Main ideas

Using a *disagreement classifier* to reduce annotation cost in structured prediction problems

We seek an algorithmic scheme that:

- address the annotation cost problem
- minimizes Type II error (which leads to biased labels) **Our approach:**
- only queries for labels when its uncertain
- uses expert and heuristic function annotations
- trains the difference classifier using Apple Tasting
- uses the difference classifier to decide who to query
- reduce expert annotations without affecting performance

Annotation cost problem

In *imitation learning* training proceeds by producing structured outputs one piece at a time and, at every step, asking the expert "what would you do here?" and learning to mimic that choice.

Do we have to ask for annotation *at every step*?

Apple Tasting for One-Sided Learning

The *difference classifier* is trained on one-sided feedback (it only observes errors when it predicts "disagree" between expert and heuristic function)

if it predicts "disagree" then it gets to see the truth, but if it predicts "*agree*" it never finds out if it was wrong

We use "STAP" an Apple Tasting¹ Algorithm that randomly samples from the difference classifier predictions that are predicted "disagree" and changing them to "agree".

Formally, STAP switches the difference classifier "disagree" predictions with probability:

$\sqrt{(m+1)/t}$

(*m* is the number of mistakes) (t is the number of "agree" predicted so far)

(Helmbold et al., Information and Computation 2000)^{\perp}

Active Imitation Learning with Noisy Guidance Kianté Brantley¹, Amr Sharaf ¹, Hal Daumé III^{1,2} ¹University of Maryland, ²Microsoft Research

Our approach: Named entity recognition example

$\hat{y}_{1:9} =$	0	0	PER	0	0	PER	0	0 ORG	$\pi^*(s_1)$	$_{0}) = 0$	RG	$\pi^{h}(s$	(10) = 0	ORG	$y^{\text{disagree}} = F$	alse <i>s</i> ₁₀
x =	After	completing	his l	Ph.D).,	Ellis	worked	at Bell	Labs	from	1969	to	1972	2 on	probability	theory
<i>y</i> =	0	0	0	0	0	PER	0	O ORG	ORG	0	0	0	0	0	0	0
$y^{h} =$	0	0	PER	0	0	0	0	O ORG	ORG	0	0	0	0	0	0	0

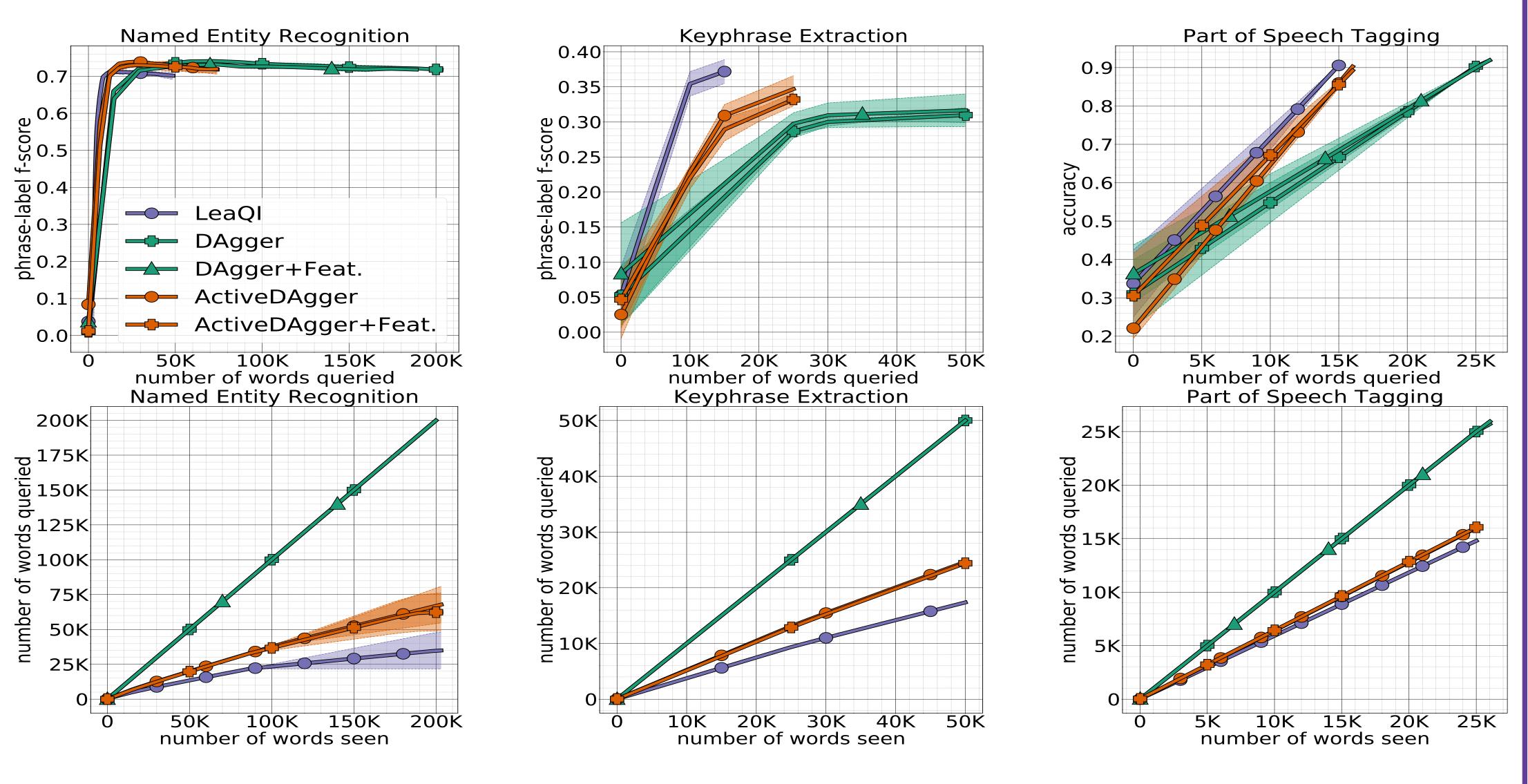
At state s ₁₀	if age	
• state representation is x_{10} combined with $\hat{y}_{1:9}$	• que	
• expert label at $t = 10$ is $y_{10} = 0$ RG	• que	
• heuristic label at $t = 10$ is $y_{10}^h = 0$ RG	 if ag 	
 if agent is certain at s₁₀ we <i>do not</i> query for a label 	• if <u>di</u> : -	

Experiments Details

Named Entity Recognition	Keyphrase Extra
CoNLL'03	SemEval 2017
English BERT	SciBERT
offline gazetteer	unsupervised ke
P 88%, R 27%, F 41%	P 20%, R 44%,
	CoNLL'03 English BERT offline gazetteer

Experiments Results

The **top row** shows performance (*f-score or accuracy*) with respect to the number of queries to the expert. The **bottom row** shows the *number of queries* as a function of the number of words seen.



ent is uncertain at s₁₀ ery difference classifier $\hat{d}_i = h_i(S_{10})$ ery AppleTaste-STAP($s_{10}, \pi^h(s_{10}), \hat{d}_i$) gree we query the heuristic function Aggregate data to train the agent *isagree* we query the expert Aggregate data to train the agent Aggregate data to train the difference classifier

raction Task 10

Part of Speech Tagging Universal Dependencies M-BERT Dictionary from Wiktionary 10% coverage, 67% acc

keyphrase model F 27%