Extracting Architectural Patterns from Web Data

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Abstract. Knowledge about the reception of architectural structures is crucial for architects or urban planners. Yet obtaining such information has been a challenging and costly activity. With the advent of the Web, a vast amount of structured and unstructured data describing architectural structures has become available publicly. This includes information about the perception and use of buildings (for instance, through social media), and structured information about the building's features and characteristics (for instance, through public Linked Data). In this paper, we present the first step towards the exploitation of structured data available in the Linked Open Data cloud, in order to determine well-perceived architectural patterns.

1 Introduction and Motivation

Urban planning and architecture encompass the requirement to assess the popularity or perception of built structures (and their evolution) over time. This aids in understanding the impact of a structure, identify needs for restructuring, or to draw conclusions useful for the entire field, for instance, about successful architectural patterns and features. Thus, information about how people think about a building that they use or see, or how they feel about it, could prove to be invaluable information for architects, urban planners, designers, building operators, and policy makers alike. For example, keeping track of the evolving feelings of people towards a building and its surroundings can help to ensure adequate maintenance and trigger retrofit scenarios where required. On the other hand, armed with prior knowledge of specific features that are well-perceived by the public, builders and designers can make better-informed design choices and predict the impact of building projects.

The Web contains structured information about particular building features, for example, size, architectural style, built date, etc. of certain buildings through public Linked Data. Here in particular, reference datasets such as Freebase[1] or DBpedia[2] offer useful structured data describing a wide range of architectural structures.

The perception of an architectural structure itself has historically been studied to be a combination of the aesthetic as well as functional aspects of the structure [3, 4]. The impact of such buildings of varying types on the built environment, as well as how these buildings are perceived, thus varies. For example, intuitively we can say that in

[1] http://www.freebase.com/
[2] http://dbpedia.org/

case of churches, the appearance plays a vital role in the emotions induced amongst people. However, in case of airports or railway stations, the functionality aspects such as the efficiency or the accessibility may play a more significant role. This suggests that the impact of particular *influence factors* differs significantly between different *building types*.

In this paper, we present our work regarding the alignment of *Influence Factors* with structured data. Firstly, we identified the influence factors for a predefined set of architectural structures. Secondly, we align these factors with structured data from DBpedia. This work serves as a first step towards semantic enhancement of the architectural domain, which can support semantic classification of architectural structures, semantic analysis, and ranking, amongst others.

2 Crowdsourcing Influential Factors and Ranking Buildings

Recent research works in the field of Neuroscience [1, 2], reliably suggest that neurophysiological correlates of building perception successfully reflect aspects of an architectural rule system that adjust the appropriateness of style and content. They show that people subconsciously rank buildings that they see, between the categories of either high-ranking ('sublime') or low-ranking ('low') buildings. However, what exactly makes a building likeable or prominent remains unanswered. *Size* could be an influential factor. At the same time, it is not sound to suggest that architects or builders should design and build only big structures. For instance, a small hall may invoke more sublime feelings while a huge kennel may not. This indicates that there are additional factors that influence building perception. In order to determine such factors, we employ Crowdsourcing.

An initial survey was conducted using LimeService[3] with a primary focus on the expert community of architects, builders and designers in order to determine influential factors. The survey administered 32 questions spanning over the background of the participants and their feelings about certain buildings, of different types (*bridges*, *churches*, *skyscrapers*, *halls* and *airports*). We received 42 responses from the expert community. The important influential factors that surfaced from the responses of the survey are presented below.

For *bridges*, *churches*, *skyscrapers* and *halls*: history, surroundings, materials, size, personal experiences, and level of detail. For *airports*: Ease of access, efficiency, appearance, choice/availability, facilities, miscellaneous facilities and size.

Based on these influential factors we acquired perception scores of buildings on a Likert-scale, through crowdsourcing. By aggregating and normalizing these scores between **0** and **1**, we arrived at a ranked list of buildings of each type within our dataset.

3 Correlating Influential Factors with Relevant Structured Data

In order to determine patterns in the perception of well-received structures (as per the building rankings), we correlate the influential factors of buildings with concrete properties and values from DBpedia.

[3] `http://www.limeservice.com/`

Table 1: DBpedia properties that are used to materialize corresponding Influence Factors.

Airports	Bridges	Churches	Halls	Skyscrapers
dbpedia-owl: runwaySurface, dbpedia-owl: runwayLength, dbprop:cityServed, dbpedia-owl: locatedInArea, dbprop:direction	dbprop:architect, dbpedia-owl: constructionMaterial, dbprop:material, dbpedia-owl:length, dbpedia-owl:width, dbpedia-owl:mainspan	dbprop: architectureStyle, dbprop: consecrationYear, dbprop:materials, dbprop:domeHeightOuter, dbprop:length, dbprop: width, dbprop:area, dbpedia-owl:location, dbprop:district	dbpedia-owl: yearOfConstruction, dbprop:built, dbprop: architect, dbprop:area, dbprop:seatingCapacity, dbpedia-owl:location	dbprop:startDate, dbprop:completionDate, dbpedia-owl:architect, dbpedia-owl:floorCount

Table 1 depicts some of the properties that are extracted from the DBpedia knowledge graph in order to correlate the influence factors corresponding to each structure with specific values.

By doing so, we can analyze the well-received patterns for architectural structures at a finer level of granularity, i.e., in terms of tangible properties. In order to extract relevant data from DBpedia for each structure in our dataset, we first collect a pool of properties that correspond to each of the influence factors as per the building type (see Table 1). In the next step, by traversing the DBpedia knowledge graph leading to each structure in our dataset, we try to extract corresponding values for each of the properties identified. The properties thus extracted semi-automatically, are limited to those available on DBpedia. In addition, it is important to note that not all structures of a particular type have the same properties available on DBpedia. Therefore, although all the identified values accurately correspond to the structure, the coverage itself is restricted to the data available on DBpedia (see Table 2).

Table 2: Coverage of properties related to '*size*', extracted from DBpedia for different architectural structures in our dataset.

Airports	Bridges	Churches	Halls	Skyscrapers
`runwayLength`: 95%	`length`: 67.79%	`architectureStyle`: 36.69%	`seatingCapacity`: 65.67%	`floorCount`: 91%

4 Application and Conclusions

By correlating the influence factors to specific DBpedia properties, we can identify patterns for well-perceived architectural structures. In order to demonstrate how such observed patterns for architectural structures can be used, we choose the influence factor '*size*' of the structure. Although, this approach can be directly extended to other influence factors and across different kinds of architectural structures, due to the limited space we restrict ourselves to showcasing this influence factor.

We observe that for each airport, we can extract indicators of size using the DBpedia property `dbpedia-owl:runwayLength`. Similarly, in case of bridges the influence factor '*size*' can be represented using the DBpedia properties `dbpedia-owl:length`,

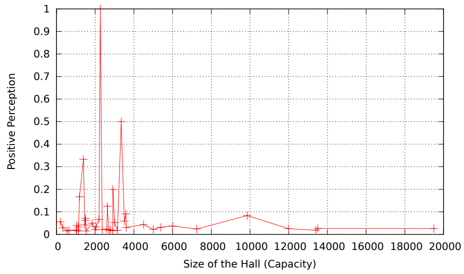

Fig. 1: Influence of Size in the perception of Halls.

`dbpedia-owl:width` and `dbpedia-owl:mainspan`, for halls we can use the DBPedia properties `dbprop:area` and `dbprop:seatingCapacity`, while we can use `dbpedia-owl:floorCount`, and `dbprop:height` to consolidate the well-perceived patterns for Skyscrapers. We thereby extract corresponding property values for each structure in our dataset[4] using the DBpedia knowledge graph.

Figure 1 depicts the influence of *size* in the perception of halls. We observe that halls with a seating capacity between 1000-4000 people are well-perceived with the positive perception, varying between **0.1** and **1**. The perception scores are obtained through the aggregation of results from the crowdsourcing process. Similarly, as a result of the quantitative analysis of churches, by leveraging the rankings and correlating with the property `dbpedia-owl:architecturalStyle`, we find that the most well-received styles of churches in Germany are (i) *Gothic*, (ii) *Gothic Revival*, and (iii) *Romanesque*.

With this, we demonstrated that by correlating building characteristics with extracted data from DBpedia, one is able to compute and analyze architectural structures quantitatively. Thus, our main contribution includes semantic analysis and quantitative measurement of public perception of architectural structures based on structured data. As future work, we plan to develop algorithms that exploit properties from the structured data on the web in order to provide multi-dimensional architectural patterns like 'skyscrapers with x size,y uniqueness, and z materials used are best perceived', which architects and urban planners can benefit from.

References

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[4] Our dataset and building rankings:
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