

# ACCESS AND REUSE OF OPEN GOVERNMENT STATISTICAL DATA - CHALLENGES

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- ① INTRODUCTION
- ② RELATED WORK
- ③ MULTI-DIMENSIONAL SEMANTIC DATA CUBE
- ④ MORE IMPLEMENTATION DETAILS
- ⑤ CONCLUSION AND FUTURE WORK

# Motivations

- 1 Building a transparent and accountable government through available open statistical data sources on the Web.
- 2 However, current statistical data sources are used only for humans but not for machines (or software agents), which have limitation on finding insight of data correlations across subject-domains.
- 3 The truth is that multiple statistical data sources are hard to consume simultaneously by humans.
- 4 We need an environment which without too much human intervention for (statistical) data publishing, accessing, dissemination, filtering, capturing, integration, reusing, and visualization.
- 5 Unfortunately, this vision is far from complete.



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# Major Challenges and Solutions

## MAJOR CHALLENGES

- 1 Syntactically, open government statistical data are offered in heterogeneous formats.
- 2 Semantically, these statistical data lack clear semantics to describe what they really mean
- 3 So statistical data are limited for integration, analysis, reuse, and visualization.

## SOLUTIONS

- 1 RDF(S)-based ontology is used to express the statistical data format and also describe its semantics.
- 2 Link Open Data (LOD) principles allow data integration from multiple sources by machines.
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# Research Goals and Contributions

## RESEARCH GOALS

- 1 Investigating current research status about semantic statistics.
- 2 Exploiting seamlessly statistical data exchange and integration techniques.
- 3 Verifying the feasibility to realize semantic statistics concept.
- 4 Implementing a statistical data integration and query platform.

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## Related Work

Related studies are:

- OnLine Analytical Processing (OLAP) [5] [9].
- Statistical Data and Metadata EXchange (SDMX) [3] [8].
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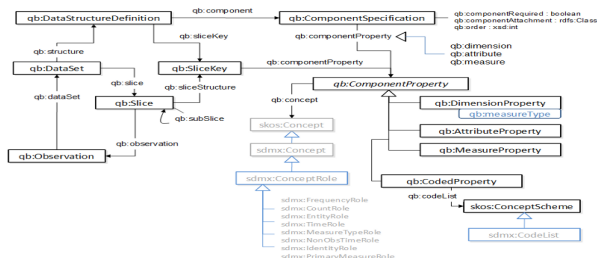
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# W3C RDF Data Cube

## Information Model for RDF Data Cube [14]

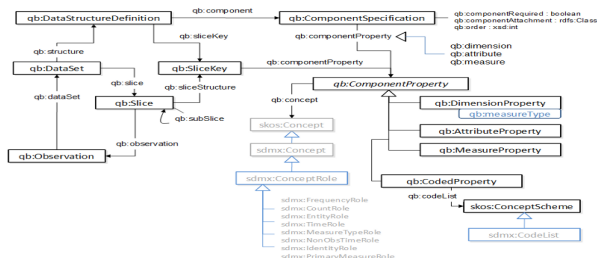


## Builds upon the following existing RDF vocabularies

- ▶ SKOS for concept schemes
- ▶ SCOVO for core statistical structures
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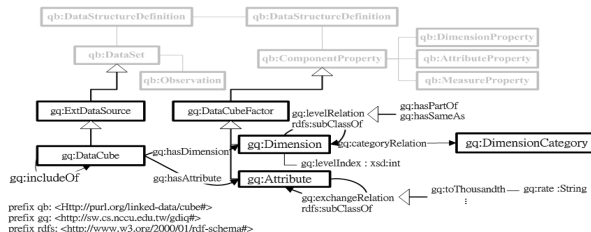


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# RDF Data Cube with its Extension

## Data Cube Extension for Integration and Reuse

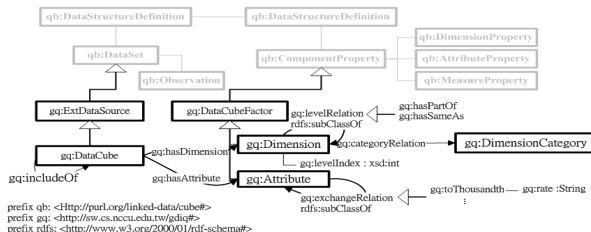


### Integration Library

## Some facts

- ▶ RDF data cube do not provide vocabularies for data integration and reuse from multiple sources.
- ▶ RDF data cube and its extension only provide vocabularies for domain independent ontology descriptions.
- ▶ We still lack annotation and query environment for insight discovery from statistical data correlations across subject-domains.

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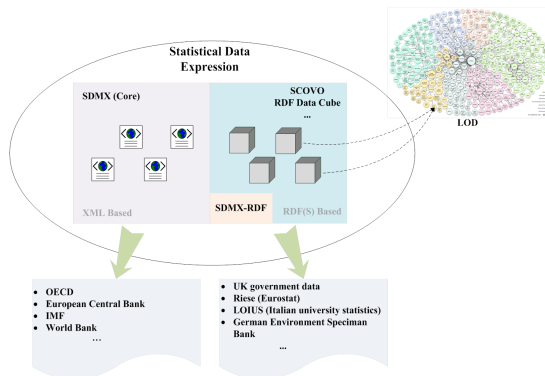
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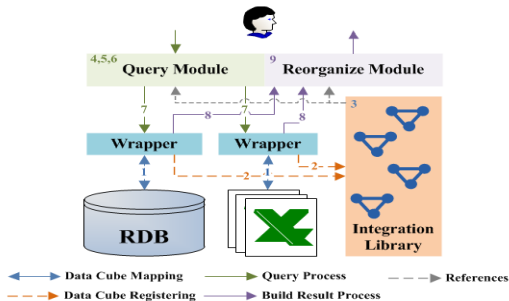
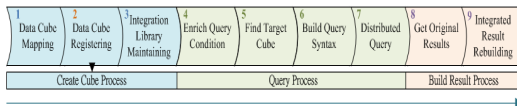


## SDMX vs. SCOVO/RDF Data Cube





# Statistical Data Integration Processes and Framework



# A Simple Example for Data Correlations Discovery

Average salary

	Mining and Quarrying		Manufacturing		Financial and Insurance	
	Average salary	Annual growth(%)	Average salary	Annual growth(%)	Average salary	Annual growth(%)
2008	39,940	-1.81	34,123	0.17	52,150	-6.57
2009	40,636	1.74	32,518	-4.7	52,420	0.52
2010	40,975	0.83	33,383	2.66	54,507	3.98
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The index of industrial production

	Mining and Quarrying		Manufacturing		Electricity and Gas Supply	
	The index of industrial production	Annual production growth rate(%)	The index of industrial production	Annual production growth rate(%)	The index of industrial production	Annual production growth rate(%)
2008	79.07	-4.69	106.65	-1.56	101.11	-1.81
2009	72.43	-8.4	98.15	-7.97	97.83	-3.24
2010	83.25	14.94	126.22	28.6	102.81	5.09
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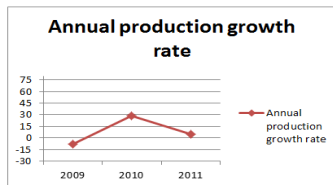
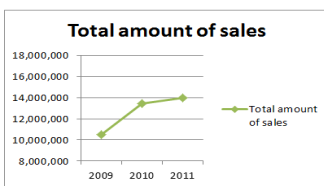
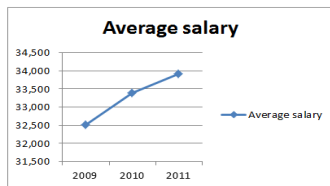
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Number of Enterprises and sales

		Count of companies	Total amount of sales (Thousand of NT\$)
2009-01	B.Mining and Quarrying	1,314	45,028
	C.Manufacturing	129,096	166,457,893
	D.Electricity and Gas Supply	369	30,214
2009-02	B.Mining and Quarrying	1,306	6,187,706
	C.Manufacturing	128,700	1,115,169,731
	D.Electricity and Gas Supply	368	86,732,785
2009-03	B.Mining and Quarrying	1,309	59,600
	C.Manufacturing	128,349	210,905,779
	D.Electricity and Gas Supply	369	52,463

# A Simple Example for Data Correlations Discovery (conti.)

	Average salary	Annual production growth rate	Total amount of sales
2009	32,518	-7.97	10,502,912
2010	33,383	28.6	13,474,671
2011	33,920	5.12	13,954,562



# Mapping from RDB/Excel to RDF

Dimension Property		Measure Property	Attribute Property	
Date	Industry	Companies	Amount	Fields
2009	Manufacturing	129,956	13,111,206	Records
2010	Electricity and natural gas supply	415	757289	

```
eg:rec1 a qb:Observation;
qb:dataset eg:dataset1;
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gdiq-attribute:unit "Companies" ;
gdiq-measure:value 129956
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Dimension Property    Attribute Property

Date	Purpose			Residence	
	Business Thousand People	Tourism Thousand People	Visit Thousand People	Japan Thousand People	USA Thousand People
2009	796	2,298	414	1,001	369
2010	938	3,246	497	1,080	396

Measure Property

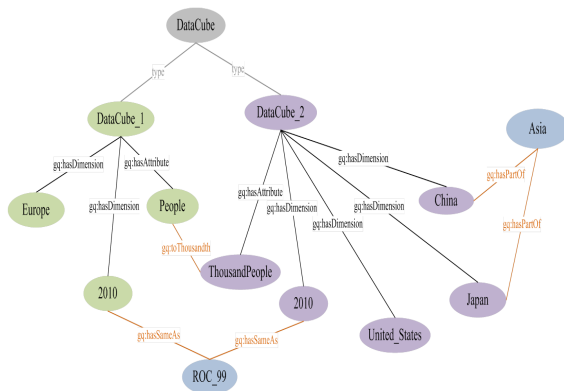
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eg:cv1 a qb:Observation;
qb:dataSet eg:dataset2;
gdiq-dimension:Date "2009";
gdiq-dimension:Purpose "Business";
gdiq-attribute:unit "Thousand People" ;
gdiq-measure:value 796;
.

eg:cv2 a qb:Observation;
qb:dataSet eg:dataset2;
gdiq-dimension:Date "2009";
gdiq-dimension:Residence "Japan";
gdiq-attribute:Unit "Thousand People" ;
gdiq-measure:value 1001;
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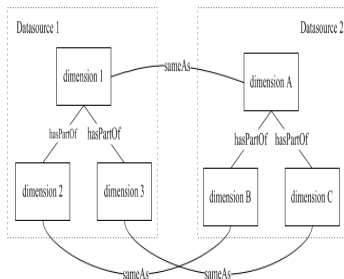
# Core Ontology for Semantic Statistics





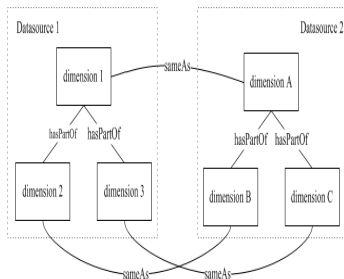
# Data Cube Dimensional Relationships

## A. Horizontal Relation

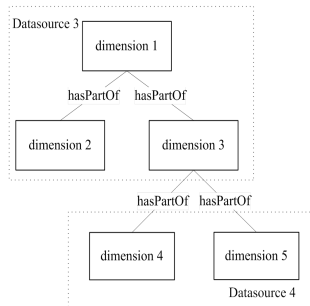


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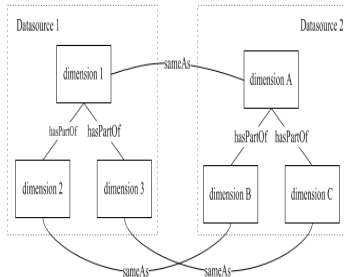


## B. Vertical Relation

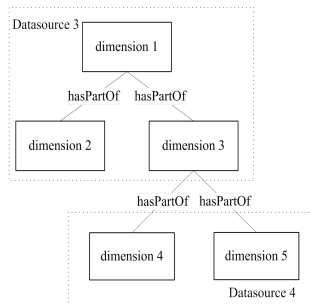


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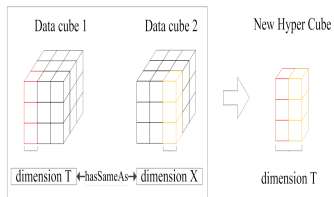
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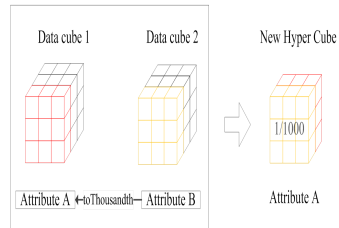
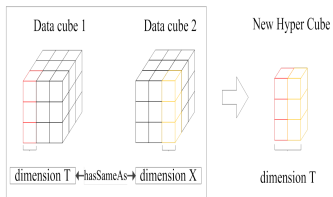
## C. Exchange Relation



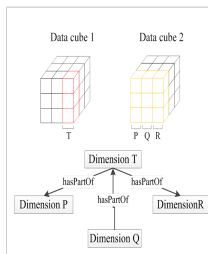
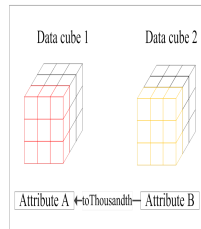
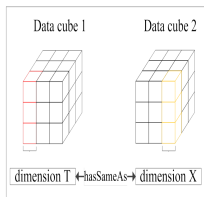
# Measurement Transformation



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# Query Interface

Integrate Query Configuration

Select Dimension

Var	URI
v1	http://sw.cs.nccu.edu.tw/mdip.rdf#Asia
v1	http://sw.cs.nccu.edu.tw/mdip.rdf#Europe
v2	http://sw.cs.nccu.edu.tw/mdip.rdf#ROC_99

Select Attribute

Var	URI
attv	http://sw.cs.nccu.edu.tw/mdip.rdf#ThousandPeople

Select Datasource

URI

PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>  
 prefix dq: <http://purl.org/linked-data/cube#>  
 SELECT ?ob ?v1 ?v2 ?val ?attv  
 WHERE {  
 ?bnk1 dq:dimension ?dim1 .  
 ?bnk2 dq:dimension ?dim2 .  
 ?bnk3 dq:measure ?mea .  
 ?bnk4 dq:attribute ?att .  
 ?ob rdf:type dq:Observation .  
 ?ob ?dim1 ?v1 .  
 ?ob ?dim2 ?v2 .  
 ?ob ?mea ?val .  
 ?ob ?att ?attv .  
 }  
 }

Go! Reset

Registered Data Cubes

Endpoint	
http://localhost:2024/sparql	Unregister
http://localhost:2021/sparql	Unregister
http://localhost:2022/sparql	Unregister
http://localhost:2023/sparql	Unregister

Register by SPARQL endpoint:

http://

Register

# Conclusion

- ① We have designed and implemented a process for statistical data access and reuse from multiple public data sources.
- ② We have built an infrastructure for (statistical) data accessing, capturing, integration, reusing, and simple visualization without too much human intervention.
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## Future Work

- 1 Experiment on more empirical open government's statistical datasets to verify the feasibility of semantic statistics integration concepts.
- 2 Offer an annotation and query environment for various domain experts to interpret and annotate their insight of statistical data correlations discovery across subject-domains.
- 3 Establish a process to access and reuse direct big data instead of indirect statistical datasets to realize the semantic statistics integration concept without violating the data protection principles.



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