3rd Workshop for Natural Language Processing Open Source Software (NLP-OSS) 6 Dec 2023 @ EMNLP 2023 in Singapore

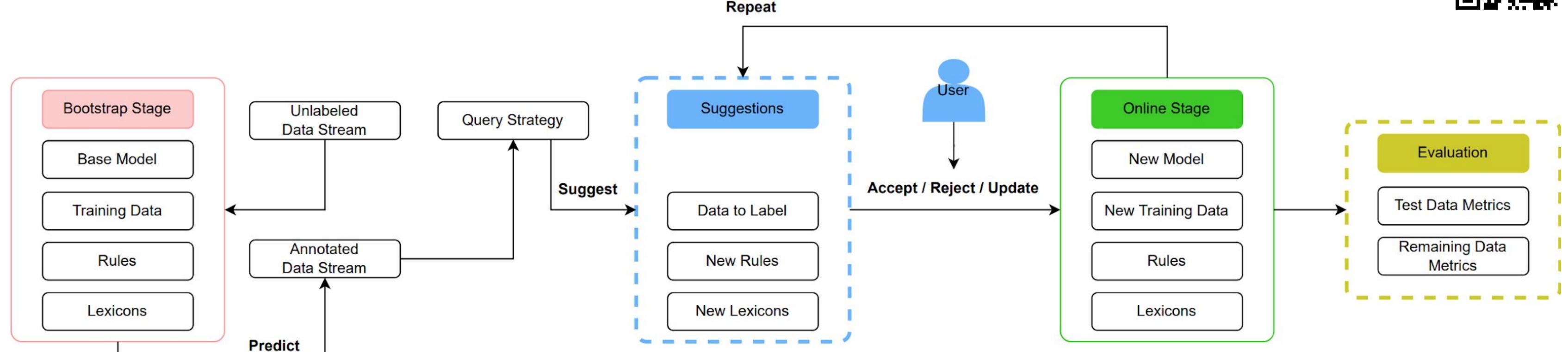
Shubhanshu Mishra* (shubhanshu.com), Jana Diesner (University of Illinois at Urbana-Champaign), *Work done while at UIUC

ArXiv: https://arxiv.org/abs/2211.13786

Dataset: https://doi.org/10.5281/zenodo.7236430

Code: https://github.com/socialmediaie/pytail





Problem formulation

- Given a large unlabeled corpus, can we:
 - label it efficiently using fewer human annotations?
 - allow human-in-the-loop injection of rules?
 - update models efficiently to work with new data?
- Proposal:
 - Use active learning for data labeling
 - Use interface to surface and inject prominent rules
 - Use incremental learning algorithms for model
- Highly applicable to social media data:
 - Model should adapt to new and streaming data

PyTAIL Benchmark for Social Media Active Learning

- Tasks for Social Media Text Classification: Abusive, Sentiment, Uncertainty
- 10 tasks, 200K social media posts
- Derived from Social Media IE Multi Task Benchmark https://doi.org/10.5281/zenodo.5867160

Table 2: Performance of query strategies across datasets using around 10% training dat	1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
	ery strategies across datasets lising arolind 10% training dataset
Table 2. I diffillative of quely strategies across datasets asing around to /e training dat	of y strategies across datasets using around 10% training dataset.

task	dataset	round	N	N_{left}	$\%_{used}$	Full	Rand	E_{top}	E_{prop}	M_{top}	M_{prop}	
Test Dataset												
ABUSIVE	Founta	42	41,861	37,661	0.10	0.79	0.77	0.78	0.78	0.79	0.77	
	WaseemSRW	14	13,072	11,672	0.11	0.82	0.79	0.78	0.77	0.78	0.76	
SENTIMENT	Airline	9	8,725	7,825	0.10	0.82	0.76	0.78	0.79	0.77	0.77	
	Clarin	45	44,299	39,799	0.10	0.66	0.63	0.61	0.62	0.63	0.63	
	GOP	8	7,121	6,321	0.11	0.67	0.63	0.64	0.63	0.62	0.64	
	Healthcare	1	590	490	0.17	0.59	0.64	0.60	0.61	0.60	0.60	
	Obama	2	1,777	1,577	0.11	0.63	0.56	0.60	0.58	0.59	0.57	
	SemEval	13	12,145	10,845	0.11	0.65	0.59	0.60	0.61	0.58	0.61	
UNCERTAINITY	Riloff	2	1,201	1,001	0.17	0.78	0.77	0.76	0.77	0.76	0.79	
	Swamy	1	555	455	0.18	0.39	0.39	0.40	0.39	0.34	0.31	
Remaining Dataset												
ABUSIVE	Founta	42	41,861	37,661	0.10	NaN	0.77	0.80	0.78	0.81	0.78	
	WaseemSRW	14	13,072	11,672	0.11	NaN	0.78	0.79	0.77	0.80	0.76	
SENTIMENT	Airline	9	8,725	7,825	0.10	NaN	0.75	0.79	0.79	0.80	0.78	
	Clarin	45	44,299	39,799	0.10	NaN	0.62	0.62	0.62	0.64	0.63	
	GOP	8	7,121	6,321	0.11	NaN	0.62	0.64	0.62	0.63	0.63	
	Healthcare	1	590	490	0.17	NaN	0.53	0.56	0.53	0.47	0.50	
	Obama	2	1,777	1,577	0.11	NaN	0.54	0.56	0.57	0.56	0.56	
	SemEval	13	12,145	10,845	0.11	NaN	0.61	0.62	0.62	0.63	0.62	
UNCERTAINITY	Riloff	2	1,201	1,001	0.17	NaN	0.80	0.82	0.84	0.82	0.81	
	Swamy	1	555	455	0.18	NaN	0.37	0.40	0.40	0.33	0.36	