Toward a semi-automated item nonresponse detector model for open-response data

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Outline

- Background and context
  - COVID-19 pandemic
  - Open-text data: value and challenges
  - Item nonresponse detection: the technology and development of the model
- Evaluating the model: our approach
- Evaluation results
- Discussion/Next steps

Background and context

COVID-19 pandemic

- Numerous new COVID-19 related survey items
- Circumstances prevented our usual approach: in-depth cognitive interviewing to inform closed-ended online survey web probes
- Adapted and innovated our methods to include both closed and open-ended probes and experimental designs for post-hoc evaluations

Open-text data: value and challenges

- Range of methodological uses for open-text data (Singer & Couper, 2017)
- Allows for responses without constraint (Schonlau & Couper, 2016) a particular advantage when little is known about a topic (Neuert et al., 2021, Scanlon, 2019; 2020)
- But higher response burden, more prone to item nonresponse, inadequate and irrelevant responses
- Coding and analysis can be labor intensive and time-consuming
- Recent advances in data science offer new efficiencies and opportunities

Item nonresponse detection: prior work

- Categorizing item non-response
  - “nonproductive” responses (Behr et al., 2012)
  - Indirect (soft) versus direct (hard) refusals (Meitinger et al., 2021)

Item nonresponse detection: prior work, cont'd

- Detecting item non-response
  - EvalAnswer* (Kaczmirek et al. (2017); available on GitHub)
    - **Complete non-response**: blank text box
    - **No useful answer**: "dfgjh"
    - **Don't knows**: "I have no idea"; "DK"; "I can't make up my mind"
    - **Refusals**: "no comment"; "see answer above"
    - **Other**: insufficient to code; "it depends"; "just do"; "just what it is"
    - **Single word**: "economy"
    - **Too fast**: < 2 seconds to answer

* https://git.gesis.org/surveymethods/evalanswer

Item nonresponse detection: prior work, cont’d

- Limitations of EvalAnswer
  - Relies on regular expressions (regex)
  - Missed some gibberish and don't know responses: "I dunno“; "no clue“
  - Flagged single word responses that are valid: "quarantine“; "furloughed“; "closings“
  - Flagged valid responses that include one of the rules:
    - “I have not bee unable to travel to see my grandsons who live away from me. I am **unsure** how this country is going to fare.” [emphasis added]
  - Marked some non-response as valid:
    - "this is not a good question“; "I think my answer is self explanatory"

Item nonresponse detection: Model development

- Trained a natural language processing (NLP) model to interpret responses.
  - Fine-tuned a Bidirectional Transformer for Language Understanding (BERT)* model using Simple Contrastive Sentence Embedding (SimCSE)**
- Refined training via human coding (active learning)

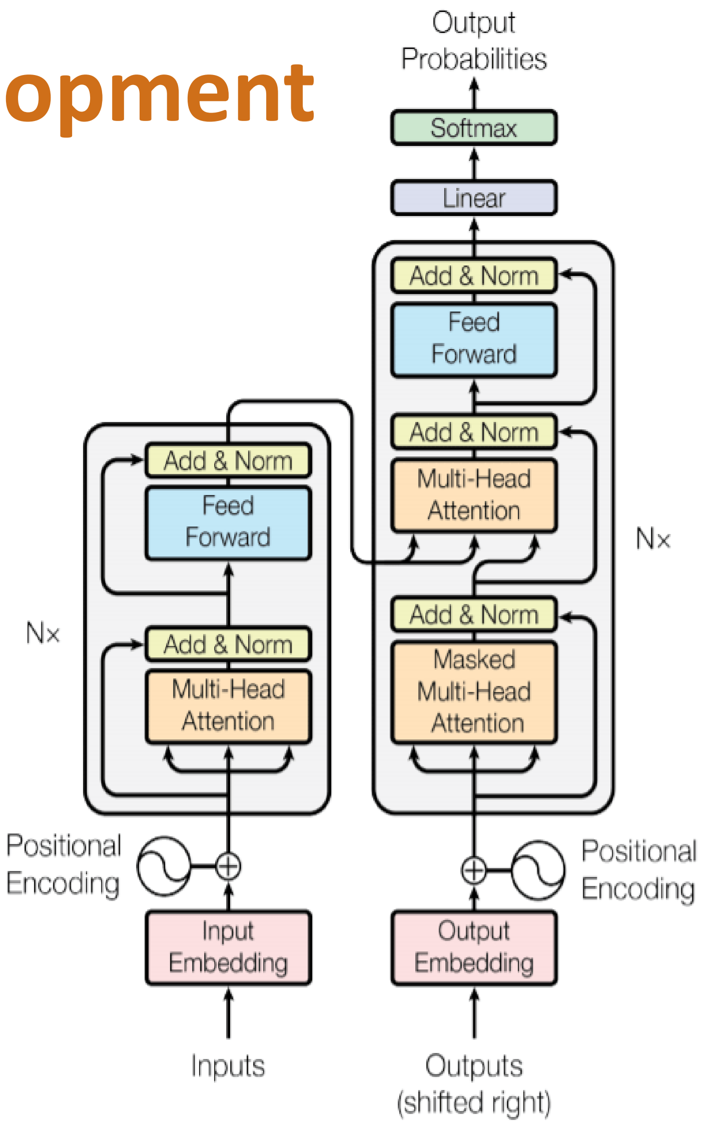


Figure 1: The Transformer - model architecture.

* https://arxiv.org/abs/1810.04805

** https://arxiv.org/abs/2104.08821

Item nonresponse detection: Model development, cont’d

- Our working taxonomy:
  - **Complete non-response**: Blank text box
  - **Gibberish** or nonsensical: “dfgjh”
  - **Don’t knows**: “I don’t know”; DK; idk
  - **Refusals**: “no comment”; “Because”; “none”
  - **Other, high-risk**: non-useful response, non-codable
  - **Valid**: useful response, codable
- The model assigns a score (0-1) for the extent to which a response falls into each of the item non-response categories

Model development: Active learning

- Round 1
  - 5 coders hand-coded 1,400 each, 200 overlapping with one other coder; full overlap for 500
  - Good consistency with most categories (gibberish, DKs, refusals)
  - Less consistency between valid versus “other, high risk” item nonresponse
  - Good results for identifying item nonresponse, but flagged more valids than we wanted
- Round 2:
  - 2 coders reviewed and arbitrated the results to retrain the model
  - Uncertainty retained in the model when warranted

The data

- NCHS's Research and Development Survey (RANDS)
https://www.cdc.gov/nchs/rands/index.htm
- RANDS During COVID-19 – Multi-round web/phone survey
- Topics: health, impacts of pandemic on health care access, COVID-19 related health care and behaviors
- Conducted using NORC at the University of Chicago's AmeriSpeak®, a probability-based panel representative of the US adult, English-speaking, non-institutionalized household population.
- Round 3 fielded May – June 2021: 5,458 Completes
    - 7,852 NORC's AmeriSpeak probability-based sample = 11.8% weighted cumulative response rate/69.5% completion rate

Model evaluation: our approach

Model evaluation: Phase 1

- Mixed-method evaluation of two web probe case studies
  - Quarantine probe (hand-coded data as source of truth)
  - Pandemic time reference probe (hand-reviewed sample as source of truth)
- Results (presented at AAPOR 2022)
  - Model did well at identifying “true” valids (high specificity); slightly less well identifying “true” item nonresponse (good sensitivity)
  - Outstanding issues:
    - Issue with false valid responses – “None”, “none”
    - How well would the model perform on other non-COVID-19 related topics?
  - Subsequently, we retrained the model and carried out a Phase 2 evaluation

Model evaluation: Phase 2

- Mixed-method evaluation of additional web probe case studies
  - Social distancing
  - Religion (new topic)

Evaluation results

Social distancing probe

- Social distancing survey questions:
  - In the last week, did you socially distance when you were…shopping, eating at a restaurant, etc. (total 7 randomized grid items)
  - [If yes, then] Did you do the following activities inside, outside, or both?
- Social distancing probe: When you were answering about social distancing in the previous questions, what were you thinking about?
- Full review of model-identified nonresponse (n=627); random sample (n=1,000) of valids
  - “Implied” sensitivity and specificity calculations

Social distancing probe: evaluation results

	Human-reviewed NR	Human-reviewed Valid	
Model NR	450	177	**627**
Model Valid	100 *= (25/1000)*3985*	3885 *= (975/1000)*3985*	**3985**
Total	**550**	**4062**	**4612**

Key take-away:
Model did a good job identifying "true" valids; slightly less well identifying "true" item nonresponse

Sensitivity **82%** (450/550)

False valids (human-coded NR):

- "Recent activity"
- "EVERYTHING"
- "Being normal"
- "Don't do it as much"
- "Money"
- "I'm tired and I want to go to bed"

Specificity **96%** (3885/4062)

False NR (human-coded valid):

- "Safty" (and variations)
- "Save life"
- "lines in the market"
- "It is necessary but a pain."
- "Courtesy"
- "ITS COMMON CERDICY AND GO WITH THE THROW"

Religion probe

- Religion survey question: Currently, how important is religion in your daily life? (very important, somewhat important, not important)
- Religion probe: Why do you say that?
- Full review of model-identified nonresponse (n=1,250); random sample (n=1,000) of valids
  - "Implied" sensitivity and specificity calculations

Religion probe: evaluation results

	Coded NR	Coded Valid	Total
Model NR	298	952	1250
Model Valid	*33 = (14/1000)*2350*	*2317 = (986/1000)*2350*	2350
Total	331	3269	3600

Key take-away:
Model did a good job identifying "true" item nonresponse; less well identifying "true" valids

Sensitivity **90%** (298/331)

False valids (human-coded NR):

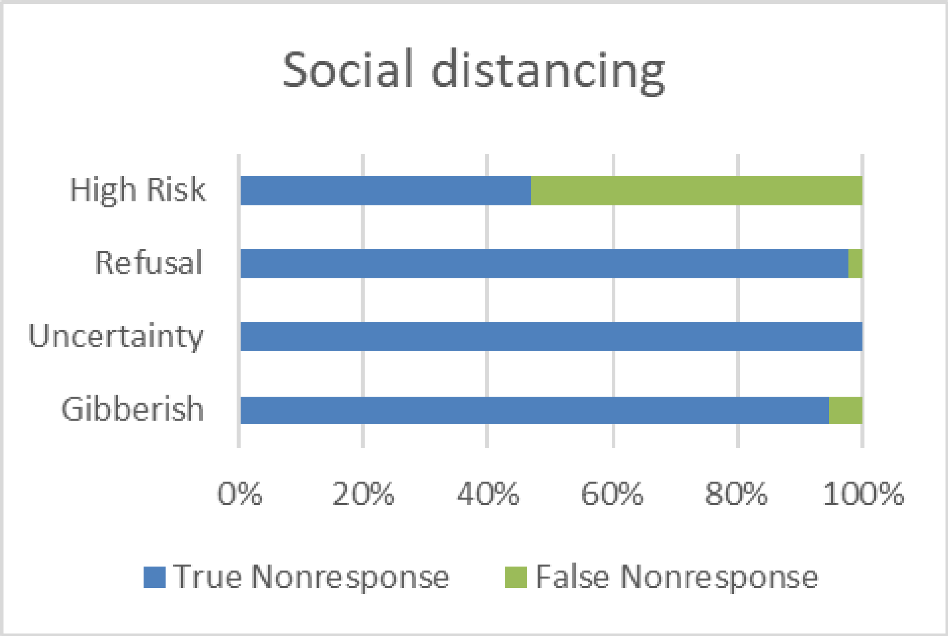
- "you asked me"
- "I JUST FEEL THAT WAY'
- "Guess"
- "Way of life"
- "Believe"

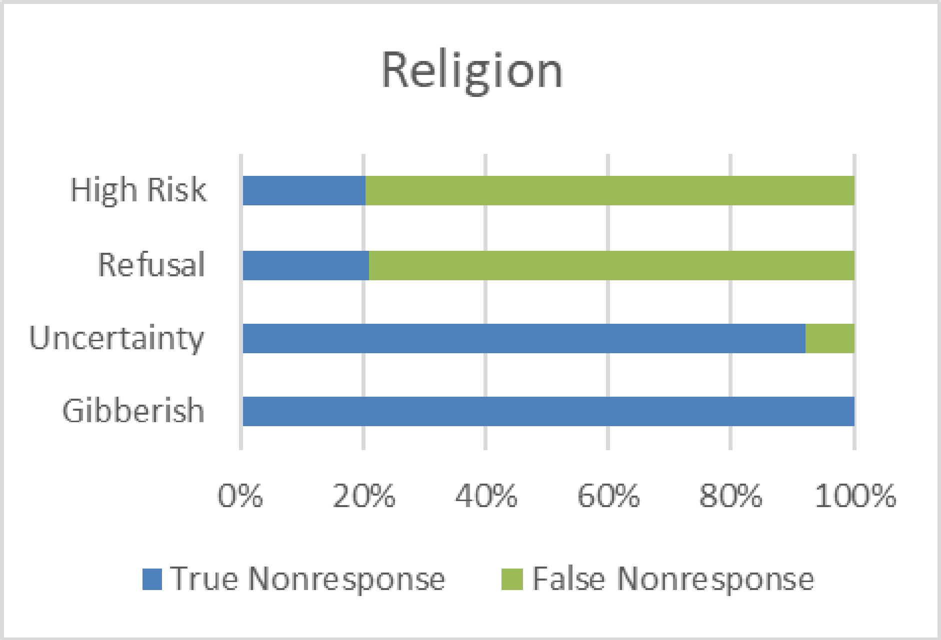
Specificity **71%** (2317/3269)

False NR (human-coded valid):

- "Faith"
- "It brings me peace"
- "I am not a religious person."
- "I worship mother earth. She is important"
- "My religion provides guides for living my life. It encompasses my beliefs, goals and guidelines for living a good and right life."

Distribution by type of item nonresponse





- Model error often concentrated in the High Risk category, as seen for Social distancing
- More error seen in Refusals for Religion

Discussion/next steps

Discussion/next steps

- Evaluation results show promise for our semi-automated item nonresponse detection model
- Next steps:
  - Release of a Semi-Automated Nonresponse Detector (SANDS) – a generalized model to share with others
  - Further evaluation and possible further training to understand and improve model performance on wider range of topics
  - Analysis to better understand the types and patterns of item nonresponse and possible subgroup differences

Thank you!!

- Please contact us with any questions
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For more information, contact CDC
1-800-CDC-INFO (232-4636)
TTY: 1-888-232-6348 www.cdc.gov

For more information contact: Amanda Wilmot awilmot@cdc.gov

Q-Bank: providing access to survey question evaluation reports, question design and performance https://wwwn.cdc.gov/qbank/

Q-Notes: designed to facilitate the management and analysis of cognitive interviews https://www.cdc.gov/nchs/ccqder/products/qnotes.htm

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