Modeling Annotator Accuracies for Supervised Learning

Abhimanu Kumar
Department of Computer Science
University of Texas at Austin
abhimanu@cs.utexas.edu
http://abhimanukumar.com

Matthew Lease
School of Information
University of Texas at Austin
ml@ischool.utexas.edu

Supervised learning from noisy labels

- Labeling is inherently uncertain
  - Even experts disagree and make mistakes
  - Crowd tends to be noisier with higher variance
- Use *wisdom of crowds* to reduce uncertainty
  - Multi-label + aggregation = consensus labels
- How to maximize learning rate (labeling effort)?
  - Label a new example?
  - Get another label for an already-labeled example?
- See: Sheng, Provost & Ipeirotis, KDD'08

Task Setup

- Task: Binary classification
- Learner: C4.5 decision tree
- Given
  - An initial seed set of single-labeled examples (64)
  - An unlimited pool of unlabeled examples
- Cost model
  - Fixed unit cost for labeling any example
  - Unlabeled examples are freely obtained
- Goal: Maximize learning rate (for labeling effort)

Compare 3 methods: SL, MV, & NB

- **Single labeling (SL):** label a new example
- Multi-Labeling: get another label for pool
  - **Majority Vote (MV)**: consensus by simple vote
  - **Naïve Bayes (NB)**: weight vote by annotator accuracy

$$
\begin{aligned}
\widehat{x} &= \operatorname*{argmax}_{x} P(X^j = x | Y^j_{1:w}) \\
&\propto P(Y^j_{1:w} | X^j) P(X^j) \\
&= \prod_{i=1}^{w} P(Y^j_i | X^j) P(X^j)
\end{aligned}
$$

Assumptions

- Example selection: random
  - From pool for SL, from seed set for multi-labeling
  - No selection based on active learning
- Fixed commitment to a single method *a priori*
  - No switching between methods at run-time
- Balanced classes
  - model & measure simple accuracy (not P/R, ROC)
  - Assume uniform class prior for NB
- Annotator accuracies are known to system
  - In practice, must estimate these: from gold data (Snow et al. ’08) or EM (Dawid & Skene’79)

Simulation

- Each annotator
  - Has parameter p (prob. of producing correct label)
  - Generates exactly one label
- Uniform distribution of accuracies U(min,max)
- Generative model for simulation
  - Pick an example x (with true label y^*) at random
  - Draw annotator accuracy $p \sim U(min,max)$
  - Generate label $y \sim P(y \mid p, y^*)$

Evaluation

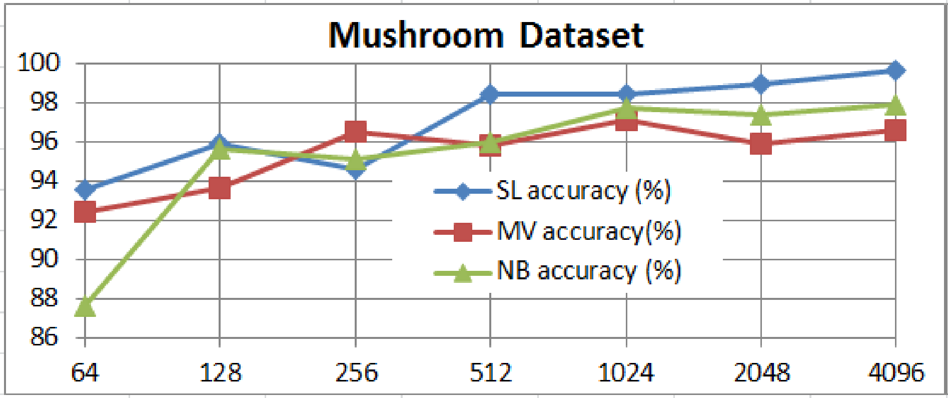
- Data: 4 datasets from UCI ML Repository
  - Mushroom
  - Spambase
  - Tic-Tac-Toe
  - Chess: King-Rook vs. King-Pawn

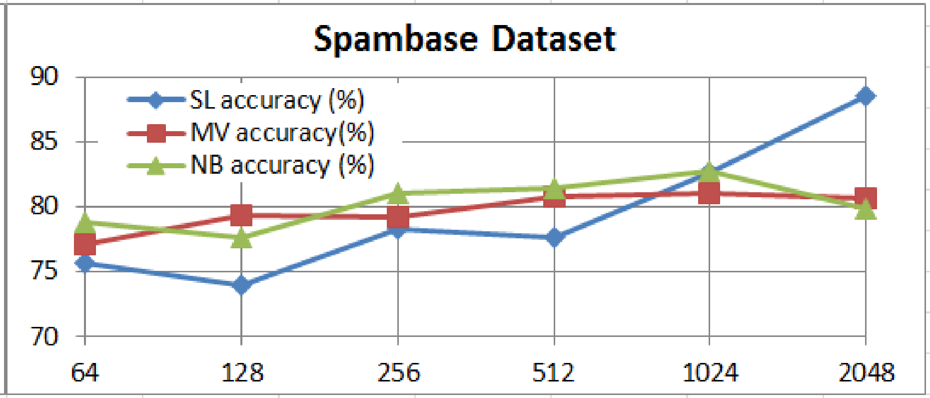
http://archive.ics.uci.edu/ml/datasets.html

- Same trends across all 4, so we report first 2
- Random 70 / 30 split of data for seed+pool / test
- Repeat each run 10 times and average results

p ~ U(0.6, 1.0)

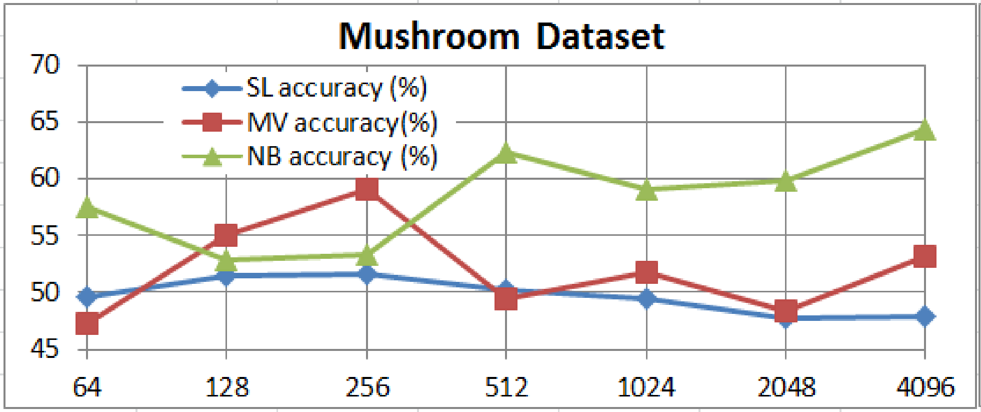
- Fairly accurate annotators (mean = 0.8)
- Little uncertainty -> little gain from multi-labeling

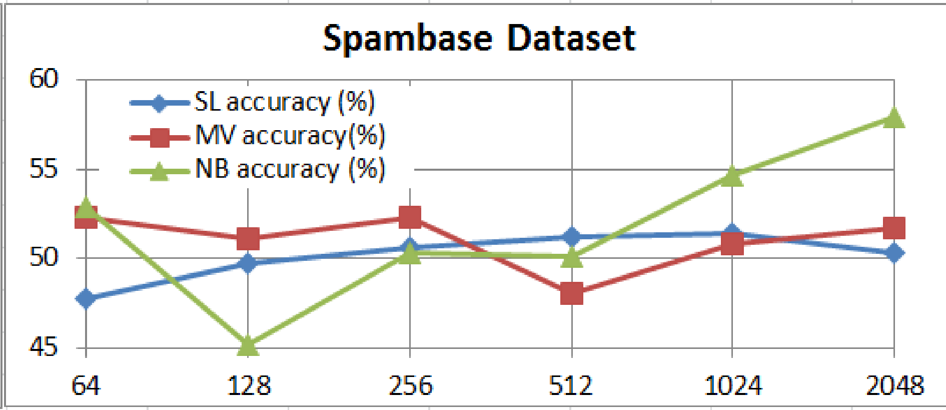




p ~ U(0.4, 0.6)

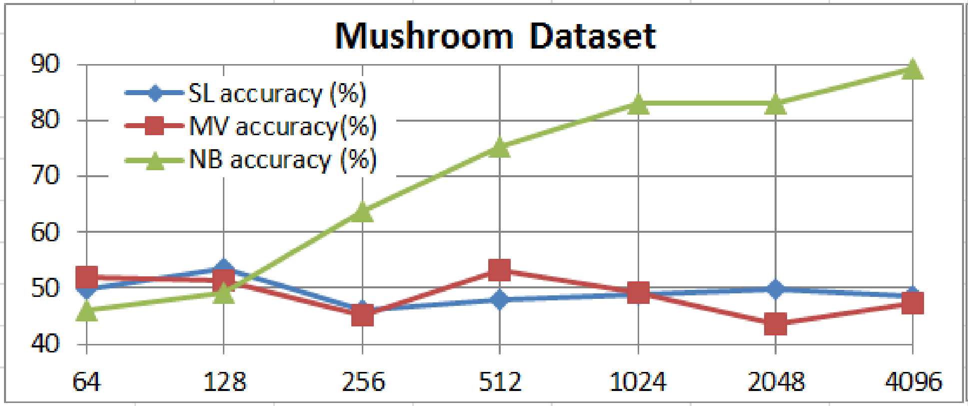
- Very noisy (mean = 0.5, random coin flip)
- SL and MV learning rates are flat
- NB wins by weighting more accurate workers

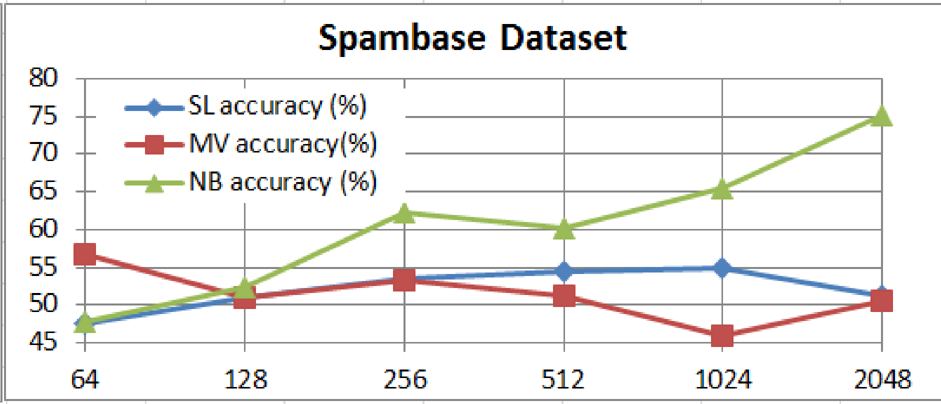




p ~ U(0.3, 0.7)

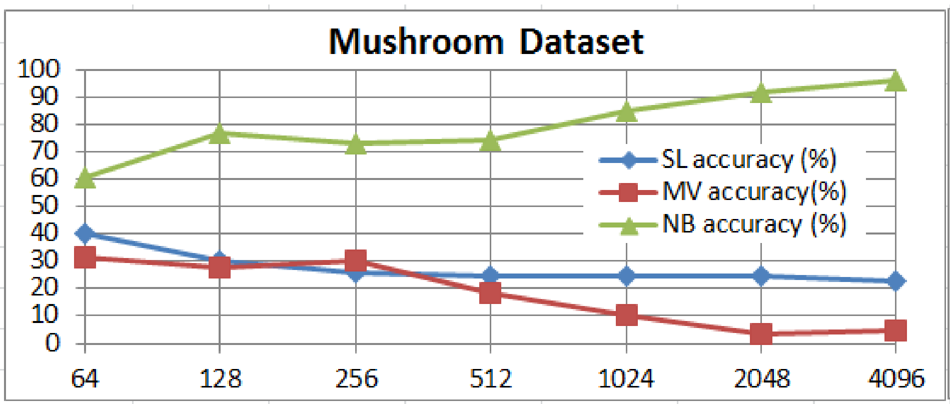
- Same noisy mean (0.5), but widen range
- SL and MV stay flat
- NB further outperforms

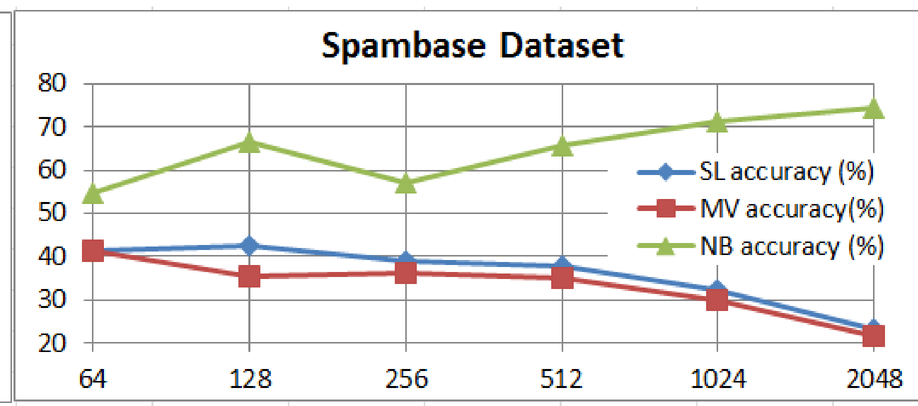




p ~ U(0.1, 0.7)

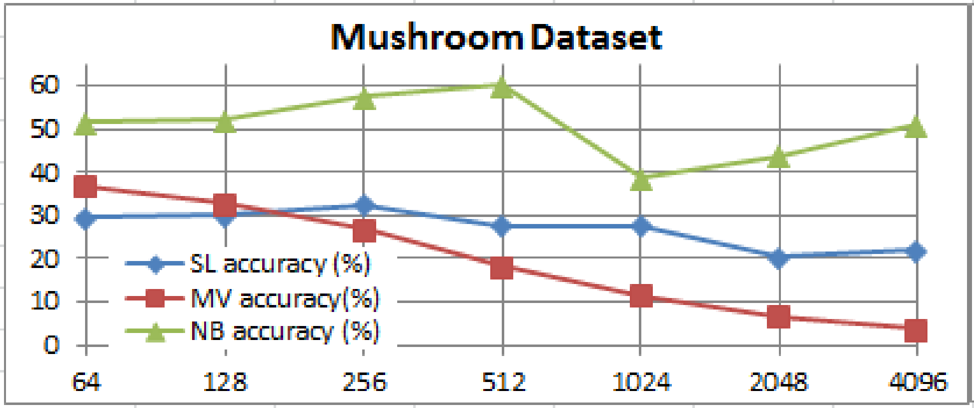
- Worsen accuracies further (mean = 0.4)
- NB virtually unchanged
- SL and MV predictions become anti-correlated
  - We should actually flip their predictions…

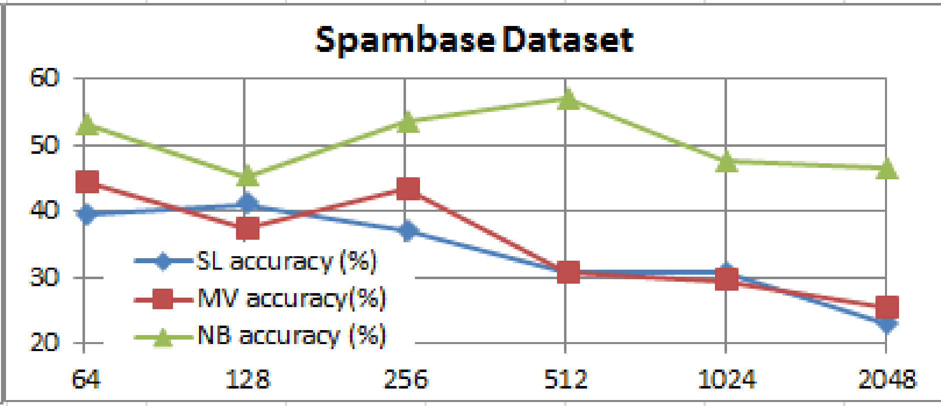




p ~ U(0.2, 0.6)

- Keep noisy mean 0.4, tighten range
- NB best of the worst, but only 50%
- Again, seems we should be flipping labels…



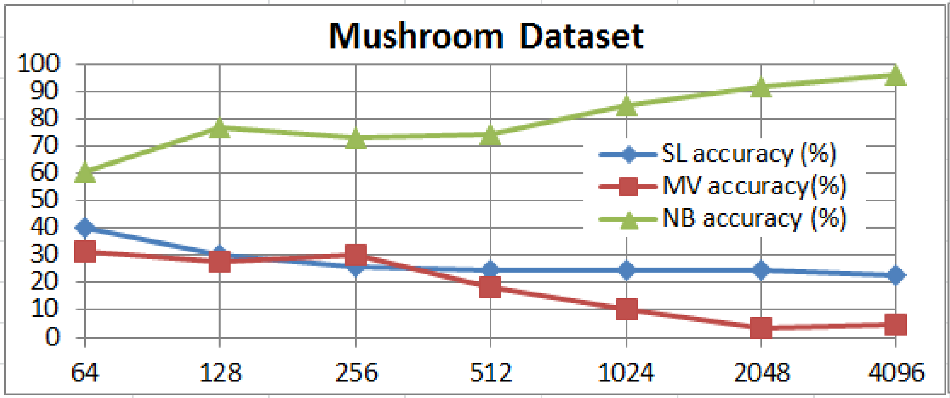


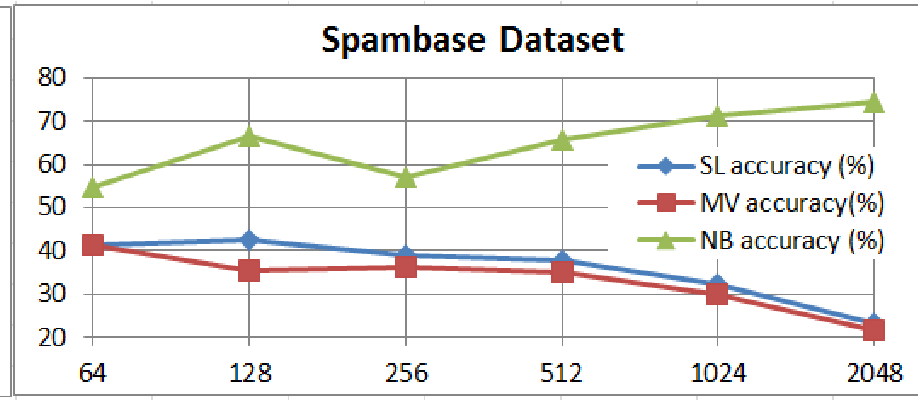
Label flipping

- Is NB doing better due to *how* it uses accuracy, or simply because it's using more information?
- If a worker's average accuracy is below 50%, we know he tends to be wrong (we've ignored this)
  – whatever he says, we should guess the opposite
- Flipping: put all methods on even-footing
  – Assume a given $p < 0.5$ produces label = y
  – Use label = (1-y) instead; for NB, use 1-p accuracy
  – Same as changing distribution so p always > 0.5

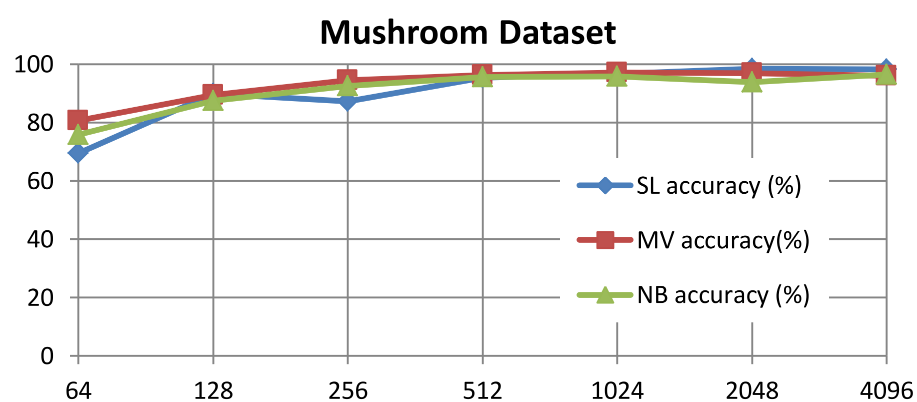
p ~ U(0.1, 0.7)

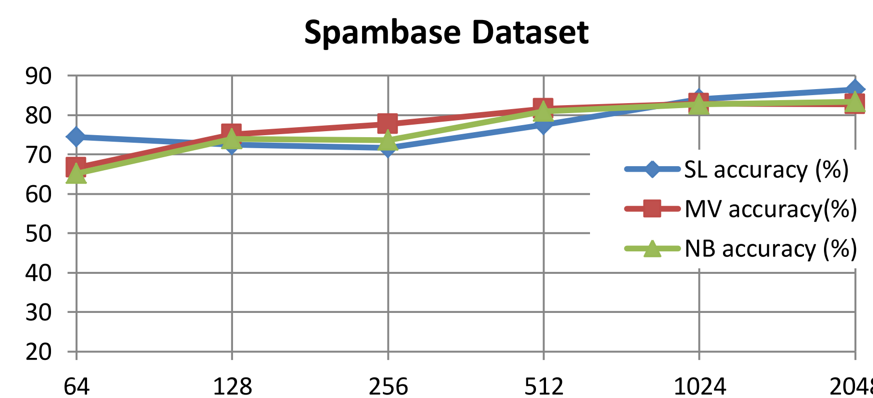
No flipping





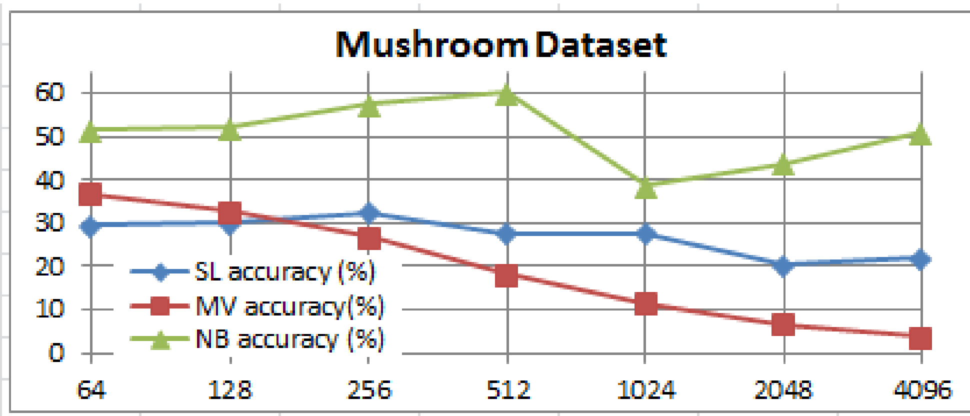
With flipping

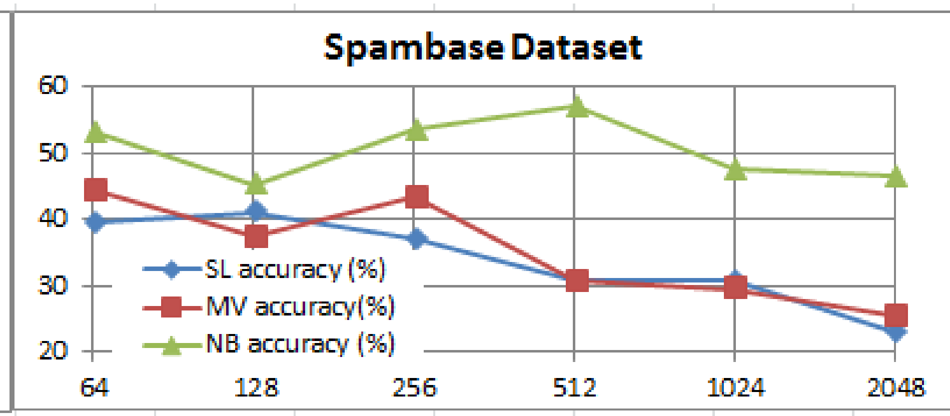




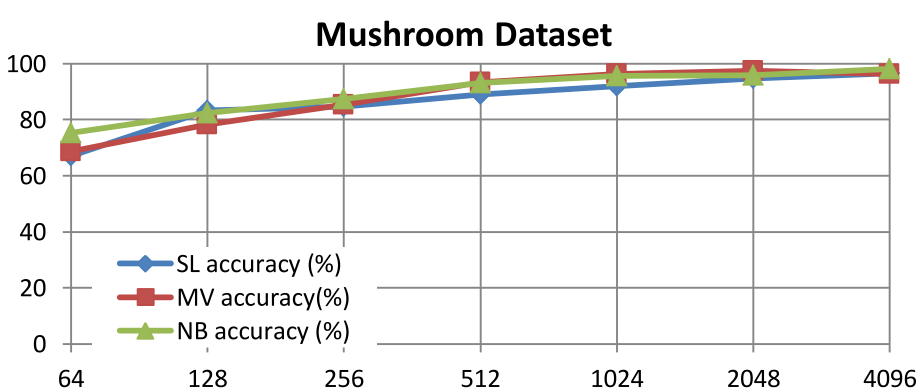
p ~ U(0.2, 0.6)

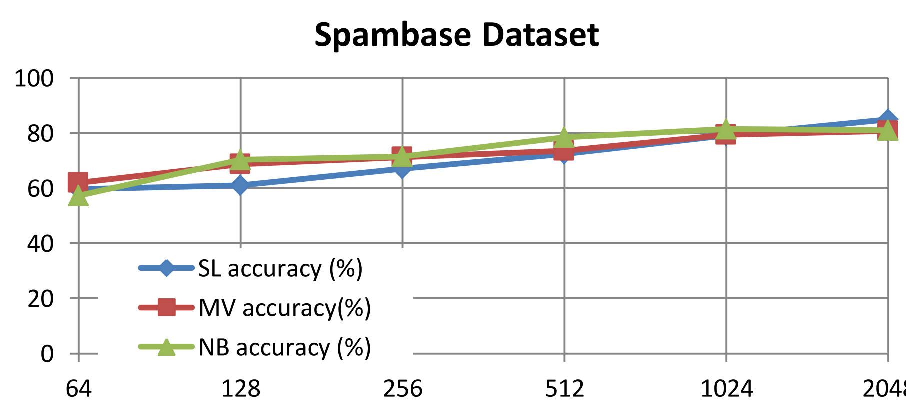
No flipping





With flipping





Department of Computer Science
THE UNIVERSITY OF TEXAS AT AUSTIN

THE UNIVERSITY OF TEXAS
SCHOOL OF
information

Conclusion

- Take-home: modeling accuracies matters, even if single labeling and majority vote
- But what about…
  - When accuracies are estimated (noisy)?
  - With real annotation errors (real distribution)?
  - With different learners or tasks (e.g. ranking)?
  - With dynamic choice of new example or re-label?
  - With active learning example selection?
  - With imbalanced classes?
  - …

Recent Events (2010 was big!)

http://ir.ischool.utexas.edu/crowd

- Human Computation: HCOMP 2009 & HCOMP 2010 at KDD
- IR: Crowdsourcing for Search Evaluation at SIGIR 2010
- NLP
  - The People's Web Meets NLP: Collaboratively Constructed Semantic Resources: 2009 at ACL-IJCNLP & 2010 at COLING
  - Creating Speech and Language Data With Mechanical Turk. NAACL 2010
  - Maryland Workshop on Crowdsourcing and Translation. June, 2010
- ML: Computational Social Science and Wisdom of Crowds. NIPS 2010
- Advancing Computer Vision with Humans in the Loop at CVPR 2010

- Conference: CrowdConf 2010 (organized by CrowdFlower)

Upcoming Crowdsourcing Events

http://ir.ischool.utexas.edu/crowd

Special issue of Information Retrieval journal on Crowdsourcing (papers due May 6, 2011)

Upcoming Conferences & Workshops

- CHI 2011 workshop (May 8)
- HCOMP 2011 workshop at AAAI (papers due April 22)
- CrowdConf 2011 (TBA)
- SIGIR 2011 workshop? (in review)
- TREC 2011 Crowdsourcing Track

Thanks!

Special thanks to our diligent crowd annotators and their relentless dedication to science…