

Spam Track

Past, Present and Future

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Academic evaluations

vector-space, batch test/training sets, machine learning methods, *accuracy* as evaluation measure

In-house evaluations (& testimonials)

MrX Corpus (Cormack & Lynam)

capture real user's email July '03 – Feb '04

careful construction of *gold standard*

on-line testing

open-source '*Bayesian*' and *rule-based* filters

ROC analysis

Tension between privacy and archival corpus

standardized filter interface and toolkit

Private corpora (MrX, SB, TM)

MrX runs available on request

Public corpus

90,000 messages (Enron + seeded spam)

download: (google for TREC spam corpus)

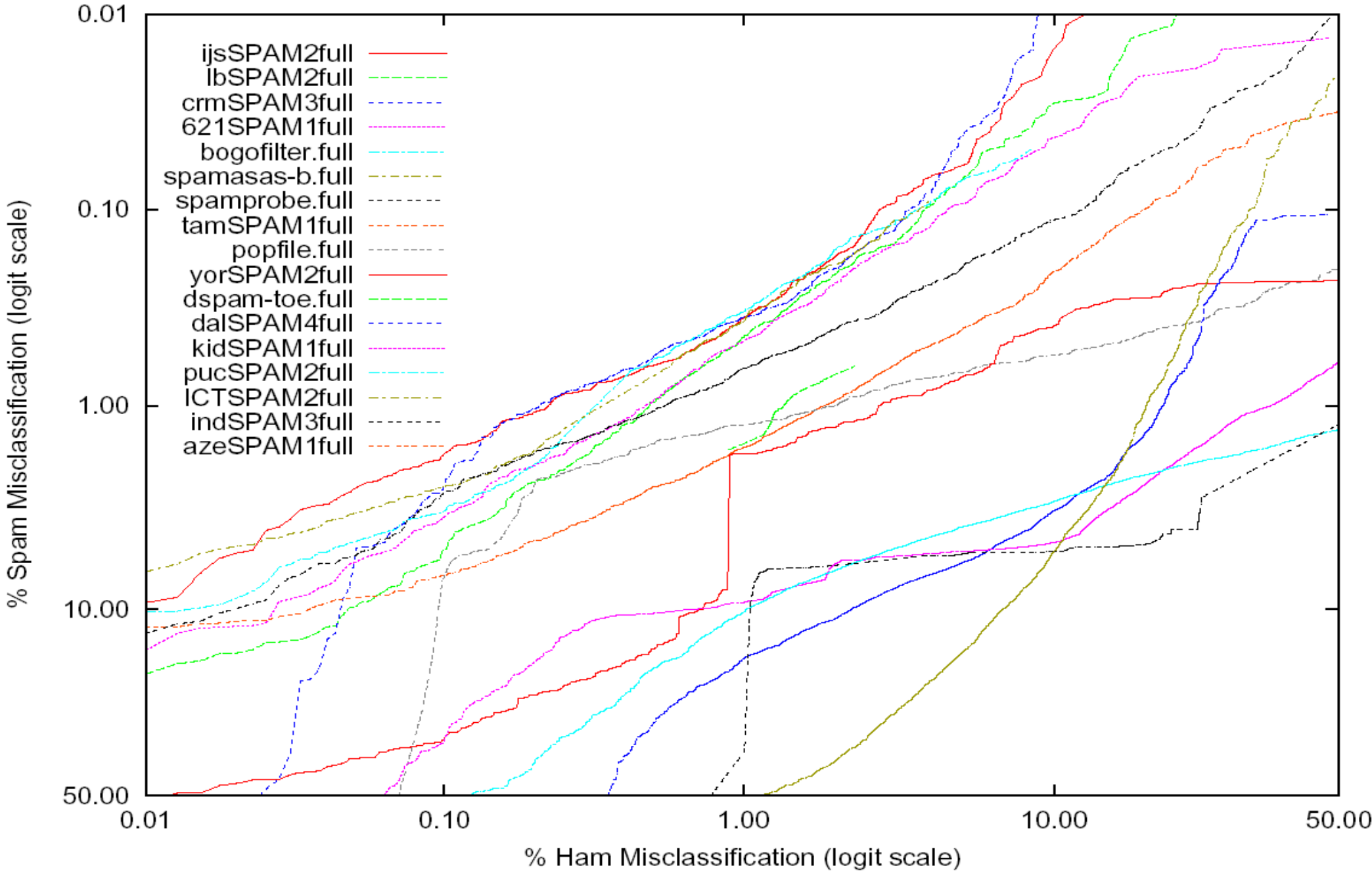
amusement: spamorham.org (J. Graham-Cumming)

Online classification task

idealized user gives immediate, accurate feedback



ROC Curves – TREC 2005



Logistics of preparing/submitting/evaluating

Public & private corpora yield comparable results

Compression models worked very well (Bratko)

Why no (strong) machine learning methods?

Is ideal user realistic? Effect of delay/error?

Are spammers defeating these methods faster than we can evaluate them?

What about other real-time aspects? Blacklists, greylists, spam warehouses?

TREC vs ML-style evaluation

DMC – bit-wise compression-based method

Stacking (fusion) of the TREC 2005 filters

ECML Discovery Challenge

Design of TREC 2006

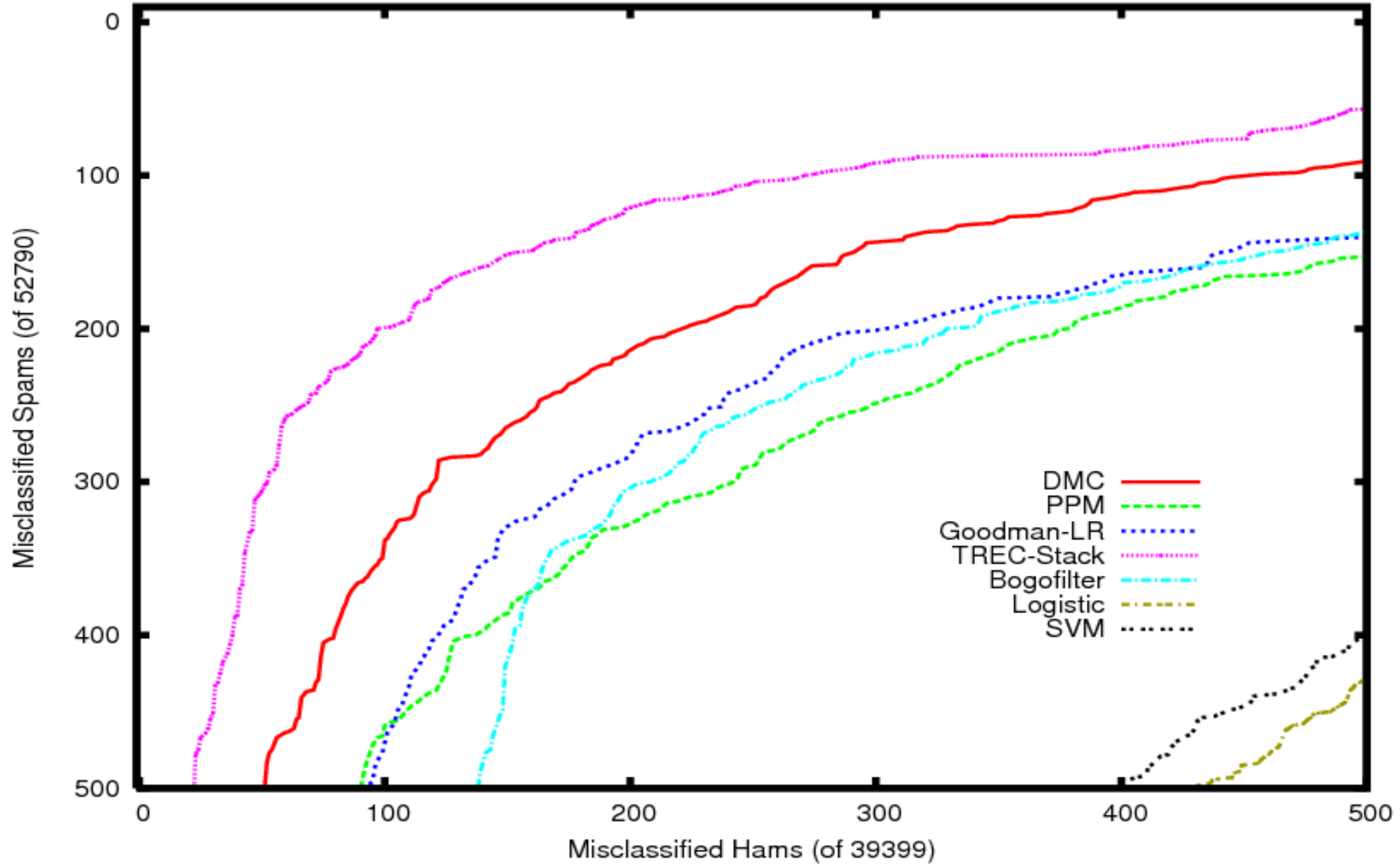
TREC 2005 + delayed feedback + active learning

TREC 2006

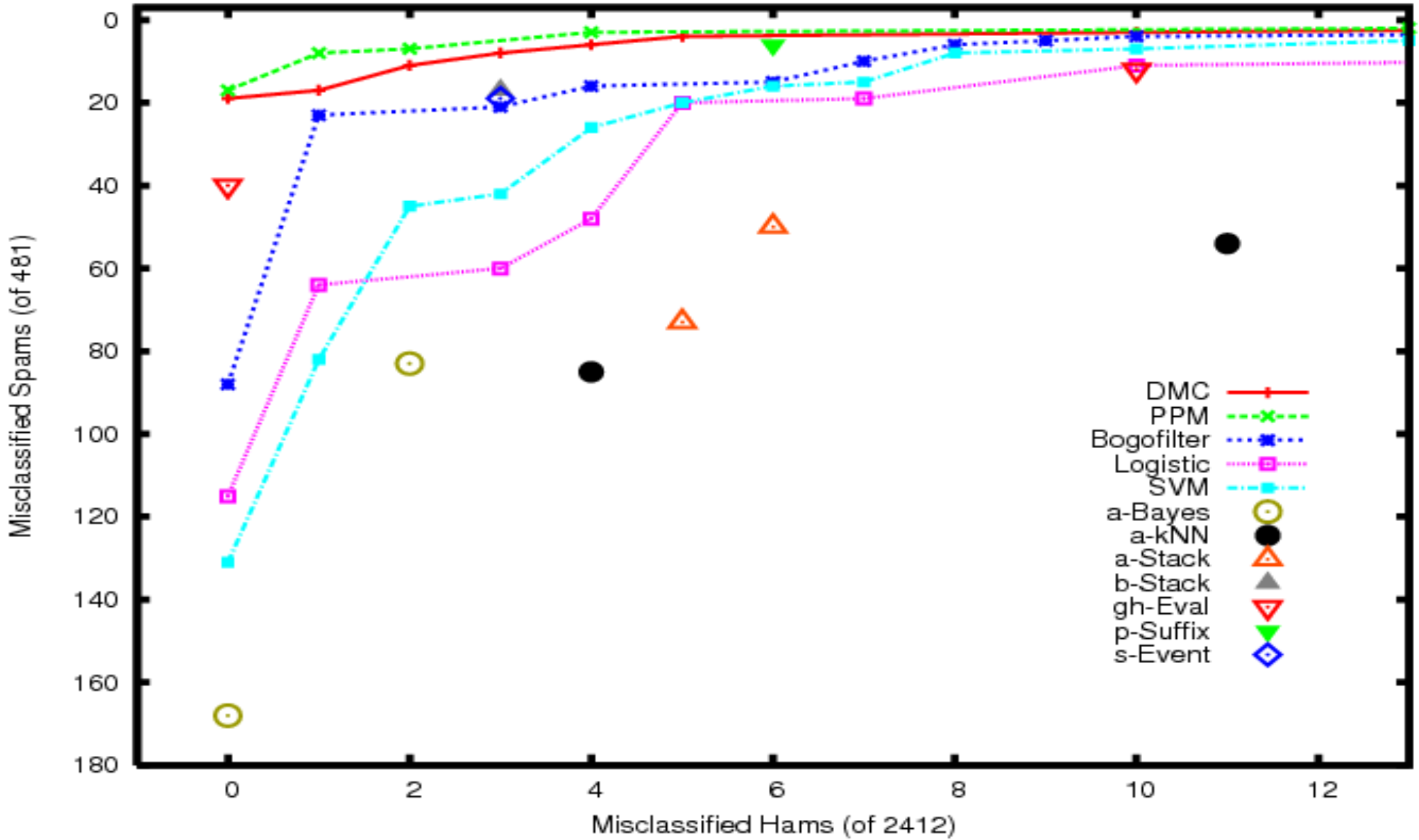
TREC 2007

Other evaluations?

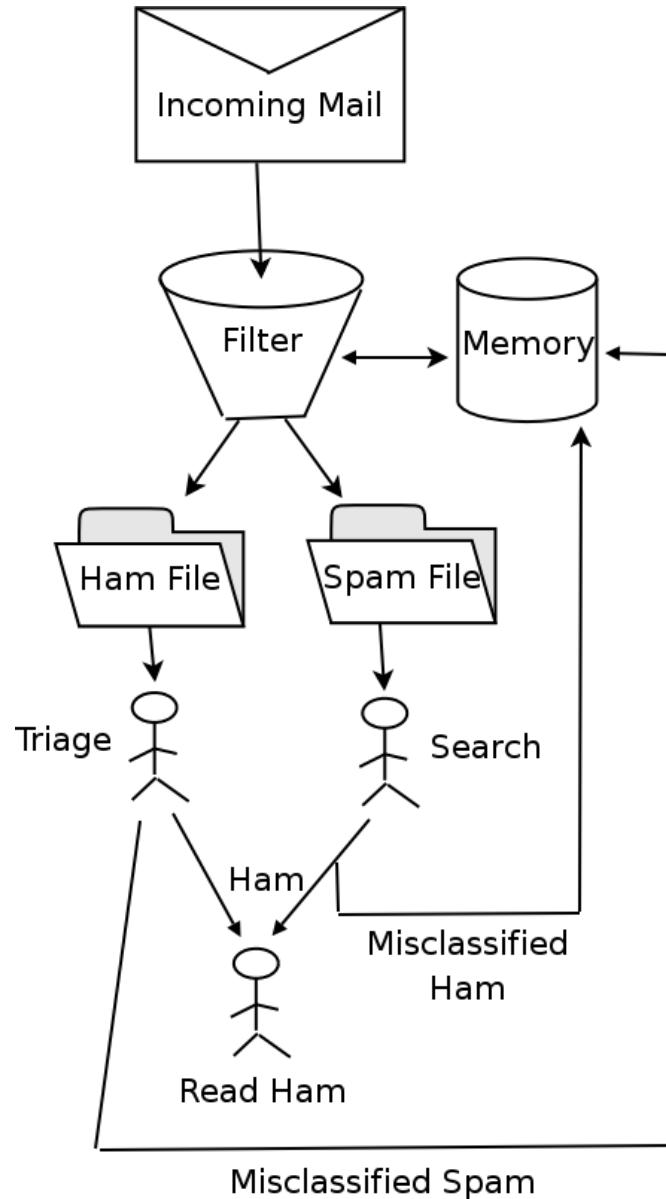
Since TREC 2005



Ling Spam Corpus



Spam Filter Usage



Filter Classifies Email

Human addressee

Triage on ham File

Reads ham

Occasionally searches
for misclassified ham

Report misclassified
email to filter

Immediate Feedback

reprise TREC 2005 *idealized user*

Delayed Feedback

lazy user reports classification later, in batches

batch size random, avg 500 -- 1000 messages

Active Learning

sequence of unclassified messages

filter requests true classification for some

predict future sequence of messages

Filter is invoked through standard commands:

initialize

create necessary files & servers (cold start)

classify *filename*

read *filename* which contains exactly 1 email message

write one line of output:

classification score auxiliary_file

train *judgement filename classification*

take note of gold-standard *judgement*

finalize

clean up: kill servers, remove files

Filter implements a shell program:

for $n = 100, 200, 400, \dots$

 read training data (1st 90% of corpus)

 for i from 1 to n

 request classification for 1 message

 for each message in test data (last 10% of corpus)

 output classification

 erase memory

Newer versions of private corpora

MrX (2003-04) ==> MrX II (2005-06)

SB (2004-05) ==> SB II (2005-06)

(Mostly) English public corpus

Web retrieval of mbox-format files (1993-2006)

Augmented by spam-trap spam (2006) spoofed to simulate delivery to (paired) web message

Chinese public corpus (Courtesy CCERT)

Mailing list ham

Spam trap spam

Corpora

Private Corpora

	Ham	Spam	Total
MrX2	9039	40135	49174
SB2	9274	2695	11969
Total	18313	42830	61143

Public Corpora

	Ham	Spam	Total
trec06p	12910	24912	37822
trec06c	21766	42854	64620
Total	34677	67766	102442

Run Tag Suffixes

Corpus / Task	Filter Suffix
trec06p / immediate feedback	pei
trec06p / delayed feedback	ped
trec06c / immediate feedback	pci
trec06c / delayed feedback	pcd
MrX2 / immediate feedback	x2
MrX2 / delayed feedback	x2d
SB2 / immediate feedback	b2
SB2 / delayed feedback	b2d

Active Run Tag Suffixes

pei.*nnn* – Public English, *nnn* training examples

cei.*nnn* – Public Chinese, *nnn* training examples

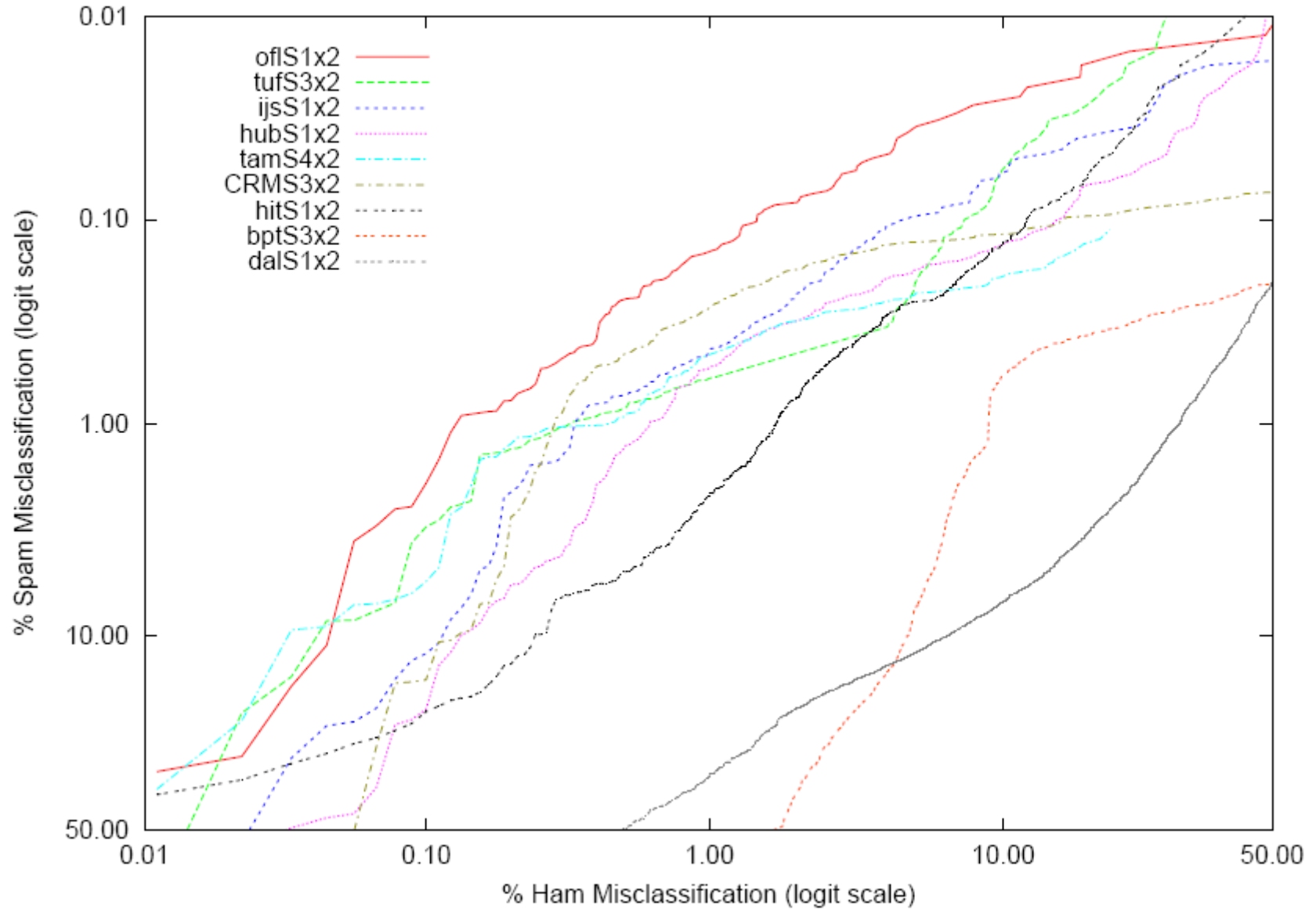
x2.*nnn* – MrX II, *nnn* training examples

b2.*nnn* – Mrx II, *nnn* training examples

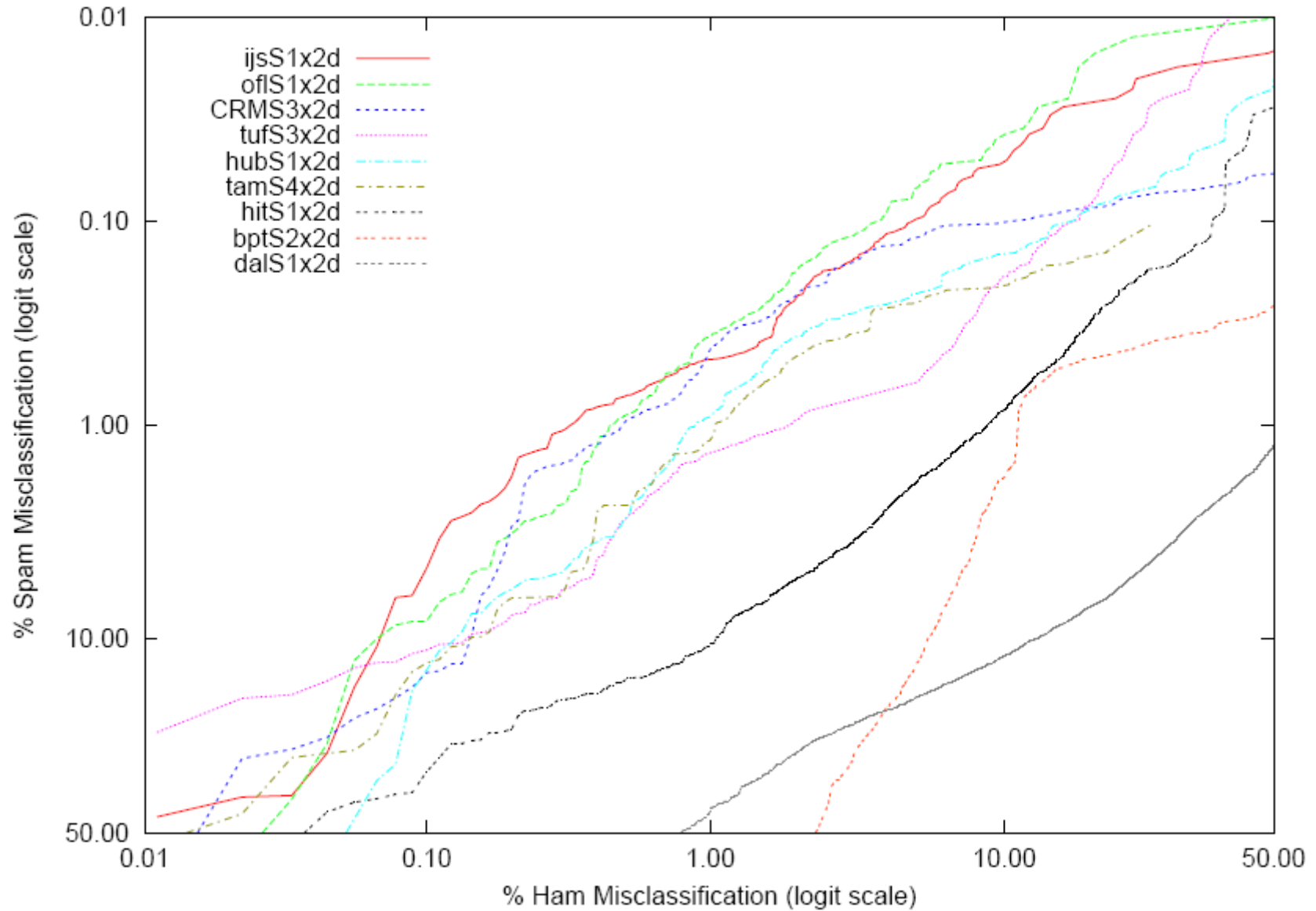
Participant Filters

Group	Filter Prefix
Beijing University of Posts and Telecommunications	bpt
Harbin Institute of Technology	hit
Humboldt University Berlin & Strato AG	hub
Tufts University	tuf
Dalhousie University	dal
Jozef Stefan Institute	ijs
Tony Meyer	tam
Mitsubishi Electric Research Labs (CRM114)	CRM
Fidelis Assis	ofl

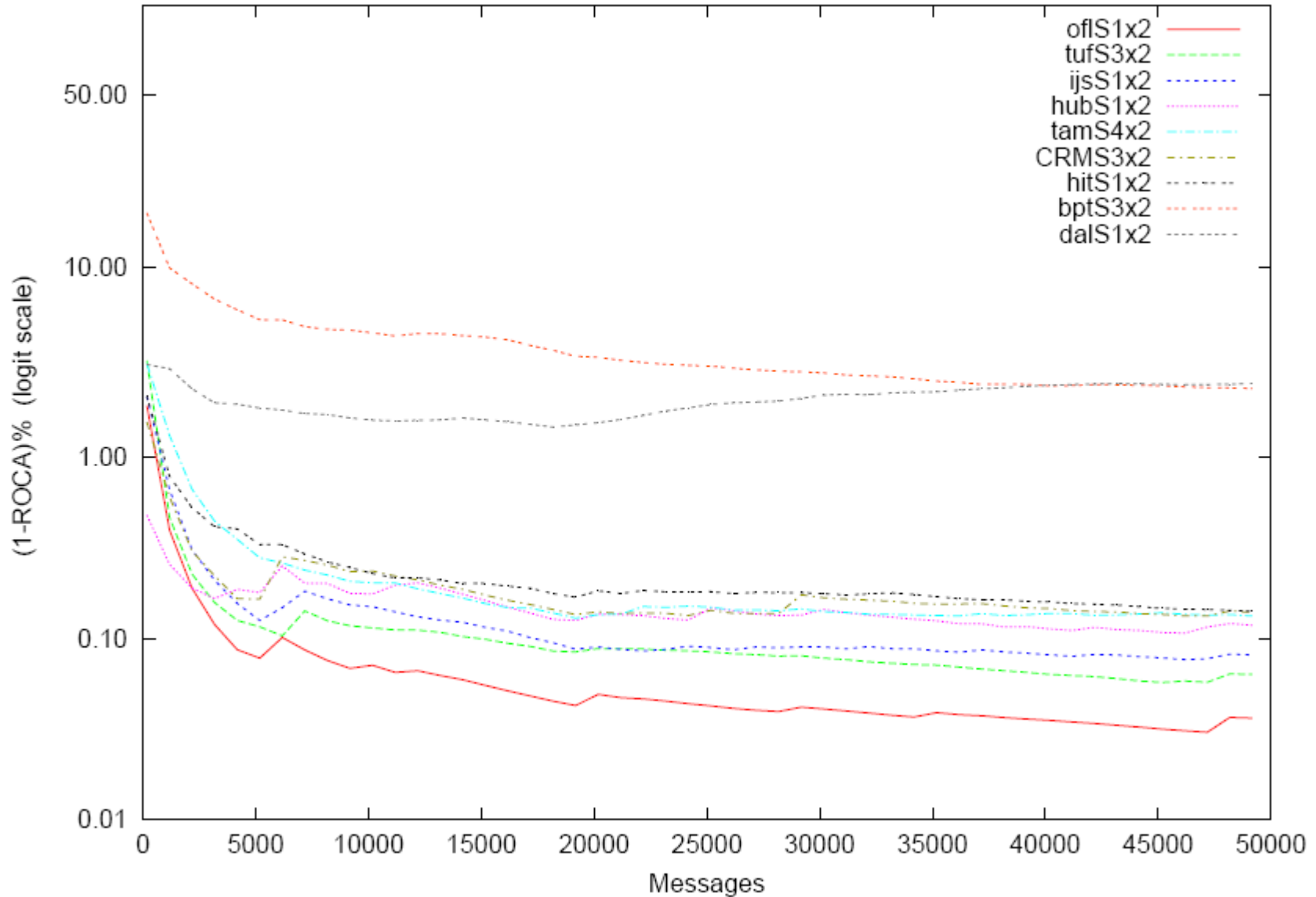
MrX II – Immediate Feedback



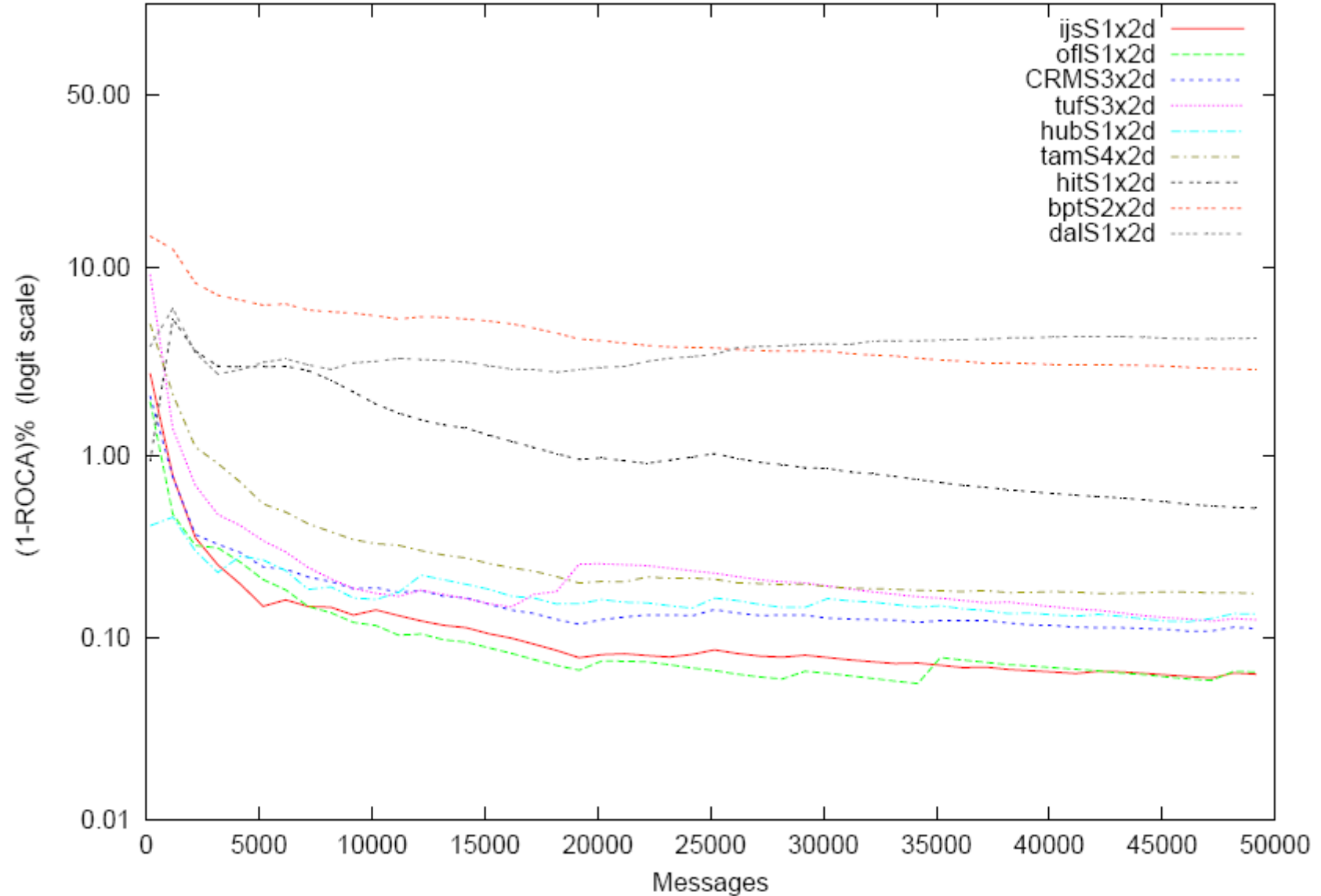
MrX II – Delayed Feedback



MrX II immediate learning curve

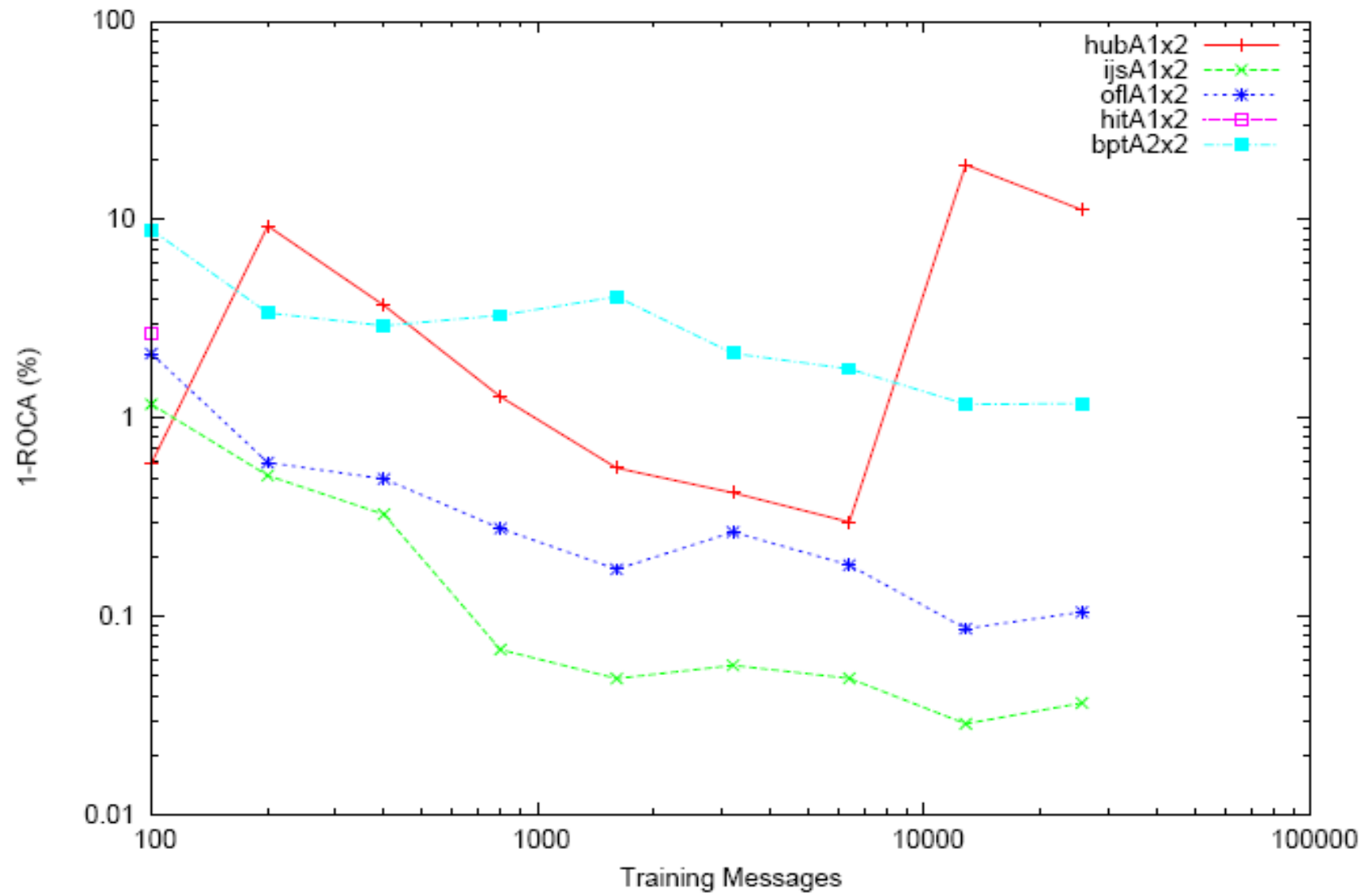


MrX II delay – learning curves



Mrx II – Active Learning

ROC



1-ROCA (%)

Run	X2	X2d	100	200	400	800	1600	3200	6400
Ofi	0.04	0.07	2.11	0.60	0.49	0.28	0.17	0.27	0.18
DMC	0.05	0.09	1.80	0.14	0.08	0.08	0.13	0.08	0.08
Tuf	0.06	0.13							
Ijs	0.08	0.06	1.17	0.51	0.33	0.07	0.05	0.06	0.05
Bogo	0.09								
Hub	0.12	0.14	0.59	0.60	0.37	0.50	0.36	0.42	0.28
Tam	0.13	0.18							
Crm	0.14	0.11							
Hit	0.14	0.52	2.66						
Bpt	2.35	3.08	9.10	3.40	2.90	3.27	3.91	2.12	1.77
Dal	2.50	4.34							

1-ROCA (%) Multi-corpus results

Filter\Feedback	Aggregate		trec06p		trec06c		MrX2		SB2	
	immediate	delay	immediate	delay	immediate	delay	immediate	delay	immediate	delay
ofs1	0.0295	0.1914	0.0540	0.1668	0.0035	0.0666	0.0363	0.0651	0.1300	0.3692
ofs3	0.0327	0.1908	0.0562	0.1702	0.0035	0.0601	0.0523	0.0824	0.1249	0.3174
ofs2	0.0365	0.2018	0.0597	0.2045	0.0104	0.1297	0.0525	0.0931	0.1479	0.3659
tufs2	0.0370	0.1079	0.0602	0.2038	0.0031	0.0104	0.0691	0.1449	0.3379	0.6923
ofs4	0.0381	0.1828	0.0583	0.1965	0.0077	0.0855	0.0718	0.1155	0.1407	0.2941
tufs1	0.0445	0.1262	0.0602	0.2110	0.0023	0.0081	0.0953	0.1991	0.3899	0.8361
ijsS1	0.0488	0.2119	0.0605	0.2457	0.0083	0.1117	0.0809	0.0633	0.1633	0.4276
tufs3	0.0705	0.1497	-	-	-	-	0.0633	0.1263	0.3350	0.6137
tufs4	0.0749	0.1452	-	-	-	-	0.0750	0.1314	0.3199	0.5696
CRMS3	0.0978	0.1743	0.1136	0.2762	0.0105	0.0888	0.1393	0.1129	0.2983	0.4584
CRMS2	0.1011	0.1667	0.1153	0.2325	0.0094	0.0975	0.1592	0.1143	0.4196	0.6006
CRMS1	0.1081	0.2165	0.1135	0.2447	0.0218	0.0784	0.1498	0.1341	0.3852	0.6346
hubS3	0.1674	0.2170	0.1564	0.1958	0.0353	0.0495	0.2102	0.2294	0.6225	0.8104
hubS4	0.1717	0.2400	0.1329	0.2006	0.0233	0.0330	0.1385	0.1763	0.5777	0.6784
hubS1	0.1731	0.2013	0.1310	0.1418	0.0238	0.0319	0.1180	0.1359	0.5295	0.5779
hubS2	0.1945	0.2716	0.1694	0.2952	0.0273	0.0369	0.1450	0.1827	0.4276	0.5306
hitS1	0.2112	0.8846	0.2884	0.5783	0.2054	1.3803	0.1412	0.5184	0.5806	1.2829
CRMS4	0.2375	1.5324	0.4675	2.1950	0.0579	1.7675	0.3056	0.4898	0.9653	2.0009
tamS4	0.2493	0.4480	0.2326	0.4129	0.1173	0.2705	0.1328	0.1755	0.4813	0.9653
tamS1	0.3008	1.0910	0.4103	0.8367	0.0473	0.1726	0.4011	0.6714	0.5912	4.5170
tamS2	0.9374	3.2366	1.2414	3.9352	0.4464	1.5370	-	-	6.5258	23.8125
tamS3	1.5309	2.2236	1.0602	1.8279	0.2899	1.0860	0.9514	1.5965	1.8462	6.0056

Orthogonal sparse bigrams with threshold training
for headers (Assis, p 461 of notebook)

Perceptron with margin (Tufts) – incremental
classical machine learning

Uncertainty sampling & pre-training (Humboldt U.)

Train on most recent examples (IJS)

Short message prefixes (Tufts, also DMC)

Are Spammers Winning?

	MrX	MrX II
Ijs	.08 (.04 - .10)	.08 (.05 - .12)
Of1	.07 (.04 - .11)	.05 (.03 - .10)
Tuf	.04 (.03 - .05)	.06 (.04 - .09)
DMC	.04 (.03 - .05)	.05 (.03 - .09)
Bogofilter	.05 (.03 - .06)	.09 (.07 - .11)

A horizontal yellow brushstroke with a textured, hand-painted appearance, spanning across the top of the slide.

What's Next?