

Knowledge Engineering and Business Intelligence

Repetition

Preliminary Note

- These slides guide through the topics of the module Knowledge Engineering and Business Intelligence
- It is intended as a collection of the main content that you need to know to pass the exam.
- Instead, it provides a structure of the module in order to stimulate discussions and questions of the students



Knowledge-Based Systems





University of Applied Sciences and Arts Northwestern Switzerland School of Business

Knowledge Engineering

Knowledge Engineering



Knowledge-Representation and Reasoning



ົ Prof. Dr. Knut Hinkelmann

Rule-Based



Decision Tables and Rule-Based Systems

Eligibility			
A	Degree valid	University Registered	eligible
	yes,no	yes, no, unclear	yes,no
1	yes	yes	yes
2	no	-	no
3	-	no	no
4	-	unclear	no

- Rule 1:
 - IF Temperature = low THEN heating power is increased
- Rule 2:
 - IF Temperature = normal AND humidity = low
 THEN heating power is normal

Facts:father(peter,mary)
father(peter,john)
mother(mary,mark)
mother(jane,mary)Rules:father(X,Y) \rightarrow parent(X,Y)
mother(X,Y) \rightarrow parent(X,Y)
father(X,Y) AND parent(Y,Z) \rightarrow grandfather(X,Z)
mother(X,Y) AND parent(Y,Z) \rightarrow grandmother(X,Z)
parent(X,Y) AND parent(X,Z) \rightarrow sibling(Y,Z)

Forward and Backward Chaining

- Backward Chaining
 - If you already know what you are looking for
- Forward Chaining
 - If you don't necessarily know the final state of your solution



Fuzzy Logic – Vague Knowledge

IF Temperature = *normal* AND humidity = *high* THEN heating power is *high*





Knowledge Graphs - Ontologies



Example of an Ontology



KnowledgeNets, **Triples** and **Types**



triple(a,rdf:type,Person)

triple(a,name,bob).
triple(a,age,33).
triple(a,friend,b).
triple(a,like,c).

triple(b,rdf:type,Person)

triple(b,name,jane).
triple(b,age,26).
triple(b,friend,d).

triple(c,rdf:type,Whiskey)

triple(c,name,lagavulin).
triple(c,age,16).

triple(d,rdf:type,Person)

triple(d,name,tom).
triple(d,age,24).
triple(d,friend,b).
triple(d,owns,f).

triple(f,rdf:type,Car)

triple(f,name,wildcat).
triple(f,brand,porsche).
triple(f,type,911).

Ontology Engineering

Class Hierachy

Annotation properties		Datatypes		Individuals	
Classes	Object properties		Data properties		
Class hierar	Class hierarchy: course				
14 📭 🗴	🐮 📴 Asserted 👻				
V Owl:Thi	ing ademic_Staff lecturer dule <mark>course</mark>				

Properties

🔏 UniversityOntology (http://www.semanticweb.org/knut.hinkelmann/ontologies/2020/4/UniversityOntology) : [C:\Cloud\FHNW\0365_G_KEBI - Generaf\2 —	
File Edit View Reasoner Tools Refactor Window Help	
V UniversityOntology (http://www.semanticweb.org/knut.hinkelmann/ontologies/2020/4/UniversityOntology)	arch
) is_taught_by	
Active ontology × Entities × Individuals by class × DL Query ×	
Annotation properties Datatypes Individuals = is_taught_by - http://www.semanticweb.org/knut.hinkelmann/ontologies/2020/4/University	Ontology
Classes Object properties Data properties Annotations Usage	
Object property hierarchy: is_taught_by DITENS Annotations: is_taught_by DI	
TL C. X Asserted Amontations	
▼ witepObjedProperty L is_taught_by	
	- 14
Chara DILEEN Description: is taught by	
Functional Equivalent To (+)	
Inverse functiona	
Transitive	
Symmetric Inverse Of 🕀	
Asymmetric	
Reflexive Comarks (recreation)	
Ranges (intersection) 🕀	
is_taught_by some lecturer	0
Division With C	
No Reasoner set. Select a reasoner from the Reasoner menu 🗹 Show Inferen	es 🖹

Instances

KuntersityOntology (http://www.semanticweb.org/knut.hinkelm	ann/ontologies/2020/4/University	/Ontology) : [C:\Cloud\Fl	HNW\O365_G_KEBI - General\2 —	o ×
File Edit View Reasoner Tools Refactor Window <	Help ut.hinkelmann/ontologies/2020)/4/UniversityOntology)		 Search
Active ontology × Entities × Individuals by class × DL Que	ery ×			
Annotation properties Datatypes Individuals Classes Object properties Data properties	Annotations Usage	manticweb.org/knut.hin	kelmann/ontologies/2020/4/Univers	ityOntology#KE
Individuals: KEBI	Annotations: KEBI			2080
	Annotations 🕀			
knut				
	Description: KEBI		Property assertions: KEBI	
	Types 🛟		Object property assertions 🕒	
	course	90X0	is_taught_by knut	90×0
	Same Individual As 🕀		Data property assertions 🕂	_
	Different Induiduele		credits 6	0000
			Engineering and Business Intelligence"	0000
			Negative object property assertions	
			Negative data property assertions	
			Negative data property assertions	,

Queries

SPARQL query:

PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#> PREFIX owl: <http://www.w3.org/2002/07/owl#> PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#> PREFIX xsd: <http://www.w3.org/2001/XMLSchema#> SELECT ?instance

WHERE { ?instance rdf:type lecturer}

h

A Two-step Approach for Building a Knowledge Base



Knowledge **Knowledge Modeling** Communication/ Analysis/ **Decision Making** Models human-interpretable models Reality





Ontology-based Metamodeling





Ontology-Based Metamodel

- Single environment for modelling and ontology
- Model elements are directly created as instances in the ontology



Class hierarchy: ManualTask

Ø

Flow Object
Flow Object

🔻 😑 Task

CallActivity
SubProcess

BusinessRuleTask
 ManualTask
 ReceiveTask
 ScriptTask
 SendTask
 ServiceTask

owl:Thing
 Artifact
 Association
 BusinessProcess
 BusinessProcessEvent
 ConnectingObject

2080×

Asserted -



University of Applied Sciences and Arts Northwestern Switzerland School of Business

Machine Learning

Machine Learning: Learning (Tacit) Knowledge from Data



Machine Learning: General Idea



Training

- Collect data for the problem
- Use the data to learn how to solve the type of problem
- Result: Knowledge base

Application

 Use the learned knowledge for new problems

Learning Decision Trees: Generalisation of Data



		Status	income	accept	
1	No	Single	125K	No	
2	Yes	Married	160K	Yes	
3	Yes	Single	70K	No	
4	No	Married	120K	No	
5	Yes	Divorced	95K	Yes	
6	Yes	Married	60K	No	
7	No	Divorced	220K	No	
8	Yes	Single	85K	Yes	
9	Yes	Married	95K	No	
10	Yes	Single	90K	Yes	
Training Data					



Model: Decision Tree

Credit Worthiness				
	Employed	Marital Status	Taxable Income	Accept
	Yes, No	Single, Divorced, Married	Integer	Yes, No
1	No			No
2	Yes	Single	> 80K	Yes
3	Yes	Divorced	> 80K	Yes
4	Yes	Single	≤ 80K	No
5	Yes	Divorced	≤ 80K	No
6	Yes	Married	> 100K	Yes
7	Yes	Married	≤ 100K	No

Model: Decision Table

Tid

Neural Networks

"Non-deep" feedforward neural network

n

Deep neural network





Two ways of Learning from Experience



- There are two ways of learning from data
 - Machine Learning:
 - Learn a set of rules from data
 - Apply this model for any new case
 - Case-Based Reasoning (CBR):
 - For a new situation find the most similar data set and take the conclusion
 - If no appropriate data set is found, solve the new case ad hoc and store it

CBR Cycle



Retrieve ...

most similar case or cases

Reuse ...

the information and knowledge in that case to solve the problem

Revise ...

the proposed solution if necessary

Retain ...

the parts of this experience likely to be useful for future problem solving

Source: K.-D. Althoff & A. Aamodt: Relating case-based problem solving and learning methods to task and domain characteristics. AI Communications 1996

Similarity Calculation for Attribute-Value Pairs

Cases resp. meta-data are represented by n attributes A_1 ,..., A_n

each attribute A_i has type T_i



Local similarity: for each attribute a similarity function is defined

- $sim_{Ai} (x_i, y_i)$: $T_i \times T_i \rightarrow [0..1]$
- local similarity measures depend on the type of the attribute

Global similarity: combining values for local similarity

- $sim(A,Q) = F(sim_{A1}(x_1,y_1), sim_{A2}(x_1,y_1), ..., sim_{An}(x_n,y_n))$
- F: $[0..1]n \rightarrow [0..1]$ is called an **aggregation function**



University of Applied Sciences and Arts Northwestern Switzerland School of Business

Business Intelligence

strategic operative **Bl** overview Which credit applications should What are our goals? ۲ be accepted? Questions Are we reaching our goals? Who are potential csutomers for If not, where is the problem? • the new product? measure, Ad hoc find aggregate, Analyses queries, patterns visualise OLAP (data *mining*) dimensional modelling Date Day_DJ_Week Month Month_Name Quarter Quarter_Name Year Data Warehouse Date_3d Store_3d Product_3d Units_Sold Id EAN_Code Product_Neme Brand Product_Cotegory ETL IE ETL raw data

Business Intelligence



ETL process



The process of

- extracting relevant data from source systems
- transforming the data into the target format defined for the DWH or data mart
- loading the data into the DWH

Business Performance Management



Quelle: (Niven 2003)

KPI Visualisation

- (usually) needs to highlight
 - the target value
 - the actual value
 - the ranges of «red (poor), yellow (satisfactory), green (good)», if defined



Star Schema for Relational Data Warehouses /Marts to support OLAP



Star Schema:

logical database schema, which places dimension tables of a relational database aroung a fact table for easy querying

Maping of multidimensional data to two-dimensional tables.

Dicing and Slicing

- An OLAP cube can be regarded as a multidimensional cube
- From a cube only two dimensions are visible on a two-dimensional interfact (e.g. as a table)



- Slicing
 - Contraining one dimension
 - Dicing
 - Constraining several dimensions
- Pivoting
 - "turning" the cube to show other dimension
- Roll-up/Drill-down Split/Merge
 - Aggregate or detailing views

OLAP Operation – Slicing and Dicing

