Realizing the Relationship Web: Morphing Information Access on the Web from Today's Document- and Entity-Centric Paradigm to a Relationship-Centric Paradigm

Amit P Sheth
Wright State University - Main Campus, amit.sheth@wright.edu

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Realizing the **Relationship Web:**
Morphing information access on the Web from today’s document- and entity-centric paradigm to a relationship-centric paradigm

ACM Multimedia International Workshop on the Many Faces of Multimedia Semantics
September 28, 2007, Augsburg, Germany

**Amit Sheth**
Kno.e.sis Center, Wright State University,
Dayton, OH

This talk also represents work of several members of Kno.e.sis team, esp. the Semantic Discovery and Semantic Sensor Data. [http://knoesis.wright.edu](http://knoesis.wright.edu)
Thanks, M. Perry, C. Ramakrishnan, C. Thomas
“An object by itself is intensely uninteresting”.

Grady Booch, Object Oriented Design with Applications, 1991

Entities + Relationships also needed to model & study Events
Increasing depth and sophistication in dealing with semantics by dealing with (identifying/searching to analyzing) documents, entities, and relationships.

<table>
<thead>
<tr>
<th>Future</th>
<th>Relationships</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current</td>
<td>Entities</td>
</tr>
<tr>
<td>Past</td>
<td>Documents/Media</td>
</tr>
</tbody>
</table>
**What**: Which thing or which particular one

**Who**: What or which person or persons

**Where**: At or in what place

**When**: At what time

**How**: In what manner or way; by what means

**Why**: For what purpose, reason, or cause; with what intention, justification, or motive
<table>
<thead>
<tr>
<th></th>
<th>Object</th>
<th>Location</th>
<th>Time</th>
<th>Relationships</th>
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<td>X</td>
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<td>X</td>
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</tbody>
</table>

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Semantics and Relationships

Semantics is derived from relationships. Consider the linguistics perspective.

“Semantics is the study of meaning. ... We may distinguish a number of legitimate ways to approach semantics:

• ... 
• the relationship between linguistic expressions (e.g. synonymy, antonymy, hyperonymy, etc.): sense;
• the relationship to linguistic expressions to the "real world": reference. “

Ontologies use KR language to support modeling of relationships.

Why is this a hard problem?

Are objects/entities equivalent/equal(same)?

How (well) are they related?

- Implicit vs explicit; formal/assertional vs social consensus based; powerful (beyond FOL): partial, probabilistic and fuzzy match

- Degrees of relatedness and relevance: semantic similarity, semantic proximity, semantic distance, ....
  - [differentiation, disjointedness]
  - related in a “context”

- Even is-a link involves different notions: identify, unity, essense (Guarino and Wetley 2002)

Semantic ambiguity, also based on incomplete, inconsistent, approximate information/knowledge
Issues - Relationships

• Identifying Relationship (extraction)
• Expressing (specifying, representing) relationships
• Discovering and Exploring Relationships
• Hypothesizing and Validating Relationships
• Utilizing/exploiting Relationships for Semantic Applications (in document search, querying metadata, inferencing, analysis, insight, discovery)
Create/extract as much (semantics) metadata automatically as possible; Use ontologies to improve and enhance extraction.
Blue-chip bonanza continues

Dow above 9,000 as HP, Home Depot lead advance; Microsoft upgrade helps techs.
August 22, 2002: 11:44 AM EDT

By Alexandra Tolin, CNN/Money Staff Writer

New York (CNN/Money) - An upgrade of software leader Microsoft and strength in blue chips including Hewlett-Packard and Home Depot were among the factors pushing stocks higher at midday Thursday, with the Dow Jones industrial average spending time above the 9,000 level.

Around 11:40 a.m. ET, the Dow Jones industrial average gained 65.06 to 9,022.09, continuing a more than 1,300-point resurgence since July 23. The Nasdaq composite gained 9.12 to 1,418.37.

The Standard & Poor's 500 index rose 9.61 to 958.97.

Hewlett-Packard (HPQ: up $0.33 to $15.03, Research, Estimates) said a report shows its share of the printer market grew in the second quarter, although another report showed that its share of the computer server market declined in Europe, the Middle East and Africa.

Home Depot (HD: up $1.07 to $33.75, Research, Estimates) was up for the third straight day after topping fiscal second-quarter earnings estimates on Tuesday.

Tech stocks managed a turnaround. Software continued to rise after Salomon Smith Barney upgraded No. 1 software maker Microsoft (MSFT: up $0.55 to $52.83, Research, Estimates) to "outperform" from "neutral" and raised its price target to $59 from $56. Business software makers Oracle (ORCL: up $0.18 to $10.94, Research, Estimates), PeopleSoft (PSFT: up $1.17 to $20.67, Research, Estimates) and BEA Systems (BEAS: up $0.28 to $7.12, Research, Estimates) all rose in tandem.
Semantic Annotation (Extraction + Enhancement)

Value-added Voquette Semantic Tagging

Value-added relevant metatags added by Voquette to existing COMTEX tags:
- Private companies
- Type of company
- Industry affiliation
- Sector
- Exchange
- Company Execs
- Competitors
Semantic Metadata Enhancement

Enabling powerful linking of actionable information and facilitating important semantic applications such as knowledge discovery and link analysis.

(user’s task of manually retrieving all the information he needs to know is greatly minimized; he can spend more time making effective decisions)
**Braves refuse to offer Galarraga arbitration**

Posted: Thursday December 07, 2000 6:15 PM

ATLANTA (AP) -- The Braves refused to offer salary arbitration to Andres Galarraga on Thursday, apparently ending the first baseman's career in Atlanta.

Atlanta did offer arbitration to six of its former players who became free agents: pitchers Andy Ashby, Terry Mulholland, John Burkett and Scott Kamieniecki; first baseman Wally Joyner and outfielder Bobby Bonilla.

Ashby agreed to a one-year contract that pays $1.2 million. The three-year agreement reached with Kamieniecki expires at the end of the month and his arbitration salary of $4.2 million.

Galarraga's salary for the 2001 season was $11.8 million and his contract expires at the start of the month.

After missing the 1999 season because of cancer, Galarraga had 100 RBIs.

Free agents not offered arbitration by their former teams won't have to go through the arbitration process until May 1.

The Braves made an offer Wednesday morning, but Galarraga said it was too low. Galarraga is seeking a two-year contract.

Players offered arbitration have until Dec. 19 to accept or reject the offers and can negotiate with their former teams through Jan. 8.

---

**Auto Categorization**

**Semantic Metadata**
Ontology-directed Metadata Extraction
(Semi-structured data)
# Semantic Extraction/Annotation of Experimental Data

## ProPreO: Ontology-mediated provenance

<table>
<thead>
<tr>
<th>m/z</th>
<th>parent ion charge</th>
<th>parent ion m/z</th>
<th>fragment ion m/z</th>
<th>fragment ion abundance</th>
<th>ms/ms peaklist data</th>
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</table>
## Video metadata and search

<table>
<thead>
<tr>
<th>Technique</th>
<th>Who’s trying it</th>
<th>How it works</th>
<th>Wired</th>
<th>Tired</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scanning the script</td>
<td>Blinkx, TVEyes</td>
<td>Everything said in a clip is tracked through voice recognition software, closed-caption information, or a combination of the two.</td>
<td>Hunts down TV news references to, say, Lindsay Lohan.</td>
<td>A mere mention of her name doesn't guarantee Lindsay is in the clip.</td>
</tr>
<tr>
<td>Identifying what’s being shown</td>
<td>Google, UCSD's Statistical Visual Computing Lab, VideoMining</td>
<td>Algorithms try to figure out what's in the video by monitoring attributes like behavior and movement (VideoMining), faces (Google), and objects (UCSD).</td>
<td>Finds friends, public figures, or specific actions like car chases.</td>
<td>The tech is stuck in the lab or limited to specialized search tasks.</td>
</tr>
<tr>
<td>Analyzing links and metadata</td>
<td>Dabble, Google</td>
<td>Conventional search spiders scan the text around a video and the pages that link to it.</td>
<td>The fastest and best way to search for video data.</td>
<td>Can't &quot;see&quot; what's in the videos or locate specific action in a long clip.</td>
</tr>
</tbody>
</table>
Semantic Sensor ML – Adding Ontological Metadata

Mike Botts, "SensorML and Sensor Web Enablement," Earth System Science Center, UAB Huntsville
Relationships on the Web: early work
Creating “logical web” through Media Independent Metadata based Correlation
Metadata Reference Link (<A MREF ...>)

• <A MREF KEYWORDS=<list-of-keywords>; THRESH=<real>>Document Description</A>

• <A MREF ATTRIBUTES(<list-of-attribute-value-pairs>)>Document Description</A>
Creating “logical web” through
Media Independent Metadata based Correlation

MREF
Model for Logical Correlation using Ontological Terms and Metadata

Framework for Representing MREFs

Serialization (one implementation choice)

Some interesting information on dams is available here. “information on dams” is defined by an MREF defining keywords and metadata (which may be used for a query).
Potential locations for a future shopping mall identified by all regions having a population greater than 500 and area greater than 50 sq meters having an urban land cover and moderate relief can be viewed here

=> media-independent relationships between domain specific metadata: population, area, land cover, relief

=> correlation between image and structured data at a higher domain specific level as opposed to physical “link-chasing” in the WWW
Query Results

Geographical Information about the Region

County = Clarke
Block = 731

Census Information about the Region

Area = 34
Population = 73

Spatial Location of Region

Land Cover of Region

No more regions satisfy the given constraints

CLEANUP AND QUERY AGAIN
• Some relationships may not be manually asserted, but according to statistical analyses of text, experimental data, etc.

• ➔ allow association of provenance data with classes, instances, relationship types and direct relationships or statements
A simple relationship?

Smoking

Cancer

Number of cases (in tent)

Genetic susceptibility factor

Tobacco consumption (g/day)
Knowledge Enabled Information and Services Science

Complex Relationships - Cause-Effects & Knowledge discovery

VOLCANO

LOCATION

PYROCLASTIC FLOW

ASH RAIN

BUILDING

DESTROYS

Cools Temp

DESTROYS

KILLS

WEATHER

PLANT

PEOPLE

LOCATION

ENVIRON.
Knowledge Discovery - Example

Earthquake Sources

Nuclear Test Sources

Nuclear Test May Cause Earthquakes

Is it really true?

Complex Relationship:
How do you model this?
A nuclear test could have *caused* an earthquake if the earthquake occurred *some time after* the nuclear test was conducted and *in a nearby region*.

\[
\text{NuclearTest Causes Earthquake} \\
\leq \text{dateDifference( NuclearTest.eventDate, Earthquake.eventDate ) < 30} \\
\text{AND distance( NuclearTest.latitude, NuclearTest.longitude, Earthquake.latitude, Earthquake.longitude ) < 10000}
\]
For each group of earthquakes with magnitudes in the ranges 5.8-6, 6-7, 7-8, 8-9, and >9 on the Richter scale per year starting from 1900, find number of earthquakes

Number of earthquakes with magnitude > 7 almost constant. So nuclear tests probably only cause earthquakes with magnitude < 7.
Now possible – Extracting relationships between MeSH terms from PubMed
Schema-Driven Extraction of Relationships from Biomedical Text

An excessive endogenous or exogenous stimulation by estrogen induces adenomatous hyperplasia of the endometrium.

- Entities (MeSH terms) in sentences occur in modified forms
  - “adenomatous” modifies “hyperplasia”
  - “An excessive endogenous or exogenous stimulation” modifies “estrogen”
- Entities can also occur as composites of 2 or more other entities
  - “adenomatous hyperplasia” and “endometrium” occur as “adenomatous hyperplasia of the endometrium”
An excessive endogenous or exogenous stimulation by estrogen induces adenomatous hyperplasia of the endometrium.
An excessive endogenous or exogenous stimulation modifies some entities and induces composite entities, such as adenomatous hyperplasia of the endometrium, which can be represented in RDF as:

- **Modified entities**:
  - estrogen
  - modified_entity1
  - modified_entity2

- **Composite entities**:
  - adenomatous
  - hyperplasia
  - modified_entity2
  - composite_entity1

The figure illustrates the relationships using the terms:
- `hasModifier`
- `hasPart`
- `induces`
Blazing Semantic Trails in Biomedical Literature

“The physician, puzzled by her patient's reactions, strikes the trail established in studying an earlier similar case, and runs rapidly through analogous case histories, with side references to the classics for the pertinent anatomy and histology. The chemist, struggling with the synthesis of an organic compound, has all the chemical literature before him in his laboratory, with trails following the analogies of compounds, and side trails to their physical and chemical behavior.” [V. Bush, As We May Think. The Atlantic Monthly, 1945. 176(1): p. 101-108.]
DISCUSSION

Identification of the substrates for BRCA1-dependent ubiquitination activity is important for understanding how mutation of BRCA1 is associated with loss of tumor suppression activity. The currently identified substrates include histone proteins, p53, PSEN1, aminopeptidase D2, and centrosomal proteins including NPM1 and (gamma)-tubulin (24, 51–53). Among these, only the modification of (gamma)-tubulin by BRCA1/BARD1 has been shown to affect the biology of breast cells. It has been shown that failure to ubiquitinate (gamma)-tubulin results in centrosome amplification (24). The BRCA1/BARD1 proteins are known to regulate multiple processes in the cell, including transcription, DNA repair, and centrosome dynamics (5, 55–59). Although the ubiquitination of (gamma)-tubulin may in part explain the BRCA1-dependent regulation of centrosome dynamics, it was unclear whether the BRCA1-dependent ubiquitination activity also regulated the transcription and DNA repair function of BRCA1.

We had proposed that the BRCA1-dependent ubiquitination activity may function in DNA repair by modification of RANAPII that transcribes DNA near a lesion (14, 15). This proposed role for BRCA1 in transcription-enhanced repair could be important following UV damage or double strand breaks. One prediction of this model was that BRCA1/BARD1 ubiquitination activity would be targeted to the elongating, hyperphosphorylated form of RANAPII. In vivo, RANAPII is phosphorylated on Ser-5 proximal to the promoter and on Ser-2 further downstream (23). Thus, the principal form of RANAPII that elongates through a gene is the Ser2* variant, which we now show is not a substrate for BRCA1/BARD1. The model that BRCA1-dependent ubiquitination directly links transcription elongation to repair is thus not supported. Instead, we found that Ser-5 phosphorylation of RANAPII is a generalized response to UV irradiation, and BRCA1-dependent ubiquitination modifies the RANAPII. It has been observed that transcriptionally engaged RANAPII does become phosphorylated on Ser-5 by the action of extracellular signal-regulated kinases 1 and 2 (60). The data are most consistent with a model whereby DNA damage causes phosphorylation of a subpopulation of RANAPII, followed by ubiquitination by BRCA1/BARD1 and subsequent degradation at the promoters.

In these experiments we found that overexpression of BRCA1 in cells could stimulate the damage-induced ubiquitination of RANAPII. When we inhibited BRCA1 expression by transfection of short interfering RNA specific for BRCA1, we did not observe a decrease in ubiquitination of RANAPII. We interpret these results to indicate that one or more other ubiquitin ligases can execute this function. Several other factors have been implicated in the ubiquitination of RANAPII, including Checkmate.

PMID-10037099

In the mouse two-stage skin carcinogenesis model, tumor promotion is a distinct, rate-limiting step that determines the formation of premalignant tumors. As discussed above, the role of tumor promoters in human cancer is more complex because human exposure tends to involve sporadic low doses of complex mixtures of carcinogens, co-carcinogens, and tumor-promoting agents. Nonetheless, studies of rodent tumor models of liver, bladder, colon, and breast cancers—and analyses of human tumor formation—suggest that processes analogous to tumor promotion by TPA on the mouse skin are a common feature of carcinogenesis (1). Thus, epigenetic changes in cell signaling, such as altered growth factor production and receptor expression, and elevated synthesis of inflammatory and mitogenic factors, such as cytokines and eicosanoids, are key targets for inhibiting tumor promotion.

Tumor Progression

As noted earlier, tumor progression involves the accumulation of additional genetic alterations in an initiated cell clone and generally gives a growth advantage to the progressing clone. In progression, a focal lesion consisting of a population of initiated and promoted cells ultimately becomes an invasive malignant tumor. One frequently observed genetic alteration that appears to contribute to malignant progression is mutation in the p53 [also known as TP53] tumor suppressor gene (62). The p53 gene product is a transcription factor that regulates the expression of a number of DNA-damage and cell cycle-regulatory genes and genes regulating apoptosis. By enhancing transcription of these critical genes, p53 regulates the cellular response to DNA damage (63). p53 also plays a role in maintaining genomic stability (64). Genomic instability, a hallmark of spontaneous malignant progression, is characterized by sequential chromosomal aberrations, such as duplications, deletions, and loss of...
Semantic Trails can be built over a Web of Semantic (Meta)Data extracted (manually, semi-automatically and automatically) and gleaned from

- **Structured data** (e.g., NCBI databases)
- **Semi-structured data** (e.g., XML based and semantic metadata standards for domain specific data representations and exchanges)
- **Unstructured data** (e.g., Pubmed and other biomedical literature)

and

- **Various modalities** (experimental data, medical images, etc.)
Applications

“Everything's connected, all along the line. Cause and effect. That's the beauty of it. Our job is to trace the connections and reveal them.”

Jack in Terry Gilliam’s 1985 film - “Brazil”
Ahmed Yaseer:
- Appears on Watchlist ‘FBI’
- Works for Company ‘WorldCom’
- Member of organization ‘Hamas’
Example of Fraud prevention application used in financial services

Scores the entity based on the content and entity relationships

Semi-structured Government Data
Un-structure text, Semi-structured Data

Watch Lists, Law Enforcement, Regulators
Public Records, World Wide Web content, BLOGS, RSS

Establishing New Account

Knowledge Enabled Information and Services Science

Global Investment Bank
Hypothesis driven retrieval of Scientific Text

Knowledge Enabled Information and Services Science
File Name: 3416116

Abstract: The rates of growth of 29 hepatic metastases from 15 patients with primary colorectal carcinoma were studied using serial computed tomography (CT). Eleven metastases were found by the surgeon at laparotomy (overt metastases); the remaining eighteen were not evident to the surgeon at laparotomy, but were detected by CT scan during the immediate postoperative period postoperative (occult metastases). An estimate of tumour volume doubling time was obtained from a semi-logarithmic plot of tumour cell number against time. The mean doubling time for the overt metastases (s.e.m.) compared with 86 days for the occult metastases. The age of the overt metastases was estimated from the growth curve assuming a process of surgery was necessary. The corresponding age of the overt metastases (s.e.m.) is 2.3 ± 0.4 years.
Relationship Web takes you away from “which document” could have information I need, to “what’s in the resources” that gives me the insight and knowledge I need for decision making.

NY's 'Halo 3' launch was no riot, but it was close

By Caroline McCarthy
Staff Writer, CNET News.com
Published: September 24, 2007, 11:35 PM PDT

reporter's notebook NEW YORK--Late Monday night, George Clooney waltzed into a midtown Manhattan hotel, with the camera flashes of the paparazzi following him into the lobby.

A block away at the Best Buy store on Fifth Avenue and 44th Street, those waiting for the launch of Microsoft's Halo 3 video game couldn't have cared less.
Events and STT dimensions

- Powerful mechanism to integrate content
  - Describes the Real-World occurrences
  - Can have video, images, text, audio all of the same event
  - Search and Index based on events and STT relations

- Many relationship types
  - Spatial:
    - What events happened near this event?
    - What entities/organizations are located nearby?
  - Temporal:
    - What events happened before/after/during this event?
  - Thematic:
    - What is happening?
    - Who is involved?

- Going further
  - Use integrated STT analysis to explore cause and effect
Example Scenario: Sensor Data Fusion and Analysis

- How do we determine if A-H = A-L? (Same time? Same place?)
- How do we determine if E-H = E-L? (Same entity?)
- How do we determine if E-H or E-L constitutes a threat?
Sensor Data Pyramid

- Raw Sensor (Phenomenological) Data
- Feature Metadata
- Entity Metadata
- Relationship Metadata
- Expressiveness

Data

Information

Semantics/Understanding/Insight
Sensor Data Architecture

**Knowledge**
- Object-Event Relations
- Spatiotemporal Associations
- Provenance Pathways

**Information**
- Entity Metadata
- Feature Metadata

**Data**
- Raw Phenomenological Data

**Analysis Processes**
- Semantic Analysis
- Entity Detection
- Feature Extraction
- Fusion
- Collection

**Annotation Processes**
- SML-S
- O&M
- TML

**Ontologies**
- Object-Event Ontology
- Space-Time Ontology

**Sensors** (RF, EO, IR, HIS, acoustic)
Current Research Towards STT Relationship Analysis

- Modeling Spatial and Temporal data using SW standards (RDF(S))\(^1\)
  - Upper-level ontology integrating thematic and spatial dimensions
  - Use Temporal RDF\(^3\) to encode temporal properties of relationships
  - Demonstrate expressiveness with various query operators built upon thematic contexts

- Graph Pattern queries over spatial and temporal RDF data\(^2\)
  - Extended ORDBMS to store and query spatial and temporal RDF
  - User-defined functions for graph pattern queries involving spatial variables and spatial and temporal predicates
  - Implementation of temporal RDFS inferencing

---


Upper-level Ontology modeling Theme and Space

Occurrent: Events – happen and then don’t exist

Continuant: Concrete and Abstract Entities – persist over time

Named_Place: Those entities with static spatial behavior (e.g. building)

Dynamic_Entity: Those entities with dynamic spatial behavior (e.g. person)

Spatial_Occurrent: Events with concrete spatial locations (e.g. a speech)

Spatial_RRegion: Records exact spatial location (geometry objects, coordinate system info)

occurred_at: Links Spatial_Occurents to their geographic locations

located_at: Links Named_Places to their geographic locations

---

Knowledge Enabled Information and Services Science
Knowledge Enabled Information and Services Science

Upper-level Ontology

Domain Ontology

- **Dynamic_Entity**
  - **Continuant**
  - **Named_Place**
    - located_at
    - occurred_at
  - **Spatial_Occurrent**
    - **Spatial_Region**

- **Person**
  - **Politician**
  - **Soldier**
    - assigned_to
    - on_crew_of

- **Vehicle**
  - **Military_Unit**
    - **Battle**
    - **Bombing**
      - used_in

- **City**
  - **trains_at**

- **Speech**
  - **gives**
  - **participates_in**

Relationships:
- *rdfs:subClassOf* used for integration
- *rdfs:subClassOf* relationship type
Temporal RDF Graph: Platoon Membership

E1:Soldier

assigned_to [1, 10]

E2:Platoon

assigned_to [11, 20]

E3:Platoon

assigned_to [5, 15]

E4:Soldier

assigned_to [5, 15]

E5:Soldier

Time interval represents valid time of the relationship

E1 is assigned to E2 from time 1 to 10 and then assigned to E3 from time 11 to 20

Also need to handle inferencing:

\((x \text{ rdf:type Grad\_Student})\):[2004, 2006] AND
\((x \text{ rdf:type Undergrad\_Student})\):[2000, 2004]

\(\rightarrow (x \text{ rdf:type Student})\):[2000, 2006]
Unlike thematic relationships which are explicitly stated in the RDF graph, many spatial and temporal relationships (e.g., distance) are implicit and require additional computation.

Fig. 2. Storage structures for RDF data. Existing tables of Oracle Semantic Data Store are shown on the right, and our additional tables for efficiently searching spatial and temporal data are shown on the left.
Sample STT Query

```
select a from table (spatial_eval ("(?a has_symptom ?b)
  (Chemical_X induces ?b)(?a fought_in ?c)", ?c,
  "(?d member_of Enemy_Group_Y)(?d spotted_at ?e)", ?e,
  'geo_distance(distance=2 units=mile)"");
```

Scenario (Biochemical Threat Detection): Analysts must examine soldiers’ symptoms to detect possible biochemical attack

Query specifies
Formal representation of knowledge

- RDF(S), OWL, etc.

Statistical analysis

- Similarity
- Cooccurrence
- Clustering

Intelligent aggregation of knowledge

- Collaboration/Problem Solving Environments
- Decision support tools
The Semantic Web focuses on artificial agents
“Web 2.0 is made of people” (Ross Mayfield)
“Web 2.0 is about systems that harness collective intelligence.” (Tim O’Reilly)
The relationship web combines the skills of humans and machines
Putting the man back in Semantics

“Web 2.0 is about systems that harness collective intelligence.”

Web 2.0 is made of people. (Ross Mayfield)

The relationship web combines the skills of humans and machines.

Knowledge Enabled Information and Services Science
Going places ...

Knowledge Enabled Information and Services Science

Formal

Social, Informal

Implicit

Powerful

The Global Brain

Smart Marketplaces

Decentralized Communities

The Web

Relationship Web"