



Graphical association analysis for identifying variation in provider claims for joint replacement surgery

James Kemp

PhD Candidate *LINSW*



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Problem description

- Fraud and waste are costly for healthcare insurance schemes such as the Medicare Benefits Schedule (MBS)
- Detection rates for fraud in Australian public health are under international benchmarks
- Automated detection is becoming common-place, but more research is required





Decision support requirements

- Unsupervised learning
- Address more than one problem
- Interpretable results
- Claim context discovery
- Recoverable cost estimates







Data

- 10% sample of patients in the MBS, 2010-2014
- MBS provides reimbursement for medical and hospital services
- Extracted subsets for hip, knee, and shoulder replacement procedures
- Created a reference model of typical service claims in each procedure









Episodes of care

- Transaction set of "episodes" created for each procedure
- An episode is composed of all items a provider claimed for a single patient on one day
- Association analysis used to find item relationships

Patient ID	Provider ID	Item Code	Item Summary	Date
2	3	49518	Knee replacement	01-Aug
2	3	105	Professional attendance	01-Aug
2	2	17610	Anaesthetic consultation	01-Aug
2	2	21402	Anaesthetic initiation	01-Aug
2	4	51303	Surgical assistant	01-Aug



Association analysis

- Also known as market basket analysis
- Finds associations between items in transactions (baskets)
- Association rules are based on co-occurrence









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Interest measures

- Large number of possible associations
- What does 'interesting' mean for this study?
 - Occurs frequently
 - Not by chance
 - Incorporate directionality/asymmetry
- Two interest measures were chosen
 - Support
 - Conviction



Reference models

- Association analysis applied to each procedure subset
- Digraphs constructed for each procedure from association rules
- Graph components represent roles in the procedure





Provider models

- Digraphs constructed per-provider in each procedure subset
- Provider model compared to most similar role in the reference model
- Providers ranked by cost of extra items



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Validation

- Sensitivity analysis
- Comparison to ranking by a currently-used metric (mean benefit of non-procedure items, or MBNPI)
- Medical advisor opinion on top ten providers from each procedure







Results

- Typical excess items added costs of up to 192% for outlying providers, compared to reference model items
- Comparison with MBNPI showed that GAA reduced effects of atypical costly procedures, but was less effective where individual providers had wide variation in their claims
- All high-ranking providers were co-claiming items in unusual patterns compared with their peers



Limitations

- Validation limited by available resources
- Small sample meant incomplete provider data
- Ranking method does not account for number of services provided





Discussion

- Interpretable models are useful for identifying typical behaviours
- GAA useful for identifying providers, and patterns, for follow-up
- Future work could incorporate additional features









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