## Introduction

- AI can dramatically reduce crowdsourcing costs
- Binary / multiclass classification well-studied
- Multi-label classification
  - Common problem (e.g., tags on websites)
  - Previously unoptimized
- Our most sophisticated multi-label classifier:
  - Uses learned model of label co-occurrence to infer true item-label relationships
  - Chooses questions that maximize value of information toward a joint classification

## Problem Definition

- For each item, find the subset of labels that apply
  - \( n \) = # of items in dataset
  - \( m \) = # of labels
  - \( nm \) binary classification problems

## Threshold Models

- Standard threshold voting
  - \( k \) votes per binary classification problem
  - Accept iff at least \( T \) out of \( k \) votes are positive
- Observation: \( k \) votes not always needed
- **Model #1: Lossless stopping**
  - Stop after \( T \) positive votes (or \( k-T+1 \) negatives)
  - No error compared to requesting all \( k \) votes
- **Model #2: One-way heuristic**
  - Stop after \( T-1 \) positive votes and no negative votes (or \( k-T \) negatives and no positives)
  - Small amount of error

## Probabilistic Models

- **Model #3: Independent**
  - Assume labels are independent
  - \( m \) label parameters, 2 noisy worker parameters
  \[ P(label|votes) = P(label) \prod_{v \in votes} P(v|label) \]
- **Model #4: Multi-Label Naive Bayes (MLNB)**
  - Model pairwise label co-occurrence
  - \( O(m^2) \) parameters
  \[ P(label|otherLabels) = P(label) \prod_{L \in OtherLabels} P(L|label) \]
  - **Submodularity** enables greedy selection of votes on labels that achieves \((1-1/e) \approx 63\% \) of optimal

## Probabilistic Results

- **Threshold Results**
  - Optimize categorization step in Cascade algorithm for crowdsourcing taxonomy creation [2]
  - \( n = 100 \) items, \( m = 33 \) labels, \( k = 15 \) votes

## Conclusions

- **MLNB uses less than 10\% as much labor** as Cascade (standard threshold voting)
- Extension: selecting batches of questions (labels)
  - Useful in online labor marketplaces
  - Little reduction in accuracy
- See [1] for full results

## References


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