

Formalizing uncertain knowledge

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Overview of the area

- Not related to agent/person:
 - Discrete:
 - Multi-valued logic
 - Default logic
 - Other model-based systems
 - Non-discrete:
 - Probabilistic (several types!)
 - Fuzzy (possibilistic)
- Related to agent/person (not covered in this presentation):
 - Logics of knowledge and belief
 - Other “meta”-systems

Why different uncertainties 1

- Real-life rules have **exceptions**: not all birds fly, not all things fall down, etc. We **do not have statistics** on how often birds do not fly etc.
- We can numerically estimate the **probability** that on 27 oct the temperature in Tallinn falls below 0: we have statistics.
- People have **opinions which can be statistically measured**: how high percentage of people asked will say that the bar Shvips is a good place for drinks at night? For a quick snack during day? A good place to look football?

Why different uncertainties 2

- People have **opinions of different strength**: how confident are you that Trump is the U.S. president? That Oswald had co-conspirators? That aliens control everything?
- Ordinary words have somewhat measurable meaning graphs: is the man of height 2 meters **tall**? Is the man of height 1.9 meters tall? Of 1.8? Of 1.7?
- Different people have different belief and knowledge: **who knows of believes** what?

Rules with exceptions

- Since rules, logic.
- A few different logics for rules with exceptions: none of them widely used.
- First, the problem: in normal logic there are no „exceptions“. If birds fly, but Tweety is a bird and does not fly, **we have a contradiction** and all queries essentially fail.

Default Reasoning

The problem: in FOL, universally-quantified rules cannot have exceptions

$\forall x \text{ bird}(x) \rightarrow \text{can_fly}(x)$

$\text{bird}(\text{tweety})$

$\text{bird}(\text{opus}) \wedge \neg \text{can_fly}(\text{opus})$

as soon as you assert something contradictory, the knowledge base becomes inconsistent

no models satisfy $\text{can_fly}(\text{opus})$ and $\neg \text{can_fly}(\text{opus})$

arbitrary conclusions can be drawn from an inconsistent knowledge base

could add qualifying antecedents, but you have to know/anticipate all possible exceptions

$\forall x \text{ bird}(x) \wedge \neg \text{penguin}(x) \wedge \neg \text{dead}(x) \wedge \neg \text{in_cage}(x) \wedge \dots \rightarrow \text{can_fly}(x)$

Non-monotonicity

FOL is monotonic

whenever you add something to a knowledge base,
everything that was previously entailed is still true

if $KB \models \alpha$ then $KB \wedge \beta \models \alpha$

why? because adding β restricts the models to a subset, but
they all still satisfy α

Non-monotonic logics (alternatives to FOL)

default logic

circumscription

...

Default Logic: syntax

Prerequisite : Justification / Conclusion

Bird(X) : Flies(X) / Flies(X)

Bird(X) & not derivable (-Flies(X)) => Flies(X)

read as: if X is a bird *and it is not inconsistent to believe that X flies*, then conclude that X flies

thus if

KB={ bird(X) : flies(X) / flies(X),
bird(tweety),
nonliving(X) : -flies(X) / -flies(X)
nonliving(opus)
bird(opus)}

then KB \models flies(tweety) but not flies(opus)

Default Logic: semantics

define “minimal” models as models of the FOL subset (non-default sentences)

$$m_1 = \{\text{bird}(\text{tweety}) = T, \text{bird}(\text{opus}) = T, \text{flies}(\text{opus}) = F\}$$

define “extensions” of models by an operator that adds a fact from a default rule one at a time, e.g. apply to tweety...

$$m_2 = \{\text{bird}(\text{tweety}) = T, \text{bird}(\text{opus}) = T, \text{flies}(\text{opus}) = F, \text{flies}(\text{tweety}) = T\}$$

define “fixed points” as models that result from iteratively applying this operator until no more conclusions can be drawn

entailments consists of things true in some extension

Nixon diamond example:

$\text{Republican}(\text{Nixon}) \wedge \text{Quaker}(\text{Nixon})$

$\forall x \text{ Republican}(x) : \neg \text{Pacifist}(x) / \neg \text{Pacifist}(x)$

$\forall x \text{ Quaker}(x) : \text{Pacifist}(x) / \text{Pacifist}(x)$

What should we conclude? 2 possible contradictory derivations, each blocking other out.

Sceptical queries and credulous queries:

- **Sceptical:** cannot derive anything about Nixon being a pacifist
- **Credulous:** pick any possible derivation

Circumscription: syntax

introduce “abnormal” predicates in rules (never asserted as facts)

$$\forall x \text{ bird}(x) \wedge \neg \text{abnormal}_1(x) \rightarrow \text{canFly}(x)$$

$\text{bird}(\text{tweety}),$

$\text{bird}(\text{opus}),$

$\neg \text{canFly}(\text{opus})$

Circumscription: semantics

what is the minimal set of “abnormal” facts that must be assumed to be true to make the KB consistent?

if we assume $\{\text{abnormal}_1(\text{opus})\}$, then it works

convenient for large KBs where most objects are “normal”, but there are a few exceptions

the circumscription algorithm will figure out the minimal set that needs to be assumed abnormal

circumscription can be viewed as a form of “model preference”

of all possible models of some sentences, some are more plausible than others, i.e. the ones with fewer abnormal assumptions

sometimes even this is not enough to disambiguate the intended meaning...

perhaps we need to assign precedence among abnormal predicates...

Truth Maintenance Systems

in real-world applications, need to...

derive conclusions based on assumptions

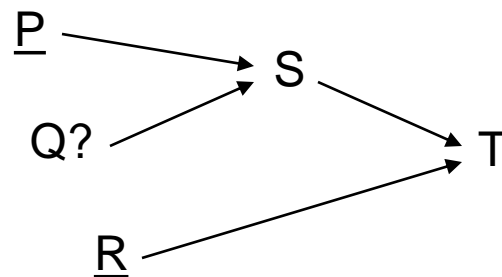
when conflicting information comes in (or facts change), need to change beliefs

if P changes from T to F, must identify and retract all consequences that depended on P

must keep track of network of *justifications*

TMS, JTMS: efficient algorithms for propagating changes in knowledge (minimal belief revision)

initially, I know P and R,
and I assume Q is true,
so I infer S and T



if later I come to find out
that T is not true, then I reason
backwards to identify that Q must
not have been true, so I retract
Q, S, and T (mark them as false)

Numeric probabilities:

Please first read a separate tutorial on probabilistic and fuzzy reasoning:

https://courses.cs.ttu.ee/w/images/b/b5/Uncertain_prob_fuzzy.ppt

and our presentation continues after that.

Combining numeric probabilities:

- Tourism recommenders as a case study
- Input and output
- Which probabilities we need?
- Simple layered semantics
- Cumulating evidence
- Rankings via meta-logical calculations

Recommender systems

- Several historical „expert systems“ were recommender systems (medicine etc)
- Google is a popularity-focused recommender
- Social network systems are recommender systems: recommend news items and possible friends and topics
- The wealth of data available online makes it possible to create recommenders for any kinds of tasks and goals

Two main recommender types

- Collaborative filtering
- Rule-based, also called content-based

Our tourism recommender project

- <http://www.sightsplanner.com>
- <http://www.sightsmap.com>

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Tallinn

Sightsplanner

The best guide to town

Each visit is unique: plan your trip to Tallinn just the way you like it

[How to use?](#)

Walk in the city

Nice walk around the medieval Old town, history and cafes

[Choose](#)

Active life

Great events, spiced with sports and outdoor activities

[Choose](#)

A night in the town

Clubs, pubs, party and dancing all night long!

[Choose](#)

Culture

Beautiful architecture, amazing paintings and concerts

[Choose](#)[Get your plan](#)or [see what's popular](#)

Less

More

+ Events



+ Museums & Arts



+ Architecture & City



+ Eating out



+ Shopping



+ Sports & Outdoor



+ Bars & Nightlife



Time

14:00

28.03.2011

Duration [1h](#) [2h](#) [3h](#) [6h](#) [8h](#)[by car](#) [on foot](#)

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Less

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+ Events



- Museums & Arts



Modern art gallery

Installation, Happening

Old history museum

Science museum

Classical art exhibition

Other art

Contemporary history

Nature museum

+ Architecture & City



- Eating out



Traditional restaurant

European restaurant

Fine dining

Fast food

Asian restaurant

Other restaurant

Pub

Cafe

Time  Duration [1h](#) [2h](#) [3h](#) [6h](#) [8h](#) [by car](#) [on foot](#)



1. Estonian History Museum - Great Guild Hall [Read more](#) [Locate on map](#)

[Museums and Arts](#) [Architecture and City](#) [Old history museum](#) [Medieval architecture](#)

In the course of time, the Great Guild Hall has played an important role in the life of the city. The permanent exhibition of the History Museum located in the building introduces Estonia's history...

Arrive 14:05

Stay

45

minutes

[Remove from selection](#)

Walk 5 minutes



2. Katariina käik (St Catherine's Passage) [Read more](#) [Locate on map](#)

[Landmark](#) [Architecture and City](#) [Medieval architecture](#)

Vene and Müürivahe Streets are connected by Katariina käik. You can see the remaining parts of St Catherine's Church in its northern end. The southern part of the passage is lined by residenti...

Arrive 14:55

Stay

20

minutes

[Remove from selection](#)

Walk 5 minutes



3. Olde Hansa [Read more](#) [Locate on map](#)

[Eating out](#) [Traditional restaurant](#)

Olde Hansa Restaurant

[See more](#)

Arrive 15:20

Stay

60

minutes

[Remove from selection](#)

Walk 10 minutes



The itinerary below is based on your category preferences, start time, duration and means of transport. This is matched with the information about sights: their types, opening times, location, typical visit time and popularity of the sight.

You can remove suggestions by clicking the "Remove from selection" link. You can set the time at each object by clicking the number of minutes next to each object. If you have changed the stay time on objects or removed some objects from the itinerary, click the "Suggest more" button to get a fresh itinerary with the new suggestions.

Suggest more or change preferences or see what's possible

Time 14:00 29.09.2011 Duration 2h 20m by car on foot

1. Katarina käik (St Catherine's Passage) See more Locate on map. Arrive 14:05 Stay 20 minutes. Remove from selection.

Walk 5 minutes

2. Kõrts See more Locate on map. Arrive 14:30 Stay 20 minutes. Remove from selection.

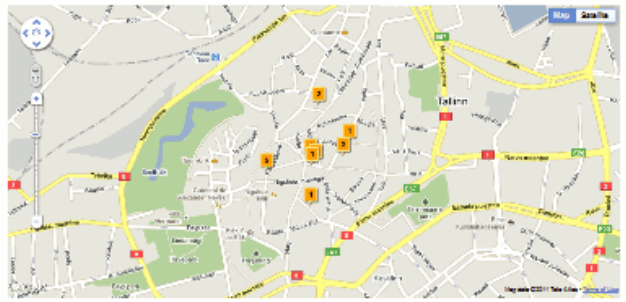
Walk 5 minutes

3. Masters Yard See more Locate on map. Arrive 15:05 Stay 40 minutes. Remove from selection.

Walk 5 minutes

4. Town Hall Square See more Locate on map. Arrive 15:50 Stay 20 minutes. Remove from selection.

Start time 14:05 | End time 16:10 | Time spent: ~2 hours and 04 minutes



Sightseeing heatmaps

help

turn heatmap off

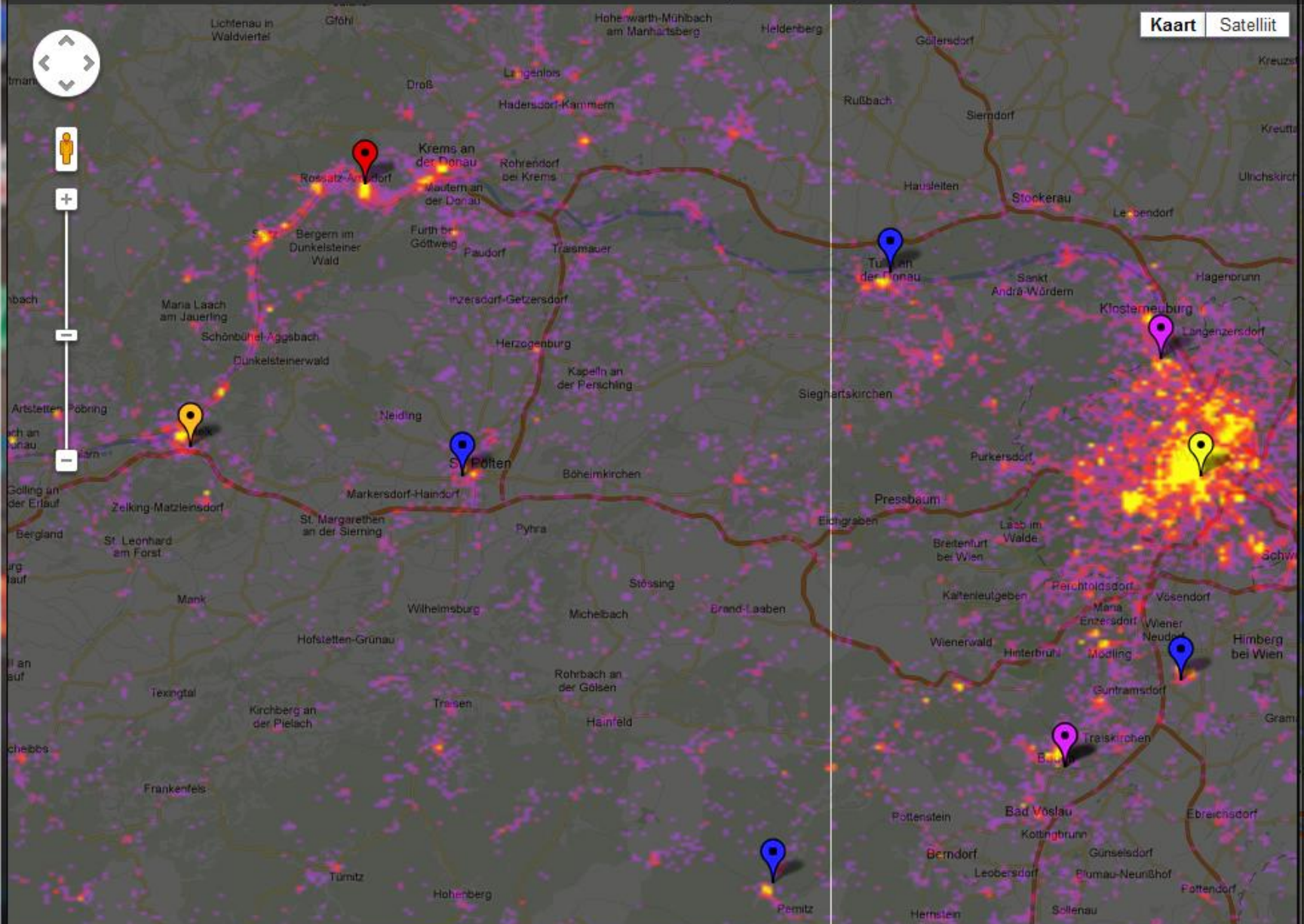
turn photos on

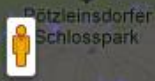
top spots

top 10

Like 2.6k

Kaart Satellit





Input 1

- **User interests:**

likes(john,nightlife,0.6)

likes(john,sports,0.8)

likes(john,music,0.7)

likes(john,heavymetal,0.9)

dislikes(john,classicalmusic,0.9)

Input 2

- **Object properties:**

type(omalley,bar,0.9)

activity(omalley,footballwatching,0.7)

popularity(omalley,1000)

type(crown,restaurant,1.0)

activity(crown,heavymetal,0.8)

popularity(crown,1500)

opentime(crown,12.00,0.9)

Input 3

- **Knowledge about the world:**

`type(X,church,M) -> type(X,architecture,M*0.9)`

`type(X,bar,M) -> type(X,drinkingplace,M)`

`type(X,restaurant,M) -> type(X,drinkingplace,M*0.7)`

`activity(X,footballwatching,M) -> activity(X,sports,M)`

`type(X,fastfood,M) -> visitminutes(X,20,0.8*M)`

`type(X,bar,M) & M>0.75 -> openat12(X,0.85)`

`description(X,S) & contains_str(S,"paintings") & contains_str(S,"gallery") ->`

`type(X,artcollection,0.8)`

Output

- **Recommendations:** numerical ranks for all tourism objects:

`rank(john,omalley,0.6)`

`rank(john,crown,0.5)`

Reasoning tasks

- **Object identities**: are two objects A and B obtained from different sources actually equal?
- **Object types from content**: using title, abstract, source etc, calculate whether the object is a city, a castle, a church, medieval, modern, a drama play, a classical music concert, a rock concert, ...
- **Generalised object types**: if we know that an object is a bar (with some confidence X), then it is also a nightlife spot (with some confidence Y)
- **Additional properties** like time of visit, opening times
- How well does an object **match user preferences**

Probabilities?

There is a large number of probability-oriented theories and several reasoning systems, yet no “mainstream” probabilistic rule-based derivation algorithms exist

Fuzzy logic, probabilistic logic, Bayes networks,

Probabilistic datalog, probabilistic prolog, ...

Mycin, Emycin, Cadiag-2, ...

Goal

Formulate a practical, correct and complete way to use probabilities in rules for the (tourism) recommender context, using object logic.

Metalogic:

0.9: $\text{type}(X, \text{church}) \rightarrow \text{type}(X, \text{architecture})$

0.8: $\text{type}(X, \text{fastfood}) \rightarrow \text{visitminutes}(X, 20)$

Object logic:

$\text{type}(X, \text{church}, M) \rightarrow \text{type}(X, \text{architecture}, M * 0.9)$

$\text{type}(X, \text{fastfood}, M) \rightarrow \text{visitminutes}(X, 20, M * 0.8)$

Which kinds of probabilities?

Non-strict sets a la „blue“, „large“, ...

Fuzzy logic : $p(A \vee B) = \max(p(A), p(B))$

0.95: $\text{type}(X, \text{church}) \rightarrow \text{type}(X, \text{architecture})$

0.7: $\text{type}(X, \text{theatre}) \rightarrow \text{type}(X, \text{architecture})$

Incomplete knowledge a la „not sure that“ ...

Probabilistic: $p(A \vee B) = p(A) + p(B) - (p(A) * p(B))$

0.8: $\text{type}(X, \text{bar}) \rightarrow \text{openat12}(X)$

Object logic:

$\text{type}(X, \text{church}, M) \rightarrow \text{type}(X, \text{architecture}, M * 0.9)$

$\text{type}(X, \text{fastfood}, M) \rightarrow \text{visitminutes}(X, 20, M * 0.9)$

Object logic layers of interpretation

$\text{Pred}(t)$: $\text{Pred}(t)$ holds.

$\text{Pred}(t,m)$: $\text{Pred}(t)$ holds with a fuzzy measure at least m .

$\text{Pred}(t,m,c)$: With confidence (probability) at least c ,
 $\text{Pred}(t)$ holds with at least a fuzzy measure m .

$\text{Pred}(t,m,c,d)$: The fact "with confidence (probability) at least c , $\text{Pred}(t)$ holds with at least a fuzzy measure m ," holds and depends on the set of clauses d .

Examples

$\text{bar}(\text{malloy}, 0.9, 1)$: we are certain that malloy is bar
with a fuzzy measure at least 0.9

$\text{bar}(\text{crown}, 0.9, 0.8)$: we are 0.8 confident that crown is
a bar with a fuzzy measure at least 0.9

Rule examples

$\text{bar}(X,M,C) \ \& \ M > L \ \rightarrow \ \text{openat12}(X,1,C*0.8):$

when we have confidence C in that X is a bar with a measure M at least L , we are $C*0.8$ confident that it is open at 12 with a measure 1.

optionally

$\text{bar}(X,M,C) \rightarrow \text{openat12}(X,1,M*C*0.8):$

example of a sure rule:

$\text{bar}(X,M,C) \rightarrow \text{can_eat_at}(X,M*0.5,C):$

Fuzzy part is easy

Use your own preferred function f and limits for fuzzy derivation

$\text{Pred}(X, M1) \ \& \ \text{Pred}(X, M2) \rightarrow \text{Pred}(X, f(M1, M2))$

$\text{Pred}(X, M) \ \& \ M > L \rightarrow \text{Pred}(X, f(M))$

Standard derivation rules in resolution hold, nothing is added.

We can enhance subsumption, provided f is monotonic:

$\text{Pred}(X, M1)$ subsumes $\text{Pred}(Y, M2)$ iff $Y = Xs$ and $M1 \geq M2$.

Probabilistic part requires tracking

Recall $P(t, M, C, D)$: C is the probability and D is the set of facts on which the atom depends upon.

Always use rules of form

$$P(\dots, D_1) \& \dots \& P(\dots, D_n) \& A_1 \& \dots \& A_n \rightarrow P(\dots, \text{union}(D_1, \dots, D_n))$$

where P atoms do contain probabilities and $A_1 \dots A_n$ do not contain probabilities

Multiplying probabilities

Generally the rules should have a form

$P_1(t_1, M_1, C_1, D_1) \& \dots \& P_n(t_n, M_n, C_n, D_n) \rightarrow$

$P(t, M, f(M_1, \dots, M_n), g(C_1, \dots, C_n, D_1, \dots, D_n), \text{union}(D_1, \dots, D_n))$

- In simple cases $g(C_1, \dots, C_n, D_1, \dots, D_n) = C_1 * \dots * C_n$
- However, if $\text{intersection}(D_1, \dots, D_n)$ is not empty, C_i -s corresponding to D_i -s with multiple occurrences should be used only once

Cumulating evidence

Use evidence cumulating rule schema:

$\text{Pred}(X, M1, C1, D1) \ \& \ \text{Pred}(X, M2, C2, D2) \ \& \ \text{Empty}(\text{Intersection}(D1, D2))$

->

$\text{Pred}(X, \min(M1, M2), (C1+C2)-(C1 * C2), \text{union}(D1, D2))$

Cumulating evidence

Example: independent facts

a) $\text{bar}(X, M, C, D) \ \& \ M > 0.75 \rightarrow \text{openat12}(X, 1, C * 0.8, D)$

b) $\text{intitle}(X, \text{"allnight"}, M, C, D) \ \& \ M > 0.75 \rightarrow \text{openat12}(X, 1, C * 0.9, D)$

c) $\text{bar}(\text{malloy}, 1, 1, \{c\})$.

d) $\text{intitle}(\text{malloy}, \text{"allnight"}, 1, 1, \{d\})$.

a,c: e) $\text{openat12}(\text{malloy}, 1, 0.8, \{c\})$

b,d: f) $\text{openat12}(\text{malloy}, 1, 0.9, \{d\})$

giving for our case ($0.8 + 0.9 = 1.7$, $0.8 * 0.9 = 0.72$, $1.7 - 0.72 = 0.98$)

$\text{openat12}(\text{malloy}, 1, 0.98, \{c, d\})$

Cumulating evidence

Example: dependent facts

f) $\text{activity}(X, \text{heavymetal}, 1, 1, D) \rightarrow \text{activity}(X, \text{music}, 1, 1, D)$.

g) $\text{activity}(X, Y, M1, C1, D1) \ \& \ \text{likes}(U, Y, M2, C2, D2) \rightarrow$
 $\text{fits}(U, X, 1, M1 * M2 * C1 * C2, \text{union}(D1, D2))$

a) $\text{likes}(\text{john}, \text{music}, 1, 0.6, \{a\})$

b) $\text{likes}(\text{john}, \text{heavymetal}, 1, 0.8, \{b\})$

c) $\text{activity}(\text{crown}, \text{heavymetal}, 1, 1, \{c\})$.

c, f: h) $\text{activity}(\text{crown}, \text{music}, 1, 1, \{e\})$.

g, a, h(cf): i) $\text{fits}(\text{john}, \text{crown}, 1, 0.6, \{a, c\})$

g, b, c: j) $\text{fits}(\text{john}, \text{crown}, 1, 0.8, \{b, c\})$

Cumulating prohibited, since i and j share c

Ranking calculation in meta-logic

- Derive all open-at-time facts.
- Derive all independent addrank facts, using:

Popularity(X,P) -> addrank(X, pf(P))

Likes(X,Y,M1) & assoc(Z,Y,M2,C,D) ->
addrank(X,Z, f(M1,M2,C),D)

Dislikes(X,Y,M1) & assoc(Z,Y,M2,C,D) ->
addrank(X,Z, nf(M1,M2,C),D)

- Sum all maximal pos/neg addrank numbers for objects.
- Filter out objects which are open at time.
- Order by rank.

Summary 1

Represent facts as $P(t, M, C, D)$ where:

M- fuzzy measure of $P(t)$ holding

C – confidence as probability of at least $P(t, M)$ holding

D – set of facts on which $P(t, M, C)$ depends

Represent rules as

$P_1(t_1, M_1, C_1, D_1) \& \dots \& P_n(t_n, M_n, C_n, D_n) \&$

$M_1 > L_1 \& \dots \& M_n > L_n \& A_1 \dots \& A_m$

->

$P(t, M, f(M_1, \dots, M_2), g(C_1, \dots, C_n, D_1, \dots, D_n), \text{union}(D_1, \dots, D_n))$

Summary 2

Add evidence cumulating rule

$\text{Pred}(X, M1, C1, D1) \ \& \ \text{Pred}(X, M2, C2, D2) \ \& \ \text{Empty}(\text{Intersection}(D1, D2))$

->

$\text{Pred}(X, \min(M1, M2), (C1+C2)-(C1*C2), \text{union}(D1, D2))$

Add extended subsumption

$\text{Pred}(X, M1, C1, D1)$ subsumes

$\text{Pred}(Y, M2, C2, D2)$

iff $Y=Xs \ \& \ M1 \geq M2 \ \& \ C1 \geq C2 \ \&$

$D1$ is a subset of $D2$

