Zero-cost Labelling with Web Feeds for Weblog Data Extraction

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Volume

[2008] 900k posts/day [2009] 133M English blogs in one month [2011] 25% of Internet users in Britain have a blog

Diversity

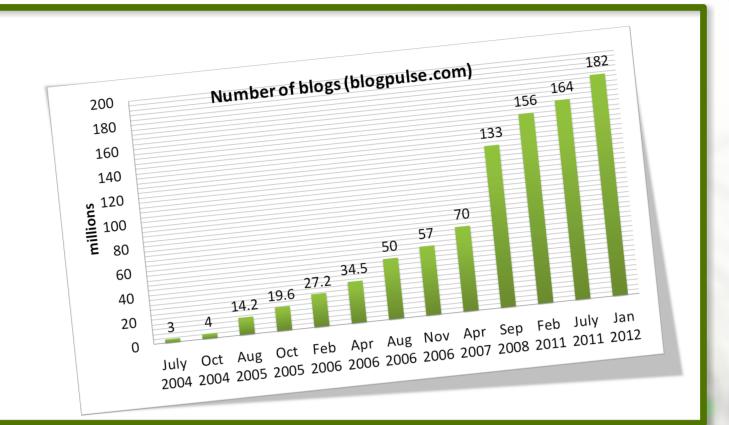
- 1634 WordPress themes
- 469 different platforms

Blog feed

Blogosphere

Web data extraction is a genuinely hard problem. The blogosphere, which constitutes a constituent part of the Web, remains bound to the limitations of modern data extraction. In general, data extraction is facing the trade-off between automation and accuracy/granularity.

The proposed model overcomes the above limitations by exploiting an inherent characteristic of weblogs: the Web Feed, commonly provided as RSS.



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Proposed Methodology Step 1: Feed Processing Step 2: ?Iter generation Fetching of learning posts Filter generation Post fetching & Application of rules Post properties Filter repository Post properties

Filter generation

- ✓ The filter is a structure that describes how to identify an HTML element.
- ✓ It is the result of the crossmatching of values between HTML documents and RSS entries



Example of a post property

The **filter** is described using three basic attributes:

- 1. Absolute Path
- 2. CSS Classes
- 3. ID of the HTML element.

Once the HTML element is matched against its value, a filter is generated which describes it in these three attributes.

Example of a filter:

IDs	CSS Classes	Absolute Path
single-date	date	html[0]/body[1]/div[1]/div[1]/div[0]/div[0]/div[1]

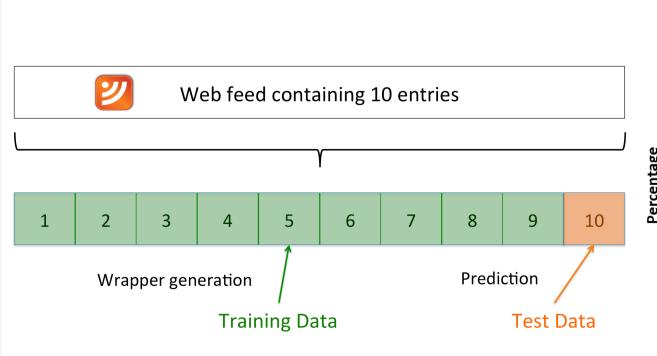
Extraction of rules

The last step transforms the filters into rules, in order to calculate the scores and select a rule for each of the desired properties. Essentially, a rule is the result of the transposition of a filter. This transposition can result in maximum three rules. Hence, a rule is described by its type (one of the three different attribute types of the filters), a value (the value of the corresponding filter's attribute) and a score, which is used to measure its expected accuracy. The need to calculate the score of each rule is justified by the inherent "noise" of the filters.

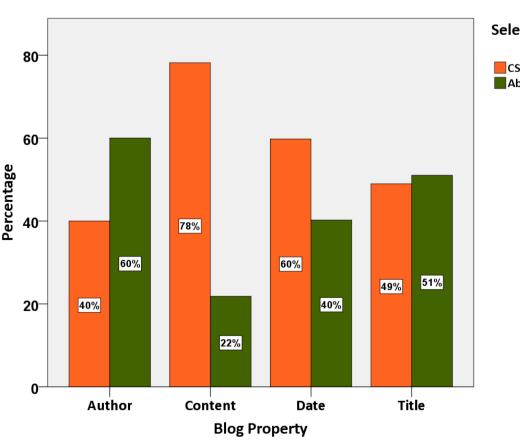
Result: Rule with the high /* Initialize all score for all the $Rules\ r \in R$ do for al

Rule Induction Algorithm **Data**: Collection of training posts P, Collection of candidate rules RResult: Rule with the highest score /* Initialize all scores r.score = 0;Rule rs = new Rule();rs.score = 0: for all the Rules $r \in R$ do for all the Posts $p \in P$ do /* Check if application r(p) of rule r, on post p succeeds if r(p) = value-property of p then r.score + +;/* Normalize score values /* Check if this is the best rule so far if r.score > rs.score then rs=r;

Evaluation



We ran 10-fold validation across 240 feeds and 2.393 posts



for different weblog properties.

The rules extracted show that the rule types vary

Selected Rule
Type

CSS Classes
Absolute Path

	Title	Content	Publication	Author
			date	
Proposed	97,3%	95,9%	89,4%	85,4%
Model	(65 misses)	(99 misses)	(253 misses)	(264 misses)
Boilerplate	0	77,4%	N/A	N/A
		(539 misses)		

81,6% relative error reduction

A significant increase of prediction accuracy is found.

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