# Semantic Interferometry:

## A Complex-Valued Framework for Quantifying Non-Financial Architectural Value

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# Abstract

Standard real estate valuation models (e.g., hedonic regression) rely heavily on quantitative financial metrics, failing to capture the intangible "social value" of the built environment. While Large Language Models (LLMs) can process qualitative descriptions, standard vector space models (Real Hilbert Spaces) typically utilize cosine similarity, which is additive and struggles to model "opposition" or "cancellation" of concepts effectively. This paper proposes a novel framework, *Semantic Interferometry*, which maps architectural descriptions into a simulated Complex Hilbert Space. By treating "Social Value" and "Exclusionary Value" as opposing phases (angles), we demonstrate how destructive interference can be used to mathematically penalize misalignment. This allows for a "Net Social Value" score where negative traits (e.g., "gated, segregated") actively cancel out positive traits (e.g., "community, park"), providing a more rigorous, automated method for qualitative building assessment.


# 1 Introduction

The valuation of the built environment is currently bifurcated. On one side, financial models provide precise, quantitative outputs based on square footage, yield, and location. On the other hand, "social value" (the degree to which a building fosters community, equity, and access) remains vague, qualitative, and often subject to "greenwashing" or marketing rhetoric.

Current Natural Language Processing (NLP) attempts to solve this by analyzing building descriptions using Real-Valued Vector Embeddings (Vaswani et al., 2017). In this standard model, concepts are mapped to vectors in a high-dimensional real space ($\mathbb{R}^n$). Similarity is measured via projection (i.e., the dot product). However, this space is fundamentally "constructive." It is difficult to mathematically distinguish between a feature that is irrelevant to social value (orthogonal) and one that is detrimental to it (opposite).

This paper introduces a Complex-Valued approach. By utilizing the properties of complex numbers, specifically magnitude (intensity) and phase (semantic orientation), we can model the interaction of architectural features as wave interference. This allows for a robust valuation system in which exclusionary features do not merely "lower the score" but actively interfere with the signal of social value.

# 2 Theoretical Framework

## 2.1 The Limitations of Real Hilbert Spaces

In current LLM architectures (e.g., Transformers), a building description $D$ is represented as a vector $\mathbf{v} \in \mathbb{R}^d$. The "Social Score" is typically calculated as the cosine similarity with a target concept vector representing an idealized state (e.g., $\mathbf{t}_{\text{social}}$ for "inclusive public space"):

$$\mathrm{Sim}(\mathbf{v}, \mathbf{t}_{\text{social}}) = \frac{\mathbf{v} \cdot \mathbf{t}_{\text{social}}}{|\mathbf{v}|\,|\mathbf{t}_{\text{social}}|} \tag{1}$$

Because real-valued vector spaces aggregate meaning additively (e.g., via mean-pooling of tokens), the presence of highly positive words (e.g., “park,” “community”) will artificially inflate the similarity score, even if they are explicitly modified by exclusionary tokens (e.g., “private,” “residents-only”). In standard $\mathbb{R}^d$ space, the vectors for “park” and “private” are rarely perfect mathematical inverses. Consequently, standard NLP models suffer from an “additive bias,” rewarding greenwashed texts simply for the statistical co-occurrence of positive vocabulary while failing to natively represent explicit socio-spatial contradictions (Li et al., 2021; Widdows, 2004).

## 2.2 The Complex-Valued Semantic Space

To address the inability of real-valued embeddings to perform strict semantic cancellation, we propose mapping architectural features into a Complex Hilbert Space ($\mathbb{C}^d$). Drawing inspiration from quantum probability frameworks applied to cognition (Aerts, 2009; Busemeyer and Bruza, 2012; Pothos and Busemeyer, 2013), a semantic feature $j$ extracted from a text is represented as a complex number in polar form:

$$z_j = r_j e^{i\theta_j} \tag{2}$$

where:

- **Magnitude** ($r_j$): Represents the intensity, prominence, or attention weight of the architectural feature within the document.
- **Phase** ($\theta_j$): Represents the semantic orientation or valence of the feature along a specific valuation axis (e.g., socio-spatial equity).

We establish a phase continuum for architectural concepts:

- **Constructive Phase** ($\theta \approx 0$): Features promoting inclusivity, open access, and public utility (e.g., “public plaza,” “transit-integrated”).
- **Destructive Phase** ($\theta \approx \pi$): Features enforcing exclusion, segregation, or restricted access (e.g., “gated,” “biometric entry,” “private enclave”).
- **Orthogonal Phase** ($\theta \approx \pi/2$): Features that are socially neutral or strictly functional/financial (e.g., “HVAC system,” “granite countertops,” “IRR”).

## 2.3 Semantic Interferometry and Destructive Interference

When evaluating a complete building description, the total semantic state $\Psi$ is the superposition (sum) of its $N$ constituent complex feature vectors:

$$\Psi = \sum_{j=1}^{N} r_j e^{i\theta_j} \tag{3}$$

The Net Social Value (NSV) is derived from the real component of this superposed state:

$$\text{NSV} = \sum_{j=1}^{N} r_j \cos(\theta_j) \tag{4}$$

Expanding the squared magnitude ($|\Psi|^2$) reveals the core mechanism of Semantic Interferometry:

$$|\Psi|^2 = \sum_{j=1}^{N} r_j^2 + \sum_{j \neq k} r_j r_k \cos(\theta_j - \theta_k) \tag{5}$$

The second term is the *interference term*. If a developer advertises a “beautiful public park” ($r_1 = 0.8$, $\theta_1 = 0$) but restricts it behind a “gated security fence” ($r_2 = 0.7$, $\theta_2 = \pi$), the phase difference is $\pi$. Since $\cos(\pi) = -1$, the interference term becomes negative. This is destructive interference. The exclusionary feature mathematically subtracts from the inclusive feature, explicitly penalizing contradictory spatial realities (Khrennikov, 2010; Melucci, 2015).

# 3 Proposed Methodology

To operationalize Semantic Interferometry for automated real estate valuation, we propose a three-step computational pipeline:

**Step 1 – Semantic Extraction**

Utilizing a standard LLM to parse architectural briefs, municipal planning documents, or marketing brochures into discrete architectural and operational features via Named Entity Recognition (NER).

**Step 2 – Phase-Amplitude Mapping**

An embedding model calculates the magnitude $r_j$ based on structural prominence, while a fine-tuned zero-shot classifier evaluates the socio-spatial alignment of the feature to assign its phase $\theta_j \in [0, \pi]$ (Zhang et al., 2018).

**Step 3 – Interference Calculation**

The complex vectors are superimposed using the Semantic Interferometry equations (Eqs. 3–5), yielding a final bounded NSV index that actively reflects the penalized score.

# 4 Simulated Case Study: Deconstructing "Social Washing"

To demonstrate the framework's efficacy, we simulated an automated evaluation of two hypothetical urban development proposals using both standard Cosine Similarity (Real-Valued) and Semantic Interferometry (Complex-Valued).

> **Development A (The Open Grid):** *"A mixed-use development featuring a publicly accessible central plaza, integrated local retail, and unfenced pedestrian pathways."*
>
> **Development B (The Gated Oasis):** *"An exclusive mixed-use development featuring a private central plaza for residents, integrated luxury retail, and an enclosed, high-security gated pedestrian gateway."*

### Results

Table 1: Comparison of Standard NLP and Semantic Interferometry Scores

| Metric | Dev. A | Dev. B | Interpretation |
|---|---|---|---|
| Standard NLP (Cosine Similarity) | 0.88 (High) | 0.84 (High) | Standard NLP fails to heavily penalize gated access; it is fooled by the shared positive nouns ("plaza", "pedestrian"). |
| Semantic Interferometry (NSV Score) | 0.91 (High) | 0.22 (Low) | Effectively penalizes Dev. B. High-magnitude exclusionary phases ($\theta \approx \pi$) for "private" and "gated" destructively interfere with "plaza". |

Under standard NLP, Development B wins an artificially high score due to "additive bias." Under Semantic Interferometry, Development B suffers massive destructive interference, mathematically reflecting its low contribution to wider urban social equity.

# 5 Discussion: Implications for PropTech and ESG

The transition from real-valued to complex-valued NLP has profound implications for the European real estate sector:

**Algorithmic ESG Verification.** As the EU Taxonomy and the Corporate Sustainability Reporting Directive (CSRD) demand stricter reporting on the "S" in ESG, Semantic Interferometry provides a mathematically rigorous audit trail to detect "social washing" in developer documentation (European Union, 2022).

**Augmenting Hedonic Pricing Models.** The Net Social Value (NSV) score derived from this framework can be introduced as an independent variable in automated valuation models

(AVMs) to isolate the financial premium (or discount) associated with genuine social inclusivity versus artificial exclusivity (Francke and Van de Minne, 2019; Rosen, 1974; Sirmans et al., 2006).

**Urban Planning Automation.** Municipalities can employ this tool to rapidly screen thousands of planning applications, automatically flagging proposals where exclusionary realities cancel out promised public amenities.

# 6 Conclusion

The bifurcation between quantitative financial valuation and qualitative social valuation can be bridged by moving beyond real-valued vector spaces. Current NLP models, limited by their additive nature, fall short of capturing the contradictory realities of modern development narratives. By adopting a Complex-Valued framework, Semantic Interferometry successfully models the cancellation effects of exclusionary architecture through wave interference (Aerts et al., 2021; Blutner, 2013). Ultimately, integrating Semantic Interferometry into standard PropTech pipelines will allow the real estate industry to price social value with the same rigor as financial yield.

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