Classification of text using Association Rule mining with Critical Relative Support based pruning

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Association Rules

The Apriori algorithm [1] is a way to generate such rules from transaction data

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Problem Statement

Find the minimal set of interesting association rules *from text*

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The dataset

BBC Insights dataset [5]

2004-2005 Time period 2,225 Documents 5 Categories



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Background

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Literature Survey

Citation

Rakesh Agrawal and Ramakrishnan Srikant; 1993 ^[1]	Apriori Algorithm proposed.
Zailani Abdullah, et al.; 2011 ^[2]	Proposed a metric (CRS) to remove uninteresting rules.
Gayathri, K.; Marimuthu, A.; 2013 ^[3]	Text classification performance is independent of size of feature space in most cases.
Kulkarni et al. 2012 ^[6]	Feature co-occurrence and association are can be used for classification
Kadhim, A.I.; Cheah, YuN; 2014 ^[4]	Term weighing and NLP reduce the dimensionality of the feature space

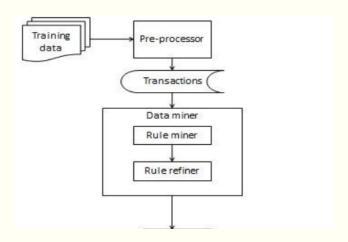
tl;dr

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Proposed Idea

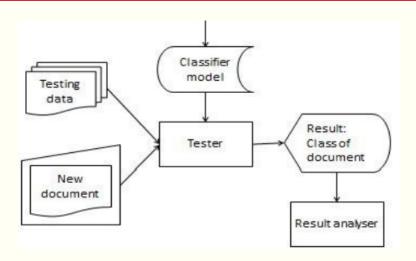
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Flowchart - Part 1



Proposed Idea 8/24

Flowchart - Part 2



Proposed Idea 9/24

Pre-Processing

Convert text document to transaction format

Tokenizing. Stop word removal. POS Tagging. Stemming. Tf-Idf.

Find representative features

Features found only in a particular class

Proposed Idea 10/24

Rule mining

$$X => Y$$

 $Y \in Classes$ Classes = { Business, Entertainment, Politics, Sports, Technology }

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Rule Filtering with CRS

Before applying CRS filtering, update support as -

$$Mod_{Supp}(X \Longrightarrow Y) = (1-a) \cdot (1-b) \cdot (1-c) \cdot supp(X \Longrightarrow Y)$$

Where,

 $a = \frac{\text{Number of documents of class Y}}{\text{Total number of documents}}$

 $b = \frac{\text{Number of representative features of class Y}}{\text{Total number of documents}}$

 $c = \frac{\text{Number of rules of class Y}}{\text{Total number of rules}}$

Proposed Idea 12/24

Results & Conclusion

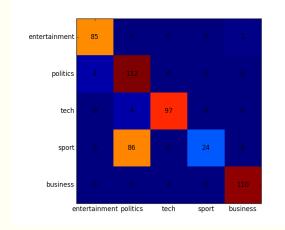
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Accuracy

81 %

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Confusion Matrix



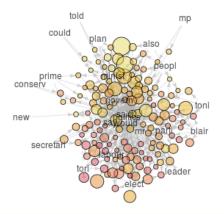
Predicted categories v/s Actual categories

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Rules - politics

politics

size: support (0.06 - 0.113) color: lift (3.74 - 5.336)

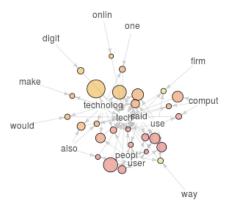


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Rules - tech



size: support (0.06 - 0.093) color: lift (3.84 - 5.453)



Results & Conclusion 17/24

Rules - sport

sport

size: support (0.06 - 0.089) color: lift (2.81 - 3.86)

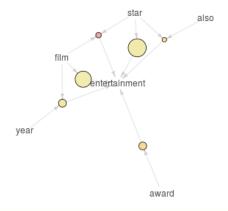


Results & Conclusion 18/24

Rules - tech

entertainment

size: support (0.06 - 0.096) color: lift (4.043 - 5.416)

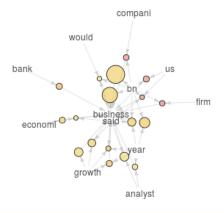


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Rules - business

business

size: support (0.061 - 0.111) color: lift (3.065 - 4.001)



Results & Conclusion 20/24

Pros

- Uses existing tools (Apriori Algorithm).
- ▶ 50% to 67% faster than Apriori.
- More transparent than other text classification Algorithms.
- Allows domain experts to tune the model.

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Cons

- Ignores the relative order of terms.
- While used for pre-processing, term frequency is not considered for classification.
- Parameters (Minimum support, Minimum confidence, Critical Relative support threshold) need to be tuned carefully.

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- Kulkarni, A.R.; Tokekar, V.; Kulkarni, P., "Identifying context of text documents using Naïve Bayes classification and Apriori association rule mining," in Software Engineering (CONSEG), 2012 CSI Sixth International Conference", Sept.2012.

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