Seminar aus Data Mining und Maschinellem Lernen

Multilabel text classification for automated tag suggestion

Adaptive selection of base classifiers in one-against-all learining for large multi-lableled collections

Hong Linh Thai

Motivation

- If you think of Web 2.0, e.g. tagging of images on Flickr or videos on You Tube, it would be really convenient if this process could be automated

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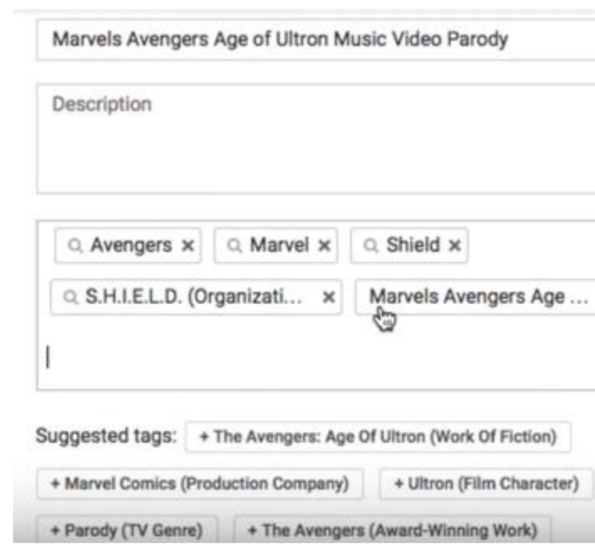

https://www.youtube.com/watch?v=9B1-u4_XvX0

Motivation

- But tagging is not only useful for images, it can be also applied to text
- Examples:
  - Automated text categorization system for high energy physics papers, 2802 abstracts, 1093 keywords [1]
  - ECML/PKDD 2008 Discovery Challenge: Tag Recommendation in Social Bookmark System, User can tag bookmarks and BibTeX entries, $815{,}000$ Tags, $400{,}000$ bookmarks and BibTeX entries [2,3]
  - ECML/PKDD 2012 Discovery Challenge: Large scale hierarchical classification with data from Wikipedia, $36{,}500 \sim 325{,}000$ Categories, $380{,}000 \sim 2{,}400{,}000$ Documents [4]

Motivation

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- But tagging is not only useful for images, it can be also applied to t
- Exa
  - A p
  - E e a W ents

Problem:

- Large data sets
- Large number of possible labels
- One object x can have multiple labels
- Want to find an automatic way to solve this problem

This calls for extreme classification / multi-label classification

Overview

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I. Motivation
II. Formal Definition – Multi-Label Classification
III. Problems / Key Challenges
IV. Approaches / Solutions
   a) Adaptive Selection of Base Classifiers in One-Against-All Learning for Large Multi-Lableled Collections, Ráez et al. [1]
   b) Multilabel Text Classification for Automated Tag Suggestion, Katakis et al. [2]

Formal Definition – Multi-Label Classification

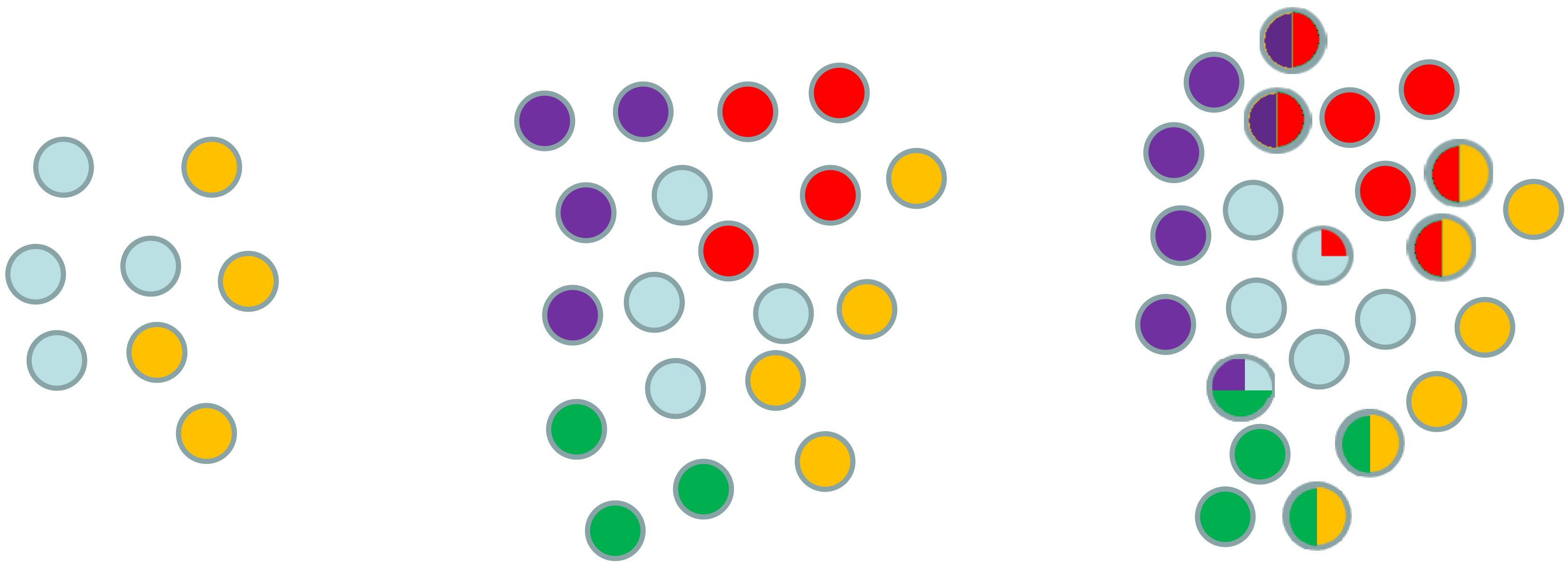
- Setting: Let $\mathcal{X} = \mathbb{R}^d$ be an d-dimensional instance space / feature space and $\mathcal{L} = \{\lambda_1, \lambda_2, \ldots, \lambda_k\}$ be the label space where k is the number of possible labels
- Goal: Given a Training Set, $S = (\boldsymbol{x_i}, \boldsymbol{Y_i}), 1 \leq i \leq n$ consisting of n training instances, where $\boldsymbol{x_i} \in \mathcal{X}$ and $\boldsymbol{Y_i} \subseteq \mathcal{L}$, to learn a function $f : \mathcal{X} \longrightarrow 2^{\mathcal{L}}$, which can predict the labels for any unseen instance

i	F_1	…	F_d	$\boldsymbol{Y_i}$
1	0.41	…	1	$\{\lambda_1, \lambda_2\}$
2	0.1	…	0	$\{\lambda_3\}$
3	0.75	…	1	$\{\lambda_1, \lambda_4, \lambda_k\}$
…	…	…	…	…

Example for a Training Set

Difference to Binary and Multi-Class Classification

- Binary Classification: Only 2 classes
- Multi-Class Classification: One instance can have only one class



Binary Classification   Multi-Class Classification   Multi-Label Classification

Multi-Label Classification Methods

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According to Tsoumakas there are 2 groups of classification methods [2,5] :

- Algorithm Adaptation Methods
  - Extend known learining algorithms to handle multi-label data directly
  - Advantage: If we can do so, we can solve the problem in one large optimization problem
  - Disadvantage: It is difficult to extend an algorithm
- Problem Transformation Methods
  - Transform multi-label problem into one or mutliple single-label classification problems
  - Advantage: Single-label problems are well known
  - Disadvantage: Depending on the transformation we can lose information

Binary Relevance (BR)

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- Assumption: Prediction of each label as an independent binary classification task
- Learn one binary classifier for each different label $f_j : \mathcal{X} \longrightarrow \{\lambda_j, \neg\lambda_j\}$
  - Positive examples are the ones for which the label is positive
  - Negative examples are the remaining ones
- Transform data set into multiple ones:

$$
\begin{array}{ccl}
 & \xrightarrow{\lambda_1} & S_1 = (\boldsymbol{x_i}, \boldsymbol{\phi}(\boldsymbol{Y_i}, \lambda_1)), 1 \leq i \leq n \\
 & & \vdots \\
S = (\boldsymbol{x_i}, \boldsymbol{Y_i}), 1 \leq i \leq n & \xrightarrow{\lambda_j} & S_j = \left(\boldsymbol{x_i}, \boldsymbol{\phi}(\boldsymbol{Y_i}, \lambda_j)\right), 1 \leq i \leq n \\
 & & \vdots \\
 & \xrightarrow{\lambda_k} & S_m = (\boldsymbol{x_i}, \boldsymbol{\phi}(\boldsymbol{Y_i}, \lambda_k)), 1 \leq i \leq n
\end{array}
$$

Binary Relevance (BR)

Example:

i	F_1	…	F_d	Y_i
1	0.41	…	1	$\{\lambda_1, \lambda_2\}$
2	0.1	…	0	$\{\lambda_3\}$
3	0.75	…	1	$\{\lambda_1, \lambda_4, \lambda_n\}$
…	…	…	…	…

λ_1

i	F_1	…	F_d	λ_1
1	0.41	…	1	1
2	0.1	…	0	0
3	0.75	…	1	1
…	…	…	…	…

$f_1 : \mathcal{X} \longrightarrow \{\lambda_1, \neg\lambda_1\}$

λ_2

i	F_1	…	F_d	λ_2
1	0.41	…	1	1
2	0.1	…	0	0
3	0.75	…	1	0
…	…	…	…	…

$f_2 : \mathcal{X} \longrightarrow \{\lambda_2, \neg\lambda_2\}$

… …

Problem Transform Methods

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According to Sorower and Zhang et al. there are 3 types [6,7] :

- Binary Relevance (BR) / First Order Strategy
  - Solve the problem label by label,
  - Transform the problem to k one vs all problems
- Ranking by Pairwise Comparison / Second Order Strategy
  - Solve the problem pairwise, voting for prediction
  - Transform the problem to $k(\mathrm{k}-1)/2$ one vs one problems
- Label Powerset / High Order Strategy
  - Create one new label for each label set
  - One large single label multi-class problem

Problems / Key Challenges

- High input / output dimension
  - Number of label sets grow exponentially, e.g. 10 label classes leads to 2^{10} possible label sets
- Highly imbalanced data
  - Also known as Class Imbalance Problem
- Very few data points per labels
- Inter-dependency of class labels
  - E.g. if something is labeled with *Frodo* and *Gandalf* the label *Lord of the Rings* will be much likely than *Titanic*
- Real time constraints

Class Imbalance Problem

- Usually multi-labeled data have an unequal distribution of classes
  - Imbalance between positive and negative samples (inner imbalance degree)
  - More frequent and less frequent classes (inter-class imbalance degree)

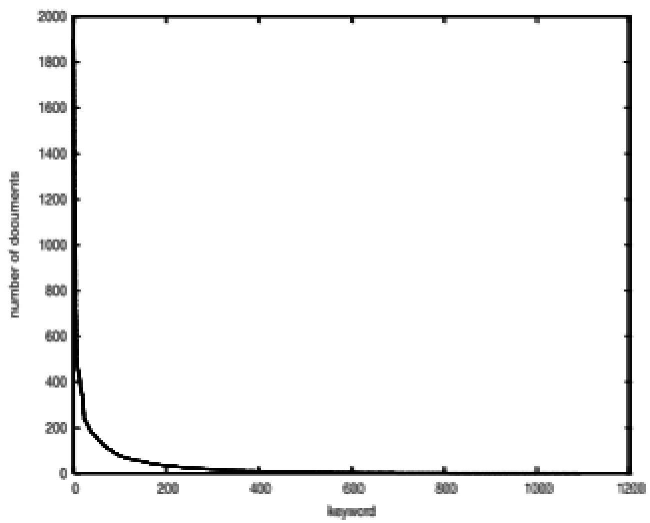
Class Imbalance Problem

Example: HEP Collection

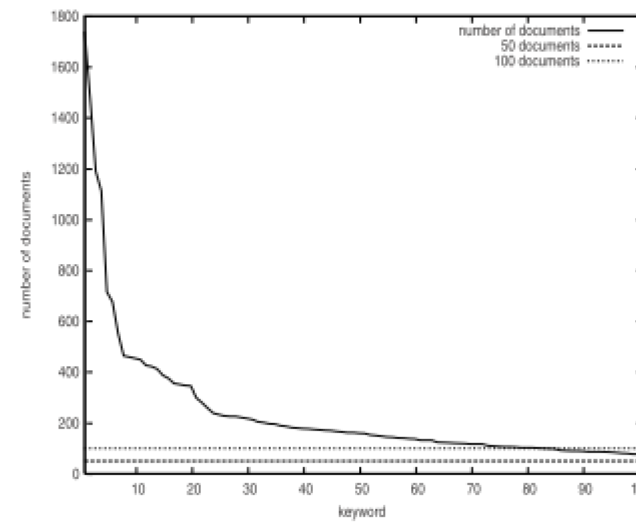
- high energy physics papers, 2802 abstracts, 1093 keywords
- Inter-class imbalance:

No. docs.	Keyword
1898 (67%)	electron positron
1739 (62%)	experimental results
1478 (52%)	magnetic detector
1190 (42%)	quark
1113 (39%)	talk
715 (25%)	Z0
676 (24%)	anti-p p
551 (19%)	neutrino
463 (16%)	W
458 (16%)	jet

10 most frequent keywords



all keywords



100 most frequent keywords

Class Imbalance Problem

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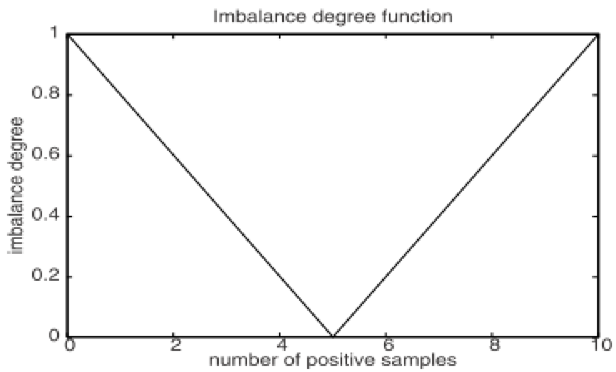
Example: HEP Collection

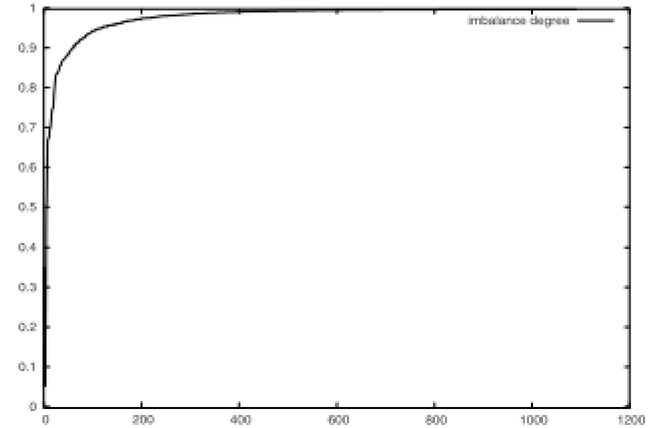
- high energy physics papers, 2802 abstracts, 1093 keywords
- Inner imbalance:



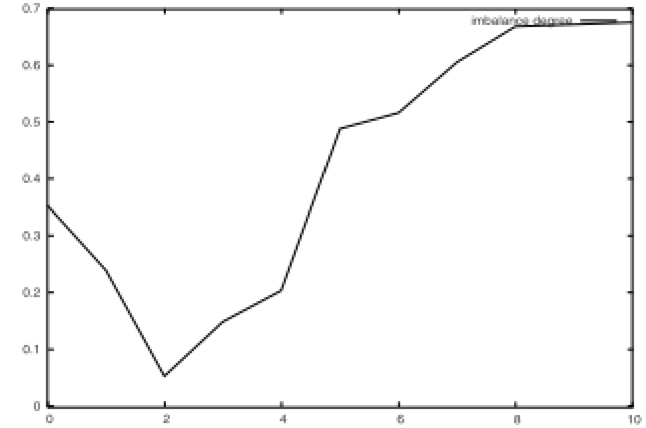
$$i_i = \left| \frac{1 - 2n_i}{n} \right|$$

n: number of samples

n_i: number of samples with label i



all keywords



10 most frequent keywords

Solution for the Class Imbalance Problem

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Ráez et al. proposed :

- Filter out the rare classes using a parameter α
  - If a classifier performs worse than α the classifier and the whole class is discarded

- Overweighting of the positive samples
  - $w_{+} = C_{-} / C_{+}$

  C_{-}: number of neg. samples

  C_{+}: number of pos. samples

Evaluation Measures

- Precision: $Prec(C_i) = \frac{tp}{tp + fp}$
  - Ratio correct preditced c_i to total predicted c_i
- Recall: $\mathrm{Rec}(C_i) = \frac{tp}{tp + fn}$
  - Ratio correct predicted c_i to total existing c_i
- F_1: $F_1(C_i) = 2\frac{Prec(C_i)\ \cdot Rec(C_i)}{Prec(C_i) + Rec(C_i)}$
  - Harmonic mean

Category c_i		Expert judgments YES	Expert judgments NO
Classifier Judgments	YES	TP_i	FP_i
	NO	FN_i	TN_i

[8]

- Macroaveraging
  - First evaluate „locally" then average „globally"
- Microaveraging
  - Use „global" confusion matrix

Category set $\mathcal{C} = \{c_1, \ldots, c_{\lvert\mathcal{C}\rvert}\}$		Expert judgments YES	Expert judgments NO
Classifier Judgments	YES	$TP = \sum_{i=1}^{\lvert\mathcal{C}\rvert} TP_i$	$FP = \sum_{i=1}^{\lvert\mathcal{C}\rvert} FP_i$
	NO	$FN = \sum_{i=1}^{\lvert\mathcal{C}\rvert} FN_i$	$TN = \sum_{i=1}^{\lvert\mathcal{C}\rvert} TN_i$

[8]

Macroaveraging vs Microaveraging

Label	Tp	Fp	Fn	Tn	precision	recall
C1	10	10	10	800	0.5	0.5
C2	90	10	10	750	0.9	0.9
Global	100	20	20	1550		

$$Prec(C_i) = \frac{tp}{tp + fp}$$

$$Rec(C_i) = \frac{tp}{tp + fn}$$

Macroaveraging: $Prec^M(C) = \frac{0.5+0.9}{2} = 0.7$

- Meassure of effectiveness on small classes
- All classes have same weight even smaller ones

Microaveraging: $Prec^\mu(C) = \frac{100}{100+20} = 0.83$

- Meassure of efffectiveness on large classes

Tag Recommendation in Social Bookmark System, Katakis et al.

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- Task: Tag Recommendation in Social Bookmark System, $815{,}000$ Tags, $400{,}000$ bookmarks and BibTeX entries
- Idea: Learn a personalized tag recommender, if item and user exist in training set just return, else predict
- Method: Naive Bayes BR Classifier from the Mulan [9] package
- Results:

Parameters			F-measure		
θ	M	N	All	Book	Bib
0.0	10	10	0.0716	0.0782	0.0633
0.0	5	5	0.0848	0.0940	0.0736
0.0	1	1	0.0700	0.0904	0.0453
0.9	10	10	0.0713	0.0752	0.066
0.9	3	3	0.0847	0.0940	0.0734
0.9	10	3	**0.0852**	**0.0942**	**0.0740**

Measure based on macroaveraging

θ: Confidence
M: Number of recommendations
N: Number of most popular tags

Automated text categorization system Ráez et al.

- Task : Automated text categorization system for high energy physics papers, 2802 abstracts, 1093 keywords
- Idea: Filter out not frequent labels to improve classification
- Method: BR Learning: SVM with over-weighting and filtering out non frequent classes + Scut to train the parameter of the SVM

Experiment	Precision	Recall	F1	Accuracy	Error	% of classes covered
No weight	74.07	33.96	43.92	98.23	1.77	33.96
No weight / Scut	**74.26**	34.44	44.38	98.24	1.76	99.95
Overweight 20	51.47	**45.84**	46.50	97.71	2.29	57.32
Auto weight	58.10	44.39	48.09	97.94	2.06	58.09
Overw. 2,5,10,20 / Scut	71.74	39.92	48.47	**98.25**	**1.75**	**100.00**
Auto weight / Scut	58.03	45.30	48.56	97.89	2.11	99.82
Overweight 2	70.74	40.45	48.78	98.21	1.79	53.36
Overweight 5	64.56	43.57	49.40	98.11	1.89	57.19
Overweight 10	62.30	45.22	50.14	98.08	1.92	57.30
Overw. 2,5,10,20	65.89	44.59	**50.53**	98.17	1.83	57.53

SVM with $\alpha = 0.0$, no filtering

Measure based on macroaveraging on documents

Automated text categorization system Ráez et al.

Results:

- Recall is lower than prediction due to rare classes
- Discarding bad classifiers improves precision, while recall does not get much worse

α	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7
Precision	65.89	70.04	70.41	70.88	71.90	71.96	71.02	67.96
Recall	44.59	44.49	43.95	42.95	40.54	36.65	31.80	23.02
F_1	50.53	**51.59**	51.32	50.77	49.21	46.11	41.70	32.83
Accuracy	98.17	98.25	98.25	98.25	98.24	98.21	98.15	98.03
Error	1.83	1.75	1.75	1.75	1.76	1.79	1.85	1.97
% classes trained	57.53	56.49	50.81	43.20	32.73	23.23	16.00	8.58

Handcrafted multiweighted SVM with filtering

α	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7
Precision	58.03	62.47	64.84	67.45	69.47	71.19	71.14	68.24
Recall	45.30	45.04	44.83	44.24	42.76	39.59	34.43	24.88
F_1	48.56	49.93	50.47	50.75	50.27	48.37	44.10	34.76
Accuracy	97.89	98.06	98.14	98.20	98.23	98.22	98.17	98.05
Error	2.11	1.94	1.86	1.80	1.77	1.78	1.83	1.95
% classes trained	99.82	85.30	77.10	68.47	55.74	42.34	30.82	16.72

Auto-weighted S-cut tresholded SVM with filtering

Measure based on macroaveraging on documents

Conclusion

- Binary Relevance learning approach is very simple, thus it does not performs quite very well on real data
- Reasons:
  - Class imbalance problem
  - Does not include any information about label dependencies
- Filtering can help to some extend, but ideally we want to be able to predict even rare labels
- Way how the measure is computed is very important for interpreting the results

→ **Nessesity of better methods**

Summary

- Introduced Multi-Label Classification
  - Showed 2 common approaches:
    - Algorithm Adaptation Methods : Fit algorithm to data
    - Problem Transformation Methods : Fit data to algorithm
  - Naive approach : Binary Relevance
  - Class Imbalance Problem
  - Basic evaluation measures, microaveraging vs macroaveraging
  - Results of BR Learning and filtering not frequent labels

References

[1] - Ráez, A. M., López, L. A. U., & Steinberger, R. (2004). Adaptive selection of base classifiers in one-against-all learning for large multi-labeled collections. In *Advances in Natural Language Processing* (pp. 1-12). Springer Berlin Heidelberg.

[2] - Katakis, Ioannis, Grigorios Tsoumakas, and Ioannis Vlahavas. "Multilabel text classification for automated tag suggestion." *ECML PKDD discovery challenge,* 75 (2008).

[3] - ECML PKDD Discovery Challenge 2008 http://www.kde.cs.uni-kassel.de/ws/rsdc08

[4] - Large Scale Hiearachical Text Classification Challenge, EMCL PKDD *discovery challenge 2012* http://lshtc.iit.demokritos.gr/LSHTC3_CALL

[5] - Tsoumakas, Grigorios, and Ioannis Katakis. "Multi-label classification: An overview." *Dept. of Informatics, Aristotle University of Thessaloniki, Greece*(2006).

[6] - Sorower, Mohammad S. "A literature survey on algorithms for multi-label learning." *Oregon State University, Corvallis* (2010).

[7] - Zhang, Min-Ling, and Zhi-Hua Zhou. "A review on multi-label learning algorithms." *Knowledge and Data Engineering, IEEE Transactions on* 26.8 (2014): 1819-1837.

[8] - Sebastiani, Fabrizio. "Machine learning in automated text categorization." *ACM computing surveys (CSUR)* 34.1 (2002): 1-47.

[9] – Mulan - Multi Label Classification Java Library, http://mlkd.csd.auth.gr/multilabel.html

[10] – Loza Meneciá, Eneldo and Fürnkranz, Johannes "Tutorial on Multilabel Classification" http://www.ke.tu-darmstadt.de/staff/eneldo/MultilabelTutorial.pdf