A Conceptual Modelling Approach to Visualising Linked Data

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Abstract. Increasing numbers of Linked Open Datasets are being published, and many possible data visualisations may be appropriate for a user's given exploration or analysis task over a dataset. Users may therefore find it difficult to identify visualisations that meet their data exploration or analyses needs. We propose an approach that creates conceptual models of groups of commonly used data visualisations, which can be used to analyse the data and users' queries so as to automatically generate recommendations of possible visualisations. To our knowledge, this is the first work to propose a conceptual modelling approach to recommending visualisations for Linked Data.

1 Introduction

There are numerous Linked Open Datasets available on the web, and supporting their visual exploration and analysis by potential users is a pressing need. Conversely, there are many possible data visualisations that might be appropriate for a given user task, *e.g.* as provided by a typical visualisation library such as D3 or Google Charts. It may therefore be hard for users to select appropriate visualisations to meet their specific exploration or analysis needs with respect to a given dataset.

We propose an approach that addresses this problem by using "visualisation patterns" expressed in OWL that characterise each distinct (from a data representation capability) group of commonly-used data visualisations, and by generating SPARQL query templates corresponding to these visualisation patterns. Our starting premise is that users formulate SPARQL queries to extract the data that they wish to see visualised; this might be direct specification of a SPARQL query by a technically knowledgeable user, or indirect construction of a SPARQL query through a visual querying tool by a non-technical user. Our OWL visualisation patterns and SPARQL query templates are used to analyse the data and the users' queries, respectively, so as to automatically generate a more focussed set of recommendations of possible visualisations to the user. We view our approach as being part of a broader set of solutions that can aid users in formulating queries and exploring Linked Data, *e.g.* it may be combined with browsing and exploration [6, 4, 19, 17, 31], faceted search [37, 2, 24] or structural summaries [5, 23].

Current approaches to visualising linked data provide a limited set of data visualisations that are oriented specifically towards visualising RDF graphs or ontologies, or that support more general data visualisation capabilities but without the intermediate conceptual abstraction and recommendation process for the user that we propose here (see Section 2). In contrast, to our knowledge ours is the first work to propose a conceptual modelling approach to recommending visualisations for Linked Data to users.

We continue the paper with a review in Section 2 of related work on data visualisation in general and visualising linked data specifically, contrasting this with our approach. Section 3 describes an example use case motivating our approach. Section 4 presents OWL specifications characterising several groups of common data visualisations, as well as SPARQL query templates corresponding to the OWL visualisation patterns. Section 5 discusses transformations that can be applied to users' SPARQL queries so that they match the SPARQL query templates. Section 6 summarises our contributions and presents possible directions for further work.

2 Related Work

Data Visualisation. The field of data visualisation is a very active one (for reviews see *e.g.* [1, 43, 39]) and is continuing to expand with the advent of 'big data' arising from web-scale applications and the need to develop new techniques for exploring such data [15]. Current data visualisation tools (*e.g.* Tableau[3], D3[4], Google Charts[5]) require users to manually select from typically tabular data, apply transformations, and select appropriate visual encodings from a vast array of possibilities. The user may therefore find it hard to understand the meaning of the data, the transformations that may be applied to it, and the range of visualisation possibilities, and may easily fail to 'see the wood for the trees'.

For these reasons, there has been work towards automated recommendation of visualisation possibilities and for ranking recommendations [20, 35, 27, 47]. The SemVis system [14] reduces the visualisation search space by using a domain ontology for mapping the source data into a visual representation ontology storing 'knowledge about visualisation tools', and a bridging ontology to map between the domain ontology and the visual representation ontology. Our work is similar in spirit to this, but we do not require the availability of a domain or a bridging ontology.

Other recent work that is close to ours is the Voyager system [48] which provides techniques aiming to aid the user in selecting appropriate visualisations, including faceted browsing of visualisation recommendations, and auto-

[3] https://www.tableau.com/products/desktop
[4] https://github.com/d3/d3/wiki/Gallery
[5] https://developers.google.com/chart/interactive/docs/examples

matic clustering and ranking of visualisations according to data properties and perceptual effectiveness principles. However, this work focusses on the visualisation of a single relational table of data. It also does not undertake matchings between the data and conceptual-level representations of visualisations.

Several works have derived taxonomies of classes of visualisation *e.g.* [36, 11, 41]. However, they focussed on properties of the data (dimensionality, dependent/independent variables, discrete/continuous, ordered/unordered) rather than capturing different visualisations as instances of a conceptual visualisation schema.

Finally, languages proposed for manipulating graphical data (*e.g.* Tableau's VizQL [38], Wilkinson's Grammar of Graphics [46], R's Tidyr package [33]) require programmers to manually select data, apply transformations, and select appropriate visual encodings.

Visualising Linked Data. Many research works and systems have addressed the visualisation of linked data (for reviews see *e.g.* [12, 32, 8]). There have been many proposals for visualising ontologies [25, 26, 45, 13] and RDF graphs [10, 22, 3, 7]. These proposals typically provide a fixed set of tree- or network-oriented data visualisations for viewing the graph structure of the data and/or the ontology, with little extensibility or customisation capability.

There are also proposals that support more general visualisation capabilities for linked data which allow end users to interactively select data and visualisations [18, 42, 34, 40, 9]. There has also been work on combining faceted search with data analytic visualisations, mainly in application-specific settings [21, 28, 24].

Graziosi et al. [16] discuss the difficulty of producing visualisations for linked data for users with little technical knowledge of semantic web technologies or programming. They present a reference model for building tools that generate customisable "infoviews" and conduct a survey of existing tools in terms of their customisation capabilities. Issues relating to the scalability of exploration and visualisation approaches in the face of large, distributed linked datasets are discussed by Bikakis and Sellis [8].

None of these works provide the conceptual abstraction of groups of visualisations nor a recommendation process for the user as we propose here.

Our own previous work [30] also proposed a conceptual modelling approach towards data visualisation. However, that was in the context of structured data sources with the assumption that strict schema information is available or inferable, and with schema-level matching being undertaken between the schema of the data on the one hand and the visualisation schema patterns on the other.

Finally, we note that our abstraction of *classes* of commonly used data visualisations generalises the visualisation capabilities of graph database systems such as GraphDB[6] which guide the user towards creating specific visualisations.

[6] http://graphdb.ontotext.com/

3 Motivating Example

To motivate our approach we consider the Mondial database [29], which is available in RDF. A small fragment of it is illustrated in Figure 1, with the relevant part of the OWL Schema illustrated in Figure 2. In these figures, the directional arrows represent properties, with the arrow going from the domain to the range to the property.

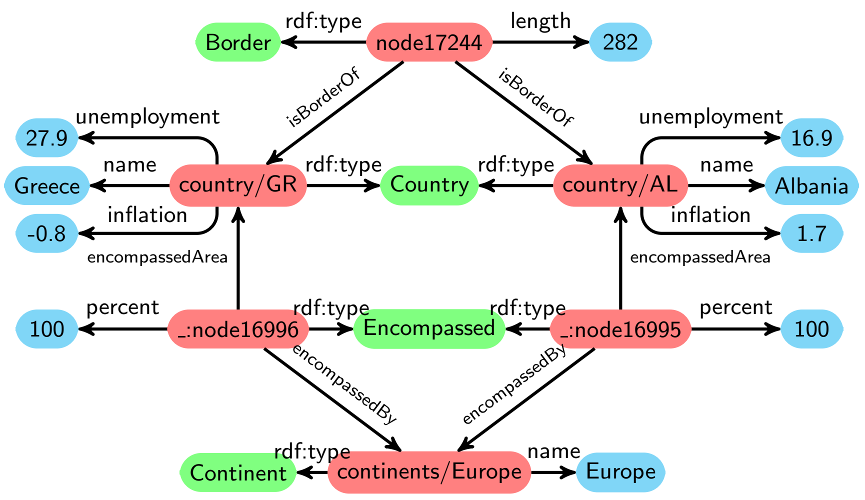


Fig. 1. RDF Graph of countries and their borders from the Mondial database

The fragment of the Mondial database that we consider here contains countries, the continents they are within (some countries may span two continents), the length of the border between pairs of countries, and the population history of countries. Figure 3 shows a number of visualisations of this data. Each is presenting different information about the Country class, but in different ways according to the properties and datatypes being queried. In this paper we assume that users formulate SPARQL queries to extract the data they are interested in viewing, but then require guidance as to which visualisation method can be used, and we use OWL schema information such as that presented in Figure 2 to guide that process.

4 OWL Patterns for Visualisation

In visualisation research, the various graphic elements of a visualisation are typically classified as **marks** (points, lines, areas, *etc*) or **channels** (colour, length, shape, coordinate, texture, orientation, movement, *etc*) of a mark [44]. We make two basic assumptions here: (1) instances of classes can be represented as a mark in a visualisation, so that a visualisation becomes a method of viewing the instances of one or more classes; and (2) each functional data property associated

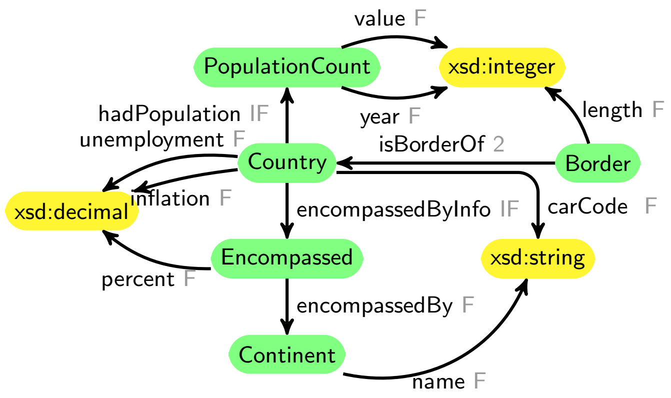


Fig. 2. Fragment of the OWL Schema for the Mondial Database. Functional properties are labelled F , inverse functional properties are labelled IF , and maximum cardinality two properties are labelled 2 .

with a class can be used to alter a channel of the mark associated with that class — we refer to such properties as **dimensions** of the class instances.

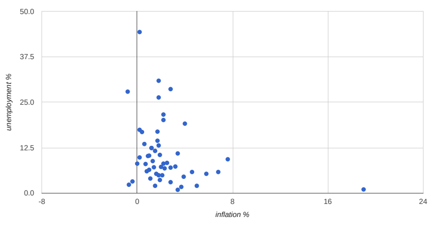
Taking an approach similar to Tableau[7], and our previous work [30], we distinguish two major types of dimensions (we note that these are different to the 'discrete' and 'continuous' dimensions of [41]):

– **discrete dimensions** have a relatively small number of distinct values, that may nor may not have a natural ordering; they are used to label a mark or to vary a channel of a mark. Examples include the code associated with a country or the year associated with a population census.
– **scalar dimensions** have a relatively large number of distinct values with a natural numeric ordering (*e.g.* integers, real numbers, timestamps, dates); these are represented by a channel associated with a mark. Examples include the population of a country in a particular year, or the area of a country.

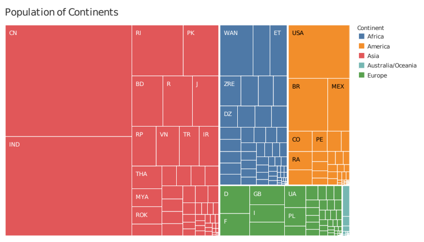
When a dimension is represented by a colour channel, then for a discrete dimension we assume that a colour key can be used, while for a scalar dimension we assume that a spectrum of colours can be used. Both discrete and scalar dimensions may have additional real-world characteristics, *e.g.* their data may be geographical, temporal, or lexical, which may suggest specific visualisations for their representation.

In the following subsections, we develop progressively more complex patterns of classes and properties, each characterising a group of possible alternative visualisations. Our approach aims to provide the user with assistance in selecting appropriate visualisations and should be viewed as being complementary to user interface design aspects such as interaction design and task-based visualisation design. To illustrate how the visualisation patterns could be applied in practice,

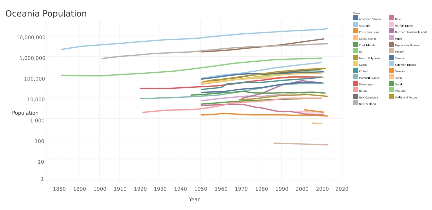
[7] https://www.tableau.com/products/desktop



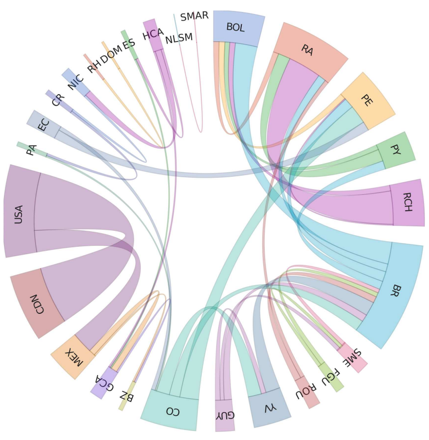
(a) Inflation v Unemployment in Europe



(b) Continent Population



(c) Population Trend in Oceania



(d) Border Length in the Americas

Fig. 3. Example visualisation of country data based on patterns

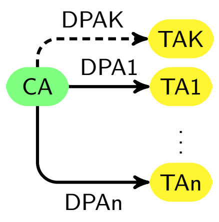
we conclude the description of each by listing the SPARQL query template that is implied by the visualisation pattern, together with the user queries matching this query template that have been used to generate the visualisations shown in Figure 3.

4.1 Class with data properties

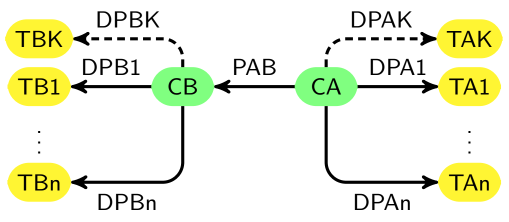
Starting from our two basic assumptions (1) and (2) above, we can identify the **graph pattern** illustrated in Figure 4(a), showing a class, CA, with one or more functional data properties, DPA1. . . DPAn. This graph pattern can be formally specified by the following **visualisation pattern**, expressed in OWL:

```
DataPropertyDomain(DPA1 CA)        DataProperty(DPA1)
DataPropertyRange(DPA1 TA1)        FunctionalProperty(DPA1)
...                                ...
DataPropertyDomain(DPAn CA)        DataProperty(DPAn)
DataPropertyRange(DPAn TAn)        FunctionalProperty(DPAn)
```

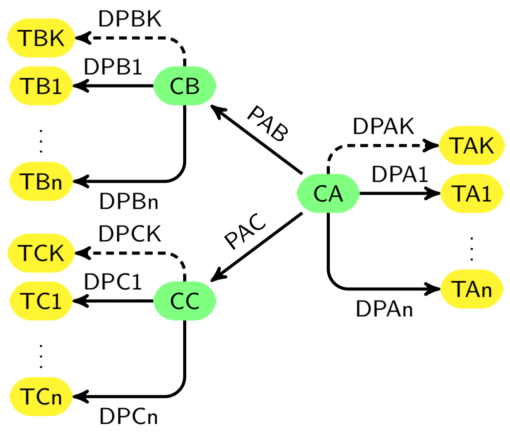
Note that here, and subsequently, we use variables CA, CB, . . . to denote classes A, B, . . . ; variables DPA1, DPA2, . . . to denote data properties of a class



(a) Class with a key data property



(b) Two classes connected by a function object property



(c) Three classes connected by two functional object properties

Fig. 4. Graph Patterns for Visualisations

A; variables TA1, TA2, . . . to denote the ranges of such data properties; variable DPAK to denote a data property of a class A that is a key; variable TAK to denote the range of such a data property; and variable PAB to denote an object property between classes A and B.

Some visualisations (such as scatter diagrams) do not require that each mark be labelled with a meaningful unique label, whilst others (such as bar charts) do require such labels if they are to be useful. We indicate such a key with a dashed line in the graph pattern, which adds the following additional statements to the OWL visualisation pattern:

```
DataPropertyDomain(DPAK CA)        HasKey(CA () (DPAK))
DataPropertyRange(DPAK TAK)        DataProperty(DPAK)
                                   FunctionalProperty(DPAK)
```

Each instance of the class CA will result in a mark, and its associated values of TA1. . . TAn will determine the channels of the mark. If there is a key TAK present, it may be used to label each mark of the visualisation.

Many visualisations match this visualisation pattern, and we list below an indicative sample, summarised in the table below:

– In a **scatter diagram** the marks are points, and two scalar dimensions TA1 and TA2 are used to alter the x and y coordinates of the points. If there is a TAK present it can be used to label the points. The colour, shape, *etc* of the point can be altered by additional optional dimensions TA3, ...
– In a **bubble chart**, the concept of a scatter diagram is refined to use a third scalar dimension TA3 to change the size of the point.
– In a **calendar chart** the marks are entries in a calendar, and hence the value of dimension TA1 must be a date to identify which slot on the calendar is used.
– Basic **bar charts** use each value of TAK to label one bar, and the scalar value of TA1 to change the length of the bar. There is a limit to the number of bars that can be displayed so that the chart remains comprehensible. In the table below, we therefore limit the cardinality of the class CA to be at most 100, constraining the selection of this type of visualisation to data that satisfies this constraint (the limit of 100 is of course subjective and would be tunable in an implementation).
– A **choropleth map** uses each value of TAK to identify regions on a map, and the scalar value of TA1 to change the colour of the region.
– In **word clouds**, the value of TAK is used to determine the word to be plotted, and the scalar value of TA1 to determine the size of the word.

The analysis above is summarised in the table below. All of these visualisations can support additional channels by altering the colour, texture, or other aspects of the mark. This is illustrated in the table by colour or texture dimensions in the optional column, which are extensible with additional dimensions of the data, mapping to additional channels in the visualisation. The notation |CA| is used to denote the number of instances of a class CA, so for example, we allow any number of instances to be visualised in a calendar chart, but restrict bar charts to have up to one hundred bars.

Visualisations for Classes with Data Properties			
Name	|CA|	mandatory	optional
Calendar Chart	1..*	TA1 temporal scalar	TAK,TA2 colour
Scatter Diagrams	1..*	TA1,TA2 scalar	TAK,TA3 colour
Bubble Charts	1..*	TA1,TA2,TA3 scalar	TAK,TA4 colour
Bar Chart	1..100	TAK, TA1 scalar	-
Choropleth Maps	1..*	TAK geographical, TA1 colour	TA2 texture
Word Clouds	1..*	TAK lexical, TA1 scalar	TA2 colour

A SPARQL query template to extract the values required for a visualisation that requires just TAK and TA1 is given below left; additional dimensions can be added to the query in the obvious way by adding :DPA2 ?TA2, *etc.* A typical user interaction scenario making use of the SPARQL query template and the OWL visualisation template is as follows. The user first formulates a SPARQL query to extract the data that they wish to see visualised; an example such query is given below right.

```
SELECT ?TAK ?TA1 ?TAn WHERE {
    ?CA rdf:type :CA ;
        :DPK ?TAK ;
        :DPA1 ?TA1 .
}
```

```
SELECT ?inflation ?unemployment WHERE {
    ?c rdf:type :Country ;
       :inflation ?inflation ;
       :unemployment ?unemployment ;
}
```

A system implementing our approach would match the user's query against the SPARQL query pattern corresponding to each group of visualisations (as presented here and in the following subsections); in this particular example, the user's query matches the SPARQL query template shown above left. The system would then validate that the OWL visualisation pattern is satisfied by matching it against the RDFS/OWL statements in the dataset that is being queried which relate to the classes and properties mentioned in the user's query. The group of visualisations that are satisfied (if any) would then be checked against the data for the additional constraints (see *e.g.* the above table) relating to individual visualisations. In our particular example, the Calendar Chart, Chloropeth Map and Word Cloud would be discounted due to the data type constraints on TA1 or TAK; and the Bar Chart would be discounted due to the cardinality constraint on CA. The remaining set of visualisations would finally be offered to the user as possible alternatives for generating their visualisation. In our particular example, a scatter diagram or bubble chart would be offered. If the user selects a scatter diagram, then the diagram shown in Figure 3(a) is produced.

We assume here that users' SPARQL queries do not contain OPTIONAL clauses and therefore only full matches with respect to the data are returned. Exploring the interplay of OPTIONAL clauses with the recommendation techniques that we propose here is an interesting area of future work.

4.2 Two classes linked by a functional property

We now consider the case where in addition to having data properties and a key data property, a class CA is the domain of an object property PAB whose range is another class CB. This is illustrated in the graph pattern in Figure 4(b) which can be specified by the OWL statements below being added to those of the previous subsection, giving an overall OWL visualisation pattern for this second group of visualisations:

```
ObjectPropertyDomain(PAB CA)
ObjectPropertyRange(PAB CB)
DataPropertyDomain(DPBK CB)
DataPropertyRange(DPBK TBK)
DataPropertyDomain(DPB1 CB)
DataPropertyRange(DPB1 TB1)
...
DataPropertyDomain(DPBn CB)
DataPropertyRange(DPBn TBn)
```

```
HasKey(CB () (DPBK))
FunctionalProperty(PAB)
DataProperty(DPBK)
FunctionalProperty(DPBK)
DataProperty(DPB1)
FunctionalProperty(DPB1)
...
DataProperty(DPBn)
FunctionalProperty(DPBn)
```

The fact that PAB is functional means the presence of a hierarchical pattern of data, with each instance of CA being associated with one instance of CB.

Visualisations that represent two classes together rather than a single class are less common, but some examples are listed below:

- In a **tree map**, rectangles representing instances of class CB are divided into rectangles representing instances of class CA, the area of which is proportional to the value of a scalar dimension TA1. Typically it is a dimension TB1 of CB that is used to colour the rectangles, and additional dimensions such as TA2 are used for texture, *etc.*
- In a **hierarchy tree**, nodes represent instances of CB that are connected by lines to circles representing instances of CA. Since the nodes are at distinct levels, optionally it is possible to use TA1 to colour one level, and TB1 to colour the other level.
- A **circle packing** represents instances of CB by circles, with instances of CA placed as circles inside the circle of their parent instance of CB. A scalar dimension TA1 is used to determine the area of the circles of CA. Similarly to a hierarchy tree, distinct dimensions can be used to colour distinct levels of the circles.
- A **sunburst** represents instances of CB by segments of a central circle, with segments of an outer circle divided representing instances of CA, placed outside of the corresponding instance of CB. The relative size of the segment is determined by TA1. Similarly to a hierarchy tree, distinct dimensions can be used to colour distinct rings of the sunburst.

We note that all of these visualisations support additional levels in the hierarchy, such that one could add a third class CC connected by functional property PBC from CB giving an additional level to the hierarchy.
The table below summarises the above analysis, where |CA PAB CB| presents the number of instances in CA that are associated via PAB to each instance of CB. The upper cardinality figures given (such as 20 for the top level of a tree map) are there to guide the user towards selection of an uncluttered visualisation, and are not a rigid limit. The restrictions proposed are subjective, and aesthetics-driven, but serve to direct users to choosing appropriate visualisations so as to avoid situations where the amount of data would ‘clutter’ a particular type visualisation. In any implementation these limits should of course be user-configurable.

Visualisations for functional properties				
Name	|CB|	|CA PAB CB|	mandatory	optional
Tree Map	1..20	1..100	TAK,TBK,TA1 scalar	TB1 colour,TA2 colour
Hierarchy Tree	1..100	1..100	TAK,TBK	TA1 colour,TB1 colour
Sunburst	1..20	1..20	TAK,TBK,TA1 scalar	TA1 colour,TB1 colour
Circle Packing	1..20	1..20	TAK,TBK,TA1 scalar	TA1 colour,TB1 colour

A SPARQL query template to extract the labels and one attribute from each of the two classes is listed below left (again additional dimensions can be added in the obvious way). A possible user SPARQL query is shown below right. Although this does not directly match the SPARQL query template on the left, in Section 5 we discuss how the filter expression appearing in the user’s query causes the concatenation of encompassedByInfo and encompassedBy to be functional, and hence match PAB in the query template. Following such a transformation, for the Mondial database the tree map and hierarchy tree are offered as alternative visualisations. If the user selects a tree map, then the diagram shown in Figure 3(b) is produced.

```
SELECT ?TBK ?TAK ?TA1 ?TB1 WHERE {
    ?CA rdf:type :CA ;
        :DPAK ?TAK ;
        :DPA1 ?TA1 .
    ?CB rdf:type :CB ;
        :DPBK ?TBK ;
        :DPB1 ?TB1 .
    ?CA :PAB ?CB .
}
```

```
SELECT ?continent ?carcode ?population
WHERE {
    ?c   rdf:type :Country ;
         :carCode ?carcode ;
         :population ?population ;
         :encompassedByInfo ?en .
    ?en  :encompassedBy ?con;
         :percent ?percent.
    ?con rdf:type :Continent ;
          :name ?continent .
    FILTER ( ?percent>50 )
}
```

4.3 Two classes linked by a key functional property

A different set of visualisations are specified if we change the HasKey(CA () (DPAK)) definition in the previous subsection to
HasKey(CA () (DPAK PAB))
so that it is the combination of TAK and CB that identify instances of CA. In this case, instances of CA are in a sense dependent on instances of CB, and a number of visualisations naturally support such a dependency, a selection of which are listed below:

- In a **line chart** each line represents an instance of CB labelled with TBK; TAK represents a scalar dimension to be plotted along the x-axis; and TA1 must be a scalar dimension to be plotted along the y-axis. XY variations of line charts allow an additional dimension TA2 to be added to the y-axis. Optionally, additional dimensions TA3 could colour the points of the line, and TB1 colour the lines.
- In a **spider chart**, each ring represents an instance of CB, labelled by TBK, and each spoke a value of CA labelled by TAK; the intersection of the ring with a spoke is determined by TA1. Similarly to line charts, additional dimensions TA2 could colour the points of intersection, and TB1 colour the lines. For this visualisation type, we require CA to be **complete** with respect to CB, by which we mean that all instances of CB should appear with the same (or almost the same) set of values for TAK so that the different instances of TBK can be can be compared for each instance of TAK.
- In a **stacked bar chart**, instances of CB are represented by a bar labelled by TBK, with one of the elements in the stack representing an instance of CA, and the length of the bar determined by a scalar dimension TA1, and it being labelled and coloured by TAK. Optionally TA2 could alter the texture of the elements. For this visualisation type too, we require CA to be **complete** with respect to CB, so that the elements in each stack can be compared.

– A **group bar chart** is similar to a stacked bar chart, with one group labelled by TBK, and each bar in the group having its height determined by TA1 and labelled and coloured by TAK. There is no need for CA to be complete with respect to CB. Optionally TA2 could alter the texture of the bars.

The table below summarises the above analysis. Again the upper cardinalities shown for |CB| and |CA| are aesthetics-driven and would be user-configurable.

Visualisations of key functional properties					
Name	|CB|	|CA|	complete	mandatory	optional
Line	1..20	1..*	no	TAK scalar,TBK,TA1 scalar	TA2 scalar,TA3/TB1 colour
Spider	3..10	1..20	yes	TAK,TBK,TA1 scalar	TA2/TB1 colour
Stacked Bar	1..100	1..20	yes	TAK colour,TBK,TA1 scalar	TA2 texture
Grouped Bar	1..20	1..20	no	TAK colour,TBK,TA1 scalar	TA2 texture

The SPARQL query template for this group of visualisations listed below left is the same as in the previous subsection. Below right is a user's SPARQL query asking for the historical population trends of countries in Oceania that matches the query template and OWL visualisation pattern, and produces Figure 3(c) if the user selects to view the data on a line chart.

```
SELECT ?TBK ?TAK ?TA1 ?TB1 WHERE {
    ?CA rdf:type :CA ;
        :DPAK ?TAK ;
        :DPA1 ?TA1 .
    ?CB rdf:type :CB ;
        :DPBK ?TBK ;
        :DPB1 ?TB1 .
    ?CA :PAB ?CB .
}
```

```
SELECT ?country ?year ?population
WHERE {
    ?c  rdf:type :Country ;
        :name ?country ;
        :encompassedByInfo ?en .
    ?py rdf:type :PopulationCount ;
        :year ?year;
        :value ?population .
    ?c  :hadPopulation ?py .
    # Filter conditions
    ?en :encompassedBy ?con .
    ?con rdf:type :Continent ;
        :name "Australia/Oceania" .
}
```

4.4 Three classes linked by functional properties

As illustrated in the graph pattern in Figure 4(c), suppose that we introduce a third class CC structured in a similar way to CB, through the following OWL statements:

```
ObjectPropertyDomain(PAC CA)          HasKey(CC () (DPCK))
ObjectPropertyRange(PAC CC)           FunctionalProperty(PAC)
DataPropertyDomain(DPCK CC)           DataProperty(DPCK)
DataPropertyRange(DPCK TCK)           FunctionalProperty(DPCK)
DataPropertyDomain(DPC1 CC)           DataProperty(DPC1)
DataPropertyRange(DPC1 TC1)           FunctionalProperty(DPC1)
...                                   ...
DataPropertyDomain(DPCn CC)           DataProperty(DPCn)
DataPropertyRange(DPCn TCn)           FunctionalProperty(DPCn)
```

and that the HasKey on CA is changed to
HasKey(CA () (PAB PAC))
so that instances of CA are identified by combinations of instances of CB and CC. With this visualisation pattern, we can regard CA as modelling a many-many relationship between the two classes CB and CC, leading to a group of visualisations that target a network view of data, such as the following:

- In **sankey** diagrams, the left hand elements of the diagram represent instances of CB, the right hand elements represent instances of CC, and the width of the flow between the left and right elements represents scalar dimension TA1. Optionally, a second attribute TA2 may be represented by varying the colour of the connection.
- In **network** charts, instances of CB and CC are represented by nodes in the graph, with an instance of CA that is connected to both an instance of CB and an instance of CC being represented by an edge between these two nodes. A optional scalar attribute TA1 can vary the colour of the line.
- In **chord** diagrams, instances of CB and CC are represented by points on the perimeter of the circle, with the value of TA1 varying the width of the connection between pairs of points. Again, a second attribute TA2 of the many-many relationship may be represented by varying the colour of the connection.
- In **heatmap** tables, instances of CB and CC are represented by cells of a table, with the colour of the cell varied using TA1. Optional attribute TA2, can be represented using texture.

We note that network charts, chord diagrams and heatmap tables can be used to represent **reflexive** relationships where CB and CC are the same class (let us say CB), so that the nodes/cells represent instances of CB, and CA has two properties associating it to CB.

The table below summarises the above analysis. Whilst most of this group of visualisations support optional dimensions being represented as a colour channel, an exception is heatmaps, which require the use of colour in a mandatory channel, and hence in this case we illustrate the optional dimensions by the use of texture.

Visualisations for a non-functional property					
Name	|CB|	|CC|	reflexive	mandatory	optional
Sankey	1..20	1..20	no	TA1 scalar	TA2 colour
Network Chart	1..1000	1..1000	yes	-	TAK,TA1 colour
Chord	1..100	1..100	yes	-	TA1 size,TA2 colour
Heatmap	1..100	1..100	yes	TA1 colour	TA2 texture

A SPARQL query template to capture the keys of CB and CC and one attribute of CA is listed below left, and again additional attributes can be added in the obvious way. The SPARQL below right matches this template, and if the user selects a chord diagram, the diagram shown in Figure 3(d) is produced.

```
SELECT ?TBK ?TCK ?TA1 WHERE {
    ?CA rdf:type :CA ;
        :PAB ?CB ;
        :PAC ?CC ;
        :DPA1 ?TA1 .
    ?CB rdf:type :CB ;
        :DPBK ?TBK .
    ?CC rdf:type :CC ;
        :DPCK ?TCK .
}
```

```
SELECT ?country1 ?country2 ?length WHERE {
    ?b rdf:type :Border ;
       :isBorderOf ?c1 ;
       :isBorderOf ?c2 ;
       :length ?length .
    ?c1 rdf:type :Country ;
        :carCode ?country1 .
    ?c2 rdf:type :Country ;
        :carCode ?country2 .
    # Filter conditions
    FILTER (?country1<?country2)
}
```

5 Transformations to match Visualisation Patterns

It will often be the case that an RDF graph does not contain the precise structure required by a visualisation pattern. This is for two main reasons:

- The schema of the data is not fully defined, for example it is often the case that OWL hasKey properties are not specified (*e.g.* the original Mondial schema omits these, despite the keys being defined in the relational version of the database), and even RDFS functionalProperty declarations are sometimes not specified where they could have been (*e.g.* in YAGO, www.mpi-inf.mpg.de/yago-naga/yago/).
- The loosely structured nature of linked data results in inconsistency and variants of data, so that data may need to be filtered and restructured before being used for a particular visualisation or group of visualisations.

We therefore describe in this section two indicative transformations that can be applied to users' SPARQL queries to make them match a visualisation pattern.

Functional Subqueries: if a user SPARQL query can be rewritten to contain a subquery returning ?X and ?Y, such that the value of ?X functionally determines the value of ?Y, then we can regard the subquery as matching any pattern requiring a functional property of the form ?X :PXY ?Y.

Taking the example from Section 4.2 we can apply a rewriting as follows:

User Query

```
SELECT ?continent ?carcode ?population
WHERE {
    ?c  rdf:type :Country ;
        :carCode ?carcode ;
        :population ?population ;
        :encompassedByInfo ?en .
    ?en :encompassedBy ?con;
        :percent ?percent.
    ?con rdf:type :Continent ;
         :name ?continent .
    FILTER ( ?percent>50 )
}
```

Transformed Query

```
SELECT ?continent ?carcode ?population
WHERE {
    ?c  rdf:type :Country ;
        :carCode ?carcode ;
        :population ?population .
    ?con rdf:type :Continent ;
         :name ?continent .
    SELECT ?c ?con
    WHERE {
       ?c  :encompassedByInfo ?en .
       ?en :encompassedBy ?con;
           :percent ?percent.
       FILTER ( ?percent>50 )
    }
}
```

In general, we can determine that the variables of such a subquery obey the functional property if either the properties that bind them together are functional (which is not the case in this example), or if the subquery when executed obeys the functional property (which is the case in this example).
Denormalisation of attributes: Suppose we wish to extend the scatter diagram in Figure 3(a) to include information about the population of a country, and the continent it is within, with the user SPARQL query below left:

User Query

```
SELECT ?carcode ?inf ?unemployment
         ?continent ?population
WHERE {
    ?c   rdf:type :Country ;
         :carCode ?carcode ;
         :inflation ?inf;
         :unemployment ?unemployment;
         :population ?population ;
         :encompassedByInfo ?en .
    ?en  :encompassedBy ?con;
         :percent ?percent.
    ?con :name ?continent .
    FILTER ( ?percent>50 )
}
```

Transformed Query

```
SELECT ?carcode ?inf ?unemployment
         ?continent ?population
WHERE {
    ?c   rdf:type :Country ;
         :carCode ?carcode ;
         :inflation ?inf;
         :unemployment ?unemployment;
         :population ?population .
    SELECT ?c ?continent
    WHERE {
       ?c   :encompassedByInfo ?en .
       ?en  :encompassedBy ?con;
            :percent ?percent.
            :name ?continent .
       FILTER ( ?percent>50 )
    }
}
```

The introduction of population matches the pattern for an additional dimension of Country, but the name property is not a dimension of Country. However we can ‘denormalise’ the name dimension of Continent by using a subquery, which relates the instances of the Country class with name of Continent.

6 Summary and Conclusions

In this paper we have proposed a conceptual modelling approach to matching linked data and visualisations. Our approach uses a set of “visualisation patterns” expressed in OWL each of which abstracts a group of potential visualisation alternatives. For each visualisation pattern, we define a corresponding SPARQL query template. The OWL visualisation patterns and SPARQL query templates are used to analyse the data and the users’ queries, respectively, so as to make appropriate recommendations of groups of meaningful data visualisations to the user. We have also described transformations for denormalising data, handling non-functional properties as classes, and applying filters to use non-functional properties in visualisations that normally require functional properties.

By providing a set of OWL visualisation patterns each characterising the data representation capabilities of a group of common data visualisations, we make it easier for the user to select a visualisation that is meaningful in relation to their query and the data, narrowing their choice to a more focussed set of visualisations. An alternative scenario that would also be supported by our approach is where the user has a particular visualisation in mind to visualise a part of the data, in which case we can use the OWL visualisation pattern to validate that the data satisfies the requirements for generating that visualisation and we can instantiate the associated SPARQL query template in order to retrieve the data and populate the visualisation.

Future work includes implementing and empirically evaluating our approach with groups of users, investigating how the approach can be implemented as extensions of tools such as Tableau, and investigating the possibility of using it in a "top-down" approach, starting with a desired visualisation type, and using that to generate SPARQL queries and drill down into data. We also need to perform an exhaustive analysis of the full range of visualisations supported by state-of-the art tools, and extend the indicative groups listed in Section 4 as necessary. This analysis may also give rise to additional visualisation groups, characterised by additional OWL visualisation patterns. Other directions of future work include investigating and providing customisation features for users, and exploring the scalability of our approach when applied to large distributed heterogeneous linked datasets that need to be accessed via query or API endpoints.

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