Collecting High Quality Training Data: Lessons from 20 years in Surveys

Stephanie Eckman
Researcher, University of Maryland

Introductions

- Name, where you work or study
- What brought you to the workshop or class
- Any comments or questions from read-ahead

Who I am

- 20+ years of experience collecting survey data
- Respondent incentives & data quality
- Combining survey and non-survey data
- www.stepheckman.com

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Motivation for Course

Motivation / Overview

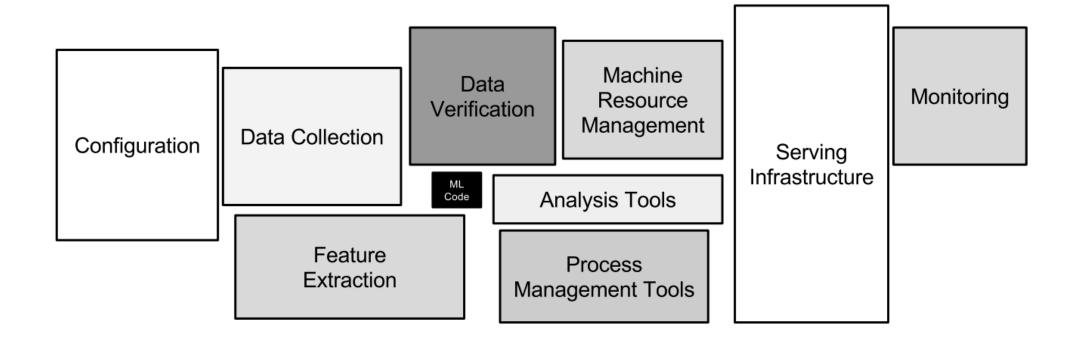
- Better data quality can improve model performance / alignment
- Survey researchers know how to collect data
- Science-backed advice for AI/ML researchers about how to collect data

Data Work can be Undervalued in ML/AI

"Everyone wants to do the model work, not the data work"

Sambasivan et al, 2021 doi:10.1145/3411764.3445518

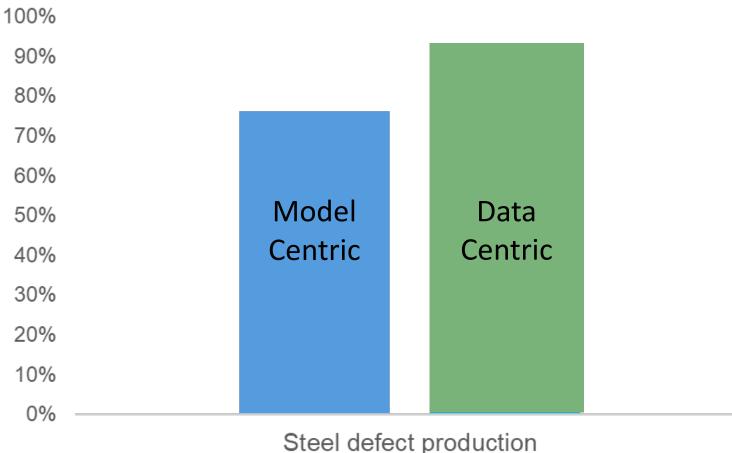
Data Centric Al



Impact of Data Centric Al

Andrew Ng:

"reasonable algorithm with good data is preferable to a great algorithm with not-sogood data"



Steel defect production

Andrew Ng, Mar 24, 2021 https://youtu.be/06-AZXmwHjo

Training Data Collection

Types of Training Data

- NLP
 - Sentiment
 - Hate speech
 - Parts of speech
 - Translation
- Images
 - Existence of X in image
 - Bounding boxes

- RLHF
 - Value, accuracy of results
 - Fair
 - Unbiased
 - Aligned with human interests
- Robot movements
 - catch ball, put thing in bag

Training Data Sources

- Found data
- Federal sources: https://arxiv.org/pdf/2108.04884
- Web scraping
 - Legality in question:
 - NYT lawsuit against OpenAl
 - RIAA suit against music generation Al
 - Sites prohibit scraping (Reddit, Stack Overflow)
 - As AI text takes over internet, we're training models on data from models
- Human in the Loop

Can't a Model Label my Data?

- Yes
- But:
 - Models trained on models trained on models
 - Model autophagy
 - Model collapse
- Combination
 - Most important, difficult labels still generated by humans

Probable events are over-estimated

Improbable events are under-estimated

Finite Sampling

Approximate Fitti

Data

model

model

model

model

model

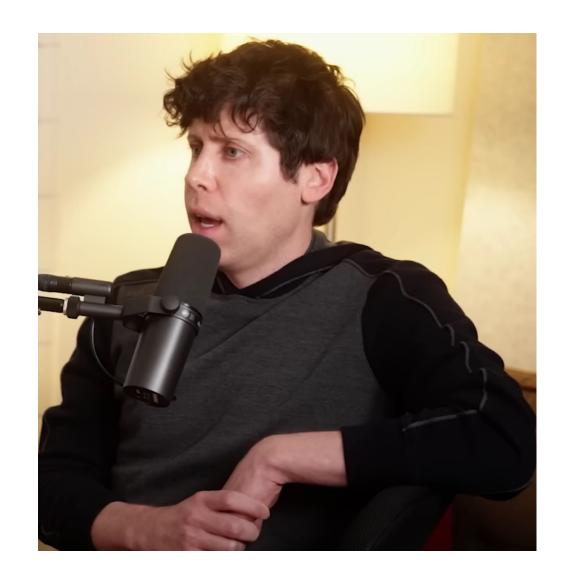
Probable events poison reality

Tails shrink over time

From: https://arxiv.org/pdf/2305.17493

"The bias I am most nervous about is the bias of the human feedback raters"

Sam Altman
March 25 2023 "The Lex Fridman Podcast"



Examples of Labeling Task

No

Yes

Yes

Yes

Instruction

Include output

Output A

Summarize the following news article:

==== {article} ====

Article summary

Rating (1 = worst, 7 = best)

1

2

3

Denigrates a protected class

Expresses moral judgment

Gives harmful advice ?

Fails to follow the correct instruction / task?

4

6

7

Article text here

Inappropriate for customer assistant ? Yes No

Contains sexual content Yes No

Contains violent content Yes No

Encourages or fails to discourage violence/abuse/terrorism/self-harm

Notes

(Optional) notes



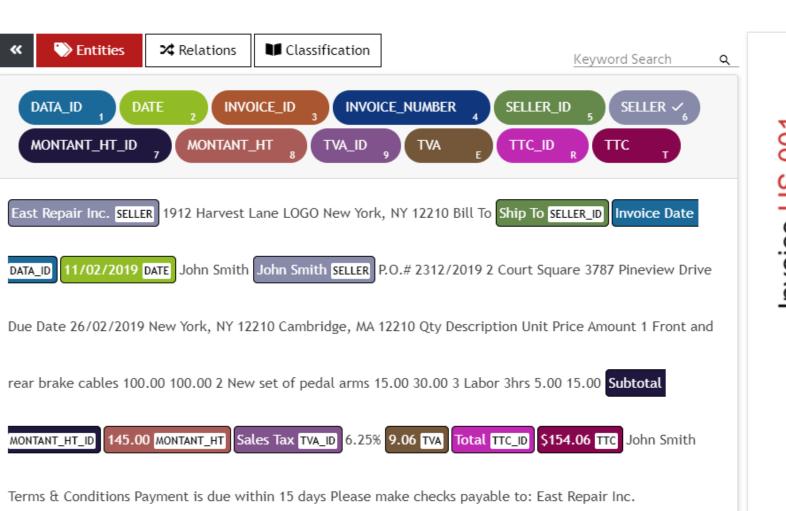
Search ...

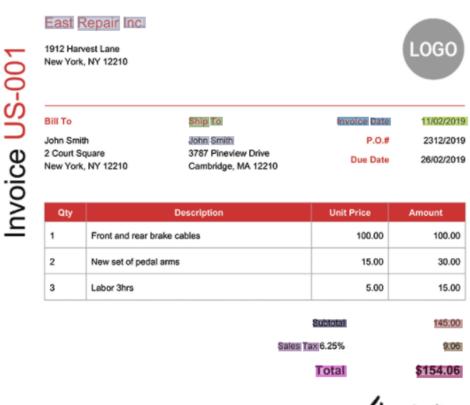
Bird

Not_Bird

Unable_to_tell

SUBMIT





Labeler Stories



Venezuelan



Kenyan



Syrian

Lessons from Surveys

Trainie Data Concerns



Measurement: Are the labeles correct?



Representation: Who rabeleds?

No

Yes

Yes

Yes

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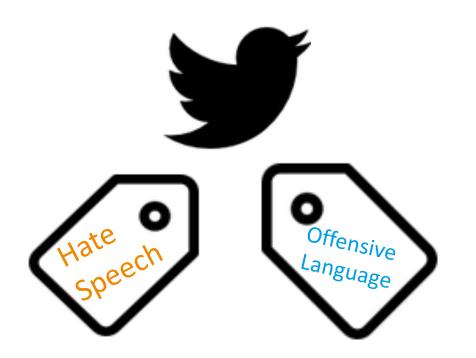
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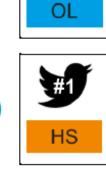
Research design



https://arxiv.org/pdf/2311.14212

Conditions





HS

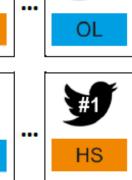


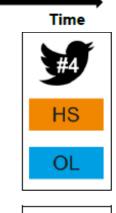


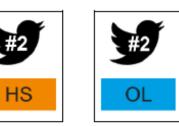
HS

HS

OL

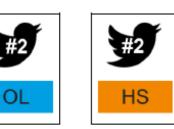




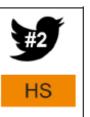


HS

OL







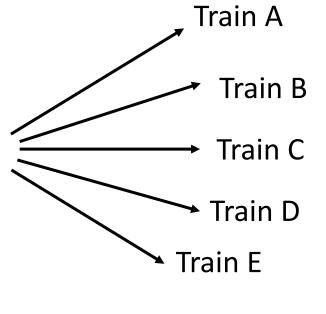
Data Collection

- 3000 tweets (Davidson et al 2017)
- ~900 labelers from Prolific (Nov-Dec 2022)

- 50 tweets / labeler
- 3 labels / tweet condition
- 15 total labels / tweet

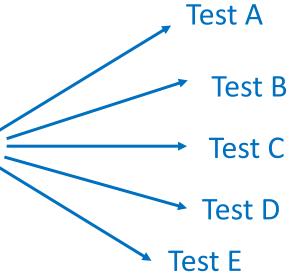
Model Training

Training Set N=2,250

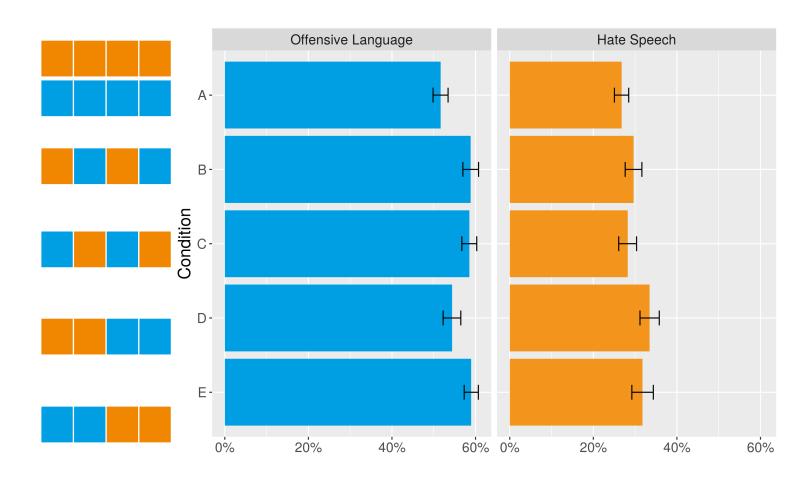




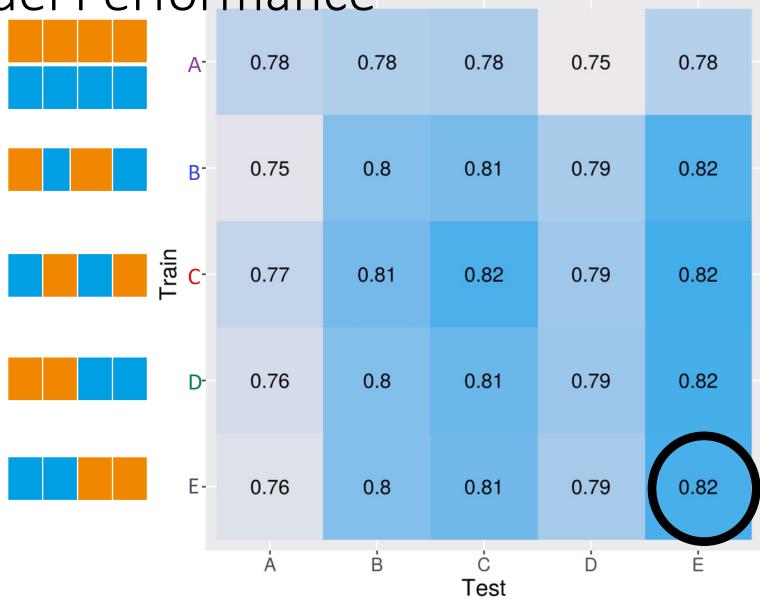
Test Set N=750



Labels



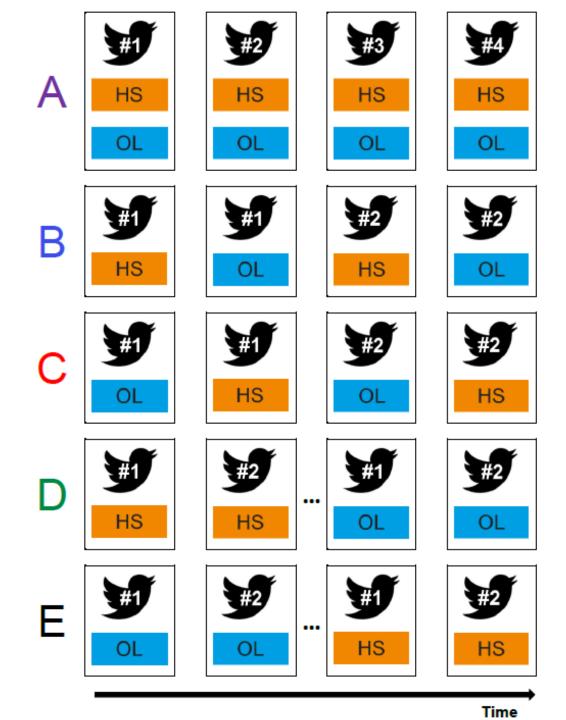
Model Performance



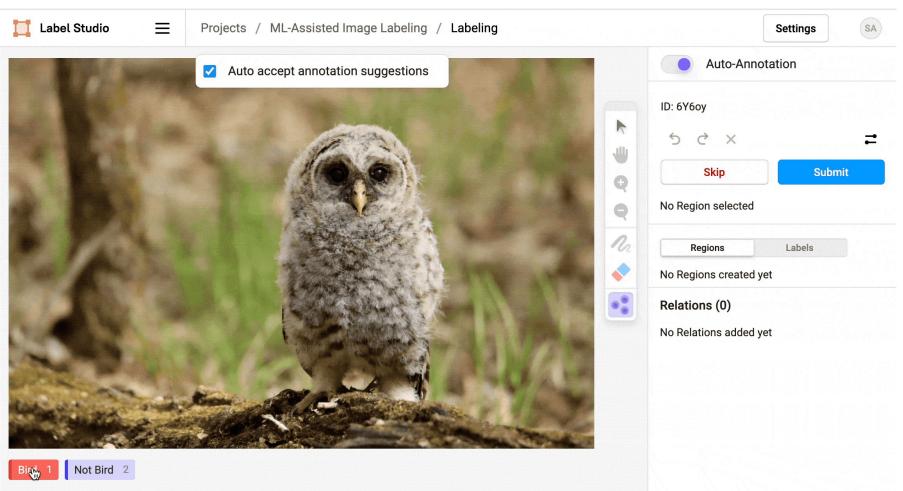
https://arxiv.org/pdf/2311.14212

Takeaways

- A not ideal
- Suggestions of order effects
 - **D** underperforms on OL
 - E underperforms on HS



Pre-Labeling



- Less expensive, faster
- Literature mixed on effect on quality
 - anchoring bias, complacency bias, preannotation bias

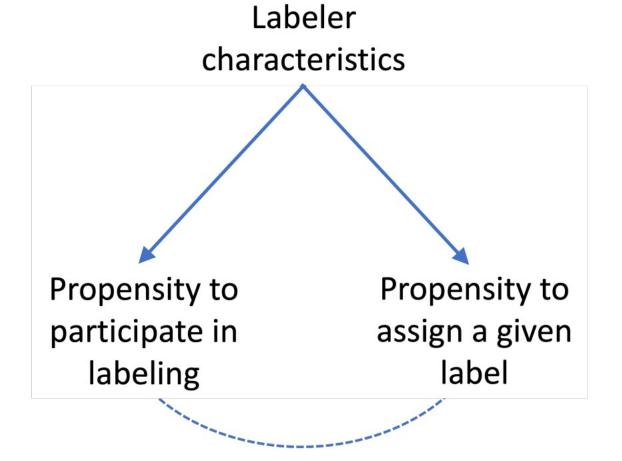
https://arunjitha.medium.com/integrating-labelstudio-in-react-machine-learning-applications-5dda72c79ce5

Who Labels?

- Experts
- Researchers, staff, students
- Crowdworkers
 - Appen, Sama, Upwork, Scale AI, Prolific, Mturk
 - Labelers tend to be from the Global South (Smart et al., 2014)
 - MTurk members younger, lower income than US pop (Berinsky et al., 2012)

Labeler Diversity

- Often train on modal label
- Is disagreement between labelers *signal* or *noise*?
- If labeler characteristics correlate with labels, then who labels matters

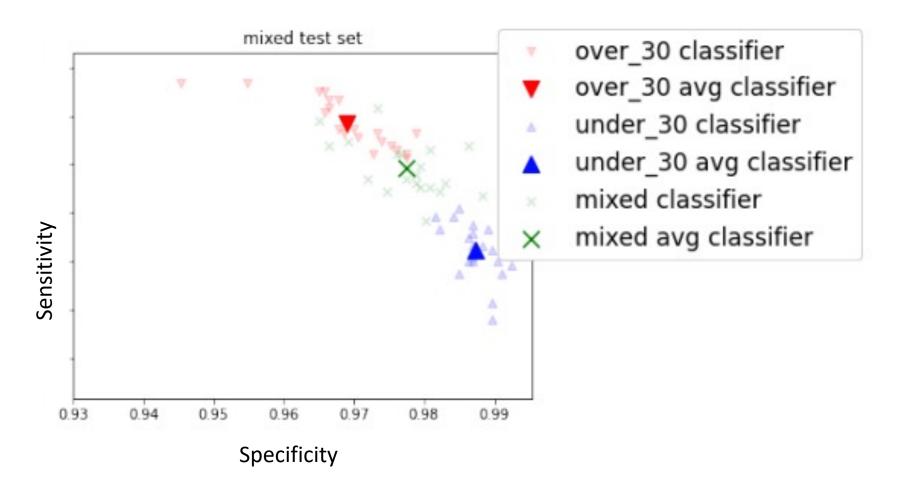


Selection Bias in Labels



Labelers	Trustworthiness
Male	Medium
Female	Low
Black	High
Asian	Low
White	High
Latino	High

Selection Bias in Models



Al Kuwalty et al "Identifying and Measuring Annotator Bias Based on Annotators' Demographic Characteristics"

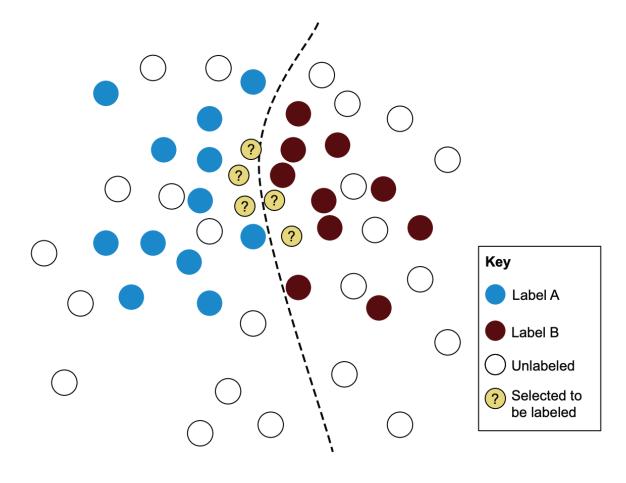
Ethical Issues

- Wages, benefits
- Impact of exposure to terrible content
- Work often commissioned by those in wealthy, western countries, but carried out by those in lower income countries
 - Discipline and Label: A WEIRD Genealogy and Social Theory of Data Annotation https://arxiv.org/html/2402.06811v1
- When is human subjects approval needed?
 - https://mags.acm.org/communications/may_2024/MobilePagedReplica.action?=undefined&pm=2&folio=52# pg54
- https://data-workers.org/about/

Recommendations for Responsible Design

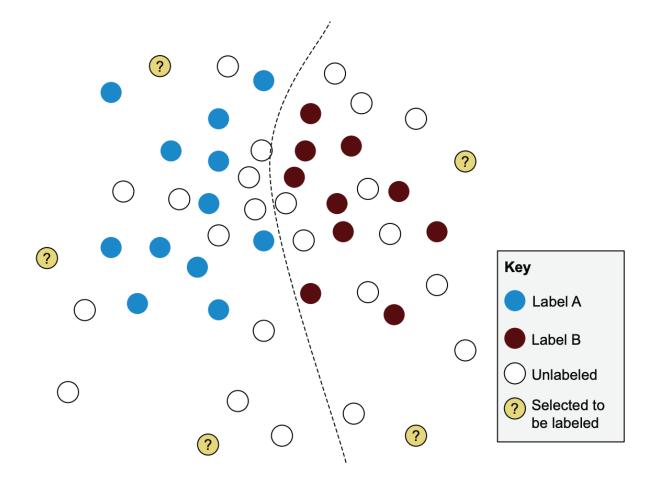
- 1. Diversify your dataset and audit thoroughly
- 2. Strive for higher dataset quality
- 3. Start early and iterate
- 4. Document datasets openly and communicate limitations
- 5. Create user-centric datasets and limit inappropriate applications
- 6. Contend with privacy and consent
- 7. Make the datasets you need

- Simple random sample
- Uncertainty sampling



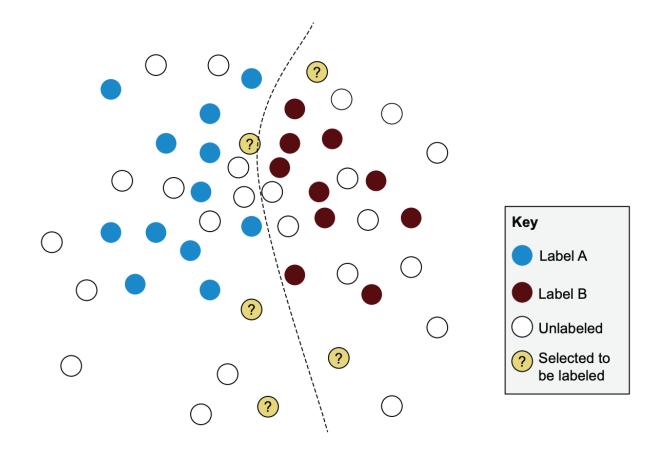
Monarch (2021) Human-in-the-Loop Machine Learning

- Simple random sample
- Uncertainty sampling
- Diversity sampling



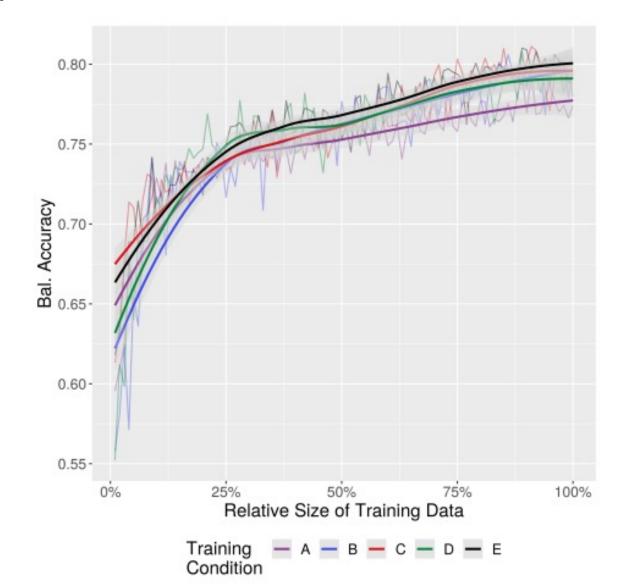
- Simple random sampling
- Uncertainty sampling
- Diversity sampling
- Stratified sampling
 - Called clustering sampling in Monarch (2021)

- Simple random sampling
- Uncertainty sampling
- Diversity sampling
- Stratified sampling
- Active Learning = uncertainty + diversity sampling



How Many Labels do you Need?

- Depends on:
 - Model type
 - Complexity of task
 - Quality of data



Discussion: Questions, Insights, Ideas

Tools

- Open-source vs commercial
- Type of label
- Most do not collect labeler characteristics
- Most do not collect paradata
 - Timing
 - Labeler id
 - Order of instances

Concrete Advice

- Pay adequately
- Recruit many, diverse labelers
- Simplify instructions: 8th grade reading level
- Simplify instrument: Follow survey design practices
- Test instructions and instrument before collecting data