# Can machine learning identify untrustworthy clinical trials?



TRANSLATOR
Funded by NIH's National Center for Advancing Translational Sciences

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#### **Introduction to Clinical Trial Data:**

- clinicaltrials.gov is the publicly accessible database managed by the NIH and National Library of Medicine
- Contains over 500,000 trials
- We have > 900 snapshots starting from 2017
- Used in research, but not quality controlled:



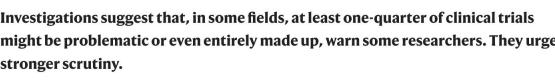
The U.S. government does not review or approve the safety and science of all studies listed on this website.

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"The study **sponsor** or investigator submits information about their study to ClinicalTrials.gov and is **responsible** for the safety, science, and **accuracy** of any study they list"

### **Untrustworthy Trials:**

Medicine is plagued by untrustworthy clinical trials. How many studies are faked or flawed?





nature

- An analysis of 150 randomized control trials showed 44% trials contained "at least some flawed data: impossible statistics, incorrect calculations or duplicated numbers or figures"<sup>2</sup>
- In a review of 110 trials, publication and <u>clinicaltrial.gov</u> information differed, where 80% of secondary outcome and 35% of serious adverse events reporting had inconsistencies<sup>3</sup>

#### **Clinical Trial Data Use in Translator:**

• Translator ingests data from clinicaltrials.gov

Trial is Phase 4 and FDA approved: **assertion** that intervention treats disease

Trial exists in <u>clinicaltrials.gov</u>: **prediction** that intervention treats disease

Ideally, Translator would NOT ingest untrustworthy trials

**Objective:** Classify clinical trials into trustworthy or untrustworthy (faked, sloppy) using machine learning

#### Selection criteria:

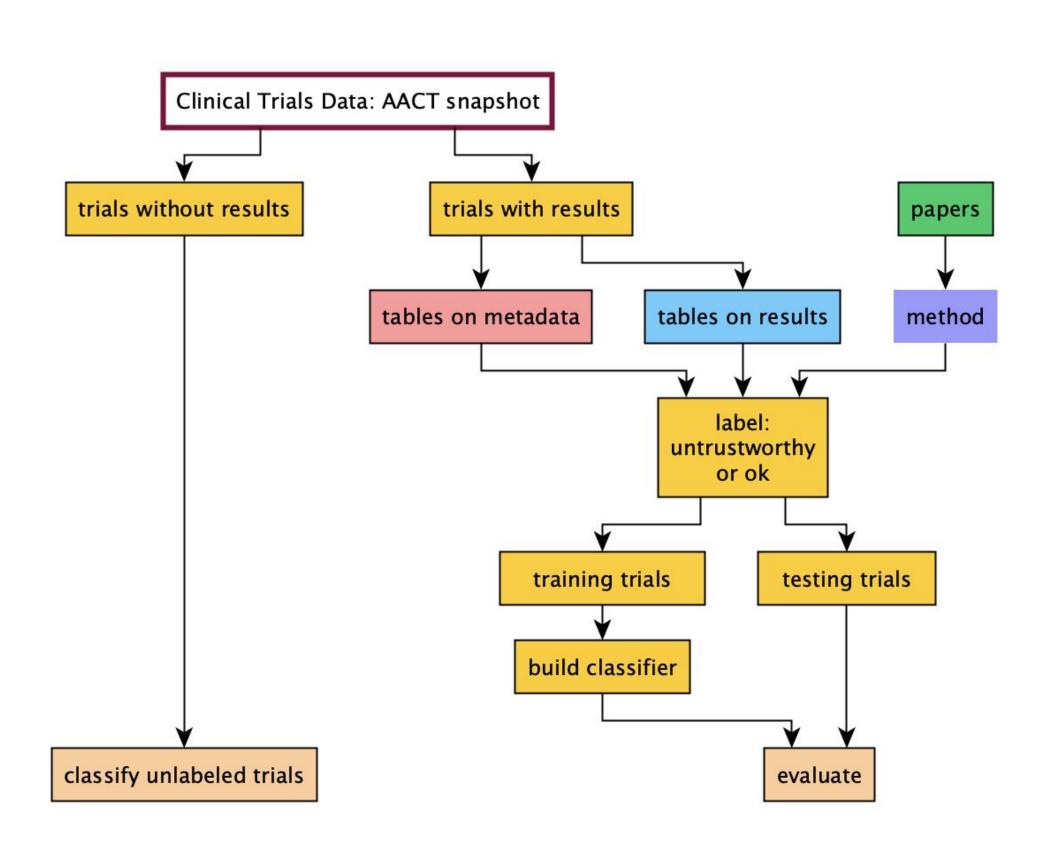
- 1. Was an associated paper retracted?
- 2. Was the study information posted retroactively?
- 3. Do key features have low stability scores?

Stability:  $S = 1 - \frac{R-1}{N-1}$ 

R: # times value changed
N: # of snapshots (value could have changed

For every column in every trial, out of all the times a value could change, how often did it?

#### Workflow:

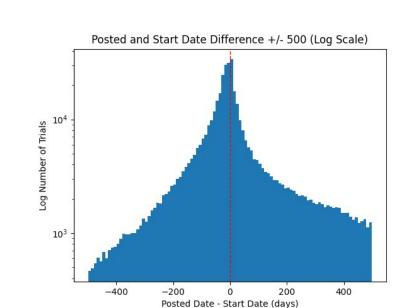


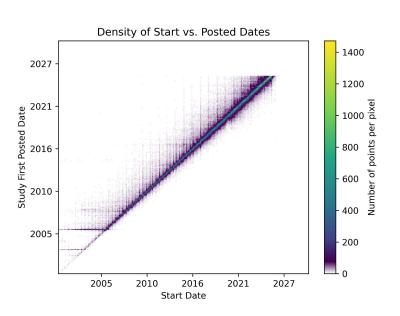
#### What would you consider untrustworthy?

Please leave a sticky note-your thoughts are welcome

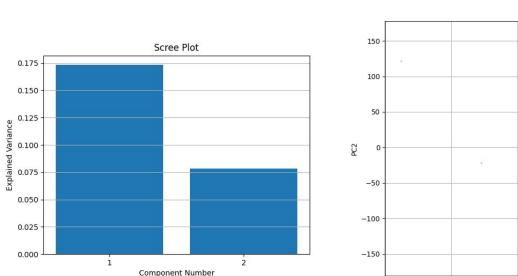
## Labeling Trustworthy or Ok (In Progress)

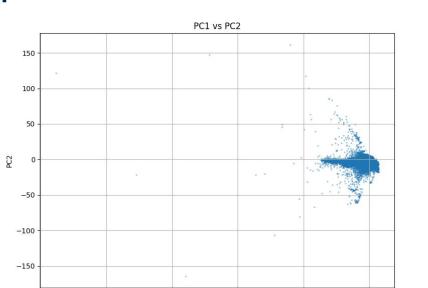
- 1) Using PubMed database, link trial to retracted paper
- 2) Data visualization: examined retroactive studies

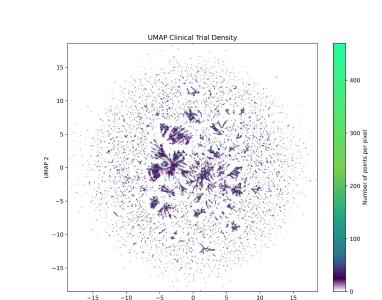




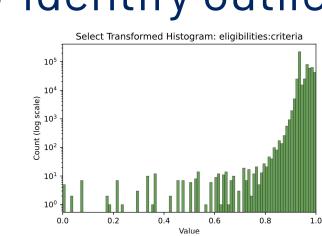
 PCA with stability score data for feature selection→ PC1 & PC2 capture only small fraction of variance Next, UMAP applied to examine structure







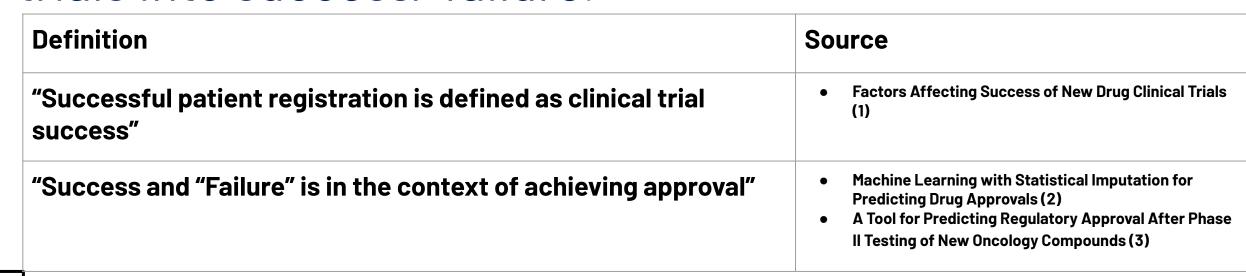
4) Identify outliers from stability data



- 132 plots, one for each feature
- outlying trials identified as having more outlying features
- features expected to change (such as updated\_at date) disregarded

#### **Future Work:**

Eventually after examining or filtering based on the trustworthiness of the trials, we could classify phase 3 trials into success/ failure.



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#### Sources:

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