Is a Data-Driven Approach still Better than Random Choice with Naive Bayes classifiers?

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Abstract. We study the performance of data-driven, a priori and random approaches to label space partitioning for multi-label classification with a Gaussian Naive Bayes classifier. Experiments were performed on 12 benchmark data sets and evaluated on 5 established measures of classification quality: micro and macro averaged F1 score, subset accuracy and Hamming loss. Data-driven methods are significantly better than an average run of the random baseline. In case of F1 scores and Subset Accuracy - data driven approaches were more likely to perform better than random approaches than otherwise in the worst case. There always exists a method that performs better than a priori methods in the worst case. The advantage of data-driven methods against a priori methods with a weak classifier is lesser than when tree classifiers are used.

Keywords: multi-label classification, label space clustering, data-driven classification

1 Introduction

In our recent work [11] we proposed a data-driven community detection approach to partition the label space for the multi-label classification as an alternative to random partitioning into equal subsets as performed by the random k-label sets method proposed by Tsoumakas et. al. [13]. The data-driven approach works as follows: we construct a label co-occurrence graph (both weighted and unweighted versions) based on training data and perform community detection to partition the label set. Then, each partition constitutes a label space for separate multi-label classification sub-problems. As a result, we obtain an ensemble of multi-label classifiers that jointly covers the whole label space. We consider a variety of approaches: modularity-maximizing techniques approximated by fast greedy and leading eigenvector methods, infomap, walktrap and label propagation algorithms. For comparison purposes we evaluate the binary relevance (BR) and label powerset (LP) - which we call a priori methods, as they a priori assume a total partitioning of the label space into singletons (BR) and lack of any partitioning (LP).

The variant of RAkEL evaluated in this paper is an approach in which the label space is either partitioned into equal-sized subsets of labels. This approach is

called RAkELd - RAkEL distinct as the label sets are non-overlapping. RAkELd takes one parameter - the number of label sets to partition into k. We assumed that all partitions are equally probable and that the remainder of the label set smaller than k becomes the last element of the otherwise equally sized partition family.

In [11] we compared community detection methods to label space divisions against RAkELd and a priori methods on 12 benchmark datasets (*bibtex* [6], *delicious* [14], *tmc2007* [14], *enron* ([7]), *medical* [9], *scene* [1], *birds* [2], *Corel5k* [4], *Mediamill* [10], *emotions* [12], *yeast* [5], *genbase* [3]) over five evaluation measures with Classifier and Regression Trees (CART) as base classifiers. We discovered that data-driven approaches are more efficient and more likely to outperform RAkELd than binary relevance or label powerset is, in every evaluated measure. For all measures, apart from Hamming loss, data-driven approaches are significantly better than RAkELd ($\alpha = 0.05$), and at least one data-driven approach is more likely to outperform RAkELd than a priori methods in the case of RAkELd's best performance. This has been the largest RAkELd evaluation published to date with 250 samplings per value for 10 values of RAkELd parameter k on 12 datasets published to date.

In this paper we extend our result and evaluate whether the same results hold if instead of using tree-based methods, we employ a weak and Gaussian Naive Bayesian classifier from the scikit-learn python package [8]. The experimental setup remains identical to the one presented in tree-based scheme, except for the change of base classifier. Bayesian classifiers remain of interest in many applications due to their low computational requirements.

We thus repeat the research questions we have asked in the case of tree-based classifiers, this time for Naive Bayes based classifiers:

RH1: Data-driven approach is significantly better than random ($\alpha = 0.05$) **RH2**: Data-driven approach is more likely to outperform RAkELd than a priori methods

RH3: Data-driven approach is more likely to outperform RAkELd than a priori methods in the worst case

RH4: Data-driven approach is more likely to perform better than RAkELd in the worst case, than otherwise

2 Results

Micro-averaged F1 score. While a priori methods such as Binary Relevance and Label Powerset exhibit a higher median likelihood of outperforming RAkELd - we note that the highest mean likelihood is obtained by label propagation data-driven label space division on an unweighted label co-occurrence graph. Unweighted label propagation is also most likely to outperform RAkELd in the worst case. Thus we reject **RH2** and accept **RH3** and **RH4**. The best performing and recommended community detection method for micro-averaged F1 score - unweighted label propagation - is better than average performance of RAkELd with statistical significance, we thus accept **RH1**.

Macro-averaged F1 score. In case of macro averaged F1 score Label Powerset is the most likely to outperform RAkELd both in median and mean cases, while underperforms in the worst case. Label propagation data-driven label space division on an unweighted label co-occurrence graph is the most likely data-driven approach to outperform RAkELd - although other approaches also yield good results. Unweighted label propagation is also most likely to outperform RAkELdin the worst case. It is also better than an average run of RAkELd with statistical significance. Thus we accept **RH1**, reject **RH2** and accept **RH3** and **RH4**.

Subset Accuracy. In case of Subset Accuracy label propagation performed on an unweighted graph approach to dividing the labels space is the most resilient approach both in the worst case and in the average (mean/median) likelihood. The weighted version performers equally well in the worst case, so does unweighted infomap. As the worst case performance of three data-driven methods is greater than 0.5 we accept **RH4** for Subset Accuracy. While Label Powerset performs better than label propagation in case of the median/mean likelihood of being better than RAkELd - it performs worse by 12 pp. in the worst case. Thus while rejecting **RH2** and accepting **RH3** we still recommend using data-driven label propagation approach instead of Label Powerset. Label propagation performs better than RAkELd with statistical significance - we accept **RH1**.

Jaccard score. Among data-driven methods the label propagation performed on an unweighted graph approach to dividing the labels space is the most resilient approach both in the worst case and in the average (mean/median) likelihood. It is followed by infomap. While a priori methods are perform better in case of the median likelihood by 3 pp., they perform worse than data-driven methods in the mean and worst case. We thus confirm **RH2** and **RH3**. The worst case likelihood of data-driven methods outperforming RAkELd is not grater than 0.5 we thus reject **RH4**. Unweighted infomap performs better than the average run of RAkELd with statistical significance - we thus accept **RH1**.

Hamming Loss The data-driven methods that are most likely to outperform RAkELd are infomap and label propagation performed on a weighted label cooccurrence graph. We recommend using weighted infomap which is also most

	FG	FGW	LE	LEW	WTW
Macro-averaged F1	0.068	0.37	0.054	0.37	0.37
Micro-averaged F1	0.011	0.071	0.003	0.011	0.043
Jaccard Score	0.026	0.07	0.008	0.026	0.070

Table 1: P-values of data-driven methods performing better than an average run of RA*k*EL*d* for each measure tested using non-parametric Friedman test with Rom's post-hoc test. Only methods with p-values greater than $\alpha = 0.05$ are presented. All approaches not listed explicitly were significantly better than RA*k*EL*d* in all measures.

resilient in the worst case, although much less resilient than the desired 0.5 likelihood of outperforming RAkELd in the worst case. As a result the case of Hamming Loss we confirm **RH2** and **RH3** but reject **RH4**. Weighted infomap perform significantly better than an average run of RAkELd - we accept **RH1**.

3 Conclusion and Outlook

We have examined the performance of data-driven, a priori and random approaches to label space partitioning for multi-label classification with a Gaussian Naive Bayes classifier. Experiments were performed on 12 benchmark data sets and evaluated on 5 established measures of classification quality. Table 12 summarizes out findings. Data-driven methods are significantly better than an average RAkELd run that had not undergone parameter estimation - i.e. when results are compared against the mean result of all evaluated RAkELd parameter values. When compared against the likelihood of outperforming a RAkELd in the evaluated parameter space - in case of F1 scores and Subset Accuracy - data driven approaches were more likely to perform better than RAkELd than otherwise in the worst case. There always exists a method that performs better than a priori methods in the worst case.

Data driven methods perform better than a priori methods in the mean likelihood but worse in median when it comes to micro-averaged F1 and Subset Accuracy. This can be attributed to differences in how likelihoods per data set distribute - data-driven methods perform better in worst case, but are also less likely to be always better than RAkELd as opposed to a priori methods. The advantage of data-driven methods against a priori methods with a weak classifier is lesser than when tree classifiers are used. The authors acknowledge support from the National Science Centre research projects decision no. 2016/21/N/ST6/02382 and 2016/21/D/ST6/02948.

	Micro- averaged F1	Macro- averaged F1	Subset Accuracy	- Jaccard Similarity	Hamming Loss
RH1	Yes	Yes	Yes	Yes	Yes
RH2	Undecided	No	No	Undecided	Yes
RH3	Yes	Yes	Yes	Yes	Yes
RH4	Yes	Yes	Yes	No	No

UnweightedUnweightedUnweightedUnweightedUnweightedUnweightedUnweightedUnweightedUnweightedRecommendeddata-drivenlabel prop-label prop-lab

Table 12: The summary of evaluated hypotheses and proposed recommendations of this paper

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	Minimum	Median	Mean	Std
BR	0.369565	1.000000	0.796143	0.283117
LP	0.369565	0.999076	0.789076	0.294146
fastgreedy	0.263556	0.781778	0.737634	0.232243
fastgreedy-weighted	0.322667	0.601848	0.633698	0.160196
infomap	0.448000	0.869778	0.817113	0.194957
infomap-weighted	0.091556	0.797333	0.705199	0.299230
label_propagation	0.529778	0.908000	0.843744	0.172125
label_propagation-weighted	0.317778	0.662356	0.703653	0.243097
leading_eigenvector	0.302667	0.829778	0.748593	0.250929
leading_eigenvector-weighted	0.341778	0.632063	0.684237	0.185325
walktrap	0.321333	0.717391	0.719968	0.246686
walktrap-weighted	0.239556	0.600889	0.632683	0.221396

Table 2: Likelihood of performing better than RAkELd in Micro-averaged F1 score of every method for each data set

	BR	LP	FG	FGW	IN	INW	LPG	LPGW	LE	LEW	WT	WTW
Corel5k	0.39	0.37	0.85	0.79	0.87	0.09	0.99	0.32	0.9	0.91	0.43	0.68
bibtex	0	0	0.26	0.32	0.45	0.3	0.53	0.34	0.30	0.34	0.32	0.24
birds	0	0.999	0.62	0.6	0.66	0.66	0.66	0.66	0.79	0.62	0.95	0.34
delicious	0	0	0.78	0.59	0.87	0.59	0.87	0.62	0.83	0.72	0.54	0.58
emotions	0.43	0.37	0	0.52	0	0	0	0.57	0	0.52	0	0.57
enron	0.98	0.98	0.94	0.88	0.93	0.93	0.93	0.93	0	0.99	0.79	0.997
mediamill	0	0	0.55	0.65	0.91	0.8	0.91	0.91	0.45	0.69	0.68	0.6
medical	0	0	0.51	0.58	0.51	0.60	0.60	0.60	0.41	0.59	0.51	0.60
scene	0.37	0.37	0.72	0.63	0.80	0.80	0.80	0.80	0.72	0.63	0.72	0.63
tmc2007-500) 0	0	0.89	0.55	0	0	0	0	0.85	0.63	0	0.89
yeast	0.58	0.59	0.99	0.85	0.99	0.99	0.99	0.99	0.99	0.88	0.99	0.83

Table 3: Likelihood of performing better than RAkELd in Micro-averaged F1 score of every method for each data set. BR - Binary Relevance, LP - Label Powerset, FG - fastgreedy, FGW - fastgreedy weighted, IN - infomap, INW - infomap weighted, LPG - label propagation, LPGW - label propagation weighted, LE - leading eigenvector, LEW - leading eigenvector weighted, WT - walktrap, WTW - walktrap weighted.

	Minimum	Median	Mean	Std
BR	0.456522	1.000000	0.868708	0.222246
LP	0.434783	1.000000	0.850310	0.227355
fastgreedy	0.376444	0.836000	0.799503	0.210402
fastgreedy-weighted	0.378222	0.753333	0.679727	0.175535
infomap	0.519630	0.806861	0.810572	0.164820
infomap-weighted	0.188444	0.739130	0.728628	0.247947
label_propagation	0.519630	0.878667	0.841961	0.163304
label_propagation-weighted	0.500000	0.739130	0.751203	0.186984
leading_eigenvector	0.367111	0.806861	0.746465	0.232450
leading_eigenvector-weighted	0.358667	0.832457	0.722748	0.215705
walktrap	0.253778	0.877333	0.789586	0.225409
walktrap-weighted	0.302222	0.800444	0.745813	0.235022

Table 4: Likelihood of performing better than RAkELd in Macro-averaged F1 score of every method for each data set

	BR	LP	FG	FGW	IN	INW	LPG	LPGW	LE	LEW	WT	WTW
Corel5k	0.94	0.78	0.37	0.37	0.89	0.18	0.997	0.76	0.36	0.36	0.25	0.3
bibtex	1.0	1.0	0.53	0.57	0.67	0.52	0.88	0.55	0.52	0.61	0.6	0.47
birds	1.0	1.0	0.98	0.84	0.52	0.52	0.52	0.52	0.99	0.96	0.97	0.97
delicious	1.0	1.0	1.0	0.79	1.0	1.0	1.0	1.0	1.0	0.85	0.88	0.97
emotions	0.46	0.46	0.93	0.52	0.93	0.93	0.93	0.5	0.93	0.52	0.93	0.5
enron	1.0	0.998	0.986	0.89	0.66	0.66	0.66	0.66	0.88	0.89	0.99	0.91
mediamill	1.0	1.0	0.84	0.75	0.99	0.91	0.99	0.99	0.76	0.84	0.89	0.8
medical	1.0	1.0	0.7	0.45	0.7	0.74	0.74	0.74	0.39	0.45	0.70	0.74
scene	0.46	0.43	0.65	0.65	0.74	0.74	0.74	0.74	0.65	0.65	0.65	0.65
tmc2007-500	1.0	1.0	0.99	0.8	1.0	1.0	1.0	1.0	0.92	0.83	1.0	0.98
yeast	0.7	0.68	0.8	0.83	0.81	0.81	0.81	0.81	0.81	1.0	0.81	0.91

Table 5: Likelihood of performing better than RAkELd in Macro-averaged F1 score of every method for each data set. BR - Binary Relevance, LP - Label Powerset, FG - fastgreedy, FGW - fastgreedy weighted, IN - infomap, INW - infomap weighted, LPG - label propagation, LPGW - label propagation weighted, LE - leading eigenvector, LEW - leading eigenvector weighted, WT - walktrap, WTW - walktrap weighted.

	Minimum	Median	Mean	Std
BR	0.217391	0.886667	0.777640	0.285316
LP	0.413043	1.000000	0.924946	0.174772
fastgreedy	0.028637	0.585333	0.621030	0.304067
fastgreedy-weighted	0.007852	0.586728	0.512003	0.225171
infomap	0.429000	0.978500	0.887924	0.203588
infomap-weighted	0.533487	0.934783	0.831424	0.195409
label_propagation	0.533487	0.998222	0.912394	0.165066
$label_propagation-weighted$	0.533487	0.934783	0.834437	0.180916
leading_eigenvector	0.000000	0.644000	0.604389	0.355451
leading_eigenvector-weighted	0.000000	0.568988	0.499787	0.304284
walktrap	0.133487	0.600000	0.625201	0.295569
walktrap-weighted	0.000000	0.608696	0.499824	0.331589

Table 6: Likelihood of performing better than RAkELd in Subset Accuracy of every method for each data set

	BR	LP	FG	FGW	IN	INW	LPG	LPGW	LE	LEW	WT	WTW
Corel5k	0.34	0.87	0.59	0.68	0.99	0.59	0.998	0.83	0.0	0.0	0.34	0.0
bibtex	0.89	1.0	0.37	0.69	0.96	0.61	0.998	0.7	0.64	0.73	0.37	0.31
birds	0.996	0.997	0.029	0.007	0.53	0.53	0.53	0.53	0.09	0.0	0.13	0.03
delicious	1.0	1.0	0.997	0.63	1.0	0.999	1.0	1.0	1.0	0.79	0.79	0.92
emotions	0.21	0.41	1.0	0.48	1.0	1.0	1.0	0.61	1.0	0.48	1.0	0.61
enron	0.86	1.0	0.58	0.57	0.98	0.98	0.98	0.98	0.79	0.67	0.6	0.65
mediamill	1.0	1.0	0.45	0.29	0.96	0.87	0.96	0.96	0.41	0.38	0.57	0.28
medical	1.0	1.0	0.43	0.64	0.43	0.64	0.64	0.64	0.33	0.65	0.43	0.64
scene	0.63	0.93	0.63	0.3	0.93	0.93	0.93	0.93	0.63	0.3	0.63	0.3
tmc2007-500	1.0	1.0	0.75	0.59	1.0	1.0	1.0	1.0	0.75	0.57	1.0	0.87
yeast	0.62	0.96	0.999	0.76	0.999	0.999	0.999	0.999	0.999	0.92	0.999	0.88

Table 7: Likelihood of performing better than RAkELd in Subset Accuracy of every method for each data set. BR - Binary Relevance, LP - Label Powerset, FG - fastgreedy, FGW - fastgreedy weighted, IN - infomap, INW - infomap weighted, LPG - label propagation, LPGW - label propagation weighted, LE - leading eigenvector, LEW - leading eigenvector weighted, WT - walktrap, WTW - walktrap weighted.

	Minimum	Median	Mean	Std
BR	0.326087	1.000000	0.784597	0.303331
LP	0.369565	1.000000	0.847350	0.240611
fastgreedy	0.183372	0.756000	0.674557	0.274675
fastgreedy-weighted	0.177367	0.586957	0.591697	0.194144
infomap	0.411085	0.925333	0.831944	0.218665
infomap-weighted	0.053778	0.804889	0.686328	0.327207
label_propagation	0.411085	0.974500	0.86552	0.203504
$label_propagation-weighted$	0.239111	0.630435	0.689132	0.281967
leading_eigenvector	0.308000	0.777333	0.693396	0.272005
leading_eigenvector-weighted	0.116859	0.653745	0.624674	0.222935
walktrap	0.359556	0.696444	0.668188	0.252658
walktrap-weighted	0.080370	0.586957	0.580375	0.244502

Table 8: Likelihood of performing better than RAkELd in Jaccard Similarity of every method for each data set

	BR	LP	FG	FGW	IN	INW	LPG	LPGW	LE	LEW	WT	WTW
Corel5k	0.35	0.47	0.76	0.8	0.9	0.05	0.996	0.24	0.78	0.83	0.43	0.57
bibtex	1.0	1.0	0.31	0.42	0.86	0.40	0.99	0.45	0.42	0.45	0.36	0.28
birds	1.0	0.999	0.18	0.18	0.41	0.41	0.41	0.41	0.32	0.12	0.45	0.08
delicious	1.0	1.0	0.7	0.53	0.77	0.44	0.77	0.47	0.74	0.7	0.49	0.49
emotions	0.33	0.37	0.98	0.52	0.98	0.98	0.98	0.63	0.98	0.52	0.98	0.63
enron	0.993	1.0	0.84	0.82	0.97	0.97	0.97	0.97	0.999	0.87	0.74	0.88
mediamill	1.0	1.0	0.54	0.65	0.93	0.80	0.93	0.93	0.44	0.68	0.7	0.6
medical	1.0	1.0	0.41	0.55	0.41	0.55	0.55	0.55	0.31	0.56	0.41	0.55
scene	0.39	0.85	0.80	0.59	0.93	0.93	0.93	0.93	0.8	0.59	0.8	0.59
tmc2007-500	1.0	1.0	0.89	0.6	1.0	1.0	1.0	1.0	0.85	0.65	1.0	0.9
yeast	0.57	0.63	0.994	0.85	0.994	0.994	0.994	0.994	0.994	0.91	0.994	0.82

Table 9: Likelihood of performing better than $\mathrm{RA}k\mathrm{EL}d$ in Jaccard Similarity of every method for each data set

	Minimum	Median	Mean	Std
BR	0.110667	0.558538	0.579872	0.376954
LP	0.080889	0.652174	0.592830	0.379345
fastgreedy	0.208889	0.418222	0.513625	0.276367
fastgreedy-weighted	0.111111	0.260870	0.302981	0.223065
infomap	0.112889	0.735111	0.684758	0.292563
infomap-weighted	0.204889	0.847826	0.727799	0.291282
label_propagation	0.111111	0.735111	0.684971	0.312656
$label_propagation-weighted$	0.237778	0.735111	0.714660	0.237049
leading_eigenvector	0.121333	0.498029	0.552381	0.315482
leading_eigenvector-weighted	0.111111	0.260870	0.337735	0.227415
walktrap	0.111111	0.418667	0.541611	0.331449
walktrap-weighted	0.094226	0.328113	0.387505	0.228658

Table 10: Likelihood of performing better than $\mathrm{RA}k\mathrm{EL}d$ in Hamming Loss of every method for each data set

	BR	LP	\mathbf{FG}	\mathbf{FGW}	IN	INW	LPG	LPGW	LE	LEW	WT	WTW
Corel5k	0.11	0.15	0.42	0.35	0.33	0.96	0.23	0.86	0.21	0.22	0.42	0.42
bibtex	0.11	0.08	0.31	0.24	0.11	0.20	0.11	0.24	0.27	0.24	0.17	0.26
birds	1.0	0.99	0.27	0.16	0.7	0.7	0.7	0.7	0.37	0.2	0.41	0.09
delicious	0.11	0.11	0.34	0.11	0.36	0.24	0.36	0.39	0.41	0.11	0.11	0.2
emotions	0.43	0.30	1.0	0.28	1.0	1.0	1.0	0.54	1.0	0.28	1.0	0.54
enron	0.40	0.69	0.31	0.3	0.73	0.73	0.73	0.73	0.94	0.57	0.27	0.43
mediamill	0.998	0.999	0.21	0.23	0.74	0.51	0.74	0.74	0.12	0.31	0.35	0.22
medical	1.0	1.0	0.77	0.94	0.77	0.88	0.88	0.88	0.79	0.93	0.77	0.88
scene	0.65	0.65	0.52	0.26	0.85	0.85	0.85	0.85	0.52	0.26	0.52	0.26
tmc2007-500	1.0	1.0	0.57	0.17	1.0	1.0	1.0	1.0	0.5	0.26	1.0	0.64
yeast	0.56	0.55	0.94	0.3	0.94	0.94	0.94	0.94	0.94	0.33	0.94	0.33

Table 11: Likelihood of performing better than RAkELd in Hamming Loss of every method for each data set. BR - Binary Relevance, LP - Label Powerset, FG - fastgreedy, FGW - fastgreedy weighted, IN - infomap, INW - infomap weighted, LPG - label propagation, LPGW - label propagation weighted, LE - leading eigenvector, LEW - leading eigenvector weighted, WT - walktrap, WTW - walktrap weighted.