On the Use of PU Learning for Quality Flaw Prediction in Wikipedia

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Who are we?





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Methodological Design

- Using a state-of-the-art document model
- Finding a good algorithm for classification tasks
 - Exploiting the characteristics of this algorithm

Methodological Design

- Using a state-of-the-art document model
 - 73 features from the document model used in [1]. They were selected following the guidelines in [2].

Text Features

LENGTH: character / sentence / word count, etc.

STRUCTURE: mandatory sections count, tables count, etc.

STYLE: prepositions / stop words / questions rate, etc.

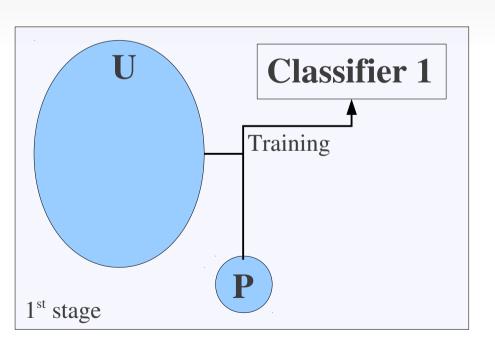
READABILITY: Gunning-Fog / Kincaid indexes, etc,

Network Features

In-link count. Internal link count, Inter-language link count

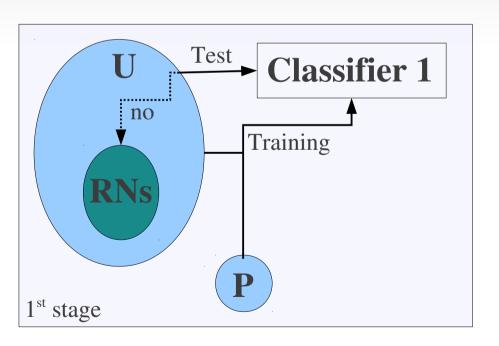
^[1] Anderka, M., Stein, B., Lipka, N.: Predicting Quality Flaws in User-generated Content: The Case of Wikipedia. In: 35rd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval. ACM (2012) ^[2] Dalip, D., Goncalves, M., Cristo, M., Calado, P.: Automatic quality assessment of content created collaboratively by Web communities: a case study of Wikipedia. In: 9th ACM/IEEE-CS Joint Conference on Digital Libraries. ACM (2009).

 This method uses as input a small labelled set of the positive class to be predicted and a large unlabelled set to help learning.[3]



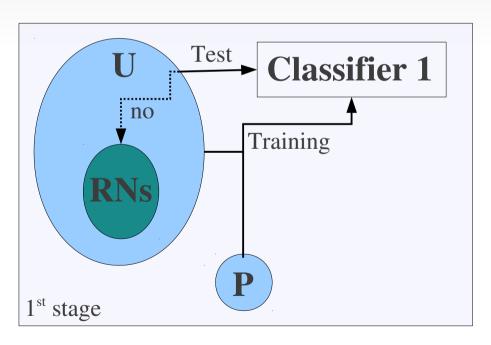
^[3] Liu, B., Dai, Y., Li, X., Lee, W.S., Yu, P.: Building text classifiers using positive and unlabeled examples. In: Proceedings of the 3rd IEEE International Conference on Data Mining, 2003.

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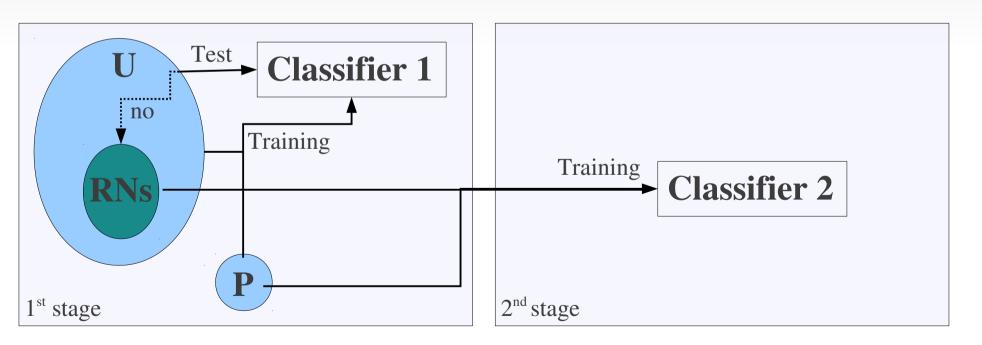




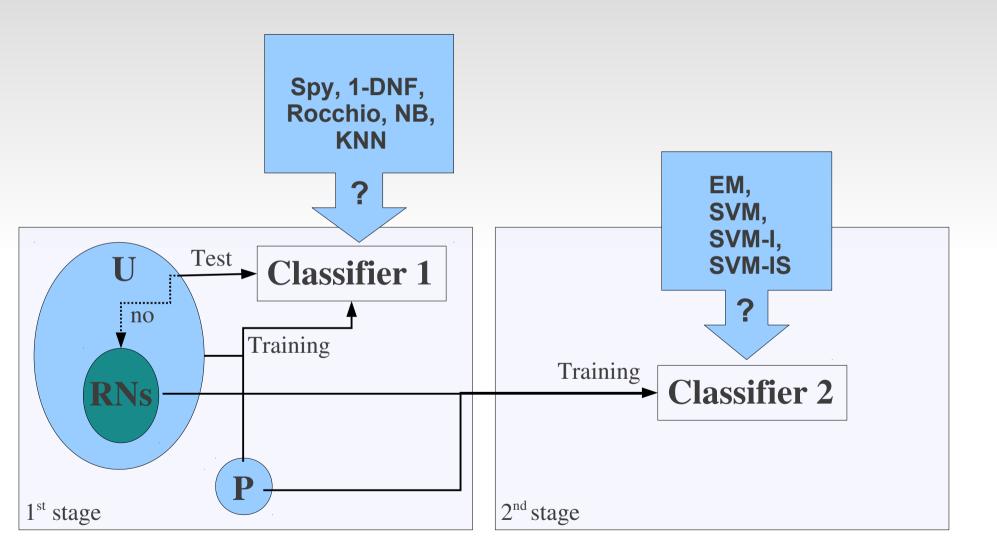
Research questions

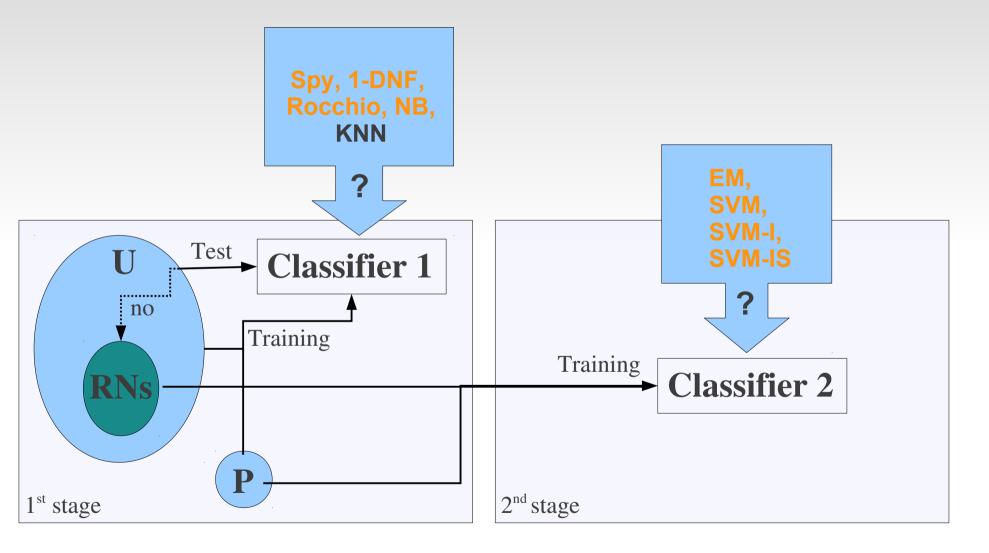
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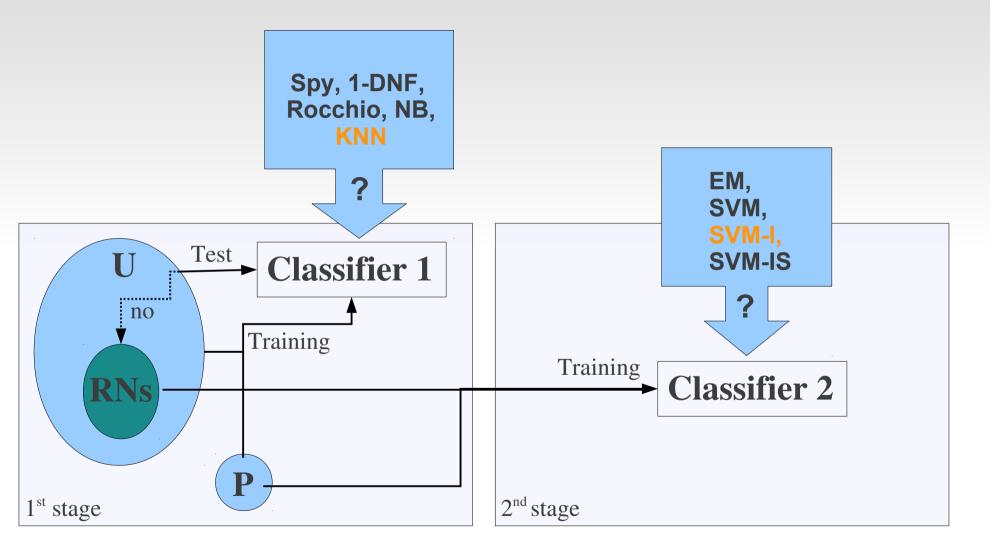


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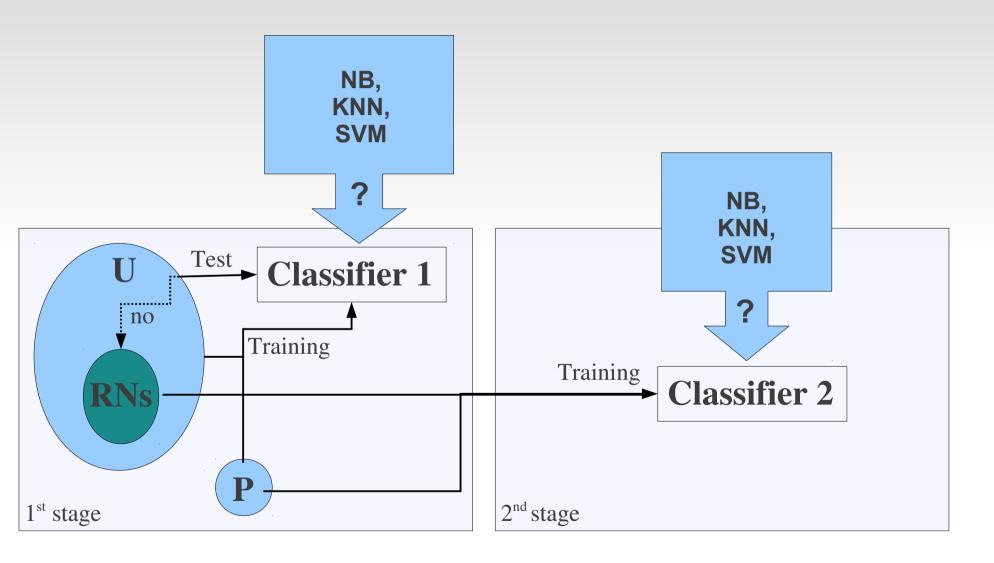


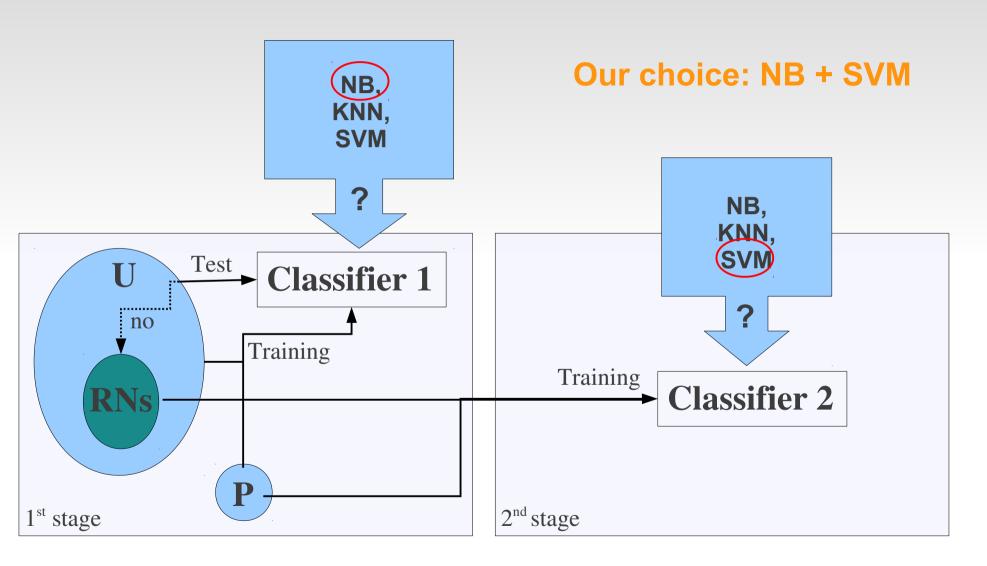


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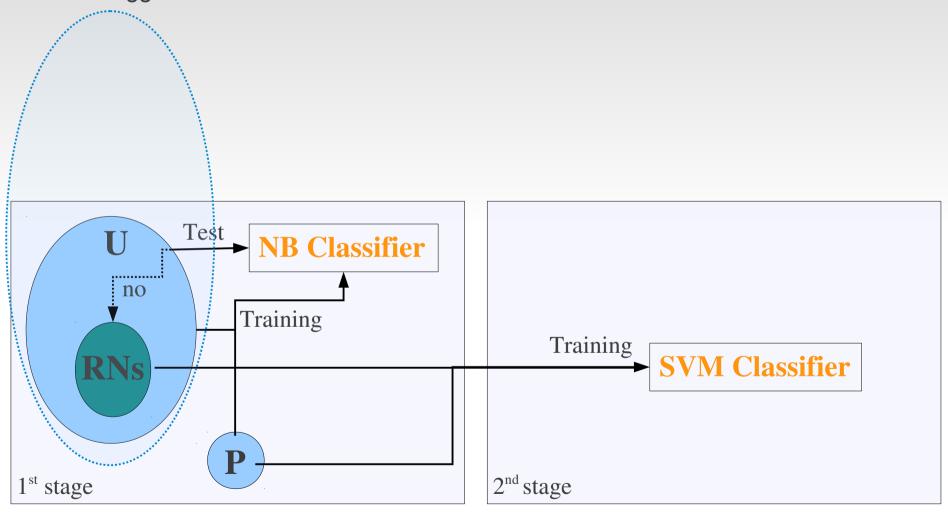


B. Zhang and W. Zuo. Reliable Negative Extracting Based on kNN for Learning from Positive and Unlabeled Examples. Journal of Computers, 4(1):94–101, 2009.

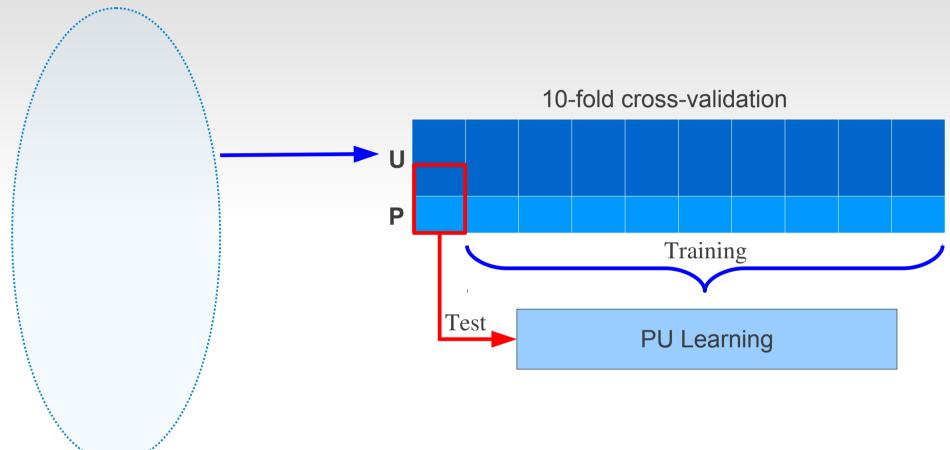


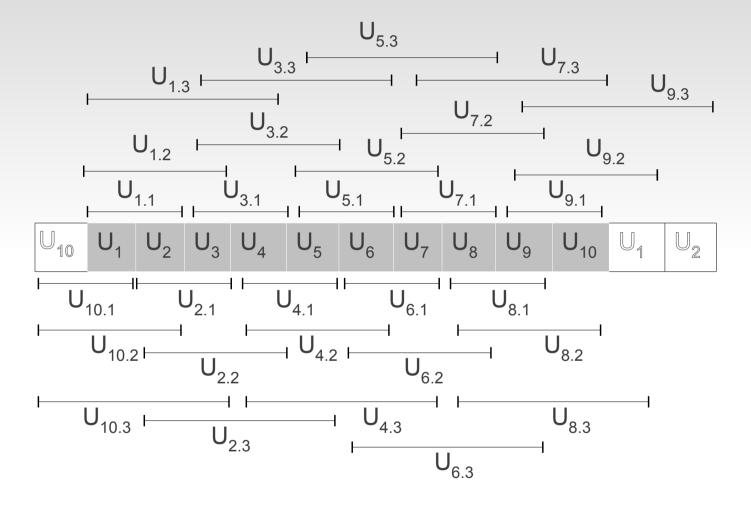


50000 untagged documents



50000 untagged documents





$$|U_i| = 5000$$
, for i=1..10

1-sample

$$U_{1.0}=U_{1}$$

$$U_{1.1}=U_{1}+U_{2}$$

$$U_{1.2}=U_{1.1}+U_{3}$$

$$U_{1.3}=U_{1.2}+U_{4}$$

2-sample

10-sample

$$U_{10.0} = U_{10}$$

$$U_{10.1} = U_{10} + U_{1}$$

$$U_{10.2} = U_{10.1} + U_{2}$$

$$U_{10.3} = U_{10.2} + U_{3}$$

 $(P + U_{i,j})$, i=1..10, $j=0..3 \Rightarrow 40$ different training sets

Training	Test
Proportions 1:5, 1:10, 1:15, 1:20	P size 110

1-sample

 $U_{1.0}=U_{1}$ $U_{1.1}=U_{1}+U_{2}$ $U_{1.2}=U_{1.1}+U_{3}$ $U_{1.3}=U_{1.2}+U_{4}$

2-sample

$$\begin{aligned} & \mathsf{U}_{2.0} \! = \! \mathsf{U}_2 \\ & \mathsf{U}_{2.1} \! = \! \mathsf{U}_2 \! + \! \mathsf{U}_3 \\ & \mathsf{U}_{2.2} \! = \! \mathsf{U}_{2.1} \! + \! \mathsf{U}_4 \\ & \mathsf{U}_{2.3} \! = \! \mathsf{U}_{2.2} \! + \! \mathsf{U}_5 \end{aligned}$$

10-sample

$$U_{10.0} = U_{10}$$

$$U_{10.1} = U_{10} + U_{1}$$

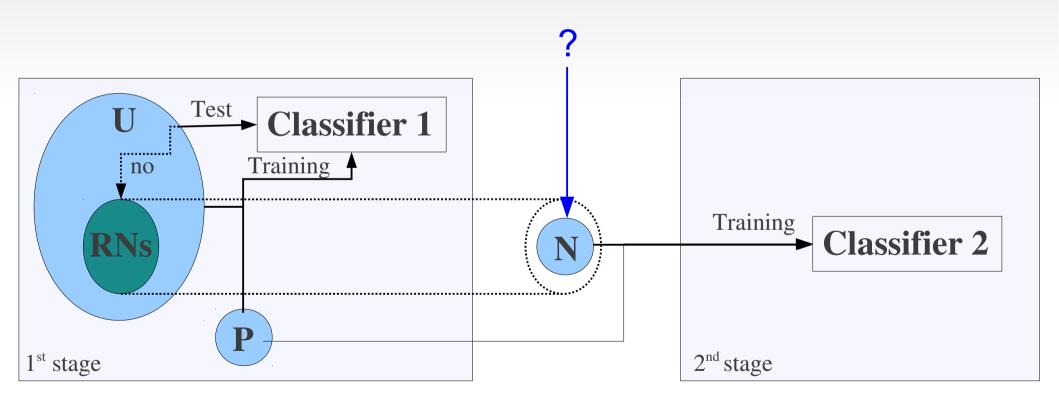
$$U_{10.2} = U_{10.1} + U_{2}$$

$$U_{10.3} = U_{10.2} + U_{3}$$

 $(P + U_{i,j})$, i=1..10, $j=0..3 \Rightarrow 40$ different training sets

Training	Test
P size Proportions 1000 1:5,1:10, 1:15, 1:20	P size 110

	Advert	Empty	No-foot	Notab	OR	Orphan	PS	Ref	Unref	Wiki
Recall	0.58	0.98	0.57	0.99	0.3	1	0.74	0.61	0.99	0.97



- 1. Selecting all RNs as negative set. [3]
- 2. Selecting IPI documents by random from RNs set.
- 3. Selecting the |P| best RNs (those assigned the highest confidence prediction values by classifier 1).
- 4. Selecting the IPI worst RNs (those assigned the lowest confidence prediction values by classifier 1).

^[3] Liu, B., Dai, Y., Li, X., Lee, W.S., Yu, P.: Building text classifiers using positive and unlabeled examples. In: Proceedings of the 3rd IEEE International Conference on Data Mining, 2003.

Table 2. Recall and fn values for RNs selection strategies

Strategy		fn pred	liction rates		Recall		
	Average	Median	Average	Median			
1	22.17	3	0	110	0.80	0.97	
2	4.48	1	0	26	0.96	0.99	
3	4.00	4	0	10	0.96	0.96	
4	4.17	1	0	30	0.96	0.99	

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Table 3. Average recall values per flaw

Strategy		Flaws								
	\mathbf{Advert}	Empty	No-foot	\mathbf{Notab}	\mathbf{OR}	Orphan	\mathbf{PS}	\mathbf{Ref}	\mathbf{Unref}	Wiki
1	0.58	0.98	0.57	0.99	0.30	1.00	0.74	0.61	0.99	0.97
2	0.90	0.99	0.86	0.99	1.00	1.00	0.90	0.99	0.99	0.98
3	0.95	0.98	0.94	0.99	0.97	0.99	0.95	0.96	0.97	0.95
4	0.90	0.99	0.89	0.99	1.00	1.00	0.89	0.99	0.99	0.99

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	1	0.58	0.98	0.57	0.99	0.30	1.00	0.74	0.61	0.99	0.97
	2	0.90	0.99	0.86	0.99	1.00	1.00	0.90	0.99	0.99	0.98
	3	0.95	0.98	0.94	0.99	0.97	0.99	0.95	0.96	0.97	0.95
	4	0.90	0.99	0.89	0.99	1.00	1.00	0.89	0.99	0.99	0.99

SVM: Which kernel?

- Linear SVM (WEKA's default parameters)
- RBF SVM
 - $\gamma \in \{2^{-15}, 2^{-13}, 2^{-11}, \dots, 2^{1}, 2^{3}\}$
 - $C \in \{2^{-5}, 2^{-3}, 2^{-1}, \dots, 2^{13}, 2^{15}\}$

Conclusions

• What classifier in each stage?

NB + SVM

Untagged sampling strategy

Some unlabelled sets are more promising

- RBF kernel: U_6 sub-sample $\rightarrow 60\%$ of the flaws.
- Linear kernel: U_{4} sub-sample $\rightarrow 60\%$ of the flaws
- In general, $U_{i,j}$, i=1..10, j=2 or $j=3 \rightarrow$ best results.
- Strategies for selecting RNs as true negatives
 - $2 \approx 4 > 3 > 1$, ">" means "better than".

- Which SVM kernel and parameters?
 - RBF was better than Linear kernel.
 - High penalty value for the error term (C = 2^{15}) and very low γ values ($\gamma \in \{2^{-11}, 2^{-9}, 2^{-7}, 2^{-5}\}$).
- Semi-supervised methods seem very promising.
- As current work, we are developing new features based on factual content measures^[4] to assess Advert, Notability and Original Research quality flaws.

^[4] E. Lex, M. Völske, M. Errecalde, E. Ferretti, L. Cagnina, C. Horn, B. Stein, and M. Granitzer. Measuring the quality of web content using factual information. In Proceedings of the 2nd joint WICOW/AIRWeb workshop on Web quality (WebQuality'12), pages 7–10. ACM, April 2012.

Questions?

Thanks very much for your attention!

Motivation

SVM: Which kernel?

Linear SVM (WEKA's default parameters)

Table 4. Recall and fn values for RNs selection strategies

Strategy		fn pred		Recall		
	Average	Average	Median			
2	21	21.5	4	49	0.81	0.80
3	6.20	6	0	20	0.94	0.94
4	20	21	1	44	0.82	0.81

RBF SVM

$$\gamma \in \{2^{-15}, 2^{-13}, 2^{-11}, \dots, 2^{1}, 2^{3}\}$$

Table 5. Best γ values

Advert	Empty	No-foot	Notab	OR	Orphan	\mathbf{PS}	Ref	Unref	Wiki
2^{-7}	2^{-7}	2^{-5}	2^{-11}	2^{-9}	2^{-9}	2^{-5}	2^{-9}	2^{-9}	2^{-9}

$$C \in \{2^{-5}, 2^{-3}, 2^{-1}, \dots, 2^{13}, 2^{15}\} \longrightarrow C = 2^{15}$$

