A Correlated Worker Model for Grouped, Imbalanced and Multitask Data

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¹Presenter
Overview

- A model of workers in crowdsourcing.
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- Idea: Transfer knowledge of worker quality.
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- Variational EM learning.
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  - Biomed Citation Screening: imbalanced, grouped.
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- Apply to two datasets:
  - Biomed Citation Screening: imbalanced, grouped.
  - Galaxy Classification: multiple tasks.
Background

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- But (usually) lower quality.
- Common solution: collect 5 labels for each instance ...
- ... then aggregate them.

- Most previous work: improve (the estimates of) labels.
- Our work: improve (the estimates of) worker qualities.
Motivation
for estimating worker qualities
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Diagnostic insights.
Motivation
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Help workers improve.
Motivation
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Diagnostic insights.

Help workers improve.

Intelligent task routing (assign work to workers).
Worker Quality Measure

Accuracy: simple but not enough.
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Accurary: simple but not enough.

→ Confusion matrix: \( \Pr(\text{worker label} | \text{true label}) \)
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→ Confusion matrix: \( \Pr(\text{worker label}|\text{true label}) \)

Binary task (this work):

- Sensitivity: \( \Pr(\text{positive}|\text{positive}) \).
- Specificity: \( \Pr(\text{negative}|\text{negative}) \).
Setting

Input

- Crowd labels for each instance.
- No instance-level features (future work).
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Eval. Metric
- RMSE on sen. and spe.
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Output

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Eval. Metric

- RMSE on sen. and spe.
- gold sen. spe.: gold labels in whole dataset.
Challenges

Sparsity: many workers do only a few instances.
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Data is imbalanced:
- A lot more negative than positive
- Difficult to estimate sensitivity
Idea

Transfer knowledge of worker quality

▶ Between classes.
▶ Within group.
▶ In multiple tasks.
Previous models
(Raykar et. al. 2010; Liu & Wang 2012; Kim & Ghahramani 2012)

Hidden vars:
- True label for each instance.
- Confusion mat. (sen. + spe.) for each worker.
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Assumptions:
- Sen. & Spe. are independent params.
- A single group of workers.
- Multiple tasks: independent models.
Our Model

Assumptions:

- Sen. & Spe. are correlated.
- Multiple groups of workers (group membership is known).
- Sen. & Spe. in multiple tasks are correlated.
The Base Model
(i indexes instances, j indexes workers)

\[ U_j, V_j \sim \mathcal{N}(\mu, C) \]
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\[ L_{ij} | Z_i = 0 \sim \text{Ber}(S(V_j)) \]
1. Worker Groups:
   - Know group membership.
   - Model each group $k = \text{a Normal dist } (\mu_k, C_k)$. 
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   ▶ $(Sen_1, Spe_1)$ correlates with $(Sen_2, Spe_2)$. 
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1. Worker Groups:
   - Know group membership.
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2. Multiple tasks:
   - Assume two tasks.
   - $(\text{Sen}_1, \text{Spe}_1)$ correlates with $(\text{Sen}_2, \text{Spe}_2)$.
   - $(U_1, V_1, U_2, V_2) \sim \mathcal{N}(\mu, C)$
Inference
For the Base Model

Approach: Variational EM

- E-step: infer $\Pr(U_{1..m}, V_{1..m}, Z_{1..n} | L)$. 
Inference
For the Base Model

Approach: Variational EM

- **E-step**: infer $\Pr(U_{1:m}, V_{1:m}, Z_{1:n}|L)$.
- **M-step**: maximize parameters $\mu, C, \theta$. 
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For the Base Model

Approach: Variational EM
- E-step: infer $\Pr(U_{1..m}, V_{1..m}, Z_{1..n}|L)$.
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Variational Inference:
- Approximate the (complex) posterior $\Pr(\cdot)$...
- ... by a simpler function $q$. 
Inference
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Variational Inference:
- Approximate the (complex) posterior $\Pr(\cdot)$...
- ... by a simpler function $q$.
- Minimize $\mathbb{KL}(q||p)$ ...
- ... equivalent to maximize a log-likelihood lower bound.
Inference

Meanfield Assumptions:

- \( q \) factorizes:

\[
q(U_{1..m}, V_{1..m}, Z_{1..n}) = \prod_{j=1}^{m} q(U_j) q(V_j) \prod_{i=1}^{n} q(Z_i)
\]
Inference

Meanfield Assumptions:

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$$q(U_{1..m}, V_{1..m}, Z_{1..n}) = \prod_{j=1}^{m} q(U_j) q(V_j) \prod_{i=1}^{n} q(Z_i)$$

- Factors:

$$q(U_j) = \mathcal{N}(\tilde{\mu}_{uj}, \tilde{\sigma}_{uj}^2)$$
$$q(V_j) = \mathcal{N}(\tilde{\mu}_{vj}, \tilde{\sigma}_{vj}^2)$$
$$q(Z_i) = \text{Ber}(\tilde{\theta}_i)$$
Inference

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- Optimize with respect to

$$\{\tilde{\mu}_{uj}, \tilde{\sigma}_{uj}^2, \tilde{\mu}_{vj}, \tilde{\sigma}_{vj}^2 | j = 1...m\}$$
and $$\{\tilde{\theta}_i | i = 1...n\}$$
Optimization

Coordinate Descent: update one var at a time.
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Update $Z_i$:

$q^*(Z_i = 1) \propto \exp\left\{ \log \text{Ber}(1|\theta) + \sum \mathbb{E}_{U_j \sim q(U_j)} \log \text{Ber}(L_{ij}|S(U_j)) \right\}$

$q^*(Z_i = 0) \propto \exp\left\{ \log \text{Ber}(0|\theta) + \sum \mathbb{E}_{V_j \sim q(V_j)} \log \text{Ber}(L_{ij}|S(V_j)) \right\}$
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Intuition:

- $Z_i \approx \text{Prior} + \sum \mathbb{E}(\text{Crowd labels for } i)$
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Intuition:
- $Z_i \approx \text{Prior} + \sum \mathbb{E}(\text{Crowd labels for } i)$
- $\mathbb{E}$ wrt worker quality.
Optimization

Update $U_j$:

$$q^*(U_j) \propto \exp \left\{ \mathbb{E}_{V_j \sim q(V_j)} \log \mathcal{N}(U_j, V_j|\mu, C) + \sum q(Z_i = 1) \log \text{Ber}(L_{ij}|S(U_j)) \right\}$$
Optimization

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- $U_j = \text{logit sensitivity of worker } j$. 
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- $U_j = \text{logit sensitivity of worker } j$.
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Intuition:

- $U_j =$ logit sensitivity of worker $j$.
- $U_j \approx \mathbb{E}(\text{correlation with specificity}) + ...$
- ... instances that worker $j$ has labeled.
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Intuition:

- $U_j = \text{logit sensitivity of worker } j$.
- $U_j \approx \mathbb{E}(\text{correlation with specificity}) + ...$
- $... \text{ instances that worker } j \text{ has labeled.}$

(Similar equation for $V_j$)
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Problem: $\mathbb{E}()$ difficult to compute.
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Solution: Laplace Variational Inference (Wang & Blei, 2013)
  
  ▶ Approximate these update equations...
  
  ▶ ... by Laplace approximation.
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Solution: Laplace Variational Inference (Wang & Blei, 2013)
- Approximate these update equations...
- ... by Laplace approximation.
- Details in the paper.
Learning

E-step: Infer posterior distribution over hidden vars.
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E-step: Infer posterior distribution over hidden vars.

M-step: maximize $\mu, C, \theta$ under posterior.

- $\mu, C$: sample mean and Covariance.
- $\theta$: average of $\{\tilde{\theta}_i|i = 1...n\}$. 
Evaluation

Citizen Science:
Citizen Science:

- Workers **volunteer** ...
- ... to help science.
- Different from traditional crowdsourcing:
  - large scale.
  - (usually) higher quality.
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Two real world scenarios:

- Biomedical Citation Screening.
- Galaxy Morphological Classification.
Scenario 1

Biomedical Citation Screening:
- Motivation: biomedical literature is huge.
- Need to find relevant citations.
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- Identify Randomized Control Trials reports.
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The RCT dataset:
- Identify Randomized Control Trials reports.
- Very imbalanced (3% positive).
- Workers: from in 2 groups...
- ... experts and novices
Scenario 1

Baselines:

- Majority Vote.
- Two Coin (Raykar et al. 2010).
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Our method: two versions
- Full-Cov: the full model.
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- Full-Cov: the full model.
- Diag-Cov: constrain $C$ to be diagonal.
Scenario 1

Baselines:
- Majority Vote.
- Two Coin (Raykar et. al. 2010).

Our method: two versions
- Full-Cov: the full model.
- Diag-Cov: constrain $C$ to be diagonal.
  - only model worker groups ...
  - ... but not model sen-spec correlation.
Results: Sensitivity

![Graph showing the relationship between RMSE and number of items for different methods: Majority Vote, Two Coin, DiagCov, and FullCov. The graph indicates that the RMSE decreases as the number of items increases for all methods.]
Results: Specificity
Discussion

Our method has two parts: group and correlation.
Discussion

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- Group provides most improvement.
Discussion

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- Group provides most improvement.
- Correlation gives additional boost for sen.
Scenario 2

Galaxy Morphological Classification:
- Motivation: Few astronomers, lot of galaxies.
Scenario 2

Galaxy Morphological Classification:
- Motivation: Few astronomers, lot of galaxies.

Galaxy Zoo 2 dataset:
- Multiple questions: galaxy shape? number of spiral arms?...
- Have volunteers answering questions.
Scenario 2

Setting:

- Given all labels in source task ...
- ... and some labels in target task.
- Predict worker sen. and spe. in target task.
Scenario 2

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- Predict worker sen. and spe. in target task.

Compare:
- Single: only consider target labels.
- Accum: merge source labels to target.
- Multi: our multi-task model.
Result: Sensitivity
Result: Specificity
Discussion

Multi is surprisingly bad.

- Tasks are different, naive merge is bad.
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Our method

- has good improvement ...
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- Again, tasks are different...
- Many workers better in source task ...
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Discussion

Multi is surprisingly bad.
- Tasks are different, naive merge is bad.

Our method
- has good improvement ...
- ... although sometimes modest.
- Again, tasks are different...
- Many workers better in source task ...
- ... but worse in target task.
- Our method still as good as the baseline.
Conclusion

Summary

- Model correlation to transfer knowledge.
- Empirically improve estimates of worker quality.
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Future work

- Extend: instance-level features.
- Application: tasks/instances routing.
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➤ Empirically improve estimates of worker quality.

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➤ Extend: instance-level features.
➤ Application: tasks/instances routing.

Question?