The Image of a Famous Architect as a Whole as it Appears in Academic Discourse

Comparison of conceptual diversity and interpretation using text mining

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Abstract. This paper proposes a novel approach that leverages artificial intelligence to quantitatively analyse the 'image of the architect' as it appears in academic discourse. This method employs neural networks to examine linguistic expressions associated with architects and their works within a socio-cultural context. Using Word2Vec, a natural language processing technique, we investigated word-usage patterns related to Pritzker Prize laureates and influential modern architects, including Le Corbusier, Mies van der Rohe, and Frank Lloyd Wright. By employing the skip-gram model in Word2Vec, the semantic relationships between the linguistic expressions associated with different architects were identified, providing insights into their perceptions in academic texts. A vocabulary-trend analysis revealed commonalities and differences in their perceptions, highlighting the unique perspectives of each architect and their associated keywords. Furthermore, a cluster analysis was employed to visualise the distinct associations between their architectural approaches, philosophies, and particular terms, facilitating a deeper understanding of the relationship between language and architecture. Therefore, this study contributes to a multidimensional understanding of architects' perceptions and offers an objective evaluation of their portrayal in academic texts.

Keywords. Word2Vec, text mining, polysemy of words, architectural representation, semantic analysis, public perception

1. Introduction

1.1. WORDS IN ARCHITECTURE

This study focuses on two main aspects. The first is the crucial role of 'words' in architecture. They are indispensable for shaping and comprehending architectural concepts. For example, investigations of literature and historical materials have

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revealed that the vocabulary associated with modernist architecture has evolved over time and is subject to diverse interpretations by architects (Forty, 2000). Numerous studies have qualitatively examined architectural language to understand the theories and philosophies of architects.

For instance, research has demonstrated the potential to understand how architects consider different factors and develop unique design processes through their language (Joseph, 2010). Although these findings are valuable, they often lack objectivity. To address this issue, recent advancements in quantitative word-analysis techniques, such as text mining, have gained prominence. Although various studies have actively employed these techniques in other fields, their application in the field of architecture is limited. One notable study demonstrated the potential of text mining to quantitatively analyse the composition of Rem Koolhaas's theories and writings (Yazici & Ozturk, 2023). This research highlighted the valuable of applying text mining to architectural theory. However, it primarily focused on the language of architects themselves. By contrast, this study examined the language used by non-architects to discuss architecture, a perspective currently lacking in literature.

1.2. RECEPTION OF ARCHITECTS BY NON-ARCHITECTS

The second focus of this study is 'the reception of architects by non-architects'. A discrepancy often exists between the intentions of architects when designing buildings and the impressions derived by non-architects from them. Architects are sensitive to subtle design differences and highly value originality, whereas non-architects tend to perceive designs more simplistically (Mondal & Hou, 2022). This can lead to differing preferences, with architects preferring modern designs that emphasise 'comfort', whereas non-architects favouring classical Roman styles (Ilbeigi et al., 2019). Furthermore, while architects prioritise aesthetic value and symbolic significance, the general public is more concerned with practicality, social impact, and the preservation of regional culture (Bianco, 2018). Considering that architecture encompasses not only creativity but also public and social dimensions, understanding how non-architects perceive and interpret architecture is crucial.

1.3. RELATED WORK

A study that focuses on both 'words ‘and 'architectural images as accepted by non-architects' is 'The Reception History of John Ruskin’ (Emoto, 2015). This study qualitatively examines how John Ruskin was historically received in America, not through Ruskin's own discourse but through extensive third-party discussions. Considering the publicness and sociality of architecture, this highlights the importance of understanding how people perceive architecture. The applicability of quantitative analysis to such extensive data is high, and text and image searches can be integrated to support architectural design (CAI, 2024). However, no study has quantitatively presented the composition of architectural images for each architect by considering the context of extensive language-expression data from non-architects.

1.4. RESEARCH OBJECTIVES

To address the aforementioned gaps, we first collected extensive language expressions related to architectural images through Web scraping. Next, instead of relying on simple word frequencies or co-occurrence probabilities, we employed deep-learned-based text mining, which considers context, to analyse the word similarities for each architect. This approach allowed us to identify words with high similarity to a representative 'word' as a concept, which was then interpreted as a factor influencing that word.

For example, consider the word 'building'. As it is not a dictionary definition, the concept of 'building' within an architectural image is subjective and varies among architects. In one architectural image, the primary factor associated with 'building' might be 'form', whereas in another, it could be 'materials/structure/thought', among others. If the similarity between 'building' and 'form' within a particular architect's context is high, it indicates a close relationship in its meaning and usage, allowing 'building' to be interpreted as 'form'. This study presents the composition of such concepts for each architect and a representative concept. To the best of our knowledge, no prior research has quantitatively presented the composition of architectural images for renowned architects in this manner. Therefore, this study aimed to quantitatively present the factors that constitute representative 'words' as concepts within the 'architectural image' (architecture image accepted by non-architects), expressed in language by quantifying the similarity between words in context. This approach represents the novelty of our study.

Similar approaches have been employed in recent studies that used machine learning for architectural image classification. For example, Chen et al. (2021) developed a hierarchical multi-label classification model based on deep learning to recognise architectural images and demonstrated new avenues for analysing architectural elements, functionalities, and styles using large-scale datasets.

Building on these approaches, this study employed academic text data and Word2Vec (Mikolov et al., 2013) to capture similarities in the usage of terms and clarify architectural images. Inspired by the methods of collecting, organising, and interpreting the vast collection of related materials in 'The Reception History of John Ruskin', this study explored architectural images from a broader perspective using widely available text-based information on the Internet. Additionally, recent advancements in natural language processing (NLP) technologies, which enable the contextual analysis of substantial volumes of text, were an inspiration for this study.

2. Research Overview

2.1. RESEARCH FLOW

Figure1 illustrates the list of target architects and an overview of the research workflow. This study followed a structured process, including the collection of texts related to Pritzker Prize laureates (2012–2021) and modern architectural masters, preprocessing the data, training Word2Vec models, and analysing word similarities. Key trends and unique features were visualized using clustering techniques and diagrams to uncover linguistic patterns in academic discourse. Details of each step are provided in the following sections.

Year	Architect/Group	Country	Collected Words
2012	Wang Shu	China	20,142
2013	Toyo Ito	Japan	22,392
2014	Shigeru Ban	Japan	22,480
2015	Frei Otto	Germany	18,631
2016	Alejandro Aravena	Chile	19,132
2017	RCR Arquitectes	Spain	18,264
2018	Balkrishna Doshi	India	18,664
2019	Arata Isozaki	Japan	19,082
2020	Grafton Architects	Ireland	18,915
2021	Lacaton & Vassal	France	21,485
The three great masters of modern architecture	Le Corbusier	Switzerland	22,283
	Mies van der Rohe	Germany	20,025
	Frank Lloyd Wright	USA	20,974

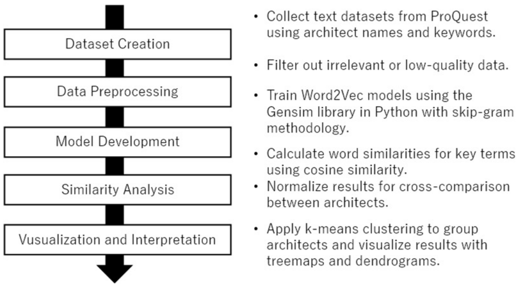


Figure1. Target architects/architectural groups and research Flow

2.2. DATASET

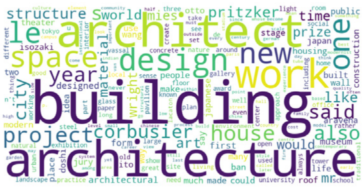
Clarivate's ProQuest platform, which is one of the largest and most reliable academic information databases, was used to create the text dataset. ProQuest provides access to various sources, including academic journals, newspaper articles, dissertations, books, and reports, allowing comprehensive cross-referencing of 13 databases. The search was conducted using the architect's name along with the term 'architect', and only articles in English with full-text access were selected. In addition to filtering based on academic relevance, news articles were included to offer a broader societal perspective. These were further refined based on their relevance to architects' work. Relevant data were organised in a Google Spreadsheet, documenting search terms, article titles, authors, publication years, countries, and URLs. Each dataset comprised 18,000–22,000 words per architect, thereby providing a robust foundation for text analysis.

2.3. MODEL AND LEARNING CONDITIONS

Word2Vec uses neural networks to represent words as real-valued vectors (i.e., word embeddings). By obtaining distributed word representations, it enables the quantification and exploration of similarities between words. In this study, the skip-gram method was used to predict the words surrounding the target word. Skip-gram is particularly effective in capturing rare-word associations. The vector dimensions were set to 100, window size (number of context words considered around the target) was set to 3, and number of training iterations was set to 500. A separate Word2Vec model was created for each architect, ensuring that it could capture both common and unique word patterns relevant to their context and work. The training and evaluation processes were implemented using Jupyter Notebook.

2.4. SELECTION OF SUBSTITUTED WORDS

The trained model output similarities with other words in the text by substituting specific words. For these substituted words, we selected ten words (hereinafter referred to as 'related words') representing concepts related to architecture from among the top 20 most frequent words in the dataset: building, architecture, architect, work, design, space, project, house, city, and structure (Figure2).



Rank	Word	Count	Rank	Word	Count	Rank	Word	Count
1	building	1,588	8	new	651	15	also	516
2	architecture	1,492	9	le	638	16	corbusier	501
3	architect	1,311	10	project	630	17	city	487
4	work	965	11	house	605	18	pritzker	477
5	design	733	12	year	561	19	structure	470
6	one	668	13	s	541	20	like	448
7	space	668	14	said	522			

Figure2. Word Cloud and Top 20 Most Frequent Words in the Dataset.
The architectural terms are highlighted in yellow

2.5. OUTPUT PROCESSING

The similarity between the substituted words was output as a cosine similarity and the values were normalised to a range of 0–1. To conduct a comprehensive analysis of word similarities across different architects and terms, it was necessary to standardise the range of values across all patterns. As it was difficult to analyse all 100 output words, an effective range was determined by observing the point at which the similarity variations stabilised. Specifically, the moving average was calculated at 10-word intervals based on the difference in similarity rankings of up to 100 words, and the similarity threshold was set at a point immediately before the moving average fell below the median value. This approach ensured that the analysis focused on the most significant word associations.

2.6. INTERPRETATION OF THE RESULTS

The output for each substituted word was interpreted as representing the 'image of the architect as seen from the perspective of the words' by people. Additionally, the proportion of words within the effective range for each architect was considered to represent the elements that constituted the their image. By comparing the results for each word with across different architects, we could discern the trends of how each architect was perceived from different perspectives. Furthermore, the meanings and values of the output words were analysed to explore the causes and characteristics within these trends.

3. Results

3.1. MODEL TRAINING AND CONVERGENCE

As shown in Figure3, the training of all Word2Vec models converged successfully, indicating that the models effectively captured the semantic relationships within the text data specific to each architect's body of work. Furthermore, the meanings and values of the output words were analysed to explore the causes and characteristics within these trends.

To facilitate a comprehensive understanding of architectural concepts, ten representative words were selected based on their significance in the field, as described in Section 2.4. These words include 'building', 'architecture', 'architect', 'work', 'design', 'space', 'project', 'house', 'city', and 'structure'. Using the trained models, we explored similar words for each term to investigate the nuanced language associated with each architect.

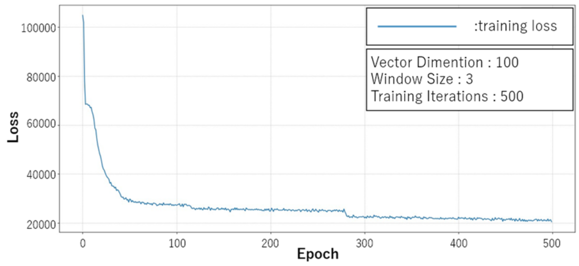


Figure3. Training progression of the Word2Vec model (Ito)

3.2. DETERMINING THE EFFECTIVE RANGE OF SIMILAR WORDS

After extracting the similar words for each term, we investigated the effective range of similarities to determine an appropriate threshold for selecting meaningful words. This involved analysing the similarity scores and identifying the cutoff point where the words remained contextually relevant. Figure4 illustrates the results of determining the effective range of similar words for 'architecture' in the context of Le Corbusier. The graph shows that the similarity scores decreased as the ranks of similar words increased. Based on this trend, we established a threshold that balances the inclusion of relevant terms with the exclusion of less pertinent ones. The high average number of similar words for 'architect' suggests a diverse perception of architects associated with this term, encompassing various perspectives and contexts. Conversely, a lower average for 'architecture' indicates a more common or shared understanding of the concept across different architects.

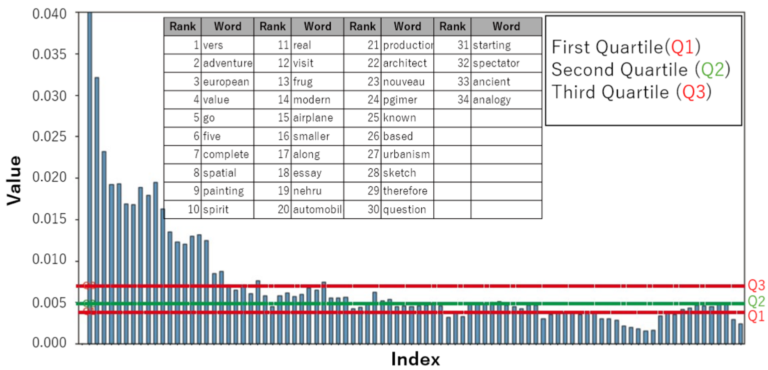


Figure4. Results of exploring the effective range of similar words
for 'Architecture' in Le Corbusier's context

3.3. ANALYSIS OF EFFECTIVE SIMILAR WORDS

The number of effective similar words for each architect and target word is summarised in Figure 5. The maximum number of effective similar words was 54, found in Shigeru Ban's 'work' from 2014 and Balkrishna Doshi's 'structure' from 2018. The minimum was 0, observed in Frei Otto's 'house' from 2015, indicating that the term 'house' did not appear in his dataset.

Words like 'house' and 'structure' exhibited large variations in the number of effective similar words across different architects. By contrast, terms such as 'city', 'building', and 'project' showed smaller variations, indicating more consistent usage across different architects.

Additionally, an analysis of the average values for each term revealed a high average of 39.0 similar words for the term 'architect', and a lower average of 33.9 for 'architecture'.

Terms	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Cor busier	Mies	Wright	Max	Min	SD	AVG
building	43	36	49	32	37	33	51	26	33	33	35	37	39	51	26	6.67	37.23
architecture	45	34	38	40	38	15	45	22	35	27	34	35	33	45	15	8.17	33.92
architect	43	34	52	33	44	46	32	47	42	43	19	36	36	52	19	8.21	39.00
work	38	33	54	29	45	31	41	43	38	30	21	24	49	54	21	9.36	36.62
design	29	43	30	29	41	44	30	22	40	43	35	44	45	45	22	7.40	36.54
space	29	37	39	51	44	33	30	40	37	49	42	26	29	51	26	7.54	37.38
project	36	34	41	28	39	39	41	23	34	29	37	20	42	42	20	6.81	34.08
house	46	41	41	0	43	39	50	34	25	34	51	33	40	51	0	12.63	36.69
city	46	35	33	42	38	20	36	39	38	40	31	42	32	46	20	6.27	36.31
structure	36	33	22	19	32	27	54	28	51	36	40	26	42	54	19	10.07	34.31

2012 Wang Shu ; 2013 Toyo Ito ; 2014 Shigeru Ban ; 2015 Frei Otto ; 2016 Alejandro Aravena 2017 RCR Arquitectes ;
2018 Balkrishna Doshi ; 2019 Arata Isozaki ; 2020 Grafton Architects ; 2021 Lacaton & Vassal

Figure5. Effective similar word counts and statistical results
(maximum, minimum, standard deviation, average) for key architectural terms

3.4. ANALYSIS OF COMMON WORDS

Cluster	building	architecture	architect	work	design	space	project	house	city	structure
Cluster 1	2015, 2016, 2017, 2018, 2019	2013, 2014, 2015, 2016, 2017, 2019, Corbusier	2012, 2013, 2015, 2018, 2020, 2021, Corbusier, Mies	2016, 2017, 2018, 2019, 2021, Corbusier, Mies, Wright	2012, 2014, 2017, 2018, 2020, 2021, Mies, Wright	2017, 2018, 2020, Corbusier	2013, 2014, 2016, 2020, 2021, Wright	2019, 2021	2012, 2018, 2020, Mies	2013, 2014, 2015, 2017, 2021, Mies
Cluster 2	2021, Mies, Wright	2012, Wright	2014, 2016	2013, 2014, 2015, 2020	2013, 2016, 2019, Corbusier	2014, 2019, 2021	2012, 2015, Corbusier	2012, 2013, 2014, 2016, 2017, 2018, 2020, Corbusier, Mies, Wright	2013, 2014, 2015, 2016, 2019, 2021, Corbusier, Wright	2012, 2019, Corbusier, Wright
Cluster 3	2012, 2013, 2014, 2020, Corbusier	2018, 2020, 2021, Mies	2017, 2019, Wright	2012	2015	2012, 2013, 2015, 2016, Mies, Wright	2017, 2018, 2019, Mies	2015	2017	2016, 2018, 2020

2012 Wang Shu ; 2013 Toyo Ito ; 2014 Shigeru Ban ; 2015 Frei Otto ; 2016 Alejandro Aravena 2017 RCR Arquitectes ;
2018 Balkrishna Doshi ; 2019 Arata Isozaki ; 2020 Grafton Architects ; 2021 Lacaton & Vassal

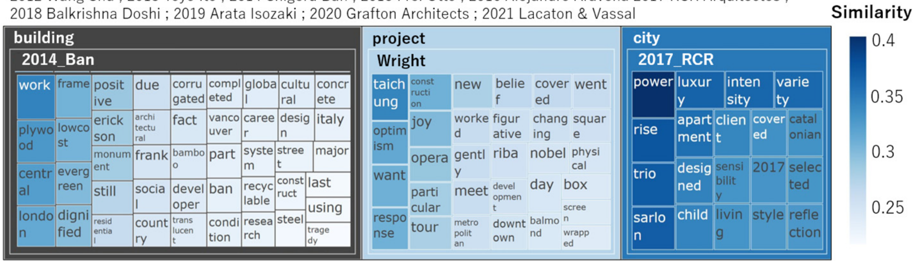


Figure6. Top: Target architects/architectural groups and numbers of collected words
Bottom: Synonym treemap of architects forming independent clusters by search term

To further understand these trends, clustering was performed on each architec-tural model trained using Word2Vec. Using the 42 common words across all models and their cosine similarities with the ten search terms as feature values, we applied k-means clustering (with three clusters) after normalisation. This approach allowed us to group architects based on linguistic similarities and to identify patterns in how they are discussed in academic discourse.

Figure 6 presents the classification of architects and architectural groups based on the clustering results. Specific terms, such as 'work', 'design', and 'city', exhibited distinctive feature values and formed independent clusters. The treemaps illustrate the similar words within these clusters, highlighting the lin-guistic patterns associated with each architect.

Differences were observed between architects who frequently appeared in the same clusters and those who did not. For instance, pairs such as Ito and Ban, Doshi and Grafton, and Doshi and Mies were consistently classified together, whereas Wang and Isozaki appeared together only once.

Figure 7 shows the dendrogram for Wang and Isozaki regarding the target word 'design' and the corresponding treemaps based on the cosine similarities of the 42 common words. Even when the same words appeared as similar terms to 'design', the degree of association differed between the two architects.

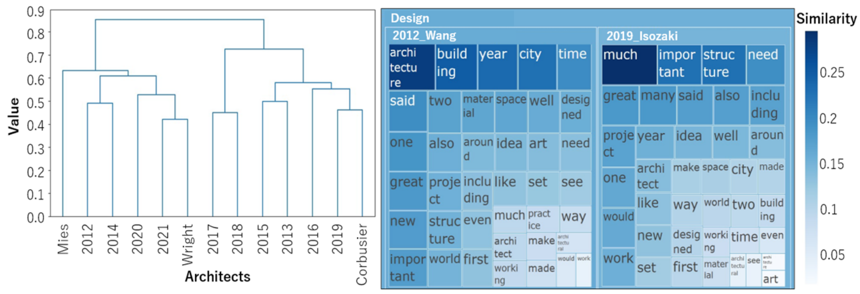


Figure7. Dendrogram and treemap results of common words associated with Wang and Isozaki's 'design'

4. Discussion

The analysis of effective similar words revealed that certain architectural concepts are interpreted differently by various architects. The significant variations in the number of similar words for terms such as "house" and "structure" indicate that these concepts hold different levels of importance or are associated with different ideas in each architect's work. For instance, Frei Otto's focused use of "structure" aligns with his specialisation in lightweight structures, whereas Balkrishna Doshi's broader interpretation suggests a more diverse application of the concept in his work.

On the other hand, the consistent usage of terms such as "city," "building," and "project" by different architects underscores their fundamental role in architectural discourse. These concepts appear to be universally significant, reflecting common themes and concerns within the field.

The clustering analysis of common words further highlighted how architects can be grouped based on linguistic similarities. The formation of clusters among certain architects suggests shared perspectives or thematic overlaps in their works. For example, the frequent clustering of Ito and Ban may indicate similarities in their approaches to architecture such as innovation and a focus on contemporary issues.

The contrast in the treemaps of Wang and Isozaki's "design" demonstrates how cultural context and individual philosophy influence the associations with key architectural terms. Wang's emphasis on tradition and sustainability contrasts with Isozaki's focus on innovation and urbanism, illustrating the diverse interpretations of "design" within the architectural community.

As mentioned in Section 1, prior researchers have often focused on architects' own discourse to understand their philosophies and approaches (e.g., Yazici & Ozturk, 2023; Emoto, 2015). In contrast, we quantitatively analysed how architects are perceived by others in academic texts, providing insights into their public image and societal interpretations. This offers a novel perspective for objectively evaluating the construction of architects' images within the academic community, complementing existing qualitative analyses.

These findings contribute to a deeper understanding of the diverse ways in which architects are discussed and perceived, highlighting the importance of considering external perspectives in architectural analysis. Future research could expand this approach by incorporating a broader range of data sources and exploring additional linguistic and cultural factors that influence the perception of architects and their work.

5. Conclusion

In this study, we employed text-mining techniques to quantitatively analyse the image of architects in academic discourse to clarify the diversity of linguistic expressions and the interpretive differences associated with each architect. Specifically, we analysed the vocabulary similarities using Word2Vec, focusing on Pritzker Prize laureates and modern architectural masters such as Le Corbusier, Mies van der Rohe, and Frank Lloyd Wright. The results confirmed that each architect emphasises different concepts, leading to unique portrayals in academic texts.

Furthermore, by applying k-means clustering to the cosine similarity values of shared words, we identified patterns in the classification of architects in relation to each search term. This clustering revealed how specific keywords are associated with each architect, highlighting their unique perspectives and approaches.

These results demonstrate the effectiveness of the proposed method in highlighting the differences in the perspectives and approaches of each architect for each search term. The combination of Word2Vec and clustering techniques proved valuable for capturing the values, philosophies, and cultural influences of each architect, as reflected in their linguistic expressions. Additionally, this method enabled a quantitative comparison of their philosophies and design approaches, objectively illustrating the commonalities and differences in their recognition and discussion within academic texts.

A quantitative approach using Word2Vec and clustering techniques was introduced in this study, in place of traditional qualitative analyses, providing a new perspective for evaluating architectural images based on a wide range of text data. Future research should focus on enhancing the data quality by expanding the range of information sources and refining the model to account for finer linguistic nuances and contextual variations. Moreover, incorporating advanced NLP techniques, such as bidirectional encoder representations, is expected to deepen the contextual understanding of words, further enriching the analysis.

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