Multi-Label Classification with Meta Labels

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17 December 2014

Overview

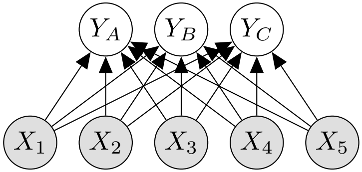
Multi-label classification:

$\subseteq \{\texttt{beach}, \texttt{sunset}, \textit{foliage}, \texttt{field}, \textit{mountain}, \texttt{urban}\}$

- Most multi-label classification methods can be expressed in a general framework of meta-label classification
- Our work combines labels into meta-labels, so as to learn dependence efficiently and effectively.

Multi-label Learning

With input variables X, produce predictions for *multiple* output variables Y. The basic binary relevance approach,

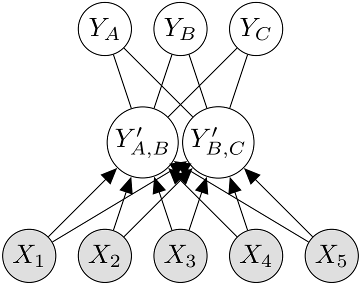


- does not capture label dependence (among Y-variables)
- does not scale to large number of labels

The label powerset approach models label combinations as class values in a multi-class problem.

Meta Labels

We introduce a layer of meta-labels,



- captures label dependence
- meta-labels can be fewer than the original number of labels
- and are deterministically decodable into the labels

Producing Meta Labels

dataset		binary relevance			label powerset	meta labels	
instance	labels	Y_A	Y_B	Y_C	$Y_{A,B,C}$	$Y_{A,C}$	$Y_{B,C}$
1	B	0	1	0	B	$\emptyset$	B
2	B,C	0	1	1	BC	$\emptyset$	BC
3	C	0	0	1	C	$\emptyset$	C
4	B	0	1	0	B	$\emptyset$	B
5	A,C	1	0	1	AC	AC	C
6	A,C	1	0	1	AC	AC	C
7	A,C	1	0	1	AC	AC	C
8	A,B,C	1	1	1	ABC	$\emptyset$	BC
9	C	0	0	1	C	$\emptyset$	C

- *binary relevance*: 9 exs, 3×2 binary classes
- *label powerset*: 9 exs, 1×5 multi-class

Producing Meta Labels

dataset		binary relevance			label powerset	meta labels	
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7	A,C	1	0	1	AC	AC	C
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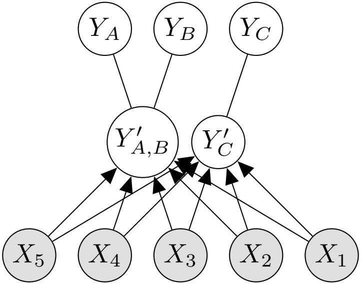
- *binary relevance*: 9 exs, 3×2 binary classes
- *label powerset*: 9 exs, 1×5 multi-class
- *pruned meta labels*: 9 exs, 2 meta labels, of 2 and 3 values

$$Y'_{AC} \in \{\emptyset, AC\}, Y'_{BC} \in \{B, C, BC\}$$

(one possible formulation)

Example 2

There is no need to model labels together if there is no strong dependence between them,



$$Y'_{A,B} \in \{\emptyset, B, AB\},\ Y'_C \in \{\emptyset, C\}$$

(e.g., no strong relation between C and the other labels)

General process for classification with meta-labels

1. Make a partition (either overlapping or disjoint) of the *label set*
2. Relabel the meta-labels, deciding on how many values each label can take (i.e., possibly pruning some)
3. Train classifiers to predict meta-labels from the input instances
4. Make predictions into the meta-label space
5. Recombine predictions into the label space

Voting Using Meta Labels

Table : Meta-label Vote, e.g., for $Y'_{AB} \in \{\emptyset, B, AB\}$

v	A	B	$p(Y'_{AB} = v \mid \tilde{\mathbf{x}})$
$\emptyset$	0	0	0.0
B	0	1	0.9
AB	1	1	0.1
P_{AB}	0.1	1.0	

Table : Labelset Voting: From Meta-labels to Labels

	A	B	C
P_{AB}	0.1	1.0	
P_{BC}		0.7	0.3
$\sum_k P_{k,j}$	0.1	1.7	0.3
$\hat{\mathbf{y}}$ (> 0.5)	0	1	0

Results

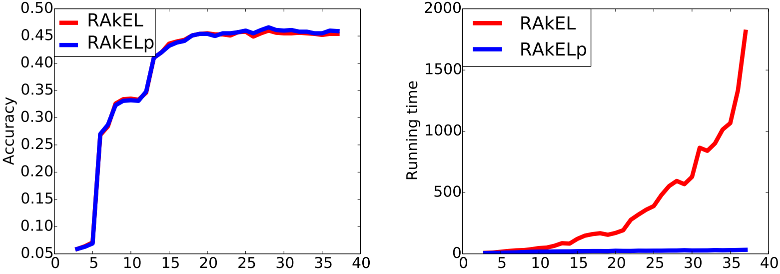


Figure : On Enron (1700 emails, 53 labels). RAkEL: random ensembles of 'label-powerset method' on subsets of size k (horizontal axis) vs RAkELp: with pruned meta-labels

Summary

- General framework of meta-labels for multi-label classification
- Unifies various approaches from the literature
- New models RAkELp and EpRd have large improvement in running time
- Part of solution for LSHTC4 (1st place) and WISE (2nd Place) Kaggle challenges
- Code available at

`http://meka.sourceforge.net`

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