

Psittacines of Innovation? Assessing the True Novelty of AI Creations

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Abstract

We examine whether Artificial Intelligence (AI) systems generate truly novel ideas rather than merely regurgitating patterns learned during training. Utilizing a novel experimental design, we task an AI with generating project titles for hypothetical crowdfunding campaigns. We compare within AI-generated project titles, measuring repetition and complexity. We compare between the AI-generated titles and actual observed field data using an extension of maximum mean discrepancy—a metric derived from the application of kernel mean embeddings of statistical distributions to high-dimensional machine learning (large language) embedding vectors—yielding a structured analysis of AI output novelty.

Results suggest that (1) the AI generates unique content even under increasing task complexity, and at the limits of its computational capabilities, (2) the generated content has face validity, being consistent with both inputs to other generative AI and in qualitative comparison to field data, and (3) exhibits divergence from field data, mitigating concerns relating to intellectual property rights. We discuss implications for copyright and trademark law.

Keywords: Novelty, Creativity, Artificial Intelligence, Copyright Law, Intellectual Property Protection.

Introduction

"Use of texts to train LLaMA to statistically model language and generate original expression is transformative by nature and quintessential fair use—much like Google's wholesale copying of books to create an internet search tool was found to be fair use in Authors Guild v. Google, Inc., 804 F.3d 202 (2d Cir. 2015)."

—R. Kadrey, S. Silverman, & C. Golden v. Meta Platforms, Inc., No. 3:23-cv-03417-VC.

"Oh, for that? It will mean that 95% of what marketers use agencies, strategists, and creative professionals for today will easily, nearly instantly and at almost no cost be handled by the AI — and the AI will likely be able to test the creative against real or synthetic customer focus groups for predicting results and optimizing. Again, all free, instant, and nearly perfect. Images, videos, campaign ideas? No problem."

—Sam Altman, OpenAI, <https://www.forum3.com/book-artificial-intelligence>.

A wealth of literature advances perspectives on creativity, measuring, *inter alia*, the role of organizational forces (Mumford 2011, Woodman et al. 1993), analytical conditions (Amabile et al. 1988), psychological traits (Simonton 2000), and componential views of creativity (Amabile 2011). Preeminent among these viewpoints is the role of novelty—the extent to which ideas are original and unexpected—as contrasted with being derivative—that is, developed from or influenced by existing concepts, themes, works, or ideas (Boden 2004). Some scholars posit that truly creative acts require novelty, as repeating existing ideas cannot be considered maximally creative, even if those ideas are combined in new ways (Sternberg 1999). Yet, others argue that impactful creative acts balance novelty with utility (Ivcevic 2007).

A central and enduring challenge in machine creativity is assessing the extent to which AI can engage in ‘transformative’ thought—a use or adaptation of existing knowledge in a manner that adds new expression, meaning, or message, significantly altering the original work. A perspective, now typified in the literature through the characterization of generative AI as a ‘stochastic parrot’ (Bender et al. 2021), envisions AI as repeating existing patterns ad-hoc and ad nauseam, with minor changes in word use (psittacines=parrots), but without awareness and understanding—a severely limiting view as it implies the absence of true novelty, and therefore, true creativity. This viewpoint is presented under the umbrella of ‘connectionist’ AI, where neural networks operate via distributed representation, distinct from classical cognitive architectures aligned with symbolic AI (e.g., Fodor and Pylyshyn 1988 and subsequent literature).

Recent results provide contrasting evidence. In a direct measurement of linguistic novelty, McCoy et al. (2023) show that while the local structure of AI’s outputs is substantially less novel than human

baselines, the larger scale structures exhibit as much if not more novelty. Perhaps more directly addressing the theoretical critique, and the argument of a need for systematic compositionality, Lake and Baroni (2023) show that novelty can manifest in connectionist AI (which includes most typical commercial AI today such as the GPT series in text, the Dall-E series in text-to-image, Elevenlabs in text-to-speech, etc.) even in the absence of explicit mechanisms for symbol manipulation, as was previously thought essential for true creativity (Chomsky et al. 2023, Pearl and Mackenzie 2018).

Beyond the realm of scientific enquiry, commercializing AI surfaces legal implications (Franceschelli and Musolesi 2022, Samuelson 2023, Zhong et al. 2023). AI's use of prior art¹—the extent to which it is transformative vs. derivative—is central to the puzzle. If AI's outputs are too similar in purpose, structure, and form to originals, then that might imply both that a source may lay claim to the outputs and that the development of AI technology may require licensing—findings that would substantially alter the economics of AI development.

Moreover, a recent report by the Congressional Research Service on ‘Generative Artificial Intelligence and Copyright Law’² identifies several issues at the crux, including “the nature of human involvement in the creative process,” such as whether a human contributes a noncopyrightable ‘idea’ or a copyrightable ‘work’. In general, the perspectives factor an intrinsic lack of purpose in an AI’s outputs—it takes the view that the AI’s outputs are akin to calculated randomness—such that a novel idea may be discovered by a human operator, or even prompted by one, but akin to a human taking a photograph of nature, purpose is only endowed by the human’s interpretations and not fundamentally by the algorithm. Consequently, there is doubt and debate about whether the development of AI should be rewarded by qualifying its products for intellectual property protection³; as of date, ‘stochastic parrots’ do not qualify for intellectual property protections (Garon 2023, Lemley 2023), and novelty is solely perceived as accruing from a human operator.

In business, these issues crystallize as concerns relating to the extent to which ideas obtained from AI are actionable and commercializable. Some evidence suggests that AI may have better product ideation capabilities than humans (Girotra et al. 2023). Consequently, it has become typical for businesses to seek product name suggestions, descriptions, and other communications from AI (Harreis et al. 2023, Palmer 2023). These practices have become so prevalent that AI is forecasted to cause significant technological

¹Evidence that proves an invention is already known or existed, encompassing all publicly available information that could be relevant to claims of originality and inventiveness.

²Accessed at: <https://crsreports.congress.gov/product/pdf/LSB/LSB10922>

³37 CFR Part 202, Copyright Registration Guidance: Works Containing Material Generated by Artificial Intelligence, accessed at: <https://public-inspection.federalregister.gov/2023-05321.pdf>

displacement.

For instance, in marketing, a domain highlighted to be at significant risk of displacement, recent research by Felten et al. (2023) found telemarketers ranked first in a list of occupations threatened by exposure to AI. Other notable entries included management analysts (27), market research analysts and marketing specialists (75), and marketing managers (130). In occupations threatened by image-generative AI, advertising and promotions managers ranked 36th, and marketing managers ranked 37th.

However, while the evidence indicates that AI can generate useful ideas, the question remains: does it generate novel ideas? Some findings suggest that as much as 60% of AI's outputs may contain plagiarized content (Copyleaks 2024). Therefore, understanding the opportunities and threats posed by AI fundamentally requires deciphering its capability for novelty.

Measuring novelty, however, requires the development of novel methodology. Akin to how a monkey hitting random keys on a typewriter for an infinite amount of time will almost surely (meaning with near certainty) produce a specific text, such as the complete works of William Shakespeare, a generative AI (accounting for language and modality) will almost surely produce any text, whether it be human or AI-generated. Thus, a brute-force comparison between two large-scale collections of texts, whether human or AI-generated, will always yield some similar phrases and ideas.

Instead, our program of inference relates to: are the human and AI data-generating processes distinct such that any observed similarities relate to chance rather than regurgitation? That is, given an idea in the dataset of human ideas, is it more likely that a proverbial hitting of keys (i.e., an unfolding of the stochastic process) would lead to the generation of the same idea by humans, or by AI? If the AI is regurgitative, then these likelihoods should be equal as the AI would emulate humans. If the AI is truly innovative, on the other hand, then the stochastic process describing its outputs will be distinct from the process describing the observed field data.

Addressing this issue, building on recent advances in functional kernel methods in mathematics and machine learning, we apply methods (Gretton et al. 2012) based on kernel mean embeddings (henceforth KME, Muandet et al. 2017) to non-numerical set data through the use of high-dimensional machine learning embeddings. This analytical framework not only facilitates the measurement of similarities in project titles within our specific application but also has broader implications.

In particular, it enables comparing samples from stochastic processes without necessitating that the samples be ‘comprehensive’, encompassing all data generated by the stochastic processes. For instance, as

demonstrated in Web Appendix C, our simulations reveal that as few as 10 samples from two distributions suffice to detect dissimilarity in generating processes. This stands in contrast to typical pairwise distance measures, such as cosine distance, which can compare two verbal documents but fall short in comparing two processes that generated collections of verbal documents.

We organize our paper as follows: We begin by introducing our proposed methodology. We then provide evidence on the efficacy of AI in product innovation, focusing specifically on the extent to which AI can serve as a tool for developing novel brand names or product names to enhance communications. We task an AI with generating novel project titles for crowdfunding campaigns, which serves as the application domain for our study. We analyze the AI-generated titles to assess repetition and complexity and then compare these titles to observed field data. To facilitate this comparison, we introduce a novel methodology—namely, maximum mean discrepancy (MMD) from the domain of KME. We explain the theory behind this method and demonstrate its application to our problem. The final section discusses our results, establishes our contributions, and concludes.

Methodology

Our analysis unfolds in four steps. Initially, we generate fresh AI outputs for comparison with prior art. We situate our study in online communications, where AI has already begun to play a pivotal role (Huh et al. 2023), and where novelty is of inherent concern. Specifically, we focus on a domain where AI outputs can be quantitatively compared against representative samples of prior art—namely, crowdfunding. As noted earlier, our method is intrinsically designed for data samples as neither the prior art data nor the generative AI’s outputs can be conclusively captured in the modern, interconnected world—both processes can and do continually generate information.

We task an AI with generating new project titles for crowdfunding campaigns, operating in independent passes, each pass yielding 20 novel project titles, conditional on previously generated titles. This process demonstrates the AI’s capabilities in novel ideation, showcasing its potential for creativity, which we then compare to a real-world distribution of observed communications. The second step involves collecting detailed data on accessible projects on Kickstarter, a prominent crowdfunding portal.

The third and fourth steps are methodological in nature and utilize the data collected in the first and second steps. In the third step, we provide the two datasets—one generated by AI and one collected—to an

advanced language model to map them from non-numerical (textual) data to numerical data. This process involves applying the concept of machine learning embeddings, such that each project title is expressed in a vector space where distance corresponds to semantic similarity. We apply textual embeddings in our project. However, the literature has seen the emergence of machine learning embeddings for other modes of data, including multi-modal embeddings, which are now accessible both through open-source models as deployed using libraries such as HuggingFace and through publicly accessible APIs. These factors make our methodology much more universal than our specific application.

The fourth step develops and applies a methodology to determine if the *sample* of observed project titles is systematically and predictably distinct in *distribution* from the *sample* of project titles generated by the AI. The emphasis on distributional distance, as opposed to measuring the distance between the samples from the distributions, is pivotal. Both datasets—the data describing the generative process and the field data describing the ecological distribution—are representative but not exhaustive in the following sense: Given time, any data-generating process will ‘repeat’ itself—the same ideas will be generated by a process. Therefore, if we were to employ conventional metrics such as cosine distance to compare the samples pairwise, it is highly likely that we would both obtain some examples of similarity and examples of dissimilarity in the outputs within each process (i.e., both humans and AI will repeat themselves) and across processes. The aim of the fourth step is to characterize the likelihood of similarity on a continuous scale (i.e., as a continuous distance) such that for the given samples we can assert the extent of systemic similarity—the likelihood that the stochastic processes will yield the same outputs, and thus of the AI being regurgitative.

Our extension facilitates such a comparison, enabling the examination of our focal proposition: Are project titles generated by the AI truly distinct, being systematically and predictably different from observed and existing project titles? We report comparisons across two dimensions. First, we examine the category of observed project titles to assess the extent to which the generated titles align with specific categories. Second, we consider whether the sequence in which the titles were generated by the AI influences their distinctiveness from real-world examples, investigating if the AI’s creativity is affected by the computational demands of generating novel titles compared to previously generated titles. Reporting on project title novelty across these dimensions constitutes the primary empirical contributions of our paper.

AI-Generated Data

We evaluated OpenAI's latest language model, GPT-4-Turbo, through a series of experimental runs. In each run, we created a new instance of the model with default settings. We fed the instance a list of previously generated project titles and crafted a prompt to elicit 20 unique product ideas and project titles, keeping only the novel titles. This process continued until we amassed 6,000 titles, at which point the AI's context window (128,000 tokens) neared exhaustion, marking the end of our data collection.

You have been presented with a comma-separated list of Kickstarter project titles. Your task is to generate twenty (20) more new Kickstarter project titles that are different from the list presented to you. Ensure each generated title is distinct from the prior project titles to the best of your abilities. To aid in data processing, format the list of fresh project titles as a comma-separated list. Only output the comma-separated list of novel project titles to ensure your output can be processed automatically.

The generated project titles pass initial scrutiny as they resemble typical crowdfunding titles, thereby passing the ‘sniff test’. For completeness, we provide the first 30 generated titles as exemplars in Web Appendix A, to allow readers to draw their own conclusions.

Figure 1 unveils several key themes. ‘Crafting,’ ‘game,’ and ‘adventure’ dominate the visual, suggesting a vibrant landscape of entertainment, interactive, and immersive experiences. The frequent appearance of ‘virtual,’ ‘celestial,’ and ‘digital’ underscores a strong inclination towards escapism and the exploration of fantastical or virtual realms. Words like ‘ethereal,’ ‘cosmic,’ and ‘mystic’ further indicate an interest in otherworldly experiences, painting a landscape of imagination that invites exploration beyond the mundane. A clear thematic focus on storytelling and the narrative journey is evident through ‘chronicles,’ ‘journey,’ ‘tales,’ and ‘odyssey,’ hinting at engagement with epic, narrative-driven content. This narrative richness is enhanced by terms like ‘fantasy,’ ‘magic,’ and ‘mythical,’ which highlight an enchantment with the supernatural and fantastical, inviting readers or players into worlds limited only by the imagination. ‘Nature,’ ‘space,’ ‘stars,’ and ‘universe’ suggest an engagement with nature and space, pointing towards a broader interest in exploring environmental themes, cosmic adventures, or perhaps a blend of both. Overall, the word cloud illustrates the AI’s significant potential to generate ideas across diverse thematic areas, highlighting the breadth of the AI’s creative outputs.

We designed our experiment to explore the limits of computational creativity. This was partly inspired

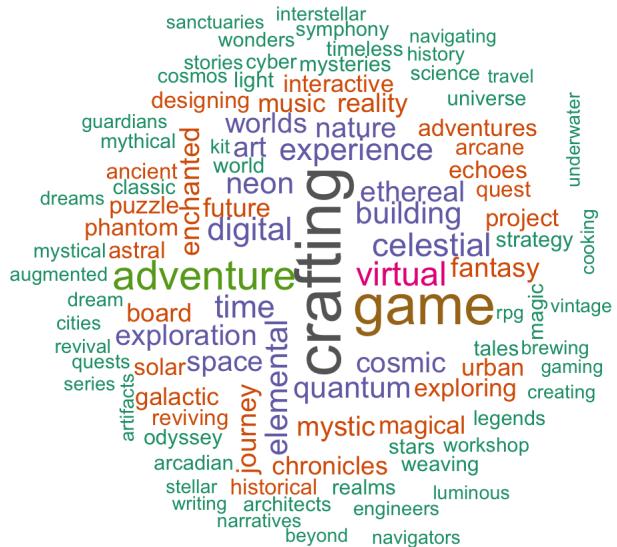


Figure 1: Word Cloud of AI-Generated Project Titles

Note: Word cloud derived from AI-generated crowdfunding project titles after excluding common stopwords and terms that do not contribute to thematic analysis.

by a desire to determine whether the AI would rely on a consistent bank of project ideas, making minor adjustments to ensure distinctiveness across titles, or whether it would explore truly novel and more esoteric concepts when pushed to generate even more distinct titles. To distinguish between these possibilities, Figure 2 plots the entropy⁴ of AI-generated project titles as a function of the order in which they were generated. The x-axis represents the order of generation, while the y-axis depicts the entropy of each title. The plot presents a smoothed fit (using generalized additive models with integrated smoothness estimation) along with associated 95% confidence intervals.

The analysis reveals an upward trend in entropy from the 1st to about the 4000th project title, with a leveling off thereafter. This upward trajectory indicates that as the AI progressed through the task, its first 4000 project titles mainly featured increasingly uncommon ideas, as reflected in vocabulary use and language. The AI was not merely rearranging a few words but presenting drastically different ideas (e.g., “Dreams of the Sky: A Hot Air Balloon Adventure”, “Nebula Echoes: A Sci-fi Graphic Novel”, and “Harmony’s Light: A Handcrafted Lantern Festival”; see Web Appendix A for more examples). Initially, its ideas were likely more mainstream, corresponding to common words, but as it was pushed for more novelty, it ventured into more complex territory. For instance, the 4000th project title, “Time Weaver’s Treasury: An Historical Artifact Game”, may be too unconventional for commercial success but became essential as the task progressed, given the challenge of generating an idea distinct from all prior ideas.

This increase in entropy tapered off when it reached a sustained peak, indicating that the AI’s vocabulary was sufficiently expansive to accommodate the complexity of the task set before it. However, even its last creation (the 6000th project title), “Galactic Gourmands: Culinary Adventures in Space”, seemed plausible. For instance, “Gourmand Go: A Cannibal Space Opera Graphic Novel” is a real Kickstarter project from Melbourne, Australia, that was successfully funded and is in the process of being printed, as of February 28, 2024. Figure 3 presents examples of AI-generated project art using GPT’s text-to-image sister AI, Dall-E 3, for both project titles. The results demonstrate that the generated project titles were within the realm of ideas familiar to the AI, as illustrated in the art the AI was able to create, providing further evidence of the real-world applicability of the AI’s outputs even under extreme circumstances.

We observed that the titles generated by the AI predominantly consisted of a product brand name or

⁴Information entropy measures the level of surprise or uniqueness in a sample from a stochastic process, corresponding to the average ‘uncertainty’ (expressed as the logarithm of the probability of occurrence) of each element in the sequence. We calculate the entropy of each project title using the empirical probability of each word (i.e., the frequency with which a word occurred divided by the total number of words in the dataset).

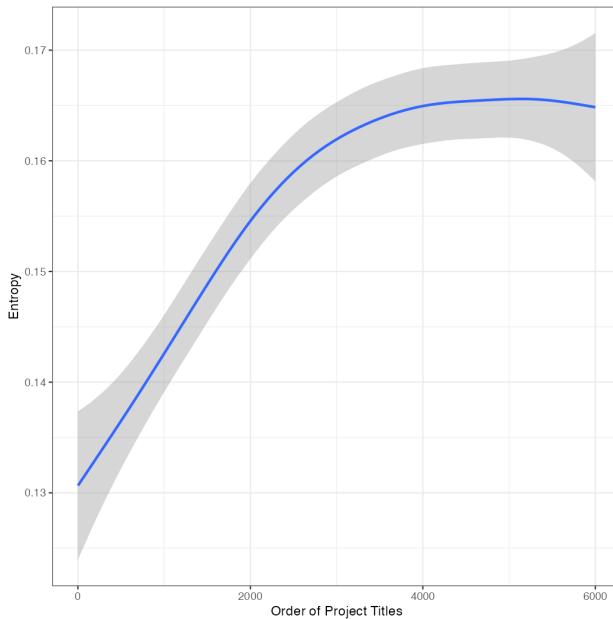


Figure 2: Entropy of AI-Fabricated Project Titles

Note: Entropy is derived from the AI-generated project titles after excluding common stopwords and terms that do not contribute to thematic analysis. The y-axis plots the entropy, and the x-axis depicts the order in which the data was generated.



(a) AI-Generated: Galactic Gourmands



(b) Real-World: Gourmand Go

Figure 3: Comparison of AI-Generated Project Art for AI-generated and Real-world Project Titles

Note: Visuals created by Dall-E, as accessed through ChatGPT, based on the project titles "Galactic Gourmands: Culinary Adventures in Space" and "Gourmand Go: A Cannibal Space Opera Graphic Novel".

tagline, such as ‘Galactic Gourmands’, followed by a descriptive phrase like ‘Culinary Adventures in Space’. This format was not predefined in our instructions; instead, it emerged organically and was observed in 5991 out of the 6000 titles generated.

These 5991 titles enable us to explore a relatively uncharted risk of intellectual property contamination stemming from AI-generated assets. Specifically, if multiple firms utilize AI to generate brand names, there’s a potential for these firms to inadvertently create very similar names, without direct copying.

We discovered that 2,451 brand names were unique, 432 were repeated once, 168 twice, 77 three times, and the remaining 194 names were repeated four or more times. Notably, the name ‘Quantum Quests’ appeared as many as 56 times. However, in instances where brand names were repeated, the AI varied the descriptions (for example, ‘Quantum Quests: A Science Adventure Board Game’, ‘Quantum Quests: Beyond the Microscopic’, and ‘Quantum Quests: Navigating the Nanoworld’).

To quantify the distinctiveness of the brand names, we calculated the Levenshtein distance—the minimum number of single-character edits, insertions, deletions, or substitutions required to change one brand name into another—across all 5,516,181 pairs of the 3,322 unique brand names.

Remarkably, the 3,322 unique brand names were indeed distinct. On average, the unique brand names differed by 15.23 characters (with a median of 15 characters and a standard deviation of 2.87 characters). The differences fell within the first quartile at 13 characters and the third quartile at 17 characters. Notably, in only 166 instances (0.003% of the data) was the difference a single character, and in just 338 instances (0.006% of the data), the difference was two characters.

This suggests that while a specific sample of the AI’s outputs may include content that the AI favors (such as the name ‘Quantum Quests’), which it generates often (‘Quantum Quests’ was generated in 56 of about 5,991 instances, or about 1% of the time), in the majority of cases, the AI’s output is likely to be unique or nearly unique across instances and passes. Thus, if an AI’s outputs are used in scenarios involving trademarks, it would be improbable (though not impossible) for another AI instance to generate the same output and for this output to be used by a competitor.

Field Data

We obtained a comprehensive list of Kickstarter projects accessible online as of February 15, 2024. The dataset includes 25,583 projects, spread across 39 categories. The largest number of projects is in Fiction (2,316), with significant numbers of projects in Comedy (2,280), Software (2,244), and Pop Culture (2,100).

The data is rich and diverse, with the following themes captured by the analogous process of forming word clouds, as conducted with the AI-generated project titles, depicted in Figure 4.

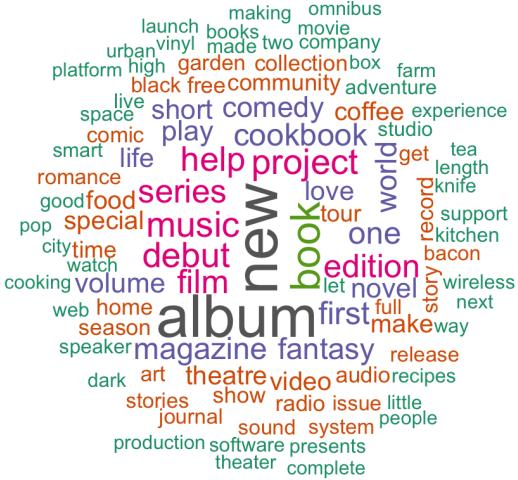


Figure 4: Word Clouds of Observed Project Titles

Note: The word cloud is derived from observed project titles after excluding common stopwords and terms that do not contribute to thematic analysis.

A key distinction between the generated titles and the observed titles lies in the emphasis placed on the word ‘new.’ The observed product titles explicitly claim novelty, whereas the generated project titles implicitly suggest novelty through a selection of unique ideas and words. Aligned with this distinction, the observed titles often relate to a call for help, as is typical in crowdfunding, while the AI-generated titles focus on a product or a description of project activities; the AI perhaps presumes that such calls would be included in the project title and text anyways.

Furthermore, the observed titles relate more closely to music and books, with ‘album,’ ‘book,’ and ‘music’ being the next most frequent words. In contrast, ‘music’ ranks as the 26th most frequent word in the generated titles, and ‘album’ and ‘book’ do not appear in the top 100 most frequent words. In addition to this difference in focus, the data reveals that the observed project titles very commonly express what the project is about (additional examples include ‘magazine,’ ‘play,’ and ‘novel’), whereas the generated titles are more abstract and broadly applicable. Finally, unlike the fantastical themes that are typical and common in

the generated titles—and even though such themes do find resonance in some observed titles—the observed titles are more concrete (e.g., ‘cookbook,’ ‘food,’ and ‘home’).

Comparison of AI-Generated and Field Data

Our prior findings suggest commonalities while also reflecting the complexities of assessing the extent of similarity in large-scale non-numerical (textual) data. For instance, our findings from the use of the Levenshtein distance are intriguing as they reflect a character-wise divergence in generated names. However, they do not account for key semantic properties, such as meaning, where word pairs such as ‘new’ and ‘novel’, ‘parrot’ and ‘psittacine’ may show dissimilarity in character-wise distance while being similar or related in semantic meaning.

Web Appendix B provides a detailed description of a novel methodology for assessing the similarity of AI-generated and observed project titles. Web Appendix C presents simulation results describing the performance of the methodology.

Briefly, we rely on the emergent literature in machine learning on functional embeddings, which are mappings from sets of objects (such as words or project titles) to a topological space of functions such that key object properties (e.g., semantic meaning) are preserved in notions of distance and angle. The literature has taken two paths. One strand defines more abstract and mathematical notions of embeddings (e.g., [Sriperumbudur et al. 2010](#)). Here, the emphasis is on establishing formal properties that may be useful in downstream analyses. Another strand seeks to discover embedding algorithms (e.g., Word2Vec, [Mikolov et al. 2013](#)). Here, the emphasis is on algorithm development and establishing the empirical properties of constructed embeddings.

Our approach derives from both. On the one hand, we employ a machine learning embedding algorithm to represent non-numerical data (project titles in our study; content more broadly) in an intermediate vector space. To best match the outputs of the AI, we advocate the use of an embedding algorithm that corresponds to the AI in question, as exposed through calls to its encoder. Thus, for GPT-4-Turbo, we employ ‘text-embedding-3-large’ in our study. Next, we use these representations to form a KME of the distribution of the non-numerical content (project titles). Here, we employ a Reproducing Kernel Hilbert Space (RKHS) of functions to embed the distribution, enabling the specification of an Integral Probability Metric (IPM) in the RKHS. Specifically, an IPM between two probability distributions P and Q over a space

X is given by:

$$IPM(P, Q) = \sup_{f \in \mathcal{F}} \left| \int_X f(x) dP(x) - \int_X f(x) dQ(x) \right|$$

Here, \mathcal{F} is a class of real-valued bounded functions defined on the space X . The integral expressions $\int_X f(x) dP(x)$ and $\int_X f(x) dQ(x)$ represent the expectation of the function f under the distributions P and Q , respectively. The supremum (sup) over the class of functions \mathcal{F} ensures that the IPM captures the largest possible difference in expectations over all functions in \mathcal{F} , thereby providing a measure of the distance or divergence between the two distributions based on the specified function class. For the metric we employ, \mathcal{F} is chosen as the class of functions from the RKHS. The metric then measures the distance between the mean embeddings of the two distributions in the RKHS.

Intuitively, the metric compares the similarity metric $IPM(P, Q)$ observed for two given sets of samples to the similarity metric that might have been observed if the samples were from the same distribution. The latter forms a bootstrap distribution of the statistic to which an estimate is compared to determine if a given set of samples are similar or different in distribution.

Results

We began by examining the degree to which the AI-generated titles align with field data across various categories. Table 1 presents the MMD statistic for each category within the Kickstarter dataset individually, as well as for the dataset as a whole. It then compares these estimates to their respective 99% confidence intervals. In the table, categories are listed in rows, while the estimated MMD statistic and its confidence interval bounds are detailed in the columns. A lower bound of ‘> -0.01’ and an upper bound of ‘< 0.01’ imply that the computed values were much less in absolute value than 0.01; we report -0.01 and 0.01 as lower and upper bound estimates to simply reporting.

Our findings indicated that the distribution of AI-generated data is significantly distinct from that of the data in each individual category, as well as from the dataset as a whole. In every instance, the MMD statistic significantly exceeds the 99% confidence interval, underscoring the distinctiveness of the AI-generated titles.

Additionally, we observed notable differences across categories. Figure 5 illustrates these category-specific effects, arranged in ascending order of their MMD estimates. This arrangement places categories

	Categories	Estimate	Lower	Upper
1	Audio	0.25	> -0.01	< 0.01
2	Comedy	0.23	> -0.01	< 0.01
3	Community Gardens	0.29	> -0.01	< 0.01
4	Cookbooks	0.32	> -0.01	< 0.01
5	Drinks	0.27	> -0.01	< 0.01
6	Fiction	0.16	> -0.01	< 0.01
7	Food	0.26	> -0.01	< 0.01
8	Journalism	0.18	> -0.01	< 0.01
9	Literary Journals	0.19	> -0.01	< 0.01
10	Literary Spaces	0.17	> -0.01	< 0.01
11	Other	0.20	> -0.01	< 0.01
12	Photo	0.18	> -0.01	< 0.01
13	Plays	0.22	> -0.01	< 0.01
14	Pop	0.29	> -0.01	< 0.01
15	Print	0.19	> -0.01	< 0.01
16	Product Design	0.21	> -0.01	< 0.01
17	Punk	0.28	> -0.01	< 0.01
18	R&B	0.27	> -0.01	< 0.01
19	Restaurants	0.29	> -0.01	< 0.01
20	Small Batch	0.30	> -0.01	< 0.01
21	Software	0.20	> -0.01	< 0.01
22	Sound	0.27	> -0.01	< 0.01
23	Spaces	0.22	> -0.01	< 0.01
24	Toys	0.27	> -0.01	< 0.01
25	Web	0.19	> -0.01	< 0.01
26	Webcomics	0.18	> -0.01	< 0.01
Overall		0.15	> -0.01	< 0.01

Table 1: Category-Specific MMD Statistic

Note: Estimate is the MMD statistic comparing the category-specific and overall observed field data to the AI-generated data. The category-specific measures were computed for all categories with at least 250 observations; categories with fewer observations were merged and termed ‘Other’. Lower and upper are the lower and upper bounds of the 99

with the smallest effect sizes—indicating greater similarity to the AI-generated data—on the bottom. Conversely, categories with the largest effect sizes—denoting lesser similarity to the AI-generated data—appear on the top.

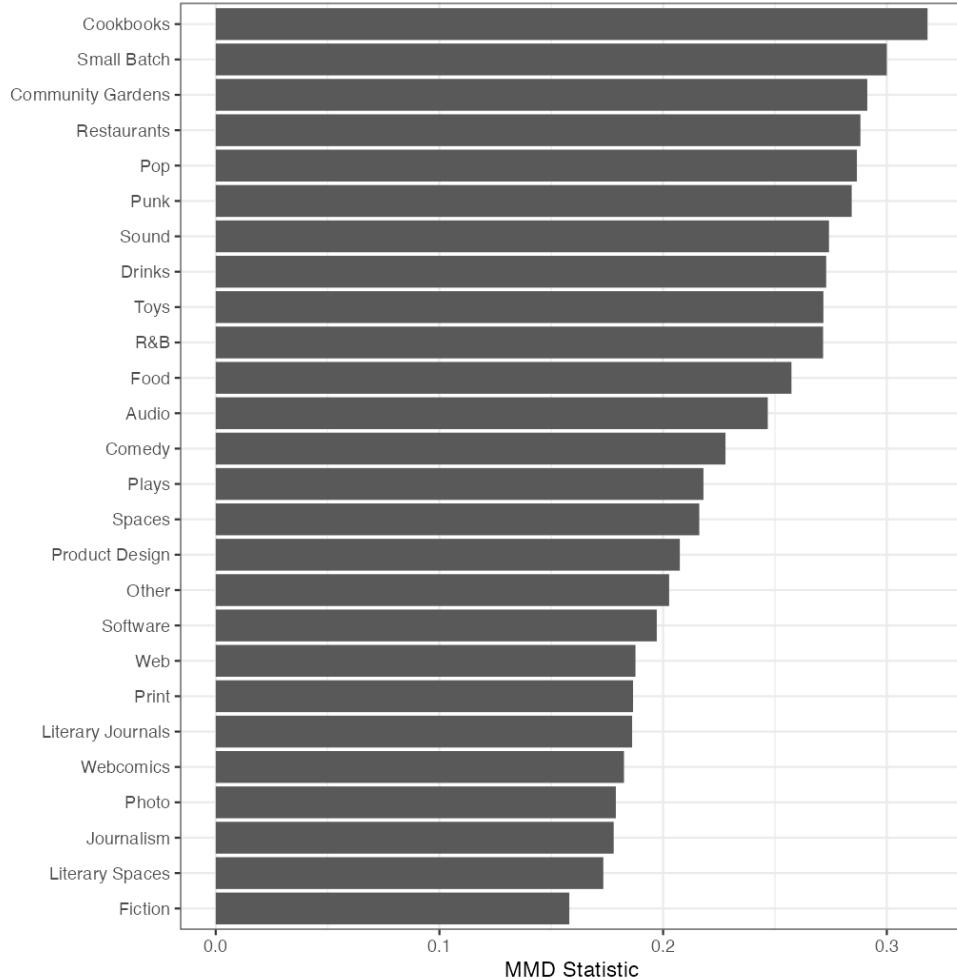


Figure 5: Waterfall Plot of Category-Specific Effects

Note: The category-specific effects are estimates of the MMD statistic when applied to category specific field data and the AI-generated data.

The figure demonstrates that the categories most akin to the AI-generated data include Fiction, Journalism, Literary Journals, Literary Spaces, Photo, Print, Web, and Webcomics. This suggests that the AI-generated titles closely align with media and written arts in terms of their thematic focus. Conversely, the categories that diverged most significantly from the AI-generated data encompass Audio, Community Gardens, Cookbooks, Food, Pop, Punk, R&B, Restaurants, Small Batch, and Toys. These categories typically involve music, food, gardening, or toys—themes prevalent in crowdfunding but less represented in the

AI-generated titles. Furthermore, the fantastical themes prevalent in the AI-generated data seem to resonate more with fiction, while categories like gardening are more grounded in practicality and realistic imagery, a distinction clearly highlighted by the MMD metric.

These observations are particularly noteworthy given that the AI was not directed to prioritize any specific categories. The AI’s focus appears to be inherently shaped by its training. This could be attributed to the abundance of written material in these domains, providing a rich dataset for a language model AI to learn from. On the other hand, categories like music and food, which may depend more on visual stimuli, might not have been as heavily emphasized during the AI’s training.

Next, we investigated how the timing of AI data generation affects our results, as presented in Table 2. The analysis divides the data into 12 sequential windows, each containing 500 titles. The table lists these windows in rows and provides the estimated MMD statistic for each, along with its lower and upper confidence bounds.

	Estimate	Lower	Upper
1-500	0.12	> -0.01	< 0.01
501-1000	0.13	> -0.01	< 0.01
1001-1500	0.13	> -0.01	< 0.01
1501-2000	0.15	> -0.01	< 0.01
2001-2500	0.15	> -0.01	< 0.01
2501-3000	0.16	> -0.01	< 0.01
3001-3500	0.16	> -0.01	< 0.01
3501-4000	0.16	> -0.01	< 0.01
4001-4500	0.16	> -0.01	< 0.01
4501-5000	0.17	> -0.01	< 0.01
5001-5500	0.17	> -0.01	< 0.01
5501-6000	0.17	> -0.01	< 0.01

Table 2: Window-Specific MMD Statistic

Note: Estimate is the MMD statistic comparing the window-specific AI generated data to the observed field data. The window-specific measures are computed for 12 non-overlapping windows of 500 project titles each. Lower and upper are the lower and upper bounds of the 99

We found that the initial data generated by the AI closely resembled the observed field data. However, as the AI was tasked with creating increasingly distinct project titles—specifically, titles that diverged from all previously generated titles—the divergence from the field data became more pronounced, as evidenced by the rising MMD statistic. This observation aligns with our findings presented in Figure 2, which show that as the AI was pushed to generate a greater number of project titles, the entropy of the generated titles

increased. This suggests that the AI employed more infrequently used words to present more esoteric ideas. As a result, the initial titles were more similar to the field data.

Contributions and Conclusion

In this paper, we make several important contributions to the literature (Ding 2020, Ma and Sun 2020). First, we address a significant gap in our understanding of AI's capacity for novelty and creativity. While prior research has examined AI's potential for automating various tasks (Davenport et al. 2020, Huang and Rust 2021), there has been limited empirical investigation into AI's ability to generate truly novel and unique content. By focusing on crowdfunding and using a state-of-the-art language model, we provide compelling evidence that AI can indeed generate ideas that are distinct from human-generated examples and from each other, thereby challenging notions of AI as merely a 'stochastic parrot.' This finding not only demonstrates AI's potential in enhancing and complementing human innovation, it underscores its transformative potential in reshaping information systems—offering novel solutions in the way information is generated, processed, and utilized.

Second, we introduce a novel methodological approach to compare the distributions of unstructured textual data. This approach employs KMEs, which have primarily been used for structured data in natural language data. The proposed method enables researchers to quantitatively assess the similarity between samples drawn from different text distributions, such as AI-generated and human-written content. This methodological innovation has broad potential applications where unstructured data is prevalent.

Third, we contribute to ongoing debates in the literature on the nature of creativity and the role of AI in creative industries. Our results suggest that AI's capacity for novelty increases as it is pushed to generate more content, but also that there may be limits to this capacity. The AI-generated titles were found to align more closely with certain real-world categories (e.g., media and written arts) than others (e.g., music and food), indicating that AI's creative output may be influenced by biases in its training data. These nuances highlight the need for further research on the factors that shape AI's creative capabilities and how they might interact with human creativity.

For managers considering the use of AI, our findings present both opportunities and challenges. On the one hand, they suggest that AI could be a powerful tool for ideation and creative problem-solving, potentially streamlining the creative process and leading to more innovative campaigns. On the other hand,

the question of legal responsibility for AI-generated content remains a gray area. Even as AI demonstrates a significant capacity for novelty, if an AI-generated idea is found to infringe on existing copyrights or trademarks, it is unclear where the liability would fall.

At a societal level, our findings contribute to the ongoing debate about the role and status of AI-generated content. As AI's creative capabilities continue to advance, issues of intellectual property rights, attribution, and accountability are becoming increasingly pressing. If AI-generated ideas are truly novel, it raises questions about whether and how they should be protected under intellectual property laws. There may be a need to develop new legal frameworks that acknowledge the unique nature of AI creativity and provide appropriate protections and attributions. This is a complex issue that requires further discussion and collaboration among policymakers, legal experts, and industry stakeholders.

Web Appendix A: Examples of Generated Project Titles

The main manuscript explores the capacity of artificial intelligence (AI) to generate novel marketing communications, with a specific focus on crowdfunding project titles. This Web Appendix supplements analysis by providing 30 examples of AI-generated project titles. These titles were produced by GPT-4-Turbo, a state-of-the-art language model, as part of an experimental setup designed to gauge the AI's creativity.

No.	Project Titles
1	Dreams of the Sky: A Hot Air Balloon Adventure
2	Nebula Echoes: A Sci-fi Graphic Novel
3	Harmony's Light: A Handcrafted Lantern Festival
4	Pixel Kingdom: The Ultimate Retro Video Game
5	Whispering Shadows: An Urban Fantasy Thriller
6	Waves of Sound: The Next Generation Music App
7	Guardians of the Green: An Eco-Friendly Board Game
8	Magical Kingdoms: An Augmented Reality Puzzle Adventure
9	Rustic Brews: A Craft Beer Making Kit
10	Starlight Voyages: An Interactive Space Opera
11	Origins of Olympus: A Mythological Strategy Game
12	Echoes of the Past: A Historical Documentary Series
13	Creatures of the Deep: An Underwater Exploration Game
14	Vintage Vibes: A Classic Car Restoration Project
15	Pathways of the Mind: A Psychological Thriller Novel
16	Silver Screen Dreams: An Independent Film Project
17	Spectrum: An Art Installation Celebrating Diversity
18	Tales from the Cryptid: A Monster Hunting Adventure
19	Infinite Imagination: A Children's Storybook App
20	Chronicles of the Cursed: A Dark Fantasy Comic Series
21	Mystical Forest: An Enchanted Board Game
22	Northern Lights: A Photographic Journey
23	Forgotten Realms: An Archaeological Adventure
24	Pioneers of the Lost World: A Survival Video Game
25	Electric Dreams: Building the Future of Energy
26	Echoes in the Void: A Space Exploration Graphic Novel
27	Ancient Whispers: A Virtual Reality Mystery
28	Thunderstrike: A Superhero Role-Playing Game
29	Artisan's Alley: A Craftsmanship Documentary
30	Dragon's Breath: A Fantasy Battle Arena Game

Table 3: Examples of AI-Generated Project Titles

Note: The first 30 project titles generated by GPT-4-Turbo.

Web Appendix B: Comparing AI-Generated and Field Data

Our methodology leverages the emerging literature in machine learning on embeddings. An embedding is a mapping from a set of objects (such as words or project titles) to a mathematical space (most typically a vector space) such that object properties (e.g., semantic meaning) are preserved in notions of distance and angle. The literature has taken two paths in its discussion of embeddings. One strand of literature defines more mathematical notions of embeddings (e.g., [Sriperumbudur et al. 2010](#)). Here, the emphasis is on establishing formal properties that may be useful in downstream analyses based on embeddings. Another strand of literature seeks to discover and use machine learning embedding algorithms (e.g., [Mikolov et al. 2013](#)). Here, the emphasis is on the development of algorithms and establishing the empirical properties of the embeddings they construct.

We employ existing approaches in the following ways. Leveraging advances in machine learning embedding algorithms, we map project titles (more broadly, marketing content) to an intermediate space such that location and distance correspond to semantic meaning. To best match the outputs of the AI, we advocate the use of the embedding algorithm that corresponds to the AI, as exposed through calls to its encoder. Thus, for GPT-4-Turbo, we employ ‘text-embedding-3-large’.

We relate this embedding to a Kernel Mean Embedding (KME) of the distribution of project titles. Here, we employ the concept of a Reproducing Kernel Hilbert Space (RKHS) of functions. Below, we provide a discussion tailored to our use case; additional details can be found within the referenced books and articles, with an exhaustive presentation in Berlinet and Thomas-Agnan ([2011](#)). We also refer the interested reader to Muandet et al. ([2017](#)) who provide an accessible and thorough discussion of KME.

RKHS and KME. Pertinent to its use for comparing distributions, the defining characteristic of an RKHS is its structure as a Hilbert space—a concept from functional analysis that generalizes Euclidean space—comprising functions with certain properties. Specifically:

1. **Functions as Elements:** The elements of an RKHS are functions that map elements from an input domain to the real numbers (\mathbb{R}). The RKHS is a collection of such functions that share the space’s defining properties. While the input domain may be a subset of \mathbb{R}^n , for data of the form that we investigate, an RKHS is likely to be most useful when the input domain comprises non-numerical elements; if the AI’s outputs are strictly numerical, a well-established literature in marketing and

econometrics provides means for density estimation and testing.

2. Hilbert Space Structure: A Hilbert space is a complete vector space equipped with an inner product.

This structure allows for the definition of geometric concepts such as angles and lengths (norms) in the space. An RKHS is a particular type of Hilbert space where the vectors are functions, and thus, it inherits all the properties of a Hilbert space, including completeness, which ensures that limits of sequences of functions in the space also belong to the space.

3. Reproducing Property: What distinguishes an RKHS from other function spaces is the reproducing property. For every function f in the RKHS and every point x in the domain, the value of the function at that point, $f(x)$, can be reproduced by the inner product of f with a kernel function $k(\cdot, x)$ associated with the space: $f(x) = \langle f, k(\cdot, x) \rangle$. This kernel function $k(x, y)$ is a bivariate function whose arguments are points in the domain, and it essentially provides a way to “probe” the function f at any point x through the inner product.

4. Kernel Functions: The existence of a kernel function k that defines the inner product between functions in the space is fundamental. The kernel function itself captures the geometry and topology of the function space and allows for the implicit representation of high-dimensional or even infinite-dimensional feature spaces, which is a cornerstone of kernel methods in machine learning.

5. Kernel Mean Embedding (KME): KME leverages the machinery of RKHS to embed probability distributions into a Hilbert space. Unlike the RKHS itself, which is inherently a space of functions, a KME represents a probability distribution as a single point (or vector) in the RKHS. Thus, while RKHS deals with functions, KME is about embedding distributions into the space defined by these functions.

Specifically, given a probability distribution P over a domain X , and a reproducing kernel k that induces an RKHS \mathcal{H} , the KME of P into \mathcal{H} is defined as the expected value of the feature maps (associated with k) over P . Mathematically, the embedding μ_P of P is given by:

$$\mu_P = \mathbb{E}_{X \sim P}[k(X, \cdot)] = \int_X k(x, \cdot) dP(x)$$

Here, $k(X, \cdot)$ represents the feature map associated with the kernel k , mapping samples X from the domain to functions in \mathcal{H} . $\int_X k(x, \cdot) dP(x)$ is a Bochner integral.

MMD in Structured Data We form an RKHS through a characteristic Mercer kernel to enable the computation of distances between distributions as the distances between the corresponding KME in the RKHS without computing the high-dimensional features or taking expectations. This process can be viewed as analogous to the use of the kernel trick in support vector machines (SVM) to compute distances between points in a high-dimensional feature space without computing high-dimensional features (Steinwart and Christmann 2008). Specifically, we can distinguish between samples from two distributions through the computation of the following test statistic (Gretton et al. 2012):

$$\text{MMD}^2(P, Q) = \left\| \frac{1}{m} \sum_{i=1}^m \phi(x_i) - \frac{1}{n} \sum_{j=1}^n \phi(y_j) \right\|_{\mathcal{H}}^2.$$

Here, $\phi(\cdot) = k(x, \cdot)$ is the feature map that embeds the data into the RKHS \mathcal{H} , x_i and y_j are samples from distributions P and Q respectively, m and n are the number of samples from P and Q respectively. The double bars $\|\cdot\|_{\mathcal{H}}$ denote the norm in the RKHS.

MMD in Unstructured Data If our input data were numerical, then the model structure described above would suffice. However, since our data is non-numerical, we consider a compositional structure:

$$\phi(\cdot) = \phi_2(\phi_1(x, \cdot)).$$

Here, ϕ_1 is an injective map from the non-numerical data to an intermediate Banach space (a complete normed vector space), and ϕ_2 is a map such that its composition with ϕ_1 yields $\phi(\cdot)$ (i.e., ϕ_2 is implicitly defined through ϕ_1 and ϕ_2). This structure has the following interpretation: ϕ_1 serves to express non-numerical data numerically in a vector space with sufficient dimensionality to distinguish between any two distinct elements (i.e., in our study, ensuring each project title has a distinct textual representation), while ϕ_2 ensures that ϕ possesses sufficient richness so that μ_P accurately describes P . This approach yields the statistic:

$$\text{MMD}^2(P, Q) = \left\| \frac{1}{m} \sum_{i=1}^m \phi_2(\phi_1(x_i)) - \frac{1}{n} \sum_{j=1}^n \phi_2(\phi_1(y_j)) \right\|_{\mathcal{H}}^2.$$

Finally, an application of the kernel trick enables this statistic to be computed without requiring the computation of the compositional feature map. Specifically, an unbiased estimate of MMD^2 is provided by

the equation:

$$\widehat{MMD}^2(P, Q) = \frac{1}{m(m-1)} \sum_{i=1}^m \sum_{\substack{j=1 \\ j \neq i}}^m k(x_i, x_j) + \frac{1}{n(n-1)} \sum_{i=1}^n \sum_{\substack{j=1 \\ j \neq i}}^n k(y_i, y_j) - \frac{2}{mn} \sum_{i=1}^m \sum_{j=1}^n k(x_i, y_j)$$

Here, the components of this equation are interpreted as follows:

- $k(\cdot, \cdot)$ is the kernel function used within the RKHS. In our reporting, ϕ_1 is a mapping established by the AI, and ϕ_2 corresponds to the second-order homogeneous polynomial kernel. As the support is discrete, these suffice to form a characteristic kernel.
- x_i and x_j are samples drawn from distribution P .
- y_i and y_j are samples drawn from distribution Q .
- m and n are the sample sizes for samples drawn from distributions P and Q , respectively.
- The first term $\frac{1}{m(m-1)} \sum_{i=1}^m \sum_{\substack{j=1 \\ j \neq i}}^m k(x_i, x_j)$ calculates the average of the kernel evaluations over all unique pairs of samples from P .
- The second term $\frac{1}{n(n-1)} \sum_{i=1}^n \sum_{\substack{j=1 \\ j \neq i}}^n k(y_i, y_j)$ calculates the average of the kernel evaluations over all unique pairs of samples from Q .
- The third term $-\frac{2}{mn} \sum_{i=1}^m \sum_{j=1}^n k(x_i, y_j)$ subtracts twice the average of the kernel evaluations between samples from P and samples from Q .

Web Appendix C: Simulations

In this Web Appendix, we outline the performance of our proposed methodology designed for comparing sets of unstructured data, with a focus on collections of verbal documents. The simulations aim to assess the methodology's capability to differentiate between sets of verbal data generated from distinct stochastic processes.

For these simulations, we engaged an AI with two specific prompts: one to generate brand names with a humorous undertone and another for brand names with a solemn tone. This dichotomy was chosen because it mirrors common distinctions in real-world brand naming practices—such as the playful name of a pizza parlor versus the gravitas of a funeral home's name.

This approach of instructing the AI to produce brand names under contrasting thematic conditions—humorous versus solemn—serves as a direct method to explore a broader issue: how varying instructions lead to differences in the stochastic processes underlying the generation of brand names. This principle can be applied to other scenarios where differences arise from distinct reasons.

From this exercise, we collected 100 humorous and 100 solemn brand names generated by the AI. A selection of these names is presented below in Table 4, showcasing the AI's ability to generate a diverse range of thematic expressions.

Our presented methodology aims to establish a test statistic that relates any two sets of verbal documents, such as these brand names. Thus, for instance, when presented with the brand names in Table 4, one might ask whether the first 15 brand names in the table are distinct from the last 15 brand names. How would one statistically test for such a difference?

To measure these differences, as a first step, we use the ‘text-embedding-3-large’ embedding, as also employed in our main analysis. Figure 6 comprises two subfigures. Subfigure 6a visualizes the cosine distance of the embedding of the first 50 funny brand names generated by the AI, where we use only 50 names to make the figure easier to read. Subfigure 6b provides a similar visualization for the first 50 solemn brand names.

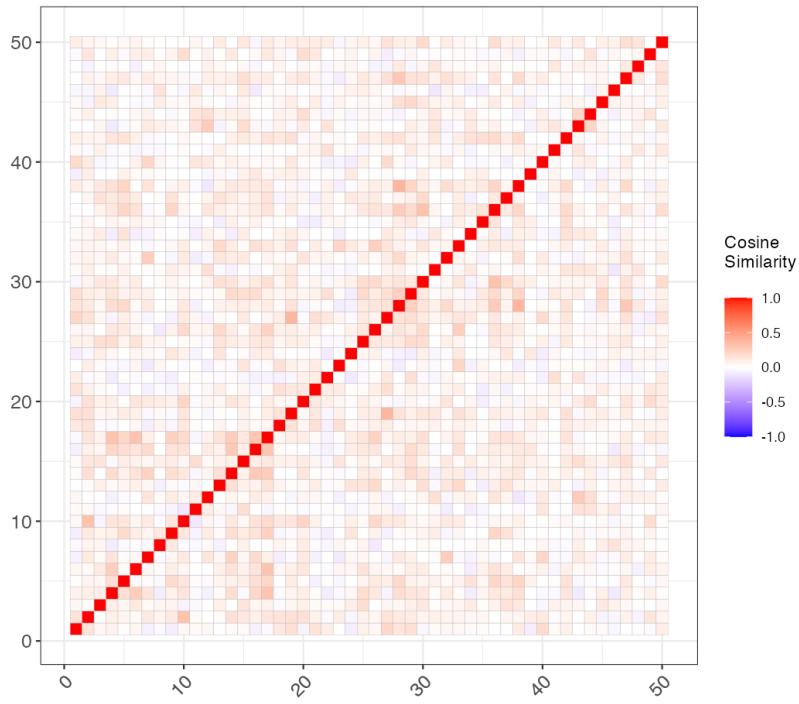
Figure 7 visualizes the first 50 funny and 50 solemn brand names together. In all figures, the color of each square indicates how similar or dissimilar each pair of brand names is, as measured using cosine similarity, which is a typical measure of similarity in machine learning.

We observe that the embeddings of the brand names show systematic differences, whereby the funny

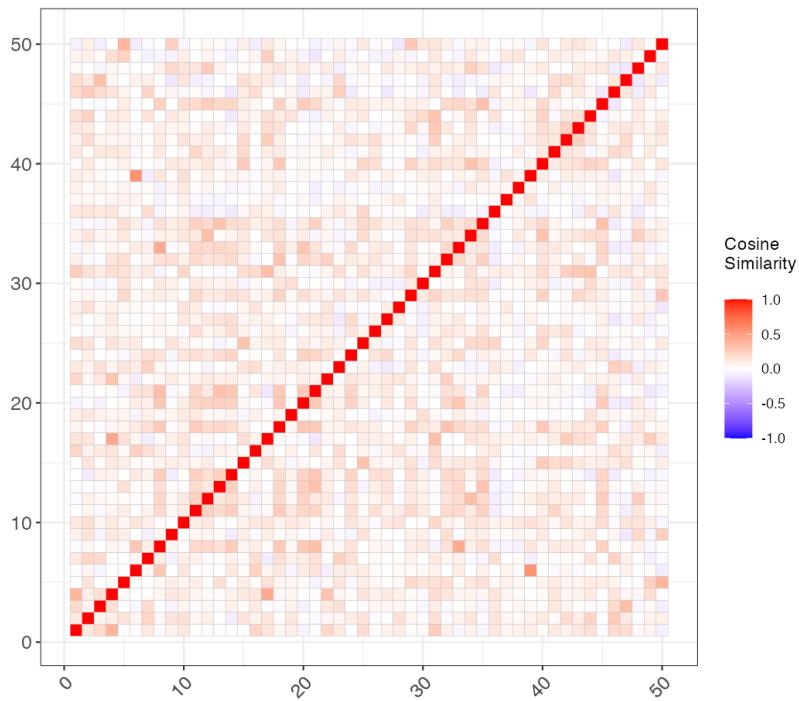
No.	Type	Brand Names
1	Funny	Loaf & Devotion
2	Funny	Bread Pitt
3	Funny	Sofa So Good
4	Funny	Lord of the Fries
5	Funny	Wok This Way
6	Funny	The Codfather
7	Funny	Planet of the Grapes
8	Funny	Indiana Jeans
9	Funny	Thai Tanic
10	Funny	Pita Pan
11	Funny	Brewed Awakening
12	Funny	Tequila Mockingbird
13	Funny	Eggscellent
14	Funny	Jurassic Pork
15	Funny	Bean Me Up
16	Solemn	Serene Streams
17	Solemn	Eternal Oak
18	Solemn	Harmony Haven
19	Solemn	Tranquil Pathways
20	Solemn	Noble Quest
21	Solemn	Zenith Peak
22	Solemn	Evermore Estates
23	Solemn	Pinnacle Trust
24	Solemn	Sage Wisdom
25	Solemn	Infinite Horizons
26	Solemn	Legacy Builders
27	Solemn	Unity Financial
28	Solemn	Virtue Ventures
29	Solemn	Paramount Partners
30	Solemn	Guardian Gate

Table 4: Examples of AI-Generated Brand Names

Note: A list of the first 15 funny and the first 15 solemn brand names generated by GPT-4-Turbo.



(a) Cosine Distance Among AI-Generated Funny Brand Names



(b) Cosine Distance Among AI-Generated Solemn Brand Names

Figure 6: Cosine Distance Between AI-Generated Brand Names

Note: Cosine distance between embeddings of the brand names.²⁷

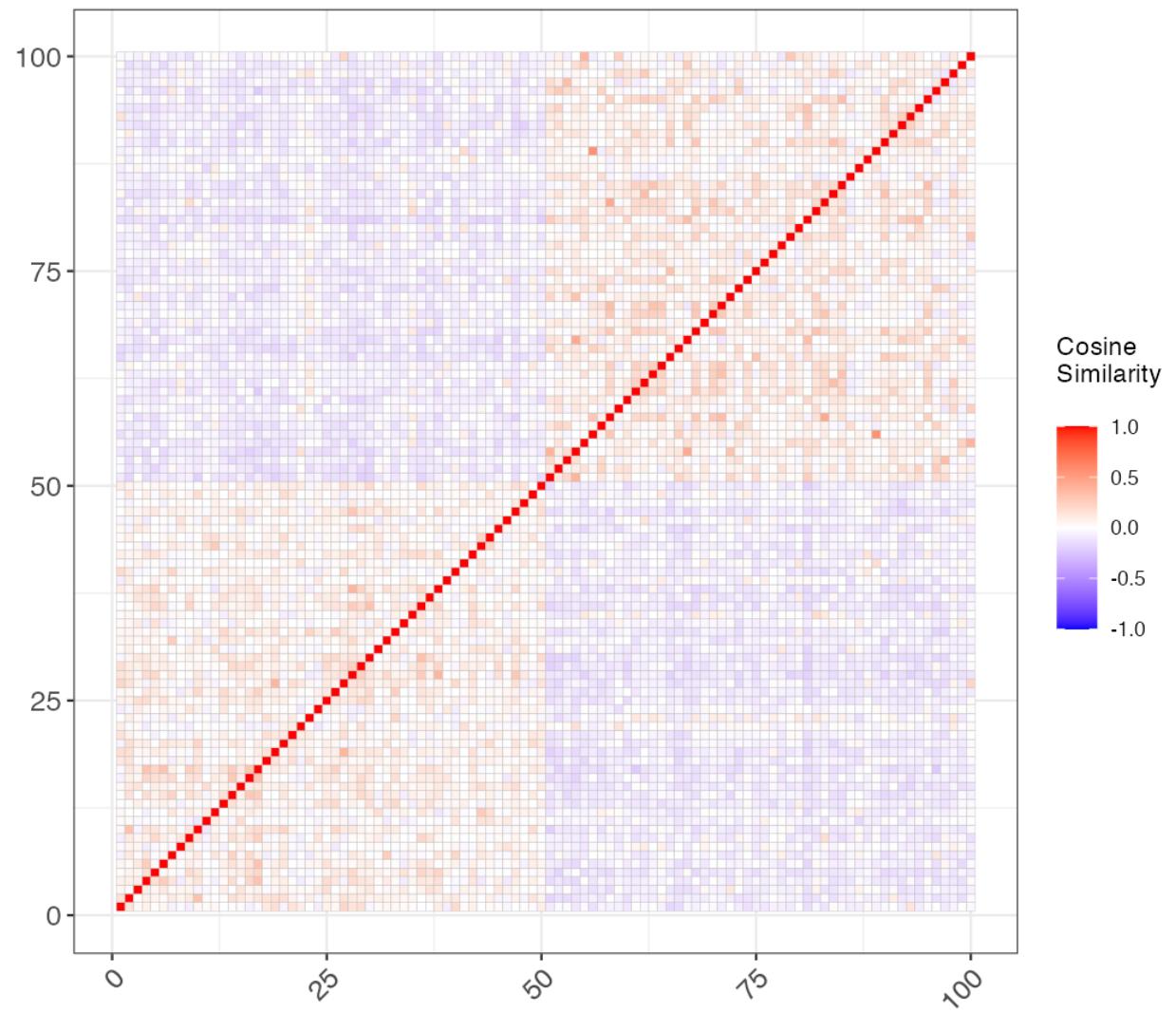


Figure 7: Cosine Distance Between AI-Generated Funny and Solemn Brand Names

Note: Cosine distance between embeddings of the brand names. The first 50 brand names are funny, and the last 50 are solemn.

brand names exhibit high cosine similarity among themselves, and the solemn brand names exhibit high cosine similarity among themselves. However, the two blocks of brand names are highly dissimilar in terms of cosine dissimilarity. Thus, the figure demonstrates that the use of the embedding enables the identification of the pairwise similarity and dissimilarity of each document in each collection—each brand name in each set of brand names.

While there exist several alternatives for measuring pairwise distances, there are few alternatives for comparing two sets of verbal documents. This is because classic measures such as Euclidean and cosine distance operate pairwise, and topic models seek to derive broader themes that can be compared between sets of documents. In measuring the distance between distributions, we aim to measure both the themes discussed in the documents and the words used to discuss them. This is equivalent to deriving a distance in both topic intensities and word-topic distributions in topic models, while accounting for estimation inaccuracies in the measurement of both distributions and without imposing structure on the distance function employed on these distributions.

In contrast, the MMD metric enables us to compare any set of brand names to another set of brand names without knowledge of identity to establish if the sets of brand names are distinct. When employed against the set of funny and solemn brand names, this test translates to measuring if the data-generating process through which the funny brand names were generated is statistically distinct from the data-generating process through which the solemn names were generated.

Note, the method does not require the set of samples to be ‘comprehensive’ in the sense of being the complete data—any 10 observations in our simulation from the set are sufficient to indicate if the distributions are the same. This is because fundamentally the method is designed for situations where samples are taken from a distribution.

This is a crucial requirement of comparing any set of documents to the output of generative AI, as the AI can always be used to generate more data, and where our field data is representative but not ‘complete’—there are other projects that are not covered in our data. The use of classical methods such as pairwise cosine distance might have been difficult to reconcile with the idea of the data being a representative sample. However, as the distribution-based test provides a comparison at the level of the data-generating process through the likelihood of the generated words, it does not require either sample to be complete for the method to provide substantive guidance.

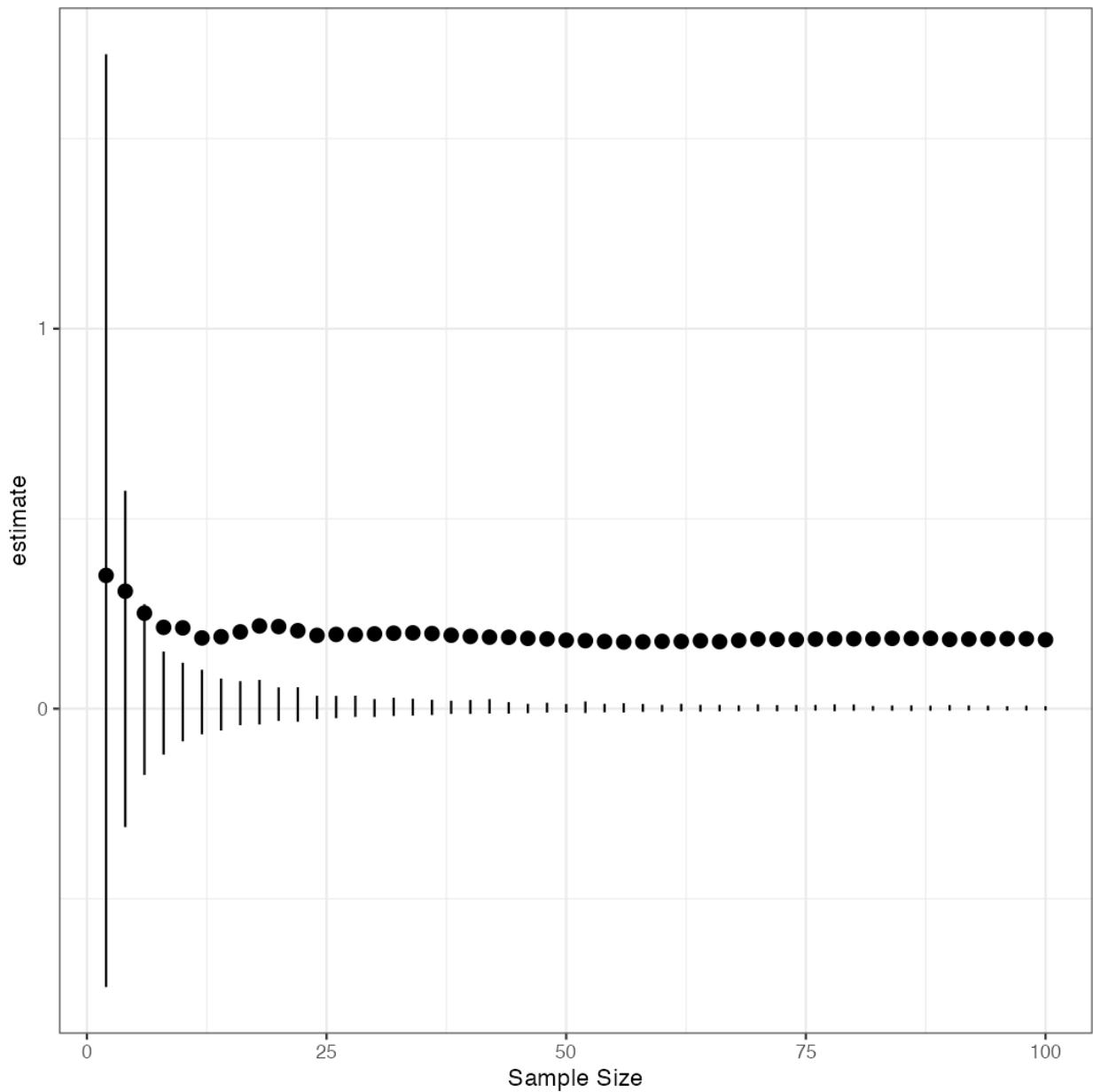


Figure 8: MMD Statistic and Confidence Interval for Varying Sample Sizes

Note: MMD statistic and 99% confidence interval for varying sample sizes. The sample size is on the x-axis. The statistic and confidence interval are represented on the y-axis. In cases where the point estimate falls outside the confidence interval, the data rejects the null hypothesis that both samples are from the same distribution.

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