COARSE-TO-FINE, COST-SENSITIVE CLASSIFICATION OF E-MAIL



Jay Pujara jay@cs.umd.edu Lise Getoor <u>getoor@cs.umd.edu</u>

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Parallel Coarse-to-Fine Problems

Structure in output

- Labels naturally have a hierarchy from coarse-to-fine
- □ Structure in input
 - Features may have an order or systemic dependency
 - Acquisition costs vary: cheap or expensive features
- Exploit structure during classification
- Minimize costs

E-mail Challenges: Spam Detection



- Most mail is spam
- Billions of classifications
- Must be incredibly fast

E-mail Challenges: Categorizing Mail



- E-mail does more, tasks such as:
 - Extract receipts, tracking info
 - Thread conversations
 - Filter into mailing lists
 - Inline social network response
- Computationally intensive processing
- Each task applies to one class

Features have costs & dependencies



IP is known at socket connect time, is 4 bytes in size

Features have costs & dependencies



The Mail From is one of the first commands of an SMTP conversation From addresses have a known format, but higher diversity

Features have costs & dependencies



The subject, one of the mail headers, occurs after a number of network exchanges. Since the subject is user-generated, it is very diverse and often lacks a defined format

Coarse task is constrained by feature cost



Fine task is constrained by misclassification cost

Approach: Granular Cost Sensitive Classifier

Training:

- \Box Loss functions of form: L= α FC + (1- α) MC
- \square Choose $\alpha_{\rm c}$ and $\alpha_{\rm f}$ for coarse and fine tasks
- Calculate margin threshold where feature acquisition decreases loss across training data Test:
- Compute decision margin with available features
 Acquire features until margin above threshold
 Classify instance

Experimental Setup

Class	Messages		
Spam	531	Feature	C
Business	187	IP	•
Social Notwork	222	MailFrom	
	223	Subject	.5
Newsletter	1/4		
Personal/Other	102		

- Data from 1227 Yahoo! Mail messages from 8/2010
- Feature costs calculated from network + storage cost

Results

Feature Set	Feature Cost	Misclass Cost		
		Coarse	Fine	Overall
Fixed: IP+MailFrom	.490	.098	.214	.164
GCSC: α_c =.3, α_f =.05	.479	.091	.174	.141
Fixed: IP+MailFrom+Subject	1.00	.090	.176	.144
GCSC: α_c =.15, α_f =.01	.511	.088	.175	.140

- Evaluated NB & SVM base classifiers, NB results shown
- Compare fixed features vs. GCSC with 10-fold L1O CV
- Same feature cost, decrease misclassification cost
- Decrease feature cost, same misclassification cost

Dynamics of choosing $\alpha_{\rm c}$ and $\alpha_{\rm f}$

As $\alpha_{\rm c}$ increases, disparity in costs for different values of $\alpha_{\rm f}$ widens

Conclusion

- Examine a problem setting with coarse-to-fine structure in both input and output
- Propose a classifier, mapping input to output
 - at different granularities
 - sensitive to feature and misclassification costs
- Demonstrate results superior to baseline
- Details at http://bit.ly/jay_c2f_2010

Questions?