BiasLab: Explainable Political Bias Detection via Dual-Axis Human Annotations and Rationale Indicators

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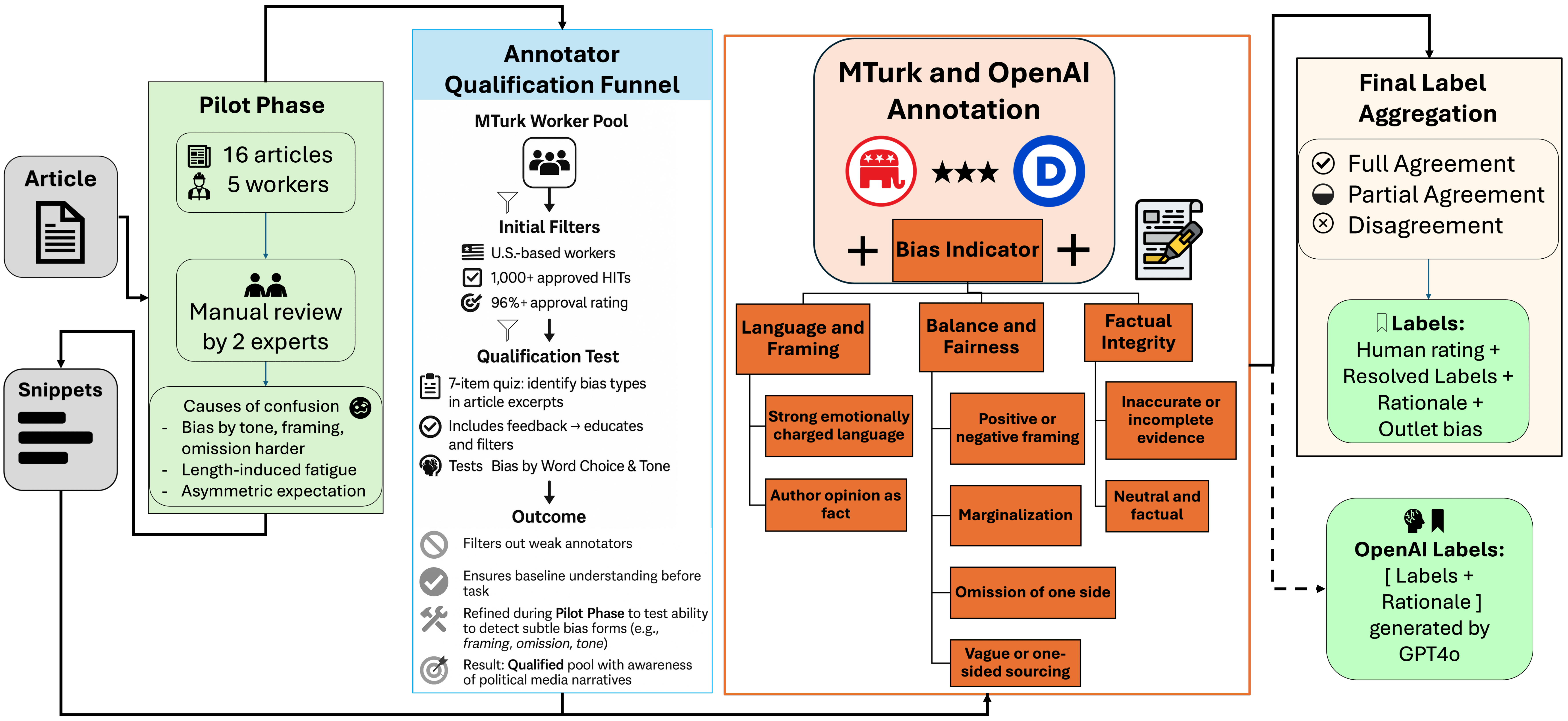
Annotation Pipeline



Article

Snippets

Pilot Phase
16 articles
5 workers
Manual review by 2 experts
Causes of confusion
- Bias by tone, framing, omission harder
- Length-induced fatigue
- Asymmetric expectation

Annotator Qualification Funnel
MTurk Worker Pool
Initial Filters
U.S.-based workers
1,000+ approved HITs
96%+ approval rating
Qualification Test
7-item quiz: identify bias types in article excerpts
Includes feedback → educates and filters
Tests Bias by Word Choice & Tone
Outcome
Filters out weak annotators
Ensures baseline understanding before task
Refined during **Pilot Phase** to test ability to detect subtle bias forms (e.g., *framing, omission, tone*)
Result: **Qualified** pool with awareness of political media narratives

MTurk and OpenAI Annotation
★★★
D
+ Bias Indicator +
Language and Framing
Strong emotionally charged language
Author opinion as fact
Balance and Fairness
Positive or negative framing
Marginalization
Omission of one side
Vague or one-sided sourcing
Factual Integrity
Inaccurate or incomplete evidence
Neutral and factual

Final Label Aggregation
Full Agreement
Partial Agreement
Disagreement
Labels: Human rating + Resolved Labels + Rationale + Outlet bias

OpenAI Labels: [Labels + Rationale] generated by GPT4o

Pipeline overview: *Each article is split into snippets. Annotators rate tone toward both parties and select rationale indicators with highlighted text.*

Dataset Overview

- **900 partisan political articles** curated across major U.S. events (2016–2018)
- **300 articles annotated** via MTurk with dual-axis bias labels for both parties

Dual-Axis Human Ratings

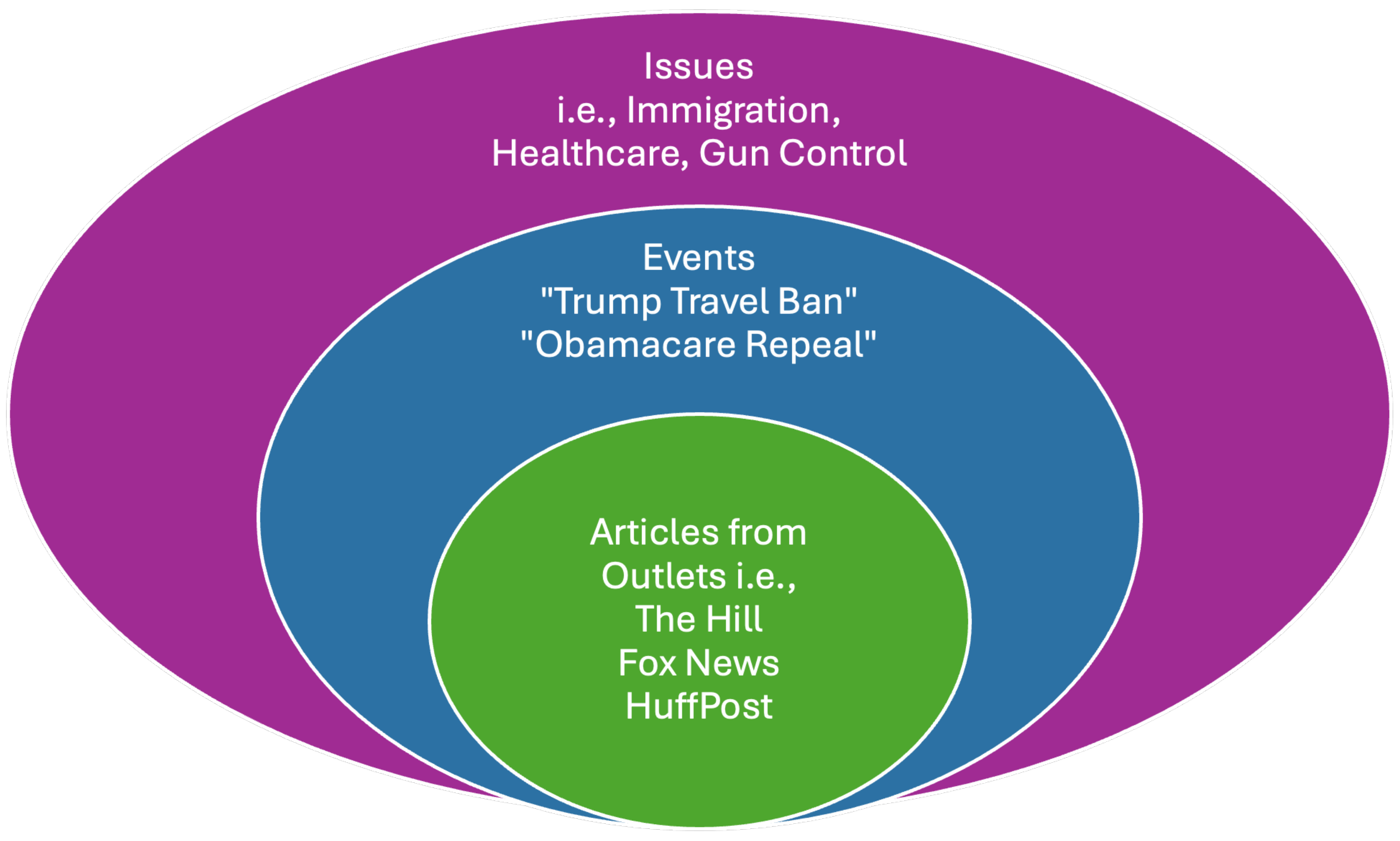
Democratic

Negative	Somewhat Negative	Neutral	Somewhat Positive	Positive

Republican Party

Negative	Somewhat Negative	Neutral	Somewhat Positive	Positive

- Each annotation also includes **bias rationale indicators** (e.g., *labeling, omission, framing*)
- Articles link to event metadata for reuse



Issues
i.e., Immigration, Healthcare, Gun Control
Events
"Trump Travel Ban"
"Obamacare Repeal"
Articles from Outlets i.e.,
The Hill
Fox News
HuffPost

Dataset structure: Articles are nested within events and issue categories.

- **Designed for** alignment, disagreement, and rationale modeling

How BiasLab Captures Perceived Bias

Example Annotation Entry

Title: *Anti-Trump celebs plan 'People's State of the Union'*
Event: President Trump will deliver his first State of the Union

Article Snippet (excerpt):
A group of **Hollywood elites**, *progressive groups, and other Trump opponents are planning a "People's State of the Union" to counter the president's first official address. The event, coordinated by unions, organizers of the Women's March and Planned Parenthood, is being marketed as a celebration of the "resistance," closer to "the people's point of view," USA Today reported.*

Marked Bias Indicators:

- **Marginalization of one side** (Indicator 4): *"A group of Hollywood elites . . . celebration of the resistance"*
- **Emotionally charged language** (Indicator 0): *"Hollywood elites," "social activists," "public alternative"*

Worker Labels: Right, Right
Final Human Label: Right
Outlet Bias: Right

Key Takeaways

Perceived bias ≠ Outlet ideology
More prevalent for subtle right-leaning content

- **Snippet-level tone + Rationale** annotations help expose interpretive judgments
- GPT-4o mimics both strengths and blind spots in human bias judgment
- Structured annotations support **alignment** and **interpretability modeling**, not just classification

Usable for critique modeling, alignment feedback, explainability tasks, and temporal drift analysis.

Dataset, Paper and Code

H.A.R.M.O.N.I. Lab
Human-Aligned, Resilient, Multimodal, Open-ended, Novelty-Informed Intelligence