Ranking Error-Correcting Output Codes for Class Retrieval

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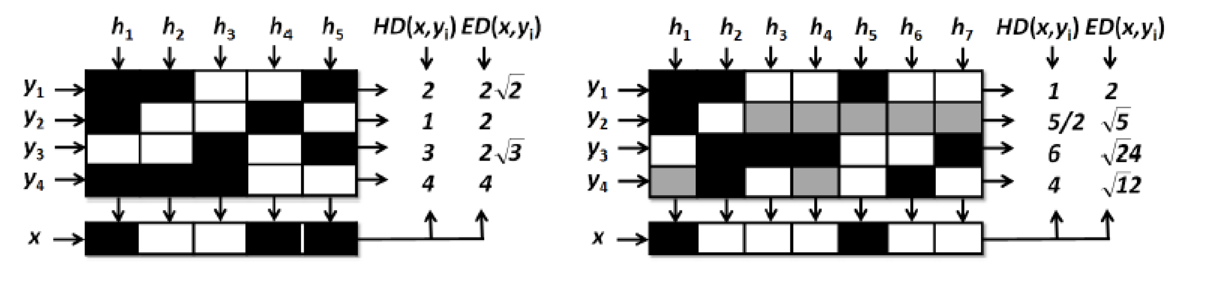
ABSTRACT

Error-Correcting Output Codes (ECOC) is a general framework for combining binary classification in order to address the multi-class categorization problem. In this paper, we include contextual and semantic information in the decoding process of the ECOC framework, defining an ECOC-rank methodology. Altering the ECOC output values by means of the adjacency of classes based on features and class relations based on ontology, we defined a new methodology for class retrieval problems. Results over public data show performance improvement when using the new ECOC-rank in the retrieval process.

1.ECOC Rrank

Retrieval systems retrieve huge amount of data for each query. Thus, sorting the results from most to less relevant cases is required. Based on the framework and application, there exists different ways for ranking the results based on the associated criteria. In the decoding process of the ECOC framework [2], a ”distance” associated to each class is computed. This ”distance” can be then interpreted as a ranking measure. However, this ranking is the most trivial way for sorting the results. Moreover, the output of the ECOC system does not take into account any semantic relationship among classes, which may be beneficial for retrieval applications. As an example of an image retrieval system, suppose the query of ”Dog”. In the feature space, it is possible that there exists high similarity between ”Dog” and ”Bike”, so based on features, the ranking will be higher for ”Bike” than for some other class which can be semantically more similar to ”Dog”, such as ”Cat”. On the other hand, it is easy to see that similar to based on features also is important, and thus, a trade-off between appearance and semantics is required. In order to embed class semantic and contextual information in the ranking process, we define two matrices that will be used to vote the ranking process: one based on adjacency and another one based on ontology. These matrices are n £ n matrices for n number of classes, where each entry represents the similarity between two classes. By multiplying the ranking vector of the ECOC output by these matrices, we alter the output ranking and improve retrieval results. The rest of this section describes the design of the class adjacency matrix, ontology matrix, and their use to modify the output ECOC rank.

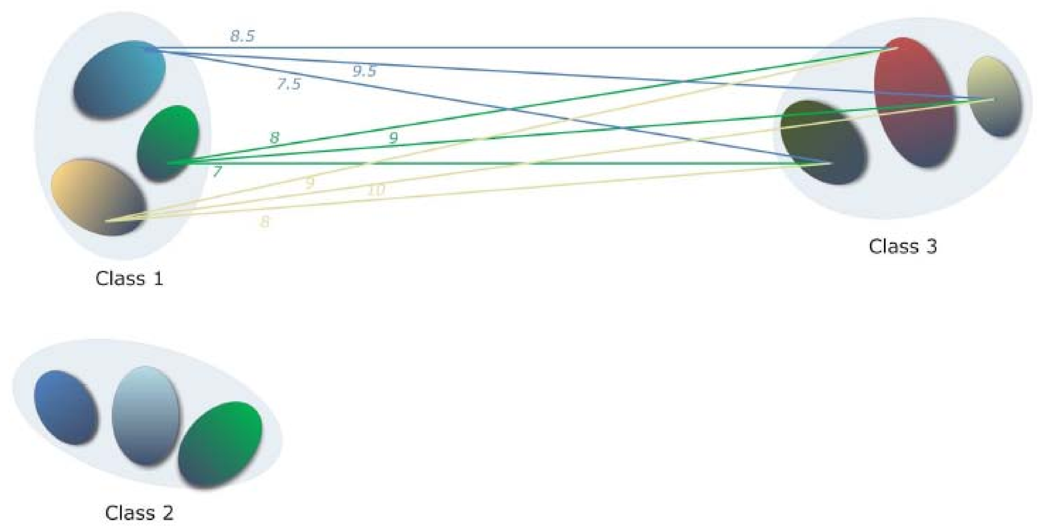


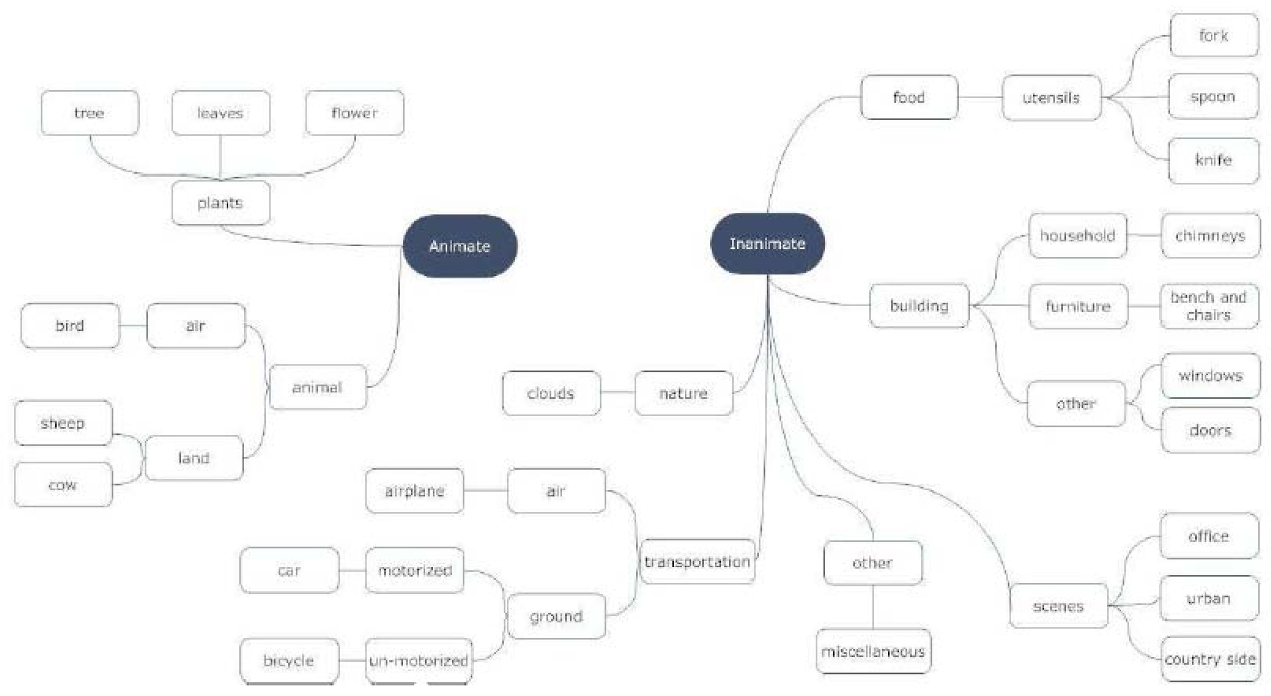
(a) (b)

(a) Binary ECOC design for a 4-class problem. An input test codeword x is classified by class c_2 using the Hamming or the Euclidean Decoding. (b) Example of a ternary matrix M for a 4-class problem. A new test codeword x is classified by class c_1 using the Hamming and the Euclidean Decoding.

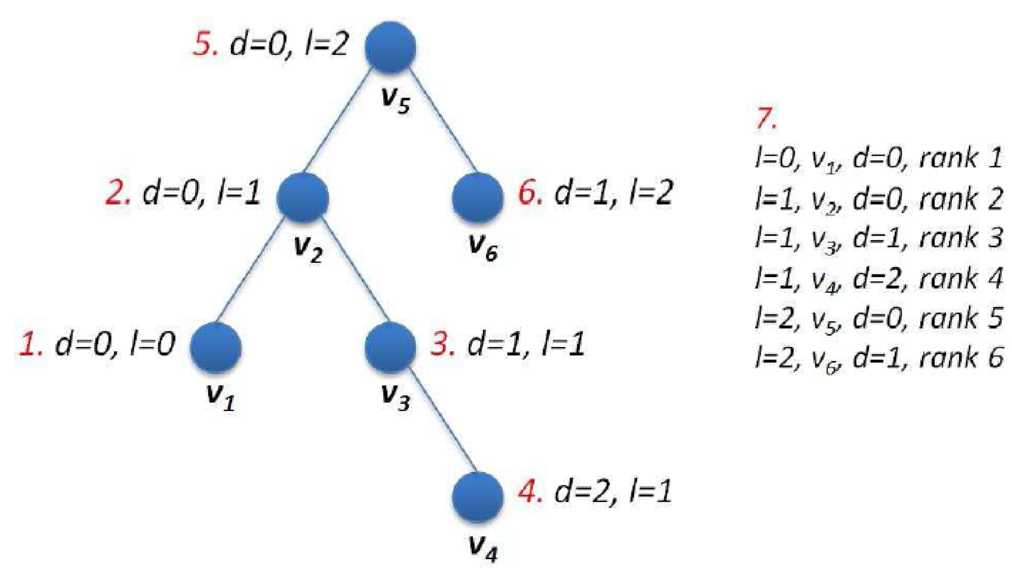
$$M_D = \begin{pmatrix} 1 & 4 & 8.5 \\ 4 & 1 & 10 \\ 8.5 & 10 & 1 \end{pmatrix}$$

$$M_A^{\text{Likelihood}} = \begin{pmatrix} 1 & 0.25 & 0.12 \\ 0.25 & 1 & 0.1 \\ 0.12 & 0.1 & 1 \end{pmatrix}, M_A = \begin{pmatrix} 0.73 & 0.18 & 0.08 \\ 0.19 & 0.74 & 0.07 \\ 0.09 & 0.08 & 0.81 \end{pmatrix}$$





Taxonomy of object categories of the MSRCORID data set.



2. Validation measurements

In order to analyze the retrieval efficiency, we defined an ontology distance based on taxonomy trees to look for the retrieved classes at the first positions of the ranking process. As explained in the previous section, the ranking result R is a sorted set of classes, where the first items have the highest rank. Then, we define an ontology distance m based on the taxonomy tree and adjacency matrices. Each ci in R is accepted if its ontology distance di compared to the true label class is less than m. The accepted results in the end of the list R are not desired, so another parameter k is used to analyze the results of the first positions of the ranking. If there are more than N accepted classes based on the value of m at the first positions defined by k, then we achieve a test hit. In order to perform a realistic analysis, we included this validation procedure in a stratified 10-fold evaluation procedure. The algorithm that summarizes the retrieval validation is shown in below table:

ECOC-Rank evaluation.

Given the sorted list of classes based on their rank $R = \{r_1, .., r_n\}$

For each item r_i in the top k positions of R

$acceptedCount = 0$

1) $d = OntologyDistance(r_i, TrueLabel)$

2) if $d > m$ then $acceptedCount+ = 1$

1) If $acceptedCount > N$ then Hit

3.RESULTS

Data: The data used in our experiments consists on two public data sets: Caltech 256 [4] and ’Microsoft Research Cambridge Object Recognition Image data set’

Performances of Caltech 256 data set for different methods and parameters using Gentle Adaboost ECOC base classifier and ontology distance evaluation.

Problem	Adjacency	Ontology	Adj & Ont	Raw
m=0.001	0.4394	0.6901	0.4389	0.5530
m=0.0001	0.0718	0.1479	0.0719	0.0785

Performances of Microsoft Research Cambridge Object Recognition Image data set for different methods and parameters using Gentle Adaboost ECOC base classifier and ontology distance evaluation.

Problem	Adjacency	Ontology	Adj & Ont	Raw
ADA m=0.001	0.3154	0.1744	0.2996	0.1568
ADA m=0.0001	0.1777	0.0659	0.1576	0.0667
SVM m=0.001	0.3714	0.1798	0.3001	0.2038
SVM m=0.0001	0.2511	0.0676	0.1577	0.0950

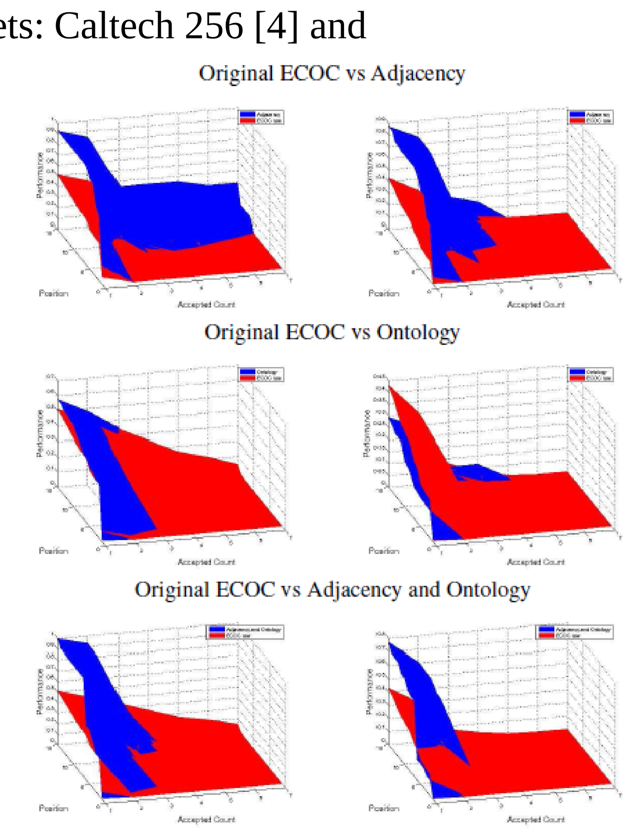


Figure 6: Results on Microsoft Research Cambridge Object Recognition Image data set for RBF SVM ECOC base classifier. Left column using ontology distance m=0.001 and right column using m=0.0001.

4. CONCLUSIONS

In this paper we altered the decoding process of the ECOC framework to define a new measure of semantic ranking that is applied on class retrieval problems. In order to include contextual and semantic information, we defined two matrices that mutates the ECOC output. An adjacency matrix is defined based on the feature space, and an ontology matrix is designed based on taxonomy trees. Results over public data show performance improvement when using the new ECOC-rank in the retrieval process.