

Cartography: AI Slop Detection

This cartography analyses **AI slop** – low-effort, undesirable AI-generated content that clutters the information ecosystem. The project aims define this emerging concept, build a dataset, and develop a detection system. The outcome will support both an academic publication and a Python library.

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What is Slop

See Appendix A for references on slop.

See Appendix B for sources of slop for the creation of a dataset.

AI slop is a nascent term without a clear academic definition, though it is gaining currency online. No peer-reviewed research directly addresses it; only two preprints (Chakrabarty et al., 2025; Krincewicz et al., 2025) mention it with limited analysis. This project aims to provide conceptual clarity.

The prevailing metaphor for slop is pollution — a form of informational debris that, while not necessarily false, overwhelms meaningful discourse. It is linked to spam (computer science), bullshit (philosophy), and broader forms of information disorder (Wardle & Derakhshan, 2017). Unlike misinformation, slop is not always factually wrong but is often perceived as unauthentic or vacuous.

AI slop thrives in environments where plausibility is prioritized over accuracy and volume trumps quality. But the phenomenon is not new; humans have long generated meaningless content for profit: content farms, paper mills, clickbait, fake reviews, SEO traps, and more.

Examples of slop

- **“Shrimp Jesus”**: surreal AI-generated Facebook images spreading for engagement (Placido, 2024)
- **“Vegetative electron microscopy”**: nonsensical term in fraudulent scientific papers (Joelving, 2025)
- **Clarkesworld magazine**: flooded with AI-generated stories, halting submissions (Clarke, 2024)
- **Fake Amazon products**: listings with AI errors in titles (Tangermann, 2025)

Vulnerable Systems

Submission-based systems are especially at risk:

- Bug reports and open source projects (Purdy, 2025)
- Job/fellowship applications (Hoover, 2025)
- Publishing and literary contests (Clarke, 2023)
- Academic papers and grants (Tran, 2023)

Media and cultural studies

Related concepts:

- **Post-truth**: Facts replaced by beliefs (Oxford Languages, 2016)
- **Enshittification**: Platforms deteriorate to extract value (Doctorow, 2023)
- **Dead Internet Theory**: Bots dominate online content (Muzumdar, 2025)
- **Infodemic**: Crisis-driven information glut (World Health Organization, n.d.)
- **Curation**: Required to manage overload

Interest in fake news and misinformation surged post-2016, often described in terms of infection, contamination and flooding. AI intensifies this, threatening to exacerbate information overload.

People are scared of fake news (Barthel, 2016; Cellan-Jones, 2017; World Economic Forum, 2024).

Ironically, information about misinformation is often misleading. While evidence suggests that fake news are not so problematic (Stockwell, 2024; Allen et al. 2020; Arguedas et al, 2022), organizations tackling this issue are still subject to the pressures that generate misinformation. Vendors of technical solutions and academics alike lean into the perceived risk.

This suggests that the true aim of the initiative is not to “neutralize the poison,” but rather to enhance the perception of trust within the information environment. Misinformation should be approached as a complex issue that resists

simple technical fixes for deeply rooted social problems (Singh 2024). While tools like detection algorithms may offer some assistance, they should be seen as just one component within a broader interdisciplinary strategy.

Slop operates like disinformation (Illing, 2020; Wardle & Derakhshan, 2017) in spreading confusing, repetitive, and low-value content. Market incentives — from click-driven ad revenue to “publish or perish” academia — fuel the production of slop (Knibbs, 2024; Labbé et al., 2025).

The tension is echoed in AI ethics: AI content is capable not only of being deceptive, but highly persuasive (Chen & Shu, 2024; Costello et al., 2024). Simultaneously, mystifying the technology helps maintain its allure and its perceived threat (Tully et al., 2025; Carpenter, 2024), reinforcing the cycle.

Information integrity

See Appendix C for products and organizations in AI detection, fact checking and scientific integrity.

The tooling ecosystem highlights the difference between customer-facing software which informs interpretation of sources and the automated decision making implementation required by social media and search engines.

- **AI Detectors:** Tools like GPTZero and Pangram exist but are imperfect (Weber-Wulff et al., 2023; Sadasivan et al., 2023). Slop’s low effort makes concealment less common.
- **Fake News:** Mostly addressed through source credibility instead of textual analysis (Peters, 2022), which raises concerns about bias (Cameron, 2016).
- **Spam Filters:** Google favors high-quality content regardless of it is machine-generated or not (Google Search Central, 2023; Gomes, 2017).
- **Content Farms:** Identified by traits like AI refusal boilerplate, generic domains, and SEO-driven repackaging (Peters, 2022).
- **Paper Mills:** Targeted using linguistic fingerprints, paraphrase artifacts, and citations to retracted work (Cabanac, 2021).

Philosophy and psychology

See Appendix D and E for foundational texts and psychological scales.

Bullshit is discourse indifferent to truth-value, focusing on impression rather than accuracy (Frankfurt, 2009; Cohen 2004; Easwaran,). This differs from lying (intentional falsehood) and applies well to AI-generated content. AI systems “hallucinate” but are better understood as bullshitting - generating plausible-sounding text without regard for truth (Hicks et al., 2024). This extends to users generating text for others (homework cheating) and potentially “bullshitting themselves” through AI assistance (Prada, 2025).

In psychology, the scientific study of bullshit typically focuses on susceptibility scales and their relationship to related phenomena such as fake news. This approach defines bullshit as *unclarifiable* content, deliberately sidestepping the philosophical emphasis on the speaker’s intent—specifically, the lack of concern for truth. Similarly, the notion of “slop” hinges largely on the reader’s perception of inauthenticity, and may even be measurable through indicators of writing quality (Chakrabarty et al., 2025). Research on “pseudoprofound bullshit” (Pennycook et al., 2015; Čavojová, 2022) demonstrates that individuals differ in their receptivity to meaningless yet superficially impressive statements. Higher susceptibility is associated with lower analytical thinking, greater reliance on intuition, endorsement of epistemically suspect beliefs, and diminished scientific literacy.

Cognitive psychology approaches epistemically suspect beliefs through the lens of heuristics and biases (Kahneman & Tversky, 1974), conceptual metaphors and frames (Lakoff & Johnson, 2008), and motivated reasoning. These same cognitive mechanisms may help explain susceptibility to slop, particularly in relation to phenomena such as the illusory truth effect (where repeated exposure increases perceived truthfulness), confirmation bias (the tendency to favor information that confirms existing beliefs), and information overload (where emotionally charged content captures limited attention resources).

This body of literature frames bias as the exploitation of vulnerabilities in human rationality (Pennycook & Rand, 2019a; Klineciewicz et al., 2025; Wardle & Derakhshan, 2017; Muzumdar et al., 2025). However, it often neglects the performative and emotional dimensions of communication—treating misinformation primarily as a problem of information transfer rather than as a socially and affectively embedded practice (Wardle & Derakhshan, 2017). Moreover, this perspective tends to reflect the researchers’ own epistemic assumptions and preferred thought-styles, a critique that has also been raised in disciplines such as economics (Infante et al., 2016) and sociology (Barker, 2011).

Dataset and Detection Strategy

See Appendix B for sources of slop for the creation of a dataset.

See Appendix F for archives, datasets and data sources for fake news, rumours, hate speech, nonsense, bullshit, politics, corporate jargon, dadaism, quote aggregators, new age blogs, conspiracy theories, scams, fringe beliefs, thought leaders, etc.

Scope

- Focus on text, not images
- Audience-facing: Not personal use
- Ambiguity: Not outright falsehoods or illegal content
- Detection over intervention

- Asynchronous instead of real-time detection
- Content-level analysis instead of contextual analysis
- Motivated but non-expert users

Data Sources

Slop:

- Retracted scientific papers
- Content farm articles
- AI-generated submissions to magazines
- Papers with known AI fingerprints

Not slop:

- Wikipedia
- Peer-reviewed papers
- Reputable journalism
- Literary classics
- Algorithmic nonsense (Mathgen)
- Authentic rhetoric (politics, advertisement, thought leadership)

Technical considerations

See Appendix E for linguistic and statistical metrics, deep learning interpretability techniques and relevant tooling

NLP classification tasks can be broadly divided into those with objectively verifiable answers—such as fake news detection or identifying machine-generated content—and those that lack clear ground truth, including rumours, hate speech, stereotypes, clickbait, and spam. *Slop* falls into this latter category, which presents significant challenges for data collection and labeling. In such cases, fine-grained, multidimensional labeling schemes may be more appropriate than binary classifications, as seen in datasets like LIAR, NELA, and SARC.

Methods for detecting AI-generated text generally fall into three categories: linguistic pattern analysis, statistical methods, and fact verification (Tang et al., 2023). Other taxonomies make similar distinctions, categorizing approaches by stylistic, complexity-based, and psychological features (Aich et al., 2022). While identifying linguistic patterns in slop is valuable in itself, the highest performance on such detection tasks tends to come from fine-tuned deep learning models (King et al., 2024; Chakrabarty et al., 2025; Chen & Shu, 2024).

However, deep learning models introduce issues of interpretability—particularly problematic in contexts involving algorithmic decision-making and subjective, bias-prone judgments. Evidence suggests that black-box interpretability methods often yield suboptimal or misleading results (Heap et al., 2025; Gonen & Goldberg, 2019).

Current approaches to similar tasks include (Doughman et al., 2024; Wang et al., 2024) prompting LLMs for analysis (Chen & Shu, 2024), machine learning classifiers (LR-GLTR), and fine-tuned deep learning models (RoBERTa-M4). Evaluation includes cross-domain testing, interpretability (SHAP/LIME), and human annotation.

Challenges and Opportunities

Challenges:

- **Subjectivity:** What constitutes slop varies by context and viewer
- **Domain dependence:** Models may not generalize across topics/formats (Fortuna et al., 2022)
- **Adversarial nature:** Producers actively try to avoid detection
- **Annotation difficulty:** Creating reliable ground truth labels

Opportunities:

- **Novel Area:** Computational bullshit detection is understudied
- **Practical Utility:** Educators, editors, and publishers need solutions
- **Interdisciplinary Scope:** Involves computer science, psychology, philosophy, and media studies
- **Real-World Impact:** Potential address real problems

Research Gaps:

- No established slop dataset exists
- Limited computational approaches to bullshit detection
- Need for interpretable, generalizable models

Conclusion

AI slop is a novel form of information pollution that demands dedicated research. Unlike fake news or spam, slop is defined by its low-effort, often meaningless nature. This project seeks to:

This project aims to:

1. Create the first annotated slop dataset
2. Develop robust and interpretable detection methods
3. Establish computational frameworks for bullshit detection

With clear theoretical grounding and practical application, the project aims to shape discourse on AI content quality and offer tools for those curating the digital information landscape. The work addresses urgent needs in academic integrity, content moderation, and information reliability while contributing to computational approaches to philosophical concepts. It can be considered successful if its slop definition contributes to the conversation on AI-generated

content quality and the technical artifact generated is adopted by its target audience (publishers, educators, recruiters, or content moderators).

Word Count: This document contains 1800 words (without supplementary material and references).

AI Disclaimer: AI tools (ChatGPT, NotebookLM, ResearchRabbit) were extensively used for formatting, summarization, and research.

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Appendix A - Slop Literature

Preprints

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Appendix B - Sources of slop

Science integrity

- PPS flagged papers: PubPeer - Acknowledgement to reviewers (2015)
- Retraction watch data: crossref / retraction-watch-data · GitLab
- PPS data: [PPS – Problematic Paper Screener](https://dbrech.irit.fr/pls/apex/f?p=9999:1::::)
- Beall’s List of Potential Predatory Journals and Publishers
- The Tadpole Paper Mill – Science Integrity Digest

Journalism

- Newsguard:
 - Famadillo. Com
 - GetIntoKnowledge. Com
 - BestBudgetUSA. Com
 - HarmonyHustle. Com
 - HistoryFact. In
 - CountyLocalNews. Com
 - TNewsNetwork. Com
 - CelebritiesDeaths. Com
 - WaveFunction. Info
 - ScoopEarth. Com
 - FilthyLucre. Com
 - Biz Breaking News
 - News Live 79
 - Daily Business Post
 - Market News Reports
- Synthetic Echo
 - Espn24. Co. Uk
 - NbcSportz. Com
 - NbcSport. Co. Uk
 - Cbsnewz. Com
 - Cbsnews2. Com
 - BbcSportss. Co. Uk
 - 247bbcnews. Com
 - Foxnigeria. Com. Ng
- Confessions of an AI Clickbait Kingpin | WIRED
 - <http://thehairpin.com>

- <http://antoniocarluccio.com>
- <http://pope2you.net>
- <http://trumpplaza.com>
- <http://thefrisky.com>
- Slop books: Publishing.ai
- AI influencers: AnnaIndianaAI
- Artificial Intelligence Incident Database

Appendix C - Products and organizations

AI detectors

- **GPTZero**
- **Pangram**
- BurhanUITayyab/GPTZero: An open-source implementation of GPTZero
- Perplexity of fixed-length models
- Oct4Pie/zero-zerogpt: Bypassing AI Content Detectors
- Zapier: Sapling, Winston AI, ZeroGPT, GPTZero, Copyleaks, Smodin
-

Information Reliability

- **Reporters’ Lab Tech and Check:** Fact-Check Insights, MediaVault, ClaimReview, MediaReview, Squash, Alerts, FactStream,
- **NewsGuard:** Reliability ratings, misinformation fingerprints, AI Safety.
- **Meedan**
- NewsCord
- Newswhip: Spike, Analytics, API, Patents
- Aos Fatos: Radar, Fátima
- MBFC’s Data API
- The Trust Project
- Hamilton 2.0
- ClaimBuster
- FakeOut

PolitiFact, **Full Fact**, ProPublica, The Markup, bellingscat, Open Knowledge Brasil, The Bureau of Investigative Journalism (TBIJ), Centre for Investigative Journalism (CIJ), Agência Pública, The Pudding, AllSides, Ground News

Science integrity

- **Problematic Paper Screener**
- **ClearSkies**
- Seek & Blastn
- ImageTwin
- Argos
- Morressier

- Signals
- Plagiarism detection tools – Science Integrity Digest
- Image checking tools – Science Integrity Digest
- List of science integrity resources

Nonprofits and research

- **First Draft**
- **Data & Society**
- Google News Lab

Third-parties & implementation

- TextureAI
- Storyzy
- Bad Idea Factory: truth goggles, talking point trackers
- Ridgeway Information
- Dimensions AI

Appendix D - Philosophy

Bullshit

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Appendix E - Psychology

Scales

- Pseudo-Profound Bullshit Receptivity Scale
- Scientific Bullshit Receptivity Scale
- Belief in Science Scale
- Social and Economic Conservatism Scale
- Free Market Belief Scale
- Faith in Intuition Scale
- Need for Cognition Scale
- Science Literacy Scale
- Acquiescence Bias Measure
- Social and Economic Conservatism Scale
- General Bullshit Receptivity Scale (GBRS)
- New (Non-Transcendental) Bullshit Receptivity Scale (NBSR)
- Bullshit Receptivity Scale (BSR)
- Epistemically Suspect Beliefs Scale (ESB)
- Conspiracy Mentality Questionnaire (CMQ)
- Pseudoscientific Beliefs (PSB)
- Paranormal Belief Scale (PBS)
- Ontological Confusion (OC)
- Analytic Thinking (CRT)
- Big Five Inventory (BFI) – Extra-Short Version
- Daily Spiritual Experience Scale (DSES) – Shortened Version

Papers

Defrancesco, E., & Strapparava, C. (2023). *The PBSDS: A dataset for the detection of pseudoprofound bullshit*. <https://cris.fbk.eu/handle/11582/343408>

Evans, A., Sleegers, W., & Mlakar, Ž. (2020). Individual differences in receptivity to scientific bullshit. *Judgment and Decision Making*, 15(3), 401–412. <https://doi.org/10.1017/S1930297500007191>

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Appendix F - Detection and Metrics

Linguistic & Stylistic Analysis

Task	Description	Tool (s)
POS tagging	Identifies part-of-speech (nouns, verbs, etc.)	spaCy, nltk
Dependency parsing	Analyzes syntactic relationships between words	spaCy
Function word usage	Frequency of articles, prepositions, conjunctions	spaCy, textdescriptives, custom counts
Sentence length / complexity	Measures sentence structure and depth	textdescriptives, textstat, spaCy
Average word length	Basic lexical sophistication metric	textdescriptives, custom
Vocabulary size / density	Lexical diversity and information richness	textdescriptives, trunajod, lexicalrichness
Character n-grams	Stylometric fingerprinting based on sequences of characters	scikit-learn, nltk
Stylometry (repetitiveness, etc.)	Measures text style, redundancy, and structure	trunajod, textdescriptives, textstat
Readability	Calculates metrics like Flesch-Kincaid, Gunning Fog	textstat
Burrows' Delta	Stylometric distance based on function words	linguistic-features, custom

Semantic & Emotional Content

Task	Description	Tool (s)
Sentiment analysis	Positive, negative, or neutral tone	<code>nltk.vader</code> , <code>TextBlob</code> , <code>spaCy</code> , <code>transformers</code>
Emotion detection	Extracts emotions like joy, anger, sadness	<code>text2emotion</code> , <code>NRCLEX</code> , <code>affectpy</code>
Topic modeling	Identifies main topics/themes in text	<code>gensim.LDA</code> , <code>BERTopic</code>
Topic entropy	Entropy over topic distribution (topic coherence)	<code>scipy.stats.entropy</code> + topic probabilities

Statistical & Distributional Features

Task	Description	Tool (s)
TF-IDF vectorization	Weighs word importance relative to a corpus	<code>scikit-learn</code>
Jaccard similarity	Token-based set similarity between texts	<code>scikit-learn</code> , <code>nltk</code> , <code>rapidfuzz</code>
Cosine similarity (Embeddings)	Semantic similarity between text vectors	<code>sentence-transformers</code> , <code>scikit-learn</code>
Fuzzy string matching	Approximate text comparison	<code>rapidfuzz</code> , <code>fuzzywuzzy</code>
Perplexity	Measures how predictable a text is (lower = more fluent)	<code>transformers</code> (GPT-2/3 models)
Zipf's Law	Word frequency distribution conformity	<code>powerlaw</code> , custom
Shannon entropy	Measures lexical randomness/complexity	<code>scipy.stats.entropy</code> , custom
KL divergence	Divergence between two probability distributions	<code>scipy.stats.entropy</code> , <code>numpy</code>
Jensen-Shannon divergence	Symmetrized, bounded version of KL divergence	<code>scipy</code> , custom
Likelihood ratios / Bayesian	Probabilistic comparisons or classification	<code>scikit-learn</code> , <code>pymc</code> , <code>pyro</code>

Authorship & Fact-Checking

Task	Description	Tool (s)
Stylometric authorship detection	Measures author's stylistic fingerprint	<code>trunajod</code> , <code>JStylo</code> (Java), <code>stylo</code> (R), custom

Sources:

Chen, C., Wang, H., Shapiro, M., Xiao, Y., Wang, F., & Shu, K. (2022). *Combating Health Misinformation in Social Media: Characterization, Detection, Intervention, and Open Issues* (No. ArXiv: 2211.05289). ArXiv. <https://doi.org/10.48550/arXiv.2211.05289>

Tang, R., Chuang, Y.-N., & Hu, X. (2023). *The Science of Detecting LLM-Generated Texts* (No. ArXiv: 2303.07205). ArXiv. <https://doi.org/10.48550/arXiv.2303.07205>

Linguistic-Based Detection of Fake News in Social Media | Mahyoob | International Journal of English Linguistics | CCSE

Antypas, D., J. Camacho-Collados, A. Preece, and D. Rogers. 2021. “COVID-19 and Misinformation: A Large-Scale Lexical Analysis on Twitter.” In *Proceedings of ACL*.

Stylometric Fake News Detection Based on Natural Language Processing Using Named Entity Recognition: In-Domain and Cross-Domain Analysis

Buchholz, M. G. (2023). *Assessing the Effectiveness of GPT-3 in Detecting False Political Statements: A Case Study on the LIAR Dataset* (No. ArXiv: 2306.08190). ArXiv. <https://doi.org/10.48550/arXiv.2306.08190>

Leon Fröhling and Arkaitz Zubiaga. 2021. Featurebased detection of automated language models: tackling gpt-2, gpt-3 and grover. *PeerJ Computer Science*, 7: e443.

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Aich, A., S. Bhattacharya, and N. Parde. 2022. “Demystifying Neural Fake News Via Linguistic Feature-Based Interpretation.” In *Proceedings of the COLING*.

Mewada, A., & Dewang, R. K. (2023). A comprehensive survey of various methods in opinion spam detection. *Multimedia Tools and Applications*, 82(9), 13199–13239. <https://doi.org/10.1007/s11042-022-13702-5>

Wu, J., Yang, S., Zhan, R., Yuan, Y., Chao, L. S., & Wong, D. F. (2025). A Survey on LLM-Generated Text Detection: Necessity, Methods, and Future Directions. *Computational Linguistics*, 51(1), 275–338. https://doi.org/10.1162/coli_a_00549

Deep learning

Techniques: SHAP, LIME, SAE, Ablation

Aich, A., S. Bhattacharya, and N. Parde. 2022. Demystifying Neural Fake News Via Linguistic Feature-Based Interpretation.

Niven, T., & Kao, H.-Y. (2019). Probing Neural Network Comprehension of Natural Language Arguments.

McCoy, R. T., Pavlick, E., & Linzen, T. (2019). Right for the Wrong Reasons: Diagnosing Syntactic Heuristics in Natural Language Inference

Tools

- GLTR
- LIWC
- GitHub - brucelee/lftk: [BEA @ ACL 2023] General-purpose tool for linguistic features extraction; Tested on readability assessment, essay scoring, fake news detection, hate speech detection, etc.
- TRUNAJOD: A text complexity library for text analysis built on spaCy — TRUNAJOD 0.1.1 documentation
- GitHub - novoic/blabla: Novoic's linguistic feature extraction library
- NLP feature extraction from LIWC in Python | by Shivika K Bisen | Bright AI | Medium
- GitHub - HLasse/TextDescriptives: A Python library for calculating a large variety of metrics from text
- `spacy`, `textdescriptives`, `textstat`, `trunajod`, `linguistic-features`, `nltk`, `textblob`, `text2emotion`, `NRCLEX`, `scikit-learn`, `sentence-transformers`, `transformers`, `scipy`, `powerlaw`, `rapidfuzz`

Surveys on classification tasks

- **Classification in general**
 - london.ac.uk/sites/default/files/study-guides/introduction-to-natural-language-processing.pdf
- **Machine generated content**
 - A Survey on LLM-Generated Text Detection: Necessity, Methods, and Future Directions | Computational Linguistics | MIT Press
- **Misinformation/Disinformation/Fake news/Rumour**
 - A survey on fake news and rumour detection techniques - ScienceDirect
 - [1708.01967] Fake News Detection on Social Media: A Data Mining Perspective
- **Spam**
 - A systematic literature review on spam content detection and classification [PeerJ]
 - A comprehensive survey of various methods in opinion spam detection | Multimedia Tools and Applications
- **Clickbait**
 - Prompt-tuning for Clickbait Detection via Text Summarization
- **Propaganda**
 - [2007.08024] A Survey on Computational Propaganda Detection
- **Hallucination**

- A Survey on Hallucination in Large Language Models: Principles, Taxonomy, Challenges, and Open Questions | ACM Transactions on Information Systems
 - Survey of Hallucination in Natural Language Generation | ACM Computing Surveys
- Deception
 - Intelligent techniques for deception detection: a survey and critical study | Soft Computing
- Hate speech/toxicity/stereotype/offensive language
 - Hate speech, toxicity detection in online social media: a recent survey of state of the art and opportunities | International Journal of Information Security
- Stylometry/authorship attribution
 - Surveying Stylometry Techniques and Applications | ACM Computing Surveys
- Stance
 - [2409.15690] A Survey of Stance Detection on Social Media: New Directions and Perspectives
- Satire/parody
 - Comprehensive Study of Arabic Satirical Article Classification
- Irony/sarcasm
 - Automatic Sarcasm Detection: A Survey: ACM Computing Surveys: Vol 50, No 5
 - A survey of automatic sarcasm detection: Fundamental theories, formulation, datasets, detection methods, and opportunities - ScienceDirect
- Sentiment
 - A survey of automatic sarcasm detection: Fundamental theories, formulation, datasets, detection methods, and opportunities - ScienceDirect
- Stereotype (King et al., 2024)
 -
- Nonsense
 - On the Cusp of Comprehensibility: Can Language Models Distinguish Between Metaphors and Nonsense? - ACL Anthology
- Metaphor
 - A Survey on Computational Metaphor Processing | ACM Computing Surveys
- Pseudoprofound bullshit
 - The PBSDS: A dataset for the detection of pseudoprofound bullshit

Appendix G - Archives and datasets

Curated by me

- Lacan__books: ~10 books by French psychoanalyst Jacques Lacan

- Official tumblr metaphysics repository: ~50 bullshit humour microblogs
- Civitai: ~60k images scraped from an AI image generation website
- Simulacro_db: hand-selected meaningful quotes from philosophy and psychoanalysis books

Generators

- New-Age Bullshit Generator
- InspiroBot
- SCIGen - An Automatic CS Paper Generator (they also have a list)
- Postmodernism Generator

Bullshit datasets

- PBSDS
- ouhenio/llms-overestimate-profoundness
- acmi-lab/pretraining-with-nonsense: Pretraining summarization models using a corpus of nonsense
- New Nonsense BEL Sentence Corpus
- APA PsycNet DoiLanding page

Not bullshit nor slop

- Authors present in the British library gift shop: Shakespeare, Orwell, Jane Austen, Sherlock Holmes, Agathe Christie.
- Well regarded but hard books: Joyce, Ezra Pound, T.S. Eliot, Burroughs.
- Time Magazine's All-Time 100 Novels (100 books)
- Most important papers in science
 - The top 100 papers : Nature News & Comment
 - These are the most-cited research papers of all time
 - Top 100 most cited publications
 - Citation impact - Wikipedia
 - Site Unreachable

Politics

- Trump Claims Database: 30,573 false or misleading claims made by Trump and fact-checked by the Washington Post.
- Declaracoes de Bolsonaro: same with 6685 claims made by Bolsonaro.
- Planalto Discursos e Pronunciamentos: Archive of pronouncements made by Lula from 2023.
- The American Presidency Project: 100,000 documents related to the study of the American presidency, including presidential debates, speeches, state of the union addresses, etc.
- Presidential Speeches | Miller Center: 50 years of U.S. presidential speeches.

- UKPOL: 80,000 speeches and press releases relating to UK politics, as well as a growing number of interviews, book reviews and other political and electoral resources.
- AgoraSpeech: meticulously curated, high-quality dataset of 171 political speeches from six parties during the Greek national elections in 2023
- ParlEE plenary speeches data set: Annotated full-text of 21.6 million sentence-level plenary speeches of eight EU states
- Leadership Studies - Research Guides at Harvard Library
 - American Rhetoric Online Speech Bank: 5000+ full text, audio and video versions of public speeches, sermons, legal proceedings, lectures, debates, interviews, other recorded media events, and a declaration or two. Full text, audio, and video database of the 100 most significant American political speeches of the 20th century.
 - Commission on Presidential Debates: Transcripts from U.S. presidential debates.
 - Great Speeches of the 20th Century: The Guardian and Observer's unique series of the best speeches of the last century.
 - Speeches at the United Nations: Speeches held before the United Nations dating back to 1946.
 - Living Room Candidate: Presidential Campaign Commercials, 1954-2012.
 - Say It Plain, Say it Loud: speeches by U.S. black leaders.
 - UN Peacekeeping - Speeches & Statements: Latest press releases, speeches, and statements from senior officials on UN Peacekeeping.
 - Trump datasets
 - * ichalkiad/datadescriptor_uselections2020
 - * alexmill/trump_transcripts
 - * christianlillelund/donald-trumps-rallies
 - * etaifour/trump-speeches-audio-and-word-transcription
 - * ryanmcdermott/trump-speeches
 - * tuenguyen/trump-speech-dataset-tts

Corporate jargon

- Manual search through SEO farms and small lists
- <https://www.buzzwordbingogame.com/>
- <http://officeipsum.com/>
- Corporate Ipsum Gobbledygook Generator
- <https://www.buzzwordipsum.com/>
- The Dictionary of Corporate Bullshit
- The BS Dictionary: Uncovering the Origins and True Meanings of Business Speak : Wiltfong, Bob, Ito, Tim: Amazon.co.uk: Books
- The Business Bullshit Book
- Who Touched Base in my Thought Shower?

Dadaism

- Category:Dada - Wikimedia Commons
- Wikipedia:The Wikipedia Library - Wikipedia
- HathiTrust Digital Library – Millions of books online
- Dada (published from Zürich and Paris), The Blind Man, Rongwrong, New York Dada, 391 (published in multiple cities), Club Dada, Der Dada, Everyman His Own Football, Dada Almanach, Le Cannibale, Littérature, De Stijl (which included Dada poetry), Mécano, and The Next Call.
- Manifestos, Cut-up technique, Sound Poetry
- Tristan Tzara, Hugo Ball, Richard Huelsenbeck, Mina Loy, Louis Aragon, Paul Eluard, Philippe Soupault, Georges Ribemont-Dessaignes, and Walter Serner. Mina Loy. Iliazd

Public domain fringe belief primary texts:

- Helena Blavatsky – *The Secret Doctrine*
- Ignatius Donnelly – *Atlantis: The Antediluvian World*
- Charles Fort – *The Book of the Damned*
- James Churchward – *The Lost Continent of Mu*
- Albert Churchward – *The Origin and Evolution of the Human Race*
- Godfrey Higgins – *Anacalypsis*
- Giordano Bruno – *The Ash Wednesday Supper*
- William Scott-Elliot – *The Story of Atlantis and the Lost Lemuria*
- **H. Spencer Lewis – _Self Mastery and Fate with the Cycles of Life

Quote aggregators

Wikiquote, BrainyQuote, Goodreads, Quote Garden, QuoteFancy, r/QuotesPorn, Wisdom Quotes, The Quotations Page, Quote Master, Bartlett's Familiar Quotations, Quotes.net, Thoughtco

New Age blogs and websites

Spirit Library, Wake Up World, In5D, The Mind Unleashed, Collective Evolution, Gaia, Elephant Journal, LonerWolf, Mystic Mamma, The Numinous, Healing Energy Tools, Zentasia, The Explorer Lounge

Fringe beliefs

Unarius, Time Cube, John Titor, Francis E. Dec, Children of the Matrix, Ramtha's School of Enlightenment, Emerald Tablet, Emerald Tablets of Thoth, Pseudolaw, Montauk Project, Timewave Zero, Pathwork, Core Energetics, The Final Theory

Authors, influencers and thought-leaders

Deepak Chopra, Eckhart Tolle, Esther Hicks / Abraham-Hicks, Rhonda Byrne, Gregg Braden, Teal Swan, Dolores Cannon, Neale Donald Walsch, Caroline Myss, Don Miguel Ruiz, Louise Hay, Joe Dispenza, Sri Sri Ravi Shankar, Byron Katie, Alan Watts

Motivational speakers

Tony Robbins (Awaken the Giant Within), Les Brown (It's Not Over Until You Win), Eric Thomas (You Owe You), Brené Brown (The Power of Vulnerability), Simon Sinek (Start With Why), Mel Robbins (The 5 Second Rule), Nick Vujicic (Life Without Limits), Jay Shetty (Think Like a Monk)

Machine Learning Datasets

- Human text: The Pile, OpenWebText, RealNews, ELI5, Enron, BNC, LOB, English Corpora
- AI-generated text: GPT-2 Output, HC3, HC3 GitHub, MULTITuDE, MAGE, TURINGBENCH, M4, OUTFOX, IDMGSP, MGTBench, LLM Detect, 150K Wikipedia GPT, Slop Cloud, Suno Prompts, Song Lyrics Genius
- Rumour: PHEME, Weibo, Twitter15, Twitter16, Multimodal RNN, WeiboRumours, CRED BANK, CED, STANKER, Weibo20, UCINLP COVID-19, ESOC COVID-19
- Hate speech: EMGSD, Chess, SemEval-2019 Task 5, Dynabench, OLID, SOLID, HateXplain, HateCheck, English Hate Speech Superset
- Deception: UNIDECOR, Deceptive Opinion Spam, Deceptive Opinion Paper, Mafiascum, SARC, iSarcasm, DeFaBel
- Hallucination: awesome-hallucination-detection (archive), DelucionQA, DefAn, HaDes, LibreEval, HaluEval, HaluBench
- Conspiracy: COCO, ConspEmoLLM, CCRS, YouTube Conspiracy, Anatomy of Conspirators, WICO Graph, Harvard DVN
- Fake news
 - CDL Misinfo Datasets.: ~100 misinfo datasets (archive)
 - Fake news detection: a survey of evaluation datasets [PeerJ]: 27 misinfo datasets (archive)
 - Fake News Datasets | MediaFutures: ~10 misinfo datasets (archive)
 - lzw108/Misinformation-datasets-fakenews-rumors-conspiracy: archive of ~30 datasets (archive)
 - FactCheck Insights: (requires asking) dataset with 200k fact-checks.
 - OpenSources: labelled 1000 news websites
 - LLMFake: This is an LLM-generated misinformation dataset containing nonfactual content created by various LLMs using seven different approaches. (Uses Politifact, CoAID and Gossipcop).
 - FakeNewsNet: BuzzFeedNews + Politifact
 - CoronaVirusFacts Alliance: Coronavirus fact-checking response.

- Survey 1: Arianna D’Ulizia, Maria Chiara Caschera, Fernando Ferri, and Patrizia Grifoni. 2021. Fake news detection: a survey of evaluation datasets. *PeerJ Computer Science* 7 (2021), e518. (archive)
- **LIAR2**: ~23K professionally labeled statements from PolitiFact
- NELA-GT-2019/2020/2022: millions of news articles with outlet-level veracity labels
- FEVER: 200k Wikipedia-based claims labeled as Supported, Refuted, or NotEnoughInfo
- RefChecker