Using Unsupervised Learning for **Data-Driven Procurement Demand Aggregation**



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background what is procurement?

PROCUREMENT

- **Acquisition** of variety of goods or services from an outside external sources
- Form: orders, • transactions, tenders, quotations
- **Data:** dates, values, quantities, requesters, vendors ...







background A*STAR Procurement Office - the client (1)

A*STAR

- Large governmental agency in Singapore (>5k employees)
- Dealing with research in multiple areas, divided into Research Institutes
- 10k-magnitude volume of purchases monthly / 100k yearly

A*STAR Procurement Office

- Oversight of procurement of all Research Institutes
- Optimise purchasing processes
- Detect lapses, inconsistencies, potential fraud

background A*STAR Procurement Office - the client (2)

A*PO - I2R collaboration on Procurement Analytics



Procurement **Fraud Detection**

Westerski et al. 2017

Procurement **Demand Forecasting**



Westerski et al. 2015

2014 - onwards

- TechnologiesDeployed systemsPatents
- Research publications

IPASS

Comprehensive Procurement Analytics

Procurement **Demand Aggregation**









background demand aggregation - the problem

How does Demand Aggregation work in an organization?





multiple vendors delivering goods for an organization



same products delivered at different prices



UNDERSTAND THE PROCESS

- Collate and combine requirements of multiple buys
- Contract suppliers based on combined demand
- Standardise and establish best-buy strategy

KNOW THE PROBLEM

- Fractured purchasing process done individually by departments and units results in similar buys for different prices from multiple suppliers
- **Big amount** of data makes it difficult to understand best options for cost savings
- Complex network of suppliers, items they provide, prices and demand over time makes it difficult to solve this multi-variate problem with standard approaches





multiple different items but belonging to similar goods category (e.g. cleaning articles)

• frame demand aggregation problem as bi-clique clustering problem

- Map purchase orders into a bipartite graph - items vs. vendors
- Bi-clique every vendor connected to every item
- Find max bi-cliques = biggest potential Demand Aggregation (DA) patterns

solution bi-clique clustering



Sample procurement bipartite graph (blue coloured edges denote 3x4 bi-clique)

solution BSC algorithm

• Practical problem

- Finding maximum edge bi-clique is an NP-complete problem
- Multiple publications with different algorithmic approaches
 - iMBEA [Zhang et al., 2014]
 - LCM-MBC [Li et al., 2007]
- On small dataset not a big issue but for our "medium" sized data -> infeasible
- Our approach: Monte Carlo algorithm (polynomial): doesn't give full list but optimal solution is good enough

Optimality proof \rightarrow Shaham et al. 2016



Subspace Bi-clique Clustering for Procurement (SBCP) - procurement domain specific adjustments

(1) **Practical BSC algorithm modifications**

• Different bi-clique expansion strategy to give more "interesting" maximal bi-cliques (ie. more even amount of vendors vs items)

• (2) Post-processing filters

- Value constraints check purchasing patterns with significant value only
- Volume constraints remove patterns with few purchase orders
- Purchasing trend constraints look for purchases that have potential to keep demand over years

Solution SBCP algorithm

of relationships



evaluation setup

• Running SBCP algorithm over the A*PO procurement database

- [**1,032,275** POs]
- A*PO officers to assess quality of detected aggregation patterns:
 - In comparison to past bulk tenders
 - Assessment for creating new bulk tenders
- 3 rounds of evaluation (earlier mentioned SBCP improvements in between)

• Input: Using 3 most recent years (2014 - 2016); 271,219 items x 7319 vendors

• **Output:** Demand Aggregation patterns along with associated Purchase Orders

evaluation results

• Overall quality of DA patterns

new valid DAs proifessional assessment = all new mined DAs

matching existing $DAs = \frac{detected \ past \ DAs}{total \ past \ DAs}$

• Assessment of POs inside patterns

$$precision = \frac{valid POs}{all mined POs}$$

valid POs recall = relevant POs



Progress of Evaluation Results

Total Score



deployment setup in production

- Integration with A*PO workflow
 - SBCP executed periodically as decisionsupport system for annual reports to management
 - Suggest new tenders
 - Update old tenders with new items/vendor
- Input/output
 - Taking a dump of procurement database
 - Analytics dashboard over the DA pattern list output



Demand Aggregation

Cases Detected	490
TOTAL VALUE	940,948,509 SGD
	30%
Vendors Involved	1002
BIGGEST CLUSTER	98M
- #PO	11999
Filters	+
Start Date	01/01/2010
	01/01/2014
	01/01/2011
MIN #PO	20
Min PO Freq	50/year
MINI VALLE	50.000
	30,000
Vendor Clustering	OFF
Engine setting	5
Start Date	01/01/2010
End Date	01/01/2014
MIN VALUE / YEAR (SGE	D) 300K
	0) 100-
THIN VOLOME / TEAR (#1	0)

DEMAND **C**LUSTERS CRITEERIA: VALUE | VOLUME | SAVINGS



CATEGORY DETAILS (SLICES | ALL)



DEMAND SLICE:

#Vendor:	2
#Items:	0
Value:	Ι2κ
Volume:	50
Savings:	5κ

BIO LABORATORIES PTE LTD
AIK MOH PAINTS & CHEMICALS
ELEMENT 14 PTE LTD
AXIL SCIENTIFIC PTE LTD
BIOMED DIAGNOSTICS PTE LTD
Genscript (Hong Kong) Limited
CRYOEXPRESS SINGAPORE PTE LTD

ITEM LIST

BIO LABORATORIE AIK MOH PAINTS ELEMENT 14 PTE **AXIL SCIENTIFIC** BIOMED DIAGNO **GENSCRIPT** (HO

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conclusions lessons learned

- Complete list of maximal bi-cliques not necessary (and unwanted)
 - Too many aggregation patterns counterproductive for end users
 - Mine and prioritise "useful" patterns (as per business requirements)
- Data Science metrics vs. Business metics
 - People who don't deal with computer science rarely understand what is "precision" / "recall" • Listen to end user what they want and assess quality from their perspective (and stick to established)
 - metrics behind the scenes only)
 - "Interesting", "non-obvious" patterns vs. "good quality"

• Clients often doesn't know what they want (multiple times during the project)

- Redefining meaning of valid demand aggregation patterns
- Be prepared to adjust the algorithm many times
- Early engagement with client helps
- Long way from reaching (1) metric goals to (2) deployment to (3) active use by client

future work

- Algorithm improvements
 - Finding Quasi bi-cliques (ie. not every vendor selling every item, allow some freedom)
 - Assessment of DA (maximal bi-clique) quality
- Going outside A*STAR and commercialising the technology
 - Method and Apparatus for Procurement Demand Aggregation. Patent [Shaham et al. 2019]
 - Startup to bring our DA technology to the market Semantist

