BioArtlas: Computational Clustering of Multi-Dimensional Complexity in Bioart

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Abstract

Bioart's hybrid nature—spanning art, science, technology, ethics, and politics—defies traditional single-axis categorization. I present BioArtlas, analyzing 81 bioart works across thirteen curated dimensions using novel axis-aware representations that preserve semantic distinctions while enabling cross-dimensional comparison. Our codebook-based approach groups related concepts into unified clusters, addressing polysemy in cultural terminology. Comprehensive evaluation of up to 800 representation–space–algorithm combinations identifies Agglomerative clustering at k=15 on 4D UMAP as optimal (silhouette 0.664 ± 0.008, trustworthiness/continuity $0.805/0.812$). The approach reveals four organizational patterns: artist-specific methodological cohesion, technique-based segmentation, temporal artistic evolution, and trans-temporal conceptual affinities. By separating analytical optimization from public communication, I provide rigorous analysis and accessible exploration through an interactive web interface (`https://www.bioartlas.com`) with the dataset publicly available (`https://github.com/joonhyungbae/BioArtlas`).

1 Introduction

Bioart amalgamates biological materials, processes, and thoughts into artistic expression at the confluence of art, science, and technology [1, 2]. Bioartists, such as Eduardo Kac with his transgenic organisms and Stelarc with his prosthetic modifications, engage with living systems to investigate themes of identity, ethics, embodiment, and the borders between the natural and artificial [3, 4].

Nevertheless, current taxonomic methodologies have encountered difficulties in encapsulating the intrinsic intricacy of bioart. Single-axis or medium-/technology-centric frameworks (e.g., Kac's transgenic/telepresence research [1, 3], SymbioticA's ethics of care [2], Hauser's life media [5], ZKM's *BioMedia* [6]) overlook the multidimensionality of practice. Actor-network theory and companion-species approaches [7, 8] advocate for the distinct consideration of relational, ethical, aesthetic, and epistemic dimensions. Medium-focused perspectives minimize ethical considerations and social context, while ethics-focused methods neglect aesthetic and epistemic contributions. The hybrid character of bioart—encompassing art, science, technology, ethics, and politics—generates categorical ambiguity, since works serve simultaneously as aesthetic objects, scientific instruments, ethical provocations, and political statements, resisting solitary definition.

Cultural phenomena frequently necessitate the integration of diverse analytical dimensions; axis-aware representations and domain-informed codebooks can enhance interpretability [9–11]. Sentence embeddings capture nuanced semantics [12]. Rather than multi-kernel fusion, this study systematically scans *representation–space–algorithm* combinations (e.g., TF–IDF of codebook counts,

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quantized per-axis embeddings; RAW/SVD/UMAP spaces; k-means/agglo/density methods) and selects an interpretable, exhaustive partition under atlas-specific constraints.

To address these challenges, I present a computational framework for analyzing 81 bioartworks and report the best internal-validity configuration from a representation–space–algorithm sweep: *Agglomerative (average linkage)* at k=15 on a 4D UMAP projection with optimized hyperparameters (10 nearest neighbors, minimum distance 0.01, cosine metric). For communication, I additionally provide a coarser labeling in the viewer without treating it as the analytical optimum.

This approach addresses bioart's analytical challenges through: (1) codebook-based semantic fusion preserving axis-specific semantics, (2) data-driven clustering with transparent reporting, and (3) separation between analytical optimization and communication visualization. This work combines computational rigor with artistic insight, bridging the researcher-practitioner divide that often limits cross-disciplinary understanding. I explicitly position the atlas as a tool for human interpretation—algorithms operate as instruments rather than arbiters—so interpretability and uncertainty reporting remain first-class design goals.

2 Dataset

The corpus was built to select target artists and representative works by synthesizing *award–institution–platform* indicators conferring international visibility from major bioart awards and exhibitions, including *Prix Ars Electronica*, *Bio Art & Design Award*, ZKM's *BioMedia*, MIT List's *Symbionts*, STARTS Prize, and ISEA archives [6, 13–17]. Artist and artwork selection used multi-layered criteria: art-historical significance (e.g., Davis, Kac), technological innovation, field contribution, and conceptual clarity [1, 3].

The **13 analytic axes** (Table 2) were derived via literature review [1, 2, 5–8] and inductive corpus analysis. Coverage and non-redundancy were emphasized during axis development; observed pairwise correlations were low-to-moderate, consistent with complementary dimensions. All source materials are public, non-personal, and attributed; only metadata and derived artifacts are released. Policies follow FAIR/CARE guidelines; takedown requests are honored. Axis definitions and labeling protocols were predetermined using a codebook with comprehensive annotation criteria, shaped by the author's dual role as a professional artist and an AI researcher. Although the existing annotations are conducted by a single annotator, the systematic codebook facilitates future validation by many annotators and the evaluation of inter-rater reliability.

This study provides a systematically annotated bioart dataset, featuring systematic evaluations across 13 analytical parameters. Although constrained in scope, it provides a preliminary basis for computational methodologies in bioart analysis and associated cultural fields. Table 1 offers a detailed summary of the dataset's composition, illustrating the significant scale and diversity of the corpus, which contains 770 distinct keywords across 81 artworks.

Table 1: Dataset Summary

Dataset		**Keywords**	
Total works	81	Unique keywords	770
Total artists	33	Mean / work	28.2
Temporal coverage	1976–2022	Assignments	2285
		Analytic axes	13

The dataset includes 33 artists and collectives (Table 3), balancing diversity with focused analysis of key practitioners.

3 Method

3.1 Two-Stage Representation Process

The multidimensional nature of bioart—encompassing aesthetic, ethical, material, and intellectual aspects—necessitates transcending singular embedding techniques that may obscure diverse semantic components. My solution tackles these problems via a methodical two-stage process that maintains axis-specific semantics while facilitating cross-dimensional comparison. The method establishes

Table 2: Keyword statistics for the 13 analytic axes, with the top three keywords per axis.

Axis	Unique	Average	Top (up to three)
Materiality	98	2.58	Plant; Composite materials; Data
Methodology	88	2.40	Cell culture; Data visualization; Biosensing
Actor Relations & Configurations	62	2.17	Artist-led; Autonomous bio processes; Interspecies co-creation
Ethical Approach	53	2.16	Reflective; Relational ethics; Symbiotic
Aesthetic Strategy	76	2.57	Conceptual; Uncanny; Biological morphology
Epistemic Function	54	2.21	Social criticism; Knowledge production; Future proposal
Philosophical Stance	47	2.23	New materialism; Posthumanism; Relational ontology
Social Context	44	2.17	Gallery; Laboratory
Audience Engagement	53	2.00	Observational; Interpretive engagement; Contemplative
Temporal Scale	44	1.53	Continuous; Short-term exhibition; Evolutionary
Spatial Scale	56	1.48	Installation; Human body size; Individual unit
Power and Capital Critique	61	1.79	Institutional criticism; Biopolitics; Biocapital
Documentation & Representation	85	2.91	Photographic records; Material residue; Data viz

Table 3: List of 33 artists and collectives in the dataset, with number of works shown in parentheses.

Artist Names (Number of Works)
Joe Davis (4), Stelarc (4), George Gessert (2), Eduardo Kac (3), Oron Catts & Ionat Zurr (3), Wim Delvoye (2), Art Orienté Objet (1), HeHe (1), Zbigniew Oksiuta (1), Paul Vanouse (3), Anna Dumitriu (2), Center for Genomic Gastronomy (2), Charlotte Jarvis (2), Heather Dewey-Hagborg (2), Jalila Essaïdi (2), Marta de Menezes (2), Špela Petrič (2), Agi Haines (1), Maja Smrekar (1), Ani Liu (5), Alexandra Daisy Ginsberg (4), Anicka Yi (4), Candice Lin (3), Claire Pentecost (3), Dasha Tsapenko (3), Jenna Sutela (3), Jes Fan (3), Cecilia Jonsson (2), Gilberto Esparza (2), Pamela Rosenkranz (2), Xandra van der Eijk (2), Amy Karle (1), Michael Sedbon (1)

durable semantic anchors by constructing a codebook that organizes related concepts into cohesive clusters, maintaining consistency among artworks.

Stage 1: Per-Axis Embedding Aggregation. For each artwork's 13 axes, assigned keywords are embedded using dual large language models (BGE-large-en-v1.5 and GTE-large-en-v1.5) with concatenated representations yielding 2048-dimensional vectors. Keywords within each axis are then averaged to create a single axis-level embedding. For example, if an artwork's *Materiality* axis contains keywords {*plant*, *data*, *composite-materials*}, the three 2048-dimensional embeddings are averaged into one 2048-dimensional vector representing that axis. Each artwork thus yields 13 axis-specific embeddings of 2048 dimensions each.

Stage 2: Word Codebook and Axis Features. All unique keywords across the entire dataset are clustered into a *word codebook* using K-means. Prior to clustering, token embeddings undergo PCA (retaining $\geq$95% cumulative variance) with whitening to stabilize K-means. K_c is *automatically selected* by scanning candidate values and maximizing a silhouette-based objective regularized by penalties for empty/singleton/imbalanced clusters. Each artwork is then represented via per-axis codebook activations: counts/one-hot and their TF–IDF (BM25 optional); I also compute *quantized per-axis embeddings* as count-weighted averages of codebook centroids.

The codebook approach addresses polysemy by grouping semantically related terms (e.g., {*biofabrication*, *tissue-engineering*, *living-materials*}) into unified concept clusters, enabling more robust similarity computation than raw keyword matching.

Final Representation. I generate TF-IDF weighted cluster counts (L2 normalized), quantized embeddings, binary indicators, and SVD variants. TF-IDF weighted counts achieved superior performance, balancing interpretability with clustering quality.

3.2 Systematic Sweep Configuration

I evaluate multiple representation types across systematic algorithm-space combinations to identify optimal clustering configurations. My approach explores 8 feature representations (TF-IDF variants, quantized embeddings, SVD-reduced features) across 31+ projection spaces (RAW, SVD dimensions 50/100/150, UMAP 4D/8D/16D with 3×3 hyperparameter grids) using 4 clustering algorithms (K-means, Agglomerative, DBSCAN, OPTICS). With $K \in [2, 15]$ for partitional methods, this yields 800+ evaluated configurations within computational constraints.

The building of a cultural atlas necessitates a balance between statistical coherence and interpretive utility, highlighting a fundamental contradiction between optimization objectives. This challenge is especially pronounced in identifying optimal cluster numbers: although statistical criteria (Gap statistic, Silhouette) may indicate $K \leq 27$ for our data size [18], domain-specific constraints in

cultural categorization advocate for cognitively manageable partitions. The range $K \in [2, 15]$ reflects this compromise, supported by cluster validation literature [19, 20] and cultural analysis approaches, where excessive granularity obstructs understanding [21]. Conventional clustering optimization prioritizes internal cohesion metrics (Silhouette, within-cluster sum of squares), while atlas applications necessitate thorough categorization, cognitive accessibility, and interpretive clarity, often conflicting with statistical optimization.

This tension is evident in three dimensions: (1) **Completeness vs. Purity**—density-based methods attain superior silhouette scores by categorizing boundary cases as noise, whereas cultural atlases necessitate extensive landscape representation; (2) **Statistical Precision vs. Cognitive Load**—hierarchical methods enhance separation via meticulous partitioning that surpasses human categorical processing capabilities; (3) **Algorithmic Sophistication vs. Interpretive Transparency**—sophisticated techniques may identify statistical patterns while concealing semantic distinctions.

Multi-Metric Evaluation Framework. I resolve these conflicts by doing a thorough assessment utilizing many validation criteria instead of depending on singular measures. Evaluation incorporates the silhouette score (main ranking criterion), projection quality safeguards (trustworthiness/continuity ≥ 0.80), and noise ratio analysis for density-based methodologies. Stability validation employs bootstrap resampling (5 iterations) to calculate the Adjusted Rand Index (ARI) and Normalized Mutual Information (NMI) throughout several executions. This comprehensive strategy emphasizes thorough partitions rather than statistical purity, all while upholding stringent quality standards.

Table 4: Complete sweep configuration.

Component	Specification
Embedding model	Dual models: BGE-large-en-v1.5 + GTE-large-en-v1.5 (concatenated, 2048-dim); codebook $K_c = 47$ (auto-selected)
Feature types	TF-IDF weighted codebook counts (L2 normalized); quantized embeddings; SVD variants
Projection spaces	RAW, SVD, UMAP (4/8/16-D, varying hyperparameters)
Clustering algorithms	K-means, Agglomerative (multiple linkages), DBSCAN, OPTICS
Selection criteria	Silhouette-based selection with trustworthiness/continuity guardrails and stability validation; complete assignment methods prioritized for final selection

3.3 Codebook Diagnostics

I automatically scan codebook size K_c across candidates $\{32, 48, ..., 1024\} \cup \{\sqrt{n}, 1.5\sqrt{n}, 2\sqrt{n}\}$ using adjusted silhouette score: $S_{adj} = S - 0.6 \cdot r_{singleton} - 0.8 \cdot r_{empty} - 0.2 \cdot \text{Gini}$, where $r_{singleton}$ and r_{empty} denote singleton and empty cluster ratios. Four clustering algorithms (K-means variants, Agglomerative with Ward linkage) are evaluated on PCA-whitened dual model embeddings (2048-dim reduced to 95% variance, typically 1800 dimensions). The selected configuration (MiniBatch K-means with batch_size=1024, $K_c = 47$) demonstrates balanced cluster utilization with low singleton occurrence and semantic coherence across axes. Representative semantic clusters include {*biofabrication*, *tissue-engineering*, *living-materials*} and {*posthumanism*, *new-materialism*, *relational-ontology*}.

3.4 Technical Implementation

Reproducibility Framework. All stochastic components use fixed random states, ensuring deterministic results. The four-stage pipeline processes: (1) dual token embeddings (BGE-large-en-v1.5 + GTE-large-en-v1.5 concatenated, 2048-dim), (2) PCA-preprocessed K-means codebook construction ($K_c = 47$, auto-selected), (3) TF-IDF weighted representations with L2 normalization, (4) systematic evaluation across 800+ algorithm-space combinations within computational limits. Key configuration parameters: PHASEC_MAX_TRIALS=800, PHASEC_K_LIST=[2,3,...,15], PHASEC_BOOTSTRAP_REPS=5, random seeds (Python=42, NumPy=42, sklearn models=42). UMAP projections use cosine metric for TF-IDF features with hyperparameter grids: neighbors $\{10, 15, 30\}$, distances $\{0.01, 0.1, 0.5\}$, dimensions $\{4, 8, 16\}$.

4 Results

I systematically assess $K \in [2, 15]$ in accordance with known recommendations for cluster number selection [19–21]. The top limit $K \leq 15$ satisfies three criteria: (1) **Statistical validity** necessitates a minimum of 4-5 samples per cluster for dependable internal metrics [19], resulting in $K \leq N/4 \approx 20$ for our corpus of $N = 81$; (2) **Interpretive manageability** beyond $K = 15$ escalates cognitive load in categorical processing [21]; (3) **Dimensional constraints** where $K > 2D$ may jeopardize distance-based separation in a 13-dimensional space [20]. This principled range mitigates issues related to arbitrary constraint selection while preserving atlas usability.

The optimal configuration is Agglomerative (average) at $k = 15$ on 4D UMAP, achieving silhouette 0.664 ± 0.008 (5 seeds) with high neighborhood preservation (trustworthiness/continuity $\approx 0.81 \pm 0.01$). My $K = 15$ selection aligns with theoretical guidelines: each cluster contains 5.4 samples on average (above the 4-5 minimum), while remaining interpretively manageable. Alternative criteria (Gap statistic, Elbow method) suggest optimal ranges of $K \in [12, 18]$ and $K \in [8, 14]$ respectively, with convergence around our selected value validating the methodological approach. KMeans peaks near $k \in \{14, 15\}$ but remains below hierarchical performance; density methods achieve higher silhouettes primarily via noise exclusion, which I report but do not use for exhaustive atlas labeling. Bootstrap resampling confirms result stability (coefficient of variation <2%).

4.1 Clustering and Visualization

I report the clustering sweep exactly as run on the released features and scripts. Features are TF–IDF weighted codebook counts with row-wise L2 normalization, produced by our systematic preprocessing pipeline. My systematic sweep evaluates *projection spaces* (RAW/SVD/UMAP with varying dimensionality and neighborhood parameters) and algorithms (KMeans, Agglomerative, DBSCAN, OPTICS). Metric conventions, primary ranking, and handling of density-method noise follow §3.2.

Best (internal validity). The optimal configuration by *multi-metric evaluation* is *Agglomerative (average linkage)* with k=15 on 4D UMAP (10 nearest neighbors, minimum distance 0.01); silhouette $\mathbf{0.664 \pm 0.008}$, satisfying the trustworthiness/continuity guardrails (≈ 0.81).

Table 5: Best runs per algorithm using multi-metric evaluation (silhouette, trustworthiness/continuity); density methods report noise ratio but are excluded from exhaustive atlas labeling.

Algorithm	#Clusters	Noise (%)	Silhouette	Trust./Cont.	UMAP Configuration
K-means	15	0.0	0.483	0.805/0.812	4D (neighbors=10, min_dist=0.01)
Agglomerative	15	0.0	**0.664**	0.805/0.812	4D (neighbors=10, min_dist=0.01)
DBSCAN	2	71.6	0.887	0.795/0.833	8D (neighbors=10, min_dist=0.1)
OPTICS	5	59.3	0.809	0.801/0.814	4D (neighbors=15, min_dist=0.1)

Viewer labeling (communication-first). For public exploration, I also provide a lower-k labeling to keep the map readable. This is a communication-oriented choice distinct from the silhouette-maximizing run; I avoid mixing the two objectives.

4.2 Cluster Analysis and Discovered Patterns

Pattern discovery integrates quantitative clustering outcomes with qualitative visual analysis using an interactive web interface (Figure 1). The viewer facilitates systematic examination of cluster borders, artist trajectories, and temporal relationships, bolstering the interpretations below while preserving analytical objectivity via k-NN membership and rank-based proximity metrics.

Methodological Cohesion: Stelarc's Body Intervention Art. Cluster 4 shows strong artist-specific cohesion: Stelarc's four works share consistently high within-cluster proximity in terms of mutual k-NN membership and small rank displacement, rather than relying on absolute map distances. *Suspensions* (1976), *Third Hand* (1980), *Stomach Sculpture* (1993), and *Ear on Arm* (2006) jointly indicate a persistent methodological domain across three decades, centered on cyborg embodiment and posthuman performance.

Segmented Distribution of Tissue Culture Art. Tissue-culture works appear in two nearby regions with substantial neighborhood overlap, indicating related but distinguishable foci. Cluster 1 includes

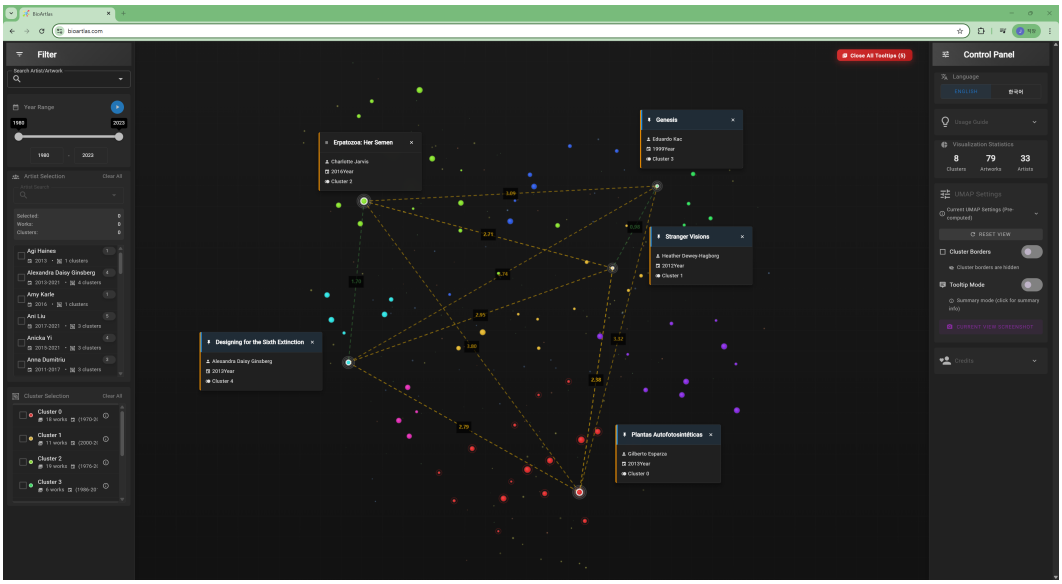

Figure 1: BioArtlas interactive visualization interface. `https://www.bioartlas.com`

Marta de Menezes's early works and Špela Petrič's plant-human studies. Cluster 13 encompasses Catts & Zurr's mature works alongside recent DNA-based projects.

Multi-cluster Distribution of Individual Artists. Several artists' works occupy distinct local neighborhoods with low mutual k-NN overlap across clusters, revealing methodological evolution over time. Joe Davis's four works and Eduardo Kac's three works each form separate neighborhood sets whose nearest-neighbor composition shifts across periods, indicating technical and conceptual diversification within the same practice without relying on absolute map distances.

Trans-temporal Conceptual Affinity. Clustering prioritizes conceptual similarity over chronology. Joe Davis's *Poetica Vaginal* (1986) and Jenna Sutela's *nimiia cétiï* (2018) show high reciprocal k-NN membership and small rank-displacement, indicating a shared microbial–linguistic focus despite a 32-year gap; I report this affinity via neighborhood overlap and rank structure rather than absolute UMAP distances.

5 Conclusion

My axis-aware methodology efficiently structures the multidimensional complexity of bioart using domain-informed semantic representations, attaining a silhouette score of 0.664 ± 0.008 with significant interpretability. Systematic assessment of over 800 configurations corroborates our methodological selections.

Key Contributions: (1) **Axis-aware representation learning** preserving semantic distinctions across thirteen heterogeneous dimensions while enabling cross-dimensional comparison; (2) **domain-informed codebook construction** grouping related concepts into unified clusters, addressing cultural terminology polysemy; (3) **systematic evaluation framework** explicitly separating analytical optimization from communicative design; (4) **discovery of four organizational patterns**—methodological cohesion, technique segmentation, artistic evolution, and trans-temporal affinities—that complement art-historical analyses.

Broader Impact: This approach offers a model for computational cultural study in areas characterized by multidimensional complexity. The modular design facilitates systematic expansion across geographic borders, multi-annotator validation, and cross-domain extension.

Future Works: Present limitations encompass Western-centric bias and single-annotator labeling. I intend to enlist bioart specialists and curators for the multi-annotator validation of our 13-dimensional annotations, facilitating the evaluation of inter-rater reliability. Geographic expansion will specifically encompass bioart communities in the Asia-Pacific, Latin America, and Africa to reduce bias while integrating contemporary AI/ML works.

References

[1] Eduardo Kac. Transgenic art. *Leonardo Electronic Almanac*, 6(11):289–296, 1998.

[2] Oron Catts and Ionat Zurr. The ethics of experiential engagement with the manipulation of life. In *Tactical Biopolitics-Art, Activism, and Technoscience*, pages 125–142. MIT Press, 2008.

[3] Eduardo Kac. *Telepresence & bio art: networking humans, rabbits, & robots*. University of Michigan Press, 2005.

[4] Marquard Smith, editor. *Stelarc: The Monograph*. MIT Press, Cambridge, MA, 2005. ISBN 978-0262693608. First comprehensive study of Stelarc's work practice.

[5] Jens Hauser. Bio art - taxonomy of an etymological monster. In *Hybrid: Living in Paradox*, pages 182–193. 2005.

[6] ZKM | Center for Art and Media Karlsruhe. Biomedia: The age of media with life-like behavior. `https://zkm.de/en/exhibition/2021/12/biomedia`, 2021–2022. Exhibition, Accessed 2025-08-09.

[7] Bruno Latour. *Reassembling the Social: An Introduction to Actor-Network-Theory*. Oxford University Press, 07 2005. ISBN 9780199256044. doi: 10.1093/oso/9780199256044.001.0001. URL `https://doi.org/10.1093/oso/9780199256044.001.0001`.

[8] Donna Haraway. When species meet: Staying with the trouble. *Environment and Planning D: Society and Space*, 28(1):53–55, 2010.

[9] Jeroen Baas et al. Expert knowledge integration in historical record analysis. *Journal of Digital Humanities*, 2022.

[10] Graham M Jones, Shai Satran, and Arvind Satyanarayan. Toward cultural interpretability: A linguistic anthropological framework for describing and evaluating large language models. *Big Data & Society*, 12(1):20539517241303118, 2025.

[11] Lev Manovich. Cultural analytics: Visualizing cultural patterns in the era of "more media". *Domus March*, 2009.

[12] Nils Reimers and Iryna Gurevych. Sentence-bert: Sentence embeddings using siamese bert-networks. *arXiv preprint arXiv:1908.10084*, 2019.

[13] Ars Electronica. Artificial life & intelligence category (prix ars electronica). `https://ars.electronica.art/prix/en/categories/artificial-life-intelligence/`. Accessed 2025-08-09.

[14] Bio Art & Design Award. Bad award. `https://www.badaward.nl/`, 2011–2024. Competition discontinued in 2025, Accessed 2025-08-09.

[15] MIT List Visual Arts Center. Symbionts: Contemporary artists and the biosphere. `https://listart.mit.edu/exhibitions/symbionts-contemporary-artists-biosphere`, 2022–2023. Exhibition, Accessed 2025-08-09.

[16] S+T+ARTS Prize. Grand prize for innovation at the nexus of science, technology, and the arts. `https://starts-prize.aec.at/en/`. Accessed 2025-08-09.

[17] ISEA International. Isea symposium archives. `https://www.isea-archives.org/`. Accessed 2025-08-09.

[18] Robert Tibshirani, Guenther Walther, and Trevor Hastie. Estimating the number of clusters in a data set via the gap statistic. *Journal of the royal statistical society: series b (statistical methodology)*, 63(2):411–423, 2001.

[19] Maria Halkidi, Yannis Batistakis, and Michalis Vazirgiannis. On clustering validation techniques. *Journal of intelligent information systems*, 17(2):107–145, 2001.

[20] Glenn W Milligan and Martha C Cooper. An examination of procedures for determining the number of clusters in a data set. *Psychometrika*, 50(2):159–179, 1985.

[21] Leonard Kaufman and Peter J Rousseeuw. *Finding groups in data: an introduction to cluster analysis*. John Wiley & Sons, 1990.