

¹ CatLLM: A Python package for Generating, Assigning, ² and Scoring Open-Ended Survey Data and Images

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DOI: [10.xxxxxx/draft](https://doi.org/10.xxxxxx/draft)

Software

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Submitted: 08 June 2025

Published: unpublished

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⁵ Summary

⁶ The rapid advancement of large language and vision models has created new opportunities
⁷ for automated text and image analysis in social science research ([Sachdeva & Nuenen, 2025](#);
⁸ [Schulze Buschoff et al., 2025](#); [Yang et al., 2024](#)). Researchers increasingly use these tools to
⁹ code open-ended survey responses, categorize qualitative data, and analyze visual content at
¹⁰ scale. Yet challenges persist due to inconsistent output formats, diverse API interfaces, and the
¹¹ lack of standardized workflows for integrating both model outputs and external data sources
¹² into traditional statistical analysis pipelines ([Rossi et al., 2024](#)). CatLLM addresses these issues
¹³ by providing a modular framework with specialized functions that not only ensure consistent
¹⁴ data structures across text and image analysis workflows, but also facilitate the automated
¹⁵ retrieval of structured data from the web. The package handles different prompting strategies
¹⁶ reactively through configurable parameters that allow users to switch between techniques such
¹⁷ as Chain-of-Thought (CoT) ([Wei et al., 2023](#)), Chain-of-Verification (CoVe) ([Dhuliawala et
al., 2023](#)), and step-back prompting ([Zheng et al., 2024](#)), enabling researchers to optimize
model reasoning based on task complexity without requiring expertise in prompt engineering.
This integration allows researchers to seamlessly combine large model outputs with real-world
datasets, maintaining compatibility with standard statistical analysis tools.

²² Statement of need

²³ Social scientists increasingly recognize the value of open-ended survey input for capturing rich,
²⁴ nuanced responses that closed-ended formats cannot provide. However, many researchers avoid
²⁵ incorporating open-ended input into their surveys due to the substantial analysis challenges they
²⁶ present. The processing of open-ended responses is notoriously time-intensive, requiring manual
²⁷ categorization and careful interpretation that can quickly become overwhelming with large
²⁸ datasets. Even when researchers do include open-ended questions, quantitative researchers
²⁹ often fail to fully utilize the resulting qualitative data due to limited time, resources, or expertise
³⁰ in analysis techniques. This analysis burden not only increases research costs but also creates
³¹ practical barriers that prevent researchers from leveraging the deeper insights that open-ended
³² responses can provide.

³³ Current solutions present several limitations for academic researchers analyzing open-ended
³⁴ survey data. General-purpose natural language processing libraries such as NLTK require
³⁵ significant programming knowledge and often involve complex workflows for custom model
³⁶ training, while tools like spaCy, though more user-friendly, still require domain expertise for
³⁷ specialized applications. Commercial platforms like Dedoose or Atlas.ti focus primarily on
³⁸ manual coding workflows and lack integration with modern language models. While some
³⁹ researchers have begun using large language models (LLMs) directly through web interfaces,
⁴⁰ this approach lacks standardization, reproducibility, and systematic output formatting necessary
for quantitative analysis.
41

42 CatLLM addresses these gaps by providing a standardized, free-to-use interface for applying state-
 43 of-the-art language and vision models to common research tasks without requiring machine
 44 learning expertise. The package enables researchers to transform diverse data sources—from
 45 open-ended survey responses and qualitative interviews to unstructured web content—into
 46 quantitative datasets suitable for statistical analysis, bridging the gap between traditional
 47 research methods and computational approaches. Recent research demonstrates that LLMs
 48 from OpenAI and Anthropic, particularly GPT-4, can effectively replicate human analysis
 49 performance in content analysis tasks, with some studies showing LLMs achieving higher inter-
 50 rater reliability than human annotators in sentiment analysis and political leaning assessments
 51 (Bojić et al., 2025). However, LLM outputs can be inconsistent across calls, posing challenges
 52 for reproducible qualitative analysis—CatLLM addresses this through frequency-based theme
 53 extraction that aggregates results across multiple independent calls rather than relying on
 54 single responses. Unlike existing tools, CatLLM provides reproducible, structured outputs while
 55 supporting multiple AI providers and maintaining cost efficiency through built-in optimization
 56 features.

Survey Response	Financial	Family	Housing Features	New Job
Because I wanted a bigger house	0	0	1	0
I needed more money, so I got a new job	1	0	0	1
We started a family and wanted a bigger house	0	1	1	0

Figure 1: Example of CatLLM Assigning Categories to Move Reason Survey Responses

57 The software has demonstrated practical impact across diverse research domains. It has been
 58 successfully applied by institutional researchers at UC Berkeley to track student experience
 59 and outcomes, in studies examining demographic differences in LLM performance using the
 60 UC Berkeley Social Networks Study (Soria, 2025), categorizing occupational data according to
 61 Standard Occupational Classification codes, and implementing automated scoring for cognitive
 62 assessments in the Caribbean-American Dementia and Aging Study (Llibre-Guerra et al., 2021).
 63 These applications demonstrate the package’s versatility in addressing real-world research
 64 challenges that require systematic analysis of unstructured data at scale.

65 The package can be easily installed and implemented:

```
pip install cat-lm
```

```
import catlm as cat
```

66 For comprehensive documentation and detailed installation instructions, see <https://github.com/chrisoria/cat-lm>.
 67

68 Features

69 The CatLLM package processes diverse data sources—including user-provided text (open-
 70 ended survey responses), image data, and unstructured content retrieved from the web—and
 71 returns structured data objects. The package enables users to customize function behavior by
 72 incorporating their specific research questions and background theoretical frameworks, allowing
 73 the language models to generate more contextually relevant and theoretically grounded outputs
 74 tailored to their analytical objectives.

75 The package extends this framework through specialized capabilities:

- 76 ▪ **Web Data Collection:** Available as part of the CatLLM ecosystem through the companion
77 package `llm-web-research` (`pip install llm-web-research`). This package retrieves
78 and structures unstructured content from web sources, transforming raw online data into
79 standardized datasets suitable for analysis alongside survey and qualitative data. Unlike
80 traditional web scraping approaches, `llm-web-research` prioritizes precision over quantity,
81 using a multi-step verification pipeline to reduce false positives and flag ambiguous queries
82 rather than returning potentially incorrect answers.
- 83 ▪ **Binary Image Classification:** Applies classification frameworks to vision models, deter-
84 mining the presence or absence of specific categories within images for systematic visual
85 content analysis.
- 86 ▪ **Flexible Image Feature Extraction:** Extracts diverse data types from images, returning nu-
87 meric, string, or categorical outputs rather than limiting analysis to binary classifications,
88 enabling more nuanced visual data collection.
- 89 ▪ **Drawing Quality Assessment:** Compares user-generated drawings against reference
90 images, producing quality scores based on similarity metrics for objective evaluation of
91 visual reproduction tasks.
- 92 ▪ **Corpus-Level Theme Discovery:** Improves reproducibility in qualitative theme identi-
93 fication by making multiple independent calls across random corpus segments, then
94 using a secondary model to standardize and consolidate the outputs. This frequency-
95 based extraction method reduces the probabilistic variability inherent in single LLM
96 calls—rather than relying on one potentially inconsistent response, the function surfaces
97 only categories that recur across many independent iterations, producing a reliable,
98 ranked list of themes most representative of the data.
- 99 This modular approach provides researchers with consistent data structures across text, image,
100 and web data analysis workflows while maintaining compatibility with standard statistical
101 analysis tools. In reliability testing across eight high-end language models processing 3,208
102 survey responses each (25,664 total classifications), the package produced valid structured
103 output for 100% of successful API calls—the small number of failures (0–18 per model) were
104 exclusively due to transient server errors rather than JSON parsing issues. Costs ranged from
105 \$0.38 (Mistral Medium) to \$27.85 (GPT-5), with processing times from 23 minutes to over 7
106 hours depending on provider rate limits. Further research is needed to evaluate performance
107 with smaller, less capable models.
- 108 The `image_multi_class` function has been applied to implement CERAD protocols ([Fillenbaum et al., 2008](#)) for scoring geometric shape drawings in the Caribbean-American Dementia
109 and Aging Study ([Llibre-Guerra et al., 2021](#)), demonstrating how general-purpose image
110 classification can be adapted to specialized research domains.

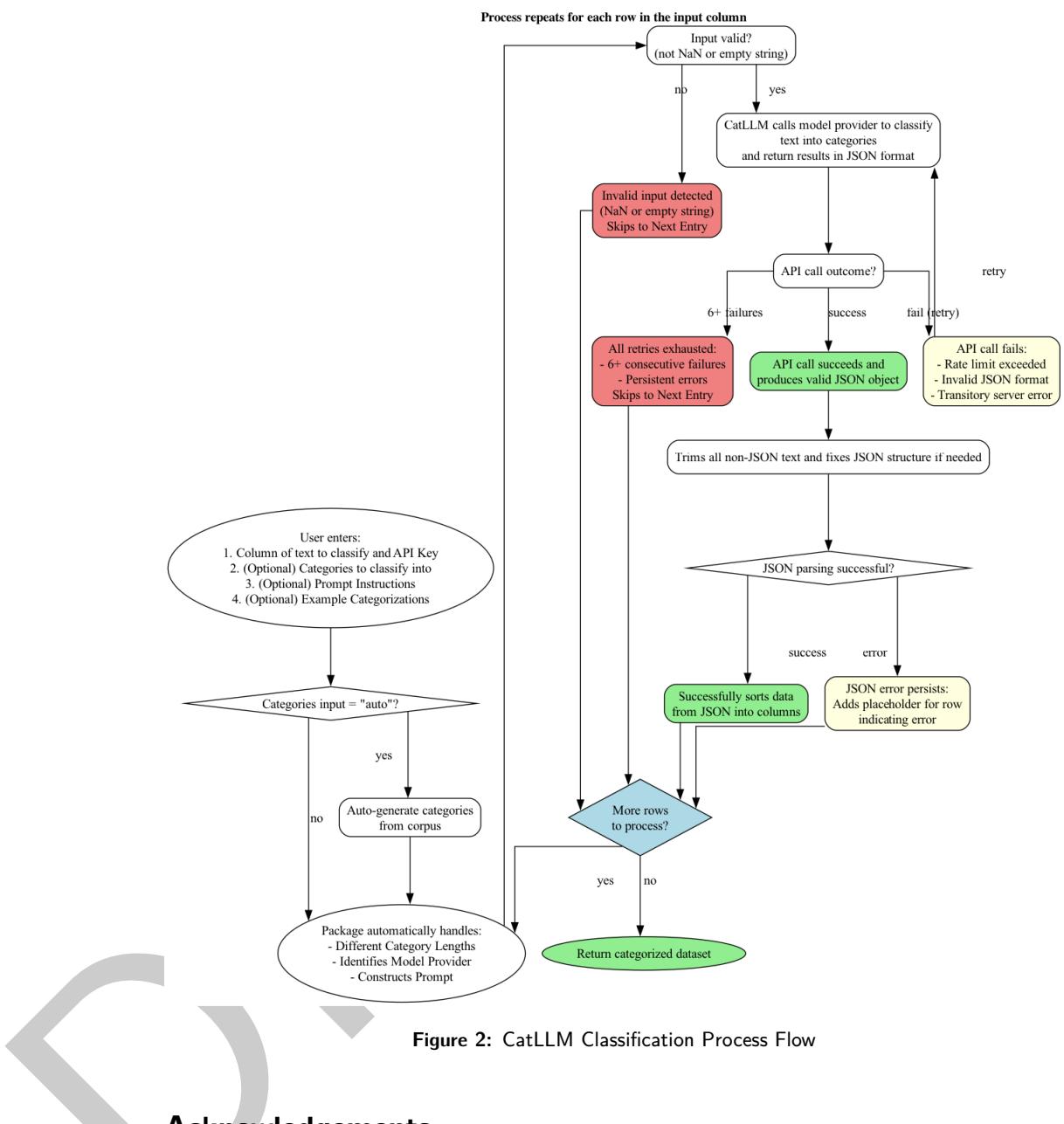


Figure 2: CatLLM Classification Process Flow

Acknowledgements

This work was supported by the UC Berkeley Mentored Research Award. The author thanks Matthew Stenberg, Sara Quigley, Madeline Arnold, and Henry Tyler Dow for assistance in testing the functions on real data. The author also acknowledges the University of California, Berkeley for providing the institutional support that enabled this research. Partial support was provided by the Center on the Economics and Demography of Aging, P30AG012839, and the Greater Good Science Center's Libby Fee Fellowship.

References

- Bojić, L., Zagovora, O., Zelenkauskaite, A., Vuković, V., Čabarkapa, M., Veseljević Jerković, S., & Jovančević, A. (2025). Comparing large Language models and human annotators in latent content analysis of sentiment, political leaning, emotional intensity and sarcasm.

- 123 *Scientific Reports*, 15(1), 11477. <https://doi.org/10.1038/s41598-025-96508-3>
- 124 Dhuliawala, S., Komeili, M., Xu, J., Raileanu, R., Li, X., Celikyilmaz, A., & Weston, J.
125 (2023). *Chain-of-Verification Reduces Hallucination in Large Language Models*. arXiv.
126 <https://doi.org/10.48550/arXiv.2309.11495>
- 127 Fillenbaum, G. G., Belle, G. van, Morris, J. C., Mohs, R. C., Mirra, S. S., Davis, P. C.,
128 Tariot, P. N., Silverman, J. M., Clark, C. M., Welsh-Bohmer, K. A., & Heyman, A. (2008).
129 CERAD (Consortium to Establish a Registry for Alzheimer's Disease) The first 20 years.
130 *Alzheimer's & Dementia : The Journal of the Alzheimer's Association*, 4(2), 96–109.
131 <https://doi.org/10.1016/j.jalz.2007.08.005>
- 132 Llibre-Guerra, J. J., Li, J., Harrati, A., Jiménez-Velazquez, I., Acosta, D. M., Llibre-Rodriguez,
133 J. J., Liu, M.-M., & Dow, W. H. (2021). The Caribbean-American Dementia and Aging
134 Study (CADAS): A multinational initiative to address dementia in Caribbean populations.
135 *Alzheimer's & Dementia*, 17(S7), e053789. <https://doi.org/10.1002/alz.053789>
- 136 Rossi, L., Harrison, K., & Shklovski, I. (2024). The Problems of LLM-generated Data in Social
137 Science Research. *Sociologica*, 18(2), 145–168. <https://doi.org/10.6092/issn.1971-8853/19576>
- 139 Sachdeva, P. S., & Nuenen, T. van. (2025). *Normative Evaluation of Large Language Models
140 with Everyday Moral Dilemmas*. arXiv. <https://doi.org/10.48550/arXiv.2501.18081>
- 141 Schulze Buschoff, L. M., Akata, E., Bethge, M., & Schulz, E. (2025). Visual cognition in
142 multimodal large language models. *Nature Machine Intelligence*, 7(1), 96–106. <https://doi.org/10.1038/s42256-024-00963-y>
- 144 Soria, C. (2025). *An Empirical Investigation into the Utility of Large Language Models in
145 Open-Ended Survey Data Categorization*. OSF. https://doi.org/10.31235/osf.io/wv6tk_v2
- 146 Wei, J., Wang, X., Schuurmans, D., Bosma, M., Ichter, B., Xia, F., Chi, E., Le, Q., & Zhou, D.
147 (2023). *Chain-of-Thought Prompting Elicits Reasoning in Large Language Models*. arXiv.
148 <https://doi.org/10.48550/arXiv.2201.11903>
- 149 Yang, Z., Du, X., Li, J., Zheng, J., Poria, S., & Cambria, E. (2024). *Large Language
150 Models for Automated Open-domain Scientific Hypotheses Discovery*. arXiv. <https://doi.org/10.48550/arXiv.2309.02726>
- 152 Zheng, H. S., Mishra, S., Chen, X., Cheng, H.-T., Chi, E. H., Le, Q. V., & Zhou, D. (2024).
153 *Take a Step Back: Evoking Reasoning via Abstraction in Large Language Models*. arXiv.
154 <https://doi.org/10.48550/arXiv.2310.06117>