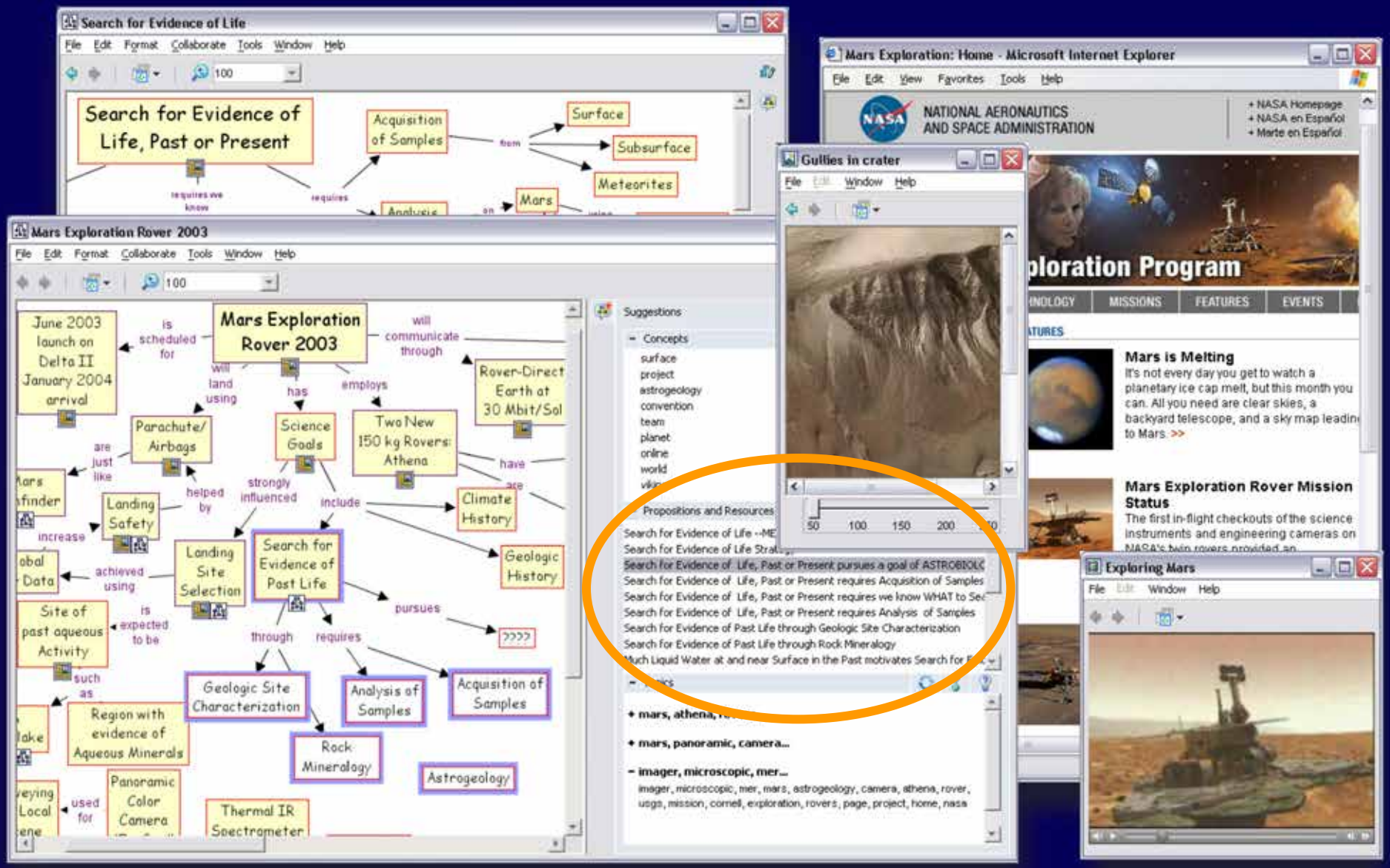

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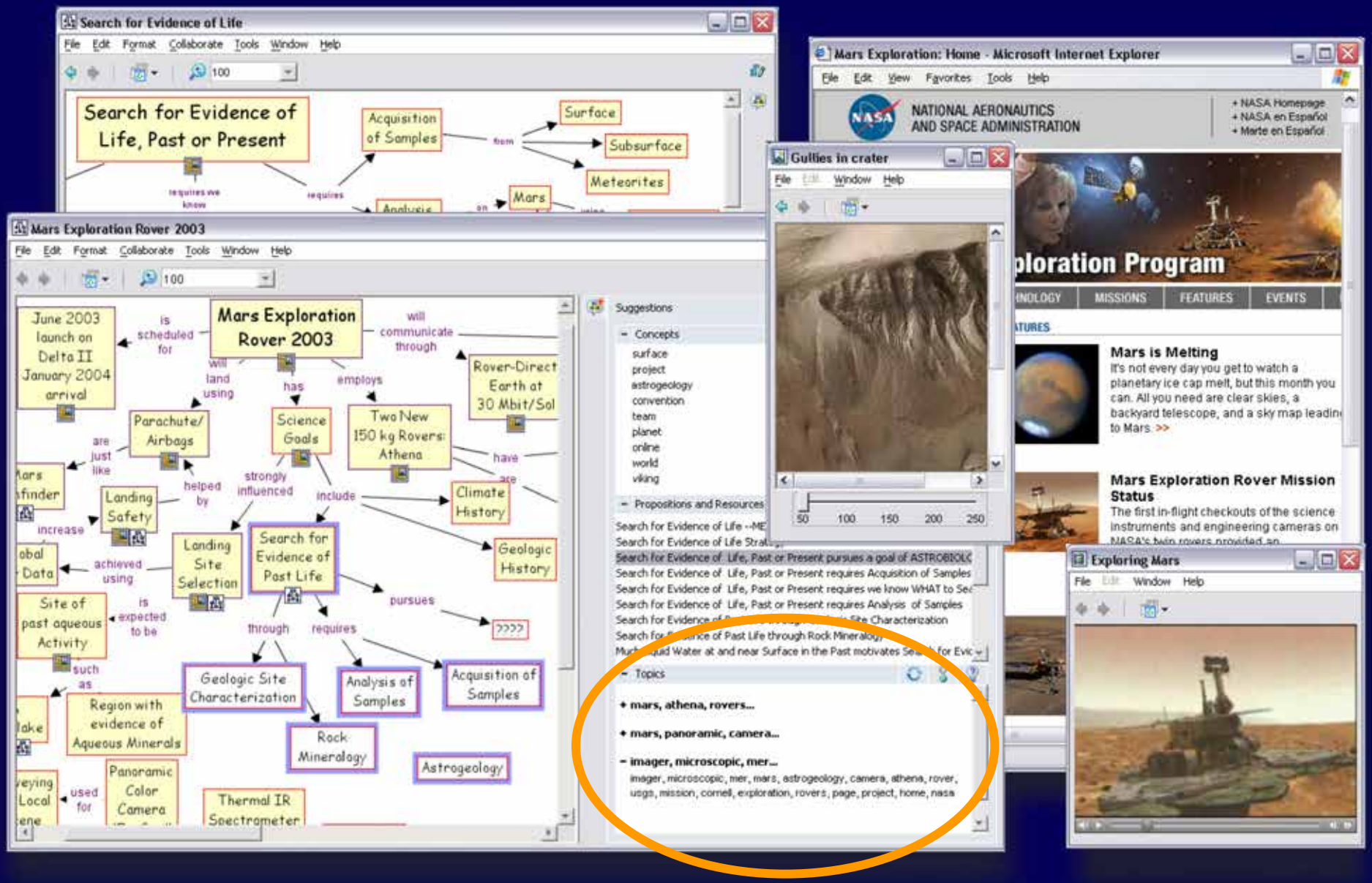

Goals for a Topic Suggester

- Make suggestions at a *higher level of topics* (rather than individual resources.)
- Satisfy criteria for topic quality:
  - Novelty
  - Diversity
  - Global Coherence
  - Coverage
  - Local quality

Road Map for Topic Suggestions

- Theoretical framework.
- Application of the theory in the implementation of a topic suggester system.
- Experimental Study.

Term Importance

- Importance of given term depends on task.
- Traditional views distinguish two notions:
  - Descriptors: terms that occur frequently in a document.
  - Discriminators: terms that occur in a document but rarely occur in the corpus.

New Challenges for Formulation of Descriptors and Discriminators

- Search methods that can reflect extensive contextual information.
- Methods for topic search.
- Methods for searching open collections of documents.

Topics, Terms and Documents

Mars

Surveyor

Exploration

Global

Opportunity

Spirit

Orbiter

Site

Landing

Camera

Rover

Selection

MGS

MOC

Images

Topics, Terms and Documents

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Topic Descriptors and Discriminators

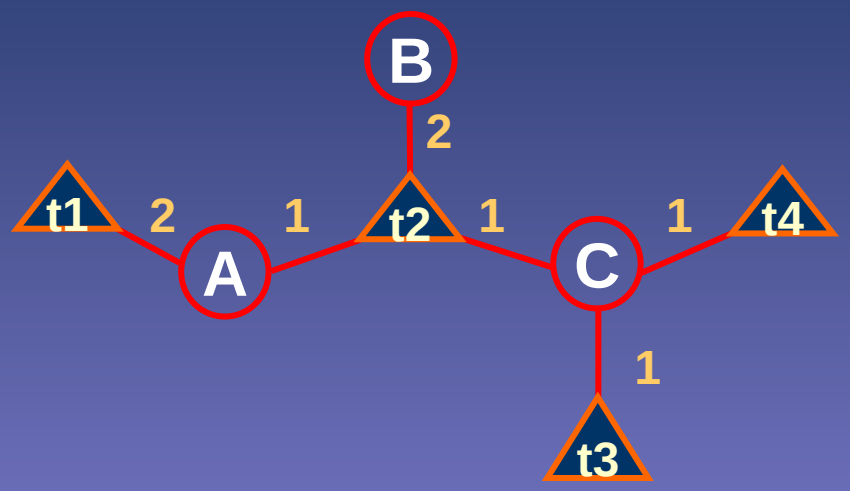
- Terms are *good topic descriptors* if they answer the question "What is this topic about?"
- Terms are *good topic discriminators* if they answer to the question "What are good query terms to access similar information?"

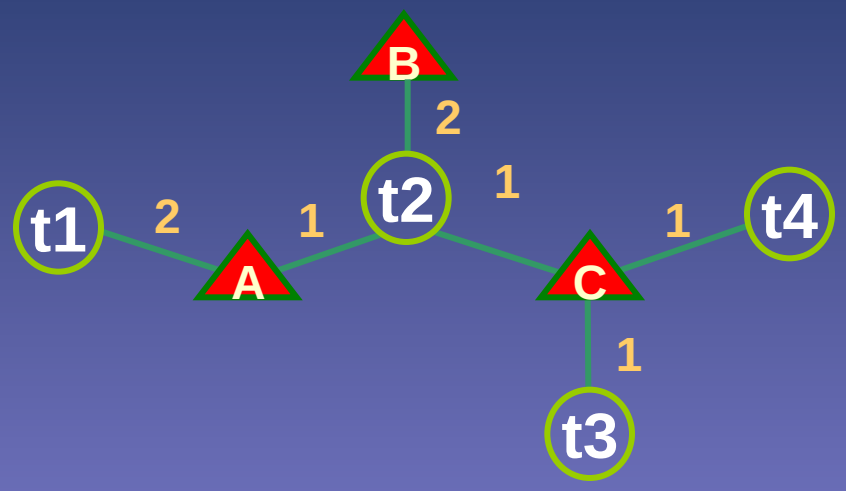
Hypotheses

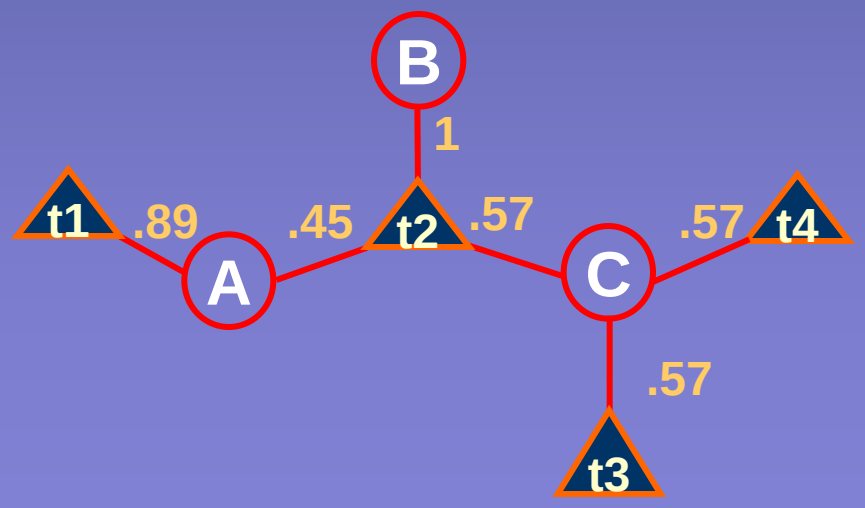
I. Terms that tend to occur frequently in the context of a given topic are good topic descriptors.

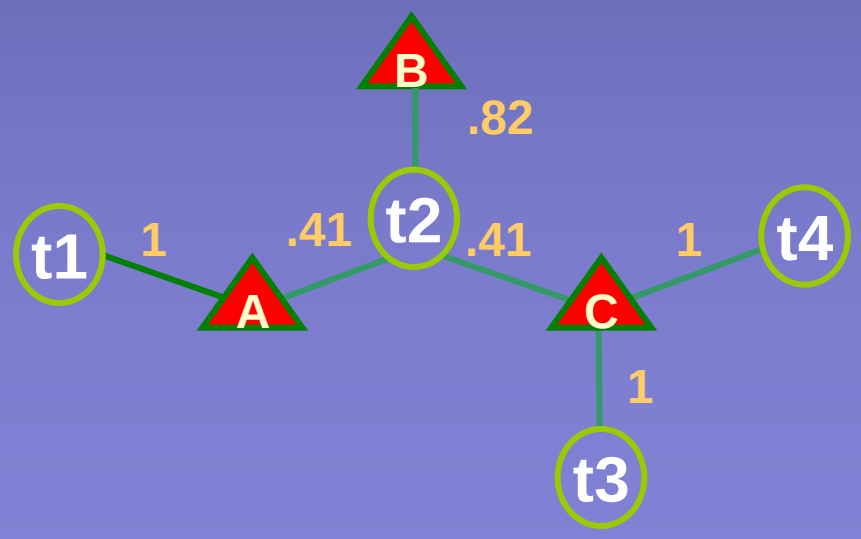
II. Terms that tend to occur only in the context of a topic are good topic discriminators.

Using Hypergraph Representations for Documents and Terms









Document-Term Duality

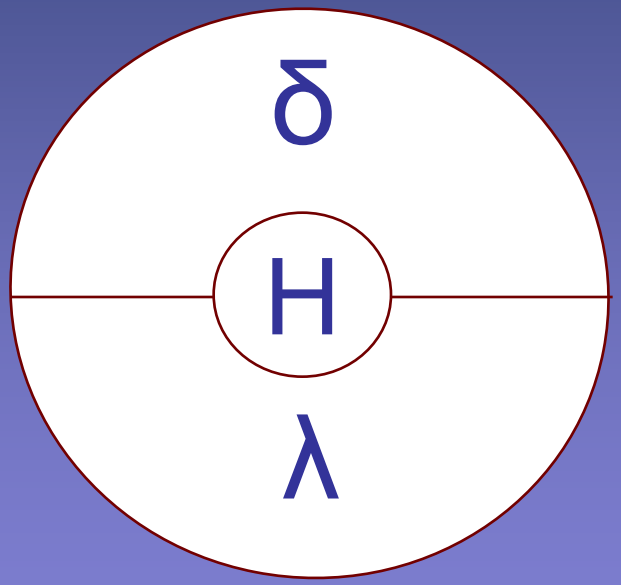
H

H[*i*,*j*]: number of occurrences of t_j in d_i

Document-Term Duality

$$\delta(t_i, d_j) = \frac{\mathrm{sgn}(\mathbf{H}^{\mathrm{T}}[i, j])}{\sqrt{\sum_{k=0}^{m-1} \mathrm{sgn}(\mathbf{H}^{\mathrm{T}}[i, k])}}$$

discriminating power of t_i in d_j



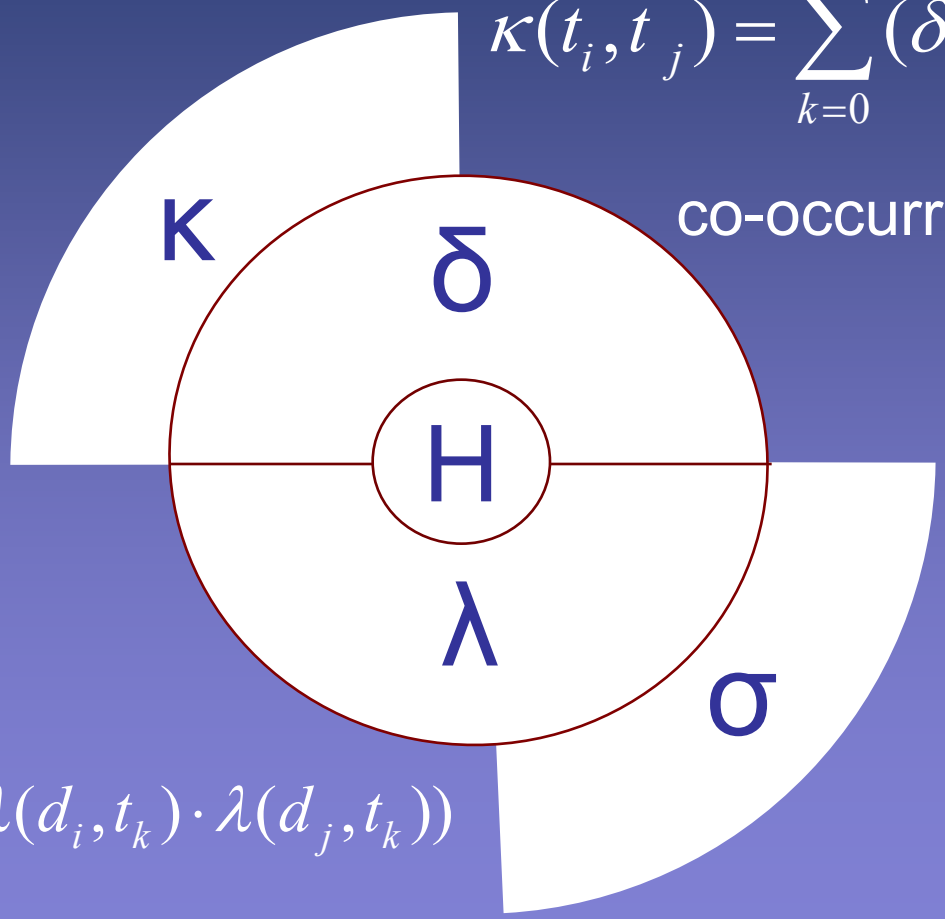
$$\lambda(d_i, t_j) = \frac{\mathbf{H}[i, j]}{\sqrt{\sum_{k=0}^{n-1} (\mathbf{H}[i, k])^2}}$$

descriptive power of t_j in d_i

Document-Term Duality

$$\kappa(t_i, t_j) = \sum_{k=0}^{m-1} (\delta(t_i, d_k) \cdot \delta(t_j, d_k))$$

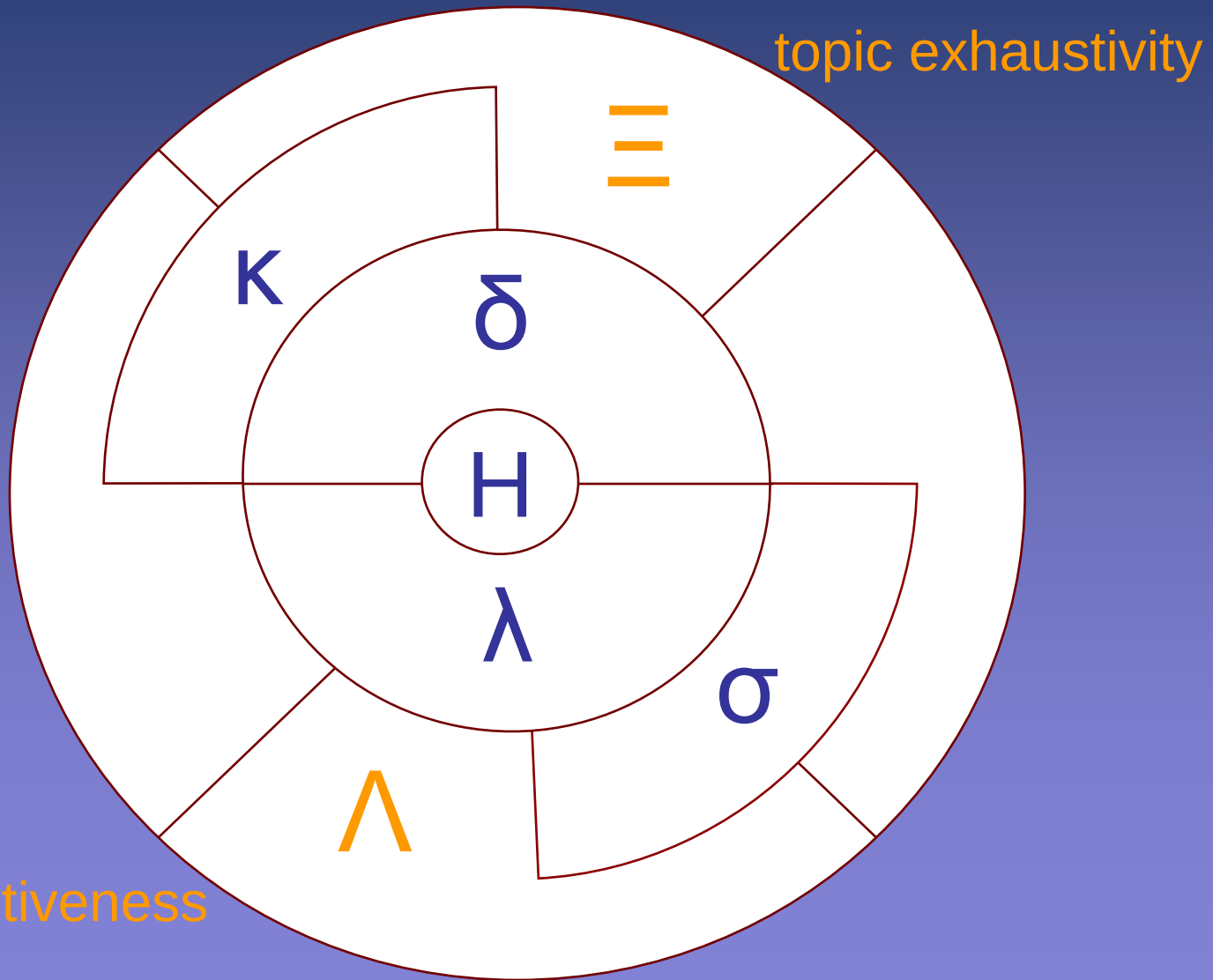
co-occurrence of t_i and t_j



$$\sigma(d_i, d_j) = \sum_{k=0}^{n-1} (\lambda(d_i, t_k) \cdot \lambda(d_j, t_k))$$

similarity between d_i and d_j

Document-Term Duality



Document-Term Duality

Topic Descriptiveness

$$\Lambda(d_i,t_j)=\begin{cases} 0 & \text{if } \sum_{k=0,\ k\neq i}^{m-1}\sigma(d_i,d_k)=0 \\ \dfrac{\sum_{k=0,\ k\neq i}^{m-1}(\sigma(d_i,d_k)\cdot\lambda(d_k,t_j)^2)}{\sum_{k=0,\ k\neq i}^{m-1}\sigma(d_i,d_k)} & \text{otherwise} \end{cases}$$

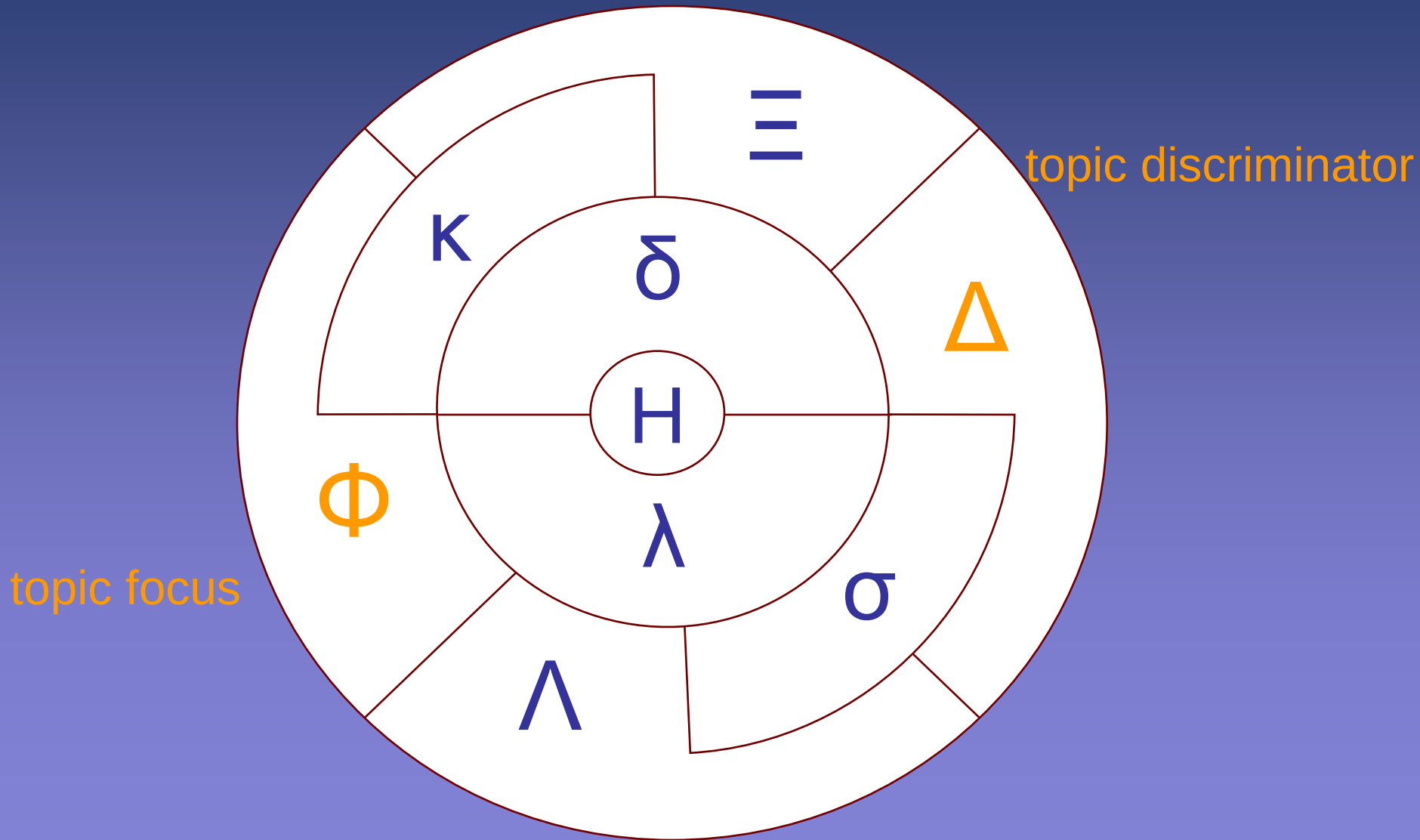
Most documents similar to d_i tend to be described by t_j

Topic Exhaustivity

$$\Xi(t_i,d_j)=\begin{cases} 0 & \text{if } \sum_{k=0,\ k\neq i}^{n-1}\kappa(t_i,t_k)=0 \\ \dfrac{\sum_{k=0,\ k\neq i}^{n-1}(\kappa(t_i,t_k)\cdot\delta(t_k,d_j)^2)}{\sum_{k=0,\ k\neq i}^{n-1}\kappa(t_i,t_k)} & \text{otherwise} \end{cases}$$

Most terms that co-occur with t_i tend to discriminate d_j

Document-Term Duality



Document-Term Duality

Topic Discriminator

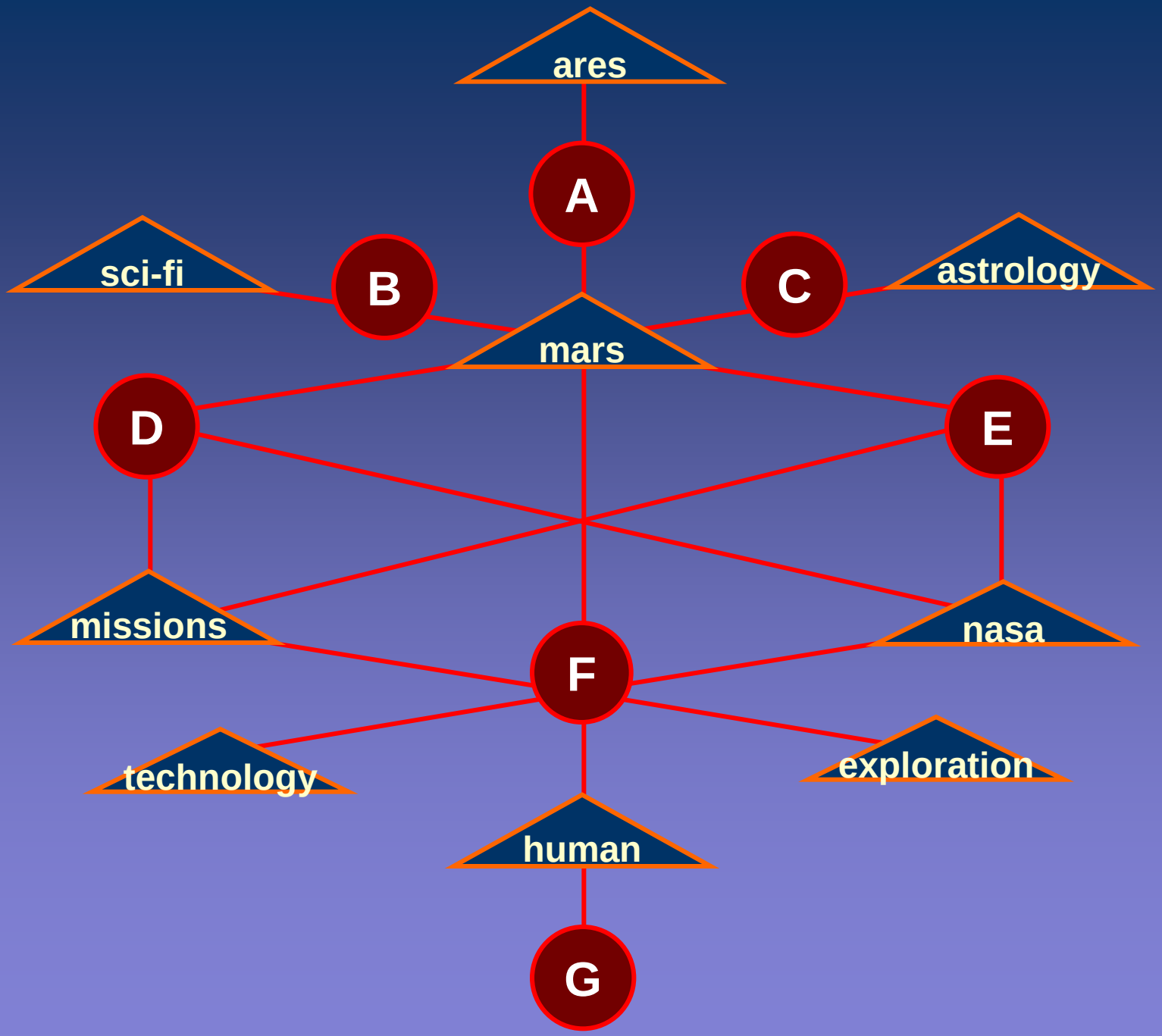
$$\Delta(t_i, d_j) = \sum_{k=0,\ k \neq j}^{m-1} (\sigma(d_k, d_j) \cdot \partial(t_i, d_k)^2)$$

Documents discriminated by t_i are similar to d_j

Topic Focus

$$\Phi(d_i, t_j) = \sum_{k=0,\ k \neq j}^{n-1} (\kappa(t_k, t_j) \cdot \lambda(d_i, t_k)^2)$$

Terms describing d_i tend to co-occur with t_j


ares
A
sci-fi
B
C
astrology
mars
D
E
missions
nasa
F
technology
exploration
human
G

Applying the Theory

- Descriptors and Discriminators are used as query terms to favor recall and precision.
- Similarity is used to filter irrelevant documents.
- The higher order dual notions are applied in the implementation of a co-clustering algorithm to obtain cohesive topics.
- Descriptors are good topic labels.
- A combination of focus and exhaustivity is used to rank documents in a topic.

EXTENDER's Cycle

1. EXTENDER starts with a Knowledge Model under construction

2. Combines terms found in concept maps to produce the first generation of Topics

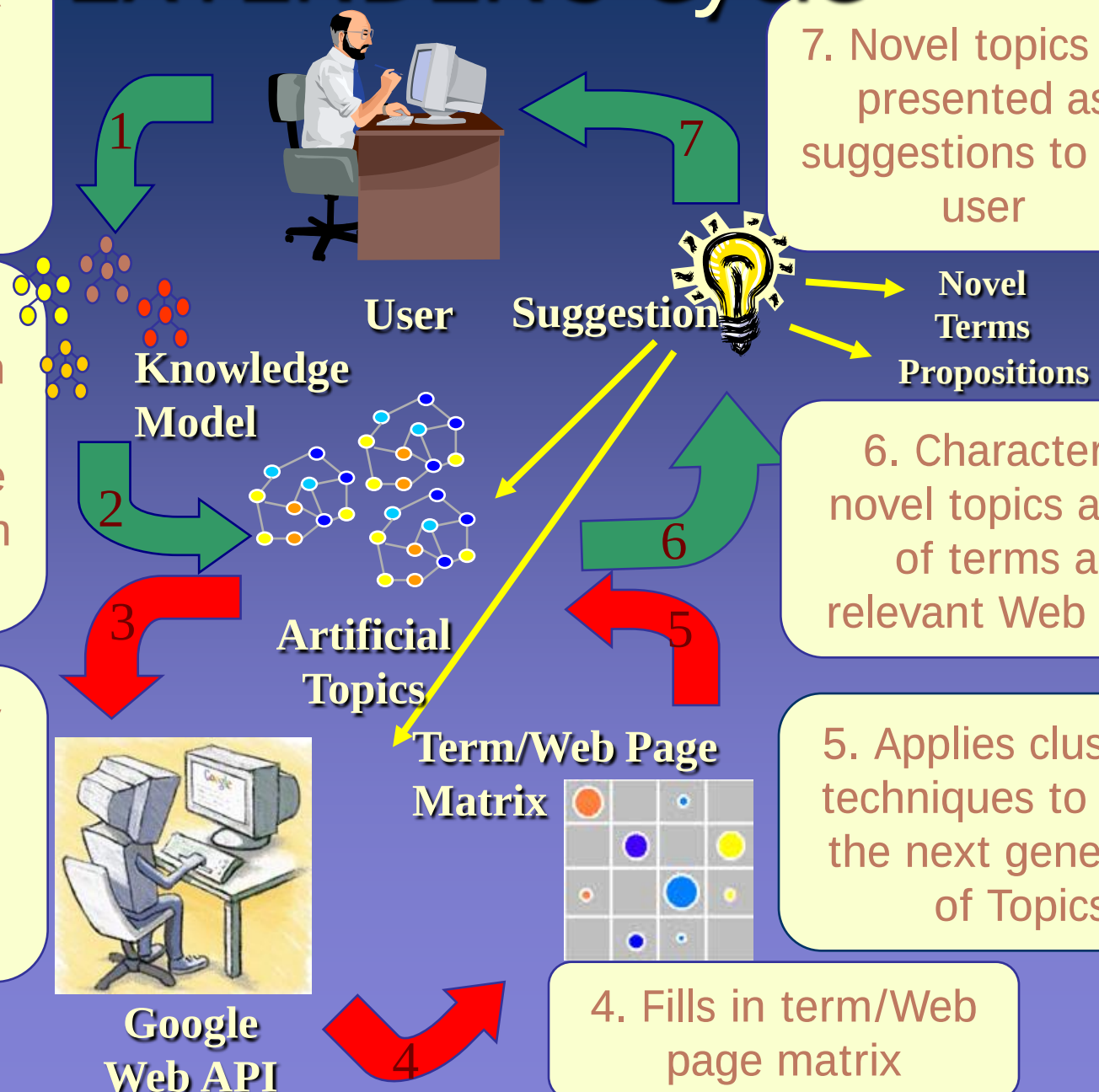
3. Incrementally searches the Web for novel but relevant material

4. Fills in term/Web page matrix

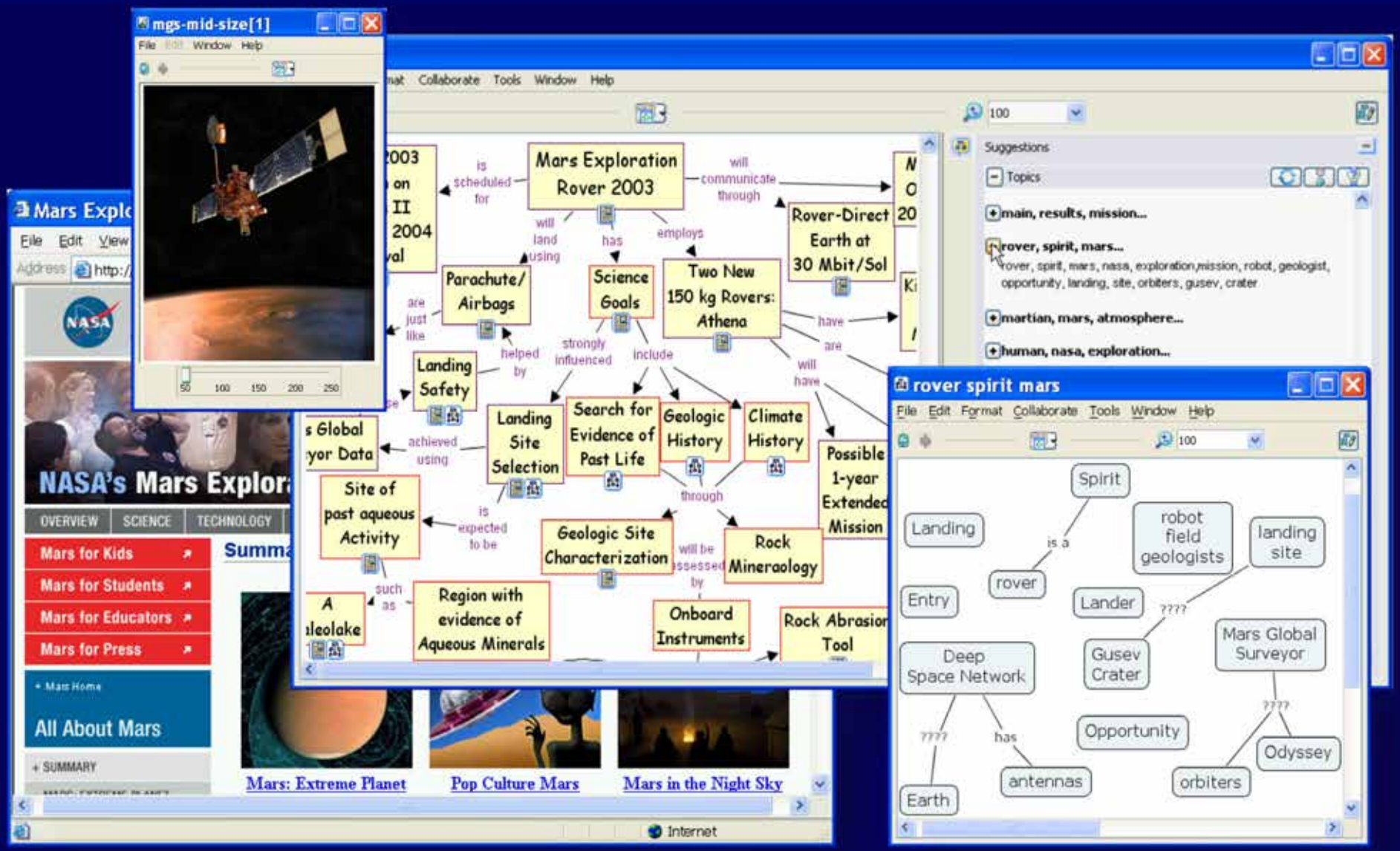
5. Applies clustering techniques to return the next generation of Topics

6. Characterizes novel topics as sets of terms and relevant Web pages

7. Novel topics are presented as suggestions to the user



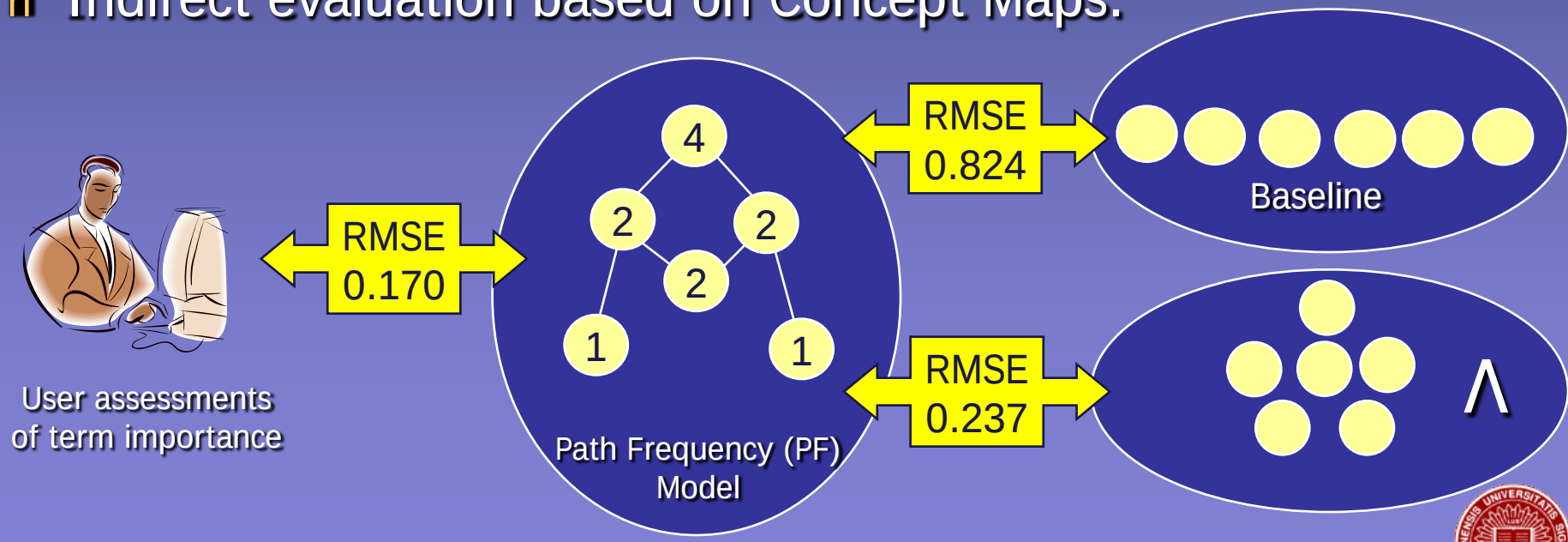
Extender Suggesting New Topics



Evaluation of Descriptor Extraction Method

How good is the descriptor extraction method in finding terms that are good descriptors of a topic?

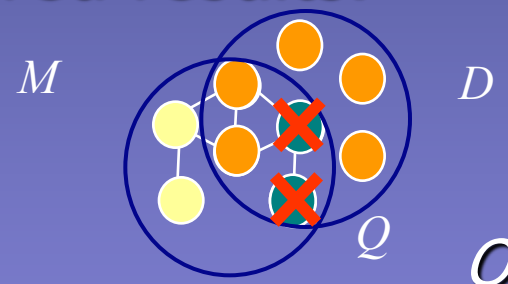
- It is difficult to evaluate descriptive power objectively.
- Indirect evaluation based on Concept Maps.



Evaluation of Discriminator Extraction Method

How good is the query formation process based on the use of topic discriminators?

- Provide an approximate measure of relevance of retrieved results.



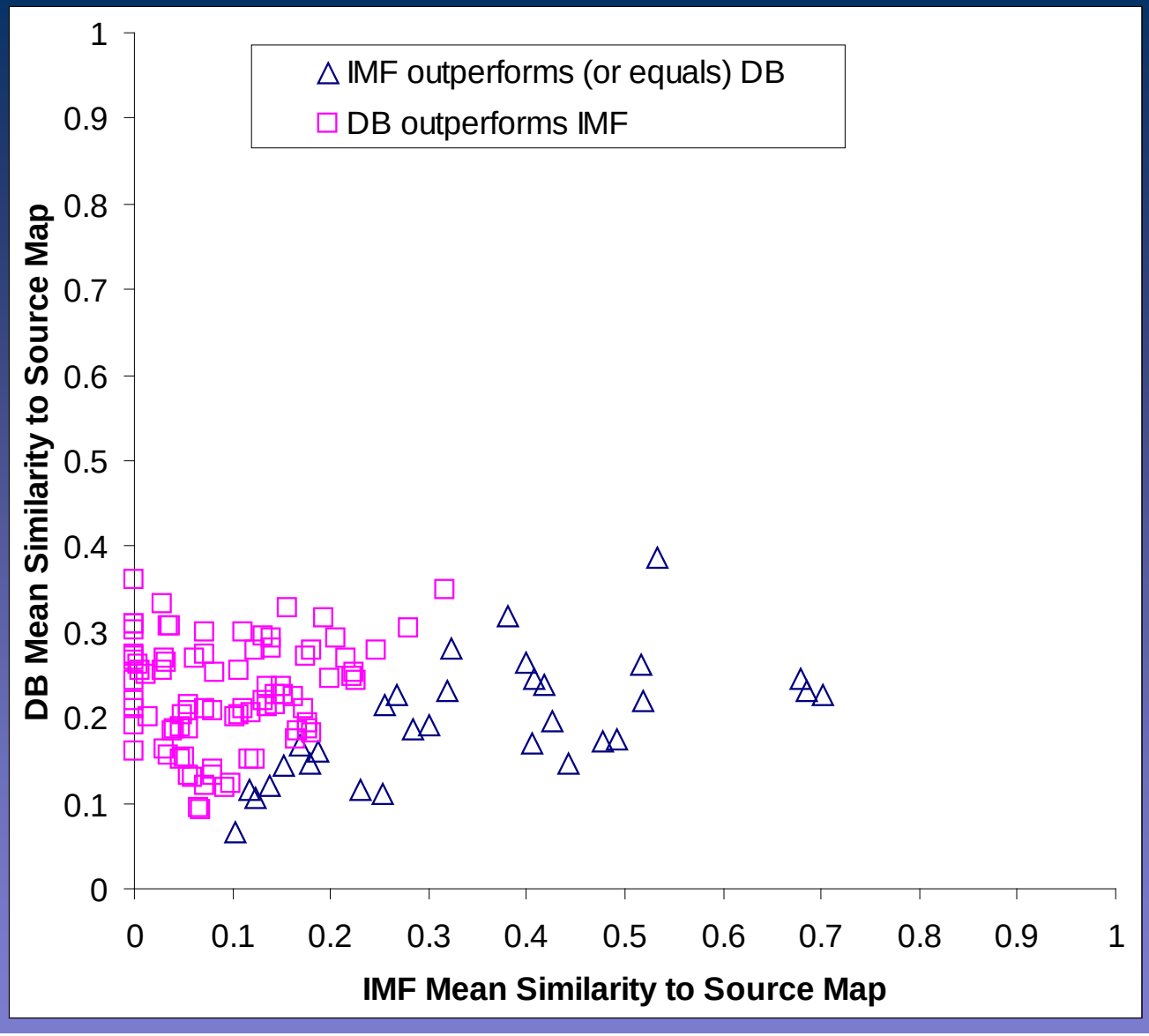
$$S(Q,M,D) = \frac{|(D \cap M) - Q|}{|(D \cup M) - Q|}$$

Q: t1 AND *t2* AND *…* AND *tn*

- Compare the performance to a baseline.

DB: use terms with highest Λ value

IMF: use terms with highest "inverse map frequency" value



	N	MEAN	STDEV	SE	95%C.I.
DB	118	0.2196	0.0645	0.0059	**(0.2079, 0.2311)**
IMF	118	0.1627	0.1563	0.0144	**(0.1345, 0.1909)**

Conclusions

- We have developed a framework for the dynamic extraction of topic descriptors and discriminators to aid information search in context.
- EXTENDER proactively supports the user's knowledge extension process by suggesting novel but related topics, using an iterative search process.
- We have presented a "bottom up" evaluation of EXTENDER's descriptor and discriminator extraction.
- We have also evaluated EXTENDER's ability to achieve our general desiderata for topic suggestions (coverage, novelty, global coherence) with encouraging results.

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