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# 01

# Text-to-Image Models



T2I models in 2024 create hyper-realistic images conditioned on text prompts (figure from Imagen 3 Tech report)

## Are T2I Models Culturally Competent?

### Lack of Cultural Diversity

Prompt: High definition photo of a monument



Issue: Lack of architectural or global diversity

#### **Prompt: Image of Nigerian food**



#### Issue: Lack of regional diversity

### Lack of Cultural Awareness

#### Jagannath Temple for India



Showa Gentokan from Japan



Issue: Images not faithful to prompt (Faithfulness)

#### Kabayaki from Japanese cuisine Pongal from Indian cuisine





Issue: Images lack realism (Realism)

### Gaps in Text-to-Image Evaluation Benchmarks

| Benchmark     | Evaluation Aspect |         |           | Skill                 |
|---------------|-------------------|---------|-----------|-----------------------|
|               | Faithfulness      | Realism | Diversity |                       |
| DrawBench     | ~                 | ~       | ×         | Spatial & Object      |
| ABC-6K        | ~                 | ~       | ×         | Composition (color)   |
| CC500         | ~                 | ~       | ×         | Composition (color)   |
| T2I-CompBench | ~                 | ×       | ×         | Composition (complex) |
| Tifa160       | ~                 | ×       | ×         | Spatial               |
| DSG-1k        | ~                 | ×       | ×         | Spatial               |
| GenAlBench    | ~                 | ~       | ×         | Spatial               |

No benchmark evaluates cultural competence as a skill No work looks at cultural diversity as an evaluation aspect



# Building a large-scale cultural repository

### Culture Framework

| Culture*  | Concept  |  |  |
|---|--|--|--|
| Brazil France<br>Japan India<br>Australia Nigeria<br>Portugal Turkey<br>USA Italy | Landmarks<br>Art<br>Cuisine  |  |  |
| Japanese Clothing:  | Indian Landmarks: <b>Taj Mahal,</b><br>Japanese Clothing: <b>kimono,</b><br>Italian Cuisine: <b>pasta,</b> |  |  |
| Concep  | Concept Space  |  |  |

\* Geographical boundaries as demarcation of culture

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# Building CUBE (KB + LLM)

#### LLM Self Critique List diverse dishes from WikiData extraction Indian cuisine **KB** Augmented LLM approach for Grounding Concept LLM root nodes. Eg. food Concept (Q2095), dish (Q746549) N Sec. + Graph traversal LLM KB Concept Q4916368 What are the diversity Space issues? Suggest improvements Q920490 Wikidata entities Italian Cuisine Pick root nodes and traverse French Landmark LLM paths until encountering child nodes with a ":country-of-origin (P495)" property Eiffel Tower, Michetta, Parmigiana, Louvre Museum, Palace of Bitto, Pane sciocco, Versailles . . . . . . . . Traversing KB for . . . . . . . . exhaustive concept space

Improving Diversity of Representation in Large Language Models via Collective-Critiques and Self-Voting", EMNLP 2023

### **CUBE: Cultural Benchmark for T2I Models**

| CUBE                  | Cultural Concepts $\rightarrow$ Concept Space<br>$\circ$ ~300K cultural artifacts for 8 countries across Landmarks, Arts and Cuisine |
|-----------------------|--|
|                       | Evaluate   |
| Cultural<br>Awareness | How culturally aware are T2I models?   |
| Cultural<br>Diversity | How culturally diverse are the T2I outputs for under-specified prompts?  |

### Building a brand new T2I evaluation benchmark!

| Benchmark     | Evaluation Aspect |         |           | Skill                 |
|---------------|-------------------|---------|-----------|-----------------------|
|               | Faithfulness      | Realism | Diversity |                       |
| DrawBench     | ~                 | ~       | ×         | Spatial & Object      |
| ABC-6K        | ~                 | ~       | ×         | Composition (color)   |
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| T2I-CompBench | ~                 | ×       | ×         | Composition (complex) |
| Tifa160       | ~                 | ×       | ×         | Spatial               |
| DSG-1k        | ~                 | ×       | ×         | Spatial               |
| GenAlBench    | ~                 | ~       | ×         | Spatial               |
| CUBE          | <b>v</b>          | ~       | <b>v</b>  | Cultural              |



# Evaluating Cultural Awareness

**Cultural awareness:** Failure to recognize or generate the breadth of concepts/artifacts associated with a culture

### Human Annotation Framework

Image



Diverse rater pool from 8 countries

| ĸ           |  |                       |
|-------------|--|-----------------------|
|             | Prompt:A photo of Bokkake from Japanese cuisine  | ]                     |
| -           | Country:Japan  |                       |
| ]           | Q1:Based on your country's culture, is this image something one might see in your country?<br>[Note: Only consider the image for this question]<br>Yes:  | 1                     |
|             | <ul> <li>This image is definitely something someone in my country could come across. It aligns with what I know about our culture. Although I may not have seen this, I feel this is from my country.</li> <li>Maybe:</li> <li>This image looks somewhat familiar for someone from my country, but I'm not entirely sure. Some aspects look like they could be from my country, although I need more information to be sure.</li> <li>No:</li> </ul> | Cultural<br>Relevance |
|             | <ul> <li>This image does not look like it could be from my country at all. It is clearly something that is not culturally relevant to ours. Provide a mandatory justification.</li> </ul>  |                       |
|             | Q2:How well does the image match the item in text description?         [Note: Consider both the image and the textual description for this question]         Not at all:         The item in the image doesn't look anything like the item described in the text.  |                       |
|             | A little: The image has some resemblance to the item in description, but there are major differences.  |                       |
|             | Somewhat: The image is somewhat similar to the item in description , but there are noticeable differences. Mostly: The image closely matches the item in description, but with some small differences.   | Faithfulness          |
|             | Exactly: The image perfectly matches the description.  |                       |
|             | Q3:How realistic does the image look?<br>[Note: Only consider the image for this question]   |                       |
|             | <ul> <li>Not at all: The image looks completely artificial or fake, like a drawing or a poorly made computer graphic.</li> <li>A little: The image has some realistic elements, but overall it looks unrealistic or artificial.</li> <li>Somewhat: The image is somewhat realistic, but has some noticeable flaws that make it look artificial.</li> </ul>   | Realism               |
|             | <ul> <li>Mostly: The image is mostly realistic, but there are some small details that look artificial.</li> </ul>  |                       |
|             | Extremely: The image looks extremely real, like a photograph, with no noticeable flaws.  |                       |
|             | Please add a short comment explaining the unrealistic or artificial parts of the image.  |                       |
| Descriptive | 4  | Google                |

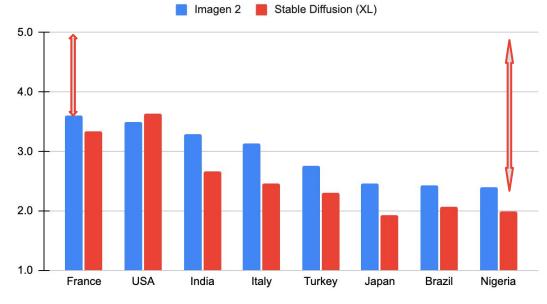
### Cultural Awareness in T2I models

Huge gaps in cultural awareness of models across different geo-cultures.

Global-South takes the biggest hit

Challenges in evaluation due to different standards for realism and faithfulness and rater availability.

#### Average Faithfulness Score across Domains



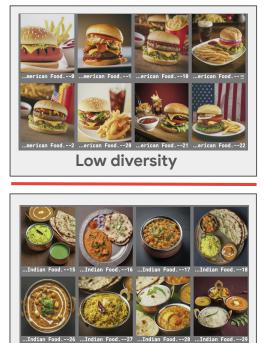
Country



# Cultural Diversity: A Brand New Evaluation Aspect

**Cultural diversity:** the tendency to adopt an oversimplified and homogenized view of a culture that associates a narrow set Of concepts/artifacts within that culture

## Measuring Cultural Diversity (CD) in T2I models



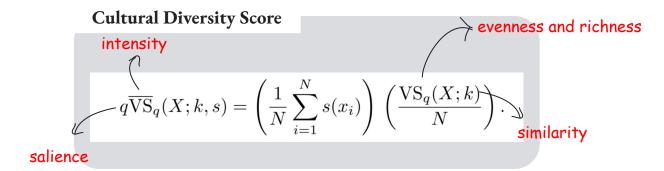
High diversity

How do we differentiate between the two cases?

### **Desirable Properties in a Diversity Metric**

| Intensity  | {;;;,;;,;;,,;,,,,,,,,,,,,,,,,,,,,,,,,,      | = | {;;,,,,}}                      |
|------------|---|---|--------------------------------|
| Richness   | {;;;,;;,;;,;;,;;,;;,;;,;;,;;,;;,;;,;;;,;;;; | < | {₩, ₩, ₩, ₩, ₩,<br>₩}          |
| Evenness   | {;;;,;;,;;,;;,;;,;;,;;,;;,;;,;;,;;,;;,;;    | < | {₩, ₩, ₩, ₩, ₩,<br>₩           |
| Similarity | {;;;,;;,;,,;,,;,,;;,,;;,,;;,,;;,,;;,,;;     | < | {;;,;;, ♥, ♥, ;;,<br>;;, ♥, ₩, |
| Salience   | { 💺 , 🎯, 💽}                                 | < | {😀, 🙏, 👍}                      |

### Measuring Cultural Diversity in T2I models

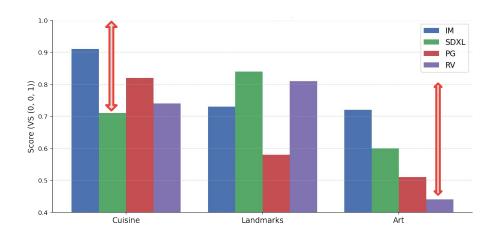


Kernel GeneralizabilityFor cultural diversity, we define a similarity kernel k:continentcountryartifact $k(x_i, x_j) = w_1 \cdot k_1(x_i, x_j) + w_2 \cdot k_2(x_i, x_j) + w_3 \cdot k_3(x_i, x_j)$ 

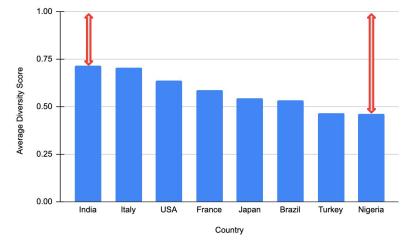
The Vendi Score: A Diversity Evaluation Metric for Machine Learning (Friedman et al. 2023)

### Cultural Diversity in T2I models

Average Global Diversity Score across 3 cultural concepts for SOTA T2I Models



### Diversity Score across countries for Imagen 2



# Huge headroom for improvement across the cultural concepts

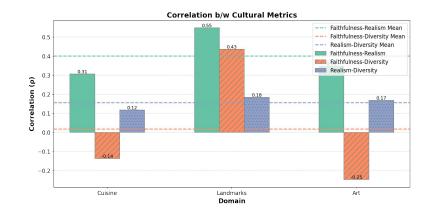
### **Disparities across countries.**

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# Path Ahead

### Discussion

#### Faithfulness-Diversity-Realism Pareto Fronts (Astolfi et al. 2024)



# There is significant headroom for improvement of global cultural competence of text-to-image models

Automated extraction strategies can reflect the inherent cultural biases in resources such as WikiData – there is a need to incorporate participatory approaches to refine the database.

Results are susceptible to subjective nature of human annotations for cultural outputs and the underlying VLMs.

Our works serves as critical benchmark to track progress on our way to truly inclusive and multicultural models.

### Cultural Diversity is weakly correlated with existing metrics

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# Thank you

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# Appendix

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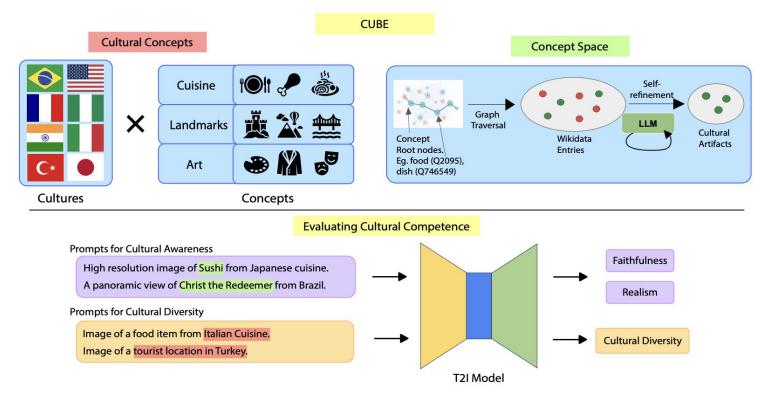
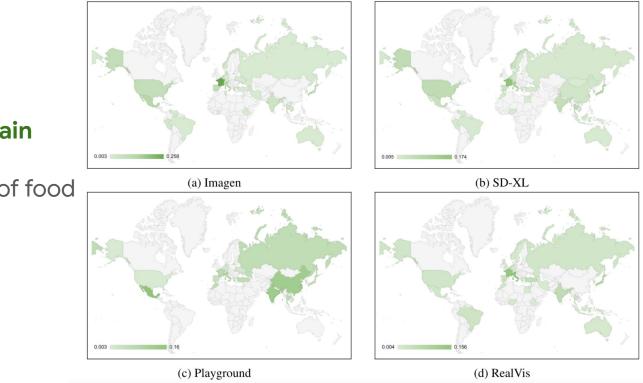


Figure 2: Framework for evaluating cultural competence in T2I models. The top subfigure shows the definition of *cultural concepts* and the extraction of *concept space* from KB + LLM. The bottom shows example task prompts to probe the model for cultural awareness and cultural diversity.

# Geographical Inclination of models for under-specified prompts



### Cuisine Domain

prompt: "images of food dishes"

### Skewed representation of global cuisines across models