Prediction of Enterprise Purchases using Markov models in Procurement Analytics Applications

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SEMANTIC COMPUTING LAB

Procurement? Problems? Analytics?

Procurement

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

environment

Challenges

- **Optimise costs** by improving efficiency of purchase management (e.g. aggregating purchases)
- **Improve on supplier service** to obtain better quality goods/ services.
- **Detect employees** of organisation who try to exploit the system to their own benefit
- **Detect suppliers** which try to benefit at the cost of the organisation

behaviour

Analytics

- **Inspect** the data (orders, personnel data, external organisations)
- **Detect purchasing trends** and opportunities to improve efficiency of procurement process
- **Find** anomalies and transactions that stand out from the rest
- **Highlight** suspicious activity

goal

Procurement Systems in Practice

[Introduction: what has been done so far?]

- **Procurement Management and Information Gathering**
  - procurement management systems | put/approve orders, manage suppliers

    SAP, Oracle, dedicated platforms
- **Data Analytics**
  - procurement management systems + common office tools

    MS Excel etc.
  - Business Intelligence tools

    Tableau, Qlikview
- **Fraud Detection**
  - commercial fraud detection frameworks

    SAS Fraud Framework, Oracle Advanced Analytics
  - fraud detection research

    Credit card fraud, insurance fraud, telecommunication fraud

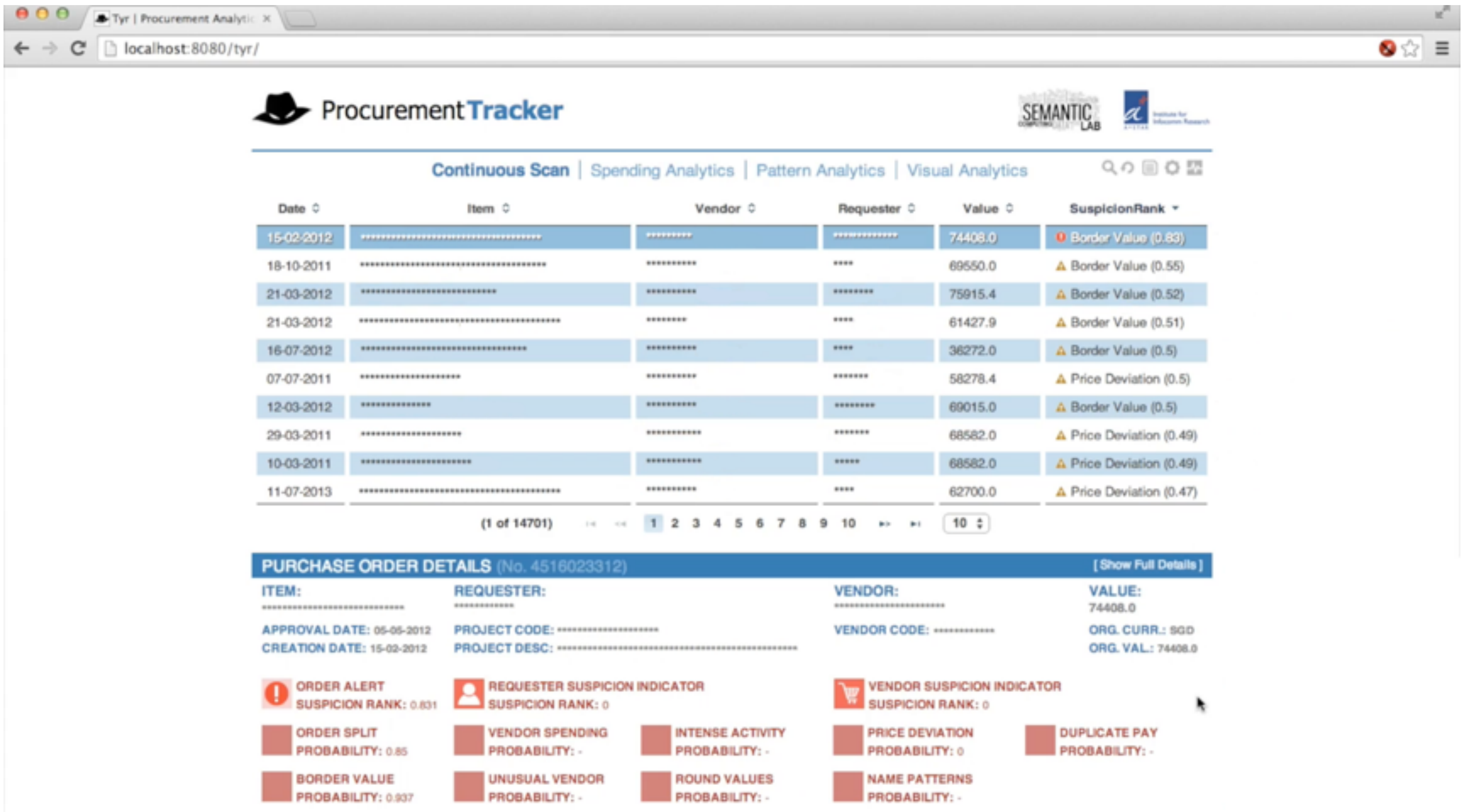
Procurement System Problems

[Introduction: Common Problems of Procurement Support Systems]

- Information overflow | lots of data gathered over long time
- Noisy data | manual input, many different users, sometimes different systems
- No all information is recorded | e.g. little or no record of past fraud (frauds are rare but when happen cost a lot)

Context

[Approach: A*STAR Procurement Analytics System]



Research Context: Procurement Analytics System built in a number of applied research projects.

Proposed Solution

[Approach: Future purchase prediction]

Research Problem: predict future procurement orders

Applications: optimise purchase aggregation, fraud detection

APPROACH

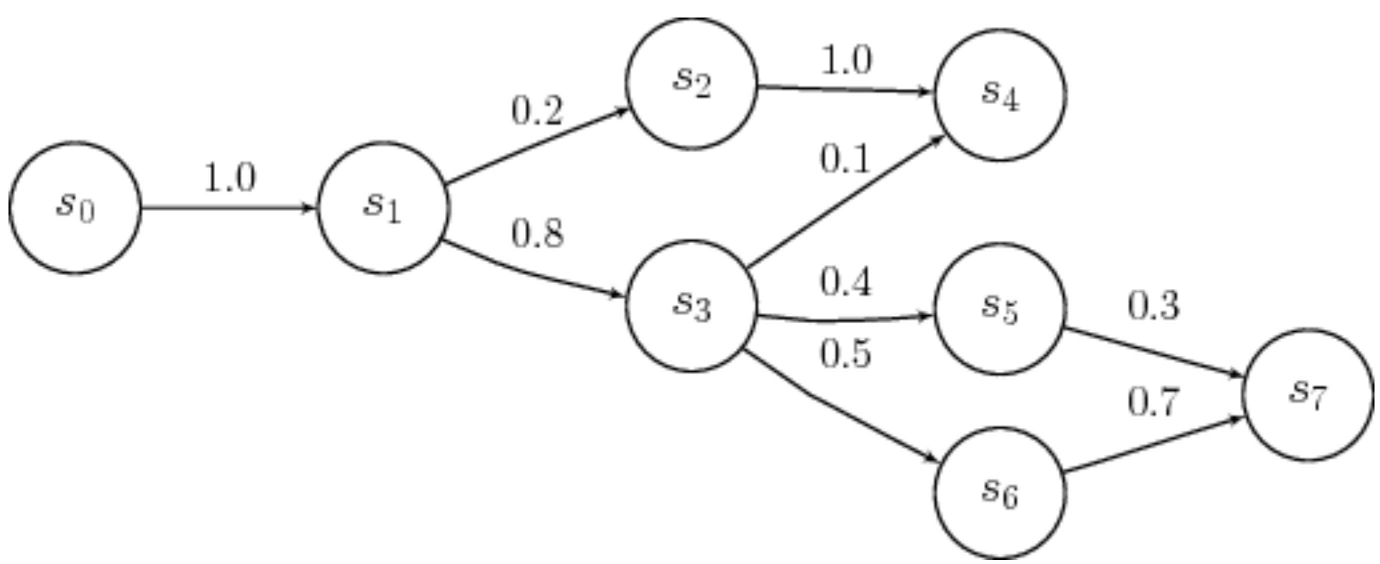
Approach: apply Markov Chains to model reoccurring purchase sequences in time and:

- predict single next item purchase
- predict multiple future item purchases

Markov Chains

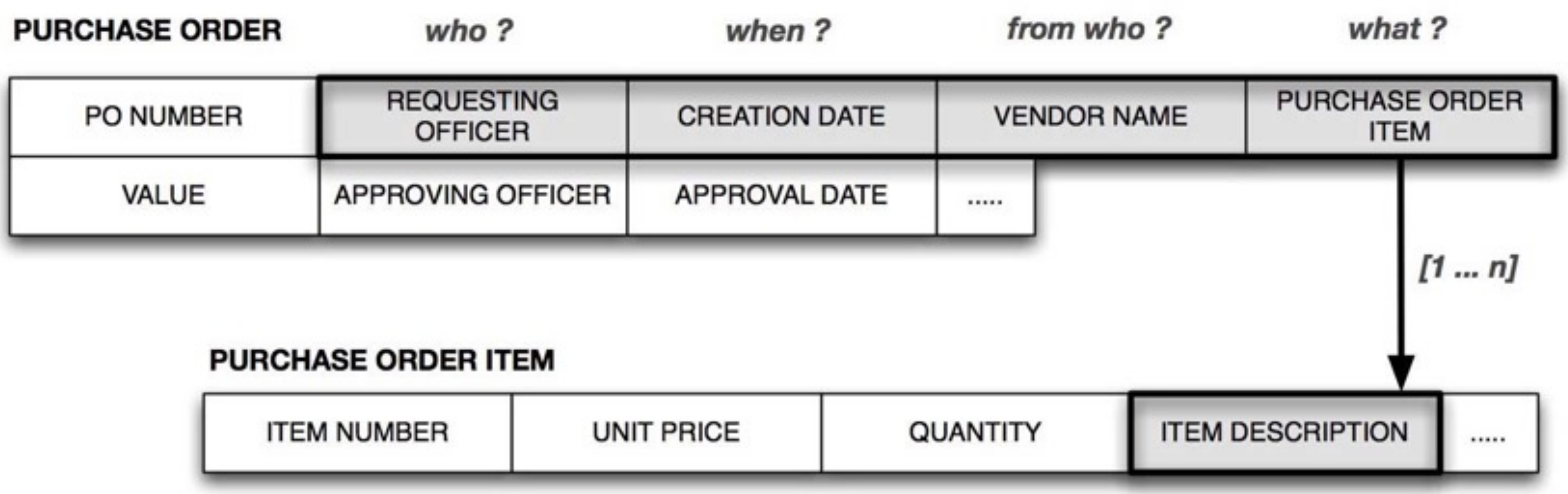
[Approach: Use of Markov Chains for time series modelling]

- Markov chains | many applications: physics, chemistry, finance…
  Hilgers 2006
- Markov Chains for Data Analytics | purchase prediction, web traffic analysis
  Bozzetto 2005; Deshpande 2004; Bertsimas 2003
- Markov Chains in Fraud Detection | credit card fraud, anomaly detection
  Khan 2003



Procurement Data Model

[Approach: dataset description]



Two main concepts:

- purchase order | record of single purchase placed by a employee on a given date
- purchase order item | detailed list of items/services within a purchase

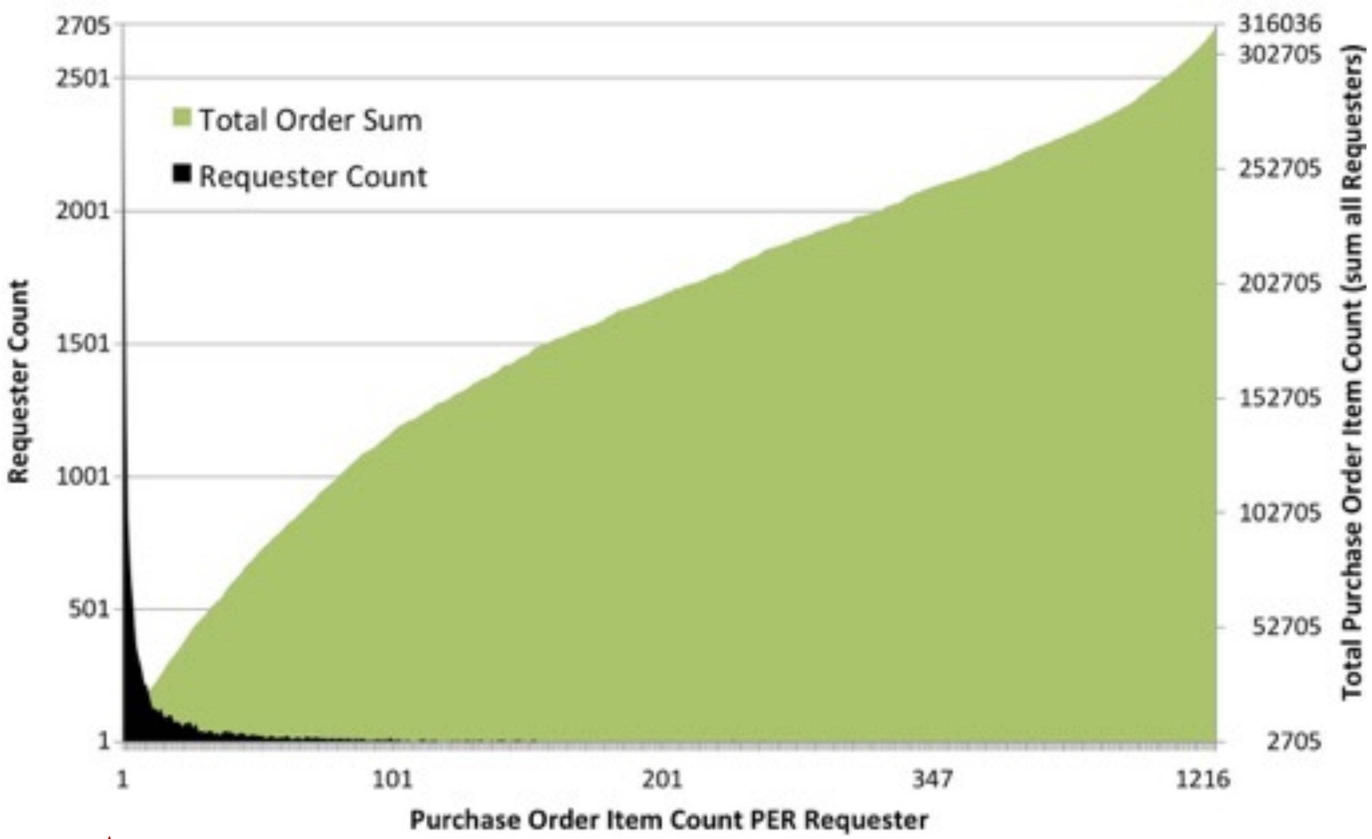
Dataset statistics

[Approach: dataset description]

Metric	Value		Metric	Value
# Purchase Order	141,286		MIN/AVG/MAX #Order PER Requester	1/ 12.7/ 1002
# Purchase Order Item	316,036		MIN/AVG/MAX #Vendor PER Requester	1/ 5.8/ 163
# Vendor	7,887		MIN/AVG/MAX #Item PER Requester	1/ 11.7/ 807
# Requester	11,312		MIN/AVG/MAX Creation Date Difference PER Requester	0/ 25.92/ 491
# Approval Officer	594			
# Item	212,652			

Dataset observations

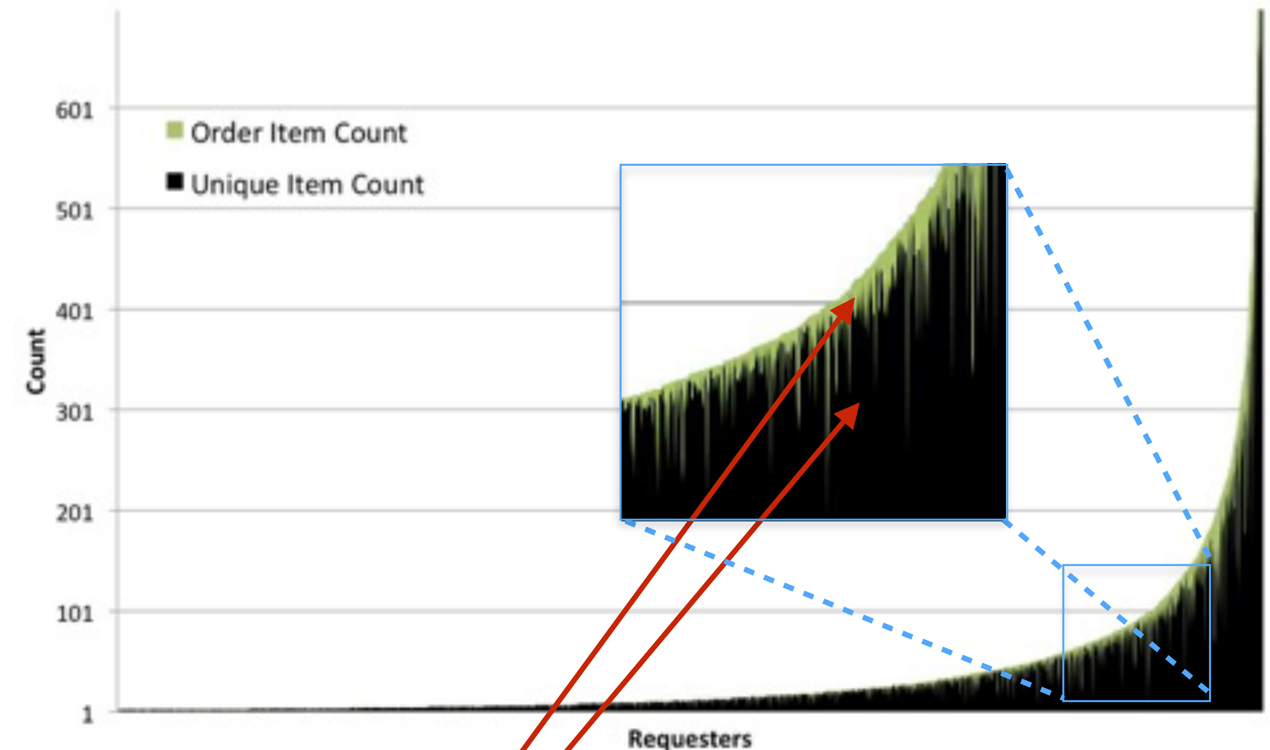
[Approach: dataset preparation and cleaning]



Majority of requesters have very few orders

...but a few actually make majority of orders

those will be of our main interest



Small difference between total purchases and unique item count

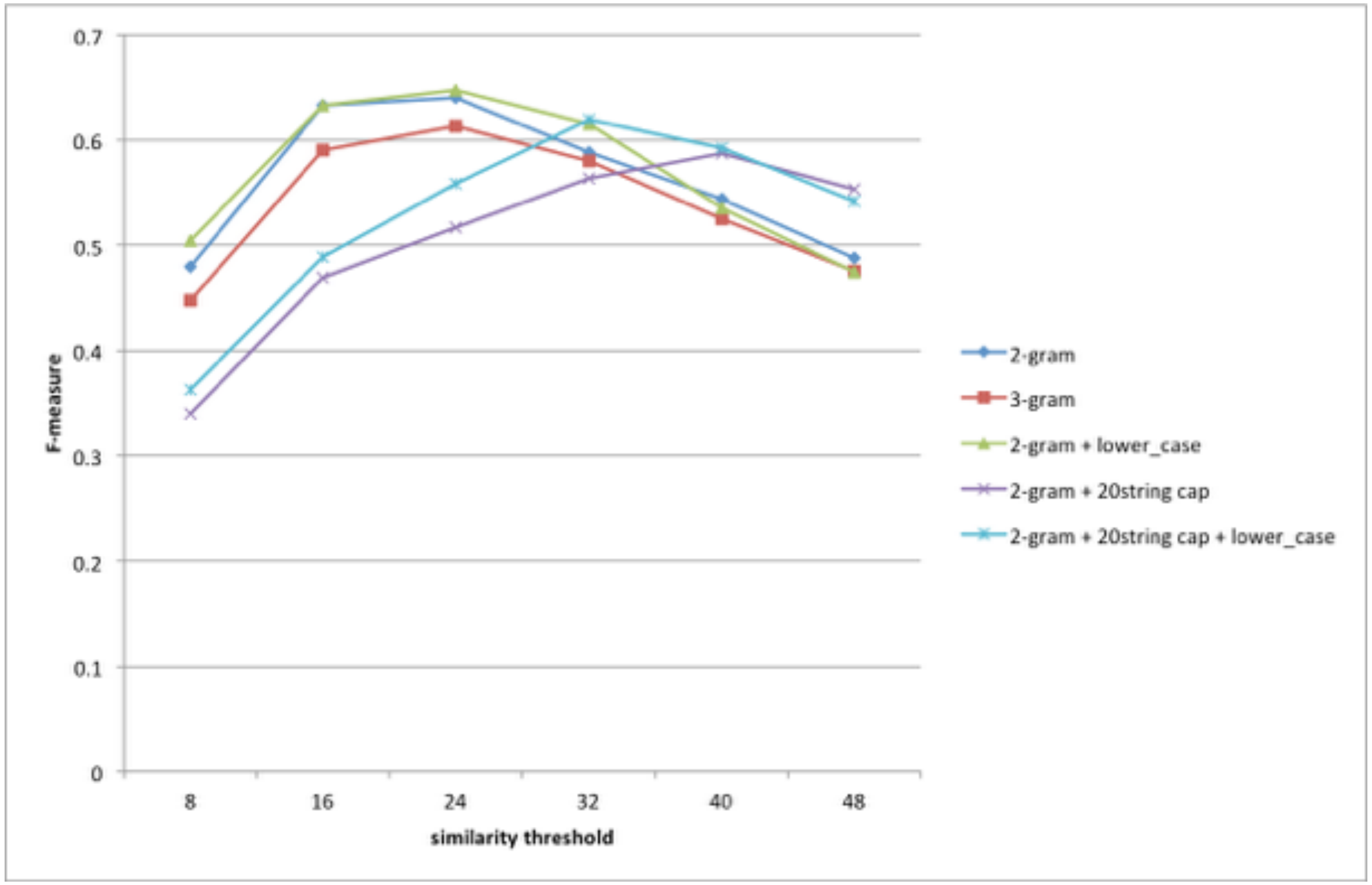
reason → manually typed item descriptions

outcome → little repeating patterns

solution → **use clustering to group similar purchases**

Clustering parameters

[Approach: dataset preparation and cleaning]



Hierarchical Clustering

- Similarity measure: q-gram distance
- Similarity threshold: number of non-matching q-grams
- Optional Criteria:
  - exclude short strings
- Evaluation setup:
  - 2000 manually annotated order items
  - 44 requesting officers

Best result → bi-gram + lower case + 24 q-gram similarity threshold

Prediction Algorithm Experiments

[Approach: purchase prediction]

Experiment setting:

- prediction of item description individually per requester
- given last purchase predict:
  - single next purchase
  - multiple next purchases

Algorithms:

- Random Sampling | pick on random from requester past items
- Probability Distribution | Cumulative Distribution Function (CDF)
- Simple Sequential Sampling | only multiple purchases experiment
- Markov Chain | first order Markov chain experiments

Experiments Results

[Approach: purchase prediction #2]

Setup	Ignored Requesters (% of all requesters)	AVG Precision/Recall for Requester (Requester Count / % of Dataset orders / precision / recall)		
		Precision >= 0	Precision > 0	Precision > 0.5
0.5 train+ Markov+ 20 order set	98.16%	212 / 15.04% / 0.34 / 0.09	96 / 5.70% / 0.74 / 0.19	67 / 1.61% / 0.97 / 0.26
0.5 train+ CDF+ 20 order set	35.58%	6438 / 97.50% / 0.04 / 0.03	1319 / 49.41% / 0.20 / 0.17	120 / 0.88% / 0.95 / 0.80
0.5 train+ Random Sampling+ 20 order set	35.58%	6438 / 97.50% / 0.04 / 0.03	1258 / 46.28% / 0.19 / 0.17	110 / 0.58% / 0.94 / 0.84
0.5 train+ Sequence Prediction+ 20 order set	35.58%	6438 / 97.50% / 0.04 / 0.04	1367 / 40.10% / 0.17 / 0.19	98 / 0.54% / 0.93 / 0.91
0.5 train+ Markov+ 20 order set+ clustering	**72.06%**	**2356 / 78.16% / 0.32 / 0.08**	**1235 / 52.47% / 0.61 / 0.15**	**600 / 12.88% / 0.96 / 0.24**
0.5 train+ CDF+ 20 order set + clustering	37.39%	6214 / 97.05% / 0.15 / 0.13	3134 / 83.76% / 0.29 / 0.25	382 / 2.59% / 0.91 / 0.75
0.5 train+ Random Sampling+ 20 order set + clustering	37.39%	6214 / 97.05% / 0.00 / 0.00	14 / 1.05% / 0.01 / 0.02	0 / 0.00% / 0.00 / 0.00
0.5 train+ Sequence Prediction+ 20 order set + clustering	37.39%	6214 / 97.05% / 0.00 / 0.00	6 / 0.31% / 0.02 / 0.03	0 / 0.00% / 0.00 / 0.00

no clustering

clustering

different requirement thresholds related to precision per requester

Best result → Markov + multiple purchase prediction (20 orders) + clustering

Conclusions

[Conclusions and Future work]

CONCLUSIONS

- only possible in organization with large procurement database
- single order prediction and use of raw data for predictions gave quite bad results
- only multiple order prediction in longer time frame (1 year) gave satisfactory results

FUTURE WORK

- prediction of vendors which repeat a lot more often item descriptions across purchases
- practical evaluation of prediction results (aggregation capabilities and cost saving implications)
- experiments with different datasets

Thanks for attention!

Questions?