NATIONAL CENTER FOR HEALTH STATISTICS

What's in a Name Field?

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Overview

Background

- Data linkage accuracy depends on the quality of the data fields.
- Data review and cleaning are essential to address data quality and improve linkage accuracy.
- Automating the data review and cleaning process reduces time-consuming manual review.

Challenges

- Type of data field (date vs name) affects the level of effort needed for review.
- Name fields may contain **non-name text** that needs to be identified and removed.

Objective

- Examine the use of artificial intelligence (AI) based large language models (LLM) and simple rule-based approaches **to identify non-name text in name fields**.

Methods

Data

- Testing data created with R (v4.1.3 (2022-03-10)) package randomNames.
- Names randomly generated from public data based on sampling gender and ethnicity.
- Name list includes records with valid first and last names (n=9,949).
- Name list supplemented with **non-name text** ("pilot study", "department funded") that might be in survey data/administrative records (n=166).
- Non-name text could appear in first or last name or both
  - » Indicates records that should be flagged for review.

Identification of non-name records

Large Language Models (LLM) with few-shot prompting

- Only applied to last name
  - » Determine how well LLM could do if data leakage was only in one field.
- GPT-3.5 fined tuned from GPT-3 using a process named Reinforcement Learning from Human Feedback to provide better results following instructions.
- Few-shot prompting uses the inherent knowledge present within LLMs adapted to the specific task using in-context learning.
  - » Provide a description of the task at hand, such as "The following are records of names from a form with a data contamination causing other form fields to be saved under the name section. Please classify the following text as an entry in the name category by responding with a 1 or 0. The following are examples:"

AI Chatbot (cdc.gov)

- Only applied to last name
  - » Determine how well LLM could do if data leakage was only in one field.
- Uses GPT-3.5, with training data up to September 2021.
- Name list provided and the following question posed: "Can you identify the words in the list that are not last names?"

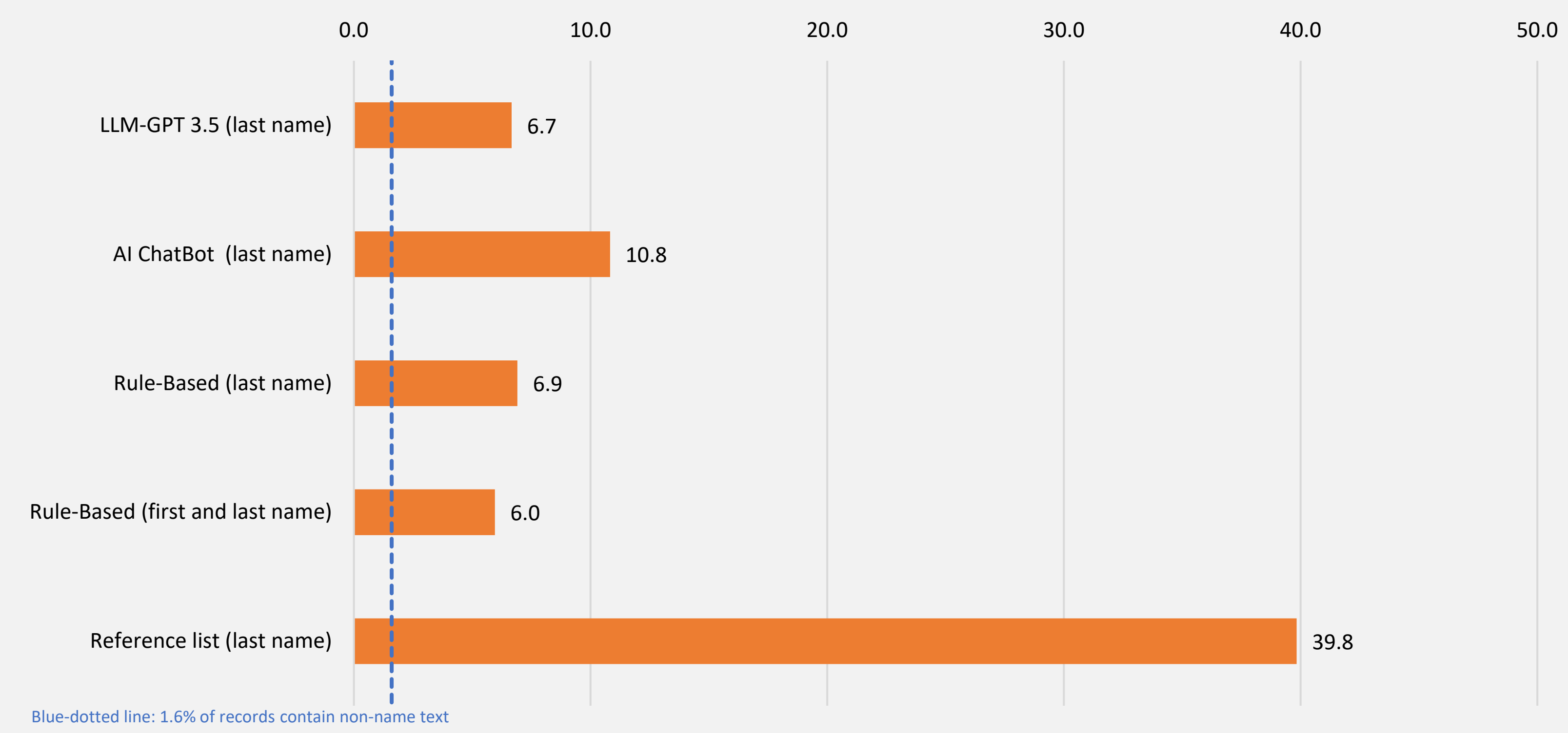
Rule-based

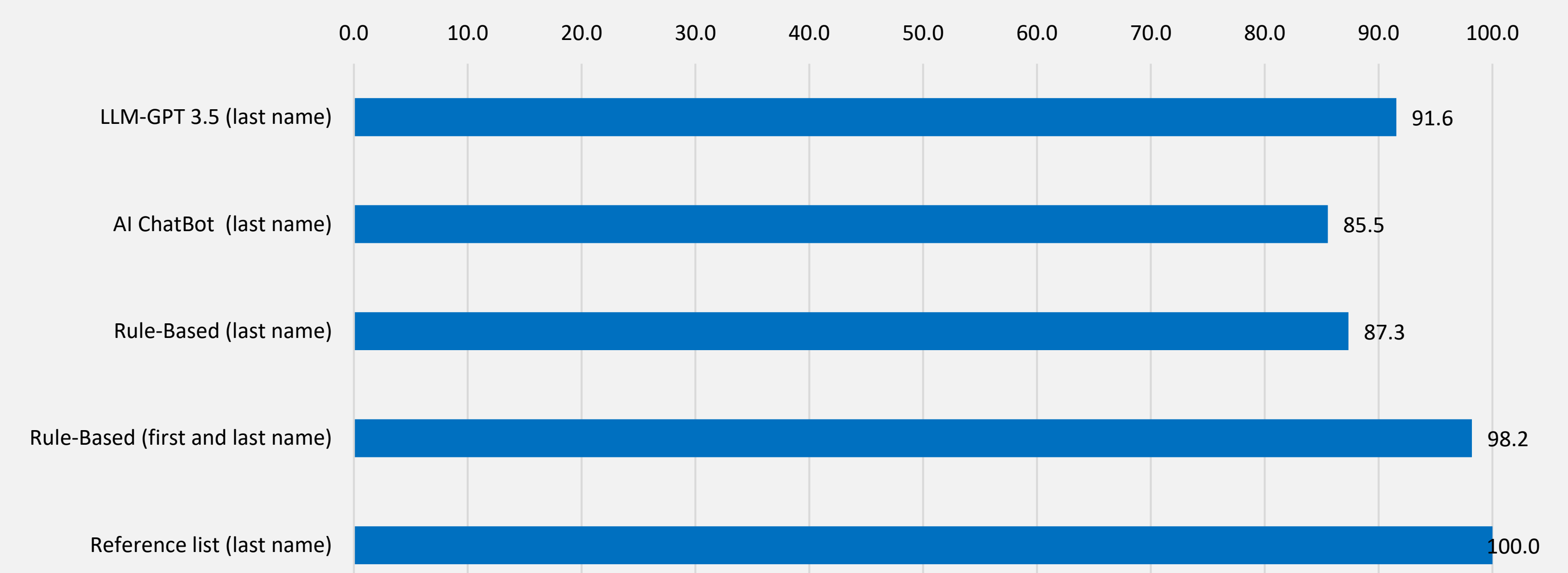
- Applied to both first and last name
- Uses name features – number of words (w) and characters (c)
  - » Last name only: (w>=2 & average c/w<=5) OR w>2 OR total c>11
  - » First and last name: (w>=3 & average c/w<=5) OR w>4 OR total c>19

Comparison with reference list of "valid" last names

Results

Number of records = 10,115 (actual names, n=9,949 / non-name text, n=166)





Types of records that were not flagged when they should have been

- LLM-GPT 3.5 (last name)
  - » Last name field contained both first and last name text and the first name field contained non-name text
- AI Chatbot (last name)
  - » Last name field contained both first and last name text and the first name field contained non-name text
  - » Last name field contained the following text: code, trial a
- Rule-based (last name)
  - » Last name field contained the following text: code, program, radiology
- Rule-based (first and last name)
  - » Last name field contained the following text: code, program, radiology; First name field contains non-name text (two words) : study patient, center study, patient services
- Comparison with reference list of "valid" names (last names)
  - » All records with non-name text flagged
  - » High percentage of false positives (close to 40% of records would require review)

Conclusions

LLM correctly identified over 90% of records with non-name text

- Pros
  - » Potentially easy to automate
  - » Reasonable number of records flagged for review
- Cons
  - » Requires expertise in LLM
  - » Application may not be approved for use with actual PII
  - » Potential issues processing large data sets
  - » Prompts and method of accessing can impact AI performance

AI ChatBot (cdc.gov) correctly identified about 85% of records with non-name text

- Pros
  - » Potentially easy to use
- Cons
  - » Application may not be approved for use with actual PII
  - » Potential issues processing large data sets
  - » Prompts and method of accessing can impact AI performance

Rule-Based (last name) correctly identified about 87% of records with non-name text, while rule-Based (first and last name) correctly identified about 98% of records with non-name text

- Pros
  - » Easy to implement with code
- Cons
  - » Criteria for the flag might change depending on the application

Reference list (last name) correctly identified all records with non-name text, but almost 40% of all records were flagged for review

- Pros
  - » Easy to implement with statistical programming code
- Cons
  - » Heavily dependent on accuracy and quality of the list used
  - » Name lists are not exhaustive and not always readily accessible
  - » Likely to flag an excessive number of records

References

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