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

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Universitat d'Alacant Universidad de Alicante

Introduction

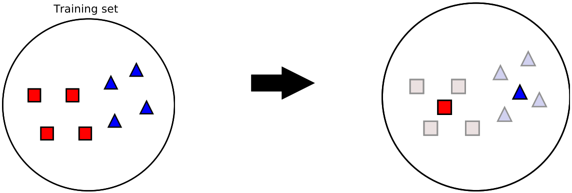
The k-Nearest Neighbor (k-NN) classifier

- 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)



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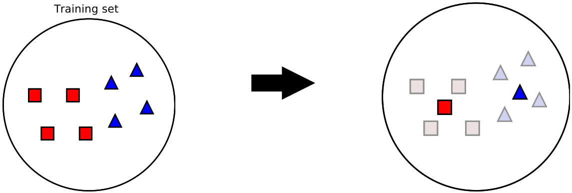
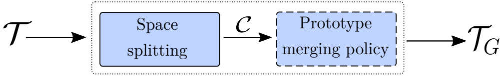


- However...
  - PG has been scarcely addressed in multilabel cases
  - Existing methods show shortages when addressing imbalance data
  - **Goal**: Tackle imbalance problems in multilabel PG

Methodology

Multilabel Prototype Generation

- Two stages
  1. Space splitting
  2. Prototype merging policy



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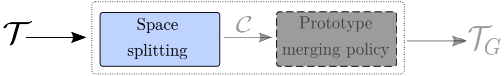

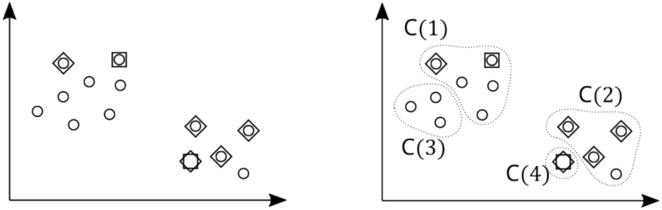

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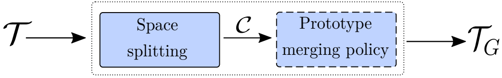

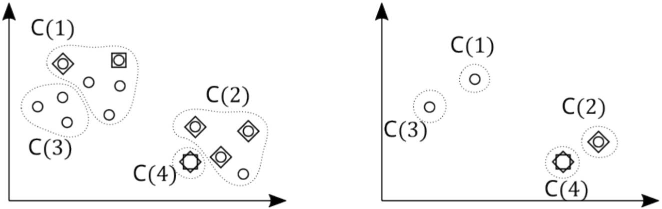

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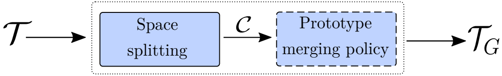
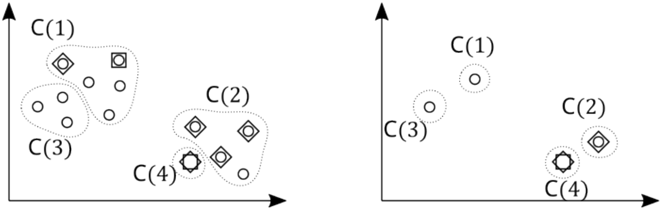




Is the square in C(1) noise? Or is is simply underrepresented?

Multilabel Prototype Generation

Imbalance metrics: IRLbl and MeanIR

- Imbalance ratio per label (λ):

$$\mathrm{IRLbl}\left(\lambda\right) = \frac{\max\limits_{\forall \lambda' \in \mathcal{Y}} \left(\sum_{i=1}^{|\mathcal{T}|} \lambda' \in \boldsymbol{y}_i \right)}{\sum_{i=1}^{|\mathcal{T}|} \lambda \in \boldsymbol{y}_i} \tag{1}$$

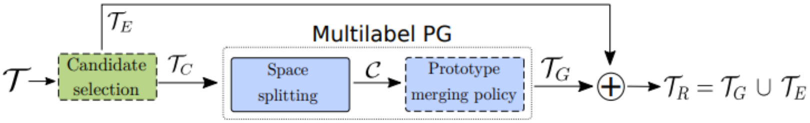
- Example $\lambda = \square$:

$$\mathrm{IRLbl}(\square) = \frac{\max(12, 4, 2)}{2} = 6 \tag{2}$$

- Mean imbalance ratio:

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

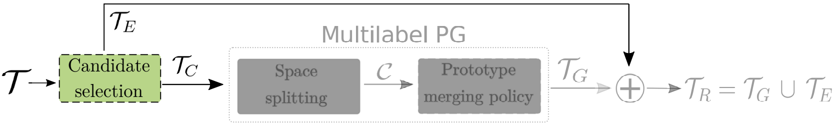
Proposal



- Two additional imbalance-aware mechanisms:
  - Candidate selection
  - Prototype merging policies

Proposal

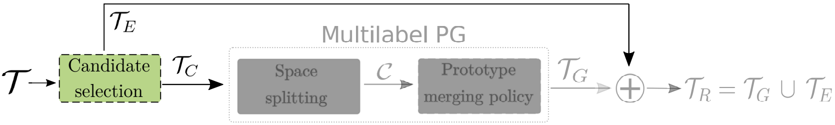
Candidate selection



- Initial set $\mathcal{T}$ is split:
  - Set $\mathcal{T}_E$ of samples with imbalanced samples
  - Set $\mathcal{T}_C$ of samples with non-imbalanced samples

Proposal

Candidate selection



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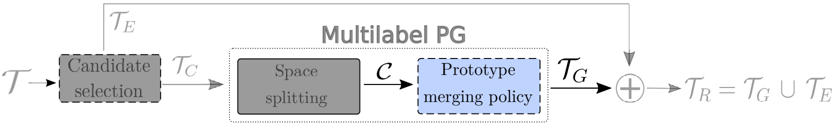
- Imbalanced samples:

$$\mathcal{T}_E = (\boldsymbol{x}_i, \boldsymbol{y}_i) : \mathrm{IRLbl}\,(\lambda) > \mathrm{MeanIR} \;\; \forall\, \lambda \in \boldsymbol{y}_i$$

Proposal

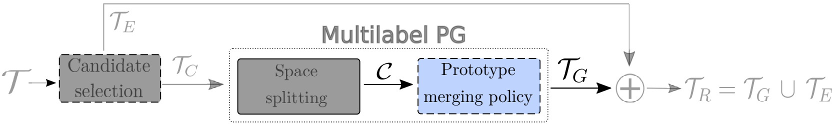
Prototype merging policy



- Policies for merging prototypes in $\mathcal{C}$:
  - Features ($\boldsymbol{x}_i$): Feature-wise mean
  - Label space ($\boldsymbol{y}_i$):
    - Base case: $|C(m)|_\lambda \geq \frac{|C(m)|}{2}$

Proposal

Prototype merging policy



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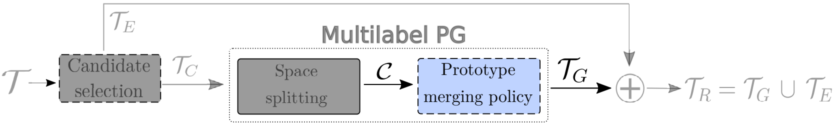
Proposal

Prototype merging policy



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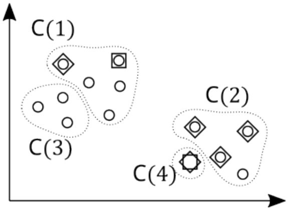
    - Proposal I: $|C(m)|_\lambda \geq \left\lfloor \frac{|C(m)|}{2 \cdot \text{IRLbl}(\lambda)} \right\rfloor$
    - Proposal II: (Base case) $\vee$ (IRLbl(λ) $>$ MeanIR)

Proposal

Prototype merging policy

- Example:

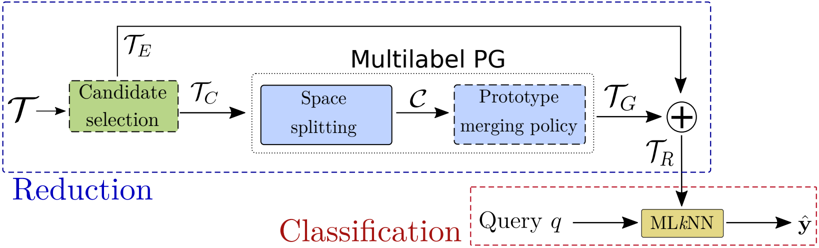


- Base policy: $C(1) = \{\circ\}$
- Policy 1: $C(1) = \{\circ, \square\}$
- Policy 2: $C(1) = \{\circ, \square\}$

Experimental set-up and results

Experimental set-up

Scheme and algorithms



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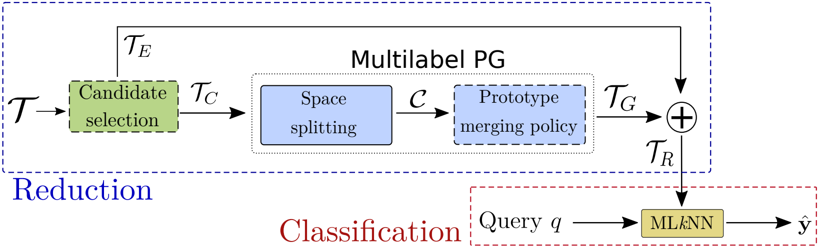

- Multilabel k-NN algorithm:
  - MLkNN ($k = 1$)

Experimental set-up

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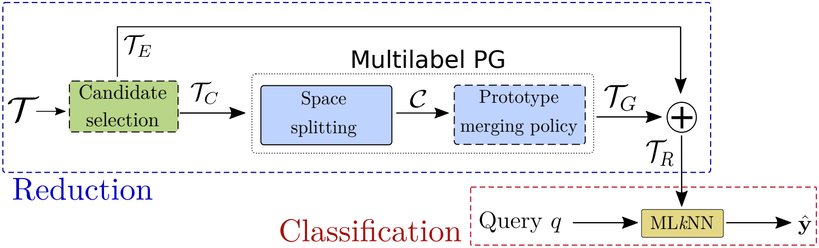

- Multilabel k-NN algorithm:
  - MLkNN ($k = 1$)
- Multilabel PG methods:
  - Multilabel Reduction through Homogeneous Clustering (MRHC)
  - Multilabel Chen (MChen)
  - Multilabel Reduction through Space Partitioning (MRSP3)

Experimental set-up

Datasets and metrics

- Datasets:

Name	Set size		MeanIR
	Train	Test	
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

Experimental set-up

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

Results

	No candidate selection ($\mathcal{T}_C = \mathcal{T}$)				Using candidate selection ($\mathcal{T}_C \subseteq \mathcal{T}$)			
	Size (%)	Merging policy			Size (%)	Merging policy		
		Base	Policy 1	Policy 2		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

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	Size (%)	Merging policy			Size (%)	Merging policy		
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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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