

# Applying Drug and Critical Term Ontologies to Australian Drug Safety Data for Adverse Event Signalling (AES) and Comparison with the Bayesian AES method MGPS

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# Outline

- Drug Safety Data (Australian Adverse Drug Reaction Advisory Committee (ADRAC) database)
- Develop new Adverse Event Signalling (AES) method
  - Using Ontologies
    - Reaction Terms (System organ class—SOC, Critical Terms)
    - Drug Terms (anatomical-therapeutic-chemical classification—ATC codes)
- Comparison with the Bayesian AES method mulit-item gamma Poisson shrinker —MGPS

# Motivation

- Existing signal detection methods
  - Proportional ratios too sensitive
  - Bayesian
    - too insensitive,
    - lack transparency
    - signal leakage
    - signal masking

# Aims

- Develop a signal method based on ontology for drugs and reactions
- Use critical reaction terms to increase signal intensity
- Exploit ATC drug classification hierarchy
- Follow significant drug-reaction associations, by traversal of the ATC tree where reaction frequencies are significant based on Chi-Square ( $\chi^2$ ) test

## Reaction Ontology—SOC terms:

Classified into 18 reaction classes

## **Drug Ontology—ATC Embeded Code:**

X99XX99 (pattern)

Level 0 – A (Alimentary tract) 14

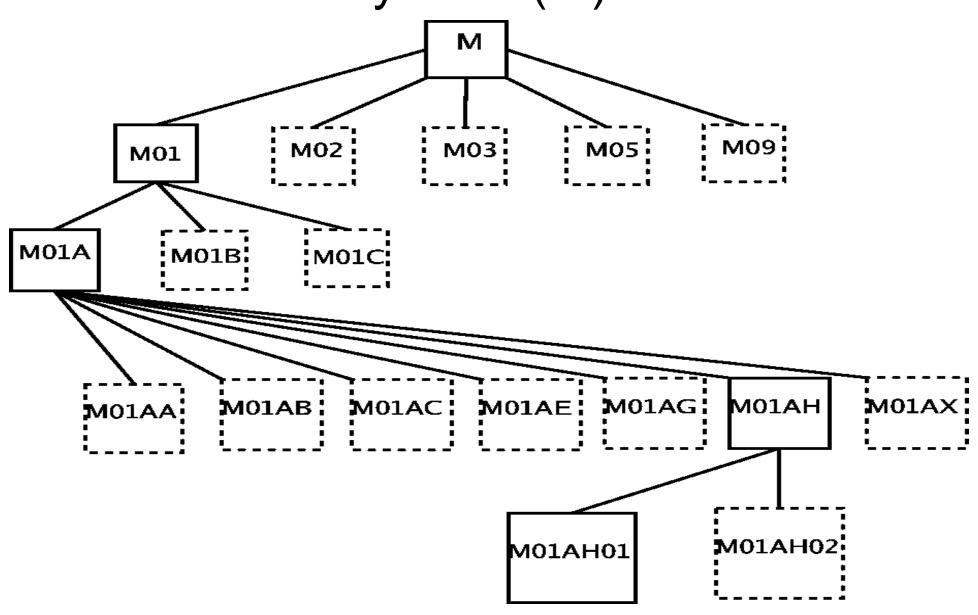
Level 1 – A01 92

Level 2 – A01A 227

Level 3 – A01AA 602

Level 4 – A01AA01 1809

# Tree Traversal for Musculo-skeletal system (M)



# Signal Method

- Step 1: Select drug and reaction class of interest
  - E.g., Musculo-skeletal system (M) and cardiovascular (SOC 1000)
- **Step2**: Find set of children in drug tree; test to see if any children have significantly more reactions (based on Chi-Square ( $\chi^2$ )
- Step 3: continue Step 2 at next level down

# Signal Level

- **OK** ≤ 15% critical terms
- Notice 15 30%
- Strong notice 30 40%
- Warning 40 50%
- Strong warning 50 60%
- Alert > 60%

# Results:

Our algorithm produced a total of 62 warnings: 42 **OK**, 9 **NO**, 4 **WA**, 3 **SW**, 4 **AL** 

The results of MGPS were ordered by **EBGM** with the highest value of 37.585

### **Definition of MGPS values:**

**EBGM**—Empirical Bayesian Geometric Mean. A more stable estimate than RR; the shrinkage estimate, computed as the geometric mean of the posterior distribution of the true RR

RR—Relative Ratio. (The same as N/E.) Observed number of cases with the combination divided by the expected number of cases with the combination

N—Observed number of cases with the combination of items

**E**—The expected number of cases with the combination

Table 1: Alert Warning Level

N	E	RR	EBGM	ATCcode	SOC	Drug_name	No_Sig*
29	32.875	0.882	0.886	A01AB03	Nervous	Chlorhexidine	26
401	103.919	3.859	3.842	B01AB01	Haemic&lymph	Heparin	220
229	124.574	1.838	1.794	C02AB01	Haemic&lymph	Methyldopa	177
27	4.301	6.278	5.644	G02BA01	Foetal	Plastic IUD	26

<sup>\*</sup> Number of signals with our algorithm for ATC/SOC pairs

Table 2: Strong Warning Level

N	Ε	RR	EBGM	ATCcode	SOC	Drug_name	No Sig
-1007			<0.00G	MO4 A □O4	Haamia O lumnh	Colonovih	105
<2887	70.470	4.600	≤0.026	M01AH01	Haemic&lymph	Celecoxib	105
123	76.476	1.608	1.546	N05AH02	Cardiovascular	Clozapine	236
150,000	11200 Cardan (100A)		4584453444		NW 95 DO 004	Meglumine	
322	113.291	2.842	2.829	V08AA20	Respiratory	diatrizoate	188

Table 3: Warning Level

N	E	RR	EBGM	ATCcode	SOC	Drug_name	No Sig
		(5)				Comb. Specific	
236	210.479	1.121	1.113	J06BB30	Nervous	immunoglobulins	690
537	113.134	4.747	4.727	J01CF05	Liver	Flucloxacillin	267
7		81 (8)		3			
<2887			≤0.026	M01AH01	Cardiovascular	Celecoxib	282
264	35.842	7.366	7.265	N05AH02	Haemic&lymph	Clozapine	587

# Conclusion

- There is no correspondence between the signal levels we defined and the values produced by MGPS
- Our AES method is quite simplistic in its present form
- Problem could be in the SOC reaction system does not have enough levels of granularity for both AES methods
- Next plan is to make more use of association rules and the use of medical ontology, e.g., employ the MedDRA for reaction ontology, make use of a medical ontology

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#### References:

- Alecu, C. Bousquet, F. Mougin, and M. C. Jaulent, 'Mapping of the who-art terminology on snomed ct to improve grouping of related adverse drug reactions', *Studies in Health Technology Information* 124 (2006), 833–838
- Manfred Hauben and Xiaofeng Zhou, 'Quantitative methods in pharmacovigilance: focus on signal detection', *Drug Safety* 26 (2003), no. 3, 159–186
- Gary Saunders, Sasa Ivkovic, Ranadhir Ghosh, and John Yearwood, 'Applying anatomical therapeutic chemical (ATC) and critical term ontologies to Australian drug safety data for association rules and adverse event signalling', *Proceedings of the Australasian Ontology Workshop* (AOW 2005) (Sydney, Australia) (Thomas Meyer and Mehmet A. Orgun, eds.), Advances in Ontologies, vol. 58, The 18th Australian Joint Conference on Arti<sup>-</sup> cial Intelligence, Australian Computer Society, December 2005, pp. 93–98