# Batch and On-line Spam Filter Comparison

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TREC – Text Retrieval Conference (On-line) chronological order, immediate feedback real email messages (and filters!) soft classification: spamminess score Receiver Operating Characteristic (ROC) Classical Evaluation (Batch) k-fold cross validation contrived email messages (and filters!) hard classification: *spam* or *ham* accuracy, weighted accuracy, Total Cost Ratio (TCR)



**TREC 2005 Public Corpus** on-line test (TREC methodology) 10-fold cross validation (random splits) 9:1 chronological split on-line test sequence batch test set tokenized, obfuscated versions of same corpora Ling Spam & PU1 Corpora 10-fold cross validation splits, tokenization, obfuscation defined by corpora



X<sup>2</sup> (Graham/Robinson) Bogofilter (*Relson, Louis et al.*) Support Vector Machine (Vapnik) SVM<sup>light</sup> (Joachims) Logistic Regression (Fisher) LR-TRIRLS (Komarek) Prediction by Partial Matching (Cleary & Witten) Adaptive PPM-D Classifier (Bratko) Dynamic Markov Modeling (Cormack & Horspool) Adaptive DMC Classifier (Cormack)



# Prediction by Partial Matching

For each class: left context occurrences left context+prediction *log-likelihood* estimate compressed length Smoothing/backoff: zero occurrence problem Adaptation: increment counts assuming in-class





Context (509 spam, 1 ham)

# ai.stanford.e



Prediction (0 spam, 1 ham)

ai.stanford.E



Prediction (509 spam, 0 ham)





CORMACK & BRATKO BATCH AND ON-INE SPAM FILTER COMPARISON LEAS 2000



### 10-Fold Cross Validation









Misclassified Hams (of 787)



Batch, On-line (1-ROCA)%

	On-line		Batch	
Method	Full Corpus	9:1 Chronological	10-fold C.V.	9:1 Chronological
DMC	.013 (.010018)	.0003 (.0000003)	.015(.012018)	.003 (.001006)
PPM	.017 (.014021)	.0007 ( $.0001$ - $.005$ )	.006 (.004009)	.003 ( $.001$ - $.008$ )
Bogofilter	.048 $(.038062)$	.002(.0001041)	.020 (.012033)	.009 (.003029)
LR	.068 $(.058079)$	.020 (.003135)	.016(.012021)	.12(.001-10.1)
SVM	.075 ( $.064$ - $.088$ )	.007 ( $.0015$ - $.033$ )	.021 (.015029)	.13(.003-5.6)



### Effect of Order/Adaptation

	Training	Testing Regimen			
Filter	Regimen	On-line Random Order	On-line Corpus Order	Batch	
DMC	Random Order	.01 (.006017)	.007 (.004011)	.009 (.006015)	
DMC	Corpus Order	.035 $(.026047)$	.037 ( $.024$ - $.057$ )	.31 (.2537)	
PPM	Batch	.0052 (.00301)	.0053 (.003009)	.0055 (.00301)	

#### Tokenization, On-line





#### Tokenization, Batch





### Tokenization/Obfuscation

	On-line		Batch	
Method	Full Corpus	9:1 Chronological	10-fold C.V.	9:1 Chronological
DMC	.013 (.010018)	.0003 (.0000003)	.015 (.012018)	.003 (.001006)
tokenized	.025 ( $.020$ - $.032$ )	.0006 (.0001006)	.025 $(.019033)$	.001 (.000013)
obfuscated	.037 ( $.030$ - $.045$ )	.0004 ( $.00000042$ )	.029 ( $.023$ - $.037$ )	.002 (.001006)
PPM	.017 (.014021)	.0007 (.0001005)	.006 (.004009)	.003 (.001008)
tokenized	.038 ( $.033$ - $.045$ )	.0016 (.0003009)	.012 (.009016)	.005(.002012)
obfuscated	.075 ( $.066084$ )	.0046 (.0016013)	.020 ( $.014$ - $.027$ )	.015 (.006035)
Bog of ilter	.048 (.038062)	.002 (.0001041)	.020 (.012033)	.009 (.003029)
obfuscated	.13(.1115)	.024 (.00414)	.055 ( $.045$ - $.068$ )	.036 (.01211)
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Gradient Descent Logistic Regression (Goodman) On-line Filter Fusion (Lynam & Cormack) Classical machine learning (Cast of thousands) Naïve Bayes (which naïve Bayes?) **kNN** Perceptron Winnow Decision trees Boosting Stacking



### Goodman's Gradient Descent LR





#### Stacking – 53 TREC Filters





### Ling Spam Corpus





## PU1 Corpus





## Conclusions

Batch and on-line are different good filters can be adapted to do both well Feature engineering is important email is not just a bag or sequence of tokens Real filters beat contrived ones even on contrived corpora PPM and DMC effectively filter spam fast (100s of messages/sec) voracious appetite for RAM (0.5 - 2.0 GB)