Visualization of Ontology Matching and Analytics

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Abstract

The semantic web provides a framework of having data on the web defined and linked such that it can be used by machines (and users), with minimal mapping and transformation, for display purposes, automation, and reuse across various applications. While many ontology mapping systems that aims to integrate data across myriad sources and schemata have been proposed, fully automatic methods are unable to incorporate all the nuances of the underlying datasets. Using visualization and user feedback, it is possible to address the difficulties that underline the data integration tasks. As the complexity of ontology matching systems increases, the amount and type of data that is used in matching strategies becomes complex; being able to visualize the alignment so that users understand and make use of the results becomes tricky. In this report, we discuss the current state of ontology matching visualization techniques and how people perceive unfamiliar visualizations.

Keywords: Ontology Matching, Visualization, Semantic Web

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The power of the unaided mind is highly overrated. Without external aids, memory, thought, and reasoning are all constrained. But human intelligence is highly flexible and adaptive, superb at inventing procedures and objects that overcome its own limits.

Donald A. Norman

1. Introduction

An ontology is a formal, explicit specification of a shared conceptualization [1]. It provides a common vocabulary to model the schema for a system as well as represent entities from the domain. The explosion of semantic web has led to an exponential growth of ontologies both in terms of the variety of schemata as well as the amount of data generated in each data set. This necessitates the development of ontology matching techniques to be able to map taxonomy, schemata, and entities between multiple sources. The absence of a gold standard (by design) to represent concepts and relationships prevents interoperability across several open and proprietary standards. Many initiatives are under way to integrate related data from myriad sources. For example, 1. the Linking Open Data Cloud Diagram[1] by Cyganiak and Jentzsch [2] shows the current state of the effort by the Open Data Movement to publish various open data sets as RDF on the Web and by setting RDF links between data items from different data sources. This is a mostly manual effort by contributors to the Linking Open Data community project and other individuals and organizations. 2. One of the objectives for the City of Chicago's Smart Data initiative is to integrate Business License information with food inspections, contracts, business data and user reviews from Yelp, TripAdvisor and Google Places, among others into a unified version of truth for researchers and

[1]http://lod-cloud.net

citizens to access from a web-based user interface [3]. Ontology Matching aims to integrate heterogeneous data sources using syntactic, semantic and external similarity measures [4]. The set of correspondences between concepts is called an alignment.

Ontology matching tools are designed to function over entity-relationship models, database and XML schemata, taxonomies, formal languages, and label frameworks such as RDF/OWL. Most matching techniques employ automated alignment techniques to find matches. Once an alignment is generated, the results are visualized for review and consumption. Typical visualizations include tree views to represent taxonomies and class hierarchies, with tables or lists of key-value pairs representing properties of entities. Correspondences between concepts and entities are represented by drawing lines that connect objects in two trees. Using visualizations to represent ontology matching tasks can improve the quality of the matching results as well as improve user experience in being able to better assimilate the relationships between concepts. As the complexity of ontology matching systems increases, the amount and type of data that is used in matching strategies becomes complex.

Typically, ontology matching focuses on linking data that are labeled in the same natural language. These monolingual mapping techniques rely on lexical comparisons made between resource labels, or their synonyms as described by a dictionary. If the source and target ontologies are in different languages, a lexical comparison is not possible. One way to work around this is to tag resource labels in multiple languages. This is time consuming and infeasible because of the number of languages available as well as the size of the datasets that will have to be tagged. Cross-lingual ontology mapping (CLOM) is the process of establishing relationships among ontological resources from two or more independent ontologies where each ontology is labeled in a different language [5]. One way of implementing CLOM is by using a translation service which converts the source (and/or target) dataset into a common language, thus reducing the problem to a mono-lingual mapping exercise. The translation process should be able to convert the entire phrase represented in the labels instead of a word-by-word translation, thus preserving context.

The accuracy of automatic methods may be improved by introducing a human in the loop to answer a small subset of questions that can help resolve conflicts across large datasets.

User involvement has been proven to be essential for enhancing the quality of the alignment [6]. Using intuitive visual analytics mechanism can help the subject matter experts (SME) make well-informed decisions [7]. Using these semi-automatic methods, SMEs can confirm matching results or invalidate them based on prior knowledge which may or may not be represented in the data. This information can be used to boost (or penalize) some features and/or methods over others, thus producing a more accurate final alignment.

Visual Analytics involves interactive visualization, data analytics and reasoning using cognitive approaches (as opposed to a fully automated algorithm). In most ontology matching implementations, visualization is an after-thought, or non-existent. There have seldom been studies that are based on user interaction and cognition that define the features (or benefits) of a visual analytics toolkit in ontology matching. However, with the explosion of Big Data, the need for accurate alignments has grown exponentially.

In this report, we discuss three recent ontology matching systems and a study about the effects of introducing new visualization techniques.

- Lee et al. [8] investigate how people make sense of unfamiliar visualizations. Understanding this helps one design new and innovative visualization techniques, especially in a field like ontology matching where there is a dearth of visual tools to navigate alignments.

- Richthammer and Pernul [9] propose a novel method to visualize the results of instance matching from a single source to multiple targets. They use an interactive tree-map based visualization that allows users to explore alternatives and reasoning behind recommendations. They discuss an implementation of the method for the MovieLens 100K dataset.

- Parra et al. [10] introduce an instance matching system that uses an interactive Venn diagram based interface and lets users manually control the importance of various matching strategies. This technique is applied into a recommender system for research talk and articles.

- Mai et al. [11] introduce a "follow-your-nose" style of visual interface for pre-existing alignments exist between two (or more) ontologies. They propose several methods that allow users to navigate between entities from various large (in their example, 45M triples) geo-data sources. They explore tabular, layered map and graph views to allow users to look at relations. They claim to be 'the first interface that supports layers from different sources and entity-to-type queries'.

We focus on the tools' ability to allow the user to use UI-based actions to slice and reorder results, intuitively identify and resolve conflicts by confirming or rejecting matches and be able to better digest the relationships between concepts and their properties. These interfaces are used to describe the user interface feature as a part of a visual analytics toolkit, but not as a survey of capabilities of these tools. These systems were picked because they implement methods other than the well-known tree and table visualizations that are common in most ontology matching products.

2. Background

Information Visualization techniques have been used for many centuries. Infographics was used to describe astrological phenomena [12], politics and economy [13], cartography and geography, medicine [14], and military. No discussion about visualization is complete without mention of Charles Minard's influential graphic about Napoleon's disastrous march on Moscow, to which Tufte [15] said it "may well be the best statistical graphic ever drawn".

The Semantic Web consists of many players who provide myriad ontologies that consists of mostly proprietary schemas. Linked Data in the semantic web is considered as a standardized approach to achieve automated interoperability of heterogeneous systems/applications. With the increasing number of heterogeneous sources, federated exploration of linked data is more important now more than ever before. To help heterogeneous systems inter-operate, ontology matching has a critical role to play. With the availability of resources (such as advanced graphics cards), use of complex visualization to help improve user experience has become more attainable. Ontology matching is associated with analogy formation, where concepts are variables in logic expressions. It is intuitive to form analogous connections between objects by linking them visually and deriving rules.

2.1. Cognitive Requirements

Visual Analytics allows for the definition of different semantics than can be associated with the alignment, including atomic (one-to-one), subsumption, part-of, equivalence, disjointness or other user defined relationships. These can also be used as building blocks to attain alignments that are rich and otherwise hard to envision without a visual interactive user interface. This is especially true now because of approaches being defined for the pervasive interoperability of the concepts used by the semantic web, both virtually as well as its interaction with the real world with the use of Internet-of-Things devices, among others. The process of writing explicit queries to look for patterns and validate mappings requires not only the cognitive presence to anticipate specific types of patterns, but also the technical expertise to be able to construct the queries, debug any issues, interpret the results and iterate to look for other patterns. A visual interface enables a *follow-your-nose* style of exploration, which a user may navigate seamlessly, slice and dice the results, and look for visual patterns that expose visual insights [11]. Several surveys of visual ontology alignment systems [16] evaluate tools against various user studies; they conclude that no system fulfills all requirements.

Today's media — including print, web, television and online videos — are actively using new visualization techniques, allowing data to tell the story. However, there is little evidence to show that users are able to make sense of unfamiliar graphics and animations (other than, of course, their ability to be able to paint a pretty picture). In [8], a "grounded model of Novice's Information Visualization Sensemaking" is proposed that can be used to describe how someone who has never seen a type of graphic makes sense of it.

Intuitive visualization allows the user to provide valuable feedback. By soliciting this feedback, ontology matching systems can better understand the underlying data. Schema mappings may be refined and annotated with metrics that identify the quality of the maps [17]. By considering and managing user feedback as a "first-class citizen" of the ontology matching exercise, several benefits may be drawn by evaluating various artifacts such as query, results, or mapping [18]. Different users may have varying requirements, or they may interpret the data differently. These quirks have to be understood and taken into consideration into matching engines that process feedback from human in the loop.

A seamless transition between visualization and interaction paradigms lets the user make decisions iteratively instead of relying complex queries to arrive at the desired outcomes. Typical ontology matching algorithms are quite sophisticated and are able to match entities and types using complex rules. However, they do not take the users' situational needs into account. The application may require user inputs that define momentary preferences, but the users may not be able to express them upfront without looking at an initial set of intermediate results. An interactive visualization tool will enable this explorative analysis and may not require any inputs from the user to get started on the matching exercise.

The use of computer-aided, interactive visual representations of data amplifies cognition and enables the user to make intuitive decisions instead of having to mentally derive the correctness of each potential match offered by the alignment. Recent research on exploring the importance of Human-Computer Interaction (HCI) on user experience with recommender systems have shown that visual features, enhanced interaction, and specific user characteristics after user engagement with the system and their decision to accept or dismiss recommendations [10]. This paradigm is a complement to that of focusing the effectiveness of a recommender system purely based on the predictive accuracy of algorithms or the exercise of generating and incorporating new sources of data into the recommendation workflow. To define the efficacy of such systems, one has to use behavioral analysis and subjective evaluation methods to see if the new interface has a positive effect on the user experience.

2.2. Ontology Matching Process

In order to integrate two data sources, we have to find similarities between (1) the various concepts and their properties, and (2) the entities that are represented within each class/concept in the ontology. This is achieved by using an ensemble of automated and semi-automated methods called matchers. Each method uses syntactic, lexical or structural algorithms to determine a similarity score between every pair of concepts (or entities). These scores are combined using weights that are determined heuristically and/or based on prior knowledge of the behavior of the concepts in the source and target data sets. The similarity scores that surpass a pre-defined threshold are considered as a preliminary match.

In some matching exercises, a gold standard is available, which describes a set of maps between the source and target ontologies. This set of maps, also known as a reference alignment, may be used to determine the efficacy of a new algorithm being tested, or in ontology competitions such as the Ontology Alignment Evaluation Initiative (OAEI) [19].

The alignment is presented to the subject matter expert who can tweak the threshold, confirm or reject the matches identified by the algorithm using prior knowledge of the data, and resolve conflicts that are presented between the source and target ontologies. The user may choose to view the similarity measures for the participating matchers as a unified metric (such as average) or view them independently. They may want to group the concepts and/or reorder them based on various properties that are intrinsic to the data or derived from the results of the matchers. Clustering and sorting concepts allows the user to recognize patterns and intuitively understand relationships between the concepts as well as the behaviors of the matchers in terms of how they prioritize the importance a (different) subset of features.

The ontology matching engine, which consists of one or more matchers, is independent of the visualization generator, whose sole purpose is to display the similarity measures generated by the matchers to the end user, and (optionally) obtain user feedback. The user feedback is routed to the matchers that support a feedback loop. These matchers will regenerate a new alignment using the (valuable) additional information now available. The new alignment is used to update the user interface to reflect the new set of maps generated. This process is repeated until a satisfactory final alignment is generated.

In this report, we treat the matchers as a set of black boxes that generate an alignment between two ontologies based on user feedback. We focus on the features that may be provided by the visualization generator, which improves user experience, and drives visual analytics. We will also explore scenarios that require the matching of plural datasets matching multiple source datasets to a single target dataset, and performing matching across a set of sources without the identification of a dataset as source or target.

2.3. Visualization Comprehension

Recently, we have seen an uptick in the variety of the visualizations that are presented to the general public. Admittedly, The New York Times produces some of the best known data visualizations [2] to help their readers "see" the underlying data. As the public is introduced to new visualizations, it is important to realize that they will help bring the underlying ideas into "focus" only if the graphics make sense. There has been little known research that study how novice users interact with visualizations, which is in contrast to the plethora of literature about the kinds of tasks and activities conducted on visualization.

A *Novice User* is defined as a person who is seeing a particular type of visualization for the first time. *Information Visualization Sensemaking* refers to the "conscious efforts to achieve understanding of how to interpret visual objects and underlying content in an information visualization" [8]. In order to understand the information visualization sensemaking activities, we have to observe novice users when they endeavor to make sense of unfamiliar visualizations. In this paper, we discuss a study by Lee et al. [8] that investigates how people make sense of unfamiliar information visualizations.

> Solving a problem simply means representing it so as to make the solution transparent.
>
> — Herbert Simon

[2] https://www.nytimes.com/interactive/2015/us/year-in-interactive-storytelling.html

3. Visual Interface Types

Visual Analytics is based on Information Visualization whose main focus is to represent large conceptual datasets in a limited screen real-estate. This is typically achieved using the basic principles of displaying summaries first, allowing the user to slice and filter the dataset, and finally, representing the individual item detail on demand (if necessary) [20]. When visualizing (semi-) automatic alignments and soliciting user feedback, the tool has to take into consideration how to present mappings to the user, understand the requirements for cognitive support of the ontology mapping tasks, role of collaboration among users, influence of the interface usability and how the system can utilize machine learning and human advantages [16].

Several aspects arise from reviewing alignments using graphical user interfaces. In spite of the perceived exponential growth and adoption of the Linked Data paradigm, the integration and use of interfaces that are capable of visualizing heterogeneous and conflated sources are seldom found. This is partially because sources typically report different values for the same attributes for the same entities. For example, DBpedia[3] and GeoNames[4] report different values for population, geographic coordinates, etc for Chicago, IL. Although some features (such as population) have a temporal timestamp associated with it, this data may not be available. In case of geo-location, the 'center' for a region (such as Chicago IL) may be calculated differently by different sources. Non-obvious relationships can be overlooked and may not be considered in the decision-making processes. As a result, it may lead to incorrect decisions or unintended consequences. Being able to see this helps the user understand some of the idiosyncrasies embedded in the datasets.

When visualizing ontology alignments, there are a few things to remember:

- There is no *one-size-fits-all* visualization. Having said that, multiple perspectives for the same dataset can only be useful if users can switch between views seamlessly.

[3] http://wiki.dbpedia.org/
[4] http://www.geonames.org/

- As the number of data sources (and hence, the number of triples) grow, aspects that may be been initially perceived as convenience attributes transform into essential features. For example, the ability to expand or collapse local nodes and edges in a graph view.

Most tools implement multiple views to visualize taxonomy-, schema- and entity-matching alignments. Some visualization techniques are described below. This is not meant to be comprehensive list of all ontology matching visualization techniques, but as an introduction to the most commonly used alignment display systems. In fact, some tools described in the following subsections implement other linked views – such as Parallel-Coordinates Plots [7], Venn Diagraphs [10], etc – that may be of interest to the reader.

3.1. Tabular and List-based Representation

Using tables and lists is the most common representation of alignment (sometimes considered a non-visualization), in which the features of the entities or classes that make up the mapping are rendered in a table format. Ex: GeoLink [11], Linked Data Scientometrics [21], etc. This may be the first step in the process of exploring the available mappings. A search interface allows the user to provide a set of filter criteria to narrow the list of entities to explore. The user can then select two (or more) objects to be compared side-by-side, which are grouped together in a predicate-object style. Each entity-type may offer a different set of features that may be explored.

All the necessary data about the classes being represented are simply "printed" as-is. This means that no analysis or interpretation of the underlying data is necessary on the part of the tool or at the time of data creation. This representation also is very useful for representing a wide and/or long array of information that can be later used to filter and/or massage to then gain insights using exploratory methods and what-if analysis methods. As a result, it gives the researcher an opportunity to interpret the results as they see fit. A typical use case is its use to display the search results for products that contain a set of keywords on an eCommerce portal.

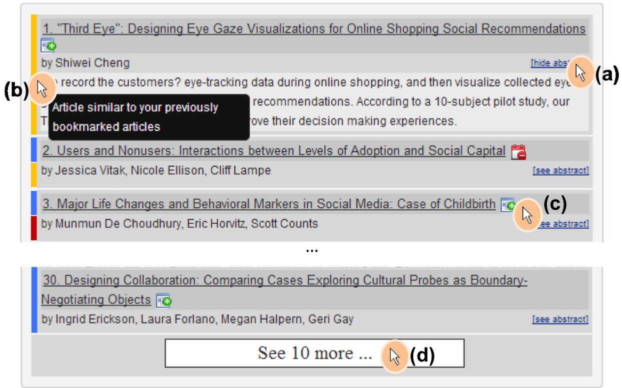

Figure 1: User interactions in the item list.

Since all the data is presented as a bag of words in paragraph, list, or table form, the user is expected to spend considerable energy in trying to assimilate the information and then come up with opinions and/or interpretations of the data. If the amount of data being presented is large, it might be hard to read and remember all the necessary information to come up with a well-informed unbiased opinion of what the data represents. Finally, it is difficult to see patterns quickly, or be able to identify outliers that may or may not be errors in the data, without being able to "see" the data in the researcher's own mind.

3.2. Linked Tree Widgets

Tree structures encode hierarchical data using connection or containment [22]. Connection may be used to create node-link diagrams, typically used to encode relationships between classes based on a user-defined attribute. Containment can be represented using Tree-Maps, discussed below. Linked Tree views represent the source and target ontologies that are shown side by side, with the mappings represented as lines that connect the matching pairs of nodes from the hierarchy. Ex: AgreementMaker [23], COMA++ [24], COGZ [25], etc. This type of visualization highlights the parent-child relationships between nodes. Although this view is typically reserved for taxonomies, it is not uncommon to see entities represented as leaf nodes of the tree.

By virtue of the fact that trees cannot contain cycles, we only need one spatial axis to represent multiple levels in the tree. They may be represented as 1. a graph, with edges that

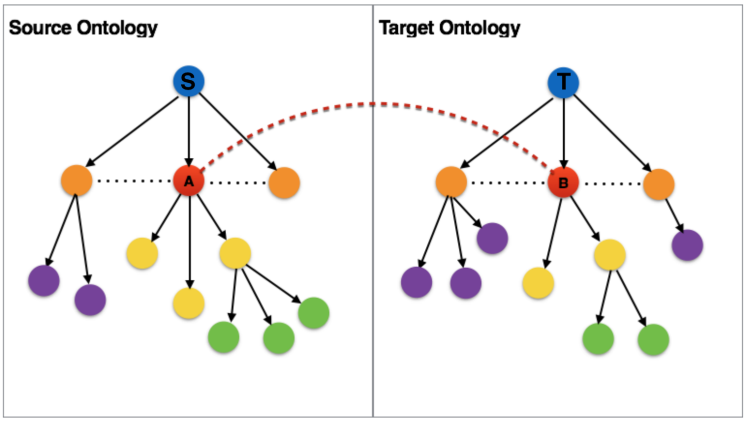

Figure 2: Tree Layout to map source to target ontology.

connect a parent concept to all of its children 2. an indented list where the X-axis represents the tree depth and the Y-axis is used to separate the nodes, or 3. a circular graph where the R-axis represents tree depth and the θ-axis is used to separate the nodes.

This layout is effective to represent linked concepts and hierarchical relationships. The optimal layout for representation of linked trees may be selected based on multiple parameters. The size of the source and target data sets play a significant role. Given that there will be at least two trees laid out side-by-side two visualize the linked alignments, tools typically use a collapsible version of the indented list representation.

Improper use of tree layouts can lead to a poor user experience. For example, if a product category in an eCommerce portal has a hundred (or more) products, it is best to not represent the individual products as a part of the tree. Doing so would necessitate extensive scrolling or large displays, which negates the original intended use of the tree structure of being able to see hierarchical relationships. Instead, one method is to terminate the tree depth at the terminal node of the taxonomy, and link the selection action on a node to list the products from the selected category in a separate view.

3.3. Cluster Visualization

This method expands on the tree view by representing the concepts as nodes in an undirected graph which may be filtered for navigation and search. This layout may be used to explore relationships between entities, as seen in figure 3. Ex: RelFinder [26], OPTIMA

[27], PROMPT [28], etc. By looking at the alignment in a graph view, the user can separate relevant relationships from irrelevant ones, and even be able to discover some of the non-obvious relationships with the use of some innovative filters. AlViz by Lanzenberger and Sampson [29], implemented as a tab plug-in for Protégé, uses J-Trees to display instance-level information and small world graphs to view the structure of the ontology.

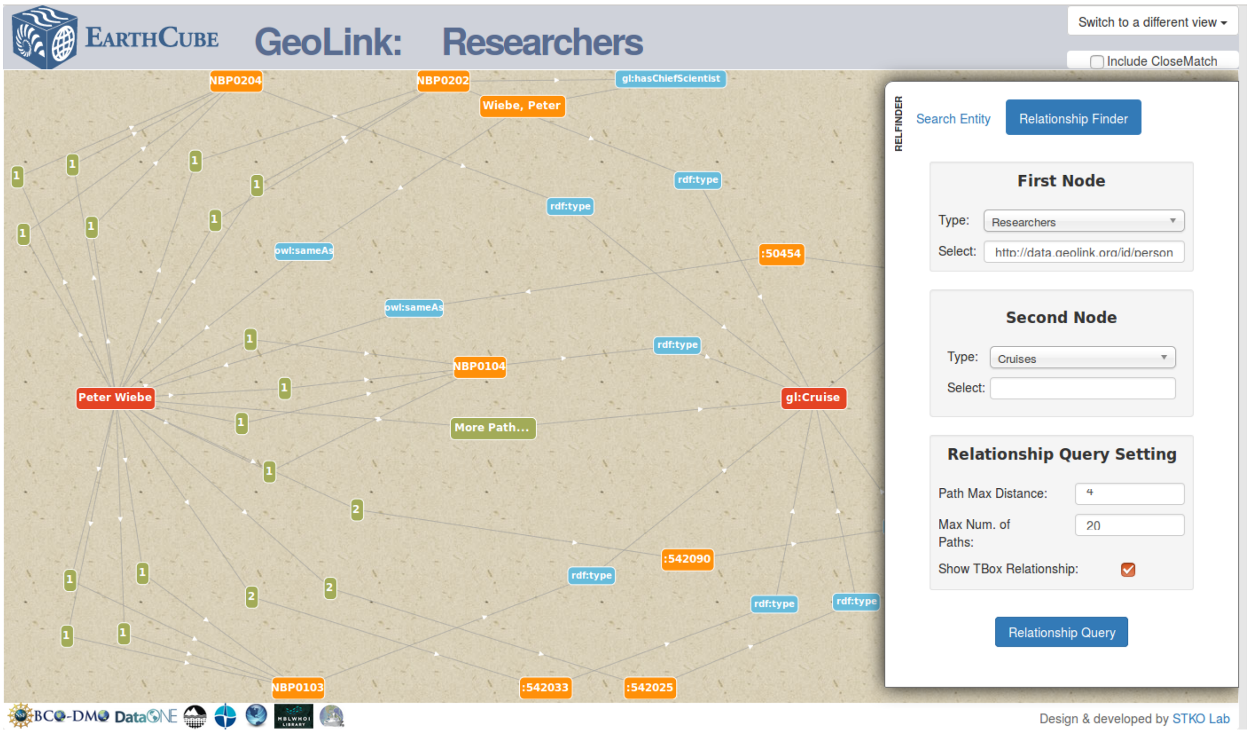

Figure 3: Graph view showing cruises and datasets related to a researcher.

Unlike tree widgets, it is possible to select an entity as the source and another entity, schema-attribute or class as the destination. The system can then perform n-degree path queries to extract all objects along the path from source to target.

Most studies about graph comprehension focus on relatively primitive visualizations without interaction techniques, such as line charts, bar graphs, or pie charts. Visualization interactive graphs that depict the mapping of classes from two (or more) large datasets can seem crowded or confusing to the user. Finally, knowledge about the content affects graph comprehension. Choosing the right set of attributes to link the nodes based on, and picking a minimal set of fields that will be used as labels for the nodes and edges is critical. This has been reinforced by historical studies, such as the one by Curcio [30], that suggest that children should be involved in graphing activities to build and expand relevant schemata needed for comprehension.

3.4. Tree-maps and Pie-Charts

Tree-maps and Pie-charts provide a space-constrained overview of the class structure, a guided navigation that displays detail information as the user navigates the hierarchy. They use nested rectangles (in treemap) or sectors that use zoom-in animations (in piecharts) to display large mono-hierarchical tree-structured data with great efficiency and high readability [31].

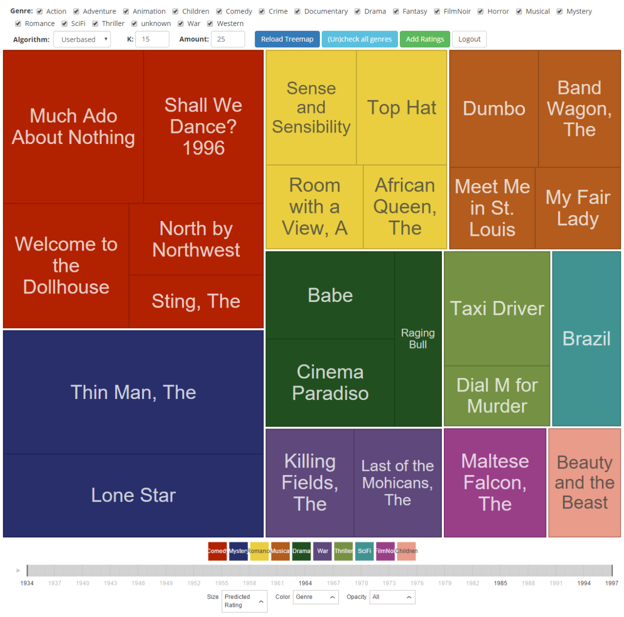

Figure 4: Treemap that uses collaborative filtering to visualize movie recommendations.

For instance, CogZ by Falconer and Storey [25] provides views based on treemaps to visualize large data sets and piecharts to display detail data, with instance-level data falling back to J-Tree views. Richthammer and Pernul [9] present an interactive treemap visualization which facilitates the users' comprehension of the overall landscape of available alternatives for a given entity and the reasoning behind the recommendations. Users may select a specific rectangle to view detailed information either as a description or in tabular format, or explore the class further using other linked views.

Various aspects of the visualization, such as the size of each rectangle (or sector), the color of each box (or group), and their opacity can be used to represent various dimensions of the underlying data. Additional information can be displayed as labels within each rectangle. This view is best suited if there are multiple potential matches for a given source entity and when they can be represented as a set of hierarchical or complementary alternatives for a user selection.

TreeMaps may only be used to visualize one-to-many relationships. Other visual layouts may be better suited if the use case requires the comparison of multiple source entities to multiple target entities. Depending on the number of classes in the target data set, the treemap algorithm may take a long time to determine the dimensions of each rectangle.

3.5. Matrix Views

These can show classes from source and target ontologies along the axes of a matrix allowing the entire mapping space to be visible. Selection action on a mapping instance may be linked to other views that provide additional information about the source and target entities, and other metadata that describes the alignment. For example, iMerge by El Jerroudi and Ziegler [32] implements a matrix browser that helps uncover underlying patterns that represent agreement in portions of the ontologies. AgreementMaker [7] can allow for the comparison of multiple matching algorithms side-by-side, and allows for the simultaneous navigation across all the matrices.

Matrix Visualizations can be effective when looking at the big picture can help gain insights about the alignment. Filter criteria may be used to focus user-analysis on a subset of the alignment. By sorting the classes along the axes using different criteria, the user may be able to identify clusters and classify the results into various buckets. Color, size, shape and orientation of the objects may be used to represent various dimensions.

Since every potential match in the alignment is visualized in the matrix views, the visualization may come off as being too noisy or too barren in some circumstances. If the number of classes are in the hundreds or thousands, there may not be enough screen real

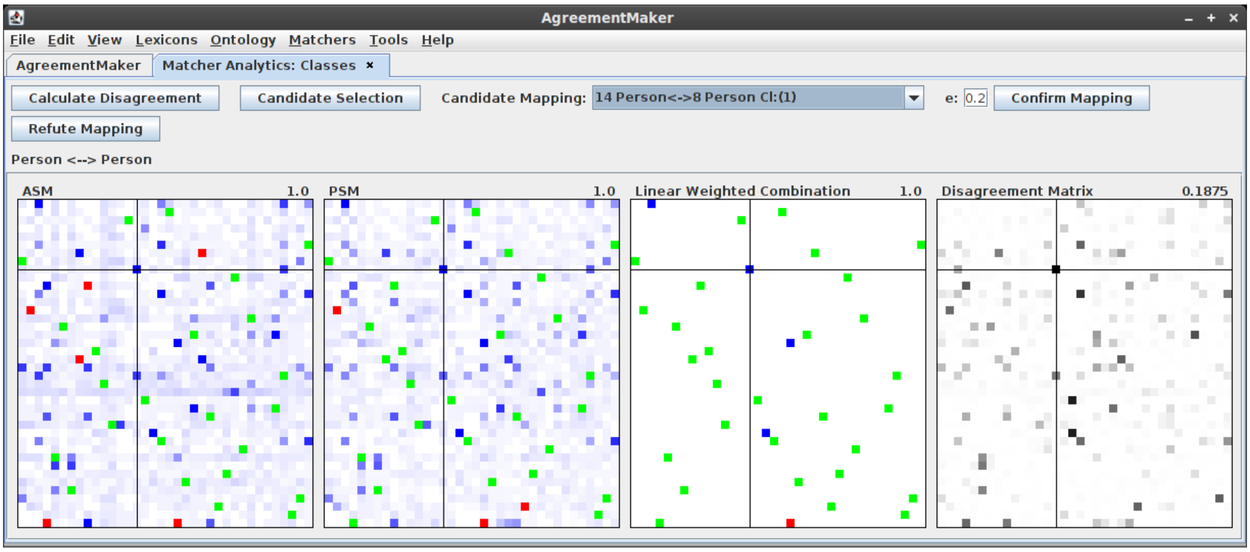

Figure 5: Matrix Layout to map instances from source to target ontologies using multiple algorithms.

estate to be able render all mappings. The intelligent use of filters and ordering can help alleviate some of these concerns.

3.6. Multi-layer Map-based Visualization

Classes and Instances that have geospatial attributes associated with them may be visualized using maps that can be represented using sprites on multiple layers. The base layer may be streets and land-use based surface types (buildings, open land, parks and forests, water bodies, etc), terrain contours rendered using gradients, or satellite imagery stitched to represent actual top-down views. The instances from the source and target ontology may be represented on different layers along with other relevant background data such as points of interest. For example, Mai et al. [11] present a multi-layer map exploration that allows the user to map out the geometries of the cruises for a selected user.

Map visualization can be very effective when the mappings represent a spatial relationship between the instances being mapped. For instance, it can show all the cruises in which a certain researcher took part in and view it along with oceanographic gazetteer features to determine which of them may have been visited. Maps are very effective to visualize time-lapsed trails that are captured as points that represent all the places that people, taxis,

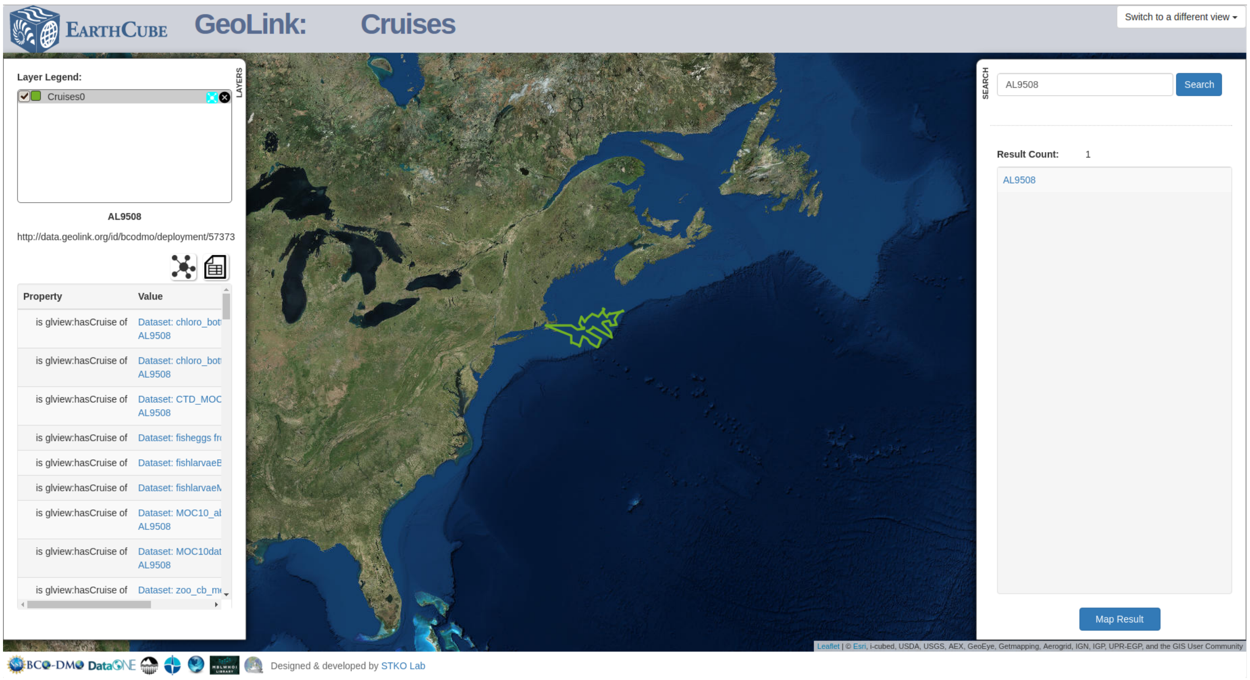

Figure 6: Map view showing cruises related to a specific researcher.

animals, or other objects have been. Because of the highly visual nature of this visualization, it may distract the user away from the original intended use. Care has to be take to include just enough background data to enhance the user experience without influencing the decision-making process.

4. Visualization Sensemaking

Thought can only be expressed within a system of signs. Mimicry is a natural form of coding; verbal language is a code of auditory signs (which must be learned in order to communicate with others); the written language is another code; graphic representation yet another. Memory storage on disks, tapes or in computers necessitates appropriate new codifications. Graphic representation is the transcription, into the graphic sign-system, of information known through the intermediary of any given sign-system. — Bertin [33]

According to Pirolli and Card [34], intelligence analysis is considered a form of sensemaking and expert skill. Experts build a set of intuitive patterns, also known as *schemas*, around the important elements of their tasks over time from extensive experience. The analyst's conceptual schema sometimes play an important role in intelligence activities. However, this model does not focus on novice users, who have never looked at a given visualization.

Klein et al. [35] propose a *data-frame* theory which postulates that "elements are explained when they are fitted into a structure that links them to other elements". They study seven sensemaking activities and describe how people construct and revise internal mental structures, called *frames*, when they make sense of external events. Depending on the *data* – the interpreted signals of events – people refine the existing *frame* – the explanatory structures that account for the data – or construct a new frame based on the seven sensemaking activities. This may also be represented as two processes: the process of creating the internal mental structure from a visualization (*internalization*) and the process of an individual making sense of a visualization using the internal mental structure (*processing*), as presented by Liu and Stasko [36].

4.1. Sensemaking activities

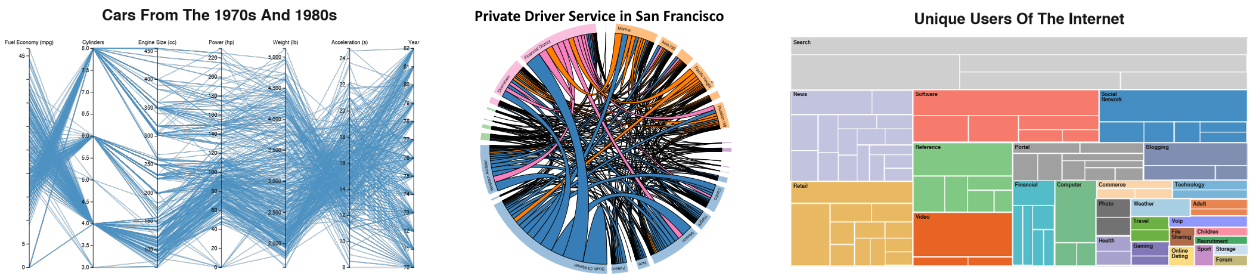

Figure 7: The three unfamiliar information visualizations used in this study: (a) the parallel-coordinates plot (PCP), (b) the chord diagram (CD), and (c) the treemap (TM).

To study the sensemaking process, users are presented one or more visualizations that they have never seen before. In NOvices information VIsualization Sensemaking (NOVIS) model, Lee et al. [8] choose three information visualizations: the parallel-coordinate plot (PCP), the chord diagram (CD), and the treemap (TM), as shown in figure 7. These visualizations represent multivariate data, network data, and hierarchical data respectively. Also, they are not covered in K-12 curricula thus ensuring that they are truly unfamiliar to the participants. The contexts of the data sets do not require specific expertise. The tools that displayed the visualization had little interactivity and did not provide any additional instructions that explain how to interpret the data.

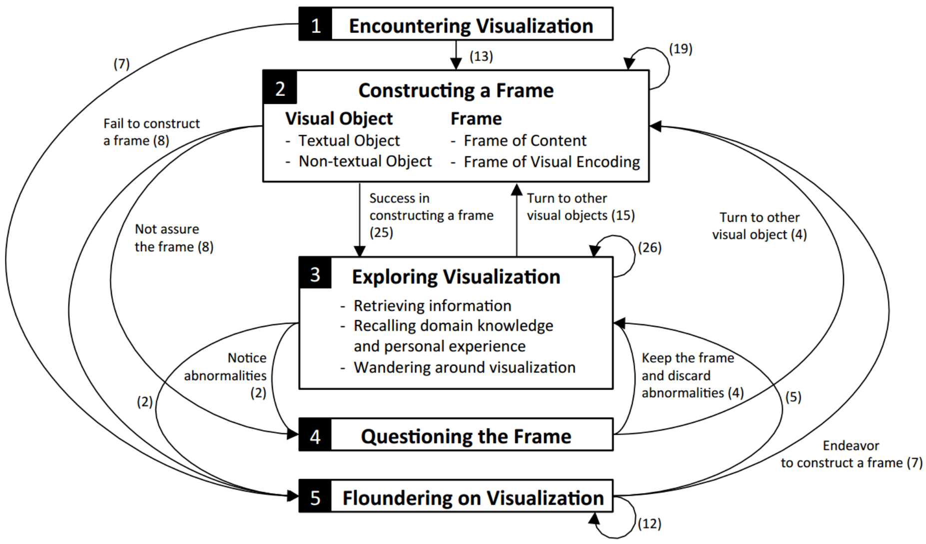

Figure 8: NOvices information VIsualization Sensemaking (NOVIS) model.

Figure 8 shows the NOvices information VIsualization Sensemaking (NOVIS) model. The arrows indicate the major transitions between the five activities and the numbers in the parentheses indicate the number of transitions between the activities that were observed from the data. The sensemaking model consists of the following activities:

1. *Encountering Visualization* is the cognitive activity in which a user looks at a whole image of an information visualization. Users do not actively try to make sense of the visualization yet, but they build an initial set of impressions about what they are seeing during this activity.

2. *Constructing a frame* is the process where the user attempts to construct a frame to make sense of the given visualization. Participants attempted to construct two types of frames – frame of content using textual objects such as title, axis labels, etc, and frame of visual encoding by conjecturing what each object in the visualization meant. Sometimes, they constructed incorrect frames, but they relied on it explore the visualization which negatively influenced further sensemaking activities.

3. *Exploring Visualization* is the cognitive activity where the user interacts with the tool to discover facts and gain insights from the visualization based on the constructed frames. This process may be classified into three distinct, but overlapping tasks:

   - Participants retrieved various information while exploring the visualization by interpreting labels and non-textual objects.
   - They recalled domain knowledge and/or personal experience, which may not gain any new insights, but helps define next steps in the exploratory process.
   - Participants read text and other objects in no specific order; this wandering is based on the frame that they built previously and what they thought they were looking for.

4. *Questioning the frame* is the process in which the user begins to doubt the constructed frame or tries to verify the frame. This happens when they encounter uncertain or abnormal visual objects that may not be compatible with the frame while exploration. Participants typically went back to previous steps to confirm or reevaluate their initial thought processes.

5. *Floundering on Visualization* happens when the user was unable to construct a reasonable frame and does not know what to do with the information visualization, which may lead to them being frustrated or confused. Contrary to wandering around the visualization, the user is not constructive about enhancing their frame; instead they feel like they have reached a dead end. At this point, they either give up on trying to make sense of the visualization, or make an effort to seek and construct a new frame so that they can start over.

6. *Miscellaneous*: In addition to these clearly identifiable stages, participants exhibited minor quibbles that include positive or negative comments, recommendations on how to improve the visualization or suggestions for new representations.

4.2. Sensemaking dynamics

Based on this classification of activities, it was found that participants floundered much less with treemaps than the other two visualizations; most time was spent in questioning the frame with the chord diagram. Participants followed a slightly different path for different visualizations, some going back from floundering on visualization to exploring the visualization; and other going from questioning a frame to constructing a new frame or to exploring the visualization.

"Cars from the '70s to '80s, so it looks like we're gonna talk about - or its talking of how fuel economy and perhaps maybe getting better and worse or how many cylinders. [...] Not really a high interest of mine. So I think that thats pretty much all that I see on just the graph."

Incorrect frames of content and visual encoding cause confusion in exploring the visualization and may lead to floundering and finally giving up on making sense of the visualization. If the initial frame construction was done rushed, subsequent analysis will lead to several road blocks, which may finally lead to floundering.

"It says Microsoft in the top one. [...] I'm wondering now why some of - how they chose the colors [...] how they color coordinated these."

It is interesting to learn that users gave up on the parallel-coordinates plot (5 attempts) much sooner than trying to figure out the chord diagram (18 attempts). It is also interesting to note that users tend to assign meanings on colors even though they may not have any particular meaning.

Unlike participants who gave up making sense of the visualization in the floundering on visualization activity, some participants gleaned visual objects from the visualization and made efforts to construct a frame. They tried to focus on a part of the visualization related to their domain knowledge or personal experience and associated the textual object to try and build a frame. Some participants focused on gleaning informative textual objects for them from the visualization, which helped them construct a frame. Some of them compared alternative frames about the objects to gain possible insights about the visual objects.

The content that is represented by the visualization arouses emotions that may lead to a positive or negative initial response, which will sway the sensemaking experience. Accounting for this can be tricky, but investigating this would be interesting. The same participant can show different sensemaking processes depending on the visualization, which reinforces the fact that the visualization format would make it easy or difficult to understand.

5. Conclusion

Computer-based interactive visualizations facilitate the cognition of abstract data. This is more true of the results of ontology matching exercise that many other types of data. The purpose of the visualization is not the picture themselves, but the rapid information assimilation, i.e., to provide insight.

The use of space to represent data has been researched upon for a long time. The advent of computers allows the use of time and interaction to allow the visualization to react to users' actions. The use of overview + detail or focus + context in the visualization provides visual transfer functions that can be used to specify complex variations of magnification across displays.

Today's ontology matching algorithms are sophisticated, but they cannot take users' momentary needs that may deviate from global preferences. Introducing a human in the loop in the decision making process using intuitive interactive visualizations enable matching processes to generate high quality mappings. Linked data driven, multiple linked view interfaces allow users to gain insights across different repositories.

Several efforts have been made to draw attention to the study of user behavior in the face of growing variety in the types of visualizations. Research about understanding users' cognitive activities should be actively conducted to develop novel information visualization techniques that are comprehensible and exposes the story from the underlying data.

We now know that "understanding" means simplifying, reducing the vast amount of "data" to the small number of categories of "information" that we are capable of taking into account in dealing with a given problem. — Bertin [33]

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