Institute for Systems Analysis
of Russian Academy of Sciences

Training Datasets Collection and Evaluation of Feature Selection Methods for Web Content Filtering

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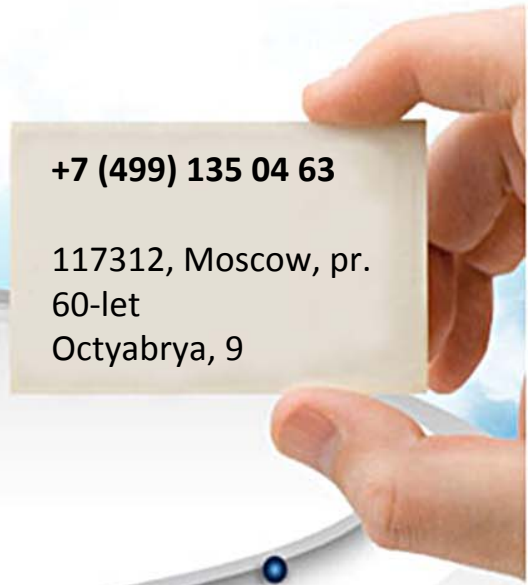

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Introduction: Content Filtering

WebSpy[1]:

- **40% of Internet** use is not related to business;
- **64% of employees** use the Internet for personal interest at work;
- average employee spends **1-2 hours per day** for unproductive browsing;
- wasting 1 hour per day employee yields approximately **$ 7500 of losses per year**.

TopTenReviews by TechMediaNetworks[2]:

- **12% of total web sites** contain pornography;
- **32% of users** complain on receiving unwanted pornographic exposure.

Solution: dynamic content filtering software (automatic classification)

Content Filtering Problem

- Methods
  - Automatic classification using machine learning
- Nature of categories varies
  - Thematic: pornography, purchase of tobacco, web proxies etc.
  - Functional: file sharing sites, social networks, chats and forums etc.
- Differs from text classification
  - Processing time is crucial
  - Desired ratio of false positives and false negatives may vary (strictness)
  - Target data constantly changes
- Consequences
  - Cannot use complex feature selection techniques
  - Need to simplify classifier retraining procedure

Work Parts

1. Upgrade previous work[1] by taking into account URLs found on a page
2. Evaluate classifiers in near-real conditions

1. Roman Suvorov, Ilya Sochenkov, Ilya Tikhomirov. Method for Pornography Filtering in the WEB Based on Automatic Classification and Natural Language Processing // in Proceedings of 15th International Conference, SPECOM 2013. Ed. Miloš Železný, Ivan Habernal, Andrey Ronzhin. Pilsen, Czech Republic, 2013, pp 233-240. ISBN 978-3-319-01930-7

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Our Previous Work: nTIC

- Thematic Importance Characteristic (nTIC)
- Calculate a measure similar to information gain, normalize it and compare with a threshold
- Use stems of words as features

$$I(d,c) = \sum_{t \in L(d)} lTF(t,d) IDF(t,c)$$

$$I(d_{bad}, c_{bad}) << I(d_{bad}, c_{good}) \quad I(d_{good}, c_{bad}) >> I(d_{good}, c_{good})$$

$$nTIC(d, c_{bad}, c_{good}) = \frac{I(d, c_{good}) - I(d, c_{bad})}{I(d, c_{good})}$$

$$nTIC(d, c_{bad}, c_{good}) > Threshold(c_{bad}, c_{good})$$

Proposed Modifications (1)

- Take into account interlinked nature of the Web
  - Use categories of the neighbor pages
  - Utilize peculiarities of URLs found on a page

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Proposed Modifications (2)

- Use categories of the neighbor pages (thematic isolation)
  1. Extract URLs from the body of a page
  2. Extract server domain names from these URLs
  3. Map domains to category labels using a dictionary
  4. Calculate weights of these labels as if they were usual lexis
  5. Treat these weights as features

- Initial dictionary is built from all open sources we have found: DMOZ, various black lists etc.
- The dictionary then expanded with resources that were classified with high confidence

Proposed Modifications (3)

- Take into account interlinked nature of the Web
  - Use categories of the neighbor pages
  - Utilize peculiarities of URLs found on a page

Proposed Modifications (4)

- Utilize peculiarities of URLs found on a page
  - Human-friendly URLs are getting more popular

- Algorithm
  1. Extract URLs from the body of a page
  2. Split each URL in a set of tokens delimited by special characters (/, ?, &, # etc)
  3. Normalize each token
  4. Calculate weights of these tokens as if they were usual lexis
  5. Treat these weights as features

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Data Collection Problem

- No etalon datasets for content filtering
- Standard datasets for text categorization misfit content filtering:
  - Categories are less thematic and more associative
  - They lack linking information (no chance to evaluate URL-based features)
- Publicly available access lists are outdated

- Possible solutions
  - Use unsupervised machine learning
  - Use methods that require less data to learn
  - Introduce a technique for datasets collecting that require small manual labor

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Thematic Crawler (1)

- Collect only pages on the topic of interest
- Subtask of focused crawling

- Create a simple system that needs almost no tuning or training

- Similar to Babouk
  - differs in walk order and page selection rule

Thematic Crawler (2)

- Main algorithm
  1. Collect seed URLs using metasearch with queries related to the subject of interest
  2. Recursively crawl pages starting from the seed URLs
     - Breadth-first order
     - If a seed URL is not a root page (e.g. http://www.isa.ru/index.php?...), download it and proceed with next seed URL
     - If a seed URL is a root page (e.g. http://www.isa.ru/), proceed recursively with **topic filtering** enabled
- Topic filtering principles
  - Maintain a list of keywords (stemming, TF-IDF) of the current walk graph (global keywords)
  - Compare current page keywords with global keywords (size of intersection)
  - Merge current page keywords into the global list and reduce it if necessary
- Parameters
  - Sizes of keywords lists to maintain
  - How often and how aggressively to reduce the global keyword list

Evaluation (1): Data and Problem

- Languages: English, Russian
- 170000 pages total from 17 “bad” categories
  - 10000 pages per category
  - 5000 pages per language within category
- 20000 “good” pages from Wikipedia and informational sites

- Multi-class and multi-label classification problem
  - If no labels are assigned to a document, it is “good” and “bad” otherwise
- Reduce to a set of binary problems using “one-vs-all” technique

- Use classic measures: accuracy, precision, recall and F1

Evaluation (2): Classifiers and Features

- Test two classifiers (nTIC and linear SVM) with two sets of featuers
  - Base - only plain lexis
  - Cat&Tok – Base + modifications to nTIC for URLs

Classifier	Feature set	Precision			Recall			F1		
		Min	Max	Avg	Min	Max	Avg	Min	Max	Avg
nTIC	Base	0.739	0.972	0.895	0.918	0.994	**0.968**	0.819	0.983	0.929
nTIC	Cat&Tok	0.812	0.986	**0.934**	0.909	0.988	0.963	0.878	0.986	**0.948**
SVM	Base	0.98	0.999	**0.996**	0.962	0.996	**0.988**	0.971	0.997	**0.992**
SVM	Cat&Tok	0.98	0.999	0.996	0.953	0.996	0.985	0.973	0.997	0.991

- Results
  - +7% to precision
  - +2% to F1
  - SVM is not improved (most probably due to optimization)

Evaluation (3): Small Feature Sets

- Content filtering software must run fast on restricted hardware as well
  - Choose smaller feature sets (original contained about 600 000 features)
  - Compare three feature selection techniques: IDF, nTIC, Information Gain (IG)

Technique	IDF			nTIC			IG		
N	P	R	F1	P	R	F1	P	R	F1
5 000	0.977	**0.948**	**0.962**	**1**	0.852	0.921	0.99	0.83	0.908
10 000	0.983	**0.962**	**0.972**	0.981	0.955	0.968	**0.99**	0.908	0.951
100 000	0.992	**0.975**	**0.984**	0.995	0.951	0.972	**0.997**	0.958	0.977

- Results
  - IDF is a good choice for most applications
  - nTIC is better for accurate content filtering in very scarce environments (on smartphones, old servers etc)

Conclusion

- Described and compared in near-real conditions
  - two classifiers (nTIC, SVM)
  - two feature extraction techniques (lexis, lexis + URL-based features)
  - three feature selection techniques (IDF, nTIC, IG)
- Thematic crawler is proposed and used for establishing near-real conditions of experiments
- Taking into account URL-based features
  - does not significantly increase quality in general case
  - may be the only features when dealing with e.g. Google Images (almost no text)
- Feature selection
  - nTIC gains better quality on small feature sets
  - Feature selection is not that important in middle- and large-scale applications

Future Work

- Develop a comprehensive classification system that
  - analyses the structure of a page, its functions and graphics
  - takes into account user's behavior.

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  - http://exactus.ru
  - http://expert.exactus.ru
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