An Exploration of Automated Grading of Complex Assignments

2016-04-26

Chase Geigle, ChengXiang Zhai, Duncan Ferguson

An Exploration of Automated Grading of Complex Assignments

An Exploration of **Automated Grading** of Complex Assignments

An Exploration of Automated Grading of **Complex Assignments**

M. Brooks et al. "Divide and Correct: Using Clusters to Grade Short Answers at Scale". In: *ACM L@S*. Atlanta, Georgia, USA, 2014, pp. 89–98. ISBN: 9781450326698

A. Nguyen et al. "Codewebs: Scalable Homework Search for Massive Open Online Programming Courses". In: *WWW*. 2014, pp. 491–502

C. P. Rosé et al. "A Hybrid Text Classification Approach for Analysis of Student Essays". In: *BEA*. ACL, 2003, pp. 68–75

(Why) Do we need these kinds of assignments?

The Applied Learning Platform (ALP)

You are a practitioner with an interest in equine medicine. During a routine visit to an area stable, your client asks you to perform a physical examination and to draw blood and collect urine from a near weaning Thoroughbred foal for future sale The potential buyer wants a routine examination before purchasing the animal. The foal is high spirited and makes the client chase him around the paddock a few times before he can be haltered. No abnormalities were found on physical examination.

HEMATOLOGY

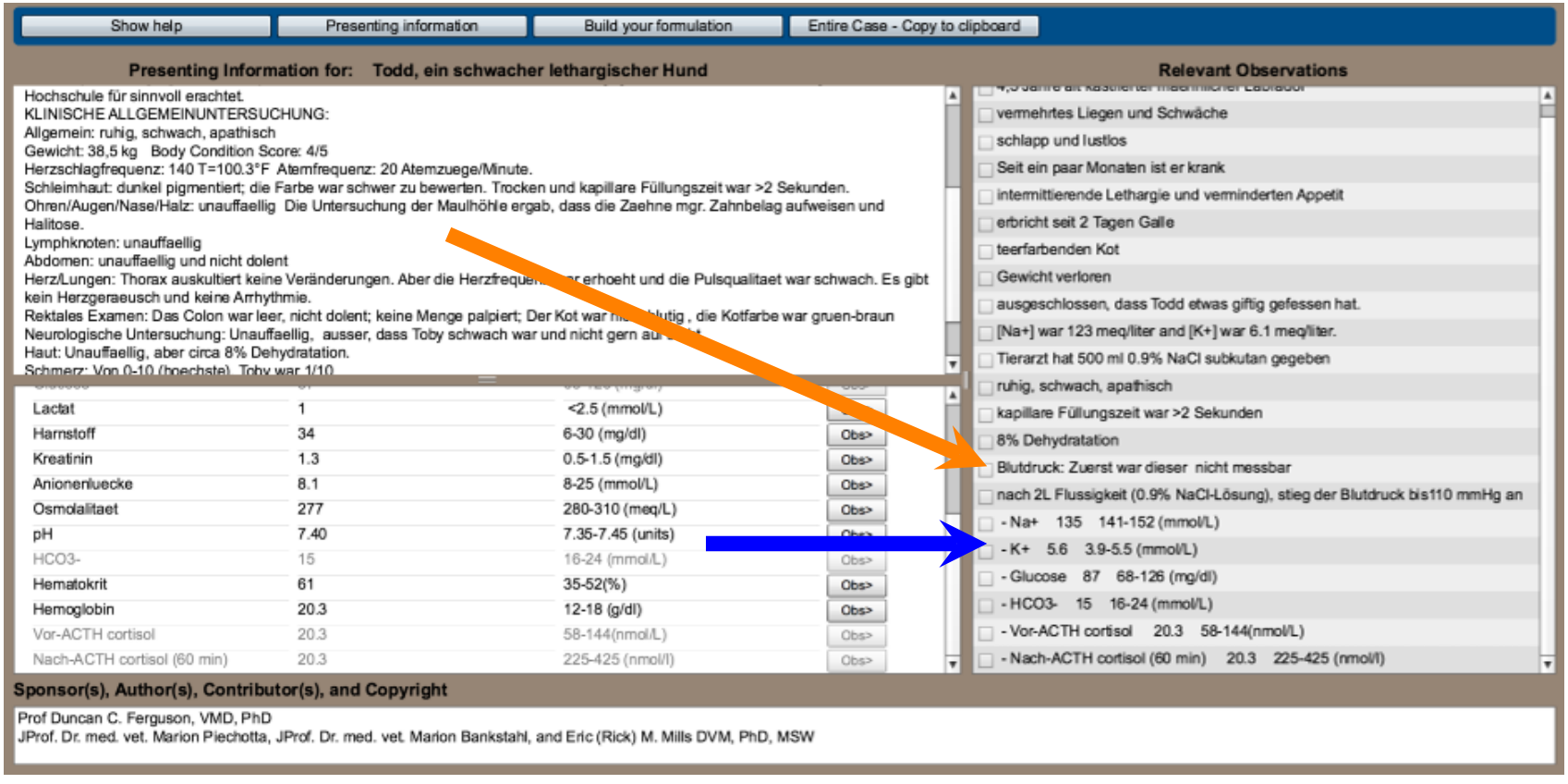
Test name	Test Result	Ref. Int.	Units
RBC	13.1	6.0-12.0	n*10^6/ul
HGB	19	10.0-18.0	g/dl
HCT	52	32.0-48.0	%
MCV	39.7	34.0-58.0	fl
MCH	14.5	13.0-19.0	pg
MCHC	36.5	31.0-37.0	g/dl
NRBC		0	n/100 wbc
ANISO			
POLYCHR			

• • • • • •

URINALYSIS (VOIDED)

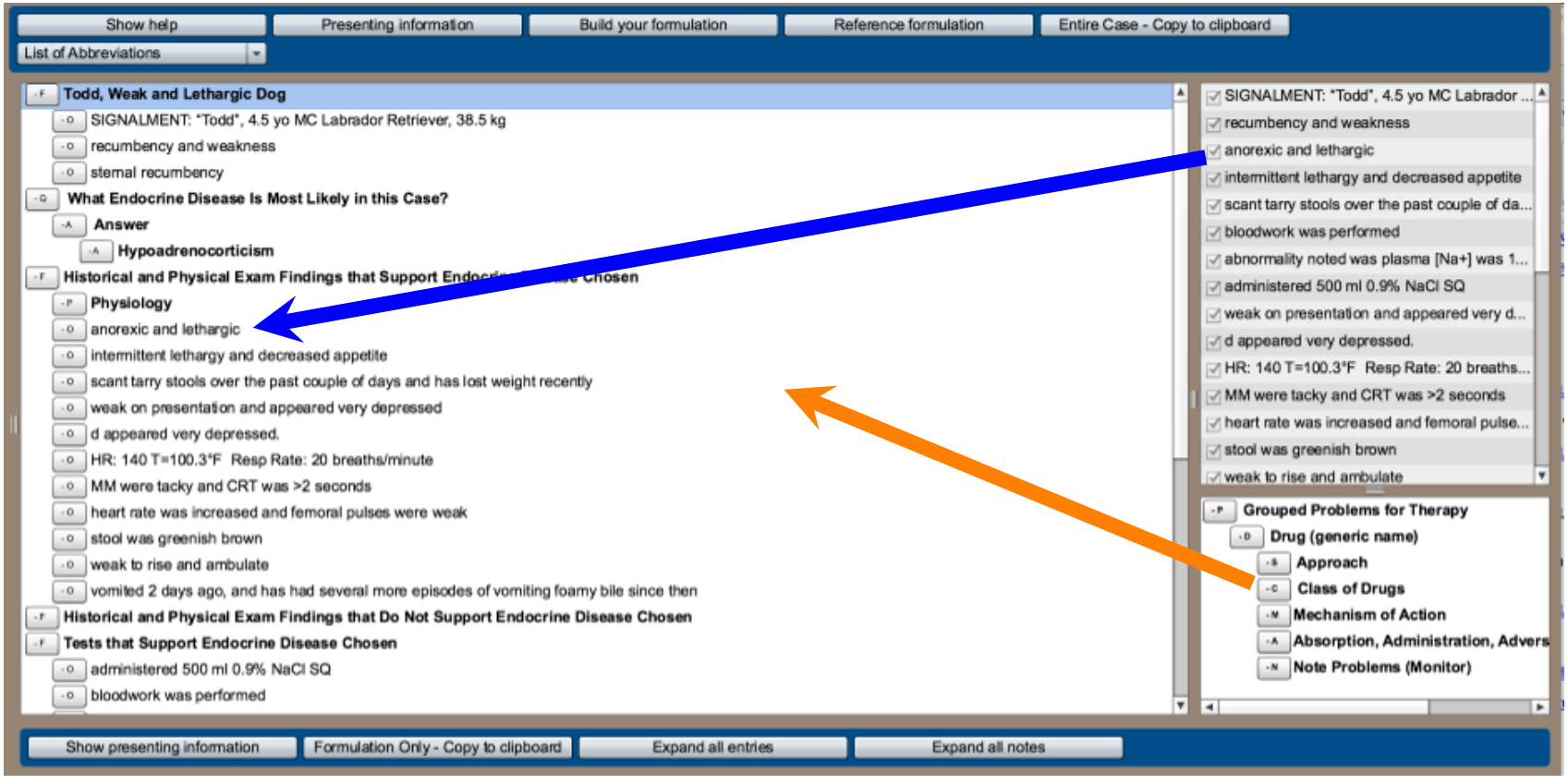
COLOR	straw	
TRANSP	clear	
S. G.	1.026	
pH	7.5	6.5-9.0

The Applied Learning Platform (ALP)



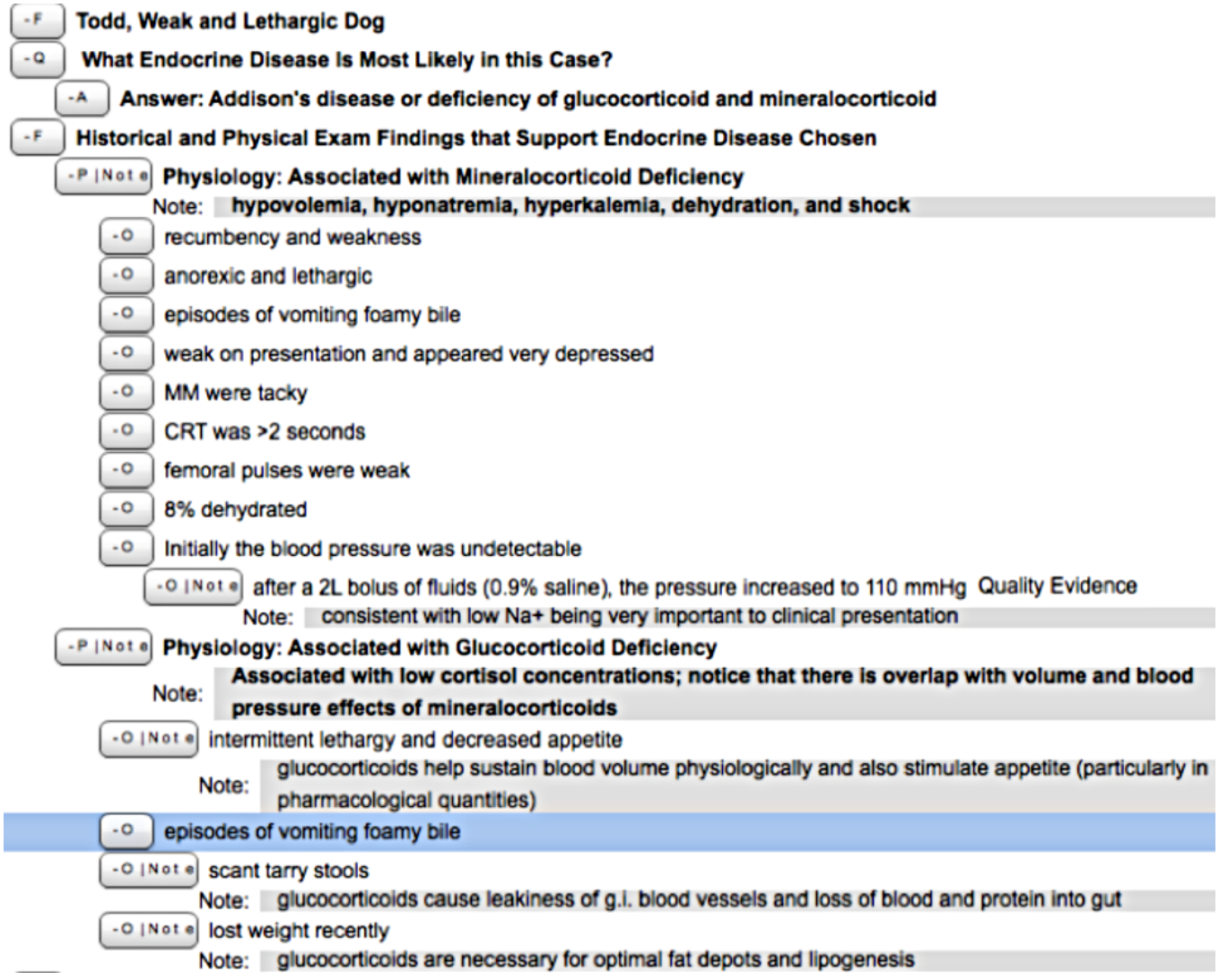
www.whenknowingmatters.com

The Applied Learning Platform (ALP)



www.whenknowingmatters.com

The Applied Learning Platform (ALP)



The Rubric—Likert; 1 (novice)–5 (expert)

Developing relevant refining (or clarifying) questions to answer based upon an honest assessment of current knowledge base	**Questions**: 2.82 ± 0.68
Approach to seeking answers to developed questions--literature search, etc.	**Answers**: 3.03 ± 0.77
Judgment of Quality of Information--awareness and application of standards of a discipline, bias detection including appropriate humility to detect one's own potential bias, application of statistical concepts	**Quality**: 3.11 ± 0.98
Analysis of an argument	**Analysis**: 2.64 ± 0.77
Clarity and communication (written or oral) of thought: conciseness, grammar, spelling, elocution	**Clarity**: 3.38 ± 0.94
Application and understanding of appropriate disciplinary content	**Application**: 2.87 ± 0.57

(Mean and standard deviation, $n = 107$)

Research Questions

1. **Feasibility:** How effective are state of the art machine learning approaches for automated grading? Are they sufficiently effective to be immediately useful in practice?

2. **Formulation and Evaluation:** What is the right way to formulate the grading problem as a machine learning problem? What is the right way to measure effectiveness?

3. **Integration:** How should an automated grader be integrated with manual instructor/TA grading? What are the trade-offs?

Feasibility of Automatic Grade Prediction

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |r(f(x_i)) - r(y_i)|$$

	Baseline	**SVOR**[1]
sim (3)	0.9358 ± 0.0882	**0.8811 ± 0.0940**
sim + sel (5)	0.9566 ± 0.1677	**0.8642 ± 0.0325**
toks (2646)	0.9075 ± 0.0789	**0.7660 ± 0.0910**†
all (2651)	0.9792 ± 0.1568	**0.7566 ± 0.0738**†

†: statistically signifigant using an unpaired t-test with $p \leq 0.05$.

Table: Effectiveness (in terms of MAE) of incorporating additional features in grade prediction for "quality" dimension using SVOR methods compared to the mode-assigning baseline. Number of features is given in parenthesis.

[1] `http://www.work.caltech.edu/~htlin/program/libsvm/`

Feasibility of Automatic Grade Prediction

	Baseline	**SVOR**
sim (3)	0.7906 ± 0.0771	**0.7830 ± 0.0836**
sim + sel (5)	**0.7623 ± 0.0649**	0.7811 ± 0.0561
toks (2646)	0.7528 ± 0.0550	**0.7415 ± 0.0597**
all (2651)	**0.7189 ± 0.0617**	0.7226 ± 0.0527

Table: Similar experiment to Table 1, but for "clarity" dimension.

- **Main takeaway:** effectiveness very much depends on
  1. rubric dimension
  2. features used

Is outright grade prediction really our goal?
(Hint: maybe it shouldn't be)

1. Annotator agreement?
   - Low in practice[2], *even for short-answer questions!*
   - Only going to be worse for complex assignments...
   - **Significant** barrier to leveraging peer grading

2. The machine will always be imperfect.
   - How sensitive is the grading process to "small" mistakes?
   - Can we reduce this sensitivity?

[2] M. Mohler and R. Mihalcea. "Text-to-text Semantic Similarity for Automatic Short Answer Grading". In: *EACL*. 2009, pp. 567–575.

Can we treat grading as a **ranking problem**?
(Hint: probably, or I wouldn't put it on a slide)

1. Annotator agreement?
   - **Much easier** to get people to agree on "is a better than b?"[3]
   - Provides an easy mechanism for **leveraging peers**: their inherent positivity (bless them) **won't bias a pairwise decision**!

2. The machine will always be imperfect.
   - **Significantly less sensitive** to minute mistakes in the ranking, as long as it is largely consistent with instructor preference
   - Grading $\rightarrow$ assigning cutoffs: quite natural!

Evaluation metric: "distance" between machine and instructor ranking (lower is better)[4]

$$NDPM = \frac{2n_d + t_x}{2(n_c + n_d + t_x)}$$

---

[3] C. Callison-Burch et al. "(Meta-) Evaluation of Machine Translation". In: *WMT*. 2007, pp. 136–158.

[4] Y. Y. Yao. "Measuring Retrieval Effectiveness Based on User Preference of Documents". In: *J. Am. Soc. Inf. Sci.* 46.2 (1995), pp. 133–145.

Is **batch-mode machine learning** the right setup?
(Hint: maybe it shouldn't be)

- **Batch-mode learning:** Grade a bunch of assignments (or provide a bunch of pairwise assessments), give them to the machine, wait for a bit, and use its output on unlabeled assignments for grading
  - This is **not very collaborative!**
  - Machine is not able to inform instructor to grade *most helpful assignments/pairs!*
  - Unclear stopping decision: how many more should I grade to get a certain level of accuracy?

Can **active learning**[5] be more effective?
(Hint: probably, or I wouldn't put it on a slide)

Active learning:

1. Grade some small number of assignments/pairs
2. Provide them to the machine to learn from
3. **The machine suggests** the next assignment/pair to grade
4. (Go to 1 until you're satisfied with the machine's output)

- Benefits:
  - This is **collaborative by design**
  - A clear stopping criterion: after each assignment/pair a new ranking is generated—stop when you're happy with it

[5] no, not that kind of active learning

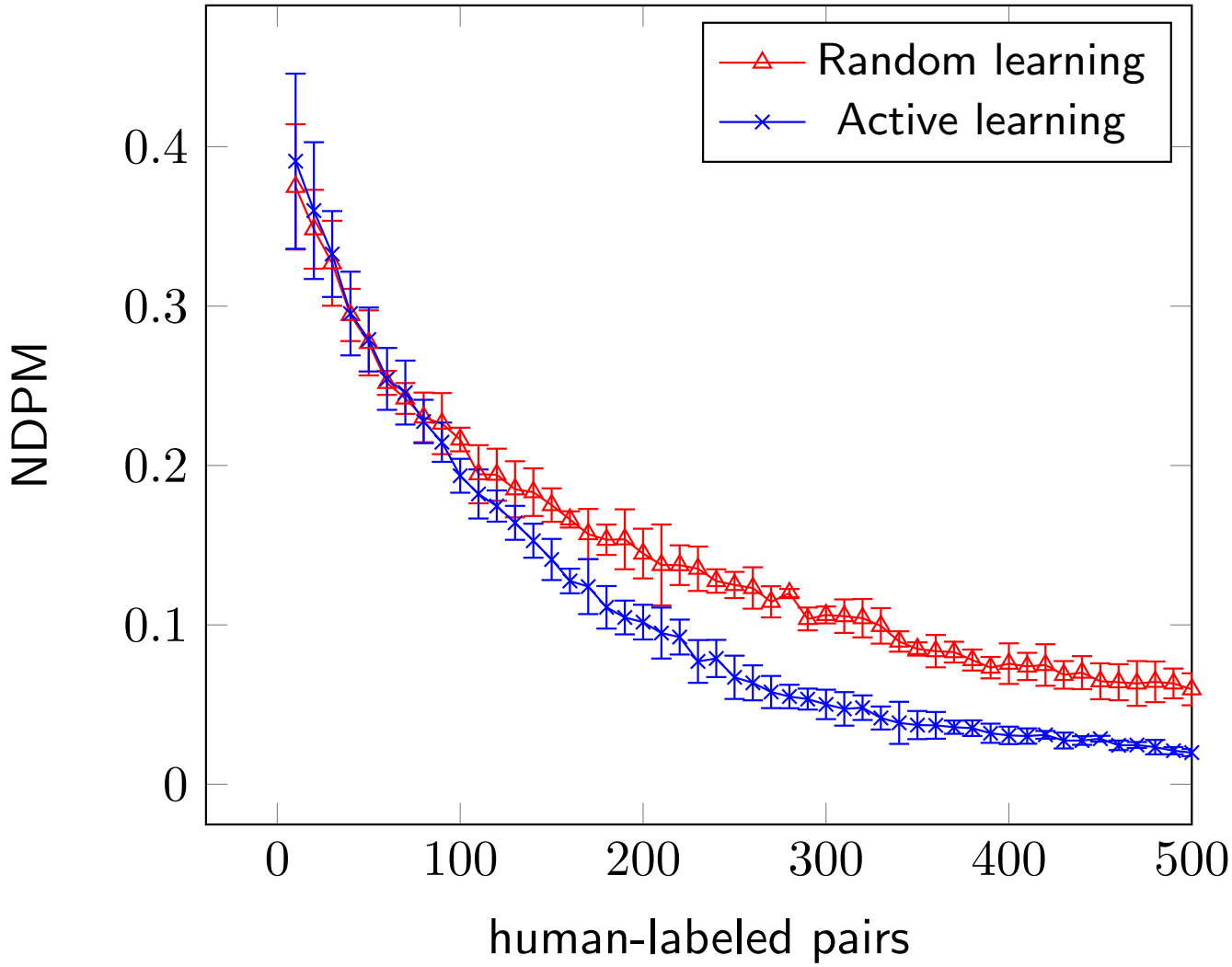


Figure: A comparison between a randomized learning solution and an active learning solution to the grading-as-ranking problem. Reported is the average NDPM (lower is better) over 5 runs, with error bars indicating one standard deviation.

Questions?

(Thanks!)