

From Fuzzy to Annotated Semantic Web Languages

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From Fuzzy to Annotated Semantic Web Languages

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About Vagueness

What are vague concepts and do they exist?

- What are the pictures about?







- A **concept is vague** whenever its extension is deemed lacking in clarity
 - **Aboutness** of a picture or piece of text
 - **Tall** person
 - **High** temperature
 - **Nice** weather
 - **Adventurous** trip
 - **Similar** proof
- Vague concepts:
 - Are abundant in everyday speech and almost inevitable
 - Their meaning is often subjective and context dependent

What are vague objects and do they exist?

- Are there vague objects in the pictures?



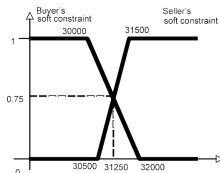




- An **object is vague** whenever its identity is lacking in clarity
 - Dust
 - Cloud
 - Dunes
 - Sun
- Vague objects:
 - Are not identical to anything, except to themselves (reflexivity)
 - Are characterised by a **vague identity** relation (e.g. a **similarity** relation)
- BTW: example of *uncertain object*: “habitable Earth-like planet in universe”

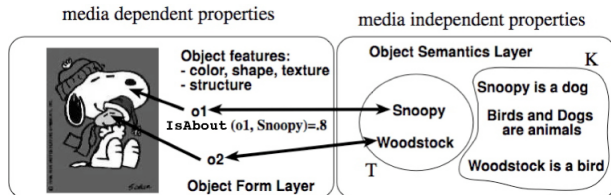
- A **statement is vague** whenever it involves vague concepts or vague objects
 - **Heavy** rain
 - **Tall** person
 - **Hot** temperature
- The **truth** of a vague statement is a matter of **degree**, as it is intrinsically difficult to establish whether the statement is entirely true or false
 - There are 33 °C. Is it **hot**?

Sources of Vagueness: Matchmaking



- A car seller sells an Audi TT for 31500 €, as from the catalog price.
- A buyer is looking for a sports-car, but wants to pay not more than around 30000 €
- Classical DLs: the problem relies on the crisp conditions on price.
- More fine grained approach: to consider prices as vague constraints (fuzzy sets) (as usual in negotiation)
 - Seller would sell above 31500 €, but can go down to 30500 €
 - The buyer prefers to spend less than 30000 €, but can go up to 32000 €
 - Highest degree of matching is 0.75 . The car may be sold at 31250 €.

Sources of Vagueness: Multimedia information retrieval

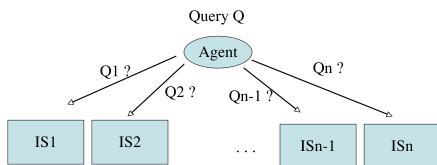


<i>IsAbout</i>		
<i>ImageRegion</i>	<i>Object ID</i>	<i>degree</i>
o1	snoopy	0.8
o2	woodstock	0.7
⋮	⋮	
⋮	⋮	

“Find top-k image regions about animals”

$Query(x) \leftarrow ImageRegion(x) \wedge isAbout(x, y) \wedge Animal(y)$

Sources of Vagueness: Distributed Information Retrieval



Then the agent has to perform **automatically** the following steps:

- 1 The agent has to select a subset of relevant resources $\mathcal{S}' \subseteq \mathcal{S}$, as it is not reasonable to assume to access to and query all resources (**resource selection/resource discovery**);
- 2 For every selected source $\mathcal{S}_i \in \mathcal{S}'$ the agent has to reformulate its information need Q_A into the query language \mathcal{L}_i provided by the resource (**schema mapping/ontology alignment**);
- 3 The results from the selected resources have to be merged together (**data fusion/rank aggregation**)

Sources of Vagueness: Vague database query

<i>HotelID</i>	<i>hasLoc</i>	<i>ConferenceID</i>	<i>hasLoc</i>
<i>h1</i>	<i>h1</i>	<i>c1</i>	<i>c1</i>
<i>h2</i>	<i>h12</i>	<i>c2</i>	<i>c12</i>
⋮	⋮	⋮	⋮

<i>hasLoc</i>	<i>hasLoc</i>	<i>distance</i>	<i>hasLoc</i>	<i>hasLoc</i>	<i>close</i>	<i>cheap</i>
<i>h1</i>	<i>c1</i>	300	<i>h1</i>	<i>c1</i>	0.7	0.3
<i>h1</i>	<i>c2</i>	500	<i>h1</i>	<i>c2</i>	0.5	0.5
<i>h2</i>	<i>c1</i>	750	<i>h2</i>	<i>c1</i>	0.25	0.8
<i>h2</i>	<i>c2</i>	800	<i>h2</i>	<i>c2</i>	0.2	0.9
⋮	⋮		⋮	⋮	⋮	

“Find top-*k* cheapest hotels close to the train station”

$$q(h) \leftarrow \text{hasLocation}(h, h1) \wedge \text{hasLocation}(\text{train}, c1) \wedge \text{close}(h1, c1) \wedge \text{cheap}(h)$$

Sources of Vagueness: Health-care: diagnosis of pneumonia



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SYSTEMS IMPROVEMENT

Seventh Edition
May 2006

Work Group Leader
John Degelau, MD
Internal Medicine,
HealthPartners Medical Group

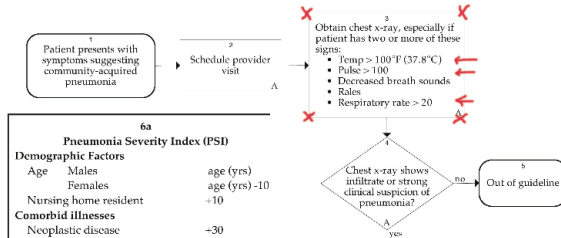
Work Group Members

Family Medicine

Garrett Trobec, MD

Health Care Guideline:

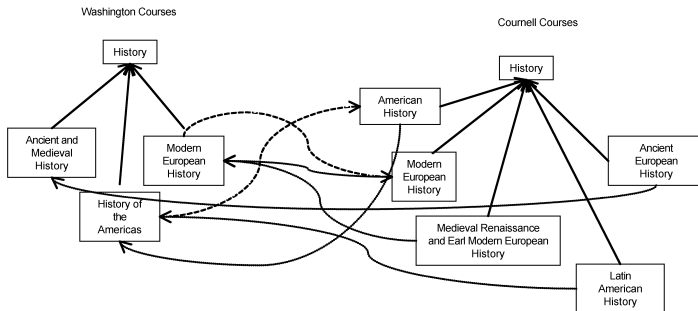
Community-Acquired Pneumonia in Adults



- E.g., *Temp = 37.5*, *Pulse = 98*, *RespiratoryRate = 18* are in “danger zone” already
- Temperature, Pulse and Respiratory rate: these constraints are rather vague than crisp

Sources of Vagueness: Ontology alignment (schema matching)

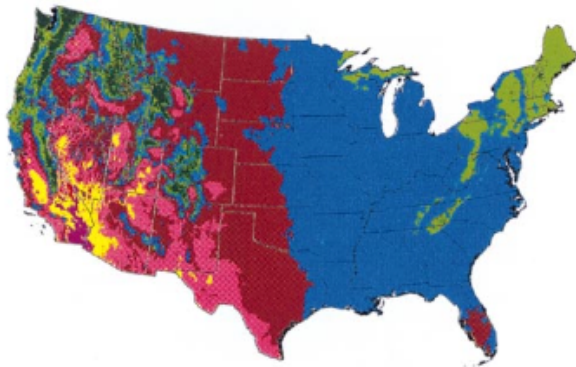
- To which **degree** are two concepts of two ontologies similar?



Sources of Vagueness: Lifezone mapping

- To which **degree** do certain areas have a specific bioclimate

Humidity Province (cells)
Superhumid (17,278)
Perhumid (42,705)
Humid (219,080)
Subhumid (139,615)
Semiarid (51,828)
Arid (11,008)
Perarid (3,841)
Superarid (153)



Holdridge life zones of USA

Sources of Vagueness: ARPAT, Air quality in the province of Lucca

I dati di domenica 21/02/2010

Sintesi dei dati rilevati dalle ore 0 alle ore 24 del giorno domenica 21/02/2010

Stazione		Tipo stazione	SO ₂ µg/m ³ (media su 24h)	NO ₂ µg/m ³ (max oraria)	CO mg/m ³ (max oraria)	O ₃ µg/m ³ (max oraria)	PM ₁₀ µg/m ³ (media su 24h)	Giudizio di qualità dell'aria
Lucca	P.za San Micheletto (RETE REGIONALE **)	urbana - traffico	1	75	---	---	37	Accettabile
Lucca	V.le Carducci	urbana - traffico	1	---	2,3	---	49	Accettabile
Lucca	Carignano (RETE REGIONALE **)	rurale - fondo	---	---	---	86 (h.16*)	---	Buona
Viareggio	Largo Risorgimento	urbana - traffico	---	---	1,8	---	n.d.	Buona
Viareggio	Via Maroncelli (RETE REGIONALE **)	urbana - fondo	4	97	---	61 (h.15*)	33	Accettabile
Capannori	V. di Piaggia (RETE REGIONALE **)	urbana - fondo	---	62	1,3	---	25	Accettabile
Porcari	V. Carrara (RETE REGIONALE **)	periferica - fondo	1	51	---	84 (h.15*)	24	Accettabile

Giudizio di qualità	SO ₂ µg/m ³ (media su 24h)	NO ₂ µg/m ³ (max oraria)	CO mg/m ³ (max oraria)	O ₃ µg/m ³ (max oraria)	PM ₁₀ µg/m ³ (media su 24h)
Buona	0-50	0-50	0-2,5	0-120	0-25
Accettabile	51-125	51-200	2,6-15	121-180	26-50
Scadente	126-250	201-400	15,1-30	181-240	51-74
Pessima	>250	>400	>30	>240	>74

Sintesi dei dati rilevati dalle ore 0 alle ore 24 del giorno domenica 14/02/2010

Stazione		Tipo stazione	SO ₂ µg/m ³ (media su 24h)	NO ₂ µg/m ³ (max oraria)	CO mg/m ³ (max oraria)	O ₃ µg/m ³ (max oraria)	PM ₁₀ µg/m ³ (media su 24h)	Giudizio di qualità dell'aria
Lucca	P.za San Micheletto (RETE REGIONALE **)	urbana - traffico	1	75	---	---	56	Scadente
Lucca	V.le Carducci	urbana - traffico	2	---	2	---	75	Pessima
Lucca	Carignano (RETE REGIONALE **)	rurale - fondo	---	---	---	87 (h.18*)	---	Buona
Viareggio	Largo Risorgimento	urbana - traffico	---	---	1,7	---	n.d.	Buona
Viareggio	Via Maroncelli (RETE REGIONALE **)	urbana - fondo	1	121	---	60 (h.17*)	45	Accettabile
Capannori	V. di Piaggia (RETE REGIONALE **)	urbana - fondo	---	79	2	---	59	Scadente
Porcari	V. Carrara (RETE REGIONALE **)	periferica - fondo	2	72	---	82 (h.16*)	63	Scadente

Giudizio di qualità	SO ₂ µg/m ³ (media su 24h)	NO ₂ µg/m ³ (max oraria)	CO mg/m ³ (max oraria)	O ₃ µg/m ³ (max oraria)	PM ₁₀ µg/m ³ (media su 24h)
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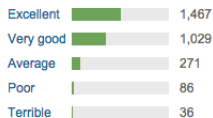
2,889 Reviews from our TripAdvisor Community



Your overall rating of this property



Traveler rating



See reviews for



Rating summary



Uncertainty vs Vagueness: a clarification

- Initial difficulty:
 - Understand the conceptual differences between **uncertainty** and **vagueness**
- Main problem:
 - Interpreting a **degree** as a measure of **uncertainty** rather than as a measure of **vagueness**

Uncertain Statements

- A statement is **true** or **false** in any world/interpretation
 - We are “**uncertain**” about which world to consider
 - We may have e.g. a probability distribution over possible worlds
- E.g., “it will rain tomorrow”
 - We cannot exactly establish whether it will rain tomorrow or not, due to our **incomplete** knowledge about our world
 - We can estimate to which **degree** this is **probable**

- Consider a propositional statement (formula) ϕ
- Interpretation (world) $\mathcal{I} \in \mathcal{W}$,

$$\mathcal{I} : \mathcal{W} \rightarrow \{0, 1\}$$

- $\mathcal{I}(\phi) = 1$ means ϕ is true in \mathcal{I} , denoted $\mathcal{I} \models \phi$
- Each interpretation \mathcal{I} depicts some concrete world
- Given n propositional letters, $|\mathcal{W}| = 2^n$
- In uncertainty theory, we do not know which interpretation \mathcal{I} is the actual one

- One may construct a **probability distribution** over the worlds

$$\begin{aligned} Pr : \mathcal{W} &\rightarrow [0, 1] \\ \sum_{\mathcal{I}} Pr(\mathcal{I}) &= 1 \end{aligned}$$

- $Pr(\mathcal{I})$ indicates the probability that \mathcal{I} is the actual world
- **Probability** $Pr(\phi)$ of a statement ϕ in Pr

$$Pr(\phi) = \sum_{\mathcal{I} \models \phi} Pr(\mathcal{I})$$

- $Pr(\phi)$ is the probability of the event: " ϕ is true"

Vague Statements

- A statement is **true** to some **degree**, which is taken from a truth space (usually $[0, 1]$)
- The convention prescribing that a proposition is either true or false is changed towards **graded propositions**
- E.g., “heavy rain”
 - The compatibility of “heavy” in the phrase “heavy rain” is graded and the degree depends on the amount of rain is falling
 - The intensity of precipitation is expressed in terms of a precipitation rate R : volume flux of precipitation through a horizontal surface, i.e. $m^3/m^2s = ms^{-1}$
 - It is usually expressed in mm/h

“Heavy rain” continued...E.g., in weather forecasts one may find:

- Rain intensity measured as precipitation rate R : volume flux of precipitation through a horizontal surface, i.e. $m^3/m^2h = mh^{-1}$

Rain. Falling drops of water larger than 0.5 mm in diameter. “Rain” usually implies that the rain will fall steadily over a period of time;

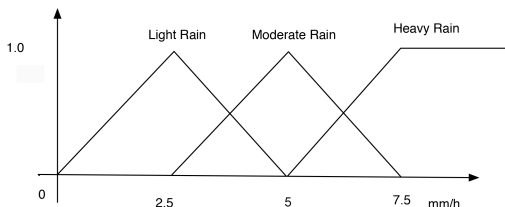
Light rain. Rain falls at the rate of 2.6 mm or less an hour;

Moderate rain. Rain falls at the rate of 2.7 mm to 7.6 mm an hour;

Heavy rain. Rain falls at the rate of 7.7 mm an hour or more.

- Quite harsh distinction: $R = 7.7mm/h \rightarrow$ heavy rain
 $R = 7.6mm/h \rightarrow$ moderate rain
- This is clearly unsatisfactory, as quite naturally
 - The more rain is falling, the more the sentence “heavy rain” is true
 - Vice-versa, the less rain is falling the less the sentence is true

- In other words, that the sentence “heavy rain” is no longer either true or false, but is **intrinsically graded**
 - Even if we have complete knowledge about the current world, i.e. exact specification of the precipitation rate
- More fine grained approach:
 - Define the various types of rains as



- Light rain, moderate rain and heavy rain are **vague concepts**

- Consider a propositional statement ϕ
- A propositional interpretation \mathcal{I} maps ϕ to a truth degree in $[0, 1]$

$$\mathcal{I}(\phi) \in [0, 1]$$

- I.e., we are unable to establish whether a statement is entirely true or false due the occurrence of vague concept
- Vague statements are truth-functional
 - Degree of truth of a statement can be calculated from the degrees of truth of its constituents
 - Note that this is not possible for uncertain statements
- Example of truth functional interpretation of vague statements:

$$\begin{aligned}\mathcal{I}(\phi \wedge \psi) &= \min(\mathcal{I}(\phi), \mathcal{I}(\psi)) \\ \mathcal{I}(\phi \vee \psi) &= \max(\mathcal{I}(\phi), \mathcal{I}(\psi)) \\ \mathcal{I}(\neg\phi) &= 1 - \mathcal{I}(\phi)\end{aligned}$$

- Recap:

- In a **probabilistic** setting each statement is either true or false, but there is e.g. a probability distribution telling us how probable each interpretation/sentence is

$$\mathcal{I}(\phi) \in \{0, 1\}, Pr(\mathcal{I}) \in [0, 1] \text{ and } Pr(\phi) = \sum_{\mathcal{I} \models \phi} Pr(\mathcal{I}) \in [0, 1]$$

- In **vagueness** theory instead, sentences are **graded**

$$\mathcal{I}(\phi) \in [0, 1]$$

- Are there sentences combining the two orthogonal concepts of uncertainty and vagueness?
- Yes, and we use them daily !
 - E.g. “there will be heavy rain tomorrow”
- This type of sentences are called **uncertain vague sentences**
- Essentially, there is
 - **uncertainty** about the world we will have tomorrow
 - **vagueness** about the various types of rain

- Consider a propositional statement ϕ
- A model for uncertain vague sentences:
 - Define probability distribution over worlds $\mathcal{I} \in \mathcal{W}$, i.e.

$$Pr(\mathcal{I}) \in [0, 1], \sum_{\mathcal{I}} Pr(\mathcal{I}) = 1$$

- Sentences are graded: each interpretation $\mathcal{I} \in \mathcal{W}$ is truth functional and maps sentences into $[0, 1]$

$$\mathcal{I}(\phi) \in [0, 1]$$

- For a sentence ϕ , consider the **expected truth** of ϕ

$$ET(\phi) = \sum_{\mathcal{I}} Pr(\mathcal{I}) \cdot \mathcal{I}(\phi) .$$

- Note: if \mathcal{I} is bivalent (that is, $\mathcal{I}(\phi) \in \{0, 1\}$) then $ET(\phi) = Pr(\phi)$

From Fuzzy Sets to Mathematical Fuzzy Logic

From Crisp Sets to Fuzzy Sets.

- Let X be a **universal set** of objects
- The **power set**, denoted 2^A , of a set $A \subset X$, is the set of subsets of A , i.e.,

$$2^A = \{B \mid B \subseteq A\}$$

- Often sets are defined as

$$A = \{x \mid P(x)\}$$

- $P(x)$ is a statement “ x has property P ”
- $P(x)$ is either **true** or **false** for any $x \in X$

- Examples of universe X and subsets $A, B \in 2^X$ may be

$$X = \{x \mid x \text{ is a day}\}$$

$$A = \{x \mid x \text{ is a rainy day}\}$$

$$B = \{x \mid x \text{ is a day with precipitation rate } R \geq 7.5\text{mm/h}\}$$

- In the above case: $B \subseteq A \subseteq X$
- The **membership function** of a set $A \subseteq X$:

$$\chi_A: X \rightarrow \{0, 1\}$$

where $\chi_A(x) = 1$ iff $x \in A$

- Note that for sets $A, B \in 2^X$

$$A \subseteq B \text{ iff } \forall x \in X. \chi_A(x) \leq \chi_B(x)$$

- **Complement** of a set A , i.e. $\bar{A} = X \setminus A: \forall x \in X$:

$$\chi_{\bar{A}}(x) = 1 - \chi_A(x)$$

- **Intersection and union**: $\forall x \in X$

$$\chi_{A \cap B}(x) = \min(\chi_A(x), \chi_B(x))$$

$$\chi_{A \cup B}(x) = \max(\chi_A(x), \chi_B(x))$$

- **Cartesian product** of two sets $A, B \in 2^X$

$$A \times B = \{\langle a, b \rangle \mid a \in A, b \in B\}$$

- A relation $R \subseteq X \times X$

- is **reflexive** if for all $x \in X$

$$\chi_R(x, x) = 1$$

- is **symmetric** if for all $x, y \in X$

$$\chi_R(x, y) = \chi_R(y, x)$$

- **Inverse** of R , $\chi_{R^{-1}}: X \times X \rightarrow \{0, 1\}: \forall x, y \in X$:

$$\chi_{R^{-1}}(y, x) = \chi_R(x, y)$$

- **Fuzzy set** A : $\chi_A: X \rightarrow [0, 1]$, or simply

$$A: X \rightarrow [0, 1]$$

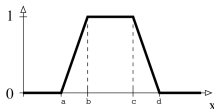
- **Fuzzy power set** over X , is denoted $\tilde{2}^X$, i.e. the set of all fuzzy sets over X
- Example: the fuzzy set

$$C = \{x \mid x \text{ is a day with heavy precipitation rate } R\}$$

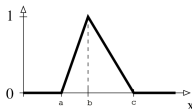
is defined via the membership function

$$\chi_C(x) = \begin{cases} 1 & \text{if } R \geq 7.5 \\ (x - 5)/2.5 & \text{if } R \in [5, 7.5) \\ 0 & \text{otherwise} \end{cases}$$

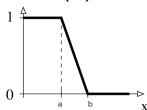
- Fuzzy membership functions may depend on the context and may be subjective
- **Shape** may be quite different
- Usually, it is sufficient to consider functions



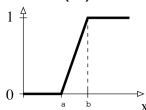
(a)



(b)



(c)



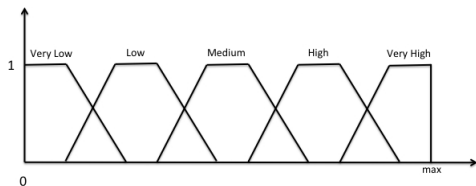
(d)

(a) Trapezoidal $trz(a, b, c, d)$; (b) Triangular $tri(a, b, c)$; (c) left-shoulder $ls(a, b)$; (d) right-shoulder $rs(a, b)$

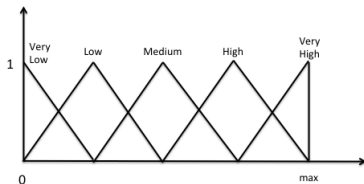
Fuzzy Sets Construction

- The usefulness of fuzzy sets depends critically on appropriate membership functions
- Methods for fuzzy membership functions construction is largely addressed in literature

- Easy and typically satisfactory method (numerical domain)
 - uniform partitioning into 5 fuzzy sets

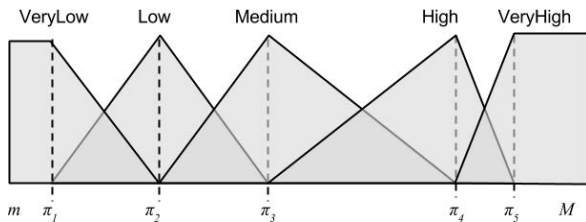


Fuzzy sets construction using trapezoidal functions



Fuzzy sets construction using triangular functions

- Another popular method is based on **clustering**
- Use **Fuzzy C-Means** to cluster data into 5 clusters
 - Fuzzy C-Means extends K-Means to accommodate graded membership
- From the clusters c_1, \dots, c_5 take the centroids π_1, \dots, π_5
- Build the fuzzy sets from the centroids



Fuzzy sets construction using clustering

Norm-Based Fuzzy Set Operations

- Standard fuzzy set operations are not the only ones
- Most notable ones are **triangular norms**
 - **t-norm** \otimes for set intersection
 - **t-conorm** \oplus (also called **s-norm**) for set union
 - **negation** \ominus for set complementation
 - **implication** \Rightarrow
 - set inclusion $A \sqsubseteq B$ is defined as

$$\inf_{x \in X} A(x) \Rightarrow B(x)$$

- \Rightarrow is often defined from \otimes as *r-implication*

$$a \Rightarrow b = \sup \{c \mid a \otimes c \leq b\}.$$

- These functions satisfy some properties that one expects to hold

Properties for t-norms and s-norms

Axiom Name	T-norm	S-norm
Taututology/Contradiction	$a \otimes 0 = 0$	$a \oplus 1 = 1$
Identity	$a \otimes 1 = a$	$a \oplus 0 = a$
Commutativity	$a \otimes b = b \otimes a$	$a \oplus b = b \oplus a$
Associativity	$(a \otimes b) \otimes c = a \otimes (b \otimes c)$	$(a \oplus b) \oplus c = a \oplus (b \oplus c)$
Monotonicity	if $b \leq c$, then $a \otimes b \leq a \otimes c$	if $b \leq c$, then $a \oplus b \leq a \oplus c$

Properties for implication and negation functions

Axiom Name	Implication Function	Negation Function
Tautology / Contradiction	$0 \Rightarrow b = 1, a \Rightarrow 1 = 1, 1 \Rightarrow 0 = 0$	$\ominus 0 = 1, \ominus 1 = 0$
Antitonicity	if $a \leq b$, then $a \Rightarrow c \geq b \Rightarrow c$	if $a \leq b$, then $\ominus a \geq \ominus b$
Monotonicity	if $b \leq c$, then $a \Rightarrow b \leq a \Rightarrow c$	

- By commutativity, \otimes and \oplus are monotone also in the first argument
- \otimes is **idempotent** if $a \otimes a = a$, for all $a \in [0, 1]$
- Negation function \ominus is **involution** iff $\ominus \ominus a = a$, for all $a \in [0, 1]$.
- Salient negation functions are:
 - Standard or Łukasiewicz negation: $\ominus_l a = 1 - a$;
 - Gödel negation: $\ominus_g a$ is 1 if $a = 0$, else is 0.
- Łukasiewicz negation is involutive, Gödel negation is not.

- Salient t-norm functions are:

Gödel t-norm: $a \otimes_g b = \min(a, b)$;

Bounded difference or Łukasiewicz t-norm:

$$a \otimes_l b = \max(0, a + b - 1);$$

Algebraic product or product t-norm: $a \otimes_p b = a \cdot b$;

Drastic product:

$$a \otimes_d b = \begin{cases} 0 & \text{when } (a, b) \in [0, 1[\times [0, 1[\\ \min(a, b) & \text{otherwise} \end{cases}$$

- Salient s-norm functions are:

Gödel s-norm: $a \oplus_g b = \max(a, b)$;

Bounded sum or Łukasiewicz s-norm: $a \oplus_l b = \min(1, a + b)$;

Algebraic sum or product s-norm: $a \oplus_p b = a + b - ab$;

Drastic sum: $a \oplus_d b = \begin{cases} 1 & \text{when } (a, b) \in]0, 1] \times]0, 1] \\ \max(a, b) & \text{otherwise} \end{cases}$

Salient properties of norms:

- Ordering among t-norms (\otimes is any t-norm):

$$\otimes_d \leq \otimes \leq \otimes_g$$

$$\otimes_d \leq \otimes_l \leq \otimes_p \leq \otimes_g .$$

- The only idempotent t-norm is \otimes_g .
- The only t-norm satisfying $a \otimes a = 0$ for all $a \in [0, 1[$ is \otimes_d .
- Ordering among s-norms (\oplus is any s-norm):

$$\oplus_g \leq \oplus \leq \oplus_d$$

$$\oplus_g \leq \oplus_p \leq \oplus_l \leq \oplus_d .$$

- The only idempotent s-norm is \oplus_g .
- The only s-norm satisfying $a \oplus a = 1$ for all $a \in]0, 1]$ is \oplus_d .
- The **dual s-norm** of \otimes is defined as

$$a \oplus b = 1 - (1 - a) \otimes (1 - b) .$$

- **Kleene-Dienes implication**: $x \Rightarrow y = \max(1 - x, y)$ is called
- **Fuzzy modus ponens**: let $a \geq n$ and $a \Rightarrow b \geq m$
 - Under Kleene-Dienes implication, we infer that if $n > 1 - m$ then $b \geq m$
 - Under r-implication relative to a t-norm \otimes , we infer that $b \geq n \otimes m$
- **composition** of two fuzzy relations $R_1 : X \times X \rightarrow [0, 1]$ and $R_2 : X \times X \rightarrow [0, 1]$: for all $x, z \in X$
 - $(R_1 \circ R_2)(x, z) = \sup_{y \in X} R_1(x, y) \otimes R_2(y, z)$
- A fuzzy relation R is **transitive** iff for all $x, z \in X$

$$R(x, z) \geq (R \circ R)(x, z)$$

Łukasiewicz, Gödel, Product logic and Standard Fuzzy logic

- One distinguishes three different sets of fuzzy set operations (called **fuzzy logics**)
 - Łukasiewicz, Gödel, and Product logic
 - Standard Fuzzy Logic (SFL) is a sublogic of Łukasiewicz
 - $\min(a, b) = a \otimes_I (a \Rightarrow_I b)$, $\max(a, b) = 1 - \min(1 - a, 1 - b)$

	Łukasiewicz Logic	Gödel Logic	Product Logic	SFL
$a \otimes b$	$\max(a + b - 1, 0)$	$\min(a, b)$	$a \cdot b$	$\min(a, b)$
$a \oplus b$	$\min(a + b, 1)$	$\max(a, b)$	$a + b - a \cdot b$	$\max(a, b)$
$a \Rightarrow b$	$\min(1 - a + b, 1)$	$\begin{cases} 1 & \text{if } a \leq b \\ b & \text{otherwise} \end{cases}$	$\min(1, b/a)$	$\max(1 - a, b)$
$\ominus a$	$1 - a$	$\begin{cases} 1 & \text{if } a = 0 \\ 0 & \text{otherwise} \end{cases}$	$\begin{cases} 1 & \text{if } a = 0 \\ 0 & \text{otherwise} \end{cases}$	$1 - a$

- Mostert–Shields theorem: any continuous t-norm can be obtained as an ordinal sum of these three

Some additional properties

Property	Łukasiewicz Logic	Gödel Logic	Product Logic	SFL
$x \otimes \ominus x = 0$	•			
$x \oplus \ominus x = 1$	•			
$x \otimes x = x$		•		•
$x \oplus x = x$		•		•
$\ominus \ominus x = x$	•			•
$x \Rightarrow y = \ominus x \oplus y$	•			•
$\ominus(x \Rightarrow y) = x \otimes \ominus y$	•			•
$\ominus(x \otimes y) = \ominus x \oplus \ominus y$	•	•	•	•
$\ominus(x \oplus y) = \ominus x \otimes \ominus y$	•	•	•	•

- **Note:** If all conditions in the upper part of a column have to be satisfied then we collapse to classical two-valued logic

- Fuzzy modifiers: interesting feature of fuzzy set theory
- A fuzzy modifier apply to fuzzy sets to change their membership function
 - Examples: **very**, **more_or_less**, and **slightly**
- A **fuzzy modifier** m represents a function

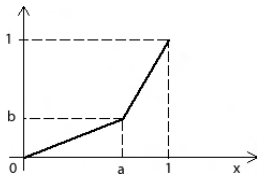
$$f_m: [0, 1] \rightarrow [0, 1]$$

Example: $f_{\text{very}}(x) = x^2$, $f_{\text{more_or_less}}(x) = \text{tri}(0, x, 1)$, $f_{\text{slightly}}(x) = \sqrt{x}$

- Modelling the fuzzy set of **very heavy rain**:

$$\begin{aligned}
 \chi_{\text{very heavy rain}}(x) &= f_{\text{very}}(\chi_{\text{heavyrain}}(x)) \\
 &= (\chi_{\text{heavyrain}}(x))^2 \\
 &= (rs(5, 7.5)(x))^2
 \end{aligned}$$

- A typical shape of modifiers: **linear modifiers** $lm(a, b)$



- Note: linear modifiers require one parameter c only

$$lm(a, b) = lm(c)$$

where $a = c/(c + 1)$, $b = 1/(c + 1)$

- OWL 2 is grounded on Mathematical Logic
- Fuzzy OWL 2 is grounded on **Mathematical Fuzzy Logic**
- A statement is no longer either true or false, but is graded
- **Truth space**: set of truth values L with some structure
- Given a statement ϕ
 - **Fuzzy Interpretation**: a function \mathcal{I} mapping ϕ into L , i.e.

$$\mathcal{I}(\phi) \in L$$

- Usually

$$L = [0, 1]$$
$$L_n = \left\{0, \frac{1}{n}, \dots, \frac{n-2}{n-1}, \dots, 1\right\} \quad (n \geq 1)$$

- **Fuzzy statement:** for $r \in [0, 1]$

$$\langle \phi, r \rangle$$

The degree of truth of ϕ is equal or greater than r

- **Examples:**
 - Fuzzy FOL: $\langle \text{RainyDay}(d), 0.75 \rangle$
 - Fuzzy LPs: $\langle \text{RainyDay}(d) \leftarrow, 0.75 \rangle$
 - Fuzzy RDFS: $\langle \langle d, \text{type}, \text{RainyDay} \rangle, 0.75 \rangle$
 - Fuzzy DLs: $\langle d:\text{RainyDay}, 0.75 \rangle$

- **Fuzzy interpretation \mathcal{I} :**

- Maps each basic statement p_i into $[0, 1]$
- Extended inductively to all statements

$$\begin{aligned}\mathcal{I}(\phi \wedge \psi) &= \mathcal{I}(\phi) \otimes \mathcal{I}(\psi) \\ \mathcal{I}(\phi \vee \psi) &= \mathcal{I}(\phi) \oplus \mathcal{I}(\psi) \\ \mathcal{I}(\phi \rightarrow \psi) &= \mathcal{I}(\phi) \Rightarrow \mathcal{I}(\psi) \\ \mathcal{I}(\phi \leftrightarrow \psi) &= \mathcal{I}(\phi \rightarrow \psi) \otimes \mathcal{I}(\psi \rightarrow \phi) \\ \mathcal{I}(\neg\phi) &= \ominus \mathcal{I}(\phi) \\ \mathcal{I}(\exists x.\phi) &= \sup_{a \in \Delta^{\mathcal{I}}} \mathcal{I}_x^a(\phi) \\ \mathcal{I}(\forall x.\phi) &= \inf_{a \in \Delta^{\mathcal{I}}} \mathcal{I}_x^a(\phi),\end{aligned}$$

where

- $\Delta^{\mathcal{I}}$ is the domain of \mathcal{I}
- \otimes , \oplus , \Rightarrow , and \ominus are the t-norms, t-conorms, implication functions, a negation functions
- The function \mathcal{I}_x^a is as \mathcal{I} except that x is interpreted as a

Example

- In Lukasiewicz logic:

$$\varphi = \text{Cold} \wedge \text{Cloudy}$$

\mathcal{I}	<i>Cold</i>	<i>Cloudy</i>	$\mathcal{I}(\varphi)$
\mathcal{I}_1	0	0.1	$\max(0, 0 + 0.1 - 1) = 0.0$
\mathcal{I}_2	0.3	0.4	$\max(0, 0.3 + 0.4 - 1) = 0.0$
\mathcal{I}_3	0.7	0.8	$\max(0, 0.7 + 0.9 - 1) = 0.6$
\mathcal{I}_4	1	1	$\max(0, 1 + 1 - 1) = 1.0$
\vdots	\vdots	\vdots	\vdots

- **Note:** given m propositional letters
 - Fuzzy interpretations over $L = [0, 1]$ are **not recursively enumerable**
 - There are n^m fuzzy interpretations over L_n

- One may also consider the following abbreviations:

$$\phi \wedge_g \psi \stackrel{\text{def}}{=} \phi \wedge (\phi \rightarrow \psi)$$

$$\phi \vee_g \psi \stackrel{\text{def}}{=} (\phi \rightarrow \psi) \rightarrow \phi \wedge_g (\psi \rightarrow \phi) \rightarrow \psi$$

$$\neg_{\otimes} \phi \stackrel{\text{def}}{=} \phi \rightarrow \mathbf{0}$$

$$\langle \phi \leq r \rangle \stackrel{\text{def}}{=} \langle \neg_{\lrcorner} \phi, \mathbf{1} - r \rangle$$

- In case \Rightarrow is the r-implication based on \otimes , then
 - \wedge_g is Gödel t-norm
 - \vee_g is Gödel s-norm
 - \neg_{\otimes} is interpreted as the negation function related to \otimes

- \mathcal{I} **satisfies** $\langle \phi, r \rangle$, or \mathcal{I} is a **model** of $\langle \phi, r \rangle$

$$\mathcal{I} \models \langle \phi, r \rangle \text{ iff } \mathcal{I}(\phi) \geq r$$

- \mathcal{I} is a **model** of ϕ if $\mathcal{I}(\phi) = 1$
- **Fuzzy knowledge base** \mathcal{K} : finite set of fuzzy statements
- \mathcal{I} **satisfies** (is a **model** of) \mathcal{K} : $\mathcal{I} \models \mathcal{K}$ iff it satisfies each element in it
- **Best entailment degree** of ϕ w.r.t. \mathcal{K} :

$$\text{bed}(\mathcal{K}, \phi) = \sup \{r \mid \mathcal{K} \models \langle \phi, r \rangle\}$$

- **Best satisfiability degree** of ϕ w.r.t. \mathcal{K} :

$$\text{bsd}(\mathcal{K}, \phi) = \sup_{\mathcal{I}} \{\mathcal{I}(\phi) \mid \mathcal{I} \models \mathcal{K}\}$$

Proposition (Fuzzy Modus Ponens)

For *r*-implication \rightarrow , for $r, s \in [0, 1]$:

$$\langle \phi, r \rangle, \langle \phi \rightarrow \psi, s \rangle \models \langle \psi, r \otimes s \rangle$$

Proposition

Salient equivalences:

$$\begin{aligned}\neg\neg\phi &\equiv \phi \quad (\text{L, SFL}) \\ \phi \wedge \phi &\equiv \phi \quad (\text{G, SFL}) \\ \neg(\phi \wedge \neg\phi) &\equiv 1 \quad (\text{L, G, } \Pi) \\ \phi \vee \neg\phi &\equiv 1 \quad (\text{L}) \\ \forall x.\phi &\equiv \neg\exists x.\neg\phi \quad (\text{L, SFL})\end{aligned}$$

Proposition

Salient equivalences:

$$\mathcal{L} + G \equiv \textit{Boolean Logic}$$

$$\mathcal{L} + \Pi \equiv \textit{Boolean Logic}$$

$$G + \Pi \equiv \textit{Boolean Logic}$$

Proposition (BED)

$bed(\mathcal{K}, \phi) = \min x. \text{ such that } \mathcal{K} \cup \{\langle \phi \leq x \rangle\} \text{ satisfiable.}$

Proposition (BSD)

$bsd(\mathcal{K}, \phi) = \max x. \text{ such that } \mathcal{K} \cup \{\langle \phi, x \rangle\} \text{ satisfiable.}$

- **Witnessed interpretation** \mathcal{I} :

$$\mathcal{I}(\exists x.\phi) = \mathcal{I}_x^a(\phi), \text{ for some } a \in \Delta^{\mathcal{I}} \quad (1)$$

$$\mathcal{I}(\forall x.\phi) = \mathcal{I}_x^a(\phi), \text{ for some } a \in \Delta^{\mathcal{I}} \quad (2)$$

- The supremum (resp. infimum) are attained at some point
- Classical interpretations are witnessed
- Fuzzy interpretations **may not be witnessed**
- E.g., \mathcal{I} is not witnessed as Eq. (1) not satisfied:

$$\begin{aligned} \Delta^{\mathcal{I}} &= \mathbb{N} \\ \mathcal{I}_x^n(A(x)) &= 1 - 1/n < 1, \text{ for all } n \\ \mathcal{I}(\exists x.A(x)) &= \sup_n \mathcal{I}_x^n(A(x)) \\ &= \sup_n 1 - 1/n = 1 \end{aligned}$$

Proposition (Witnessed model property)

In Łukasiewicz logic and SFL over $L = [0, 1]$, or for all cases in which the truth space L is finite, a fuzzy KB has a witnessed fuzzy model iff it has a fuzzy model.

- Not true for Gödel and product logic over $L = [0, 1]$
 - $\neg\forall x p(x) \wedge \neg\exists x \neg p(x)$ has no classical model
 - In Gödel logic it has no finite model, but has an **infinite** model: for integer $n \geq 1$, let \mathcal{I} such that $\mathcal{I}(p(n)) = 1/n$

$$\begin{aligned}\mathcal{I}(\forall x p(x)) &= \inf_n 1/n = 0 \\ \mathcal{I}(\exists x \neg p(x)) &= \sup_n \neg 1/n = \sup 0 = 0\end{aligned}$$

- IMHO: non-witnessed models make little sense in KR
- We will always assume that interpretations are witnessed

- We need to distinguish if truth space is $L = [0, 1]$ or $L_n = \{0, \frac{1}{n}, \dots, \frac{n-2}{n-1}, \dots, 1\}$
- Case L_n easier: given m propositional letters, there are m^n possible interpretations
- We may use
 - Operational Research
 - Analytic Tableaux, Non-Deterministic Analytic Tableaux
 - Reduction into Classical Propositional Logic

- Basic idea: translate formulae into equational constraints about truth degrees
- For a formula ϕ consider a variable x_ϕ
 - Intuition: x_ϕ will hold the degree of truth of statement ϕ
 - Example: constraints under Łukasiewicz for $\langle \neg\phi, 0.6 \rangle$

$$x_{\neg\phi} \in [0, 1]$$

$$x_\phi \in [0, 1]$$

$$x_{\neg\phi} = 1 - x_\phi$$

- We may use **Mixed Integer Linear Programming** for the encodings of constraints For Łukasiewicz:

- $x_1 \otimes_l x_2 = z \mapsto \{x_1 + x_2 - 1 \leq z, x_1 + x_2 - 1 \geq z - y, z \leq 1 - y, y \in \{0, 1\}\}$, where y is a new variable.
- $x_1 \oplus_l x_2 = z \mapsto \{x_1 + x_2 \leq z + y, y \leq z, x_1 + x_2 \geq z, y \in \{0, 1\}\}$, where y is a new variable.
- $x_1 \Rightarrow_l x_2 = z \mapsto \{(1 - x_1) \oplus_l x_2 = z\}$.

For SFL:

- $x_1 \otimes_g x_2 = z \mapsto \{z \leq x_1, z \leq x_2, x_1 \leq z + y, x_2 \leq z + (1 - y), y \in \{0, 1\}\}$, where y is a new variable.
- $x_1 \oplus_g x_2 = z \mapsto \{z \geq x_1, z \geq x_2, x_1 + y \geq z, x_2 + (1 - y) \geq z, y \in \{0, 1\}\}$, where y is a new variable.
- $x_1 \Rightarrow_{kd} x_2 = z \mapsto (1 - x_1) \oplus_g x_2 = z$.

- Negation Normal Form, $nnf(\phi)$

$$\neg \perp = \top$$

$$\neg \top = \perp$$

$$\neg \neg \phi \mapsto \phi$$

$$\neg(\phi \wedge \psi) \mapsto \neg\phi \vee \neg\psi$$

$$\neg(\phi \vee \psi) \mapsto \neg\phi \wedge \neg\psi$$

$$\neg(\phi \rightarrow \psi) \mapsto \phi \wedge \neg\psi .$$

- 1 Transform \mathcal{K} into NNF
- 2 Initialize the fuzzy theory $\mathcal{T}_{\mathcal{K}}$ and the initial set of constraints $\mathcal{C}_{\mathcal{K}}$ by

$$\begin{aligned}\mathcal{T}_{\mathcal{K}} &= \{\phi \mid \langle \phi, n \rangle \in \mathcal{K}\} \\ \mathcal{C}_{\mathcal{K}} &= \{x_{\psi} \geq n \mid \langle \phi, n \rangle \in \mathcal{K}\}\end{aligned}$$

- 3 Apply the following inference rules until no more rules can be applied

- (var). For variable x_{ϕ} occurring in $\mathcal{C}_{\mathcal{K}}$ add $x_{\phi} \in [0, 1]$ to $\mathcal{C}_{\mathcal{K}}$
- (v̄ar). For variable $x_{\neg\phi}$ occurring in $\mathcal{C}_{\mathcal{K}}$ add $x_{\phi} = 1 - x_{\neg\phi}$ to $\mathcal{C}_{\mathcal{K}}$
- (\perp). If $\perp \in \mathcal{T}_{\mathcal{K}}$ then $\mathcal{C}_{\mathcal{K}} := \mathcal{C}_{\mathcal{K}} \cup \{x_{\perp} = 0\}$
- (\top). If $\top \in \mathcal{T}_{\mathcal{K}}$ then $\mathcal{C}_{\mathcal{K}} := \mathcal{C}_{\mathcal{K}} \cup \{x_{\top} = 1\}$
- (\wedge). If $\phi \wedge \psi \in \mathcal{T}_{\mathcal{K}}$, then
 - 1 add ϕ and ψ to $\mathcal{T}_{\mathcal{K}}$
 - 2 $\mathcal{C}_{\mathcal{K}} := \mathcal{C}_{\mathcal{K}} \cup \{x_{\phi} \otimes x_{\psi} = x_{\phi \wedge \psi}\}$
- (\vee). If $\phi \vee \psi \in \mathcal{T}_{\mathcal{K}}$, then
 - 1 add ϕ and ψ to $\mathcal{T}_{\mathcal{K}}$
 - 2 $\mathcal{C}_{\mathcal{K}} := \mathcal{C}_{\mathcal{K}} \cup \{x_{\phi} \oplus x_{\psi} = x_{\phi \vee \psi}\}$
- (\rightarrow). If $\phi \rightarrow \psi \in \mathcal{T}_{\mathcal{K}}$, then
 - 1 add $\text{nnf}(\neg\phi)$ and ψ to $\mathcal{T}_{\mathcal{K}}$
 - 2 $\mathcal{C}_{\mathcal{K}} := \mathcal{C}_{\mathcal{K}} \cup \{(1 - x_{\text{nnf}(\neg\phi)}) \Rightarrow x_{\psi} = x_{\phi \rightarrow \psi}\}$

sat(\mathcal{K}): \mathcal{K} is satisfiable iff the final set of constraints $\mathcal{C}_{\mathcal{K}}$ has a solution

- bed*(\mathcal{K}, ϕ):
- Add $\neg\phi$ to $\mathcal{T}_{\mathcal{K}}$
 - Add $x_{\neg\phi} \geq 1 - x, x \in [0, 1]$ to $\mathcal{C}_{\mathcal{K}}$, x new
 - Compute final set of constraints $\mathcal{C}_{\mathcal{K}}$
 - Then, solve the optimisation problem

$bed(\mathcal{K}, \phi) = \min x$. such that $\mathcal{C}_{\mathcal{K}}$ has a solution

- bsd*(\mathcal{K}, ϕ):
- Add ϕ to $\mathcal{T}_{\mathcal{K}}$
 - Add $x_{\phi} \geq x, x \in [0, 1]$ to $\mathcal{C}_{\mathcal{K}}$, x new
 - Compute final set of constraints $\mathcal{C}_{\mathcal{K}}$
 - Then, solve the optimisation problem

$bsd(\mathcal{K}, \phi) = \max x$. such that $\mathcal{C}_{\mathcal{K}}$ has a solution

- Main property the method is based on:
 - if \mathcal{I} is model of $\langle \phi \wedge \psi, n \rangle$ then \mathcal{I} is a model of both $\langle \phi, n \rangle$ and $\langle \psi, n \rangle$;
 - if \mathcal{I} is model of $\langle \phi \vee \psi, n \rangle$ then \mathcal{I} is a model of either $\langle \phi, n \rangle$ or $\langle \psi, n \rangle$.
 - \mathcal{I} cannot be a model of both $\langle p, n \rangle$ and $\langle \neg p, m \rangle$ if $n > 1 - m$.
- A **clash** is either
 - a fuzzy statement $\langle \perp, n \rangle$ with $n > 0$; or
 - a pair of fuzzy statements $\langle p, n \rangle$ and $\langle \neg p, m \rangle$ with $n > 1 - m$
- **Clash-free**: does not contain a clash

- 1 Transform \mathcal{K} into NNF
- 2 Initialize the completion $\mathcal{S}_{\mathcal{K}} = \mathcal{K}$
- 3 Apply the following inference rules to $\mathcal{S}_{\mathcal{K}}$ until no more rules can be applied
- 4 We call a set of fuzzy statements $\mathcal{S}_{\mathcal{K}}$ **complete** iff none of the rules below can be applied to $\mathcal{S}_{\mathcal{K}}$
- 5 Note that rule (\vee) is non-deterministic
 - (\wedge). If $\langle \phi \wedge \psi, n \rangle \in \mathcal{S}_{\mathcal{K}}$ and $\{\langle \phi, n \rangle, \langle \psi, n \rangle\} \not\subseteq \mathcal{S}_{\mathcal{K}}$, then add both $\langle \phi, n \rangle$ and $\langle \psi, n \rangle$ to $\mathcal{S}_{\mathcal{K}}$
 - (\vee). If $\langle \phi \vee \psi, n \rangle \in \mathcal{S}_{\mathcal{K}}$ and $\{\langle \phi, n \rangle, \langle \psi, n \rangle\} \cap \mathcal{S}_{\mathcal{K}} = \emptyset$, then add either $\langle \phi, n \rangle$ or $\langle \psi, n \rangle$ to $\mathcal{S}_{\mathcal{K}}$
 - (\rightarrow). If $\langle \phi \rightarrow \psi, n \rangle \in \mathcal{S}_{\mathcal{K}}$ and $\langle nnf(\neg\phi) \vee \psi, n \rangle \notin \mathcal{S}_{\mathcal{K}}$, then add $\langle nnf(\neg\phi) \vee \psi, n \rangle$ to $\mathcal{S}_{\mathcal{K}}$

sat(\mathcal{K}): \mathcal{K} is satisfiable iff we find a complete and clash-free completion $\mathcal{S}_{\mathcal{K}}$ of \mathcal{K}

- For BED and BSD we need some more work
- Given \mathcal{K} , define

$$\begin{aligned}
 N^{\mathcal{K}} &= \{0, 0.5, 1\} \cup \{n \mid \langle \phi, n \rangle \in \mathcal{K}\} \\
 \bar{N}^{\mathcal{K}} &= N^{\mathcal{K}} \cup \{1 - n \mid n \in N^{\mathcal{K}}\} \\
 \epsilon &= \min\{d/2 \mid n, m \in \bar{N}^{\mathcal{K}}, n \neq m, d = |n - m|\}
 \end{aligned}$$

Proposition

Under SFL, given \mathcal{K} , then for $n > 0$

$\mathcal{K} \models \langle \phi, n \rangle$ iff $\mathcal{K} \cup \{\langle \neg\phi, 1 - n + \epsilon \rangle\}$ is not satisfiable .

Moreover, \mathcal{K} is satisfiable iff it has a model over $\bar{N}^{\mathcal{K}}$.

bed(\mathcal{K}, ϕ): Find greatest $n \in \bar{N}^{\mathcal{K}}$ such that $\mathcal{K} \models \langle \phi, n \rangle$

bsd(\mathcal{K}, ϕ): Find greatest $n \in \bar{N}^{\mathcal{K}}$ such that $\mathcal{K} \cup \{\langle \phi, n \rangle\}$ satisfiable

Non Deterministic Analytic Fuzzy Tableau

- Works for finitely-valued fuzzy propositional logic over L_n
- Works also for SFL (as in place of $[0, 1]$, we may use $\bar{N}^{\mathcal{K}}$)
- Basic idea is as for fuzzy tableau, but now we **guess** the truth degrees
 - (\wedge). If $\langle \phi \wedge \psi, n \rangle \in \mathcal{S}_{\mathcal{K}}$, $n_1, n_2 \in L_n$ such that $n_1 \otimes n_2 = n$ and $\{\langle \phi, n_1 \rangle, \langle \psi, n_2 \rangle\} \not\subseteq \mathcal{S}_{\mathcal{K}}$, then add both $\langle \phi, n_1 \rangle$ and $\langle \psi, n_2 \rangle$ to $\mathcal{S}_{\mathcal{K}}$
 - (\vee). If $\langle \phi \vee \psi, n \rangle \in \mathcal{S}_{\mathcal{K}}$, $n_1, n_2 \in L_n$ such that $n_1 \oplus n_2 = n$ and $\{\langle \phi, n_1 \rangle, \langle \psi, n_2 \rangle\} \not\subseteq \mathcal{S}_{\mathcal{K}}$, then add both $\langle \phi, n_1 \rangle$ and $\langle \psi, n_2 \rangle$ to $\mathcal{S}_{\mathcal{K}}$
 - (\rightarrow). If $\langle \phi \rightarrow \psi, n \rangle \in \mathcal{S}_{\mathcal{K}}$, $n_1, n_2 \in L_n$ such that $n_1 \Rightarrow n_2 = n$ and $\{\langle \phi, n_1 \rangle, \langle \psi, n_2 \rangle\} \not\subseteq \mathcal{S}_{\mathcal{K}}$, then add both $\langle \phi, n_1 \rangle$ and $\langle \psi, n_2 \rangle$ to $\mathcal{S}_{\mathcal{K}}$
- A **clash** is either
 - a fuzzy statement $\langle \perp, n \rangle$ with $n > 0$; or
 - a pair of fuzzy statements $\langle p, n \rangle$ and $\langle \neg p, m \rangle$ such that

$$x_p \geq n, \quad \ominus x_p \geq m, \quad x_p \in L_n$$

has no solution

Reduction to Classical Propositional Logic: Case SFL over $[0, 1]$

- Given \mathcal{K} , we know that we can use

$$L_n = \bar{N}^{\mathcal{K}} = \{\gamma_1, \dots, \gamma_n\}$$

with $\gamma_i < \gamma_{i+1}$, $1 \leq i \leq n-1$

- Basic idea: use atom $A_{\geq r}$ to represent

The truth degree of A has to be equal or greater than r

- Similarly for $A_{>r}$, $A_{\leq r}$ and $A_{<r}$

- To start with, build Crisp_{L_n}
 - For all atoms A , for all $1 \leq i \leq n-1, 2 \leq j \leq n-1$

$$A_{\geq \gamma_{i+1}} \rightarrow A_{> \gamma_i}$$

$$A_{> \gamma_j} \rightarrow A_{\geq \gamma_j}$$

- Build $\text{Crisp}_{\mathcal{K}}$:

$$\text{Crisp}_{\mathcal{K}} = \{\rho(\phi, n) \mid \langle \phi, n \rangle \in \mathcal{K}\} \cup \text{Crisp}_{L_n},$$

x	y	$\rho(x, y)$
\top	c	\top
\perp	0	\top
\perp	c	\perp if $c > 0$
A	c	$A_{> c}$
$\neg A$	c	$\neg A_{> 1-c}$
$\phi \wedge \psi$	c	$\rho(\phi, c) \wedge \rho(\psi, c)$
$\phi \vee \psi$	c	$\rho(\phi, c) \vee \rho(\psi, c)$

Proposition

Given \mathcal{K} under SFL over L_n , then $\mathcal{K} \models \langle \phi, c \rangle$ iff $\mathcal{K} \cup \{\langle \neg\phi, 1 - c^- \rangle\}$ is not satisfiable, where c^- is the next smaller value than c in L_n

sat(\mathcal{K}): \mathcal{K} is satisfiable iff *Crisp* $_{\mathcal{K}}$ satisfiable

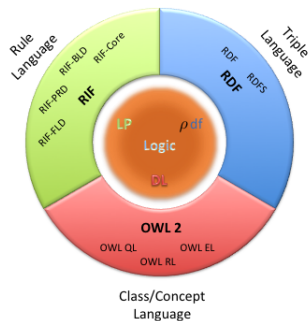
bed(\mathcal{K}, ϕ): Find greatest $c \in L_n$ such that $\mathcal{K} \models \langle \phi, c \rangle$

bsd(\mathcal{K}, ϕ): Find greatest $c \in L_n$ such that $\mathcal{K} \cup \{\langle \phi, c \rangle\}$ satisfiable

From Fuzzy to Annotated Semantic Web Languages

The Semantic Web Family of Languages

- Wide variety of languages
 - **RDFS**: *Triple language*, -Resource Description Framework
 - The logical counterpart is ρdf
 - **RIF**: *Rule language*, -Rule Interchange Format,
 - Relate to the *Logic Programming* (LP) paradigm
 - **OWL 2**: *Conceptual language*, -Ontology Web Language
 - Relate to **Description Logics** (DLs)



- **RDFS**: the triple language

$\langle \textit{subject}, \textit{predicate}, \textit{object} \rangle$

e.g. $\langle \textit{umberto}, \textit{born}, \textit{zurich} \rangle$

- Computationally: compute *closure*, $cl(\mathcal{K})$,
 - Infer all possible triples using inference rules, e.g.

$$\frac{(A, \textit{sc}, B), (X, \textit{type}, A)}{(X, \textit{type}, B)}$$

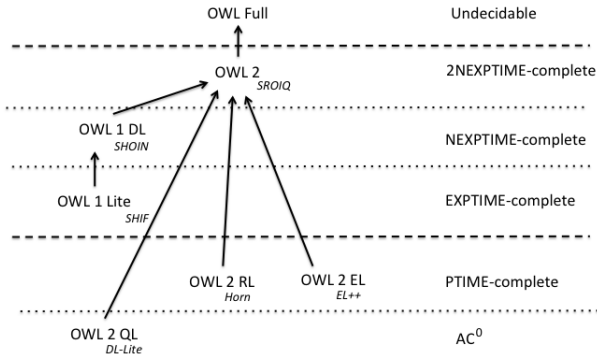
“if A subclass of B , X instance of A then X is instance of B ”

- Complexity: $\mathcal{O}(|\mathcal{K}|^2)$
- Store all inferred triples into a relational database and query via SQL

- **OWL 2** family: the object oriented language

```
class PERSON partial
  restriction (hasName someValuesFrom String)
  restriction (hasBirthPlace someValuesFrom GEOPLACE)
  ...
```

- Computationally: tableaux like algorithms



OWL 2 EL

- Useful for large size of properties and/or classes
- Basic reasoning problems solved in polynomial time
- The EL acronym refers to the \mathcal{EL} family of DLs

OWL 2 QL

- Useful for very large volumes of instance data
- Conjunctive query answering via query rewriting and SQL
- OWL 2 QL relates to the DL family *DL-Lite*

OWL 2 RL

- Useful for scalable reasoning without sacrificing too much expressive power
- OWL 2 RL maps to Datalog
- Computational complexity: same as for Datalog, polynomial in size of the data, EXPTIME w.r.t. size of knowledge base

- RIF/RuleML family: the rule language

```
forall ?Buyer ?Item ?Seller  
  buy(?Buyer ?Item ?Seller) :- sell(?Seller ?Item ?Buyer)
```

Important point: RDFS, OWL 2 and RIF/RuleML are logical languages

- RDFS: logic with intensional semantics
- OWL 2: relates to the Description Logics family
- RIF/RuleML: relates to the Logic Programming paradigm (e.g., Datalog, Datalog[±])
- OWL 2 and RIF/RuleML have extensional semantics
- We will address them from a logical point of view

The case of RDF

- Pairwise disjoint alphabets
 - **U** (RDFS URI references)
 - **B** (Blank nodes)
 - **L** (Literals)
- For simplicity we will denote unions of these sets simply concatenating their names
- We call elements in **UBL terms** (denoted t)
- We call elements in **B variables** (denoted x)

- **RDFS triple** (or **RDFS atom**):

$$(s, p, o) \in \mathbf{UBL} \times \mathbf{U} \times \mathbf{UBL}$$

- s is the **subject**
 - p is the **predicate**
 - o is the **object**
- Example:

(airplane, has, enginefault)

- ρ df (read rho-df, the ρ from restricted rdfs)
- ρ df is defined as the following subset of the RDFS vocabulary:

$$\rho\text{df} = \{\text{sp}, \text{sc}, \text{type}, \text{dom}, \text{range}\}$$

- (p, sp, q)
 - property p is a *sub property* of property q
- (c, sc, d)
 - class c is a *sub class* of class d
- (a, type, b)
 - a is of *type* b
- (p, dom, c)
 - *domain* of property p is c
- (p, range, c)
 - *range* of property p is c

- **RDF interpretation** \mathcal{I} over a vocabulary V is a tuple

$$\mathcal{I} = \langle \Delta_R, \Delta_P, \Delta_C, \Delta_L, P[\cdot], C[\cdot], \cdot^{\mathcal{I}} \rangle ,$$

where

- $\Delta_R, \Delta_P, \Delta_C, \Delta_L$ are the interpretations domains of \mathcal{I}
- $P[\cdot], C[\cdot], \cdot^{\mathcal{I}}$ are the interpretation functions of \mathcal{I}

$$\mathcal{I} = \langle \Delta_R, \Delta_P, \Delta_C, \Delta_L, P[\cdot], C[\cdot], \cdot^{\mathcal{I}} \rangle$$

- 1 Δ_R is a nonempty set of resources, called the domain or universe of \mathcal{I} ;
- 2 Δ_P is a set of property names (not necessarily disjoint from Δ_R);
- 3 $\Delta_C \subseteq \Delta_R$ is a distinguished subset of Δ_R identifying if a resource denotes a class of resources;
- 4 $\Delta_L \subseteq \Delta_R$, the set of literal values, Δ_L contains all plain literals in $\mathbf{L} \cap V$;
- 5 $P[\cdot]$ maps each property name $p \in \Delta_P$ into a subset $P[p] \subseteq \Delta_R \times \Delta_R$, i.e. assigns an extension to each property name;
- 6 $C[\cdot]$ maps each class $c \in \Delta_C$ into a subset $C[c] \subseteq \Delta_R$, i.e. assigns a set of resources to every resource denoting a class;
- 7 $\cdot^{\mathcal{I}}$ maps each $t \in \mathbf{UL} \cap V$ into a value $t^{\mathcal{I}} \in \Delta_R \cup \Delta_P$, i.e. assigns a resource or a property name to each element of \mathbf{UL} in V , and such that $\cdot^{\mathcal{I}}$ is the identity for plain literals and assigns an element in Δ_R to elements in \mathbf{L} ;
- 8 $\cdot^{\mathcal{I}}$ maps each variable $x \in \mathbf{B}$ into a value $x^{\mathcal{I}} \in \Delta_R$, i.e. assigns a resource to each variable in \mathbf{B} .

Intuitively,

- A ground triple (s, p, o) in an RDF graph G will be true under the interpretation \mathcal{I} if
 - p is interpreted as a property name
 - s and o are interpreted as resources
 - the interpretation of the pair (s, o) belongs to the extension of the property assigned to p
- Blank nodes, i.e. variables, work as existential variables: a triple $((x, p, o)$ with $x \in \mathbf{B}$ would be true under \mathcal{I} if
 - there exists a resource s such that (s, p, o) is true under \mathcal{I}

Let G be a graph over ρ df.

- An interpretation \mathcal{I} is a **model** of G under ρ df, denoted $\mathcal{I} \models G$, iff
 - \mathcal{I} is an interpretation over the vocabulary ρ df \cup $universe(G)$
 - \mathcal{I} satisfies the following conditions:

Simple:

- 1 for each $(s, p, o) \in G$, $p^{\mathcal{I}} \in \Delta_P$ and $(s^{\mathcal{I}}, o^{\mathcal{I}}) \in P[[p^{\mathcal{I}}]]$;

Subproperty:

- 1 $P[[sp^{\mathcal{I}}]]$ is transitive over Δ_P ;
- 2 if $(p, q) \in P[[sp^{\mathcal{I}}]]$ then $p, q \in \Delta_P$ and $P[[p]] \subseteq P[[q]]$;

Subclass:

- 1 $P[\text{sc}^I]$ is transitive over Δ_C ;
- 2 if $(c, d) \in P[\text{sc}^I]$ then $c, d \in \Delta_C$ and $C[c] \subseteq C[d]$;

Typing I:

- 1 $x \in C[c]$ iff $(x, c) \in P[\text{type}^I]$;
- 2 if $(p, c) \in P[\text{dom}^I]$ and $(x, y) \in P[p]$ then $x \in C[c]$;
- 3 if $(p, c) \in P[\text{range}^I]$ and $(x, y) \in P[p]$ then $y \in C[c]$;

Typing II:

- 1 For each $e \in \rho\text{df}$, $e^I \in \Delta_P$
- 2 if $(p, c) \in P[\text{dom}^I]$ then $p \in \Delta_P$ and $c \in \Delta_C$
- 3 if $(p, c) \in P[\text{range}^I]$ then $p \in \Delta_P$ and $c \in \Delta_C$
- 4 if $(x, c) \in P[\text{type}^I]$ then $c \in \Delta_C$

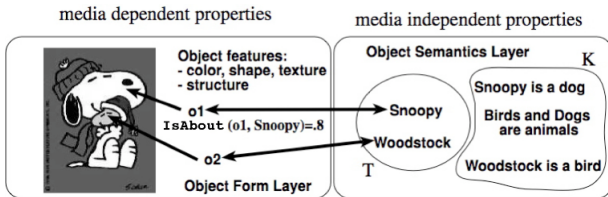
- G **entails** H under ρ df, denoted $G \models H$, iff
 - every model under ρ df of G is also a model under ρ df of H
- **Note:** often $P[[sp^I]]$ (resp. $C[[sc^I]]$) is also *reflexive* over Δ_P (resp. Δ_C)
 - We omit this requirement and, thus, do NOT support inferences such as

$$G \models (a, sp, a)$$

$$G \models (a, sc, a)$$

which anyway are of marginal interest

Example



$$G = \left\{ \begin{array}{ll} (o1, IsAbout, snoopy) & (o2, IsAbout, woodstock) \\ (snoopy, type, dog) & (woodstock, type, bird) \\ (dog, sc, animal) & (bird, sc, animal) \end{array} \right\}$$

Deduction System for RDF

1 Simple:

$$\frac{G}{G'} \text{ for } G' \subseteq G$$

2 Subproperty:

$$(a) \frac{(A, \text{sp}, B), (B, \text{sp}, C)}{(A, \text{sp}, C)} \quad (b) \frac{(A, \text{sp}, B), (X, A, Y)}{(X, B, Y)}$$

3 Subclass:

$$(a) \frac{(A, \text{sc}, B), (B, \text{sc}, C)}{(A, \text{sc}, C)} \quad (b) \frac{(A, \text{sc}, B), (X, \text{type}, A)}{(X, \text{type}, B)}$$

4 Typing:

$$(a) \frac{(A, \text{dom}, B), (X, A, Y)}{(X, \text{type}, B)} \quad (b) \frac{(A, \text{range}, B), (X, A, Y)}{(Y, \text{type}, B)}$$

5 Implicit Typing:

$$(a) \frac{(A, \text{dom}, B), (C, \text{sp}, A), (X, C, Y)}{(X, \text{type}, B)} \quad (b) \frac{(A, \text{range}, B), (C, \text{sp}, A), (X, C, Y)}{(Y, \text{type}, B)}$$

RDFS Query Answering

- We assume that a RDF graph G is *ground* and *closed*, i.e., G is closed under the application of the rules (2)-(5)
- **Conjunctive query**: is a Datalog-like rule of the form

$$q(\mathbf{x}) \leftarrow \exists \mathbf{y}. \tau_1, \dots, \tau_n$$

where

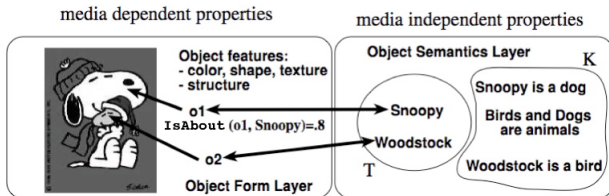
- $n \geq 1$, τ_1, \dots, τ_n are triples
 - \mathbf{x} is a vector of variables occurring in τ_1, \dots, τ_n , called the *distinguished variables*
 - \mathbf{y} are so-called *non-distinguished variables* and are distinct from the variables in \mathbf{x}
 - each variable occurring in τ_i is either a distinguished variable or a non-distinguished variable
- If clear from the context, we may omit the existential quantification $\exists \mathbf{y}$
 - For instance, the query

$$q(x, y) \leftarrow (x, \text{creates}, y), (x, \text{type}, \text{Flemish}), (x, \text{paints}, y), (y, \text{exhibited}, \text{Uffizi})$$

has intended meaning to retrieve all the artifacts x created by Flemish artists y , being exhibited at Uffizi Gallery

- A simple query answering procedure is the following:
 - Compute the closure of a graph off-line
 - Store the RDF triples into a Relational database
 - Translate the query into a SQL statement
 - Execute the SQL statement over the relational database
- In practice, some care should be in place due to the large size of data: $\geq 10^9$ triples
- To date, several systems exists

Example



$$G = \left\{ \begin{array}{ll} (o1, IsAbout, snoopy) & (o2, IsAbout, woodstock) \\ (snoopy, type, dog) & (woodstock, type, bird) \\ (dog, sc, animal) & (bird, sc, animal) \end{array} \right\}$$

Consider the query

$$q(x) \leftarrow (x, IsAbout, y), (y, type, Animal)$$

Then

$$answer(G, q) = \{o1, o2\}$$

- Triples may have attached a degree in $[0, 1]$: for $n \in [0, 1]$

$\langle (subject, predicate, object), n \rangle$

- Meaning: the degree of truth of the statement is at least n
- For instance,

$\langle (o1, IsAbout, snoopy), 0.8 \rangle$

- Fuzzy RDF triple (or Fuzzy RDF atom):

$$\langle \tau, n \rangle \in (\mathbf{UBL} \times \mathbf{U} \times \mathbf{UBL}) \times [0, 1]$$

- $s \in \mathbf{UBL}$ is the **subject**
 - $p \in \mathbf{U}$ is the **predicate**
 - $o \in \mathbf{UBL}$ is the **object**
 - $n \in (0, 1]$ is the **degree of truth**
- Example:

$$\langle (\text{audiTT}, \text{type}, \text{SportCar}), 0.8 \rangle$$

- Fix a t-norm \otimes
- **Fuzzy RDF interpretation** \mathcal{I} over a vocabulary V is a tuple

$$\mathcal{I} = \langle \Delta_R, \Delta_P, \Delta_C, \Delta_L, P[\cdot], C[\cdot], \cdot^{\mathcal{I}} \rangle,$$

where

- $\Delta_R, \Delta_P, \Delta_C, \Delta_L$ are the interpretation domains of \mathcal{I}
- $P[\cdot], C[\cdot], \cdot^{\mathcal{I}}$ are the interpretation functions of \mathcal{I}

$$\mathcal{I} = \langle \Delta_R, \Delta_P, \Delta_C, \Delta_L, P[\cdot], C[\cdot], \cdot^{\mathcal{I}} \rangle$$

- 1 Δ_R is a nonempty set of resources, called the domain or universe of \mathcal{I} ;
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- 3 $\Delta_C \subseteq \Delta_R$ is a distinguished subset of Δ_R identifying if a resource denotes a class of resources;
- 4 $\Delta_L \subseteq \Delta_R$, the set of literal values, Δ_L contains all plain literals in $\mathbf{L} \cap V$;
- 5 $P[\cdot]$ maps each property name $p \in \Delta_P$ into a function $P[p] : \Delta_R \times \Delta_R \rightarrow [0, 1]$, i.e. assigns a degree to each pair of resources, denoting the degree of being the pair an instance of the property p ;
- 6 $C[\cdot]$ maps each class $c \in \Delta_C$ into a function $C[c] : \Delta_R \rightarrow [0, 1]$, i.e. assigns a degree to every resource, denoting the degree of being the resource an instance of the class c ;
- 7 $\cdot^{\mathcal{I}}$ maps each $t \in \mathbf{UL} \cap V$ into a value $t^{\mathcal{I}} \in \Delta_R \cup \Delta_P$, i.e. assigns a resource or a property name to each element of \mathbf{UL} in V , and such that $\cdot^{\mathcal{I}}$ is the identity for plain literals and assigns an element in Δ_R to elements in \mathbf{L} ;
- 8 $\cdot^{\mathcal{I}}$ maps each variable $x \in \mathbf{B}$ into a value $x^{\mathcal{I}} \in \Delta_R$, i.e. assigns a resource to each variable in \mathbf{B} .

Let G be a graph over ρ df.

- An interpretation \mathcal{I} is a **model** of G under ρ df, denoted $\mathcal{I} \models G$, iff
 - \mathcal{I} is an interpretation over the vocabulary ρ df \cup $universe(G)$
 - \mathcal{I} satisfies the following conditions:

Simple:

- 1 for each $\langle (s, p, o), n \rangle \in G$, $p^{\mathcal{I}} \in \Delta_{\rho}$ and $P[[p^{\mathcal{I}}]](s^{\mathcal{I}}, o^{\mathcal{I}}) \geq n$;

Subproperty:

- 1 $P[[sp^{\mathcal{I}}]](p, q) \otimes P[[sp^{\mathcal{I}}]](q, r) \leq P[[sp^{\mathcal{I}}]](p, r)$;
- 2 $P[[p^{\mathcal{I}}]](x, y) \otimes P[[sp^{\mathcal{I}}]](p, q) \leq P[[q^{\mathcal{I}}]](x, y)$;

Subclass:

- 1 $P[\text{sc}^I](c, d) \otimes P[\text{sc}^I](d, e) \leq P[\text{sc}^I](c, e);$
- 2 $C[c^I](x) \otimes P[\text{sc}^I](c, d) \leq P[d^I](x);$

Typing I:

- 1 $C[c](x) = P[\text{type}^I](x, c);$
- 2 $P[\text{dom}^I](p, c) \otimes P[p](x, y) \leq C[c](x);$
- 3 $P[\text{range}^I](p, c) \otimes P[p](x, y) \leq C[c](y);$

Typing II:

- 1 For each $e \in \rho\text{df}$, $e^I \in \Delta_P$;
- 2 $P[\text{sp}^I](p, q)$ is defined only for $p, q \in \Delta_P$;
- 3 $C[\text{sc}^I](c, d)$ is defined only for $c, d \in \Delta_C$;
- 4 $P[\text{dom}^I](p, c)$ is defined only for $p \in \Delta_P$ and $c \in \Delta_C$;
- 5 $P[\text{range}^I](p, c)$ is defined only for $p \in \Delta_P$ and $c \in \Delta_C$;
- 6 $P[\text{type}^I](s, c)$ is defined only for $c \in \Delta_C$.

Example & Model

$G = \{ \langle \langle \text{audiTT}, \text{type}, \text{SportsCar} \rangle, 0.8 \rangle, \langle \langle \text{SportsCar}, \text{sc}, \text{PassengerCar} \rangle, 0.9 \rangle \}$

t-norm: Product

$\mathcal{I} = \langle \Delta_R, \Delta_P, \Delta_C, \Delta_L, P[\cdot], C[\cdot], \cdot^{\mathcal{I}} \rangle$

$\Delta_R = \{ \text{audiTT}, \text{SportsCar}, \text{PassengerCar} \}$

$\Delta_P = \{ \text{type}, \text{sc} \}$

$\Delta_C = \{ \text{SportsCar}, \text{PassengerCar} \}$

$P[\text{type}] = \{ \langle \langle \text{audiTT}, \text{SportsCar} \rangle, 0.8 \rangle, \langle \langle \text{audiTT}, \text{PassengerCar} \rangle, 0.72 \rangle \}$

$P[\text{sc}] = \{ \langle \langle \text{SportsCar}, \text{PassengerCar} \rangle, 0.9 \rangle \}$

$C[\text{SportsCar}] = \{ \langle \text{audiTT}, 0.8 \rangle \}$

$C[\text{PassengerCar}] = \{ \langle \text{audiTT}, 0.72 \rangle \}$

$t^{\mathcal{I}} = t$ for all $t \in \mathbf{UL}$

$\mathcal{I} \models G$

\mathcal{I} is a model of G

- Very simple:

$$(AG) \frac{\langle \tau_1, n_1 \rangle, \dots, \langle \tau_k, n_k \rangle, \{\tau_1, \dots, \tau_k\} \vdash_{RDFS} \tau}{\langle \tau, \bigotimes_i \lambda_i \rangle}$$

Deduction System for fuzzy RDFS

1 Simple:

$$\frac{G}{G'} \text{ for } G' \subseteq G$$

2 Subproperty:

$$(a) \quad \frac{\langle(A, \text{sp}, B), n\rangle, \langle(B, \text{sp}, C), m\rangle}{\langle(A, \text{sp}, C), n \otimes m\rangle} \quad (b) \quad \frac{\langle(A, \text{sp}, B), n\rangle, \langle(X, A, Y), m\rangle}{\langle(X, B, Y), n \otimes m\rangle}$$

3 Subclass:

$$(a) \quad \frac{\langle(A, \text{sc}, B), n\rangle, \langle(B, \text{sc}, C), m\rangle}{\langle(A, \text{sc}, C), n \otimes m\rangle} \quad (b) \quad \frac{\langle(A, \text{sc}, B), n\rangle, \langle(X, \text{type}, A), m\rangle}{\langle(X, \text{type}, B), n \otimes m\rangle}$$

4 Typing:

$$(a) \quad \frac{\langle(A, \text{dom}, B), n\rangle, \langle(X, A, Y), m\rangle}{\langle(X, \text{type}, B), n \otimes m\rangle} \quad (b) \quad \frac{\langle(A, \text{range}, B), n\rangle, \langle(X, A, Y), m\rangle}{\langle(Y, \text{type}, B), n \otimes m\rangle}$$

5 Implicit Typing:

$$(a) \quad \frac{\langle(A, \text{dom}, B), n\rangle, \langle(C, \text{sp}, A), m\rangle, \langle(X, C, Y), r\rangle}{\langle(X, \text{type}, B), n \otimes m \otimes r\rangle}$$
$$(b) \quad \frac{\langle(A, \text{range}, B), n\rangle, \langle(C, \text{sp}, A), m\rangle, \langle(X, C, Y), r\rangle}{\langle(Y, \text{type}, B), n \otimes m \otimes r\rangle}$$

Fuzzy RDFS Query Answering

- We assume that a fuzzy RDF graph G is *ground* and *closed*, i.e., G is closed under the application of the rules (2)-(5)
- **Conjunctive query**: extends a crisp RDF query and is of the form

$$\langle q(\mathbf{x}), s \rangle \leftarrow \exists \mathbf{y}. \langle \tau_1, s_1 \rangle, \dots, \langle \tau_n, s_n \rangle, s = f(s_1, \dots, s_n, p_1(\mathbf{z}_1), \dots, p_h(\mathbf{z}_h))$$

where additionally

- \mathbf{z}_i are tuples of terms in **UL** or variables in \mathbf{x} or \mathbf{y} ;
- p_j is an n_j -ary *fuzzy predicate* assigning to each n_j -ary tuple \mathbf{t}_j in **UL** a *score* $p_j(\mathbf{t}_j) \in [0, 1]$. Such predicates are called *expensive predicates* as the score is not pre-computed off-line, but is computed on query execution. We require that an n -ary fuzzy predicate p is *safe*, that is, there is not an m -ary fuzzy predicate p' such that $m < n$ and $p = p'$. Informally, all parameters are needed in the definition of p ;
- f is a *scoring function* $f: ([0, 1])^{n+h} \rightarrow [0, 1]$, which combines the scores s_i of the n triples and the h fuzzy predicates into an overall *score* to be assigned to the rule head. We assume that f is *monotone*, that is, for each $\mathbf{v}, \mathbf{v}' \in ([0, 1])^{n+h}$ such that $\mathbf{v} \leq \mathbf{v}'$, it holds $f(\mathbf{v}) \leq f(\mathbf{v}')$, where $(v_1, \dots, v_{n+h}) \leq (v'_1, \dots, v'_{n+h})$ iff $v_i \leq v'_i$ for all i ;
- the scoring variables s and s_i are distinct from those in \mathbf{x} and \mathbf{y} and s is distinct from each s_i
- If clear from the context, we may omit the existential quantification $\exists \mathbf{y}$
- We may omit s_i and in that case $s_i = 1$ is assumed
- $s = f(s_1, \dots, s_n, p_1(\mathbf{z}_1), \dots, p_h(\mathbf{z}_h))$ is called the *scoring atom*. We may also omit the scoring atom and in that case $s = 1$ is assumed.
- For instance, the query

$$\langle q(x), s \rangle \leftarrow \langle (x, \text{type}, \text{SportCar}), s_1 \rangle, \langle (x, \text{hasPrice}, y) \rangle, s = s_1 \cdot \text{cheap}(y)$$

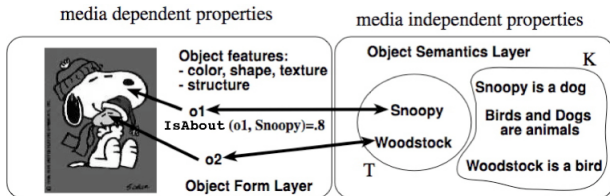
where e.g. $\text{cheap}(p) = \text{Is}(0, 10000, 12000)$, has intended meaning to retrieve all cheap sports car. Any answer is scored according to the product of being cheap and a sports car

Top-k Retrieval: Given a fuzzy graph G , and a query q , retrieve k answers $\langle \mathbf{t}, s \rangle$ with maximal scores and rank them in decreasing order relative to the score s , denoted

$$ans_k(G, q) = \text{Top}_k \text{ answer}(G, q)$$

- A simple query answering procedure is the following:
 - Compute the closure of a graph off-line
 - Store the fuzzy RDF triples into a relational database supporting Top-k retrieval (e.g., RankSQL, Postgres)
 - Translate the fuzzy query into a top-k SQL statement
 - Execute the SQL statement over the relational database
 - Few systems exists, e.g. FuzzyRDF, AnQL (<http://anql.deri.org/>)

Example



$$G = \left\{ \begin{array}{ll} \langle (o1, \text{IsAbout}, \text{snoopy}), 0.8 \rangle & \langle (o2, \text{IsAbout}, \text{woodstock}), 0.9 \rangle \\ (\text{snoopy}, \text{type}, \text{dog}) & (\text{woodstock}, \text{type}, \text{bird}) \\ \langle (\text{Bird}, \text{sc}, \text{SmallAnimal}), 0.7 \rangle & \langle (\text{Dog}, \text{sc}, \text{SmallAnimal}), 0.4 \rangle \\ (\text{dog}, \text{sc}, \text{Animal}) & (\text{bird}, \text{sc}, \text{Animal}) \\ (\text{SmallAnimal}, \text{sc}, \text{Animal}) & \end{array} \right\}$$

Consider the query

$$\langle q(x), s \rangle \leftarrow \langle (x, \text{IsAbout}, y), s_1 \rangle, \langle (y, \text{type}, \text{Animal}), s_2 \rangle, s = s_1 \cdot s_2$$

Then (under any t-norm)

$$\text{ans}(G, q) = \{ \langle o1, 0.32 \rangle, \langle o2, 0.63 \rangle \}, \quad \text{ans}_1(G, q) = \{ \langle o2, 0.63 \rangle \}$$

- Generalisation of fuzzy RDFS
 - a triple is annotated with a value λ taken from a so-called *annotation domain*, rather than with a value in $[0,1]$
 - allows to deal with several domains (such as, fuzzy, temporal, provenance) and their combination, in a uniform way
- Time
 - (*umberto*, *workedFor*, *IEI*)
 - true during 1992–2001
- Fuzzyness
 - (*WingateHotel*, *closeTo*, *RR11 Venue*)
 - true to some degree
- Provenance
 - (*umberto*, *knows*, *didier*)
 - **true** in `http://www.straccia.info/foaf.rdf`

- **Annotation Domain:** idempotent, commutative semi-ring

$$D = \langle L, \oplus, \otimes, \perp, \top \rangle$$

where \oplus is \top -annihilating, i.e.

- 1 \oplus is idempotent, commutative, associative;
 - 2 \otimes is commutative and associative;
 - 3 $\perp \oplus \lambda = \lambda$, $\top \otimes \lambda = \lambda$, $\perp \otimes \lambda = \perp$, and $\top \oplus \lambda = \top$;
 - 4 \otimes is distributive over \oplus , i.e. $\lambda_1 \otimes (\lambda_2 \oplus \lambda_3) = (\lambda_1 \otimes \lambda_2) \oplus (\lambda_1 \otimes \lambda_3)$;
- Induced partial order:

$$\lambda_1 \preceq \lambda_2 \iff \lambda_1 \oplus \lambda_2 = \lambda_2$$

- Annotated triple: for $\lambda \in L$

$$\langle (s, p, o), \lambda \rangle$$

- For instance,

$\langle (\textit{umberto}, \textit{workedFor}, \textit{IEI}), [1992, 2001] \rangle$

$\langle (\textit{WingateHotel}, \textit{closeTo}, \textit{RR11 Venue}), 0.8 \rangle$

$\langle (\textit{umberto}, \textit{knows}, \textit{didier}), \textit{http://www.straccia.info/foaf.rdf} \rangle$

Illustration by Example: Time

- An *Annotation Domain* consists of
 - A set L of annotation values
 - e.g. [1968, 2000] and {[1968, 2000], [2003, 2004]}
 - An order between elements:
 - if $\lambda \preceq \lambda'$, then $\langle \tau, \lambda \rangle$ is true to a lesser extent than $\langle \tau', \lambda' \rangle$
 - e.g. [1968, 2000] \preceq [1952, 2007] (\preceq is \subseteq)
 - Top and bottom elements:
 - $\top = [-\infty, +\infty]$, $\perp = \emptyset$
 - “Conjunction” function \otimes
 - [1992, 2001] \otimes [1968, 2000] = [1992, 2000] (\otimes is \cap)
 - “Combination” function \oplus
 - [1992, 2001] \oplus [1995, 2003] = [1992, 2003]
 - [1992, 1996] \oplus [2001, 2009] = {[1992, 1996], [2001, 2009]}

- **Fuzzy:** $\langle (WingateHotel, closeTo, RR11 Venue), 0.8 \rangle$
 - $L = [0, 1]$
 - $\otimes =$ any t-norm
 - $\vee = \max$
- **Provenance:** $\langle (umberto, knows, didier), p \rangle$
 - $L =$ DNF propositional formulae over URIs
 - $\otimes = \wedge$
 - $\vee = \vee$
- **Multiple Domains:** our frameworks allows to combine domains
 $\langle (CountryXXX, type, Dangerous), \langle [1975, 1983], 0.8, 0.6 \rangle \rangle$

Time \times *Fuzzy* \times *Trust*

- Inference rule:

$$\frac{\langle \tau_1, \lambda_1 \rangle, \dots, \langle \tau_k, \lambda_k, \{\tau_1, \dots, \tau_k\} \rangle \vdash_{\text{RDFS}} \tau}{\langle \tau, \bigotimes_i \lambda_i \rangle}$$

- Annotated conjunctive queries are as fuzzy queries, except that now variables s and s_i range over L in place of $[0, 1]$;
- A query answering procedure is similar as for the fuzzy case: compute the closure, store it on a relation database and transform an annotated CQ into a SQL query
- Computational complexity: same as for crisp RDFS plus the cost of \bigotimes , \bigoplus and the scoring function f in the body of a query
- A prototype Prolog implementation is available

<http://anql.deri.org/>

The case of Description Logics

Description Logics (DLs)

- **Concept/Class**: names are equivalent to unary predicates
 - In general, concepts equiv to formulae with one free variable
- **Role or attribute**: names are equivalent to binary predicates
 - In general, roles equiv to formulae with two free variables
- **Taxonomy**: Concept and role hierarchies can be expressed
- **Individual**: names are equivalent to constants
- **Operators**: restricted so that
 - Language is decidable and, if possible, of low complexity
 - No need for explicit use of variables
 - Restricted form of \exists and \forall
 - Features such as counting can be succinctly expressed

- **Basic ingredients:** descriptions of classes, properties, and their instances, such as

- $a:C$, meaning that individual a is an instance of concept/class C

$a:\text{Person} \sqcap \forall \text{hasChild.Femal}$

- $(a, b):R$, meaning that the pair of individuals $\langle a, b \rangle$ is an instance of the property/role R

$(\text{tom}, \text{mary}):\text{hasChild}$

- $C \sqsubseteq D$, meaning that the class C is a subclass of class D

$\text{Person} \sqsubseteq \forall \text{hasChild.Person}$

The DL Family

- A given DL is defined by set of concept and role forming operators
- Basic language: \mathcal{ALC} (*A*ttributive *L*anguage with *C*omplement)

Syntax	Semantics	Example
$C, D \rightarrow$	\top	$\top(x)$
	\perp	$\perp(x)$
	A	$A(x)$
	$C \sqcap D$	$C(x) \wedge D(x)$
	$C \sqcup D$	$C(x) \vee D(x)$
	$\neg C$	$\neg C(x)$
	$\exists R.C$	$\exists y. R(x, y) \wedge C(y)$
	$\forall R.C$	$\forall y. R(x, y) \Rightarrow C(y)$
$C \sqsubseteq D$	$\forall x. C(x) \Rightarrow D(x)$	$Happy_Father \sqsubseteq Man \sqcap \exists has_child.Female$
$a:C$	$C(a)$	$John:Happy_Father$

- Semantics is given in terms of an **interpretation** $\mathcal{I} = (\Delta^{\mathcal{I}}, \cdot^{\mathcal{I}})$, where
 - $\Delta^{\mathcal{I}}$ is the **domain** (a non-empty set)
 - $\cdot^{\mathcal{I}}$ is an **interpretation function** that maps:
 - **Concept** (class) name A into a subset $A^{\mathcal{I}}$ of $\Delta^{\mathcal{I}}$
 - **Role** (property) name R into a subset $R^{\mathcal{I}}$ of $\Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}}$
 - **Individual** name a into an element of $\Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}}$ s.t. $a^{\mathcal{I}} \neq b^{\mathcal{I}}$ if $a \neq b$ (UNA)
 - Interpretation function $\cdot^{\mathcal{I}}$ is extended to concept expressions:

$$\begin{aligned}\top^{\mathcal{I}} &= \Delta^{\mathcal{I}} \\ \perp^{\mathcal{I}} &= \emptyset \\ (C_1 \sqcap C_2)^{\mathcal{I}} &= C_1^{\mathcal{I}} \cap C_2^{\mathcal{I}} \\ (C_1 \sqcup C_2)^{\mathcal{I}} &= C_1^{\mathcal{I}} \cup C_2^{\mathcal{I}} \\ (\neg C)^{\mathcal{I}} &= \Delta^{\mathcal{I}} \setminus C^{\mathcal{I}} \\ (\exists R.C)^{\mathcal{I}} &= \{x \in \Delta^{\mathcal{I}} \mid \exists y. \langle x, y \rangle \in R^{\mathcal{I}} \wedge y \in C^{\mathcal{I}}\} \\ (\forall R.C)^{\mathcal{I}} &= \{x \in \Delta^{\mathcal{I}} \mid \forall y. \langle x, y \rangle \in R^{\mathcal{I}} \Rightarrow y \in C^{\mathcal{I}}\}\end{aligned}$$

- Finally, we say that
 - \mathcal{I} is a model of $C \sqsubseteq D$, written $\mathcal{I} \models C \sqsubseteq D$, iff $C^{\mathcal{I}} \subseteq D^{\mathcal{I}}$
 - \mathcal{I} is a model of $a:C$, written $\mathcal{I} \models a:C$, iff $a^{\mathcal{I}} \in C^{\mathcal{I}}$
 - \mathcal{I} is a model of $(a, b):R$, written $\mathcal{I} \models (a, b):R$, iff $\langle a^{\mathcal{I}}, b^{\mathcal{I}} \rangle \in R^{\mathcal{I}}$

Note on DL Naming

\mathcal{AL} : $C, D \rightarrow \top \mid \perp \mid A \mid C \sqcap D \mid \neg A \mid \exists R.T \mid \forall R.C$

C : Concept negation, $\neg C$. Thus, $\mathcal{ALC} = \mathcal{AL} + C$

S : Used for \mathcal{ALC} with transitive roles \mathcal{R}_+

U : Concept disjunction, $C_1 \sqcup C_2$

\mathcal{E} : Existential quantification, $\exists R.C$

\mathcal{H} : Role inclusion axioms, $R_1 \sqsubseteq R_2$, e.g. *is_component_of* \sqsubseteq *is_part_of*

\mathcal{N} : Number restrictions, $(\geq n R)$ and $(\leq n R)$, e.g. $(\geq 3 \text{ has_Child})$ (has at least 3 children)

\mathcal{Q} : Qualified number restrictions, $(\geq n R.C)$ and $(\leq n R.C)$, e.g. $(\leq 2 \text{ has_Child.Adult})$ (has at most 2 adult children)

\mathcal{O} : Nominals (singleton class), $\{a\}$, e.g. $\exists \text{has_child}.\{mary\}$.

Note: $a:C$ equiv to $\{a\} \sqsubseteq C$ and $(a, b):R$ equiv to $\{a\} \sqsubseteq \exists R.\{b\}$

\mathcal{I} : Inverse role, R^- , e.g. *isPartOf* = *hasPart*⁻

\mathcal{F} : Functional role, f , e.g. *functional(hasAge)*

\mathcal{R}_+ : transitive role, e.g. *transitive(isPartOf)*

For instance,

$$\begin{aligned} SHIF &= S + \mathcal{H} + \mathcal{I} + \mathcal{F} = \mathcal{ALCR}_+HIF && \text{OWL-Lite} \\ SHOIN &= S + \mathcal{H} + \mathcal{O} + \mathcal{I} + \mathcal{N} = \mathcal{ALCR}_+HOIN && \text{OWL-DL} \\ SROIQ &= S + \mathcal{R} + \mathcal{O} + \mathcal{I} + \mathcal{Q} = \mathcal{ALCR}_+ROIQ && \text{OWL 2} \end{aligned}$$

Semantics of Additional Constructs

- \mathcal{H} : Role inclusion axioms, $\mathcal{I} \models R_1 \sqsubseteq R_2$ iff $R_1^{\mathcal{I}} \subseteq R_2^{\mathcal{I}}$
- \mathcal{N} : Number restrictions, $(\geq n R)^{\mathcal{I}} = \{x \in \Delta^{\mathcal{I}} : |\{y \mid \langle x, y \rangle \in R^{\mathcal{I}}\}| \geq n\}$,
 $(\leq n R)^{\mathcal{I}} = \{x \in \Delta^{\mathcal{I}} : |\{y \mid \langle x, y \rangle \in R^{\mathcal{I}}\}| \leq n\}$
- \mathcal{Q} : Qualified number restrictions,
 $(\geq n R.C)^{\mathcal{I}} = \{x \in \Delta^{\mathcal{I}} : |\{y \mid \langle x, y \rangle \in R^{\mathcal{I}} \wedge y \in C^{\mathcal{I}}\}| \geq n\}$,
 $(\leq n R.C)^{\mathcal{I}} = \{x \in \Delta^{\mathcal{I}} : |\{y \mid \langle x, y \rangle \in R^{\mathcal{I}} \wedge y \in C^{\mathcal{I}}\}| \leq n\}$
- \mathcal{O} : Nominals (singleton class), $\{a\}^{\mathcal{I}} = \{a^{\mathcal{I}}\}$
- \mathcal{I} : Inverse role, $(R^-)^{\mathcal{I}} = \{\langle x, y \rangle \mid \langle y, x \rangle \in R^{\mathcal{I}}\}$
- \mathcal{F} : Functional role, $\mathcal{I} \models \text{fun}(f)$ iff $\forall x \forall y \forall z$ if $\langle x, y \rangle \in f^{\mathcal{I}}$ and $\langle x, z \rangle \in f^{\mathcal{I}}$ then $y = z$
- \mathcal{R}_+ : transitive role, $(R_+)^{\mathcal{I}} = \{\langle x, y \rangle \mid \exists z \text{ such that } \langle x, z \rangle \in R^{\mathcal{I}} \wedge \langle z, y \rangle \in R^{\mathcal{I}}\}$

- **Concrete domains:** reals, integers, strings, ...

(tim, 14):hasAge

(sf, "SoftComputing"):hasAcronym

(source1, "ComputerScience"):isAbout

(service2, "InformationRetrievalTool"):Matches

Minor = Person $\sqcap \exists hasAge. \leq_{18}$

- Semantics: a clean separation between "object" classes and concrete domains
 - $D = \langle \Delta_D, \Phi_D \rangle$
 - Δ_D is an interpretation domain
 - Φ_D is the set of concrete domain predicates d with a predefined arity n and **fixed** interpretation $d^D \subseteq \Delta_D^n$
 - Concrete properties: $R^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}} \times \Delta_D$
- Notation: (D) . E.g., $\mathcal{ALC}(D)$ is \mathcal{ALC} + concrete domains

- A DL **Knowledge Base** is a pair $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$, where
 - \mathcal{T} is a **TBox**
 - containing general inclusion axioms of the form $C \sqsubseteq D$,
 - concept definitions of the form $A = C$
 - primitive concept definitions of the form $A \sqsubseteq C$
 - role inclusions of the form $R \sqsubseteq P$
 - role equivalence of the form $R = P$
 - \mathcal{A} is a **ABox**
 - containing assertions of the form $a:C$
 - containing assertions of the form $(a, b):R$
- An interpretation \mathcal{I} is a model of \mathcal{K} , written $\mathcal{I} \models \mathcal{K}$ iff $\mathcal{I} \models \mathcal{T}$ and $\mathcal{I} \models \mathcal{A}$, where
 - $\mathcal{I} \models \mathcal{T}$ (\mathcal{I} is a model of \mathcal{T}) iff \mathcal{I} is a model of each element in \mathcal{T}
 - $\mathcal{I} \models \mathcal{A}$ (\mathcal{I} is a model of \mathcal{A}) iff \mathcal{I} is a model of each element in \mathcal{A}

Basic Inference Problems (Formally)

Consistency: Check if knowledge is meaningful

- Is \mathcal{K} satisfiability? \mapsto Is there some model \mathcal{I} of \mathcal{K} ?
- Is C satisfiability? $\mapsto C^{\mathcal{I}} \neq \emptyset$ for some some model \mathcal{I} of \mathcal{K} ?

Subsumption: structure knowledge, compute taxonomy

- $\mathcal{K} \models C \sqsubseteq D$? \mapsto Is it true that $C^{\mathcal{I}} \subseteq D^{\mathcal{I}}$ for all models \mathcal{I} of \mathcal{K} ?

Equivalence: check if two classes denote same set of instances

- $\mathcal{K} \models C = D$? \mapsto Is it true that $C^{\mathcal{I}} = D^{\mathcal{I}}$ for all models \mathcal{I} of \mathcal{K} ?

Instantiation: check if individual a instance of class C

- $\mathcal{K} \models a:C$? \mapsto Is it true that $a^{\mathcal{I}} \in C^{\mathcal{I}}$ for all models \mathcal{I} of \mathcal{K} ?

Retrieval: retrieve set of individuals that instantiate C

- Compute the set $\{a \mid \mathcal{K} \models a:C\}$

Reduction to Satisfiability

Problems are all **reducible** to KB satisfiability

Subsumption: $\mathcal{K} \models C \sqsubseteq D$ iff $\langle \mathcal{T}, \mathcal{A} \cup \{a:C \sqcap \neg D\} \rangle$ not satisfiable,
where a is a new individual

Equivalence: $\mathcal{K} \models C = D$ iff $\mathcal{K} \models C \sqsubseteq D$ and $\mathcal{K} \models D \sqsubseteq C$

Instantiation: $\mathcal{K} \models a:C$ iff $\langle \mathcal{T}, \mathcal{A} \cup \{a:\neg C\} \rangle$ not satisfiable

Retrieval: The computation of the set $\{a \mid \mathcal{K} \models a:C\}$ is reducible to the instance checking problem

- OWL 2: **tableaux** based algorithms
- OWL 2 EL: **structural** based algorithms
- OWL 2 QL: **query rewriting** based algorithms
- OWL 2 RL: **logic programming** based algorithms

- Tableaux algorithm deciding satisfiability
- Try to build a **tree-like model** \mathcal{I} of the KB
- Decompose concepts C syntactically
 - Apply tableau **expansion rules**
 - Infer constraints on elements of model
- Tableau rules correspond to constructors in logic (\sqcap, \sqcup, \dots)
 - Some rules are **nondeterministic** (e.g., \sqcup, \leq)
 - In practice, this means **search**
- Stop when no more rules applicable or **clash** occurs
 - Clash is an obvious contradiction, e.g., $A(x), \neg A(x)$
- Cycle check (**blocking**) may be needed for termination

Negation Normal Form (NNF)

- We have to transform concepts into **Negation Normal Form**: push negation inside using de Morgan' laws

$$\begin{aligned}\neg \top &\mapsto \perp \\ \neg \perp &\mapsto \top \\ \neg \neg C &\mapsto C \\ \neg(C_1 \sqcap C_2) &\mapsto \neg C_1 \sqcup \neg C_2 \\ \neg(C_1 \sqcup C_2) &\mapsto \neg C_1 \sqcap \neg C_2\end{aligned}$$

and

$$\begin{aligned}\neg(\exists R.C) &\mapsto \forall R.\neg C \\ \neg(\forall R.C) &\mapsto \exists R.\neg C\end{aligned}$$

Completion-Forest

- This is a forest of trees, where
 - each node x is labelled with a set $\mathcal{L}(x)$ of concepts
 - each edge $\langle x, y \rangle$ is labelled with $\mathcal{L}(\langle x, y \rangle) = \{R\}$ for some role R (edges correspond to relationships between pairs of individuals)
- The forest is initialized with
 - a root node a , labelled $\mathcal{L}(a) = \emptyset$ for each individual a occurring in the KB
 - an edge $\langle a, b \rangle$ labelled $\mathcal{L}(\langle a, b \rangle) = \{R\}$ for each $(a, b):R$ occurring in the KB
- Then, for each $a:C$ occurring in the KB, set $\mathcal{L}(a) \rightarrow \mathcal{L}(a) \cup \{C\}$
- The algorithm expands the tree either by extending $\mathcal{L}(x)$ for some node x or by adding new leaf nodes.
- Edges are added when expanding $\exists R.C$
- A completion-forest contains a **clash** if, for a node x , $\{C, \neg C\} \subseteq \mathcal{L}(x)$
- If nodes x and y are connected by an edge $\langle x, y \rangle$, then y is called a successor of x and x is called a predecessor of y . Ancestor is the transitive closure of predecessor.
- A node y is called an R -successor of a node x if y is a successor of x and $\mathcal{L}(\langle x, y \rangle) = \{R\}$.
- The algorithm returns "satisfiable" if rules can be applied s.t. they yield a clash-free, complete (no more rules can be applied) completion forest

Rule	Description
(\sqcap)	if 1. $C_1 \sqcap C_2 \in \mathcal{L}(x)$ and 2. $\{C_1, C_2\} \not\subseteq \mathcal{L}(x)$ then $\mathcal{L}(x) \rightarrow \mathcal{L}(x) \cup \{C_1, C_2\}$
(\sqcup)	if 1. $C_1 \sqcup C_2 \in \mathcal{L}(x)$ and 2. $\{C_1, C_2\} \cap \mathcal{L}(x) = \emptyset$ then $\mathcal{L}(x) \rightarrow \mathcal{L}(x) \cup \{C\}$ for some $C \in \{C_1, C_2\}$
(\exists)	if 1. $\exists R.C \in \mathcal{L}(x)$ and 2. x has no R -successor y with $C \in \mathcal{L}(y)$ then create a new node y with $\mathcal{L}(\langle x, y \rangle) = \{R\}$ and $\mathcal{L}(y) = \{C\}$
(\forall)	if 1. $\forall R.C \in \mathcal{L}(x)$ and 2. x has an R -successor y with $C \notin \mathcal{L}(y)$ then $\mathcal{L}(y) \rightarrow \mathcal{L}(y) \cup \{C\}$

Example

Is $\exists R.C \sqcap \forall R.(\neg C \sqcup \neg D) \sqcap \exists R.D$ satisfiable? Yes.

$$\mathcal{L}(x) = \{\exists R.C \sqcap \forall R.(\neg C \sqcup \neg D) \sqcap \exists R.D\}$$

x

Example

Is $\exists R.C \sqcap \forall R.(\neg C \sqcup \neg D) \sqcap \exists R.D$ satisfiable? Yes.

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x

Example

Is $\exists R.C \sqcap \forall R.(\neg C \sqcup \neg D) \sqcap \exists R.D$ satisfiable? Yes.

$$\mathcal{L}(x) = \{\exists R.C, \forall R.(\neg C \sqcup \neg D), \exists R.D\}$$

x

Example

Is $\exists R.C \sqcap \forall R.(\neg C \sqcup \neg D) \sqcap \exists R.D$ satisfiable? Yes.

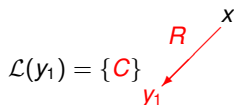
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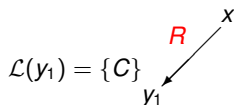
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
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
$$\mathcal{L}(x) = \{\exists R.C, \forall R.(\neg C \sqcup \neg D), \exists R.D\}$$

$$\mathcal{L}(y_1) = \{C, \neg C \sqcup \neg D\}$$


Example

Is $\exists R.C \sqcap \forall R.(\neg C \sqcup \neg D) \sqcap \exists R.D$ satisfiable? Yes.

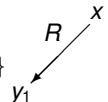
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Example

Is $\exists R.C \sqcap \forall R.(\neg C \sqcup \neg D) \sqcap \exists R.D$ satisfiable? Yes.

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$$\mathcal{L}(y_1) = \{C, \neg C \sqcup \neg D, \neg C\}$$


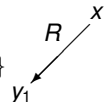
Example

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
Clash



Example

Is $\exists R.C \sqcap \forall R.(\neg C \sqcup \neg D) \sqcap \exists R.D$ satisfiable? Yes.

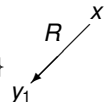
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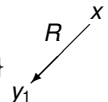
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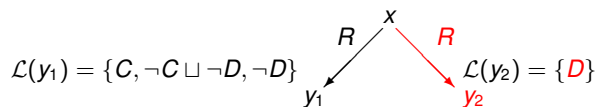
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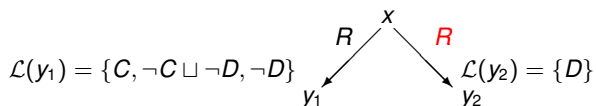
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Example

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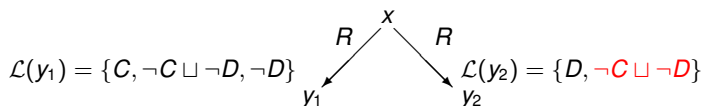
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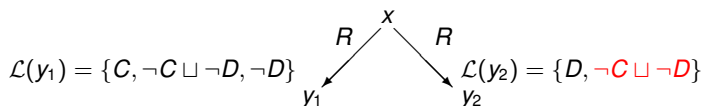
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Example

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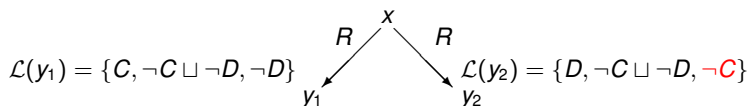
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Is $\exists R.C \sqcap \forall R.(\neg C \sqcup \neg D) \sqcap \exists R.D$ satisfiable? Yes.

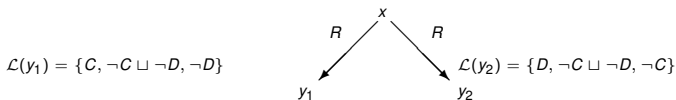
$$\mathcal{L}(x) = \{\exists R.C, \forall R.(\neg C \sqcup \neg D), \exists R.D\}$$



Example

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- Finished. No more rules applicable and the tableau is complete and clash-free
- Hence, the concept is **satisfiable**
- The tree corresponds to a **model** $\mathcal{I} = (\Delta^{\mathcal{I}}, \cdot^{\mathcal{I}})$
 - The nodes are the elements of the domain: $\Delta^{\mathcal{I}} = \{x, y_1, y_2\}$
 - For each atomic concept A , set $A^{\mathcal{I}} = \{z \mid A \in \mathcal{L}(z)\}$
 - $C^{\mathcal{I}} = \{y_1\}, D^{\mathcal{I}} = \{y_2\}$
 - For each role R , set $R^{\mathcal{I}} = \{\langle x, y \rangle \mid \text{there is an edge labeled } R \text{ from } x \text{ to } y\}$
 - $R^{\mathcal{I}} = \{\langle x, y_1 \rangle, \langle x, y_2 \rangle\}$
 - It can be shown that $x \in (\exists R.C \sqcap \forall R.(\neg C \sqcup \neg D) \sqcap \exists R.D)^{\mathcal{I}} \neq \emptyset$

Theorem

Let \mathcal{A} be an \mathcal{ALC} ABox and F a completion-forest obtained by applying the tableau rules to \mathcal{A} . Then

- 1 The rule application terminates;*
- 2 If F is clash-free and complete, then F defines a (canonical) (tree) model for \mathcal{A} ; and*
- 3 If \mathcal{A} has a model \mathcal{I} , then the rules can be applied such that they yield a clash-free and complete completion-forest.*

- We have seen how to test the satisfiability of an ABox \mathcal{A}
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 - E.g., consider $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$

$$\mathcal{T} = \{Human \sqsubseteq \exists hasMother. Human\}$$

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umberto

Clash

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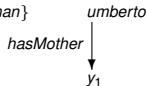
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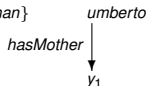


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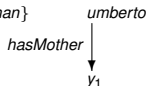


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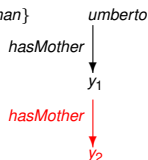
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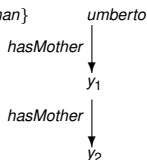
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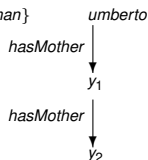
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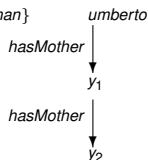
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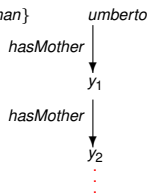
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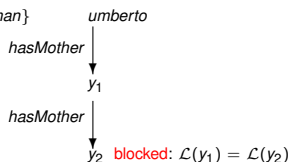
Node Blocking in \mathcal{ALC}

- When creating new node, check ancestors for equal label set
- If such a node is found, new node is **blocked**
- No rule is applied to blocked nodes

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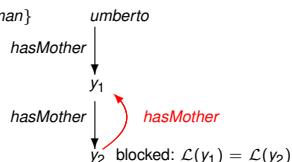
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- Block represents **cyclical** model
 - $\Delta^{\mathcal{I}} = \{umberto, y_1, y_2\}$
 - $Human^{\mathcal{I}} = \{umberto, y_1, y_2\}$
 - $hasMother^{\mathcal{I}} = \{\langle umberto, y_1 \rangle, \langle y_1, y_2 \rangle, \langle y_2, y_1 \rangle\}$

- A non-root node x is blocked if for some ancestor y , y is blocked or $\mathcal{L}(x) = \mathcal{L}(y)$, where y is not a root node
- A blocked node x is indirectly blocked if its predecessor is blocked, otherwise it is directly blocked
- If x is directly blocked, it has a unique ancestor y such that $\mathcal{L}(x) = \mathcal{L}(y)$
- if there existed another ancestor z such that $\mathcal{L}(x) = \mathcal{L}(z)$ then either y or z must be blocked
- If x is directly blocked and y is the unique ancestor such that $\mathcal{L}(x) = \mathcal{L}(y)$, we will say that y blocks x

Rule	Description
(\sqcap)	if 1. $C_1 \sqcap C_2 \in \mathcal{L}(x)$, x is not indirectly blocked and 2. $\{C_1, C_2\} \not\subseteq \mathcal{L}(x)$ then $\mathcal{L}(x) \rightarrow \mathcal{L}(x) \cup \{C_1, C_2\}$
(\sqcup)	if 1. $C_1 \sqcup C_2 \in \mathcal{L}(x)$, x is not indirectly blocked and 2. $\{C_1, C_2\} \cap \mathcal{L}(x) = \emptyset$ then $\mathcal{L}(x) \rightarrow \mathcal{L}(x) \cup \{C\}$ for some $C \in \{C_1, C_2\}$
(\exists)	if 1. $\exists R.C \in \mathcal{L}(x)$, x is not blocked and 2. x has no R -successor y with $C \in \mathcal{L}(y)$ then create a new node y with $\mathcal{L}(\langle x, y \rangle) = \{R\}$ and $\mathcal{L}(y) = \{C\}$
(\forall)	if 1. $\forall R.C \in \mathcal{L}(x)$, x is not indirectly blocked and 2. x has an R -successor y with $C \notin \mathcal{L}(y)$ then $\mathcal{L}(y) \rightarrow \mathcal{L}(y) \cup \{C\}$
(\sqsubseteq)	if 1. $C \sqsubseteq D \in \mathcal{T}$, x is not indirectly blocked and 2. $\{nnf(\neg C), D\} \cap \mathcal{L}(x) = \emptyset$ then $\mathcal{L}(x) \rightarrow \mathcal{L}(x) \cup \{E\}$ for some $E \in \{nnf(\neg C), D\}$ ($nnf(\neg C)$ is NNF of $\neg C$)

Theorem

Let \mathcal{K} be an \mathcal{ALC} KB and F a completion-forest obtained by applying the tableau rules to \mathcal{K} . Then

- 1 The rule application terminates;*
- 2 If F is clash-free and complete, then F defines a (canonical) (tree) model for \mathcal{K} ; and*
- 3 If \mathcal{K} has a model \mathcal{I} , then the rules can be applied such that they yield a clash-free and complete completion-forest.*

- We have seen how to “fuzzify” classical sets and FOL
 - Fuzzy statements are of the form $\langle \phi, n \rangle$, where ϕ is a statement and $n \in [0, 1]$
- The natural extension to fuzzy DLs consists then in replacing ϕ with a DL expression
- Several **fuzzy** variants of DLs have been proposed: they can be classified according to
 - The DL resp. ontology language that they generalize
 - The allowed fuzzy constructs
 - The underlying fuzzy logic
 - Their reasoning algorithms and computational complexity results

- In classical DLs, a concept C is interpreted by an interpretation \mathcal{I} as a set of individuals
- In fuzzy DLs, a concept C is interpreted by \mathcal{I} as a fuzzy set of individuals
- Each individual is instance of a concept to a degree in $[0, 1]$
- Each pair of individuals is instance of a role to a degree in $[0, 1]$

- $\langle a:C, n \rangle$ states that a is an instance of concept/class C with degree at least n
- $\langle (a, b):R, n \rangle$ states that $\langle a, b \rangle$ is an instance of relation R with degree at least n
- $\langle C_1 \sqsubseteq C_2, n \rangle$ states a vague subsumption relationship
 - The FOL statement $\forall x. C_1(x) \rightarrow C_2(x)$ is true to degree at least n
- **Note:** one may find also fuzzy DL expressions $\langle \alpha \geq n \rangle$, $\langle \alpha \leq n \rangle$, $\langle \alpha > n \rangle$, $\langle \alpha < n \rangle$, and $\langle \alpha = n \rangle$
- We use the form $\langle \alpha, n \rangle$, i.e. $\langle \alpha \geq n \rangle$ only
 - Remind that graded axioms are intended to be produced semi- or automatically
 - Hardly they may have the form $\langle \alpha \leq n \rangle$, $\langle \alpha > n \rangle$ or $\langle \alpha < n \rangle$

The semantics is an immediate consequence of the First-Order-Logic translation of DLs expressions

Interpretation:

\mathcal{I}	=	$\Delta^{\mathcal{I}}$	\otimes	=	t-norm
$C^{\mathcal{I}}$:	$\Delta^{\mathcal{I}} \rightarrow [0, 1]$	\oplus	=	s-norm
$R^{\mathcal{I}}$:	$\Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}} \rightarrow [0, 1]$	\neg	=	negation
			\Rightarrow	=	implication

	Syntax	Semantics
Concepts:	$C, D \longrightarrow \top$	$\top^{\mathcal{I}}(x) = 1$
	\perp	$\perp^{\mathcal{I}}(x) = 0$
	A	$A^{\mathcal{I}}(x) \in [0, 1]$
	$C \sqcap D$	$(C \sqcap D)^{\mathcal{I}}(x) = C_1^{\mathcal{I}}(x) \otimes C_2^{\mathcal{I}}(x)$
	$C \sqcup D$	$(C \sqcup D)^{\mathcal{I}}(x) = C_1^{\mathcal{I}}(x) \oplus C_2^{\mathcal{I}}(x)$
	$C \rightarrow D$	$(C \rightarrow D)^{\mathcal{I}}(x) = C^{\mathcal{I}}(x) \Rightarrow D^{\mathcal{I}}(x)$
	$\neg C$	$(\neg C)^{\mathcal{I}}(x) = \neg C^{\mathcal{I}}(x)$
	$\exists R.C$	$(\exists R.C)^{\mathcal{I}}(x) = \sup_{y \in \Delta^{\mathcal{I}}} R^{\mathcal{I}}(x, y) \otimes C^{\mathcal{I}}(y)$
	$\forall R.C$	$(\forall R.C)^{\mathcal{I}}(x) = \inf_{y \in \Delta^{\mathcal{I}}} R^{\mathcal{I}}(x, y) \Rightarrow C^{\mathcal{I}}(y)$
	$\{a\}$	$\{a\}^{\mathcal{I}}(x) = 1$ if $a^{\mathcal{I}} = x$, else 0

Assertions: $\langle a:C, r \rangle, \mathcal{I} \models \langle a:C, r \rangle$ iff $C^{\mathcal{I}}(a^{\mathcal{I}}) \geq r$ (similarly for roles)

General Inclusion Axioms: $\langle C \sqsubseteq D, r \rangle,$

● $\mathcal{I} \models \langle C \sqsubseteq D, r \rangle$ iff $\inf_{x \in \Delta^{\mathcal{I}}} C^{\mathcal{I}}(x) \Rightarrow D^{\mathcal{I}}(x) \geq r$

Some Remarks

- Like for fuzzy FOL, \forall and \exists are not complementary in general:
i.e. $\forall R.C \neq \neg \exists R.\neg C$
- $\forall R.C \equiv \neg \exists R.\neg C$ under Łukasiewicz logic and SFL
- $\langle C \sqsubseteq D, n \rangle$ may be rewritten as $\langle \top \sqsubseteq C \rightarrow D, n \rangle$
- In early works, a fuzzy GCI is of the form $C \sqsubseteq D$ with semantics:
 - \mathcal{I} is a model of $C \sqsubseteq D$ iff for every $x \in \Delta^{\mathcal{I}}$ we have that $C^{\mathcal{I}}(x) \leq D^{\mathcal{I}}(x)$
 - This is the same of fuzzy axiom $\langle \top \sqsubseteq C \rightarrow_x D, 1 \rangle$, where \rightarrow_x is an r -implication
- **Disjointness**: use $\langle C \sqcap D \sqsubseteq \perp, 1 \rangle$ rather than $\langle C \sqsubseteq \neg D, 1 \rangle$
 - they are not the same, e.g. $\langle A \sqsubseteq \neg A, 1 \rangle$ says that $A^{\mathcal{I}}(x) \leq 0.5$, for all \mathcal{I} and for all $x \in \Delta^{\mathcal{I}}$

- **Witnessed Interpretation:**
 - Infima and suprema are attained at some point

$$(\exists R.C)^{\mathcal{I}}(x) = R^{\mathcal{I}}(x, y) \otimes C^{\mathcal{I}}(y) \text{ for some } y \in \Delta^{\mathcal{I}}$$

$$(\forall R.C)^{\mathcal{I}}(x) = R^{\mathcal{I}}(x, y) \Rightarrow C^{\mathcal{I}}(y) \text{ for some } y \in \Delta^{\mathcal{I}}$$

$$(C \sqsubseteq D)^{\mathcal{I}} = C^{\mathcal{I}}(x) \Rightarrow D^{\mathcal{I}}(x) \text{ for some } x \in \Delta^{\mathcal{I}}$$

- It is customary to stick to witnessed interpretations only

- **Fuzzy knowledge base:** $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$
 - \mathcal{T} is a **fuzzy TBox**, that is a finite set of fuzzy GCI
 - \mathcal{A} is a **fuzzy ABox**, that is a finite set of fuzzy assertions
- **Acyclic fuzzy ontologies:** TBox with axioms of the form

$$A \sqsubseteq_n C \text{ (primitive GCI)}$$

$$A \stackrel{\sim}{\sqsubseteq} C \text{ (primitive GCI)}$$

$$A \stackrel{\approx}{\sqsubseteq} C \text{ (definitional GCI)}$$

- A concept name
- $A \sqsubseteq_n C$ shorthand for $\langle \top \sqsubseteq A \rightarrow C, n \rangle$
- No nominal $\{a\}$ occurs in the TBox

- We say that
 - concept name A **directly uses** concept name B w.r.t. \mathcal{T} , denoted $A \rightarrow_{\mathcal{T}} B$, if A is the head of some axiom $\tau \in \mathcal{T}$ such that B occurs in the body of τ
 - concept name A **uses** concept name B w.r.t. \mathcal{T} , denoted $A \rightsquigarrow_{\mathcal{T}} B$, if there exist concept names A_1, \dots, A_n , such that $A_1 = A$, $A_n = B$ and, for every $1 \leq i < n$, it holds that $A_i \rightarrow_{\mathcal{T}} A_{i+1}$
- TBox \mathcal{T} is **cyclic (acyclic)** if there is (no) A such that $A \rightsquigarrow_{\mathcal{T}} A$
- TBox \mathcal{T} is **unfoldable** if
 - \mathcal{T} is acyclic
 - If $A \stackrel{\sim}{=} C \in \mathcal{T}$ then A does not occur in the head of any other axiom

- \mathcal{I} **satisfies (is a model of)** $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$ iff it satisfies each element in \mathcal{A} and \mathcal{T}
- A fuzzy KB $\mathcal{K} = \langle \mathcal{T}, \mathcal{A} \rangle$ **entails** an axiom E , denoted $\mathcal{K} \models E$, iff every model of \mathcal{K} satisfies E
- We say that two concepts C and D are **equivalent**, denoted $C \equiv_{\mathcal{K}} D$ iff in every model \mathcal{I} of \mathcal{K} and for all $x \in \Delta^{\mathcal{I}}$, $C^{\mathcal{I}}(x) = D^{\mathcal{I}}(x)$
- **Best entailment degree**: for assertion of GCI ϕ

$$bed(\mathcal{K}, \phi) = \sup \{r \mid \mathcal{K} \models \langle \phi, r \rangle\}$$

- **Best satisfiability degree**: for concept C

$$bsd(\mathcal{K}, C) = \sup_{\mathcal{I} \models \mathcal{K}} \sup_{x \in \Delta^{\mathcal{I}}} C^{\mathcal{I}}(x).$$

Some Salient Fuzzy Concept Equivalences

Property	Łukasiewicz	Gödel	Product	SFL
$C \cap \neg C \equiv \perp$	•	•	•	
$C \cup \neg C \equiv \top$	•			
$C \cap C \equiv C$		•		•
$C \cup C \equiv C$		•		•
$\neg \neg C \equiv C$	•			•
$C \rightarrow D \equiv \neg C \cup D$	•			•
$C \rightarrow D \equiv \neg D \rightarrow \neg C$	•			•
$\neg(C \rightarrow D) \equiv C \cap \neg D$	•			•
$\neg(C \cap D) \equiv \neg C \cup \neg D$	•	•	•	•
$\neg(C \cup D) \equiv \neg C \cap \neg D$	•	•	•	•
<hr/>				
$C \cap (D \cup E) \equiv (C \cap D) \cup (C \cap E)$		•		•
$C \cup (D \cap E) \equiv (C \cup D) \cap (C \cup E)$		•		•
$\exists R.C \equiv \neg \forall R.\neg C$	•			•

- Recall that OWL 2 relates to $\mathcal{SROIQ}(D)$
- We need to extend the semantics to fuzzy $\mathcal{SROIQ}(D)$
- Additionally, we add
 - **modifiers** (e.g., *very*)
 - **concrete fuzzy concepts** (e.g., *Young*)
 - both additions have **explicit** membership functions
 - other extensions:
 - aggregation functions: weighted sum, OWA, fuzzy integrals
 - fuzzy rough sets, fuzzy spatial, fuzzy numbers

Number Restrictions, Inverse, Transitive roles, ...

- The semantics of the concept $(\geq n R.C)$ is: \wedge interpreted as Gödel t-norm

$$\exists y_1, \dots, y_n. \bigwedge_{i=1}^n R(x, y_i) \wedge C(y_i) \wedge \bigwedge_{1 \leq i < j \leq n} y_i \neq y_j$$

- The semantics of the concept $(\leq n R.C)$ is: \wedge interpreted as Gödel t-norm

$$(\leq n R)^{\mathcal{I}}(x) = \forall y_1, \dots, y_{n+1}. \bigwedge_{i=1}^{n+1} (R(x, y_i) \wedge C(y_i)) \Rightarrow \bigvee_{1 \leq i < j \leq n+1} y_i = y_j$$

- Note: $(\geq 1 R) \equiv \exists R.T$

- For transitive roles R we impose: for all $x, y \in \Delta^{\mathcal{I}}$

$$R^{\mathcal{I}}(x, y) \geq \sup_{z \in \Delta^{\mathcal{I}}} R^{\mathcal{I}}(x, z) \otimes R^{\mathcal{I}}(z, y)$$

- For inverse roles we have for all $x, y \in \Delta^{\mathcal{I}}$

$$R^{\mathcal{I}}(x, y) = R^{\mathcal{I}}(y, x)$$

- The semantics of functional roles $fun(R)$ is

$$\forall x \forall y \forall z. R(x, y) \wedge R(x, z) \Rightarrow y = z$$

- Similar for other $SR\mathcal{O}IQ$ constructs

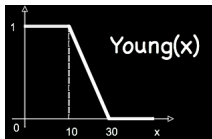
Fuzzy Concrete Domains

- E.g., *Small, Young, High, etc.* with **explicit** membership function
- Use the idea of concrete domains:
 - $D = \langle \Delta_D, \Phi_D \rangle$
 - Δ_D is an interpretation domain
 - Φ_D is the set of concrete unary fuzzy domain predicates d and **fixed** interpretation $d^D: \Delta_D \rightarrow [0, 1]$
- Specifically,

$$\mathbf{d} \quad \rightarrow \quad ls(a, b) \mid rs(a, b) \mid tri(a, b, c) \mid trz(a, b, c, d) \\ \mid \geq_v \mid \leq_v \mid =_v$$

$$C, D \quad \rightarrow \quad \forall T.\mathbf{d} \mid \exists T.\mathbf{d}$$

- Representation of **Young Person**:



$$\begin{aligned} \text{Minor} &= \text{Person} \cap \exists \text{hasAge.} \leq 18 \\ \text{YoungPerson} &= \text{Person} \cap \exists \text{hasAge.} \text{ls}(10, 30) \end{aligned}$$

- Representation of **Heavy Rain**:

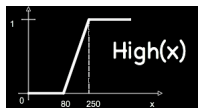
$$\text{HeavyRain} = \text{Rain} \cap \exists \text{hasPrecipitationRate.} \text{rs}(5, 7.5)$$

- *Very, moreOrLess, slightly, etc.*
- **Fuzzy modifier** m with function $f_m: [0, 1] \rightarrow [0, 1]$

$$C \rightarrow m(C) \mid \forall T.m(\mathbf{d}) \mid \exists T.m(\mathbf{d})$$

where m is a linear modifier

- Representation of **Sport Car**



$$\text{SportsCar} = \text{Car} \sqcap \exists \text{speed.very}(\text{rs}(80, 250))$$

- Representation of **Very Heavy Rain**

$$\text{VeryHeavyRain} = \text{Rain} \sqcap \exists \text{hasPrecipitationRate.very}(\text{rs}(5, 7.5)) .$$

Aggregation Operators

- **Aggregation operators**: aggregate concepts, using functions such as the mean, median, weighted sum operators
- Given an n -ary aggregation operator $@ : [0, 1]^n \rightarrow [0, 1]$
 - We fuzzy concepts by allowing to apply $@$ to n concepts C_1, \dots, C_n , i.e.

$$C \rightarrow @(C_1, \dots, C_n)$$

- Semantics:

$$@(C_1, \dots, C_n)^{\mathcal{I}}(x) = @(C_1^{\mathcal{I}}(x), \dots, C_n^{\mathcal{I}}(x)).$$

- Allows to express the concept

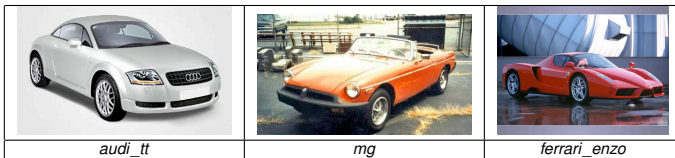
$$GoodHotel = 0.3 \cdot ExpensiveHotel + 0.7 \cdot LuxuriousHotel$$

- The membership function of good hotels is the weighted sum of being an expensive and luxurious hotel

Some Applications

- Information retrieval
- Recommendation systems
- Image interpretation
- Ambient intelligence
- Ontology merging
- Matchmaking
- decision making
- Summarization
- Robotics perception
- Software design
- Machine learning

Example (Graded Entailment)

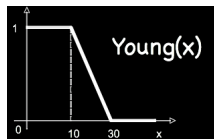


<i>Car</i>	<i>speed</i>
<i>audi_tt</i>	243
<i>mg</i>	≤ 170
<i>ferrari_enzo</i>	≥ 350

SportsCar = *Car* \sqcap \exists hasSpeed.very(High)

$\mathcal{K} \models \langle \text{ferrari_enzo}:\text{SportsCar}, 1 \rangle$
 $\mathcal{K} \models \langle \text{audi_tt}:\text{SportsCar}, 0.92 \rangle$
 $\mathcal{K} \models \langle \text{mg}:\neg\text{SportsCar}, 0.72 \rangle$

Example (Graded Subsumption)

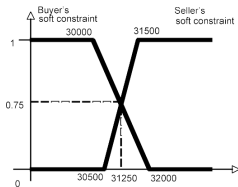


$$\begin{aligned} \text{Minor} &= \text{Person} \sqcap \exists \text{hasAge} . \leq_{18} \\ \text{YoungPerson} &= \text{Person} \sqcap \exists \text{hasAge} . \text{Young} \\ &\quad \text{fun}(\text{hasAge}) \end{aligned}$$

$$\mathcal{K} \models \langle \text{Minor} \sqsubseteq \text{YoungPerson}, 0.6 \rangle$$

Note: without an explicit membership function of *Young*, **this inference cannot be drawn**

Example (Simplified Matchmaking)



- A car seller sells an Audi TT for 31500€, as from the catalog price.
- A buyer is looking for a sports-car, but wants to pay not more than around 30000€
- Classical sets: the problem relies on the crisp conditions on price
- More fine grained approach: to consider prices as fuzzy sets (as usual in negotiation)
 - Seller may consider optimal to sell above 31500€, but can go down to 30500€
 - The buyer prefers to spend less than 30000€, but can go up to 32000€
 $AudiTT = SportsCar \sqcap \exists hasPrice.rs(30500, 31500)$
 $Query = SportsCar \sqcap \exists hasPrice.ls(30000, 32000)$
 - Highest degree to which the concept
 $C = AudiTT \sqcap Query$
is satisfiable is 0.75 (the degree to which the Audi TT and the query **matches** is 0.75)
 - The car may be sold at 31250€

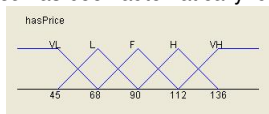
Example: Learning fuzzy GCIs from data

- Learning of fuzzy GCIs from crisp data
- Use Case: What are **Good hotels**, using TripAdvisor data?
 - Given
 - OWL 2 Ontology about meaningful city entities and their descriptions
 - TripAdvisor data about hotels and user judgments
 - We may learn that in e.g., Pisa, Italy

$\langle \exists \text{hasAmenity.Babysitting} \sqcap \exists \text{hasPrice.fair} \sqsubseteq \text{Good_Hotel}, 0.282 \rangle$

“A hotel having babysitting as amenity and a fair price is a good hotel (to degree 0.282)”

- Real valued price attribute *hasPrice* has been automatically fuzzified



Example: Multi-Criteria Decision Making

- We have to select among two sites, A_1, A_2
- There are two criteria (C_1 -Transportation Issues, and C_2 -Public Nuisance) for judgement
- There are two experts (E_1, E_2) that make judgments
- The decision matrix of the experts is shown below:

E_1		Criteria	
		0.48	0.52
Alter.		C_1	C_2
x_1	A_1	$tri(0.6, 0.7, 0.8)$	$tri(0.9, 0.95, 1.0)$
x_2	A_2	$tri(0.6, 0.7, 0.8)$	$tri(0.4, 0.5, 0.6)$

E_2		Criteria	
		0.52	0.48
Alter.		C_1	C_2
x_1	A_1	$tri(0.55, 0.6, 0.7)$	$tri(0.4, 0.45, 0.5)$
x_2	A_2	$tri(0.35, 0.4, 0.45)$	$tri(0.5, 0.55, 0.6)$

- For each expert $k = 1, 2$, for each alternative $i = 1, 2$ and for each criteria $j = 1, 2$, we define the concept

$$P_{ij}^k = \exists \text{hasScore}.a_{ij}^k$$

- Now, for each expert k and alternative i , we define the weighted concept

$$A_i^k = w_1^k \cdot P_{i1}^k + w_2^k \cdot P_{i2}^k$$

- Finally, we combine the two experts outcome, by defining the weighted concept

$$A_i = 0.5 \cdot A_i^1 + 0.5 \cdot A_i^2$$

- It can be verified that $rv(\mathcal{K}, A_1) = bsd(\mathcal{K}, A_1) = 0.26$ and $rv(\mathcal{K}, A_2) = bsd(\mathcal{K}, A_2) = 0.37$

Representing Fuzzy OWL Ontologies in OWL

- OWL 2 is W3C standard, with classical logic semantics
 - Hence, cannot support natively Fuzzy Logic
- However, **Fuzzy OWL 2**, has been defined using OWL 2
 - Uses the axiom annotation feature of OWL 2
- Any Fuzzy OWL 2 ontology is a legal OWL 2 ontology

- A java parser for Fuzzy OWL 2 exists
- Protégé plug-in exists to encode Fuzzy OWL ontologies

The screenshot shows the Protégé Fuzzy Owl plugin interface. The browser address bar displays the URL: `http://www.semanticweb.org/ontologies/2010/8/FuzzyTest.owl`. The main window title is "Fuzzy Owl".

The interface includes a menu on the left with the following options:

- Fuzzy Datatype
- Fuzzy Modified Concept
- Weighted Concept
- Weighted Sum Concept
- Fuzzy Nominal
- Fuzzy Modifier
- Fuzzy Modified Role
- Fuzzy Axiom
- Ontology
- Fuzzy Modified Datatype
- Add new datatype

The main workspace shows "Step 2" with the instruction: "Choose the type and fill with parameters". The "Type" dropdown is set to "rightshoulder". The parameters are:

- A: 200.0
- B: 300.0
- K1: 0.0
- K2: 1000.0

An "Annotate" button is visible below the parameters. To the right of the parameters is a graph showing a right-shoulder fuzzy membership function. The x-axis is labeled 'x' and has points 'a' and 'b'. The y-axis is labeled '1'. The function is 0 for $x < a$, increases linearly from 0 to 1 between $x = a$ and $x = b$, and remains at 1 for $x > b$.

On the right side, there are panels for "Annotations" and "Axiom annotations". The "Annotations" panel shows a list of annotations, including one for "HighPower" with the following XML snippet:

```
<Datatype type="rightshoulder" a="200" b="300" />
```

At the bottom of the interface, there is a status bar with the text: "To use the reasoner click Reasoner->Start Reasoner" and a checked checkbox for "Show Inferences".

Reasoning Problems and Algorithms

Consistency problem:

- Is \mathcal{K} satisfiable?
- Is C coherent, i.e. is $C^{\mathcal{I}}(x) > 0$ for some $\mathcal{I} \models \mathcal{K}$ and $x \in \Delta^{\mathcal{I}}$?

Instance checking problem:

- Does $\mathcal{K} \models \langle a:C, n \rangle$ hold?

Subsumption problem:

- Does $\mathcal{K} \models \langle C \sqsubseteq D, n \rangle$ hold?

Best entailment degree problem:

- What is $bed(\mathcal{K}, \phi)$?

Best satisfiability degree problem:

- What is $bsd(\mathcal{K}, \phi)$?

Instance retrieval problem:

- Compute the set $\{\langle a, n \rangle \mid n = bed(\mathcal{K}, a:C)\}$

Top-k retrieval problem:

- Compute the top-k ranked elements of $\{\langle a, n \rangle \mid n = bed(\mathcal{K}, a:C)\}$

Some Reductions

- \mathcal{K} is satisfiable iff $bsd(\mathcal{K}, a:\perp) > 0$, where a is a new individual.
- C is coherent w.r.t. \mathcal{K} if one of the following holds:
 - $\mathcal{K} \cup \{\langle a:C > 0 \rangle\}$ is satisfiable, where a is a new individual
 - $\mathcal{K} \not\models \langle C \sqsubseteq \perp, 1 \rangle$
 - $bsd(\mathcal{K}, C) > 0$
- $\mathcal{K} \models \langle a:C, n \rangle$ if one of the following holds:
 - $\mathcal{K} \cup \{\langle a:C < n \rangle\}$ is not satisfiable
 - $bed(\mathcal{K}, a:C) \geq n$
- $\mathcal{K} \models \langle C \sqsubseteq D, n \rangle$ if one of the following holds:
 - $\mathcal{K} \cup \{\langle a:C \rightarrow D < n \rangle\}$ is not satisfiable, where a is a new individual
 - $bed(\mathcal{K}, C \sqsubseteq D) \geq n$
- We have that

$$bed(\mathcal{K}, \phi) = \min x. \text{ such that } \mathcal{K} \cup \{\langle \phi \leq x \rangle\} \text{ satisfiable}$$

$$bsd(\mathcal{K}, \phi) = \max x. \text{ such that } \mathcal{K} \cup \{\langle \phi \geq x \rangle\} \text{ satisfiable}$$

- Algorithms for fuzzy DLs: are a mixture of classical DLs reasoning algorithms and algorithms for Mathematical Fuzzy Logic
- Fuzzy OWL 2:
 - **Fuzzy tableaux** based algorithms
 - Tableaux and non deterministic tableaux
 - Operational Research
 - **Reduction** into classical DLs
- Fuzzy OWL 2 EL: **fuzzy structural** based algorithms
- Fuzzy OWL 2 QL: **fuzzy query rewriting** based algorithms
- fuzzy OWL 2 RL: **fuzzy logic programming** based algorithms

- Works as for classical \mathcal{ALC} on completion forests
 - Blocking is as for classical \mathcal{ALC}
 - The completion forest is expanded by repeatedly applying inference rules
 - The completion-forest is complete when none of the rules are applicable
- Additionally, at each inference step we add equational constraints that have to hold
- Eventually, the initial KB is satisfiable if the final set of equational constraints has a solution
 - For the latter case, we may use a MILP solver

Description

For variable $x_{v:C}$ add $x_{v:C} \in [0, 1]$ to $\mathcal{C}_{\mathcal{F}}$. For variable $x_{(v,w):R}$, add $x_{(v,w):R} \in [0, 1]$ to $\mathcal{C}_{\mathcal{F}}$

- if $\neg A \in \mathcal{L}(v)$ then add $x_{v:A} = 1 - x_{v:\neg A}$ to $\mathcal{C}_{\mathcal{F}}$
- if $\perp \in \mathcal{L}(v)$ then add $x_{v:\perp} = 0$ to $\mathcal{C}_{\mathcal{F}}$
- if $\top \in \mathcal{L}(v)$ then add $x_{v:\top} = 1$ to $\mathcal{C}_{\mathcal{F}}$
- if $C_1 \sqcap C_2 \in \mathcal{L}(v)$, v is not indirectly blocked
then $\mathcal{L}(v) \rightarrow \mathcal{L}(v) \cup \{C_1, C_2\}$, and add $x_{v:C_1} \otimes x_{v:C_2} \geq x_{v:C_1 \sqcap C_2}$ to $\mathcal{C}_{\mathcal{F}}$
- if $C_1 \sqcup C_2 \in \mathcal{L}(v)$, v is not indirectly blocked
then $\mathcal{L}(v) \rightarrow \mathcal{L}(v) \cup \{C_1, C_2\}$, and add $x_{v:C_1} \oplus x_{v:C_2} \geq x_{v:C_1 \sqcup C_2}$ to $\mathcal{C}_{\mathcal{F}}$
- if $\forall R.C \in \mathcal{L}(v)$, v is not indirectly blocked
then $\mathcal{L}(w) \rightarrow \mathcal{L}(w) \cup \{C\}$, and add $x_{w:C} \geq x_{v:\forall R.C} \otimes x_{(v,w):R}$ to $\mathcal{C}_{\mathcal{F}}$
- if $\exists R.C \in \mathcal{L}(v)$, v is not blocked
then create new node w with $\mathcal{L}(\langle v, w \rangle) = \{R\}$ and $\mathcal{L}(w) = \{C\}$, and add $x_{w:C} \otimes x_{(v,w):R} \geq x_{v:\exists R.C}$ to $\mathcal{C}_{\mathcal{F}}$
- if $\langle C \sqsubseteq D, n \rangle \in \mathcal{T}$, v is not indirectly blocked
then $\mathcal{L}(v) \rightarrow \mathcal{L}(v) \cup \{C, D\}$, and add $x_{v:D} \geq x_{v:C} \otimes n$ to $\mathcal{C}_{\mathcal{F}}$

- Works as for classical \mathcal{ALC} on completion forests
 - Node labels $\mathcal{L}(v)$ contain, rather than DL concept expressions, expressions of the form $\langle C, n \rangle$

“The truth degree of being v instance of C is $\geq n$ ”
 - Blocking is as for classical \mathcal{ALC}
 - The completion forest is expanded by repeatedly applying inference rules
 - The completion-forest is complete when none of the rules are applicable
- Additionally, we adapt the notion of **clash**: a clash is either
 - $\langle \perp, n \rangle$ with $n > 0$; or
 - a pair $\langle C, n \rangle$ and $\langle \neg C, m \rangle$ with $n > 1 - m$
- Eventually, the initial KB is satisfiable if there is a clash-free complete completion forest

- (\sqcap). If (i) $\langle C_1 \sqcap C_2, n \rangle \in \mathcal{L}(v)$, (ii) $\{\langle C_1, n \rangle, \langle C_2, n \rangle\} \not\subseteq \mathcal{L}(v)$, and (iii) node v is not indirectly blocked, then add $\langle C_1, n \rangle$ and $\langle C_2, n \rangle$ to $\mathcal{L}(v)$.
- (\sqcup). If (i) $\langle C_1 \sqcup C_2, n \rangle \in \mathcal{L}(v)$, (ii) $\{\langle C_1, n \rangle, \langle C_2, n \rangle\} \cap \mathcal{L}(v) = \emptyset$, and (iii) node v is not indirectly blocked, then add some $\langle C, n \rangle \in \{\langle C_1, n \rangle, \langle C_2, n \rangle\}$ to $\mathcal{L}(v)$.
- (\forall). If (i) $\langle \forall R.C, n \rangle \in \mathcal{L}(v)$, (ii) $\langle R, m \rangle \in \mathcal{L}(\langle v, w \rangle)$ with $m > 1 - n$, (iii) $\langle C, n \rangle \notin \mathcal{L}(w)$, and (iv) node v is not indirectly blocked, then add $\langle C, n \rangle$ to $\mathcal{L}(w)$.
- (\exists). If (i) $\langle \exists R.C, n \rangle \in \mathcal{L}(v)$, (ii) there is no $\langle R, n_1 \rangle \in \mathcal{L}(\langle v, w \rangle)$ with $\langle C, n_2 \rangle \in \mathcal{L}(w)$ such that $\min(n_1, n_2) \geq n$, and (iii) node v is not blocked, then create a new node w , add $\langle R, n \rangle$ to $\mathcal{L}(\langle v, w \rangle)$ and add $\langle C, n \rangle$ to $\mathcal{L}(w)$.
- (\sqsubseteq). If (i) $\langle \top \sqsubseteq D, n \rangle \in \mathcal{T}$, (ii) $\langle D, n \rangle \notin \mathcal{L}(v)$, and (iii) node v is not indirectly blocked, then add $\langle D, n \rangle$ to $\mathcal{L}(v)$.

- It's a combination of the analogous method for fuzzy propositional logic and analytical fuzzy tableau
- Rule example:
 - (\sqcap). If (i) $\langle C_1 \sqcap C_2, m \rangle \in \mathcal{L}(v)$, (ii) there are $m_1, m_2 \in L_n$ such that $m_1 \otimes m_2 = m$ with $\{\langle C_1, m_1 \rangle, \langle C_2, m_2 \rangle\} \not\subseteq \mathcal{L}(v)$, and (iii) node v is not indirectly blocked, then add $\langle C_1, m_1 \rangle$ and $\langle C_2, m_2 \rangle$ to $\mathcal{L}(v)$

Reduction to Classical DLs

- Same principle as for the reduction for propositional fuzzy logic
- Needs adaption to the DL constructs: e.g. \exists, \forall and \sqsubseteq
- Examples of reduction rules for SFL:

$$\begin{aligned}\rho(A, \geq \gamma) &= A_{\geq \gamma} \\ \rho(C \sqcap D, \geq \gamma) &= \rho(C, \geq \gamma) \sqcap \rho(D, \geq \gamma) \\ \rho(C \sqcap D, \leq \gamma) &= \rho(C, \leq \gamma) \sqcup \rho(D, \leq \gamma) \\ \rho(\forall R.C, \geq \gamma) &= \forall \rho(R, > 1 - \gamma). \rho(C, \geq \gamma) \\ \rho(\forall R.C, \leq \gamma) &= \exists \rho(R, \geq 1 - \gamma). \rho(C, \leq \gamma) \\ \rho(\exists R.C, \geq \gamma) &= \exists \rho(R, \geq \gamma). \rho(C, \geq \gamma) \\ \rho(\exists R.C, \leq \gamma) &= \forall \rho(R, > \gamma). \rho(C, \leq \gamma) \\ \rho(R, \geq \gamma) &= R_{\geq \gamma} \\ \rho(\langle a:C, \gamma \rangle) &= \{a: \rho(C, \geq \gamma)\} \\ \rho(\langle C \sqsubseteq D, n \rangle) &= \bigcup_{\alpha \in \bar{N}_+^K, \alpha \leq n} \{\rho(C, \geq \alpha) \sqsubseteq \rho(D, \geq \alpha)\}\end{aligned}$$

The bad news...**undecidability!**

Proposition

Assume that fuzzy GCIs are restricted to be classical, i.e. of the form $\langle \alpha, 1 \rangle$ only. Then for the following fuzzy DLs, the KB satisfiability problem is undecidable over $[0, 1]$:

- 1 \mathcal{ELC} with classical axioms only under Łukasiewicz logic and product logic;
- 2 \mathcal{ELC} under any non Gödel-t-norm \otimes ;
- 3 \mathcal{ELC} with concept assertions of the form $\langle \alpha = n \rangle$ only under any non Gödel-t-norm \otimes ;
- 4 \mathcal{AL} with concept implication operator \rightarrow and concept assertions of the form $\langle \alpha = n \rangle$ only under any non Gödel-t-norm \otimes .
- 5 \mathcal{ELC} under SFL with weighted sum constructor.

Some decidability results..

Proposition

The KB satisfiability problem is decidable for

- *$SR\mathcal{O}I\mathcal{Q}$ under SFL over $[0, 1]$ and Gödel logic over L_n*
- *$SR\mathcal{O}I\mathcal{N}$ under Łukasiewicz logic over L_n*
- *SHI under any continuous t-norm over L_n without TBox*
- *\mathcal{ALC} with concept implication operator \rightarrow , for any continuous t-norm over $[0, 1]$ with acyclicTBox*
- *$SHIF$ with concept implication operator \rightarrow , for Łukasiewicz logic over $[0, 1]$ with acyclicTBox*
- *SI under any continuous t-norm over $[0, 1]$ without TBox*

- For OWL 2, it is like for RDFS, but annotation domain has to be a complete lattice
 - satisfiability problem is inherited from crisp variant if lattice is finite, else UNDECIDABLE (even for \mathcal{ALC} with GCIs)
- Exception for OWL profiles OWL EL, OWL QL and OWL RL: annotation domains may be as for RDFS
 - the complexity is inherited from their crisp variants, plus complexity of domain operators

Languages supported by fuzzy ontology reasoners:

Reasoner	Fuzzy DL	Logic	Degrees	Other constructors	GUI
fuzzyDL	<i>SHIF(D)</i>	Z, \perp	General	Modifiers, rough, aggregation	•
Fire	<i>SHIN</i>	Z	Numbers		•
FPLGERDS	<i>ACC</i>	\perp	Numbers	Role negatio/top/bottom	
YADLR	<i>ALCOQ</i>	Z, \perp	General	Local reflexivity	
DeLorean	<i>SROIQ(D)</i>	Z, G	General	Modifiers, rough DL	•
GURDL	<i>ACC</i>	General	Numbers		No
FRESG	<i>ACC(D)</i>	Z	Numbers	Fuzzy datatype expressions	•
LiFR	<i>DLP fragment</i>	Z	Numbers	Weighted concepts	
SMT-based solver	<i>ACE</i>	Π	No	No	
DLMedia	<i>DLR-Lite</i>	Z, G	Numbers	Image similarity	•
SoftFacts	<i>DLR-Lite</i>	Z, G	Numbers	Fuzzy datatypes	•
ONTOSEARCH2	<i>DL - Lite_R</i>	General	Numbers		•

Reasoning services offered by fuzzy ontology reasoners

Reasoner	CON	ENT	CSAT	SUB	IR	BDB	Other tasks	OPT
fuzzyDL	•	•	•	•	•	•	Defuzzification	•
Fire	•	•	•	•		•	Classification	•
FPLGERDS		•						
YADLR		Partial			•	Partial	Realisation	
DeLorean	•	•	•	•		•		•
GURDL	•	•		•				•
FRESG	•	•	•		•		Realisation	
LiFR		Partial	•	•		•		
SMT-based solver			•					
DLMedia							Top-k Image Retrieval	•
SoftFacts							Top-k CQA	•
ONTOSEARCH2							Retrieval	

“CON”, “ENT”, “CSAT”, “SUB”, “IR”, “BED”, and “OPT” represent consistency, entailment, concept satisfiability, subsumption, instance retrieval, BED, and optimisations, respectively

The case of Logic Programs

- **Predicates** are n -ary
- **Terms** are variables or constants
- **Facts** ground atoms
For instance,

has_parent(mary, jo)

- **Rules** are of the form

$$P(\mathbf{x}) \leftarrow \varphi(\mathbf{x}, \mathbf{y})$$

where $\varphi(\mathbf{x}, \mathbf{y})$ is a formula built from atoms of the form $B(\mathbf{z})$ and connectors $\wedge, \vee, 0, 1$

For instance,

$$has_father(x, y) \leftarrow has_parent(x, y) \wedge Male(y)$$

- **Extensional database** (EDB): set of facts
- **Intentional database** (IDB): set of rules
- **Logic Program** \mathcal{P} :
 - $\mathcal{P} = EDB \cup IDB$
 - No predicate symbol in *EDB* occurs in the head of a rule in *IDB*
 - The principle is that we do not allow that *IDB* may redefine the extension of predicates in *EDB*
- *EDB* is usually, stored into a relational database

- \mathcal{P}^* is constructed as follows:
 - 1 set \mathcal{P}^* to the set of all ground instantiations of rules in \mathcal{P} ;
 - 2 replace a fact $p(\mathbf{c})$ in \mathcal{P}^* with the rule $p(\mathbf{c}) \leftarrow 1$
 - 3 if atom A is not head of any rule in \mathcal{P}^* , then add $A \leftarrow 0$ to \mathcal{P}^* ;
 - 4 replace several rules in \mathcal{P}^* having same head

$$\left. \begin{array}{l} A \leftarrow \varphi_1 \\ A \leftarrow \varphi_2 \\ \vdots \\ A \leftarrow \varphi_n \end{array} \right\} \text{with } A \leftarrow \varphi_1 \vee \varphi_2 \vee \dots \vee \varphi_n .$$

- Note: in \mathcal{P}^* each atom $A \in B_{\mathcal{P}}$ is head of **exactly one** rule
- **Herbrand Base** of \mathcal{P} is the set $B_{\mathcal{P}}$ of ground atoms
- **Interpretation** is a function $I : B_{\mathcal{P}} \rightarrow \{0, 1\}$.
- **Model** $I \models \mathcal{P}$ iff for all $r \in \mathcal{P}^*$ $I \models r$, where $I \models A \leftarrow \varphi$ iff $I(\varphi) \leq I(A)$

- **Entailment**: for a ground atom $p(\mathbf{c})$

$\mathcal{P} \models p(\mathbf{c})$ iff all models of \mathcal{P} satisfy $p(\mathbf{c})$

- **Least model** $M_{\mathcal{P}}$ of \mathcal{P} exists and is **least fixed-point** of

$$T_{\mathcal{P}}(I)(A) = I(\varphi), \text{ for all } A \leftarrow \varphi \in \mathcal{P}^*$$

- M can be computed as the limit of

$$\begin{aligned} \mathbf{l}_0 &= \mathbf{0} \\ \mathbf{l}_{i+1} &= T_{\mathcal{P}}(\mathbf{l}_i) . \end{aligned}$$

- **Query**: is a rule of the form

$$q(\mathbf{x}) \leftarrow \varphi(\mathbf{x}, \mathbf{y})$$

- If $\mathcal{P} \models q(\mathbf{c})$ then \mathbf{c} is called an **answer** to q
- The **answer set** of q w.r.t. \mathcal{P} is defined as

$$ans(\mathcal{P}, q) = \{\mathbf{c} \mid \mathcal{P} \models q(\mathbf{c})\}$$

- Efficient query answering algorithms exists

- We consider fuzzy LPs, which extends classical LPs, where
 - **Truth space** is $[0, 1]$
 - **Interpretation** is a mapping $I : B_{\mathcal{P}} \rightarrow [0, 1]$
 - **Generalized LP rules** are of the form

$$R(\mathbf{x}) \leftarrow \exists \mathbf{y}. f(R_1(\mathbf{z}_1), \dots, R_k(\mathbf{z}_k), p_1(\mathbf{z}'_1), \dots, p_h(\mathbf{z}'_h))$$

- **Meaning of rules:** “take the truth-values of all $R_i(\mathbf{z}_i), p_j(\mathbf{z}'_j)$, combine them using the truth combination function f , and assign the result to $R(\mathbf{x})$ ”
- **Facts:** ground expressions of the form $\langle R(\mathbf{c}), n \rangle$
 - **Meaning of facts:** “the degree of truth of $R(\mathbf{c})$ is at least n ”
- **Fuzzy LP:** a set of facts (extensional database) and a set of rules (intentional database). No extensional relation may occur in the head of a rule

● Rules:

$$R(\mathbf{x}) \leftarrow \exists \mathbf{y}. \varphi(\mathbf{x}, \mathbf{y})$$

- 1 \mathbf{x} are the *distinguished variables*;
- 2 s is the *score variable*, taking values in $[0, 1]$;
- 3 \mathbf{y} are existentially quantified variables, called *non-distinguished variables*;
- 4 $\varphi(\mathbf{x}, \mathbf{y})$ is $f(\mathbf{R}(\mathbf{z}), \mathbf{p}(\mathbf{z}'))$, where \mathbf{R} is a vector of predicates R_i and \mathbf{p} is a vector of fuzzy predicates p_j ;
- 5 \mathbf{z}, \mathbf{z}' are tuples of constants in *KB* or variables in \mathbf{x} or \mathbf{y} ;
- 6 p_j is an n_j -ary *fuzzy predicate* assigning to each n_j -ary tuple \mathbf{c}_j the *score* $p_j(\mathbf{c}_j) \in [0, 1]$;
- 7 f is a monotone *scoring function* $f: [0, 1]^{k+h} \rightarrow [0, 1]$, which combines the scores of the h fuzzy predicates $p_j(\mathbf{c}_j)$ with the k scores $R_i(\mathbf{c}_i)$

Semantics of fuzzy LPs

- \mathcal{P}^* is constructed as follows (as for the classical case):
 - 1 set \mathcal{P}^* to the set of all ground instantiations of rules in \mathcal{P} ;
 - 2 replace a fact $p(\mathbf{c})$ in \mathcal{P}^* with the rule $p(\mathbf{c}) \leftarrow 1$
 - 3 if atom A is not head of any rule in \mathcal{P}^* , then add $A \leftarrow 0$ to \mathcal{P}^* ;
 - 4 replace several rules in \mathcal{P}^* having same head

$$\left. \begin{array}{l} A \leftarrow \varphi_1 \\ A \leftarrow \varphi_2 \\ \vdots \\ A \leftarrow \varphi_n \end{array} \right\} \text{ with } A \leftarrow \varphi_1 \vee \varphi_2 \vee \dots \vee \varphi_n .$$

- Note: in \mathcal{P}^* each atom $A \in B_{\mathcal{P}}$ is head of **exactly one** rule
- **Herbrand Base** of \mathcal{P} is the set $B_{\mathcal{P}}$ of ground atoms
- **Interpretation** is a function $I : B_{\mathcal{P}} \rightarrow [0, 1]$.
- **Model** $I \models \mathcal{P}$ iff for all $r \in \mathcal{P}^*$ $I \models r$, where $I \models A \leftarrow \varphi$ iff $I(\varphi) \leq I(A)$
- **Note:**

$$I(f(R_1(\mathbf{c}_1), \dots, R_k(\mathbf{c}_k), p_1(\mathbf{c}'_1), \dots, p_h(\mathbf{c}'_h))) = f(I(R_1(\mathbf{c}_1)), \dots, I(R_k(\mathbf{c}_k)), p_1(\mathbf{c}'_1), \dots, p_h(\mathbf{c}'_h)))$$

Fuzzy LP Query Answering

- **Least model** $M_{\mathcal{P}}$ of \mathcal{P} exists and is **least fixed-point** of

$$T_{\mathcal{P}}(I)(A) = I(\varphi), \text{ for all } A \leftarrow \varphi \in \mathcal{P}^*$$

- M can be computed as the limit of

$$\begin{aligned} \mathbf{l}_0 &= \mathbf{0} \\ \mathbf{l}_{i+1} &= T_{\mathcal{P}}(\mathbf{l}_i) . \end{aligned}$$

- **Entailment**: for a ground expression $\langle q(\mathbf{c}), s \rangle$, $s \in [0, 1]$

$$\mathcal{P} \models \langle q(\mathbf{c}), s \rangle \text{ iff least model of } \mathcal{P} \text{ satisfies } I(q(\mathbf{c})) \geq s$$

- We say that s is *tight* iff $s = \sup\{s' \mid \mathcal{P} \models \langle q(\mathbf{c}), s' \rangle\}$
- If $\mathcal{P} \models \langle q(\mathbf{c}), s \rangle$ and s is tight then $\langle \mathbf{c}, s \rangle$ is called an *answer* to q
- The **answer set** of q w.r.t. \mathcal{P} is defined as

$$\text{ans}(\mathcal{P}, q) = \{\langle \mathbf{c}, s \rangle \mid \mathcal{P} \models \langle q(\mathbf{c}), s \rangle, s \text{ is tight}\}$$

Top-k Retrieval: Given a fuzzy LP \mathcal{P} , and a query q , retrieve k answers $\langle \mathbf{c}, s \rangle$ with maximal scores and rank them in decreasing order relative to the score s , denoted

$$\text{ans}_k(\mathcal{P}, q) = \text{Top}_k \text{ ans}(\mathcal{P}, q) .$$

- Fuzzy LPs may be tricky:

$$\langle A, 0 \rangle$$

$$A \leftarrow (A + 1)/2$$

- In the minimal model the truth of A is 1 (requires infinitely many $T_{\mathcal{P}}$ iterations)!
- There are several ways to avoid this pathological behavior:
 - We may consider $L = \{0, \frac{1}{n}, \frac{2}{n} \dots, \frac{n-1}{n}, 1\}$, n natural number, e.g. $n = 100$
 - In $A \leftarrow f(B_1, \dots, B_n)$, f is bounded, i.e. $f(x_1, \dots, x_n) \leq x_i$

Example: Soft shopping agent

- I may represent my preferences in Logic Programming with the rules

$$Pref_1(x, p) \leftarrow HasPrice(x, p) \wedge LS(10000, 14000)(p)$$

$$Pref_2(x) \leftarrow HasKM(x, k) \wedge LS(13000, 17000)(k)$$

$$Buy(x, p) \leftarrow 0.7 \cdot Pref_1(x, p) + 0.3 \cdot Pref_2(x)$$

ID	MODEL	PRICE	KM
455	MAZDA 3	12500	10000
34	ALFA 156	12000	15000
1812	FORD FOCUS	11000	16000
⋮	⋮	⋮	⋮

- Problem:** All tuples of the database have a score:
 - We cannot compute the score of all tuples, then rank them. Brute force approach not feasible for very large databases
- Top-k problem:** Determine **efficiently** just the **top-k ranked** tuples, without evaluating the score of all tuples. E.g. top-3 tuples

ID	PRICE	SCORE
1812	11000	0.6
455	12500	0.56
34	12000	0.50

General top-down query procedure for Many-valued LPs

- **Idea:** use theory of fixed-point computation of equational systems over truth space (complete lattice or complete partial order)
- Assign a variable x_i to an atom $A_i \in B_{\mathcal{P}}$
- Map a rule $A \leftarrow f(A_1, \dots, A_n) \in \mathcal{P}^*$ into the equation $x_A = f(x_{A_1}, \dots, x_{A_n})$
- A LP \mathcal{P} is thus mapped into the equational system

$$\begin{cases} x_1 & = & f_1(x_{1_1}, \dots, x_{1_{a_1}}) \\ & \vdots & \\ x_n & = & f_n(x_{n_1}, \dots, x_{n_{a_n}}) \end{cases}$$

- f_i is monotone and, thus, the system has least fixed-point, which is the limit of

$$\begin{aligned} \mathbf{y}_0 &= \mathbf{0} \\ \mathbf{y}_{i+1} &= \mathbf{f}(\mathbf{y}_i) . \end{aligned}$$

where $\mathbf{f} = \langle f_1, \dots, f_n \rangle$ and $\mathbf{f}(\mathbf{x}) = \langle f_1(x_1), \dots, f_n(x_n) \rangle$

- The least-fixed point is the least model of \mathcal{P}
- **Consequence:** If top-down procedure exists for equational systems then it works for fuzzy LPs too!

Procedure $Solve(S, Q)$ **Input:** monotonic system $S = \langle \mathcal{L}, V, \mathbf{f} \rangle$, where $Q \subseteq V$ is the set of query variables;**Output:** A set $B \subseteq V$, with $Q \subseteq B$ such that the mapping v equals $lfp(f)$ on B .

1. $A := Q, dg := Q, in := \emptyset$, **for all** $x \in V$ **do** $v(x) = 0, exp(x) = 0$
 2. **while** $A \neq \emptyset$ **do**
 3. **select** $x_i \in A, A := A \setminus \{x_i\}, dg := dg \cup s(x_i)$
 4. $r := f_i(v(x_{i_1}), \dots, v(x_{i_{a_i}}))$
 5. **if** $r \succ v(x_i)$ **then** $v(x_i) := r, A := A \cup (p(x_i) \cap dg)$ **fi**
 6. **if not** $exp(x_i)$ **then** $exp(x_i) = 1, A := A \cup (s(x_i) \setminus in), in := in \cup s(x_i)$ **fi**
- od**

For $q(\mathbf{x}) \leftarrow \phi \in \mathcal{P}$, with $s(q)$ we denote the set of *sons* of q w.r.t. r , i.e. the set of intentional predicate symbols occurring in ϕ . With $p(q)$ we denote the set of *parents* of q , i.e. the set $p(q) = \{p_i : q \in s(p_i, r)\}$ (the set of predicate symbols directly depending on q).

- The top-down procedure can be extended to
 - fuzzy Normal Logic Programs (Logic programs with non-monotone negation)
 - Many-valued Normal Logic Programs under **Any-world Assumption**
 - Logic Programs, without requiring the grounding of the program
- Other approaches for top-down methods for monotone fuzzy LPs:
- Magics sets like methods: yet to investigate ...
- There are also extensions to Fuzzy Disjunctive Logic Programs with or without default negation

- If the database contains a huge amount of facts, a brute force approach fails:
 - one cannot anymore compute the score of all tuples, rank all of them and only then return the top- k
- Better solutions exists for restricted fuzzy LP languages: Datalog + restriction on the score combination functions appearing in the body

- We do not compute all answers, but determine answers incrementally
- At each step i , from the tuples seen so far in the database, we compute a **threshold** δ
- The threshold δ has the property that any successively retrieved answer will have a score $s \leq \delta$
- Therefore, we can **stop** as soon as we have gathered k answers **above** δ , because any successively computed answer will have a score below δ

Example

Logic Program \mathcal{P} is

$$q(x) \leftarrow p(x)$$
$$p(x) \leftarrow \min(r_1(x, y), r_2(y, z))$$

<i>RecordID</i>	<i>r</i> ₁			<i>r</i> ₂		
1	<i>a</i>	<i>b</i>	1.0	<i>m</i>	<i>h</i>	0.95
2	<i>c</i>	<i>d</i>	0.9	<i>m</i>	<i>j</i>	0.85
3	<i>e</i>	<i>f</i>	0.8	<i>f</i>	<i>k</i>	0.75
4	<i>l</i>	<i>m</i>	0.7	<i>m</i>	<i>n</i>	0.65
5	<i>o</i>	<i>p</i>	0.6	<i>p</i>	<i>q</i>	0.55
⋮	⋮	⋮	⋮	⋮	⋮	⋮

What is

$$Top_1(\mathcal{P}, q) = Top_1\{\langle c, s \rangle \mid \mathcal{P} \models q(c, s)\} ?$$

$$q(x) \leftarrow p(x)$$

$$p(x) \leftarrow \min(r_1(x, y), r_2(y, z))$$

	RecordID	r_1			r_2			
	1	a	b	1.0	m	h	0.95	
	2	c	d	0.9	m	j	0.85	
	3	e	f	0.8	f	k	0.75	←
→	4	l	m	0.7	m	n	0.65	
	5	o	p	0.6	p	q	0.55	
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	

Action: **STOP**, top-1 tuple score is equal or above threshold $0.75 = \max(\min(1.0, 0.75), \min(0.7, 0.95))$

Queue	δ	Predicate	Answers
—	0.75	q	$\langle e, 0.75 \rangle, \langle l, 0.7 \rangle$
		p	$\langle e, 0.75 \rangle, \langle l, 0.7 \rangle$

$$Top_1(\mathcal{P}, q) = \{ \langle e, 0.75 \rangle \}$$

Note: no further answer will have score above threshold δ

Procedure *TopAnswers*($\mathcal{L}, \mathcal{K}, q, k$)

Input: Truth space \mathcal{L} , KB $\mathcal{K} = \langle \mathcal{F}, P \rangle$, query relation $q, k \geq 1$

Output: Mapping *rankedList* such that *rankedList*(q) contains top-k answers of q

Init: $\delta = 1$, **for all** predicates p in \mathcal{P} **do**

if p intensional **then** *rankedList*(p) = \emptyset , $Q(p) := \emptyset$ **fi**

if p extensional **then** *rankedList*(p) = T_p **fi**

endfor

1. **loop**

2. **if** $A = \emptyset$ **then** $A := \{q\}$, $dg := \{q\}$, $in := \emptyset$, $rL' := \text{rankedList}$, initialise all pointers ptr_i^f to 0

3. **for all** intensional predicates p **do** $\text{exp}(p) = \text{false}$ **endfor**

fi

4. **select** $p \in A$, $A := A \setminus \{p\}$, $dg := dg \cup s(p)$

5. $\langle t, s \rangle := \text{getNextTuple}(p)$

6. **if** $\langle t, s \rangle \neq \text{null}$ **then** *rankedList*(p) := *rankedList*(p) $\cup \{\langle t, s \rangle\}$, $A := A \cup (p(p) \cap dg)$ **fi**

7. **if not** $\text{exp}(p)$ **then** $\text{exp}(p) = \text{true}$, $A := A \cup (s(p) \setminus in)$, $in := in \cup s(p)$ **fi**

8. Update threshold δ

9. **until** (*rankedList*(q) does contain k top-ranked tuples with score above query rule threshold)

or ($rL' = \text{rankedList}$) **and** $A = \emptyset$)

10. **return** top-k ranked tuples in *rankedList*(q)

Procedure *getNextTuple*(p)**Input:** intensional relation symbol p . Consider set of rules $\mathcal{R} = \{r \mid r : p(\mathbf{x}) \leftarrow f(A_1, \dots, A_n) \in \mathcal{P}\}$ **Output:** Next instance of p together with the score**Init:** Let p_i be the relation symbol occurring in A_i

1. **if** $Q(p) \neq \emptyset$ **then**
 $\langle \mathbf{t}, s \rangle := \text{getTop}(Q(p))$, remove $\langle \mathbf{t}, s \rangle$ from $Q(p)$, **return** $\{\langle \mathbf{t}, s \rangle\}$ **fi**
- loop**
2. **for all** $r \in \mathcal{R}$ **do**
3. Generate the set T of all new valid join tuples \mathbf{t} for rule r ,
 using tuples in $\text{rankedList}(p_i)$ and pointers ptr_i^f
4. **for all** $\mathbf{t} \in T$ **do**
5. $s :=$ compute the score of $p(\mathbf{t})$ using f ;
6. **if** neither $\langle \mathbf{t}, s' \rangle \in \text{rankedList}(p)$ nor $\langle \mathbf{t}, s' \rangle \in Q(p)$ with $s \preceq s'$ **then**
 insert $\langle \mathbf{t}, s \rangle$ into $Q(p)$ **fi**
- endfor**
- endfor**
- until** $Q(p) \neq \emptyset$ or no new valid join tuple can be generated
7. **if** $Q(p) \neq \emptyset$ **then** $\langle \mathbf{t}, s \rangle := \text{getTop}(Q(p))$, remove $\langle \mathbf{t}, s \rangle$ from $Q(p)$, **return** $\langle \mathbf{t}, s \rangle$
 else return null fi

Threshold computation

For an intentional predicate p , head of a rule $r : p(\mathbf{x}) \leftarrow f(p_1, p_2, \dots, p_n)$.

- consider a threshold variable δ^p
- with $r.t_{p_i}^\perp$ ($r.t_{p_i}^\top$) we denote the last tuple seen (the top ranked one) in `rankedList(p, r)`
- we define

$$\begin{aligned} p_i^\top &= \max(\delta^{p_i}, r.t_{p_i}^\top.score) \\ p_i^\perp &= \delta^{p_i} \end{aligned}$$

- if p_i is an extensional predicate, we define

$$\begin{aligned} p_i^\top &= r.t_{p_i}^\top.score \\ p_i^\perp &= r.t_{p_i}^\perp.score \end{aligned}$$

- for rule r we consider the equation $\delta(r)$

$$\delta^p = \max(f(p_1^\perp, p_2^\top, \dots, p_n^\top), f(p_1^\top, p_2^\perp, \dots, p_n^\top), \dots, f(p_1^\top, p_2^\top, \dots, p_n^\perp))$$

- consider the set of equations of all equations involving intentional predicates, i.e.

$$\Delta = \bigcup_{r \in P} \{\delta(r)\}.$$

- for a query $q(\mathbf{x})$, the threshold δ of the *TopAnswers* algorithm is defined as to be

$$\delta = \bar{\delta}^q,$$

where $\bar{\delta}^q$ is the solution to δ^q in the minimal solution $\bar{\Delta}$ of the set of equations Δ .

- note that $\bar{\delta}^q$, can be computed iteratively as least fixed-point

- The problem of determining the truth of ground q in least model of \mathcal{P} is

$$O(|\mathcal{P}^*| h(a + p))$$

where h is the cardinality of the truth space, a is max arity of functions, p is max numbers of predecessors of an atom

- The problem of determining top-k answers to q is

$$O(|\mathcal{P}^*| h(a \log |H| + |\mathcal{P}| h(\bar{a} + |D_q|)))$$

- H is Herbrand universe
- D_q is set of intentional relation symbols that *depend* on q
- $\bar{a} = \max(a, r)$, where r is the number of rules

- For Datalog, it is like for RDFS
- The complexity is inherited from their fuzzy variants if lattice is finite, else conjectured undecidable in general

That's it !