Building a Dynamic Classifier for Large Text Data Collections

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Background and motivation

Users: Need to find information

▶ One information-finding need is **locating**: we know it exists, need to find where it is.
▶ Another information-finding need is **discovery**: we don’t know it exists, we need to find out that it does.

Solutions: Search Engines and Web Directories

▶ A **Search Engine** is a machine for locating information. It uses machine learning techniques and is automated.
▶ A **Web Directory** allows browsing (information discovery). Even state-of-the-art directories are maintained manually.
A **Search Engine** presumes that the user knows what he wants, and is able to describe it in several words. Reality: the user often has a very vague idea of what he wants, and cannot describe it with relevant keywords.

A **Web Directory** is very expensive to maintain. Even state-of-the-art directories are on the decline. They are practically extinct.

**Users** have a problem...

- The information **locating** need is met by search engines.
- The information **discovery** part is lacking.
Solution: Automated Web Directory

- Uses a spider such as the search engines use, to download billions of documents.
- Uses machine learning to classify them into a hierarchical structure.
- Overcomes the economic problems of manual labour currently employed.
- Satisfies the users’ information discovery need.
State of the art

Why is this not done already?

- Momentum of old business model (Yahoo! Directory).
- No business model at all (DMOZ).
- No business at all due to competition from Google (most other directories).
- Major scientific effort going to search engines.
So... What’s the actual problem?

Why don’t you just use...

- Text classification is an old Machine Learning task.
- Many algorithms exist, and they work well.
- But... they work with static data only.

What is our data then?

- Dynamic as composition: documents added and removed constantly.
- Dynamic as content: document texts change very often.
- Dynamic as classification: document labels change often.
Classification task

What do we need to adapt?

- Detach document collection management from the indexing/classification part.
- Make the system incremental, so changes in the document collection do not necessitate full retraining.
- Make the system robust in the face of changed labeling.
- Keep classifying indefinitely! As opposed to the standard algorithms, our work is never done.
What we did to cope with the above?

- We have a web spider constantly updating the document collection. Classification is an independent process over a frozen snapshot of the data.
- We use a Multinomial Naïve Bayes (MNB) classifier which deals easily with small changes in document texts.
- We have a separate classifier for each branched node (current prototype has 3 levels, 474 classifiers, 6368 classes).
MNB: Good enough?

To classify a document using “maximum likelihood”, we find:

$$\text{argmax}_c \ p(C = c) = \ln \frac{p(C|D)}{p(\neg C|D)} = \ln \frac{p(C)}{p(\neg C)} + \sum_i \ln \frac{p(w_i|C)}{p(w_i|\neg C)}$$

(the likelihood $p$ that document $D$ belongs to class $C$ is the sum of the log likelihood of the class itself and the sum of log likelihoods of all words $w$ in the document to belong to the class; find the biggest likelihood - you have found the winner class)

Naïve: What does the algorithm assume?
Independent feature model: word occurrences in a document are independent of each other (violates Zipf’s Law).
An implicit assumption is also that labels are correct.

When normalizing (e.g. - TF/IDF), we also assume:

- Similar length (word counts) of documents across classes.
- Similar variety (unique word counts) of documents across classes.
- Similar number of documents in each class.
MNB: Not good enough...

We find all assumptions broken:

- Zipf’s Law **does** work - features are not independent.
- Document lengths vary greatly between classes, harming normalization.
- Unique word counts per document vary greatly between classes (235 words in *News* : 96 in *Business*).
- Document counts per class are drastically different (1.1 mln instances in *Regional* : 9 thousand in *News*).
- Very high labeling (wrong classification) and other noise due to *spam* and *web decay* (in the order of 15%).
Algorithm performance:

- We achieve only 47.91% accuracy in classification.
- It puts almost everything in the dominant class.
- The dominant class has 99.87% accuracy. Some others have 0.00%.
- Accuracy deviation between classes is 0.24.
Word count normalization, proposed by Frank and Bouckaert:
(Naïve Bayes for Text Classification with Unbalanced Classes,
2006, 10th European Conference on Principles and Practice of Knowledge Discovery in Databases)

\[
\hat{n}_{wd} = \alpha \times \frac{n_{wd}}{\sum_{w'} \sum_{d \in Dc} n_{w'd}}
\]

where \(n_{w'd}\) are class-specific word counts (occurrences of the word in documents of class \(c\)), replacing \(w_i\) in Eq.1 and \(\alpha = 1\).
Result from normalization

Results are still unbalanced:

- Overall accuracy goes from 47.91% to 69.44%.
- The algorithm is very good in the dominant class (Regional): 87.29%.
- Still very bad in some others: only 39.92% in Business.
- Overall deviation in accuracy: 0.15.
Why is this a problem?

**Why we still need improvement:**

- The subjective impact on users is much stronger than the objective statistical error (i.e. - if the classifier doesn’t work correctly in my favourite category, I think it’s totally useless).

- In a hierarchical structure, error propagates downwards and is multiplied at each level.  
  40% accuracy at the top level means 6.4 % only two levels down - we’d better just assign instances randomly...
What to do?

Take some ideas from spam filters:

- **Train-on-error** policy: spam filters only learn from instances where they make an error.
- This manipulates training: the filter sees a subset of the data; word count statistics and prior distributions are skewed.
- It may be unprincipled, but works better than **Train-on-everything**.

But still:

- Just as the classic MNB (with or without improvements), it’s still static.
- Learns slowly, never fully unlearns.
Our approach

We made the system truly dynamic:

- We classify continuously.
- We apply weight decay after each pass - guaranteed unlearning.
- Some of our static measures (prior distribution) are calculated dynamically - over the last 10,000 instances.
- We **Train-on-error** - so it is actually last 10,000 errors.
Our contribution

We have introduced a negative feedback loop:

- A class where the classifier has problems gets over-represented.
- Its prior distributions gets an artificial boost.
- In subsequent classification it’s more probable to put instances into it.
- We have compensated for the problem, and we don’t even need to know what it is.
- We have introduced stochastic learning into a previously static algorithm.
Results

**Much better:**

- Overall accuracy increased from 47.91% (69.44%) to 70.44%.
- More importantly: balanced results. Worst class results in *Society*: 60.82%, best in *Adult*: 83.22%.
- Overall deviation in accuracy is down **three times**: 0.05.
Conclusions

We have improvement:

- The classifier now learns from its mistakes:
  we get better results with consecutive passes.
- It minimizes error variation between classes:
  it is equally reliable in all classes.
- Faster in training:
  it trains on a subset of the data, so is 4.13 times faster.
Limitations and issues still to be addressed

- Word count normalization is in the divisor of the equation: cannot apply the technique to it since we get a positive feedback loop.
- Accuracy improvement cannot continue indefinitely: when we achieve an even error distribution, improvement stops.
- 1.46 times slower in classification due to dynamic computations overhead (can be improved with caching).
- Errors are still high due to noisy data.
- We still need manual labour, and always will.
Questions

Questions?