Interactive Medical Word Sense Disambiguation with Instance and *Feature* Labeling

S16: Sub-language and Multi-lingual NLP

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Disclosure

I and my spouse/partner have no relevant relationships with commercial interests to disclose.

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Word sense disambiguation (WSD)

Words have multiple meanings (senses)

- cold: (1) low temperature; (2) common cold; (3) chronic obstructive lung disease (COLD)

Given ambiguous word in **context**, automatically assign a **sense** from a given set

context

"The child caught a ***cold*** and kept sneezing."

computer algorithm

sense

- low temperature
- common cold
- chronic obstructive lung disease (COLD)

Critical step for many medical NLP applications

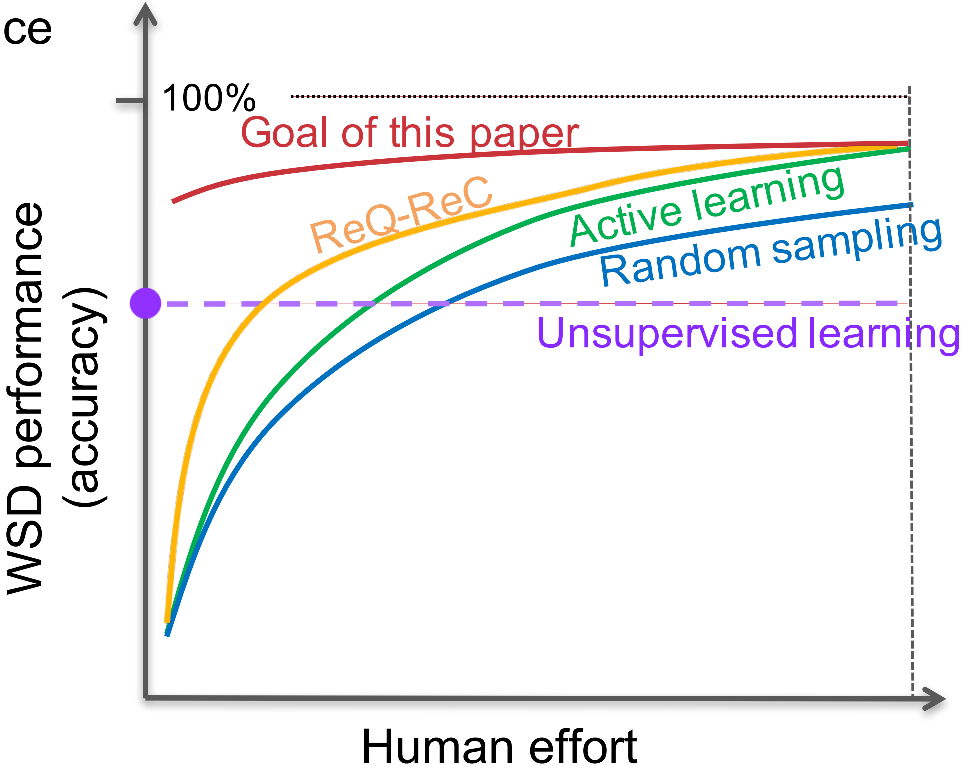
- Document indexing & classification; named entity extraction; computer-assisted review

WSD solutions

Human effort vs. algorithm performance
- Learning curve

Machine learning algorithms
- Unsupervised learning
- Supervised learning
  - labeling instances

Can we make better use of expert's domain knowledge?



Beyond instance labels

"cold"
- Chronic Obstructive Lung Disease
- Common Cold
- Low Temperature

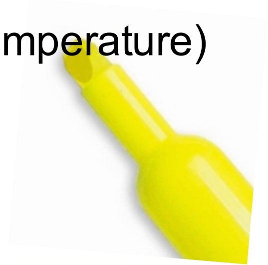
Indicative words:
- Chronic Obstructive Lung Disease: "COLD", "chronic", "obstructive", "lung", …
- Common Cold: "common", "cough", "sneeze", …

Unified
Medical
Language
System

"I know it when I see it":
- Rationale behind a sense label

"The tissue was exposed to a ***cold*** environment (5 degrees C)."

(Low Temperature)



Capture WSD domain knowledge

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(1) Type in indicative words

Chronic Obstructive Lung Disease

COLD, chronic, obstructive, lung

Common Cold

common, cough, sneeze

(2) Highlight contextual cues when labeling

The tissue was exposed to a cold environment (5 degrees C).

- Chronic Obstructive Lung Disease
- Common Cold
- Low Temperature

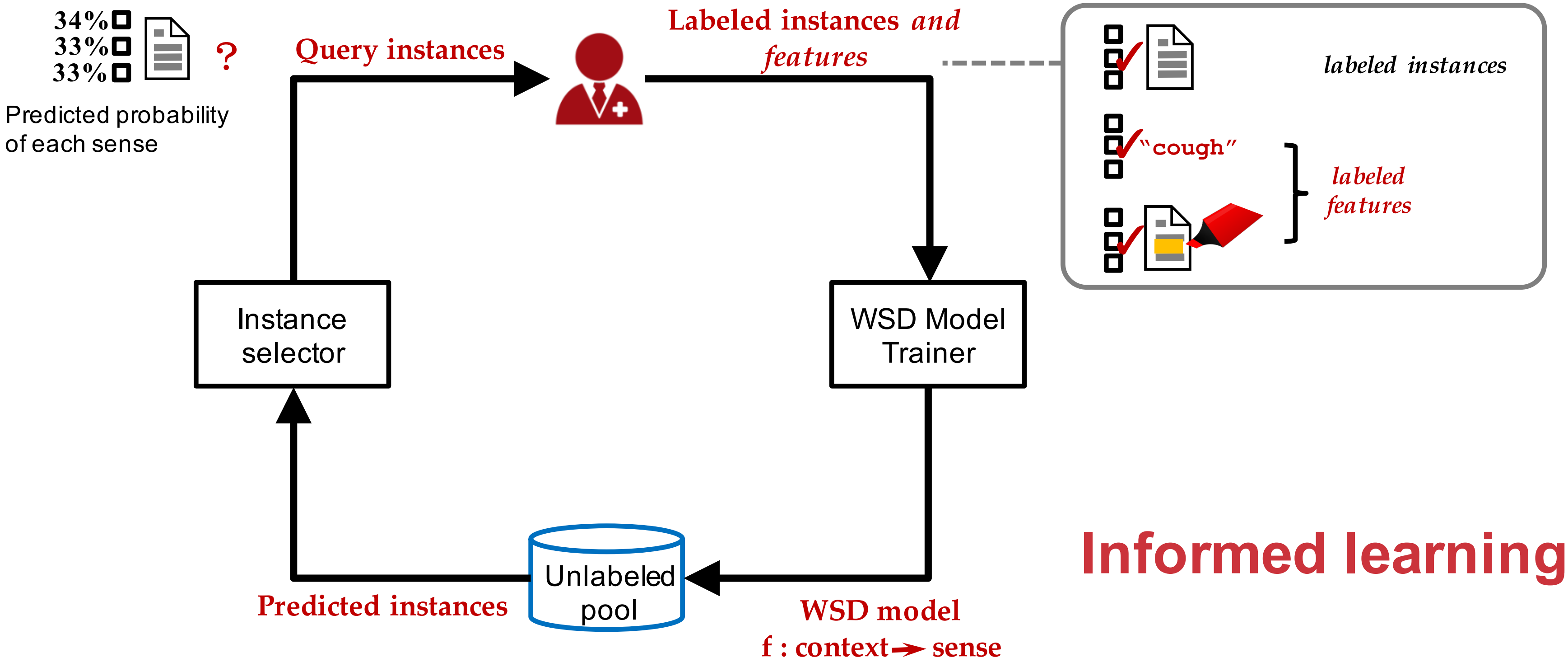
labeled instance
(without highlighting)

[textual pattern, sense] pairs

labeled features

["COLD" (all-cap),	Chronic Obstructive Lung Disease]
["chronic",	Chronic Obstructive Lung Disease]
["obstructive",	Chronic Obstructive Lung Disease]
["common",	Common Cold]
["cough",	Common Cold]
["sneeze",	Common Cold]
["<digit> degrees C",	Low Temperature]

Workflow



Informed learning

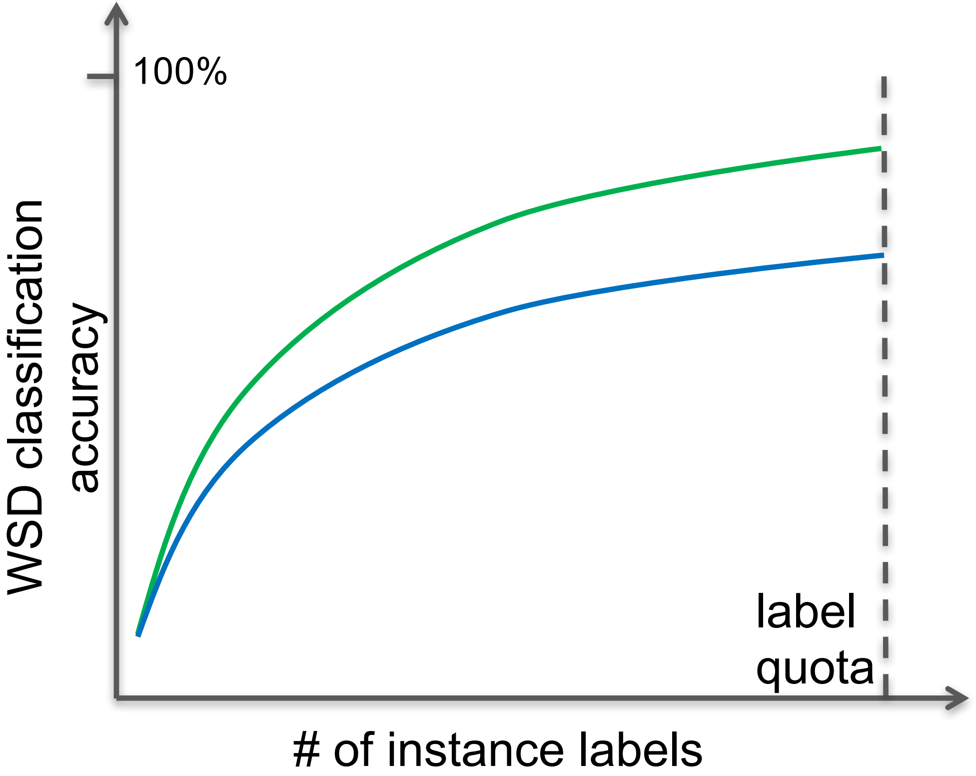
Experimental setup

Evaluation metric

- Learning curves
  - Labeled features only used at the first iteration
- Area under learning curve (ALC)

Compared methods

- Random sampling
- Active learning
- ReQ-ReC
- **Informed learning**



Evaluation Corpora

MSH: ambiguous words and abbreviations in MEDLINE abstracts

UMN: ambiguous clinical abbreviations, Univ. of Minnesota Fairview Hospital

VUH: ambiguous clinical abbreviations, Vanderbilt Univ. Hospital

	#ambiguous words	#sense/ word	#contexts/ word	#tokens/ context	majority guess accuracy
MSH	198	2.1	190	203	54.0%
UMN	75	5.4	500	61	73.8%
VUH	24	4.3	194	19	78.3%

Simulated human expert inputs

Provide labeled instances in active learning

- Sense labels in the corpora

Provide labeled features per sense (only at the first iteration)

- Words with top information gain

Chronic Obstructive Lung Disease	**Common Cold**	**Low Temperature**
obstructive	common	degrees
chronic	cough	C
lung	colds	temperatures
COLD	nasal	temperature
pulmonary	over-the-counter	exposure
COPD	OTC	gene

Simulated human expert inputs

Provide labeled instances in active learning

- Sense labels in the corpora

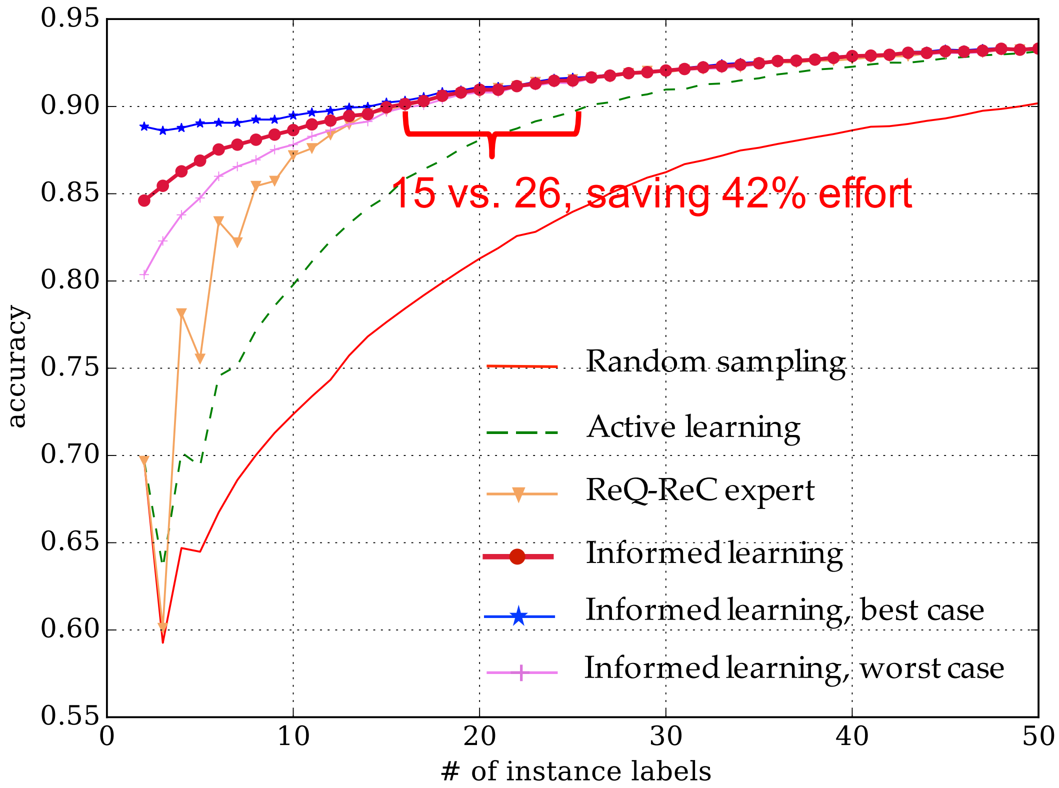
Provide labeled features per sense (only at the first iteration)

- Words with top information gain
- Making it more realistic:
  - Provide the best, 5th best, 10th best contextual words *upfront*
  - Highlight the best, 2nd best, 3rd best contextual words *in a given instance*

"Best-case scenario"

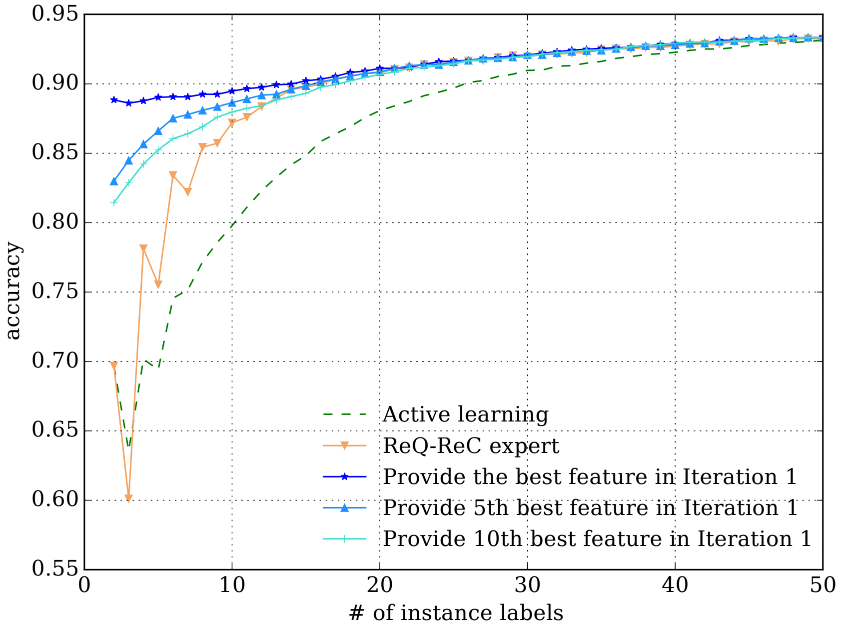
"Worst-case scenario"

MSH: 198 ambiguous words in MEDLINE

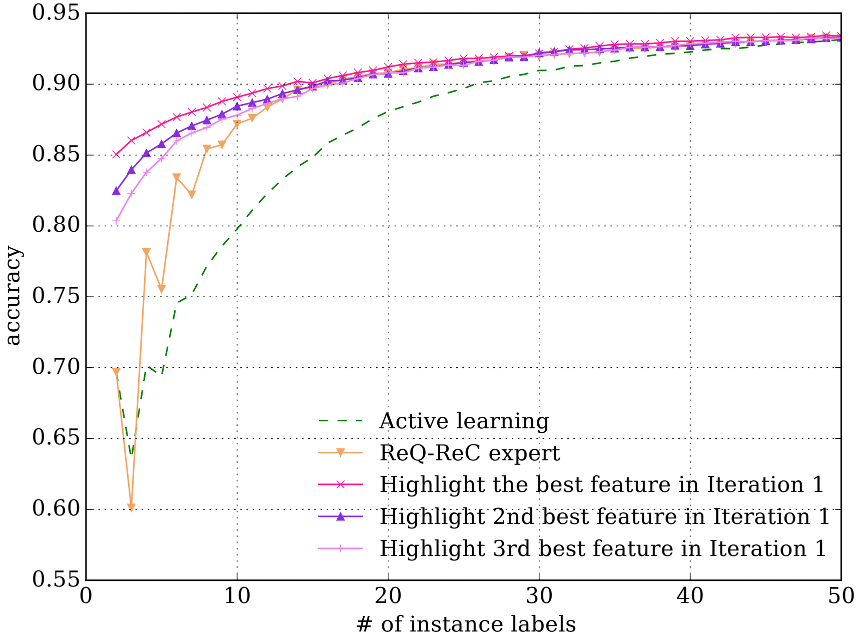


MSH drill-down analysis

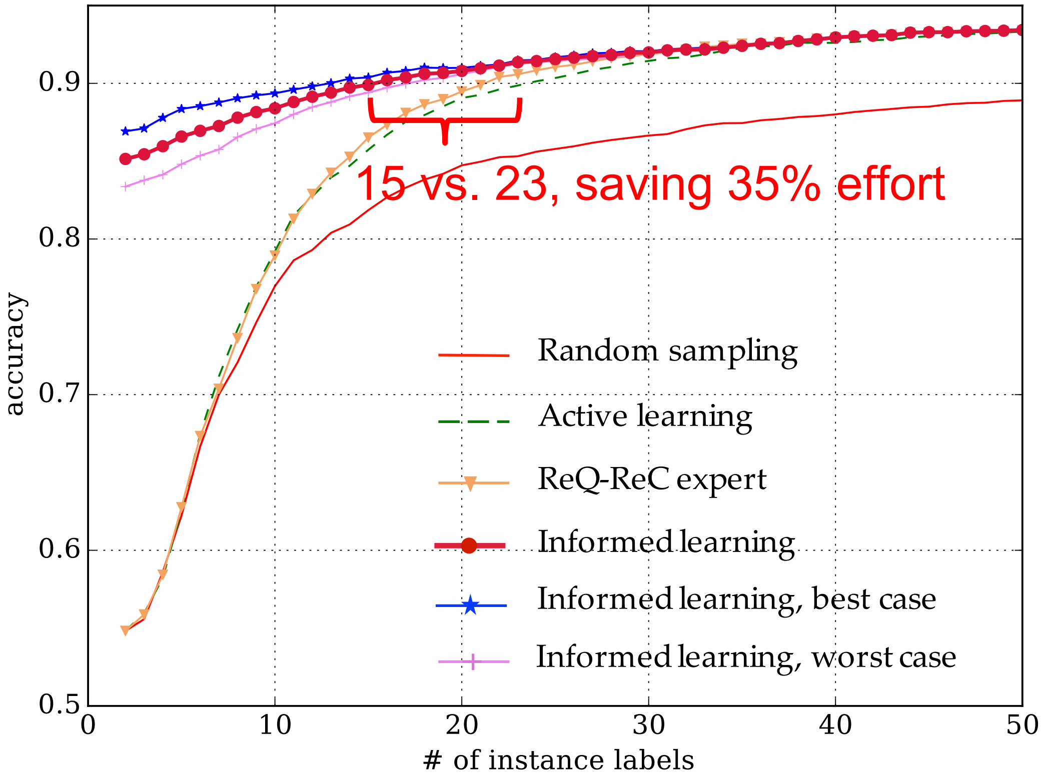
provide features upfront



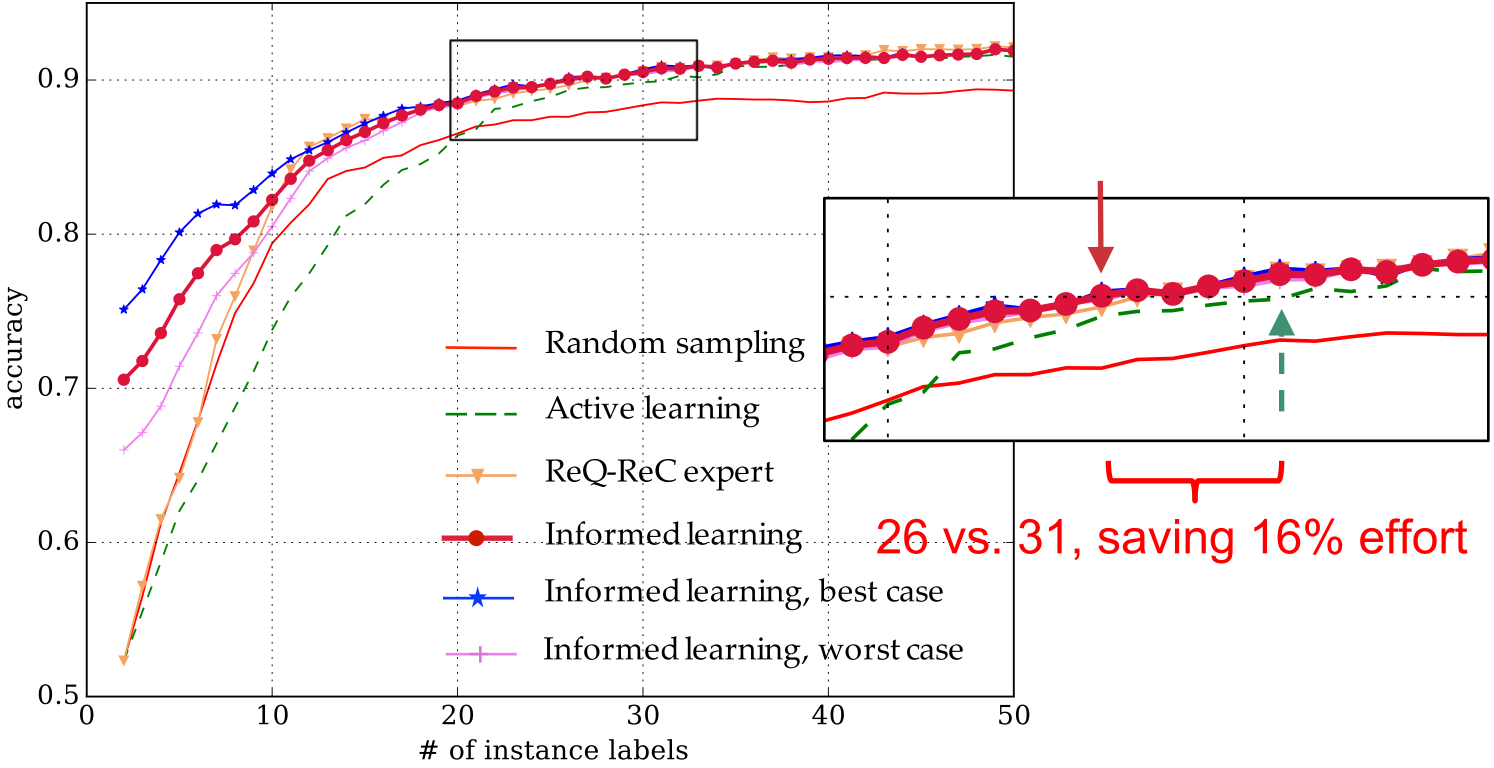
highlight features in examples



UMN: 75 ambiguous clinical abbreviations



VUH: 24 ambiguous clinical abbreviations



Area under learning curve (ALC)

	MSH	UMN	VUH
Random	0.816	0.817	0.831
Active learning	0.868	0.854	0.831
ReQ-ReC expert	0.893	0.857	0.852
Informed learning	**0.909***†	**0.909***†	**0.871***

Wilcoxon signed rank test
'$*$' : significant w.r.t. "Active learning" at $\alpha = 0.01$.
'$\dagger$' : significant w.r.t. "ReC-ReQ expert" at $\alpha = 0.01$.

Conclusion

Learning from labeled features is more efficient use of expert knowledge and time

- Labeling instances → providing/highlighting features
- Less human effort to reach desirable accuracy
- Even noisy feature labels are useful

Future work

- Inviting human experts in real-time evaluation

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Training WSD model with labeled instances & features

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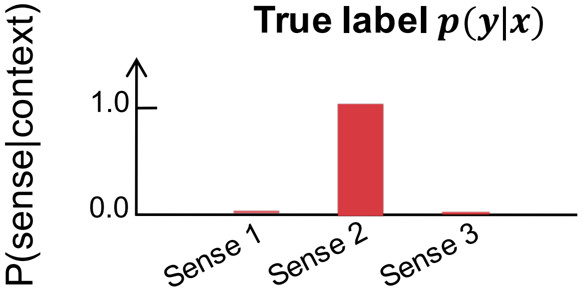
Labeled instance: [context x, sense y]

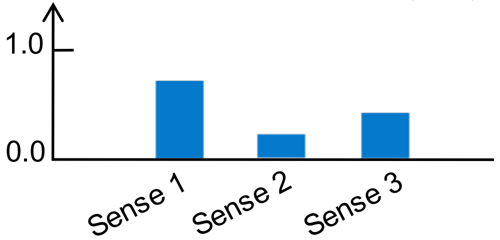
True label $p(y|x)$



cross entropy loss term

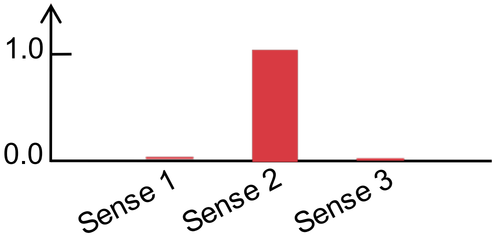
$$\sum_y p(y|x) \log \hat{p}(y|x)$$

Predicted label $\hat{p}(y|x)$



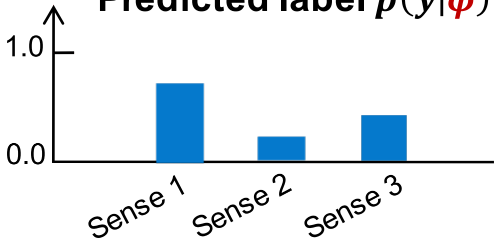
Labeled feature: [feature ϕ, sense y]

True label $p(y|\phi)$

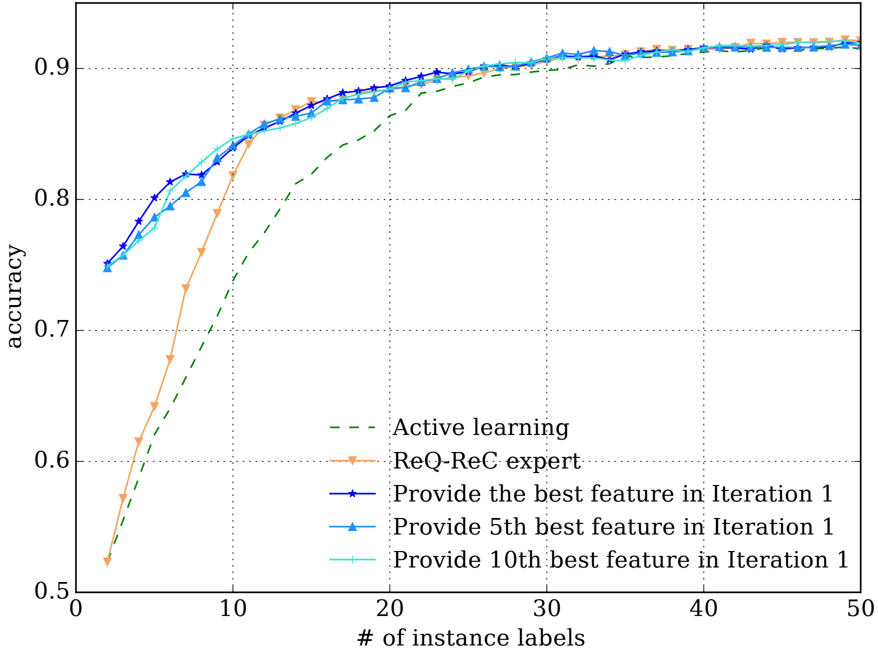


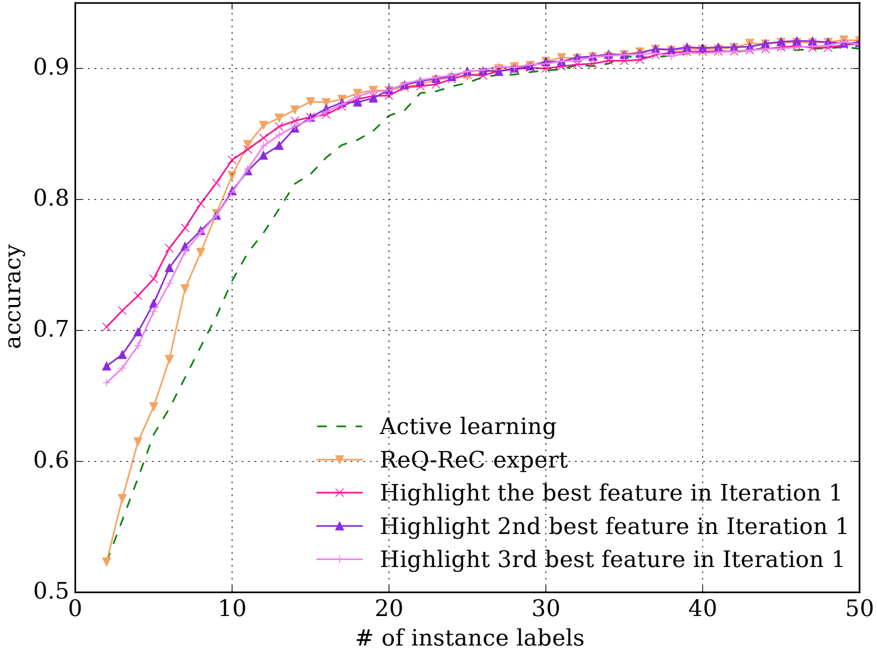
a new cross entropy loss term

Predicted label $\hat{p}(y|\phi)$ $= \dfrac{\sum_{x:\phi\in x} \hat{p}(y|x)}{|\{x:\phi\in x\}|}$



VUH drill-down analysis





UMN drill-down analysis