Efficient Learning of Classification Models from Soft-label Information by Binning and Ranking

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Abstract

- Building of classification models requires labeled examples
- Real-world data are often not labeled
- Human annotation/labeling process may be:
  - Time consuming & Costly
- **Challenge:**
- Find ways of reducing the annotation/labeling effort
- **Solution:**
- Learning with Soft-labels
  - Soft labels reflect the degree of belief of an annotator in the class labels
- **This work:**
- New method based on soft-label binning
- Reduces the number of constraints

Introduction

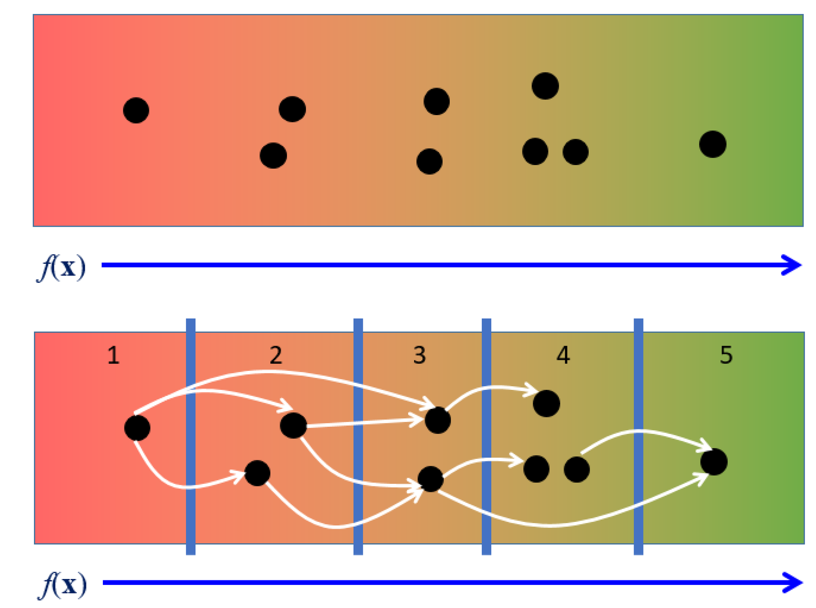
- **Soft labels:**
- represent the degree of belief of an annotator in the class label using a probabilistic score
- can facilitate learning of classification models

Class 0  Class 1

- **Caveat:**
- Humans are not good in providing consistent probabilistic assessments
  - Soft labels may be noisy
  - Learning methods should be robust to noisy soft labels

Related Work

- Existing works in literature show that there are two ways to learn with soft-label information: (1) Regression on the exact soft labels p_i, and (2) Respecting pairwise orderings rather than exact soft labels.
- **Regression on the exact soft labels p_i**
- **Idea:**
- Find a regression function f(x) that fits a logistic or linear regression model.
- **Disadvantage:**
- does not work well when soft-labels are noisy
- **Respecting pairwise orderings rather than exact soft labels**
- **Idea:**
- Find a discriminative projection f(x) that respects pairwise orderings of samples as much as possible
- **Disadvantage:**
- number of constraints is $O(N^2)$



Choosing the number of bins

How to choose the number of bins?

N bins: equivalent to all pairwise constraints
2 bins: equivalent to binary classification
The optimal number is somewhere between

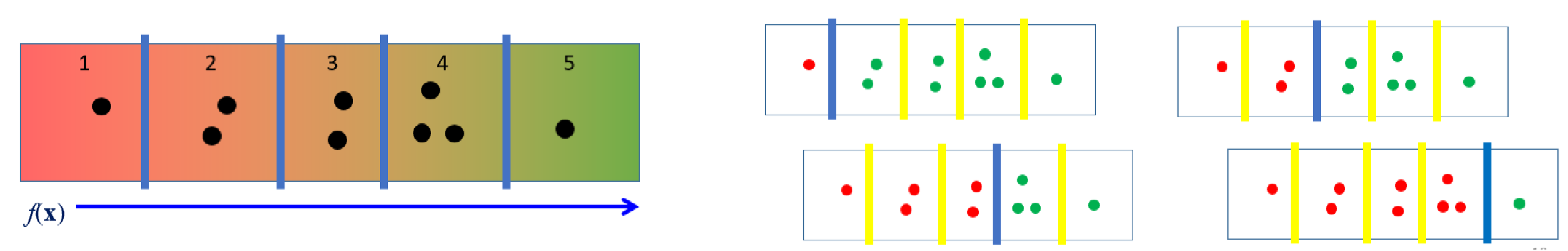
Heuristic function:

Inspired by optimal binning for discretization of continuous values

$$\#\text{of bins} = floor(\sqrt[3]{N})$$

Reducing constraints via binning

- Reformulate as ordinal regression
- **Idea:**
- solve jointly m-1 binary classifiers



- w: the set of parameters defining f(x)
- b_j: jth bin boundary
- **Advantage:**
- number of constraints is O(mN)

regularization term

errors for violating bin/sample constraints

$$\min_{\mathbf{w},\mathbf{b},\xi} \frac{\mathbf{w}^T\mathbf{w}}{2} + C\sum_{j=1}^{m-1}\sum_{i=1}^{N}\xi_{j,i}$$

$$\mathbf{w}^T\mathbf{x}_i - b_j \le \xi_{j,i} - 1 \quad \forall bin(p_i) \le j$$

$$\mathbf{w}^T\mathbf{x}_i - b_j \ge 1 - \xi_{j,i} \quad \forall bin(p_i) > j$$

$$\xi_{j,i} \ge 0 \quad \forall i, j$$

constraints defining errors between samples and bin boundaries

Experiments and Results

We test our approach on both synthetic and real-world data.

Noise generation:
Weak noise
Strong noise

BinarySVM
Labels: Binary only
Model: Support vector machine

SoftLogReg
Labels: Soft only
Model: Logistic regression

GPR
Labels: Binary + soft
Model: Gaussian process regression

SoftSvmRankPair
Labels: Binary + soft
Model: SVM + pairwise constraints

SoftSvmRankKN
Labels: Binary + soft
Model: SVM + mN random pairwise constraints

SoftSvmOrd- our method
Labels: Binary + soft
Model: SVM + bin/sample constraints

Figure 1. UCI Wine Red dataset (No noise)

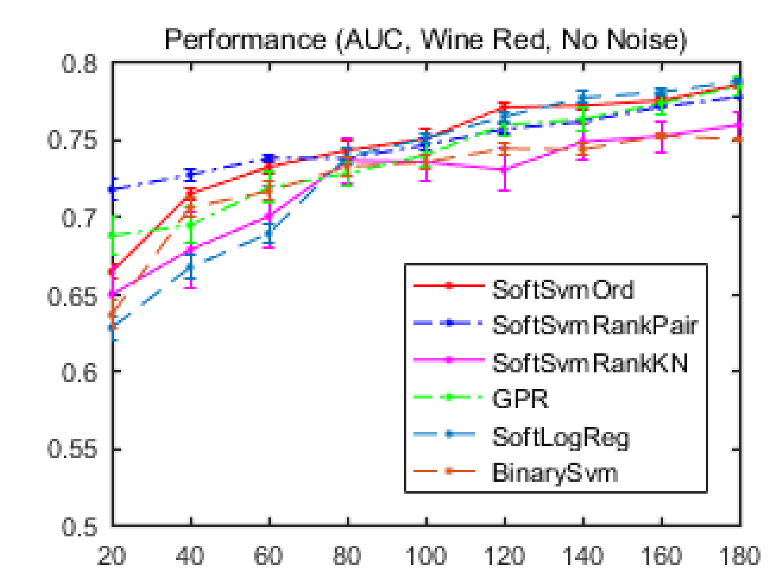


Figure 2. UCI Wine Red dataset (Weak noise)

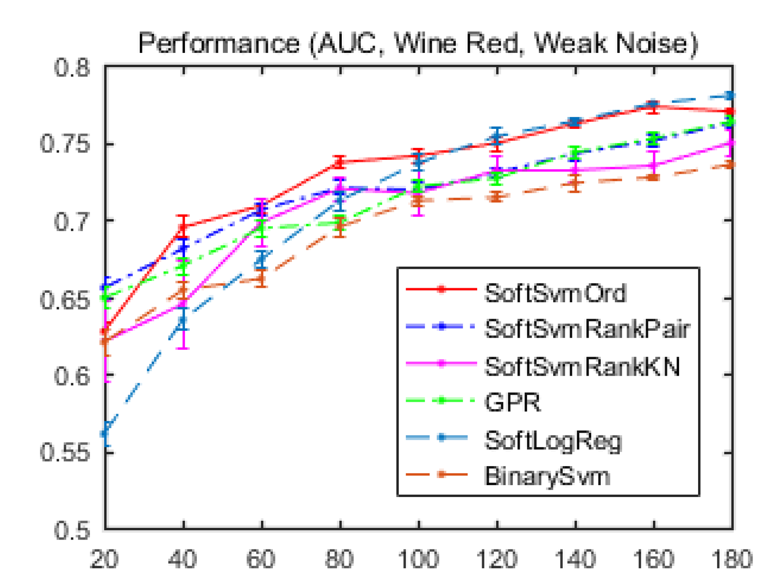
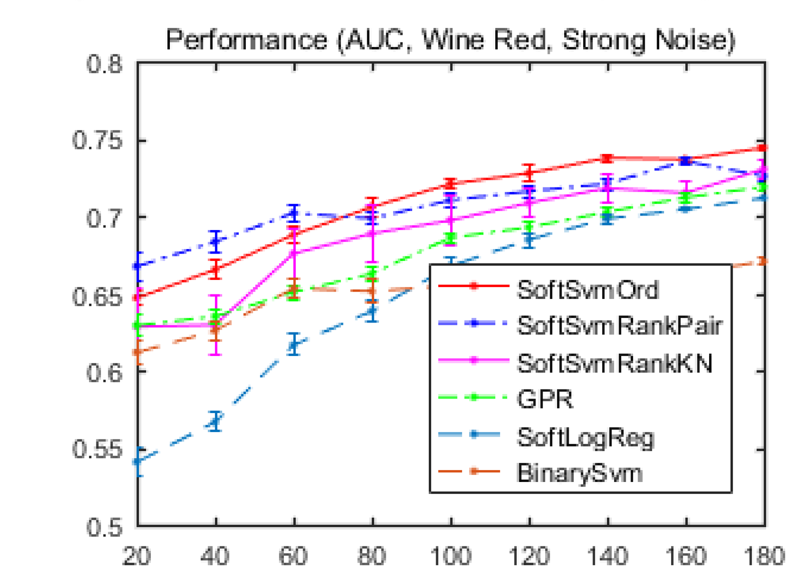


Figure 3. UCI Wine Red dataset (Strong noise)



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Conclusion

We develop a new robust method that uses soft-label information to reduce annotation effort.
Our method (1) can benefit greatly from soft-label information, and (2) is robust to different levels of soft-label noise.

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