Addressing class imbalance in Multilabel Prototype Generation for k-Nearest Neighbor classification

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Introduction

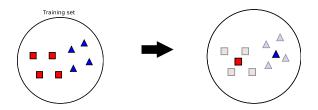
The k-Nearest Neighbor (k-NN) classifier

- Method for supervised classification
- Features
 - Compares each query to the hole dataset following a metric
 - Non-parametric method
- Drawbacks
 - Low efficiency
 - High memory usage

The k-Nearest Neighbor (k-NN) classifier

Data Reduction

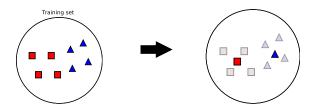
- Consists in reducing the size of the reference set
- Two main approaches:
 - * Prototype selection (PS)
 - * Prototype generation (PG)



The k-Nearest Neighbor (k-NN) classifier

Data Reduction

- Consists in reducing the size of the reference set
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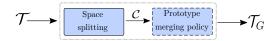
However...

- PG has been scarcely addressed in multilabel cases
- Existing methods show shortages when addressing imbalance data
- Goal: Tackle imbalance problems in multilabel PG

Methodology

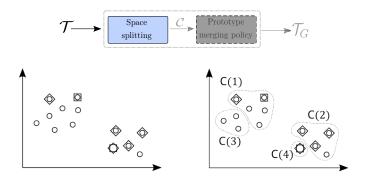
Two stages

- 1. Space splitting
- 2. Prototype merging policy



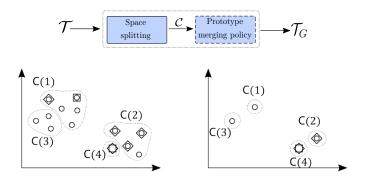
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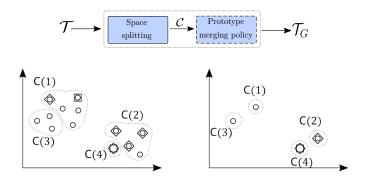
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Two stages

- 1. Space splitting
- 2. Prototype merging policy



Is the square in C(1) noise? Or is is simply underrepresented?

Imbalance metrics: IRLbl and MeanIR

• Imbalance ratio per label
$$(\lambda)$$
:

$$\mathsf{IRLbI}\left(\lambda\right) = \frac{\max_{\forall \lambda' \in \mathcal{Y}} \left(\sum_{i=1}^{|\mathcal{T}|} \lambda' \in \mathbf{y}_i\right)}{\sum_{i=1}^{|\mathcal{T}|} \lambda \in \mathbf{y}_i} \tag{1}$$

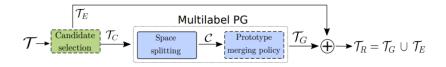


$$\mathsf{IRLbI}(\Box) = \frac{\mathsf{max}(12, 4, 2)}{2} = 6 \tag{2}$$

Mean imbalance ratio:

MeanIR =
$$\frac{1}{|\mathcal{Y}|} \sum_{\lambda \in \mathcal{Y}} \text{IRLbl}(\lambda) = \frac{1+2.4+6}{3} = 3.13$$
 (3)

Proposal



Two additional imbalance-aware mechanisms:

- Candidate selection
- Prototype merging policies

Proposal Candidate selection



Initial set T is split:

- Set \mathcal{T}_E of samples with imbalanced samples
- Set \mathcal{T}_C of samples with non-imbalanced samples

Proposal Candidate selection

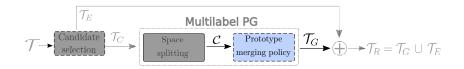


Initial set T is split:

- Set \mathcal{T}_E of samples with imbalanced samples
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Imbalanced samples:

$$\mathcal{T}_{E} = (\mathbf{x}_{i}, \mathbf{y}_{i}) : \mathsf{IRLbl}(\lambda) > \mathsf{MeanIR} \ \forall \lambda \in \mathbf{y}_{i}$$



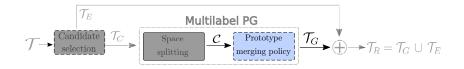
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• Policies for merging prototypes in C:

- Features (x_i): Feature-wise mean
- Label space (y_i) :

- Base case:
$$|C(m)|_{\lambda} \geq \frac{|C(m)|}{2}$$

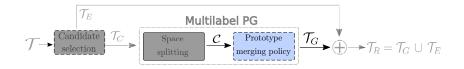


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- Proposal I:
$$|C(m)|_{\lambda} \ge \left\lfloor \frac{|C(m)|}{2 \cdot \text{IRLbl}(\lambda)} \right\rfloor$$



• Policies for merging prototypes in C:

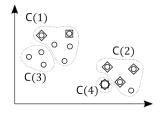
- Features (x_i): Feature-wise mean
- Label space (**y**_i):

- Base case:
$$|C(m)|_{\lambda} \geq \frac{|C(m)|}{2}$$

- Proposal I:
$$|C(m)|_{\lambda} \ge \left\lfloor \frac{|C(m)|}{2 \cdot \text{IRLbl}(\lambda)} \right\rfloor$$

- Proposal II: (Base case) \lor (IRLbl(λ) > MeanIR)

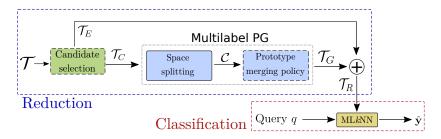




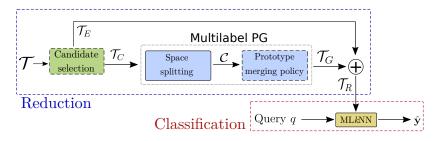
- Base policy: C(1) = $\{\circ\}$
- Policy 1: $C(1) = \{\circ, \Box\}$
- Policy 2: $C(1) = \{\circ, \Box\}$

Experimental set-up and results

Scheme and algorithms



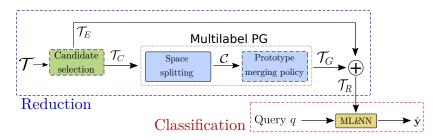
Scheme and algorithms



Multilabel k-NN algorithm:

-
$$MLkNN(k = 1)$$

Scheme and algorithms



- Multilabel k-NN algorithm:
 - MLkNN (k = 1)
- Multilabel PG methods:
 - Multilabel Reduction through Homogeneous Clustering (MRHC)
 - Multilabel Chen (MChen)
 - Multilabel Reduction through Space Partitioning (MRSP3)

Datasets and metrics

Datasets:

Name	Set	MeanIR				
	Train	Test	meann			
Low imbalance						
Scene	1,211	1,196	1.33			
Emotions	391	202	1.49			
Birds	322	323	6.10			
Yeast	1,500	917	7.27			
Bibtex	4,880	2,515	12.78			
High imbalance						
Genbase	463	199	31.60			
Medical	333	645	48.59			
rcv1subset4	3,000	3,000	170.84			
rcv1subset2	3,000	3,000	177.89			
Corel5k	4,500	500	183.29			
rcv1subset1	3,000	3,000	191.42			
rcv1subset3	3,000	3,000	192.48			

Datasets and metrics

Datasets:

Set size							
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Metrics:

- Macro F1 score
- Reduction rate: $|\mathcal{T}_R|/|\mathcal{T}|$

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Results

	No candidate selection $(\mathcal{T}_{C}=\mathcal{T})$				Using candidate selection $(\mathcal{T}_C \subseteq \mathcal{T})$			
	Size (%)	N	Merging policy		Size (%)	Merging policy		
	5120 (70)		Policy 1	Policy 2	0.20 (70)	Base	Policy 1	Policy 2
Low imbalance								
MRHC	57.83	42.44	43.70	42.87	70.65	42.34	43.36	42.34
$MChen_{10}$	9.98	30.11	36.87	27.81	40.98	36.36	40.33	36.36
MChen ₅₀	49.97	37.15	41.64	38.26	67.17	40.46	41.66	40.46
MChen ₉₀	89.89	42.20	42.29	42.26	93.23	42.99	43.00	42.99
MRSP3	66.84	40.73	43.58	41.43	78.12	41.76	43.04	41.76

- General improvement with proposed policies
- Best results with Policy 1
- Worse efficiency when using Candidate Selection

Results

	No candidate selection ($\mathcal{T}_{\mathcal{C}}=\mathcal{T}$)				Using candidate selection $(\mathcal{T}_{\mathcal{C}} \subseteq \mathcal{T})$			
	Size (%)	Merging policy		Size (%)	Merging policy			
	5126 (70)	Base	Policy 1	Policy 2	5126 (70)	Base	Policy 1	Policy 2
High imbalance								
MRHC	47.55	12.03	12.48	12.03	46.89	11.92	12.48	11.92
MChen ₁₀	9.98	7.23	9.80	7.36	12.64	7.48	9.94	7.48
MChen ₅₀	49.96	9.96	11.93	10.04	51.45	9.97	11.78	9.97
MChen ₉₀	89.58	11.91	12.08	11.91	89.74	11.83	12.04	11.83
MRSP3	60.94	11.65	13.96	12.11	61.08	8.80	10.59	8.80

- General improvement with proposed policies
- Best results Policy 1
- Similar efficiency when using Candidate Selection

Conclusions

Conclusions

- Two novel policy methods for imbalance aware
- Mechanism to prevent severely imbalanced samples from undergoing a reduction process
- Experimental validation in low imbalance and high imbalance datasets
- Promising results with different levels of imbalance ratio

Future works

- Develop similar policies for other stages of Multilabel PG
- ► Full pipeline
- Use other measurement for imbalance

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