Goal Aware Systems

Find here the tutorial material and more

https://dipapadimitriou.github.io

REFERENCES

Dimitra Papadimitriou, Georgia Koutrika, John Mylopoulos, Yannis Velegrakis:

The Goal Behind the Action: Toward Goal-Aware Systems and Applications

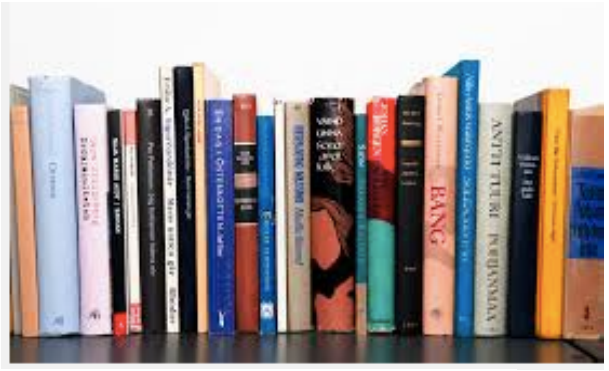
ACM Trans. Database Syst. 41(4): 23:1-23:43 (2016)

Dimitra Papadimitriou, Yannis Velegrakis, Georgia Koutrika, John Mylopoulos:

Goals in Social Media, information retrieval and intelligent agents.

ICDE 2015: 1538-1540 (tutorial)

Objects → Data



Actions → Data

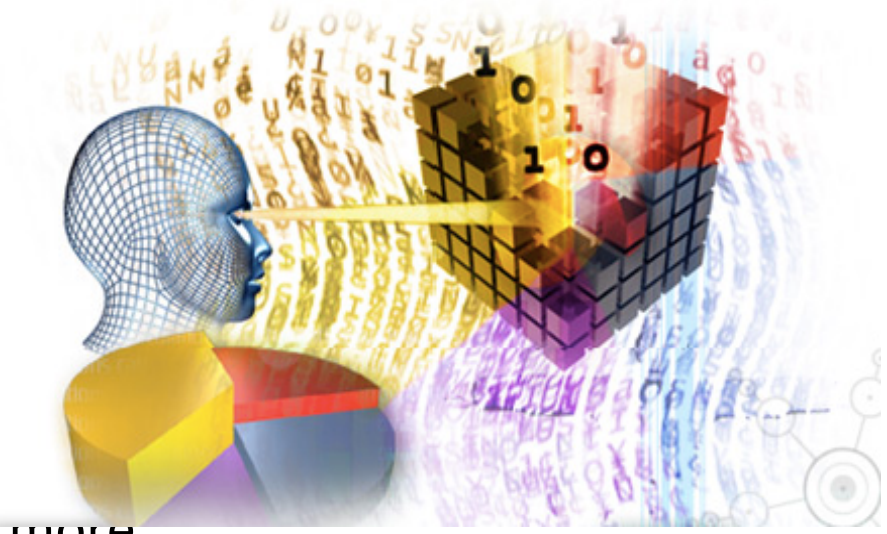
Goals

- Goals are behind every action
  - Rationalize
  - Contextualize
  - Explain

- Extensively Studied in Sociology, Psychology and Cognitive Sciences [Thomson and McEwen, 58]

Goals In Computer Science

- Many different kinds Interactions
- Recording & Mining is now prevalent
- Understand the “why”: The Motives
- Leads to applications & Systems that are more
  - Proactive
  - Adaptive
  - Efficient



Studying Goals

What We Study

- moves in natural environment (recorded by sensors)
- moves of certain human parts
- clicks, comments, menu or other item selections
- free-text input
- transactions
- interaction with other users
- preference statements
- ratings or publishing/posting of text or multimedia objects

How We Study

- Observe User Actions
- Identify Correlations
- Cross-System Inference

Goals in Social Media, Web IR and Int. Agents

1 Introduction

2 Generic Goal Framework

3 Applications

4 Personalized Search

5 Future directions

Environment

Environment

Trees: yes
Ground: yes
Grass: yes
Cars: no
Road: no

Place: park
Clothes: training clothes
Shoes: running shoes
Briefcase: no

Place: city
Clothes: suit
Shoes: suit shoes
Briefcase: yes

Trees: no
Ground: no
Grass: no
Cars: yes
Road: yes

Environment

- Infinite set of actors U
- Infinite set of variables V
  - domain D_v

- ***Environment**: Finite set of Variables* $\{v_1, v_2, \ldots, v_n\}$ from V
  - **State** S_v of a **variable** v is its value
  - **Cardinality** of the environment: Number n of variables
  - **State of the Environment** S^E: set of variable states $\{S_{v1}\ S_{v2}, \ldots, S_{vn}\}$

Action

Location* of the person changes due to *running

Trees: yes
Ground: yes
Grass: yes
Cars: no
Road: no

Place: park
Clothes: training clothes
Shoes: running shoes
Briefcase: no

Location: Y1… Y2 …. Y3 …

Place: city street
Clothes: suit
Shoes: suit shoes
Briefcase: yes

Trees: no
Ground: no
Grass: no
Cars: yes
Road: yes

Location: Y1… Y2 …. Y3 …

Action

- Finite set of actions A

Action

- act|$S^E \rightarrow S^E$

Goal Fulfillment

- Lose 5 Kg

- Go to work ✔

Place: **Office**
Clothes: suit
Shoes: suit shoes
Briefcase: yes

Generic Goal Model

- Finite set of actions A
- Finite set of goals G

Action

- act|$S^E \rightarrow S^E$

Goal g: A boolean function on the env variables

- Input: $\{v_1, v_2, \ldots, v_n\}$
- Output: boolean

Soft Goals

- Lose 5 Kg

- Satisfaction Function

Generic Goal Model

- Finite set of actions A
- Finite set of goals G

Action

- act|$S^E \rightarrow S^E$

Goal g: A boolean function on the env variables

- Input: $\{v_1, v_2, \ldots, v_n\}$
- Output: boolean

Soft Goal*: A function converging into an environment state*

Operationalization

- **Lose 5Kg**

*A **plan** is a sequence of Actions*

A plan p:< act_1, act_2,…..,act_j> is an ***operationalization*** *of a goal g if*

- $S' = act_j(act_{j-1}(\ldots act_2(act_1(S_{current}))\ldots))$
- $S' \models g$.

Probabilistic Goal Inference

- Go to work

From Actions To Goals

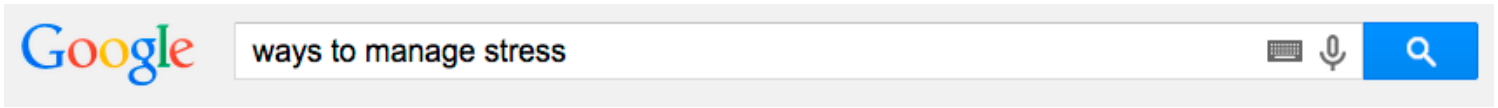
Goal: Run marathon

Action 1

Action 2

Goal: Lose weight

Action 3



Goal: Be healthy

Intentions and Motivations

- Lose 5Kg

- Chase a duck

Intention: The amount of commitment to a Goal

Motivation: A factor driving someone to perform an action

Social/cognitive models

- Feel better

Social/cognitive models

- Be happy

Putting all in Perspective

Why?	Intentions
What?	Goals
How?	Actions

Goals in Social Media, Web IR and Int. Agents

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2 Generic Goal Framework

3 Applications

4 Approaches

5 Future directions

Intelligent agents

- **Environment variables:**
  - sensor measurements
  - user inputs
  - positions of objects on the screen
  - locations of parts of objects or actors
- **Environment Changes**
  - Automatically
    - by the change of the indication of a sensor of an agent,
      - e.g., a light detector.
  - Deliberately
    - Actions

Intelligent agents

- Goal: *one and **only one** environment state*
  - No Conditions: but explicit variable states
- Goal and the environment state satisfying the goal coincide
  - $\mathbf{g \in G : G \subset S^E}$
- All the states of the environment explicitly determined
  - Easier goal recognition
  - More difficult *definition of the examined environment*
    - every possible goal should be fully represented

Intelligent “homes”

- Assisted **technologies**
- Care of the elderly

  [Geib and Goldman 2005]

  [Pereira and Anh 2009]
- Alzheimer patients [Roy 2007]

- Wireless sensors
  - Location
  - Moves of certain body parts
  - Sounds
  - Medical data: blood pressure, pulse, body temperature

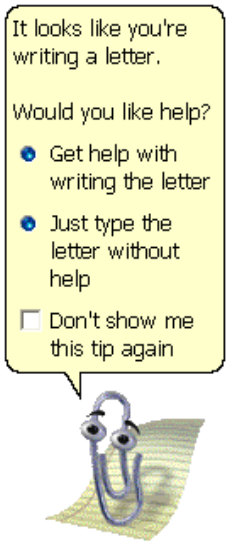
The Role of Intelligent Technology in Elderly Care [Pollack 2002]

Intelligent interfaces

- Intersection of **Artificial Intelligence** and **Human Computer Interaction** [Armentano and Amandi 2009][Lesh 1999]

- Perform user operations through the interface [Lieberman 2009]
  - Observe actions taken by the user
  - Sense the objects on the screen
  - Take actions on its own
  - Add graphics/choices
  - Complete automatically whole tasks (goal)
- Applications
  - Web browsers, Text editors, Search engines
  - **Medical computerized** systems [Bigdelou 2012]
  - Every type of application with user interaction

IUI for Office 2000/XP/2003



Interactive Narrative Managers/Games

- Virtual environments [Gold 2010][Mott 2006]
- Pedagogical Interactive Narrative
  - **Education**
  - **Gaming**
- Computational challenges for goal recognition models
  - Continuous changes
    - Unlocking new powers
    - New skills and knowledge
    - Improving skills

- Enrich the user experience
- Manage narrative conflicts
- Create personalized story events

Interactive Narrative Managers/Games

- Games
  - graphical presentations
  - interaction designs
  - simulation capabilities
  - **But:** goals and plans

CRYSTAL ISLAND [Mott 2006] [Ha 2012]

- Solving a biology mystery
  - manipulate virtual objects
  - converse with characters
  - use lab equipment and other resources
- Substantial learning and motivational benefits

Dialogue Systems

- Input: Goals expressed by users periphrastically
  - plan meeting times
  - find a good Indian restaurant nearby

[Carberry 1983b]
[Crook and Lemon 2010]
[Maragoudakis 2007]

- Output: Information about the preconditions for fulfilling it
- Interaction: level by level

- Enterprises, education, government, healthcare, entertainment
  - Customer care and helpdesk services
  - Technical support
- Knowledge bases/Informational services
  - News/Stock market
  - Entertainment topics
  - Any other type of information in a knowledge base

Web querying

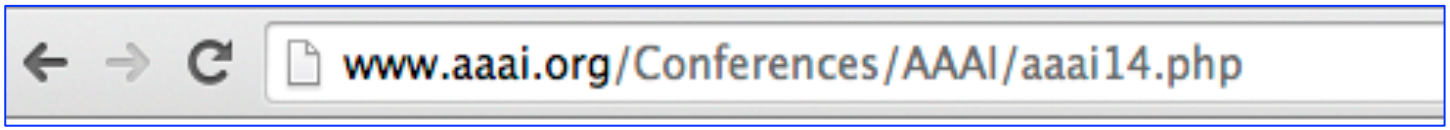
- Web: huge collection of resources
- Resources
  - static or dynamic pages
  - an object with a web presence -Internet of Things
- Features
  - actual content: words, topics or entities
  - metadata: author and creation date
  - implicit attributes: source authority and popularity
- Environment state : a function over the features of the resources returned to the user
  - the appearance of certain keywords (in a resource of the resource list)
  - diversity or topic coverage (aggregation property of the result list)

Web querying

“artificial intelligence”

“artificial intelligence trailer”

“artificial intelligence aaai 2014”

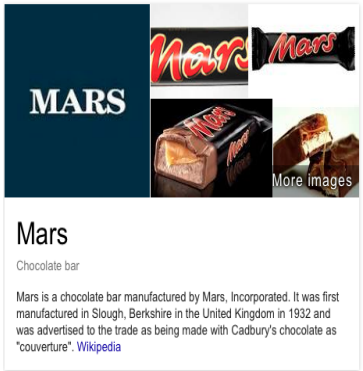


Web querying

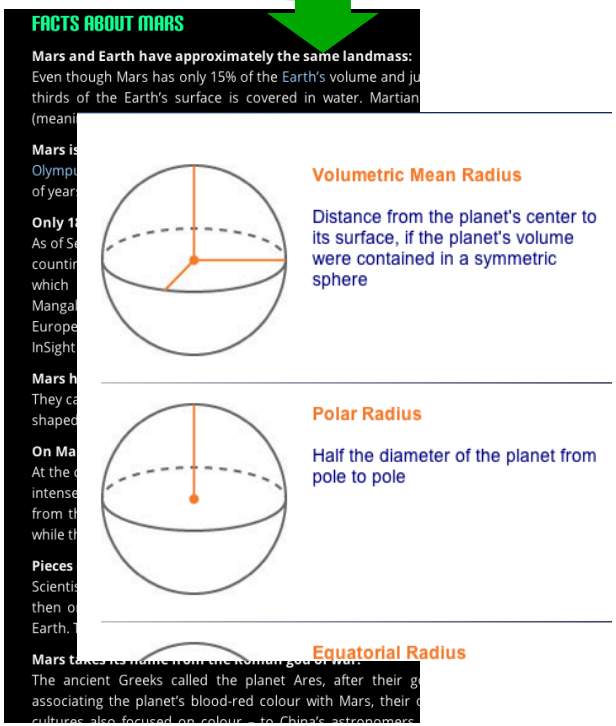
jupiter	earth
planet mars	mars pictures
life on mars	facts about mars
mars chocolate	mars one

[Sadikov 2010]

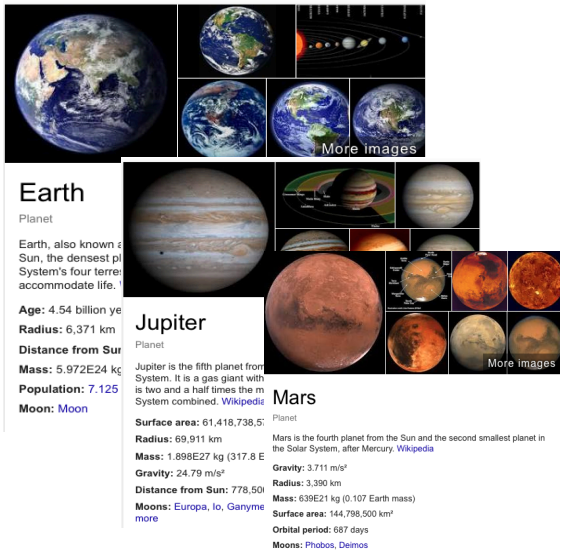
mars chocolate



planet mars facts about mars



jupiter earth



Behavioral Theories

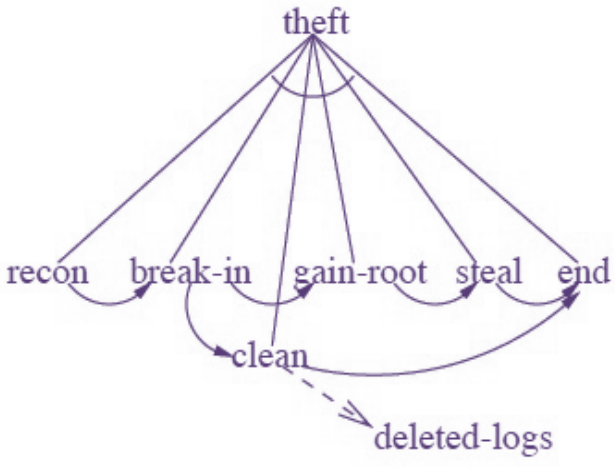
- Motivational factors - Intentions
  - up-loading video content **[Park 2011]**
  - organizing vacation trips using social media **[Cheung and Lee 2010]**
  - browsing products over social media websites and sharing interesting consumption facts with friends **[Parra-Lopez 2011]**
  - being loyal in multiplayer online role-playing games (MMORPG) **[Bagozzi and Dholakia 2002]**
  - sharing knowledge with colleagues **[Chow and Chan 2008]**
  - replying or replying with delay to communication messages on the social networking site **[De Choudhury et al. 2007]**

Exploiting Goals

- Automatic Action Execution
- State Transitions
- Interface Adaptation
- System Response Adjustment
- Side Services

Automatic Action Execution

- Perform user operations through the interface [Lieberman 2009]
  - Observe actions taken by the user
  - Sense the objects on the screen
  - Take actions on its own
  - Complete automatically whole tasks (goal)

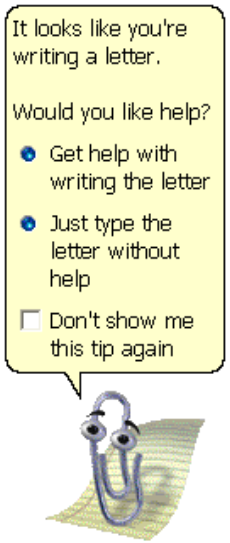


Interface Adaptation

- Intersection of **Artificial Intelligence** and **Human Computer Interaction** [Armentano and Amandi 2009][Lesh 1999]

- Perform user operations through the interface [Lieberman 2009]
  - Add graphics/choices
- Applications
  - Web browsers, Text editors, Search engines
  - Medical computerized systems [Bigdelou 2012]
  - Every type of application with user interaction

IUI for Office 2000/XP/2003



State Transitions

- Assisted technologies
  - Care of the elderly
    [Geib and Goldman 2005]
    [Pereira and Anh 2009]
  - Alzheimer patients [Roy 2007]

- Interactive Virtual Environments or Narrative managers
  - Education [Mott et al. 2006
  - Entertainment [Gold 2010][Ha et al. 2012]

Response adjustment

Web retrieval

- [Lee et al. 2005]
- [Rose and Levinson 2004]
- [Baeza-Yates et al. 2006]

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Approaches

- Complete Records
- Taxonomy-based
- Behavioral theories
- Corpus-based

➢ Text analysis

Approaches

Complete Records

Hand-coded expert knowledge

- Goals
- Action effects
- Action pre-conditions
- Plans

Alternatives

- **Plan libraries**
- **Plan graphs**
- **Action-centric approaches**

Complete Records

Plan Libraries

Recording of all possible plans

- Predefined recipes: *plan libraries*
  - all the alternatives

    hand-coded
- Closed-world reasoning [Kautz 1991]
- Limited problem domain
- Simple case: sequential plan

goal *plan*

$g \longrightarrow act_1 ; act_2; act_n$

[Kautz & Allen 1986]

[Carberry 2001]

[Geib 2001]

[Smith & Lieberman 2010]

[Sadri 2012]

Plan libraries

Construction

Plan libraries [Sadri 2012]

- Correct
- Complete
- *Sensitive to noise*

Probabilities

- A priori likelihood of different plans [Charniak & Goldman 1993]

Experts

- select the goals
- select the plans
  - all: not feasible
  - enough to cover all goals

Plan libraries

Inference

Observing

- the actions of the actors
  - not the changes in the environment states directly
- inferred actions
  - when the behavior of the agent is only partially observable

Goal recognition-Plan recognition [Kautz & Allen 1986]

$g \leftarrow (act_1 ; \ldots; act_i ; act_{i+1} ; \ldots; act_{j-1} ; act_{j+1} ; \ldots; act_{k-1} ; \ldots; act_n)$

- Assumption : "Every observed action is **purposeful**;
  it serves some plan in the library"

- Problem : "To identify a **minimal set** of top level actions
  sufficient **to explain** the set of observed actions"

Example

Problem domain: hacking
Goal (theft)
Goal (vandalism)

(**recon**) make a reconnaissance,
scan the system to determine
vulnerabilities

(**break in**) exploit the system weaknesses

(**gain root**) gain entry break in escalate privile

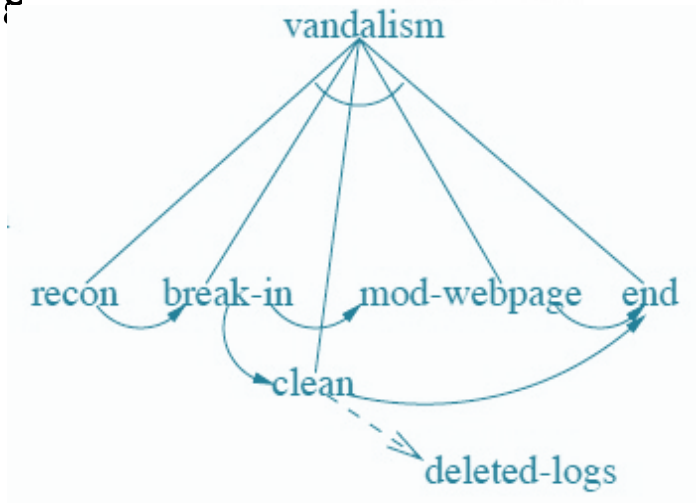
(**steal**) export desired data

(**mod-webpage**) export desired data

(**clean**) hide traces of presence

Hierarchical Plan Library

[Geib 2001]



Example

Hierarchical Plan Library

[Geib 2001]

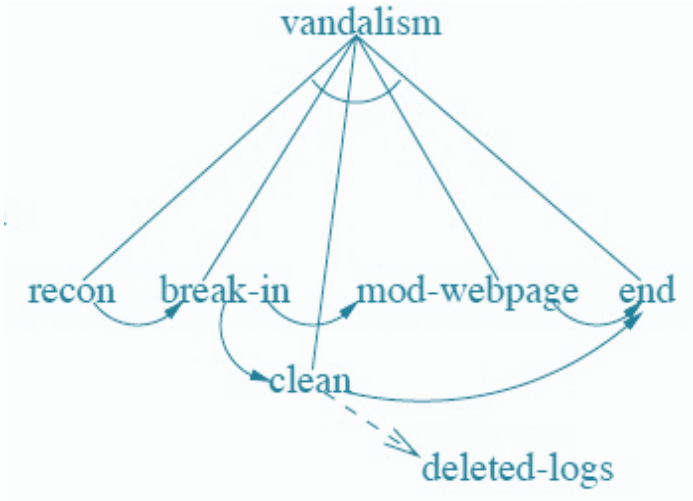
Inference

limit the searching space until

- 1 goal or 0 goal

How do we limit the space?

- based on ordering of constraints
- exclusion of disabled actions,
  - i.e., actions in all cases preceded by actions that are not observed



Plan libraries

Disadvantages

Static and hand-coded by experts

- Difficulty of gathering the knowledge
- Large updating cost
  - Especially for large libraries
- Only recognition of existing goals and plans
  - No new plans

Consistency Approaches

Plan graphs

- No Recording of all possible plans
- But observed actions to form valid plans

[Lesh & Etzioni 1995]
[Hong 2000]

- **Environment variables**
  - Proposition **nodes** storing the values of the environment variables
- **Actions**
  - Action **nodes**
- **Goals**
  - Goal **nodes**
- **Plans**/Implementations
  - **Edges**
    - Representing possible *connections* between nodes

Plan graphs

[Hong 2000]

- Domain: use of **UNIX** console
  - 35 actions
  - 249 hand-coded goals
- Time Scalability: linear (up to 10^5 candidate goals)

Example

- Observed **Actions** : {*cd papers*, *ls*}
- Either **Goal**: find a file or subdirectory in the directory "papers"
  - Successful plan (fulfills the goal)
  - Related actions (both actions contribute)
- Or subset of a longer **Plan**
  - e.g., delete a file from the folder
  - {*cd papers*, *ls*, *rm oldpaper.tex*}

Plan graphs

Construction

- **Insert** as nodes all the actions
  - recorded by the domain experts
- **Connect all** action nodes and goal nodes
  - Connection *without* inconsistency checking
- Repeatedly **prune** inconsistent goals
  - by the experts or automatically

Consistency approaches

Action centric

[Sun and Yin 2007]
[Ramrez & Gener 2009]

Recording of combinations of the environment variables as preconditions and postconditions

- Environment variables
  - **Propositions**
- States of the environment
  - **Set** of propositions
  - **First order literals connected** with logical symbols AND (∨), OR (∧)
- Action effects or post-conditions
  - Propositions that will be **removed** / **added**

Example

Action centric

[Sun and Yin 2007]

What do we perceive?

- *Objects, Important features*

Environment variables

(clean hands)	(clean hands)
(dinner)	
(present)	
(garbage)	(garbage)
(quiet)	(quiet)

Example

Action centric

[Sun and Yin 2007]

Goals

g_1	(dinner) ∨ (present) ∨ ¬(garbage) ∨ (quiet)
g_2	(dinner) ∨ (present) ∨ (garbage) ∨ (quiet)
g_3	(dinner) ∨ (garbage) ∨ (quiet)

Actions

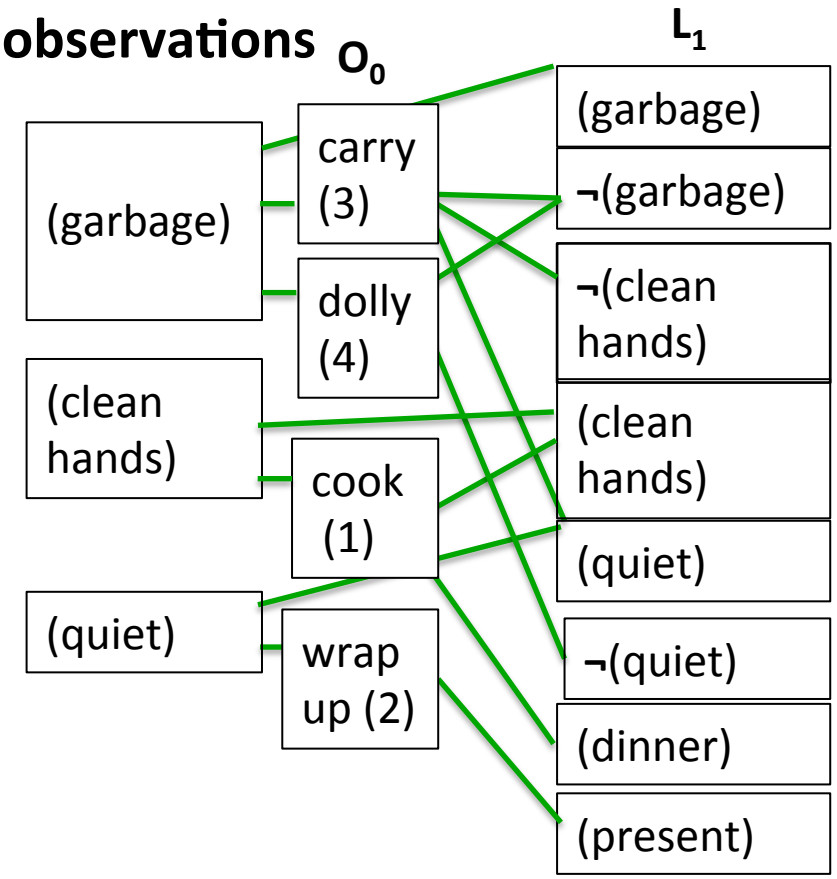
Preconditions	Effects	Explanation
(clean hands)	(dinner)	cook
(quiet)	(present)	wrap up
(garbage)	¬(garbage) ∨ ¬(clean hands) ∨ (quiet)	carry garbage
(garbage)	¬(garbage) ∨ ¬ (quiet)	dolly

Example

Action centric

[Sun and Yin 2007]

Stage 0:
0 observations O_0



Precon-ditions	Effects	Expla-nation
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2. (quiet)	(present)	wrap up
3. (garbage)	¬(garbage) ∨ ¬(clean hands) ∨ (quiet)	carry garbage
4. (garbage)	¬(garbage) ∨ ¬ (quiet)	dolly

Consistency approaches

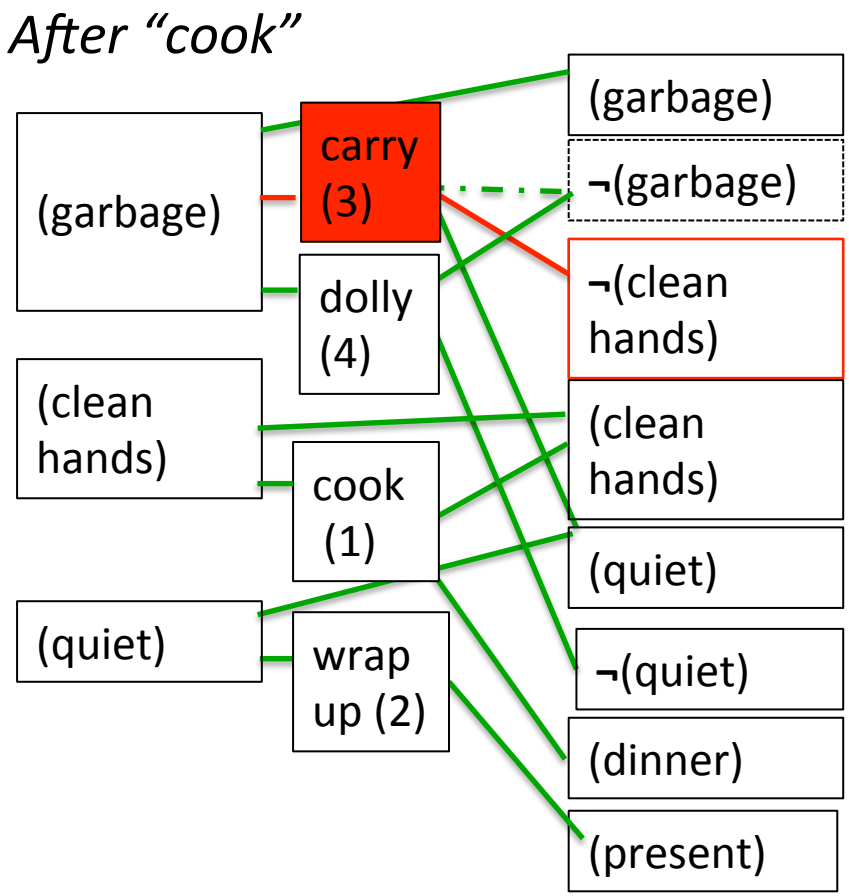
Action centric

Checking consistency constraints backwards

"*With more and more observations,*
the inaccurate judgment made before for
lack of information, can be revised later"

[Sun and Yin 2007]

Example



Action centric

[Sun and Yin 2007]

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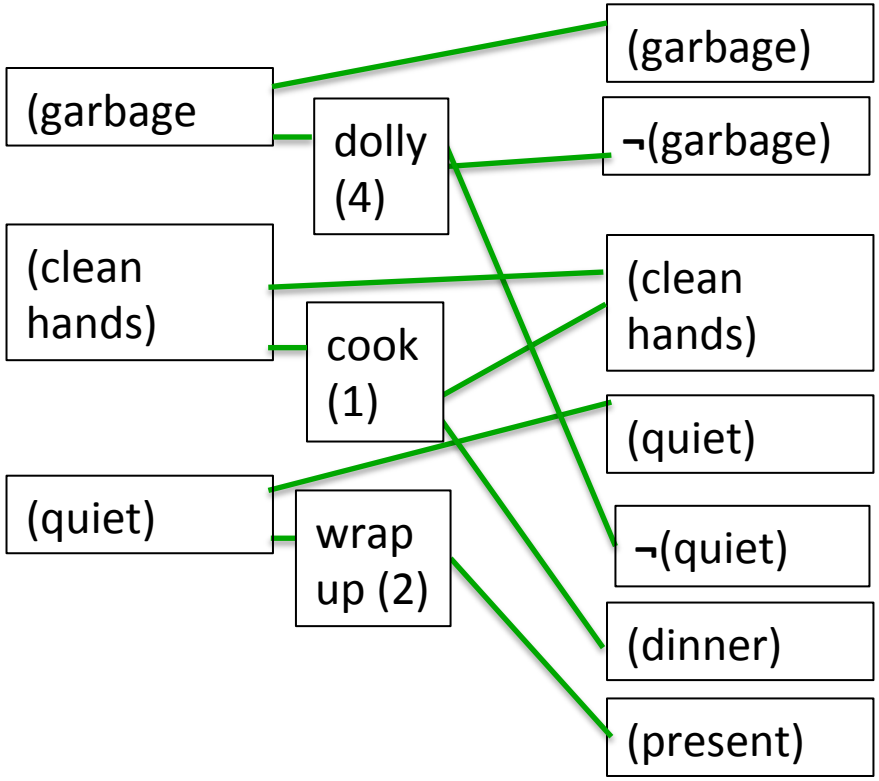
Example

Action centric

After "cook"



(dinner) ∨ (present) ∨ ¬(garbage) ∨ (quiet)

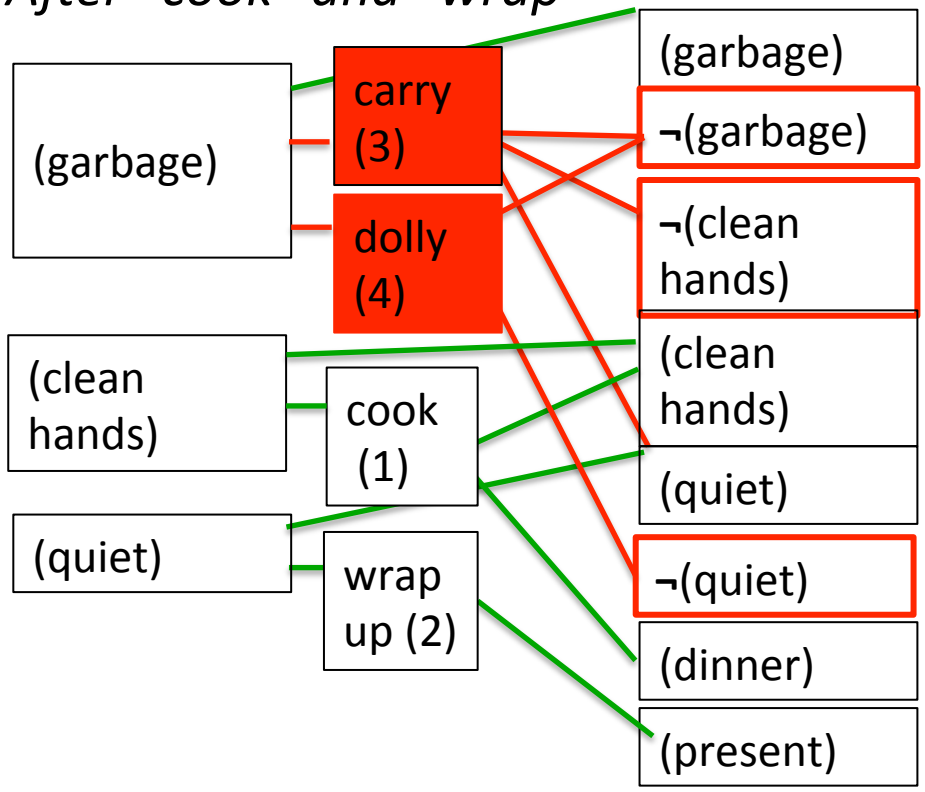
(dinner) ∨ (present) ∨ (garbage) ∨ (quiet)

(dinner) ∨ (garbage) ∨ (quiet)

Example

Action centric

After "cook" and "wrap"



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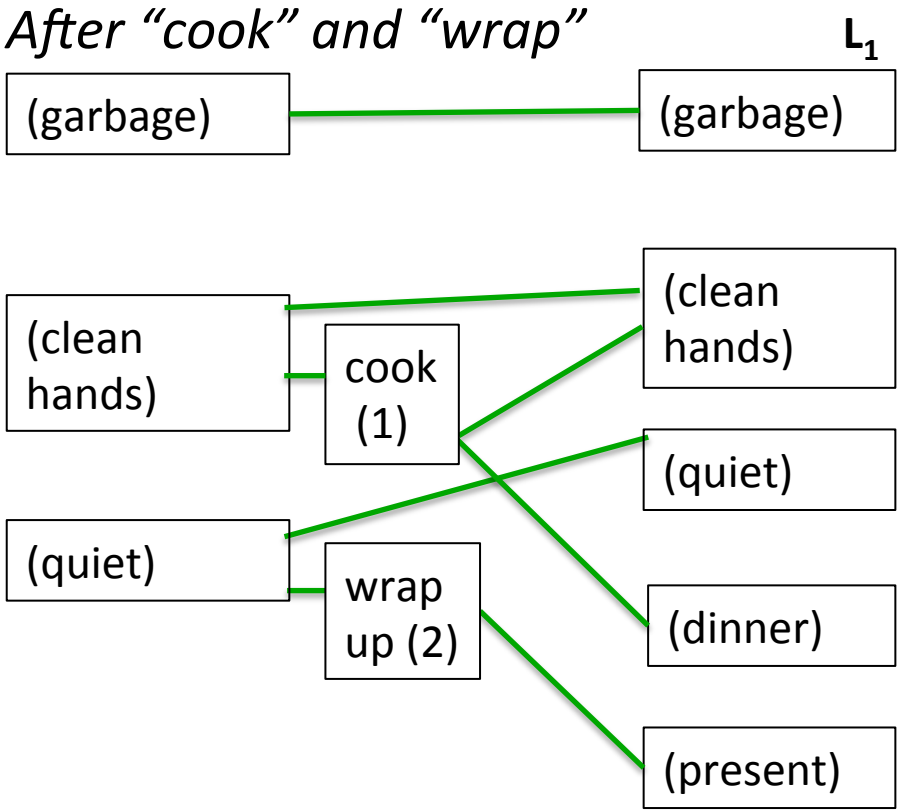
Example

Action centric



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(dinner) ∨ (present) ∨ (garbage) ∨ (quiet)
(dinner) ∨ (garbage) ∨ (quiet)

Action-centric

Consistency Checking

At time step k

Step 1

- **find all *invalid*** literals in proposition level L_k
  and update the inconsistent actions in O_{k-1}
- update all the ***valid*** actions in O_{k-1}
  - update literals that appear in their preconditions and effects

Step 2

- **If** no value action is updated in step 1
  - continue to check L_{k-1} and O_{k-2}
- **else** update the values of mutex and go back to step 2.

Step 3

- **repeat** until graph stabilizes

Action-centric

Inconsistencies

- Actions with **inconsistent effects**
  - effect-effect
- Action **interference**
  - effect-precondition
- Actions with **inconsistent preconditions**

- Mutex Variable states, i.e., fact literals
  - Negated literals: the pair of literals forms a complementary pair
  - Inconsistent support: Every pair in a level is mutex

Action-centric

Action-Centric

- Inference [Sun and Yin 2007]
  - Backward-chaining strategy

Traverse(G, t)

For each goal **g** in **G**

DO

- Take the literals of g at time step t
- Select a set of a non-mutex actions **A** supporting the goal
- add the preconditions of actions in the candidate goal
- **Traverse(G, t-1)**

Until a goal conditions are satisfied

Approaches

Taxonomies

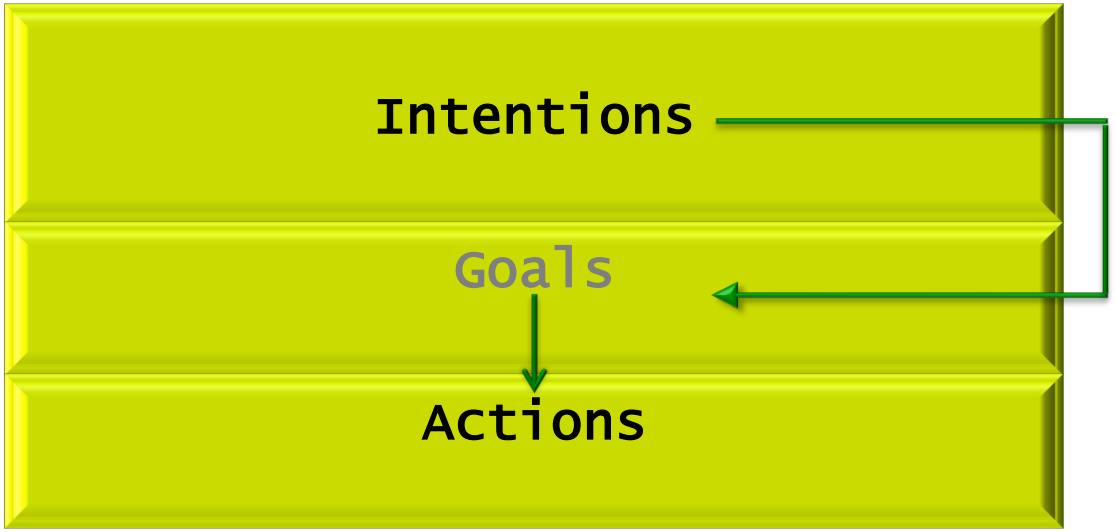
- Limited environment
  - Physical environment monitored with sensors
  - Software/Computer-based System

- **Chaotic** environment
  - Web 45 billion web pages
  - Fully observable objects
  - Intrinsic features that can be derived

Goal framework

Web querying

- Why do the users **intend** to access certain web objects?
- Intentions describe **information needs** [Broder 2002] [Baeza-Yates 2006]



Taxonomies

Web querying

- Why do the users **intend** to access certain web objects?
- What does their queries reveal about it?

Query taxonomy / Latent goals

[Broder 2002]

- Informational
- Navigational
- Transactional

[Broder 2002]
[Kang and Kim 2003]
[Lee et al. 2005]
[Rose and Levinson 2004]
[Baeza-Yates et al. 2006]

Broder's taxonomy

Informational

Query "artificial intelligence"

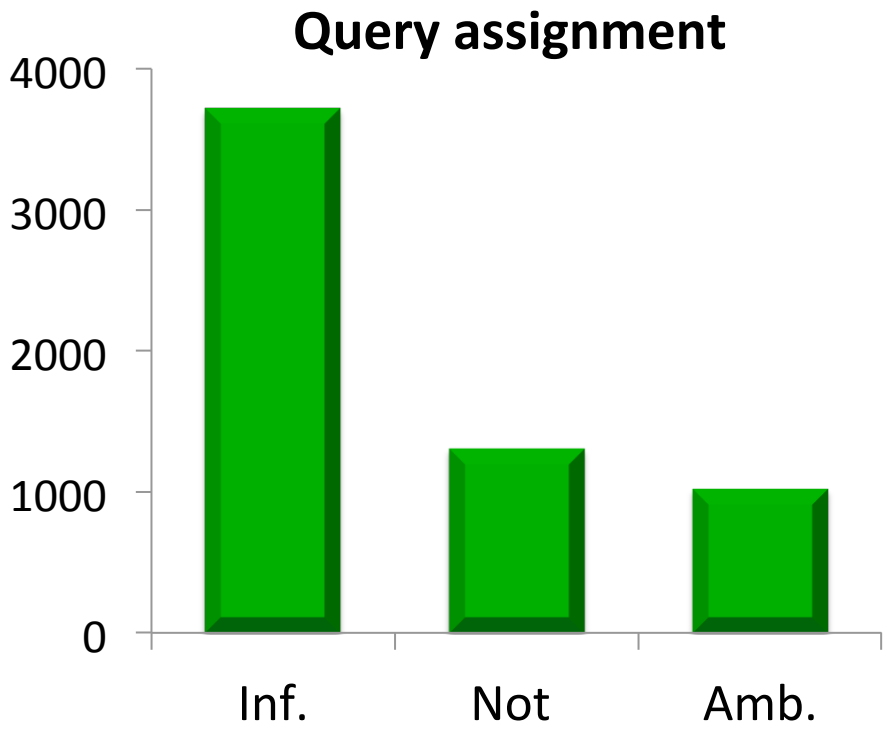
Google search engine snippets

Informational

[Baeza-Yates et al. 2006]

Theme	Inf.	Not	Amb.
Arts	66.23	14.94	18.83
Society	87.43	2.09	10.47
Games	24.44	57.78	17.78
Home	39.68	27.78	32.54
Education	81.69	10.21	8.10
Recreation	55.56	34.44	10.00
Science	88.97	4.83	6.21
Shopping	44.72	23.58	31.71
Sports	65.96	23.40	10.64
World	68.66	8.96	22.39
Computers	37.18	44.44	18.38
News	92.86	5.95	1.19
Business	82.76	9.22	8.02
Health	73.71	9.05	17.24

Manual classification: **Yahoo! Engine queries**
Probabilistic Latent Semantic Analysis



Broder's Taxonomy

Transactional

Query "artificial intelligence trailer"

A.I. Trailer (Extended Version) - YouTube

[Li 2006]

- Hyperlinks
- Anchor-texts
- Html tags
- Windows of text
  around hyperlinks or patterns

E.g. [Tt]o download \w+ (click (on)?|go to)

Transactional

- Sources related to **transactions**
  - For a query: less transactional sources than informational

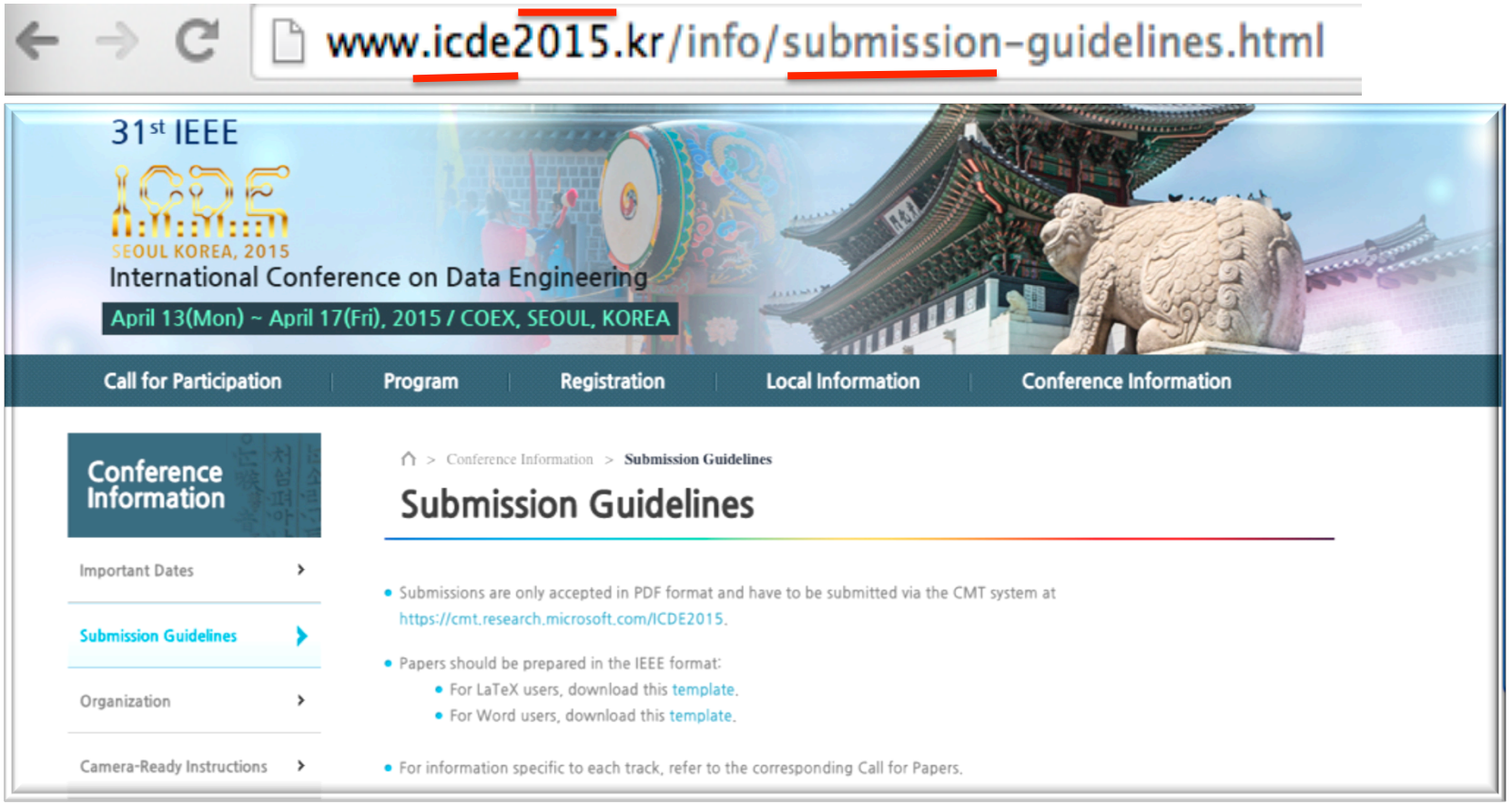
Examples [Li 2006] [Jansen 2008]

- Free/Not free downloads
  - "free online games",
  - *"family guy episode download"*
- Services
  - "property damage report."
  - University of Michigan system to file a report

Broder's Taxonomy

Navigational

Query "submission ICDE 2015"



Navigational

A specific web resource

- Known
  - External source
  - Past use
  - Assumption

Attributes [Lu 2006]

- Perfectness
- Uniqueness
- Authority

Taxonomies

Construction

Classes: a combination of

- Expert knowledge
- Extended user studies
  - questionnaires
  - interactive tools on web browsers
    - tracking user moves such as clicks
    - form submissions

Example [Baeza-Yates et al. 2006]

- to be informed
- to navigate to a site
- to execute a transaction
- to get an advice

Taxonomies

Environment variables

- **Features** for automatic assignment
- Query → Goal class

[Lee 2005]
[Baeza-Yates 2006]
[Li 2006]
[Fujii 2008]
[Jansen 2008]
[Herrera 2010]

- Anchor-text
- Urls
- Query
- User clicks (past clicks)
- Page-content

Taxonomies

Inference

- Classification of queries
- Characterization of web sources
- States “ruled by” certain web sources

- Rule-based annotators

  [Jansen et al.2008] [Lee et al. 2005][Li et al. 2006]

- Automatic classifiers

  [Baeza-Yates 2006] [Herrera2010]
  - Support Vector Machines with RBF (Radial Basis Function) kernel]

Taxonomies

Plan Success

[Hassan 2010]

- Training data into two splits;
- the first: all successful goals
- the second: all unsuccessful goals

$$\prod_{i=2}^{n} P(act_i \mid act_1,\ldots,act_{i-1}) =$$

$$\prod_{i=2}^{n} f(act_{i-1},act_i) = \sum_{i=2}^{n} l(act_{i-1},act_i)$$

- 2 Markov models for the
  2 types of plans (sequences of actions)
- Model success LL_s
- Model failure LL_f

l: loglikelihood
LL_M= l(SetOfActions)

$$pred(SetOfActions) = \begin{cases} 1, if \dfrac{LL_{M_s}}{LL_{M_f}} > \tau \\ 0, otherwise \end{cases}$$

Approaches

Behavioral theories

- Social behavior & Motivations
- *Socio-economic laws/rules that "reinforce" or "weaken"* ***intentions*** *to* ***act***
- Actions
  - Part of goals
  - Focus only on a specific action

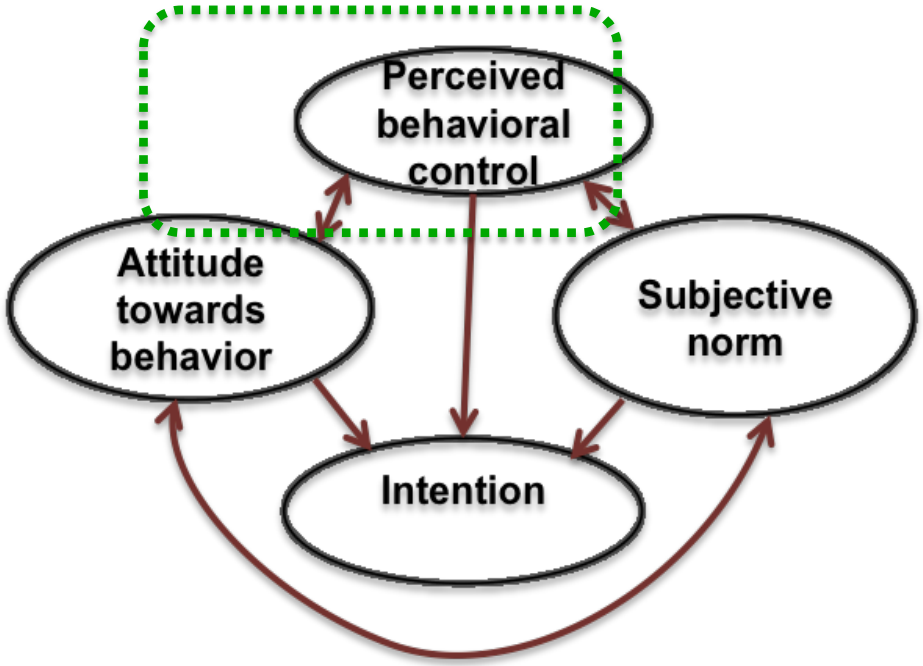
Important actions

- Direct economic profit
  - Buy not buy
- Amelioration of services
  - Recommendations
- Social analysis
  - Predict explain online social networking reality

Behavioral theories

- Theory of Reasoned Action Behavior (TRA) **[Fishbein and Ajzen 1975]**
- Theory of Planned Behavior (TPB) **[Ajzen 1991]**

- Abstract and general
  - A first draft of the model
  - Then *enriched* by motivational factors/variables

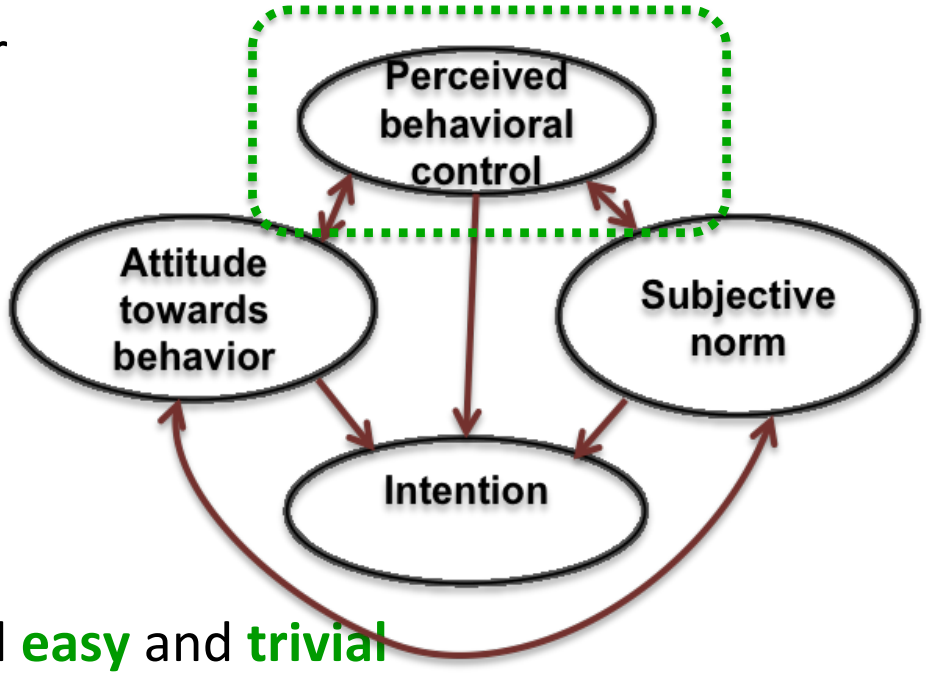


Behavioral theories

TRA

- **Intention**
- **Attitude** towards a behavior
  - her beliefs towards this behavior
- **Subjective norm**
  - the opinions of the persons that are important to the user

    approval or **disapproval**



TPB

- **Perceived behavioral control**
  - whether the action is considered **easy** and **trivial**

Example

Behavioral model
[Chow 2008]

"Sharing knowledge among colleagues in a organizational social network"

- Action
  - Add (post X)
- Social capital

  In the Relationships between people collective action and community involvement
  - Interpersonal communication
  - Social trust
  - Shared goals
- TRA
  - Intention
  - Attitude towards a behavior
  - Subjective norm

Example

Behavioral model
[Chow 2008]

H1. The more **extensive the social network** among organizational members, the more favorable will be the **attitude** towards knowledge sharing

H2. The more **extensive the social network** among organizational members, the more favorable will be the **subjective norm** with respect to knowledge sharing

H3. The greater the **social trust** among organizational members, the more favorable will be the **attitude** toward knowledge sharing.

H4. The greater the **social trust** among organizational members, the more favorable will be the **subjective norm** with respect to knowledge sharing.

H5. The greater the **shared goals** among organizational members, the more favorable will be the **attitude** toward knowledge sharing.

Example

[Chow 2008]

H6. The greater the **shared goals** among organizational members, the more favorable will be the **subjective norm** with respect to knowledge sharing.

H7. The more favorable the organizational members' **attitude** toward knowledge sharing, the greater will be the **intention** to share knowledge.

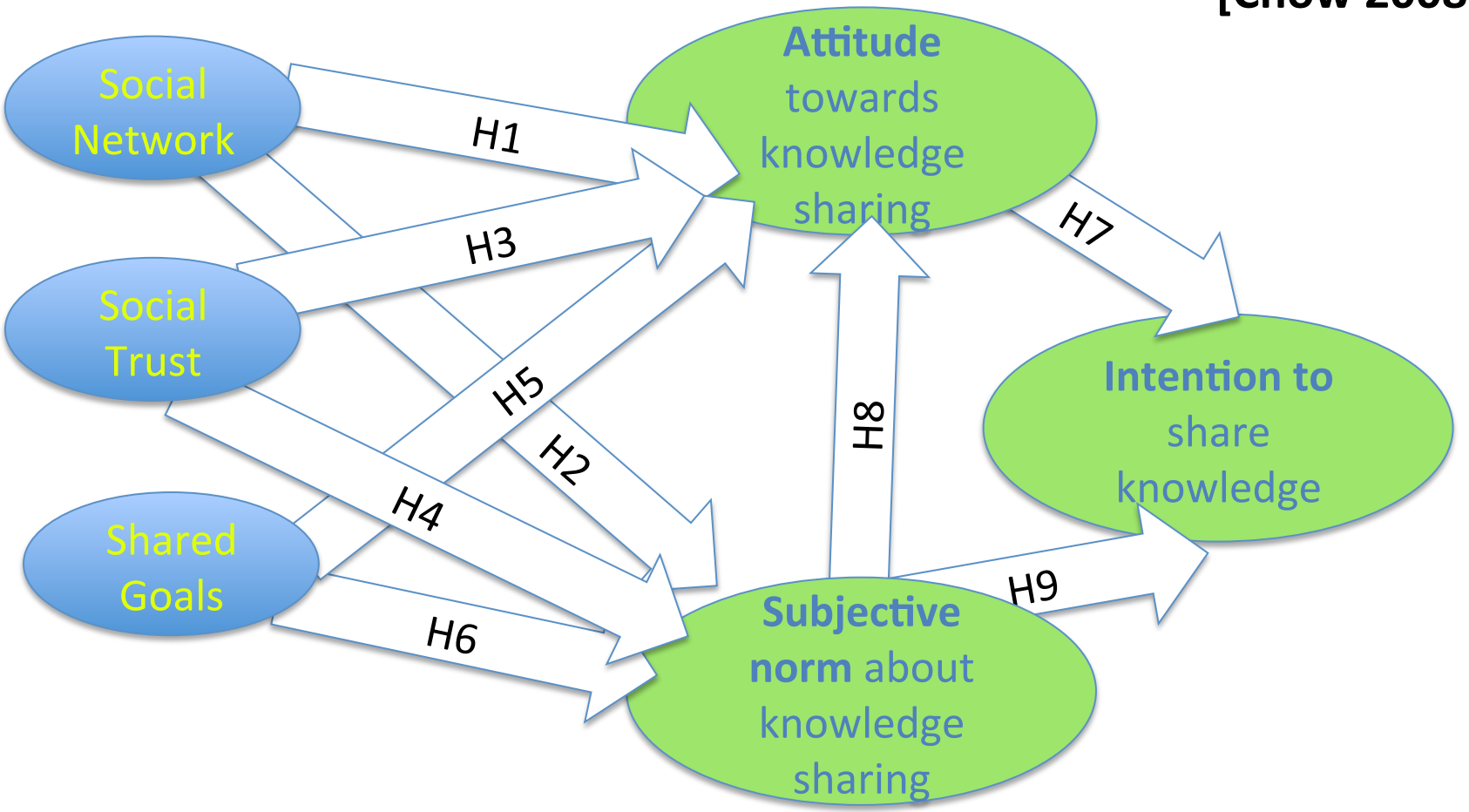
H8. The greater the organizational members' **subjective norm** with respect to knowledge sharing, the more favorable will be the **attitude** toward knowledge sharing

H9. The higher the organizational members' **subjective norm** with respect to knowledge sharing, the greater will be the **intention** to share knowledge.

Example

Behavioral model

[Chow 2008]



Behavioral theories

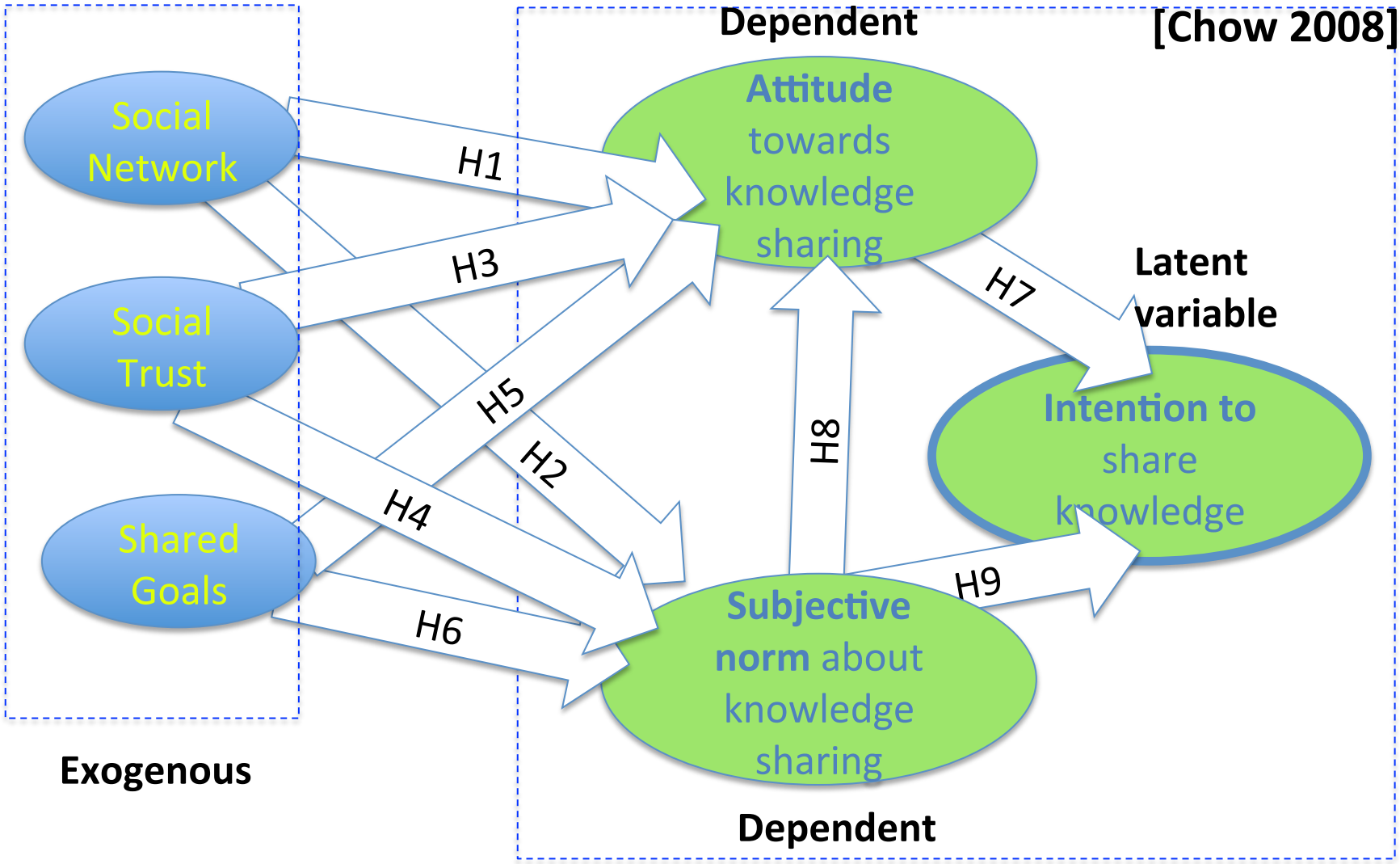
Construction

[Hsu & Lin 2008][Chow 2008]

- Selection or formulation of a **behavioral theory**
  - factors that determine human behavior

- For each one of the factors:
  - Formulation of a set of **assumptions** (hypotheses)
- Gathering of past knowledge **to test** these **hypotheses**
  - Conduction of a **survey** on real users
  - Quantified data [De Choudhury et al. 2007]

Example


Dependent
[Chow 2008]
Social Network
Social Trust
Shared Goals
Attitude towards knowledge sharing
Latent variable
Intention to share knowledge
Subjective norm about knowledge sharing
H1
H2
H3
H4
H5
H6
H7
H8
H9
Exogenous
Dependent

Example

- Experience and everyday knowledge about communication flow

[De Choudhury et al. 2007]

- Variables
  - **neighborhood context** (social network and subjective norm)
    - the number of messages by the user's contacts on the topic
    - communication in the local neighborhood
  - **topic context** (attitude)
    - user's past communication on a topic
  - **recipient context** (~ social trust)
    - the recipient's reputation

Behavioral theories

Inference

- Statistical analysis of the theoretical model
  - **valid**
  - **reliable**
- Prediction of latent variables

- Structural equation modeling (SEM)
  [Hsu & Lin 2008][Chow 2008]
- Support Vector Regression
  [De Choudhury et al. 2007]

Approaches

Corpus-based

- **Ground truth**
  - Expensive or Infeasible
- **Plan corpus**
  - Sufficient Training dataset
- **Goal recognition** [Russell and Norvig 2003]
  - **Uncertainty** expressed in probabilities

- **Uncertainty**
  - × safety
  - × high-cost in time or money
  - × high impact on human lives

Corpuses

Markov models

- **Undirected Graphical models** representing
  - a *joint probability distribution* over a set of variables

- Random (stochastic) **variables**
  - Observed: known values
  - Unknown values: may be inferred
- **Edges**
  - Conditional independence relations among the variables

Markov models

Construction

Standard methodology

[Della Pietra et al. 1997]

- Testing All Combinations of **variables** and **weights**
- Up to: accurate predictions within the plan corpus

× Exponential to the number of variables

× Requires weight assignment to each clique of the graph

Two-step methodology

[Ravikumar 2009]

[Wainwright & Jordan 2008]

- Build a model for each variable separately
  - decision tree [Lowd & Davis 2010]
  - logistic regression mode
- Combine the separate models
  - **Weight learning [Besag, 1975]**
  - Considering the training dataset
  - Maximize a given *objective function*

Markov models

Construction

[Ravikumar 2009]

- Construct an L1 **logistic regression model** for each variable
  - predicting the variable value based on the rest of the variables

- For all weights ≠ 0 in the L1 logistic regression model
  - Construct pairwise dependencies
    between the current variable and each other variable

- Add all constructed features to the model
- Learn weights according to the training data

× Only pairwise dependencies

Markov models

Goal recognition

- **Initialize**: for each goal: goal probability = prior probability

- **When observation occurs**
  - Update of goal probabilities
  - Using the conditional probabilities functions of the model

- **Finally**: select the goal with the maximum probability

  (**M**ost **P**robable **E**xplanation)

Markov chains

MM variation

Markov assumption

"An observation is dependent only on the current goal g and the precedent observations"

Markov chains

- A sequence of states
  - Usually over time

$$St_1, St_2, \ldots St_n \in E$$

- Future state
  - Dependent on fixed number of previous states
- Large order
  - Impractical
  - Exponential growth of the number of states
- Smaller order
  - Sufficient for certain problem domains

Markov chains

Probabilities

Probability functions

Data Modeled by

Conditional **P**robability **T**ables

- **Prior** probabilities that a goal is pursued
  - **P (g)**
- **State transition** probabilities
  - **P ($S_t | S_{t-1}$, g)**
- Probabilities of **action occurrences**
  - **P ($act_t | S_t$, g)**

Example

Markov chain
[Mott 2006]

- Dynamic narratives in story-worlds
- *Science mystery on a volcanic island*

Observed States encode

- Narrative states
- Character locations
- Character moves

$$St_1, St_2, \ldots St_n \in E$$

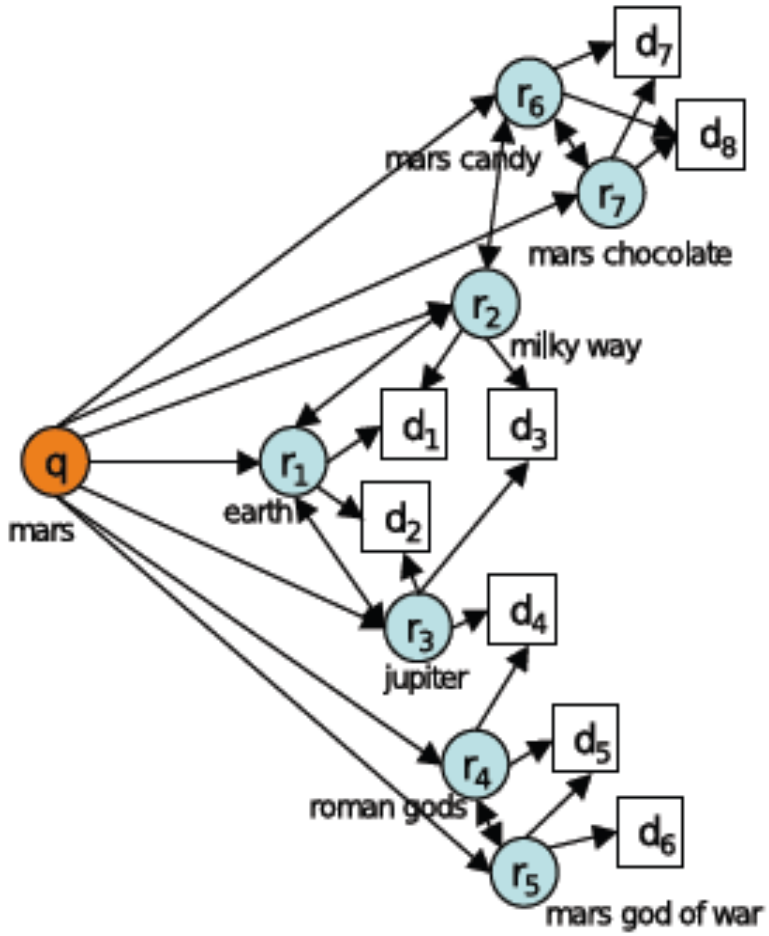
Order n

$$\operatorname{argmax} P(g) \prod_{i=1}^{n} P(\mathrm{St}_i \mid g)$$

Example

Markov chain/Absorbing nodes

[Sadikov 2010]



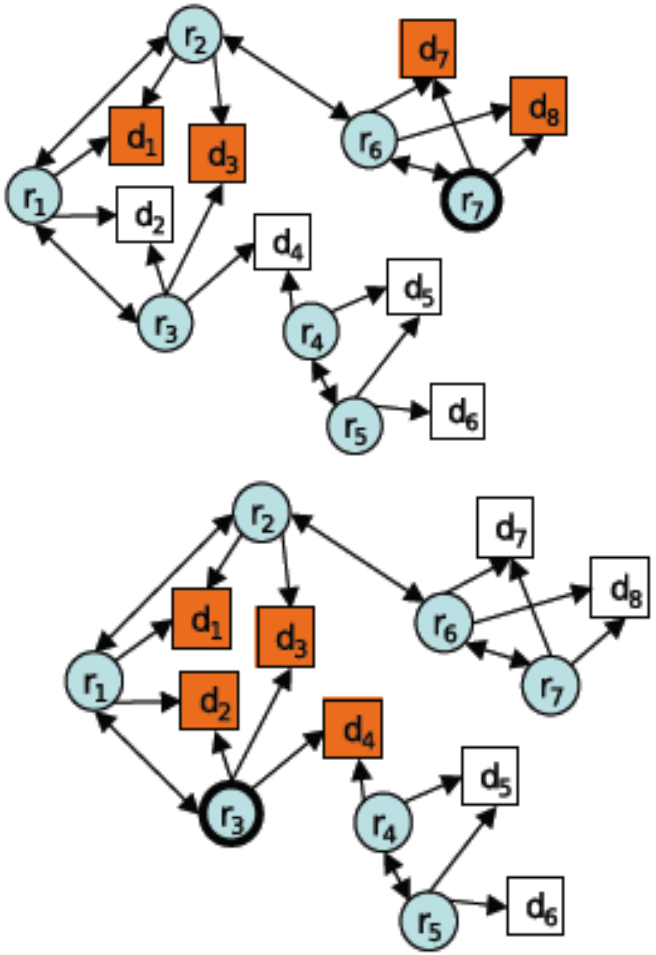
- Original Query: “mars”
- Query Refinements
  - "mars chocolate”, “mars candy”, “mars milky way”, “earth”, “roman gods”,“mars god of war”
- Documents: d1-d8

Example

Markov chain

[Sadikov 2010]

3-step random walk



Estimate probabilities from data

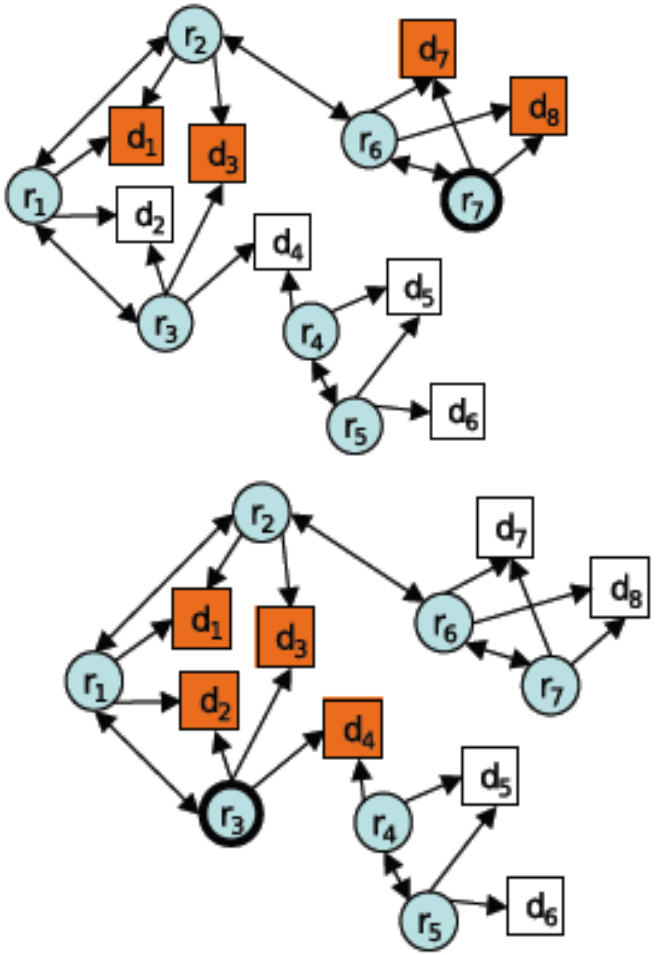
$$P[r_i, d] = \varepsilon \times \frac{n_d(d \mid r_i)}{\sum_{d_{k \in D(r_i)}} n_d(d_k \mid r_i)}$$

$$P[r_i, r_j] = (1-\varepsilon) \times \frac{n_s(r_i \mid r_j)}{\sum_{r_{k \in R(q) \cap Q(r_i)}} n_s(r_i \mid rk)}$$

Example

[Sadikov 2010]

3-step random walk



Markov chain

- 2-step transition probability
  - P×P [i,j]
- n-step transition probability
  - P^n [i,j]
    .
    .
- n∞
  - $\lim_{n\to\infty} P[i,j]$

Every row corresponding to a node r_i:
visit probability distribution vector
of the **random walk** from node r_i to
the absorbing nodes

VOMs (Variable order)

MM variation

- Probability distribution:
- Not always determined by the same fixed number of previous observations
- Variable length previous context

- VOMs as Probabilistic Suffix Trees **[Armentano and Amandi 2009]**
  Used corpus from [Blaylock and Allen, 2005] modeled after Lesh's Unix
- Determined set of **actions**: Alphabet Σ
- **Goal** g: Tree containing minimal action subsequences
  - Set of goals G: forest
- **Goal inference** by observing a sequence of actions
  - Classification to the most probable PST

HMMs (Hidden Markov Models)

MM variation

[Hoelzl 2012]

- Partially visible or Uncertain perception
- Not complete knowledge
- Partially visible or Uncertain Environment states
- Estimation of Unknown/Hidden Environment variables
  - Based on Output or Emission probabilities
  - Probability ***distribution functions*** over a set of Observed Variables

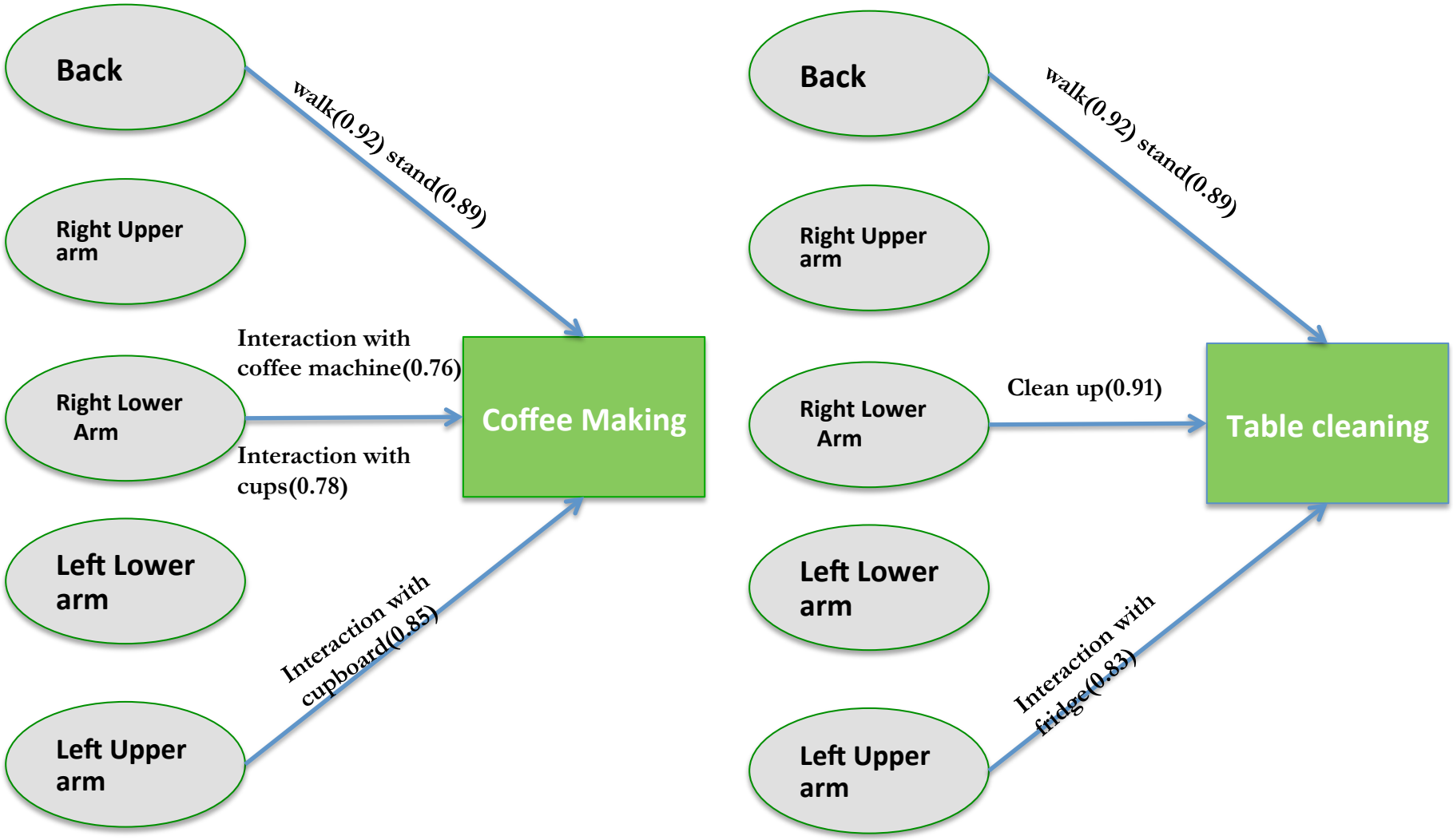
Probabilities

- Initial probabilities
- Transition probabilities (transition matrix)
- Output probabilities

Example

Hierarchical Activity Model

[Hoelzl 2012]



Input Output HMMs

MM variation
[Bengio and Frasconi 1995]

- Additional context information
  - e.g., the previous satisfied goal
- By increasing the number of observation categories in HMM
  - Increase of learning time and model complexity
  - Conceptual mixing of the known variables

When context information is available

- Modification of state transition function based on context
  - E.g., Depending on whether a goal had been recently achieved

Example [Gold 2010]

- Domain of computer games
  - Abundant context information

Markov Logic Networks

MM variation

[Ha et al. 2012]
[Kautz 1991]

- Markov Logic (ML): a statistical-relational language
- Probabilistic extension of finite first-order logic (FOL)
  - Weight reflecting the significance of FOL
  - Learned by data

$$1.\forall t,a : action(t,a)$$
$$\Rightarrow | \exists g : goal(t,g) | = 1$$

$$2.\forall t,a : action(t,a) \wedge action(t-1,a)$$
$$\Rightarrow goal(t,g)$$

$$3.\forall t,a,s,g : action(t,a) \wedge state(t,g)$$
$$\Rightarrow goal(t,g)$$

Predicate Description [Ha et al. 2012]

- action(t, a)
  Player takes an action a at time t
- loc(t, l)
  Player is at a location l at time t
- Observed state(t, s)
  The narrative state at time t is s
- Hidden goal(t, g)
  Player pursues a goal g at time t

Corpus-based

Bayesian models

[Horvitz et al. 1998]
[Huber and Simpson 2003]

Graphical models

- Nodes
  - Observable quantities
  - Latent
  - Unknown parameters
  - Hypotheses
- Edges: Causal relationships or conditional dependencies

- Directed acyclic graph
- Joint probability distributions of all the random variables of its nodes
- Conditional Probability Tables
  - the strength of the connections between the variables

Bayesian Networks

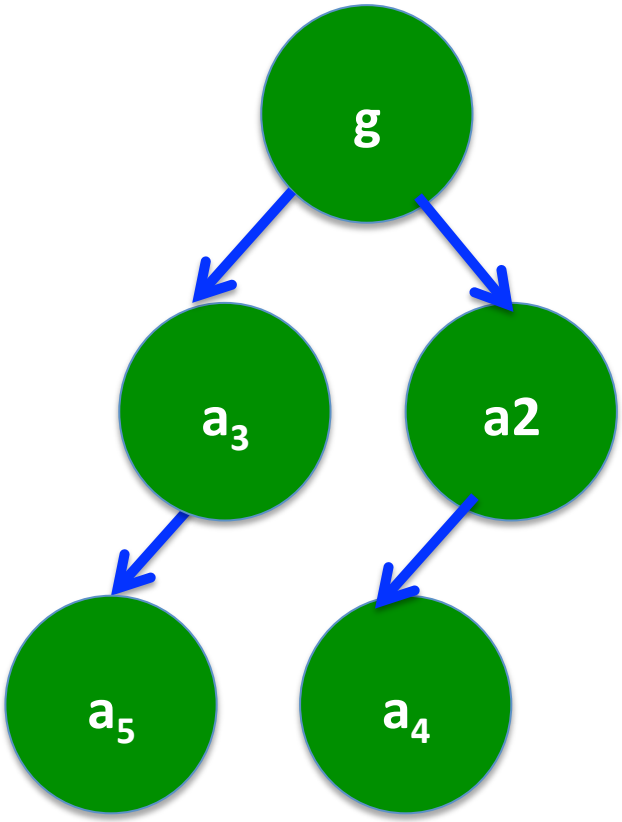
Inference

- Probabilistic inference
- Given a set of variables with known values **(evidence)**
- Inference of the random **variables of interest values**
  - NP-hard

- Filtering: Rao-Blackwellised particle filtering [Doucet 2000]
  - A combination of exact and stochastic inference
  - Reduction of complexity
  - Higher accuracy

Bayesian Networks

Inference



Independence assumption:

"Given its parents

nodes are *conditionally independent* of its non-descendants nodes"

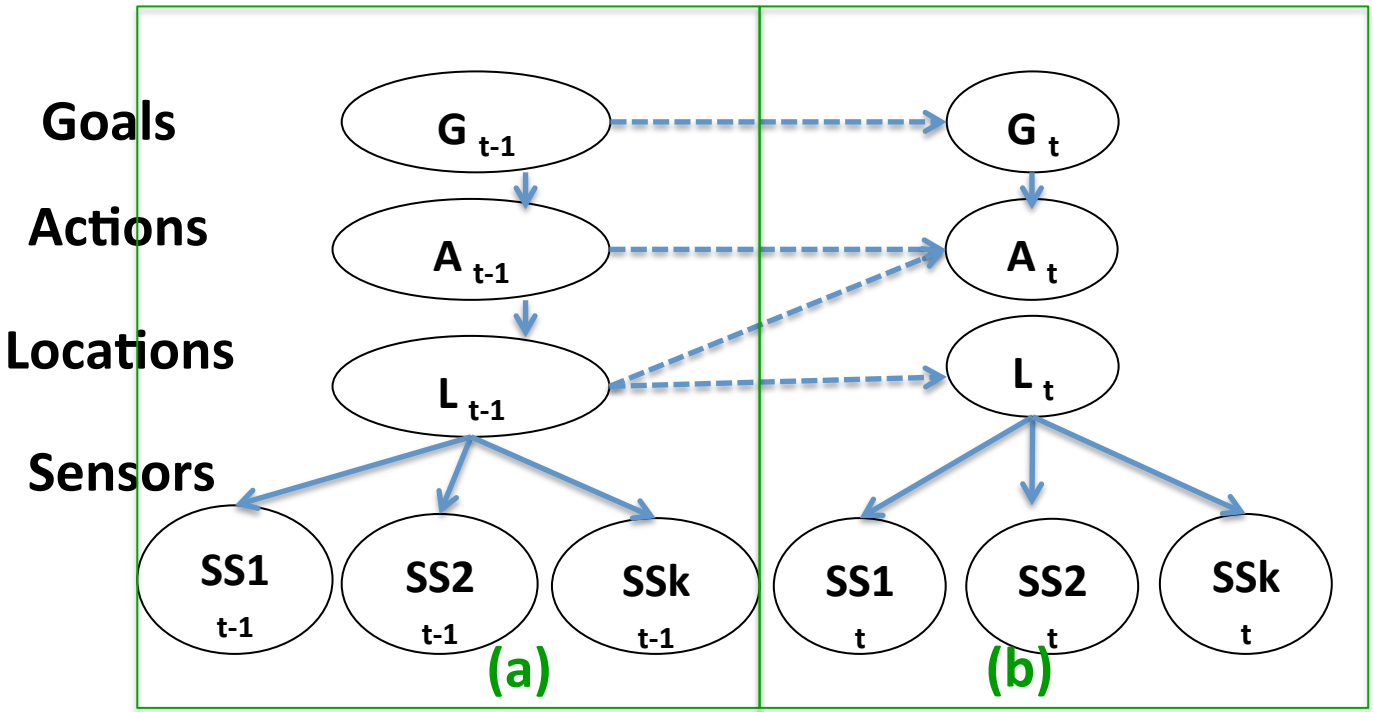
$$P(g,a_2,a_3,a_4,a_5)=$$
$$P(g)P(a_2|g)\ P(a_3|g)P(a_5|a_3)P(a_4|a_2)$$

- Simplification
  - Ordering of variables
  - Markov chain rule

Dynamic Bayes Network

- Temporal dependencies in consecutive time slices
  - Inter-slice connections
- Closer to reality
- Increased by Algorithmic and computational complexity

[Patterson et al. 2003]



GPS Data

First Level: changes in transportation

Upper Level: Meaningful trips

Approaches

Text analysis

- Rules
- Natural language processing patterns
- Text mining techniques
- External knowledge
- Expert/Common sense **knowledge**
  - motivations [Louvigne 2012]
  - intentions [Castellanos 2012]
  - goals [Castellanos 2012, Smith 2010]
  - operationalization [Strohmaier 2009]

Text analysis

- Analysis of phrases [Castellanos 2012]
  - “would like to see the princesses”
- Goal phrases
  - Rules
  - Patterns
    - Verb+ Infinitive
      - “to see the princesses”
- Intention-Commitment
  - classification on intention verbs
    - “thinking of going": weaker
    - “would like”: stronger intention

Text analysis

- **Motivations and Intentions** on Twitter [Louvigne et al. 2012]
  - *"Moi-lolita makes me want to learn french #mangolanguages just to sing it"*
  - *"Getting ready for our trip in France, time to learn some french! "*

- Textual features
  - keywords such as "because ", "so that ", "having "
- Conceptual features reflecting motivational factors
  - regarding the difficulty or the engagement of the user to the respective goal.

Text analysis

- Knowledge about **implementations** [Strohmaier 2009]
- Given a goal taxonomy by
  - Sociologists, psychologists
    - Human goal taxonomies
      - "get married"
      - "be happy"
- Frequent **co-occurrences of verb phrases**

  in **Web** pages with the textual description

Approaches

Knowledge

Complete Records	Domain Expert knowledge
Corpus	Plan corpus & Domain Expert knowledge
Taxonomies	Domain Expert knowledge & User studies & Plan corpuses
Behavioral theories	Sociology – Analysts' assumptions & User studies

Approaches

Input/Output

	Observation stream	Inference
Complete Records	Actions /Environment variable state shifts	Plans and by extension Goals
Corpus	Actions / Environment variable state shifts	Goals/Environment variable states
Taxonomies	Actions	Classes and Goals
Behavioral theories	Environment variable values	Environment variable states and Intentions

Goals in Social Media, Web IR and Int. Agents

1. Introduction
2. Generic Goal Framework
3. Applications
4. Approaches
5. Future directions

Directions

Beyond the traditional

- Data management systems
- Goal-oriented Modeling and Analysis
- Goal-aware
  - Data (Large scale data/Big data)
  - Query processing
  - Adaptive loading
  - Adaptive Indexing (Next generation architectures)
- Innovative services

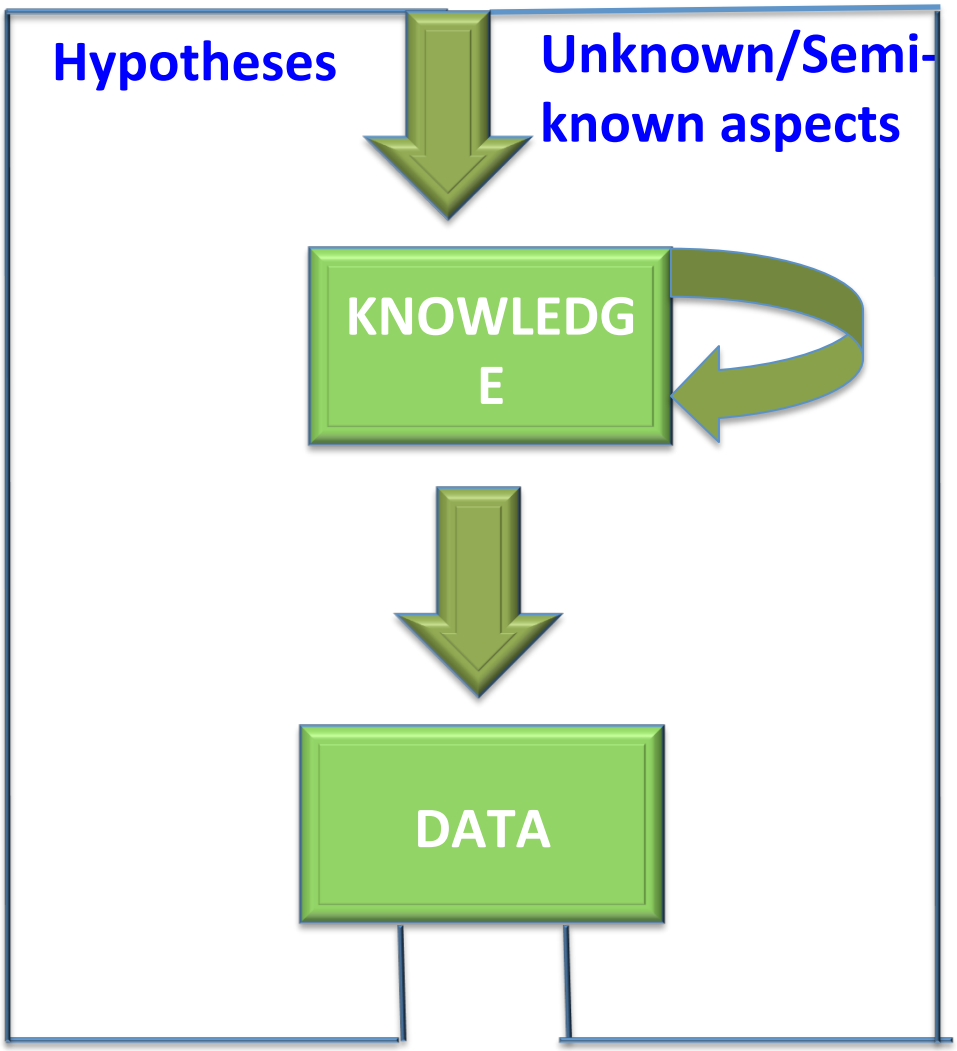
Directions

- Data-intensive analytics
  - **make sense** of the data
  - **identify** interesting patterns and relationships
  - bring **aspects of interest** into focus

Goals

- Reduce workload
- Serve better results

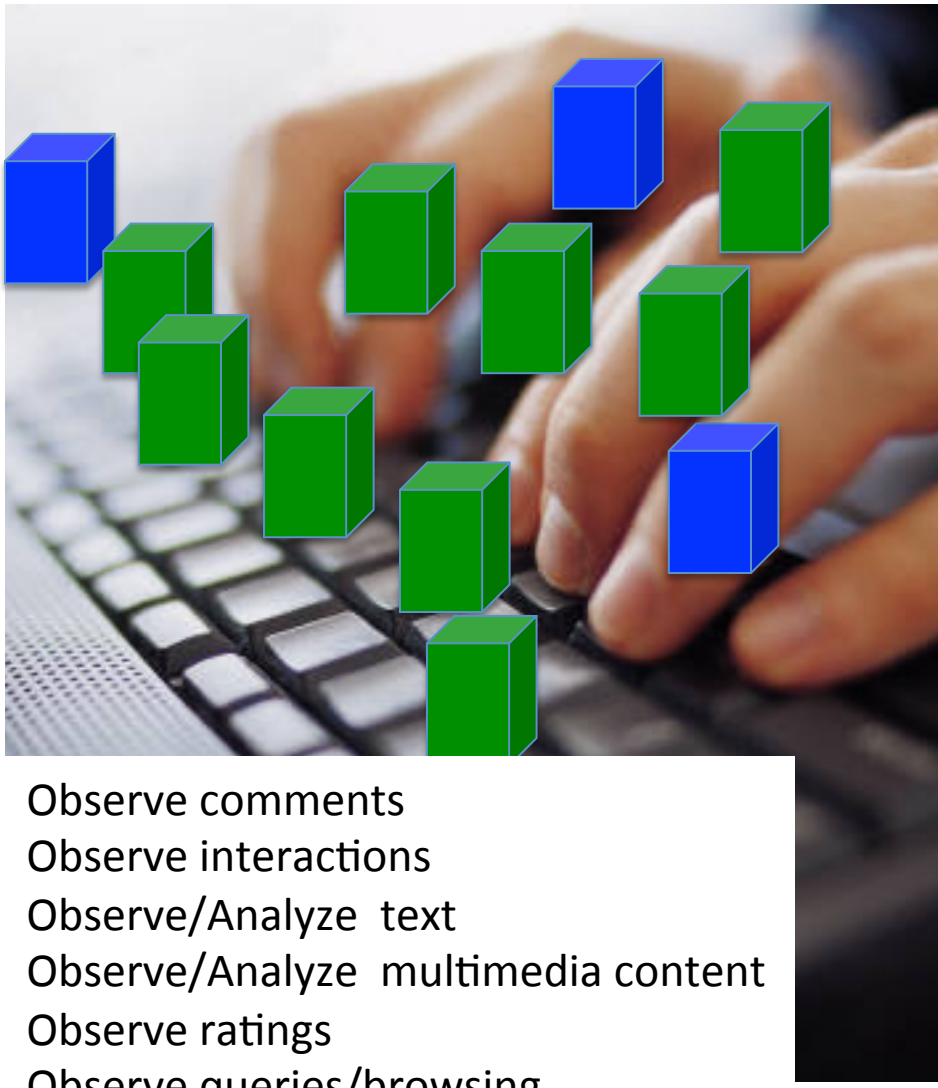
Interactive data exploration



Directions

Recommendations

- Utility of objects
- User preferences
  - Ratings/Likes
  - Interactions/Clicks
  - Purchases
- User context
  - Other users
  - User background



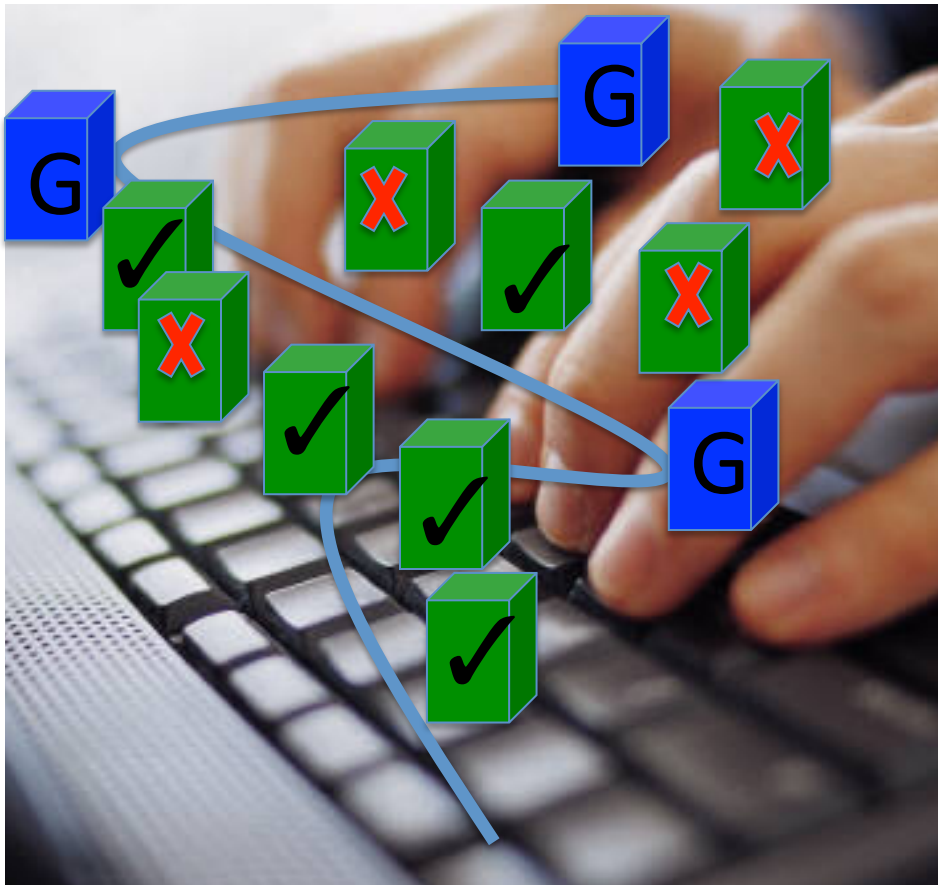
Observe comments
Observe interactions
Observe/Analyze text
Observe/Analyze multimedia content
Observe ratings
Observe queries/browsing

Directions

- Infer goals
- Infer plans
- Infer related “objects”
- Suggest products/ services
- Suggest friends
- Suggest professionals
- Suggest actions

Recommendations

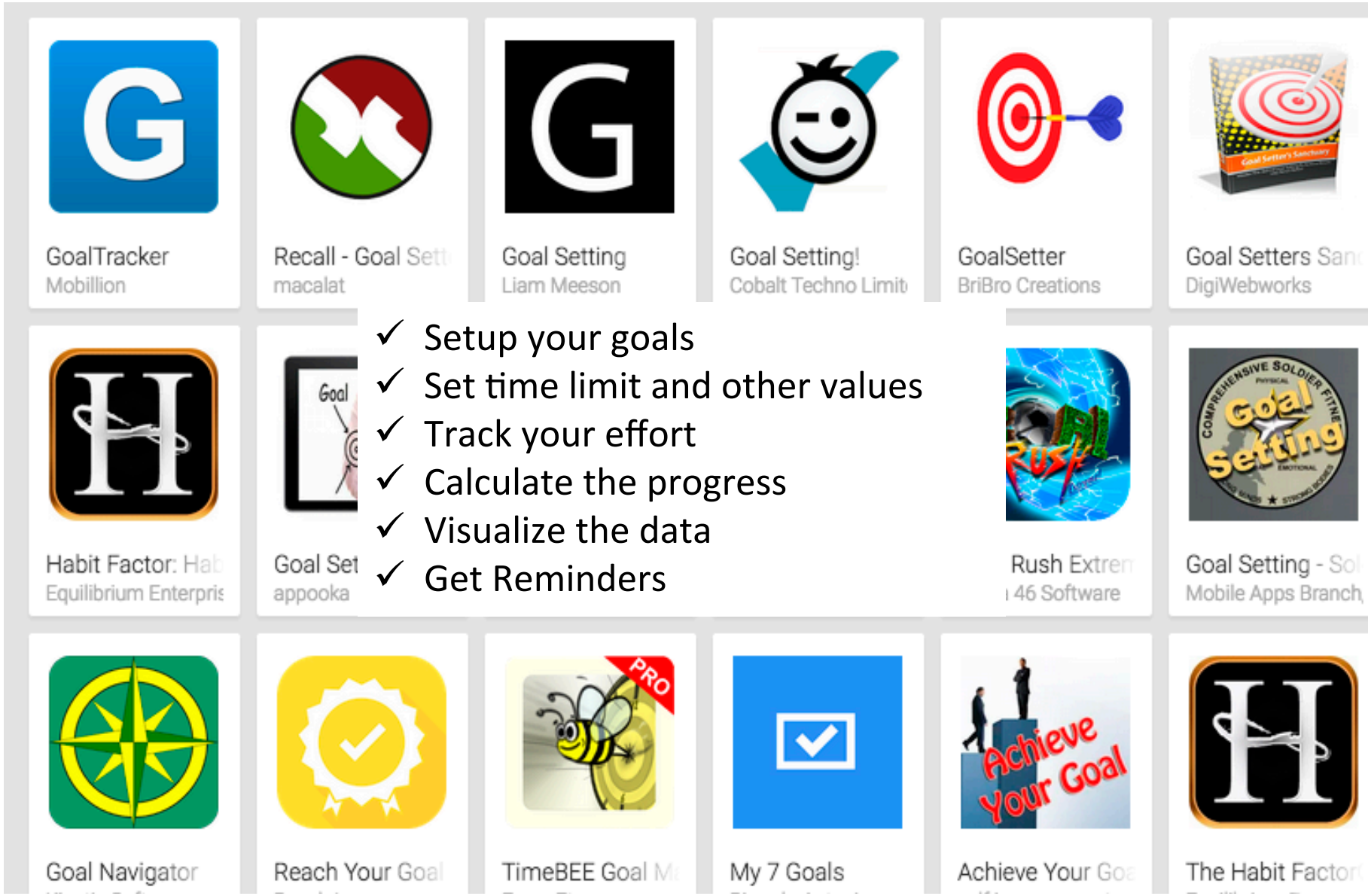
Suggest, Support, Guide, Direct to success



Make the user want
Learn and respect what the user wants

Directions

Goal setting



- ✓ Setup your goals
- ✓ Set time limit and other values
- ✓ Track your effort
- ✓ Calculate the progress
- ✓ Visualize the data
- ✓ Get Reminders

Directions

User generated Content

- Direct, Indirect economic implications
  - Advertisements/Marketing campaigns
  - E-commerce
- General Impact
  - Social sciences
  - Education
  - Life quality/Self fulfillment

Directions

Networking

- **Connecting:** Discussing, Sharing ideas
- **Real life:** Goals
  - **Commitment**: "Believing in what you're doing,"
  - **Know-how:** About fulfilling your goal

- Networking sites
  - Profiles
  - Friends
  - Targeted special services

- Special connection: similar goals
  - common problems
  - concerns
  - feelings
  - expectations

Thank you

Goal Aware Systems

Find here the tutorial material and more

https://dipapadimitriou.github.io

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