

# Bridging between Sensor Measurements and Symbolic Ontologies through Conceptual Spaces

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Stefan Dietze, John Domingue,

Knowledge Media Institute, The Open University, UK





- Background & Motivation
- Conceptual Spaces (CS)
- Utilising CS to map between symbolic Ontologies and Measurements
- Application
- Conclusions







## Introduction Ontology vs Sensor Data

### **Ontology:**

- Formal symbolic specification of shared conceptualisation
- Defined as tuple of concepts C, instances I, properties P, relations R and axioms A

$$O = \{ (C, I, P, R, A) \}$$

#### Sensor data:

- Usually consists of binary data representing measurements...
- ...describing observations of real-world phenomena
- Concurrent standards to represent sensor models and measurements (e.g. OpenGIS SensorML,O&M Encoding Standard)

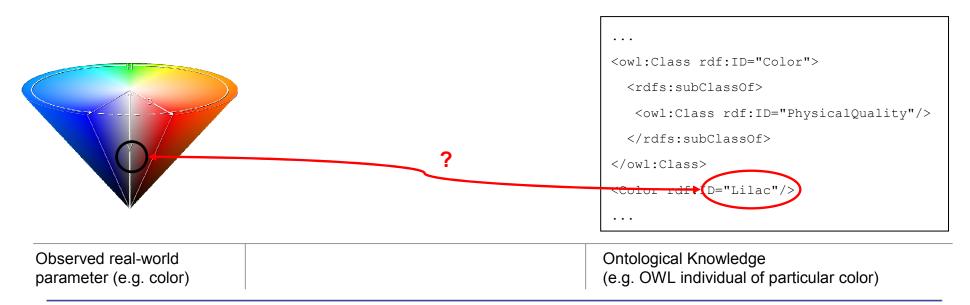






### Ontology vs Sensor Data Issues

Symbol grounding issue – ontological entities lack grounding in real-world / cognitive dimensions



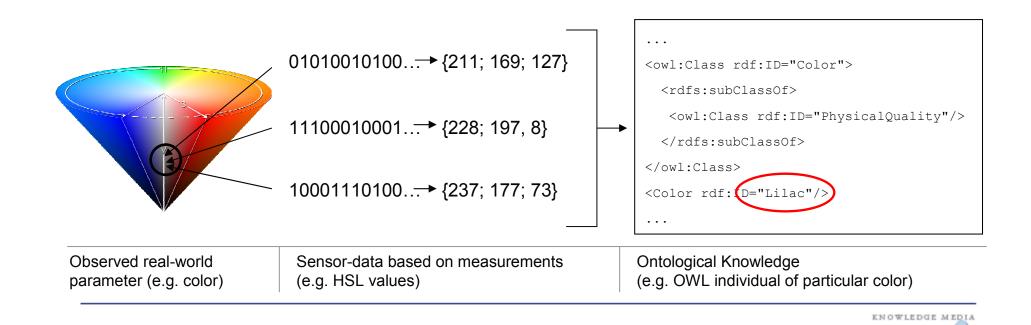






### Ontology vs Sensor Data Issues

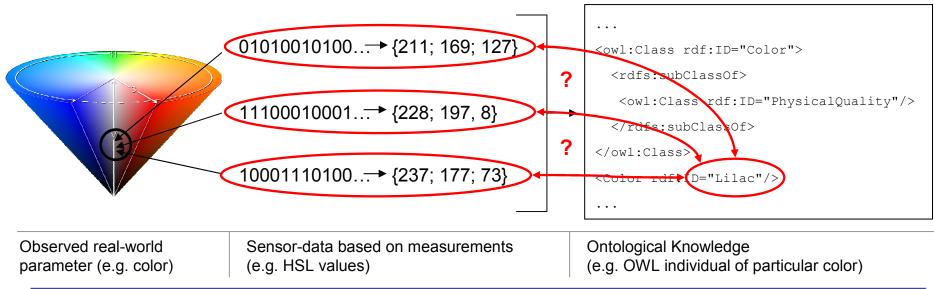
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### **Ontology vs Sensor Data** Issues

- Symbol grounding issue ontological entities lack grounding in real-world / cognitive dimensions
- Multiplicity of mappings potentially infinite amount of measurements needs to be mapped to finite set of symbols
- Lack of implicit similarity symbolic ontologies lack meaningfulness to implicitly infer on similarities







### **Ontology vs Sensor Data** Issues

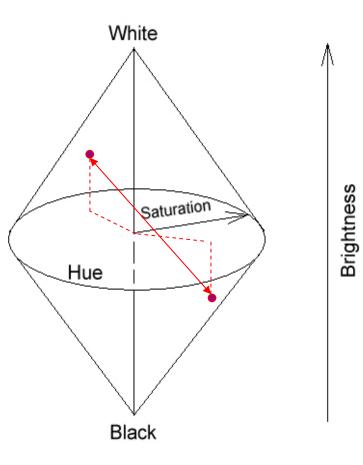
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- Multiplicity of mappings potentially infinite amount of measurements needs to be mapped to finite set of symbols
- Lack of implicit similarity symbolic ontologies lack meaningfulness to implicitly infer on similarities
- Representations needed which enable:
  - to bridge between **measurement-based sensor data** and **ontological symbols**
  - to map infinite variety of real-world observations to finite set of symbols





### **Spatial Representations** Conceptual Spaces

- Exploit measurements for similarity computation
- Multidimensional geometrical vector spaces
- Entities represented in terms of (metric-based) cognitive quality dimensions... (e.g. colors through dimensions hue, saturation, brightness)
- Instances (e.g. 2 colors) => points (vectors) in the CS
- Semantic similarity between instances => spatial distance



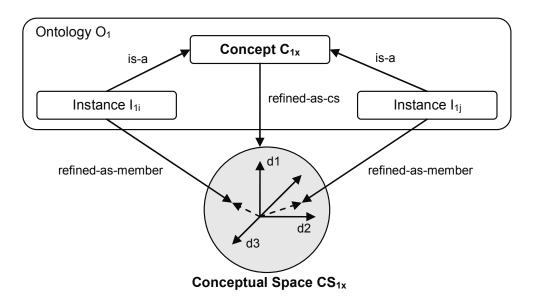




## **Two-fold Approach** Refining Ontologies through CS

CS groundings for ontological concepts (1/2):

- Refining ontologies through multiple CS
- Concept C ontology O => Conceptual Space CS
- Instance I of C => member M (vector) in CS...



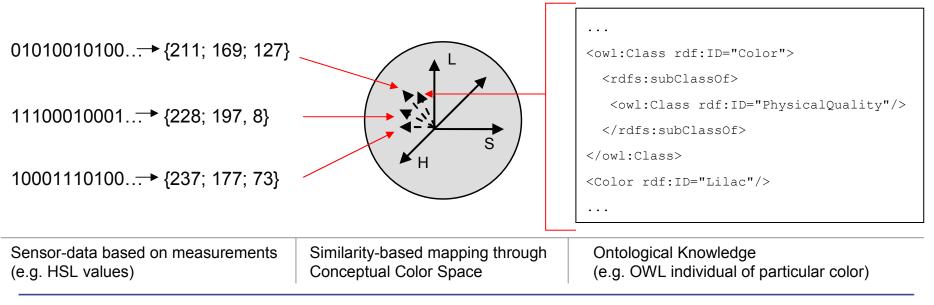




## **Two-fold Approach** Refining Ontologies through CS

CS groundings for ontological concepts (2/2):

- Similarity-computation between sensor-based measurements and ontological instances
- Common agreement at schema (i.e. CS) level...
- ... facilitated through standards for sensor measurement models

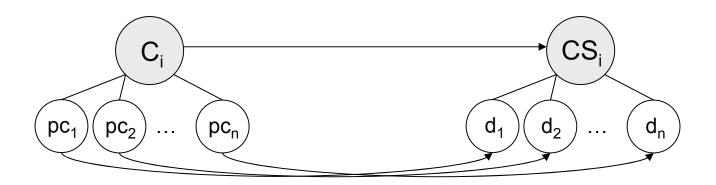






## Two-fold Approach CS Formalisation

- Representation of concept properties  $pc_j$  of  $C_i$  as dimensions  $d_j$  of  $CS_i$
- Assignment of measurement scales to each quality dimension d<sub>i</sub>
- Assignment of prominence values  $p_i$  to each quality dimension  $d_i$
- Representation of all instances  $I_{k_i}$  of  $C_i$  as members  $M_{k_i}$  in  $CS_i$
- Similarity between sensor measurements and symbolic instance = Euclidean distance in CS

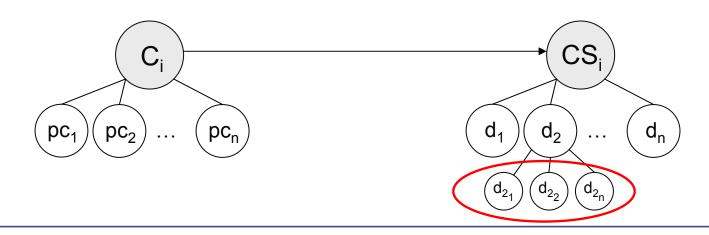






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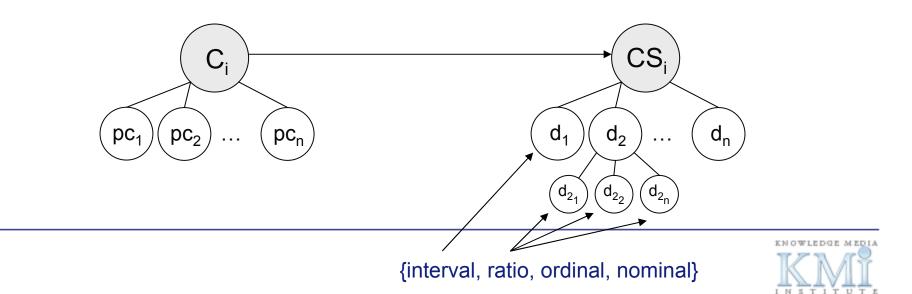






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$$trans: \{ (pc_{i1}, pc_{i2}, ..., pc_{in}) | pc_{ij} \in PC_i \} \Rightarrow \{ (p_{i1}d_{i1}, p_{i2}d_{i2}, ..., p_{in}d_{in}) | d_{ij} \in CS_i, p_{ij} \in P \}$$



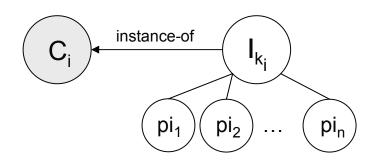






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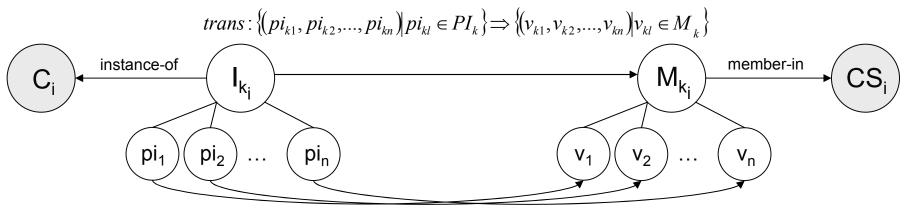




### **Two-fold Approach** CS Formalisation

Formal ontology allowing to refine ontologies through CS:

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e.g.  $M_{k_i}$ ={(20.649, 98, 0, 7.9894)}



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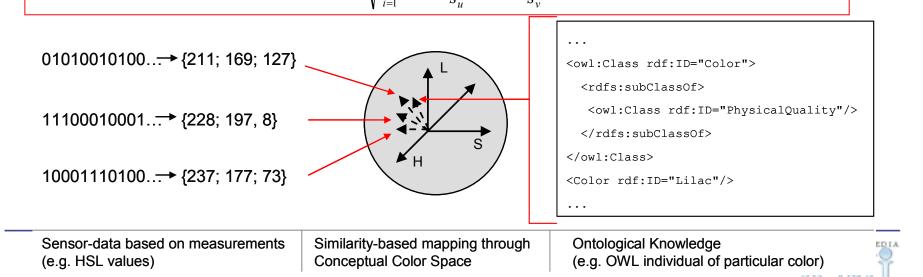


## Two-fold Approach CS Formalisation

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- Representation of instances  $I_{k_i}$  of  $C_i$  as members  $M_{k_i}$  in  $CS_i$

• Similarity between sensor measurements and symbolic instance = Euclidean distance in CS  $dist(u,v) = \sqrt{\sum_{i=1}^{n} p_i((\frac{u_i - \overline{u}}{s_u}) - (\frac{v_i - \overline{v}}{s_v}))^2}$ 

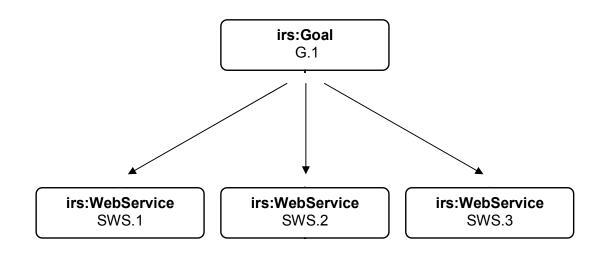






**Application** Measurement-based Service Selection

- Matchmaking of Semantic Web Services (SWS) based on context measurements
- Uses SWS reasoning environment IRS-III
- Request: "irs:Goal" context defined as set of measurements
- Matchmaking between request and x associated SWS (SWS<sub>1</sub>...SWS<sub>x</sub>)
- Implemented through mediation Web service based on similarity-computation





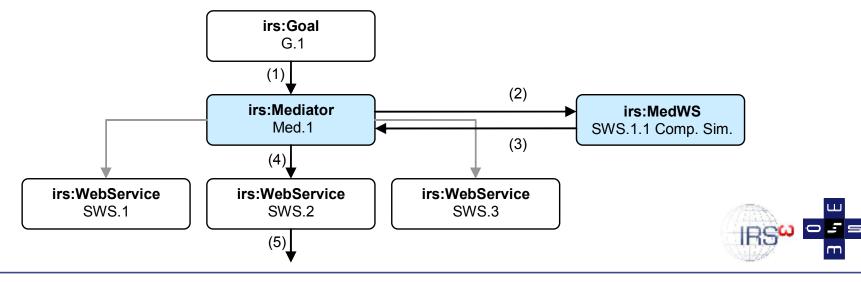






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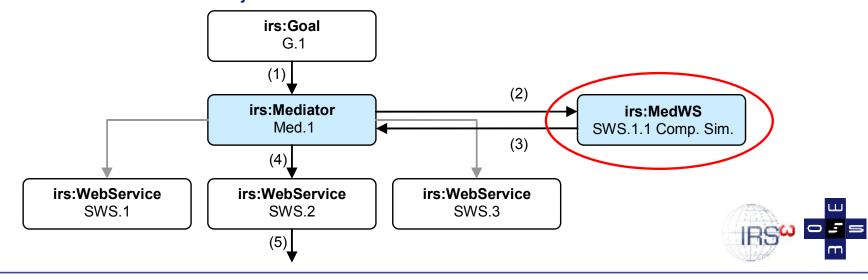


Application Measurement-based Service Selection

• MedWS SWS<sub>1.1</sub> computes x similarity values with Sim(G<sub>1</sub>,SWS<sub>j</sub>) defined as reciprocal of mean value of individual member distances:  $\left(\sum_{k=1}^{n} (dist_{k})\right)^{-1}$ 

$$Sim(G_i, SWS_j) = \left(\overline{Dist(G_i, SWS_j)}\right)^{-1} = \left|\frac{\sum_{k=1}^{n} (dist_k)}{n}\right|^{-1}$$

 dist<sub>k</sub> = distance between one particular vector (member) v<sub>i</sub> describing context of G<sub>1</sub> and one member of SWS<sub>i</sub>





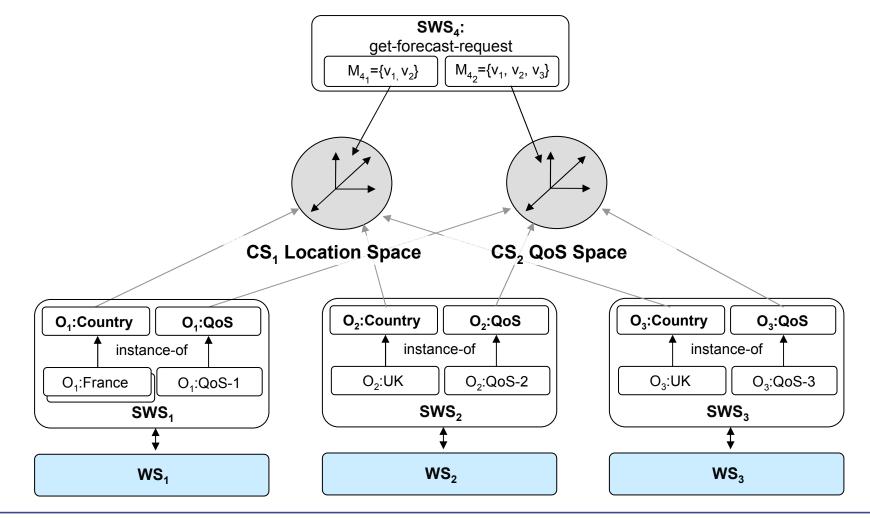


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- Automated discovery of distributed weather forecast services
- Each service targets distinct locations and Quality of Service (QoS) (represented via SWS capability description)
- Symbolic ontologies (SWS) extended with CS-based grounding (service capability parameter - locations, QoS - represented as members in CS)
- Requests (IRS-III goals) use measurements to describe context (e.g. the current location and desired QoS)
- Similarity-based service selection for a given request based on MedWS

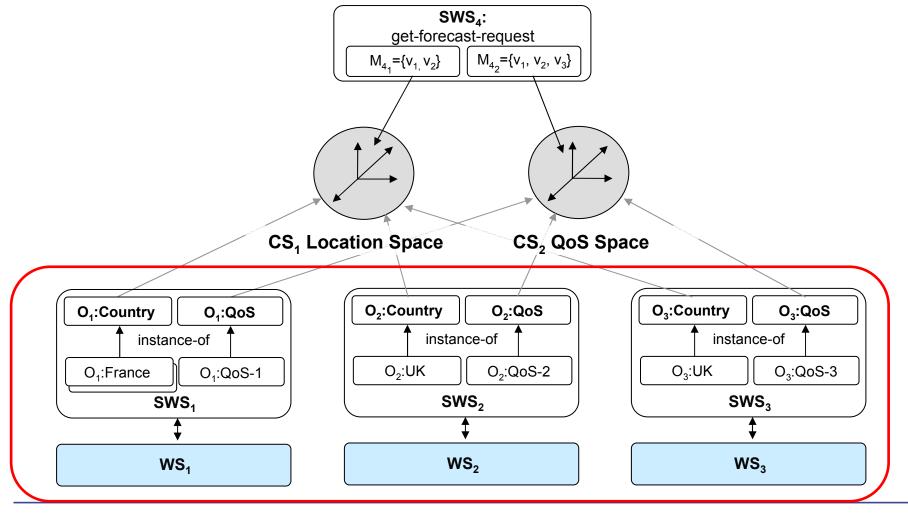






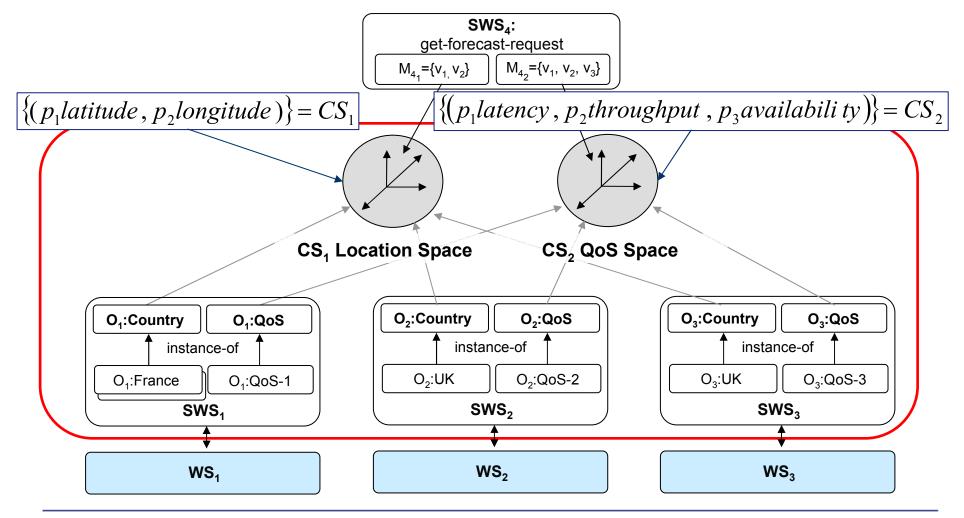


















- SWS capabilities described through conjunction of instances
- Instances refined through vectors (members)

		<b>Assumption</b> $Ass_{SWSi} = (L_{1SWSi} \cup L_{2SWSi} \cup \cup L_{nSWSi}) \cup (Q_{1SWSi} \cup Q_{2SWSi} \cup \cup Q_{mSWSi})$			
		Members $L_i$ in CS <sub>1</sub> (locations)	Members $C_j$ in $CS_2$ (QoS)		
$\left( \right)$	SWS <sub>1</sub>	L <sub>1(SWS1)</sub> ={(46.227644, 2.213755)} L <sub>2(SWS1)</sub> ={(40.463667, -3.74922)}	Q <sub>1(SWS1)</sub> ={(155, 2, 91)}		
	SWS <sub>2</sub>	L <sub>1(SWS2)</sub> ={(55.378051, -3.435973)}	Q <sub>1(SWS2)</sub> ={(15, 50, 98)}		
U	SWS <sub>3</sub>	L <sub>1(SWS3)</sub> ={(55.378048, -3.435963)}	Q <sub>1(SWS3)</sub> ={(78, 5, 95)}		
	$SWS_4$	L <sub>1(SWS4</sub> ={(55.378048, -3.435963)}	Q <sub>1(SWS4)</sub> ={(0,100,100)}		





	Locations: F	rance, Spain	Latency = Throughp Availabilit	ut = 2
	$Ass_{SWSi} = (L_{1SW}$		<b>mption</b> <sub>SWSi</sub> ) $\cup$ ( $Q_{1SWSi}$	$\cup Q_{2SWSi} \cup \cup Q_{mSWSi})$
	Members <i>L<sub>i</sub></i> in	CS <sub>1</sub> (locations)	Mem	ers <i>C<sub>i</sub></i> in CS <sub>2</sub> (QoS)
SWS1	L <sub>1(SWS1)</sub> ={(46.227644, 2.213755)} L <sub>2(SWS1)</sub> ={(40.463667, -3.74922)}		Q <sub>1(SWS1)</sub> ={(	155, 2, 91)}
SWS <sub>2</sub>	L <sub>1(SWS2)</sub> ={(55.378)	051, -3.435973)}	Q <sub>1(SWS2)</sub> ={(	15, 50, 98)}
SWS <sub>3</sub>	L <sub>1(SWS3)</sub> ={(55.378)	048, -3.435963)}	Q <sub>1(SWS3)</sub> ={(	78, 5, 95)}
SWS <sub>4</sub>	L <sub>1(SWS4</sub> ={(55.3780	)48, -3.435963)}	Q <sub>1(SWS4)</sub> ={(	0,100,100)}



#### The Open University **Measurement-based Service Selection** Prototype Application SWS₄: get-forecast-request $M_{4_2} = \{v_1, v_2, v_3\}$ $M_{4_1} = \{v_{1,} v_2\}$ **CS<sub>1</sub> Location Space** CS<sub>2</sub> QoS Space O<sub>2</sub>:Country O<sub>3</sub>:Country O₁:Country O<sub>2</sub>:QoS O<sub>3</sub>:QoS O₁:QoS instance-of instance-of instance-of O<sub>2</sub>:QoS-2 O₃:UK O<sub>2</sub>:UK O<sub>3</sub>:QoS-3 O₁:France O₁:QoS-1 SWS₁ SWS<sub>2</sub> SWS<sub>3</sub>

WS<sub>2</sub>

WS₁



WS<sub>3</sub>

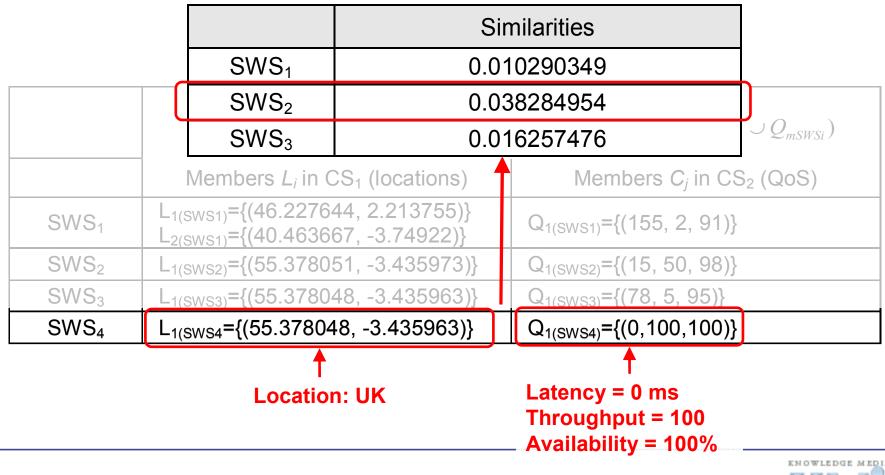


		$\begin{array}{l} \text{mption} \\ \\ P_{WSi} \end{array}) \cup (Q_{1SWSi} \cup Q_{2SWSi} \cup \cup Q_{mSWSi} \end{array}) \end{array}$
	Members $L_i$ in CS <sub>1</sub> (locations)	Members $C_j$ in $CS_2$ (QoS)
SWS <sub>1</sub>	$\begin{array}{c c} L_{1(SWS1)} = \{(46.227644, 2.213755)\} \\ L_{2(SWS1)} = \{(40.463667, -3.74922)\} \end{array}$	Q <sub>1(SWS1)</sub> ={(155, 2, 91)}
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$SWS_3$	L <sub>1(SWS3)</sub> ={(55.378048, -3.435963)}	Q <sub>1(SWS3)</sub> ={(78, 5, 95)}
SWS <sub>4</sub>	L <sub>1(SWS4</sub> ={(55.378048, -3.435963)}	Q <sub>1(SWS4)</sub> ={(0,100,100)}
	Location: UK	Latency = 0 ms Throughput = 100 Availability = 100%
		KNOWLEDGE MEL















		S	imilarities	
	SWS <sub>1</sub>	0.0	10290349	
	SWS <sub>2</sub>	0.0	38284954	
	SWS <sub>3</sub>	0.0	16257476	$\cup Q_{mSWSi})$
	Members <i>L</i> <sub>i</sub> i	n CS <sub>1</sub> (locations)	Members <i>C<sub>j</sub></i> in CS	S <sub>2</sub> (QoS)
SWS <sub>1</sub>		7644, 2.213755)} 3667, -3.74922)}	Q <sub>1(SWS1)</sub> ={(155, 2, 91)}	
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SWS <sub>3</sub>	L <sub>1(SWS3)</sub> ={(55.37	8)48, -3.435963)}	Q <sub>1(SWS3)</sub> ={( <b>1</b> 8, 5, 95)}	
SWS <sub>4</sub>	L <sub>1(SWS4</sub> ={(55.378	3048, -3.435963)}	Q <sub>1(SWS4)</sub> ={(0,100,100)}	
	Locat	ion: UK	Latency = 15 ms Throughput = 50 Availability = 98%	





### **Conclusions** Discussion and Summary

#### Some issues:

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- Additional representational effort
- => CS might just shift symbol grounding issue (i.e. dimensions lack grounding and are ambiguous)
- CS dimensions need to represent actual sensor measurements
- Ontologies/sensor data need to share common schema (CS)





### **Conclusions** Discussion and Summary

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- Additional representational effort
- => CS might just shift symbol grounding issue (i.e. dimensions lack grounding and are ambiguous)
- CS dimensions need to represent actual sensor measurements
- Ontologies/sensor data need to share common schema (CS)
- ..., however:
  - Similarity computation between symbolic instances and sensor measurements
  - Provides means to map infinite variety of potential sensor measurements to finite set of symbolic instances
  - Alignment of distinct sensor models through alignment of CS





### E-mail: <u>s.dietze@open.ac.uk</u> Web: <u>http://people.kmi.open.ac.uk/dietze</u>

