# **Biomedical Information Extraction from Semi-structured Data**

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### Introduction • Extracting information from narrative clinical records enables many applications. • The 2009 i2b2 software development challenge was to extract medication information from discharge summaries. From hospital discharge summaries... Record #111999 TREATMENT: After observing high blood sugar, patient was given 150 cc insulin once a day for one week. DISCHARGE MEDICATIONS: Tylenol 2 tabs q.d. p.o. headache ...extract six named entities and link into entries m="insulin" || d="150 cc" || mo="nm" || f="once a day" || du="for one week" || r="high blood sugar" || In="narrative" m="tylenol" || d="two tabs" || mo="p.o." || f="q.d." || du="nm" || r="headache" ||In="list" System • The core of our system is a pipeline of statistical classifiers. Modules have access to information produced by modules earlier in the pipeline. Discharge Summary Pre-processor Statistical find name Field context\_type Detection External Data find\_others Sources Field Linking

### Features

Group	Feature Types
F1	Normalized n-grams
F2	Affixes, token length, shape, and other compositional features of current and nea tokens
F3	Class labels of previous tokens
F4	N-grams in external medications list

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	Resi	lts	5 —	Dev	/(	elopm	en <sup>.</sup>	t S	et				
• H	Horizontal Exact results by feature set												
	Feature	S	Preci	sion			F-SC	core					
	F1		7	2.5		60.3		65.8					
	F1-F2	2	8	2.5		78.2	(	80.3					
	F1-F	3	8	8.4		77.9		82.8					
	F1-F4	4	8	8.1		79.4		83.5					
<ul> <li>The difference between each row is statistically significant at p&lt;=0.01.</li> <li>The final row shows external resources help.</li> </ul>													
	Pipe	lin	e v	. Si		gle Cl	as	sifi	er				
significant at p <= 0.05. $s_{2,50}^{0}$ $s_{2,50}^{0}$ $r_{7,50}^{0}$ $r_{2,50}^{0}$ r													
System Comparison													
Our	system	comn	ares f	avorah	v ·	to those wit	h mar	יזע גער	es				
	Fyart	Hnri	70nt		- J	Inovari		·izor	ital				
	Team	Prec.	Recall	F-score	Γ	Team	Prec.	Recall	F-sco	re			
Syd	ney	.896	.820	.857		Sydney	.903	.801	.840				
Ou	r system	.886	.801	.841	-	Our system	<b>.897</b>	.788	.839				
Van Mai	nchester	.840	.803	.821	-	NLM	.868	.783	.823				
NL	M	.784	.823	.803		OpenU	.858	.762	.807				
BM	E-Humboldt	.841	.758	.797		BME-Humboldt	.850	.756	.800				
	Conclusion												
<ul> <li>A machine learning approach compares favorably with rule.</li> </ul>													

- based approaches.



## GroupHealth.





• External resources can be used to improve performance. • A pipeline of classifiers outperforms a single classifier.