



JOHANNES GUTENBERG
UNIVERSITÄT MAINZ

A Probabilistic Condensed Representation of Data for Stream Mining

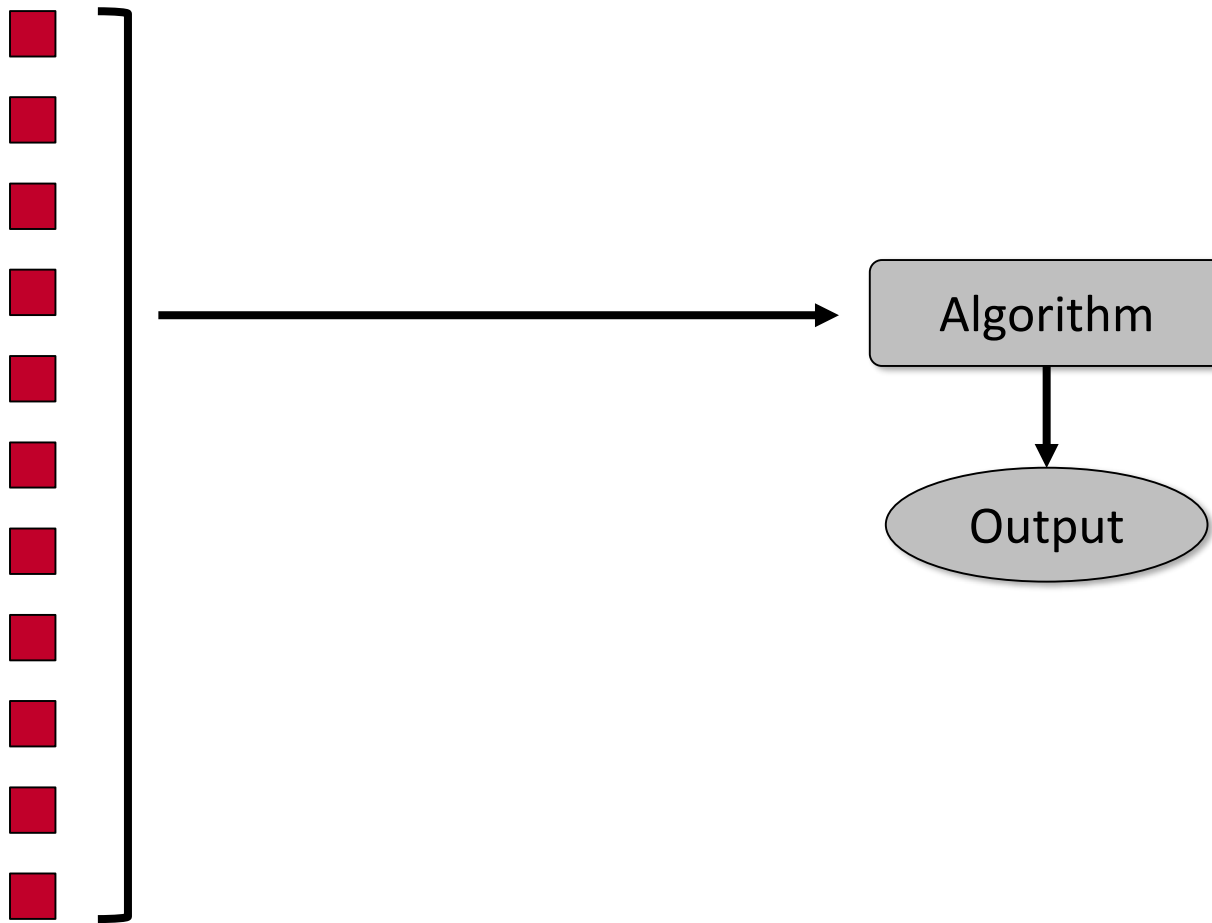
Michael Geilke, Andreas Karwath, and Stefan Kramer

Johannes Gutenberg-Universität Mainz, Germany

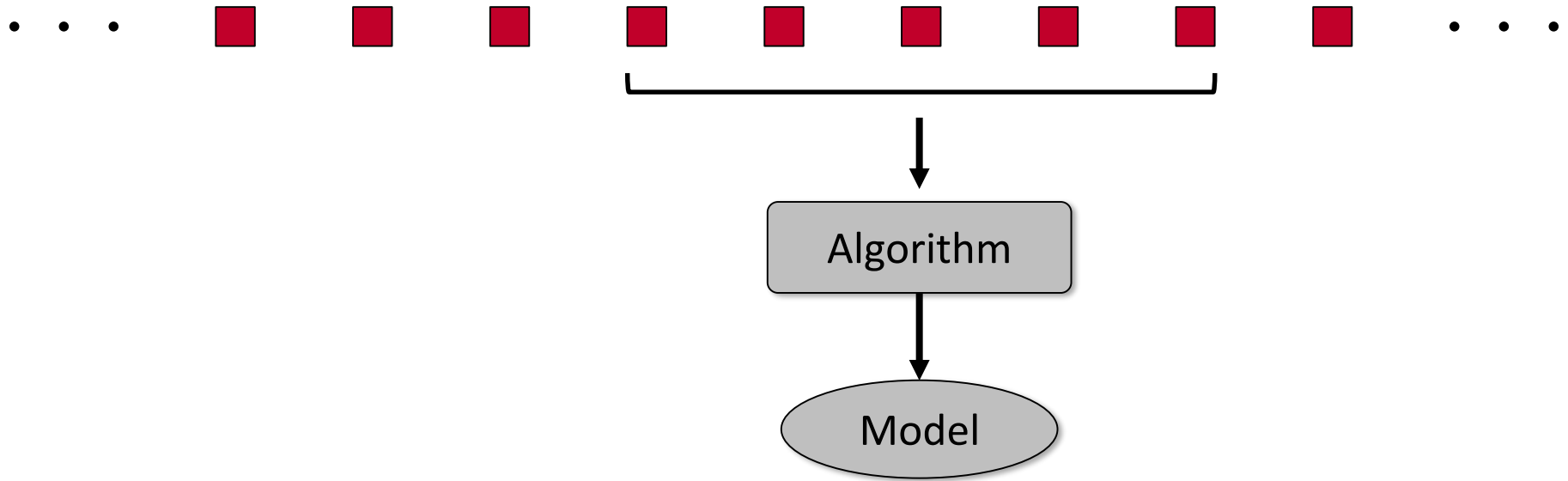
November 1, 2014



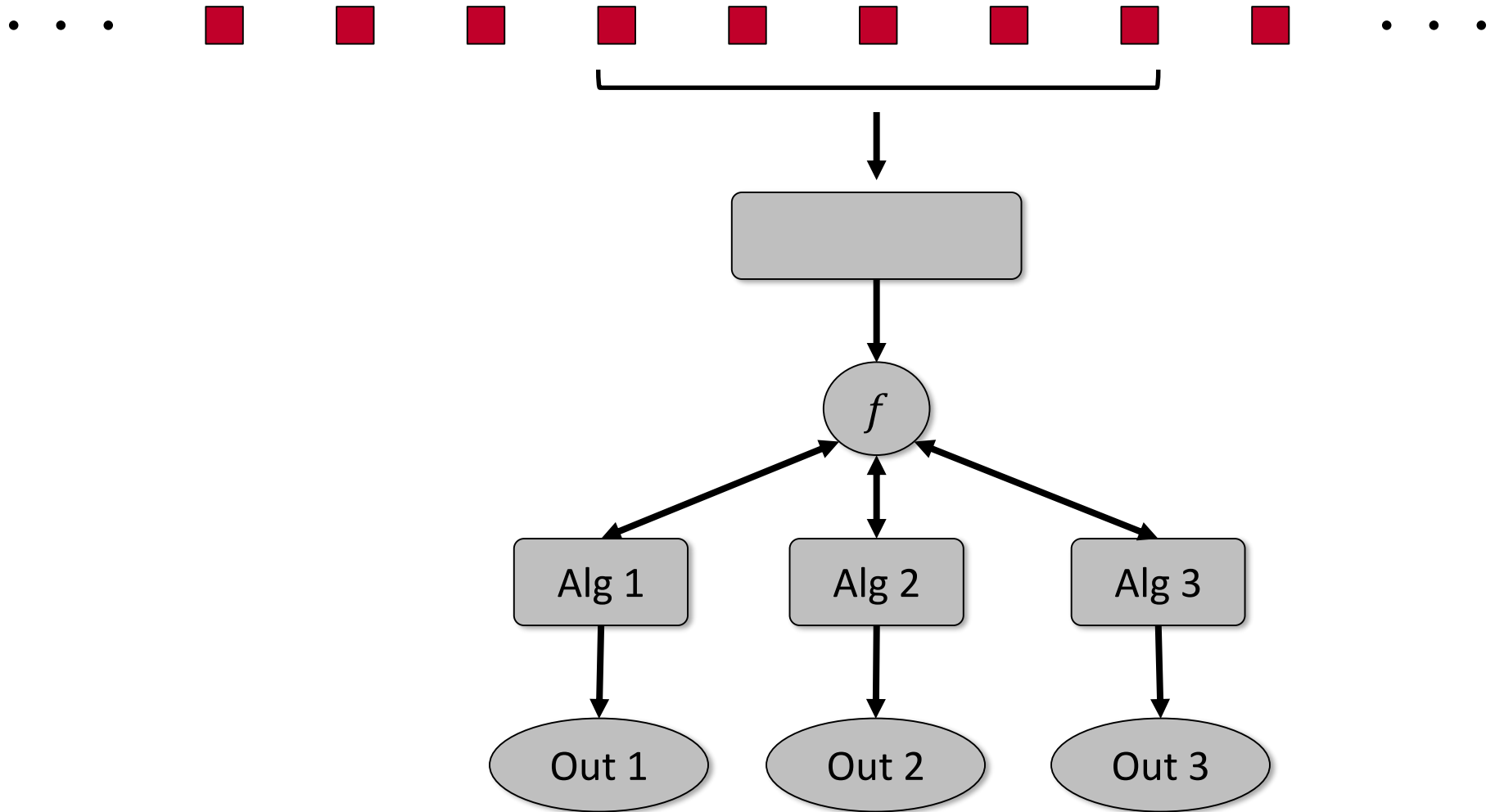
Batch Learning



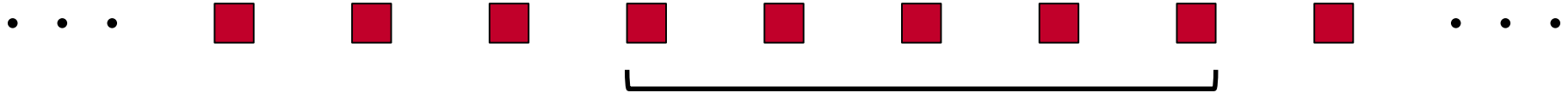
Streams



Condensed Representation

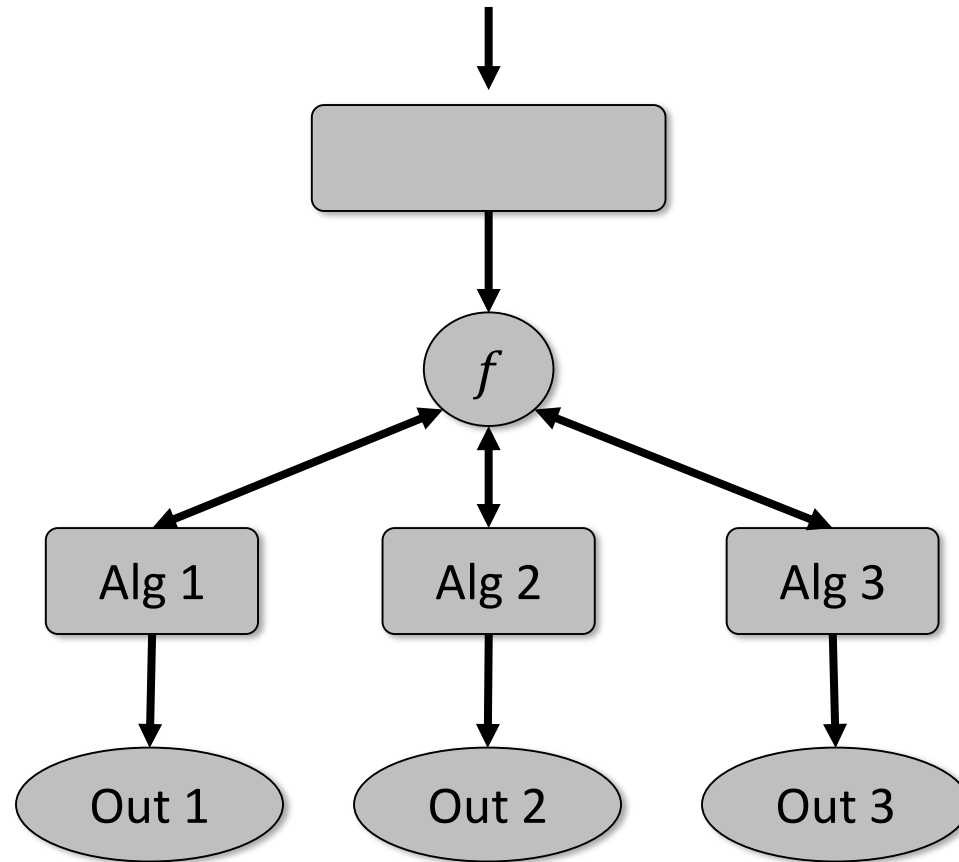


Benefits

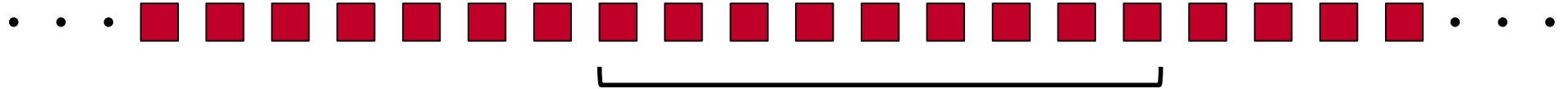


Benefits:

- volume
- speed
- unknown task
- privacy

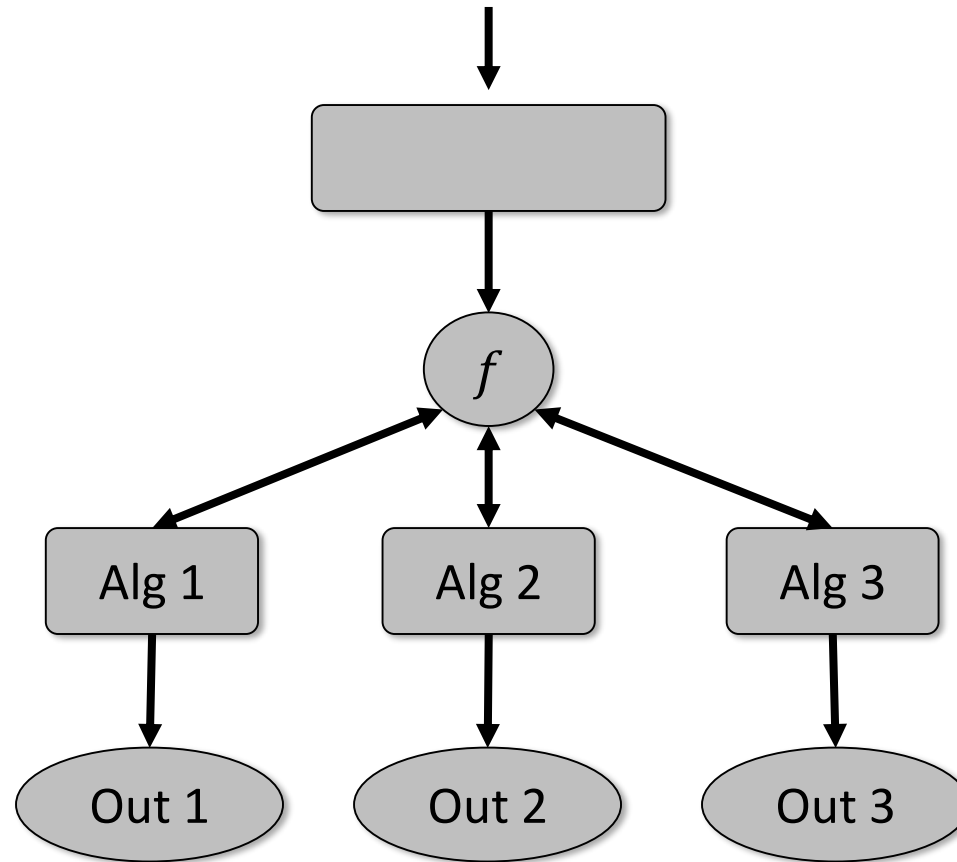


Benefits

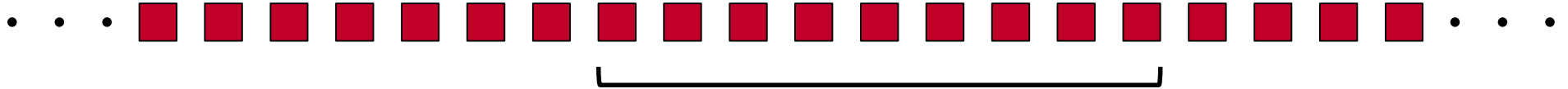


Benefits:

- volume
- **speed**
- unknown task
- privacy

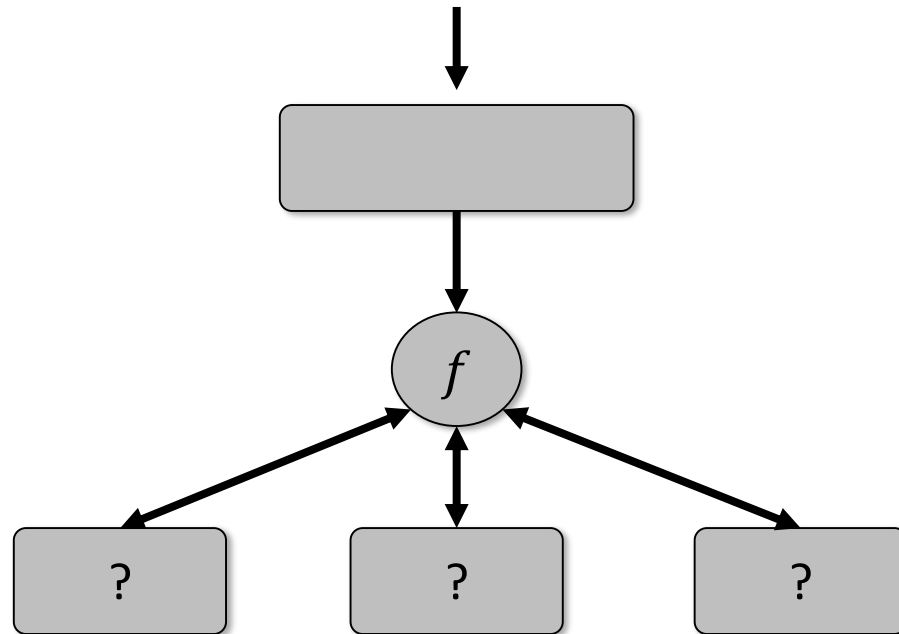


Benefits



Benefits:

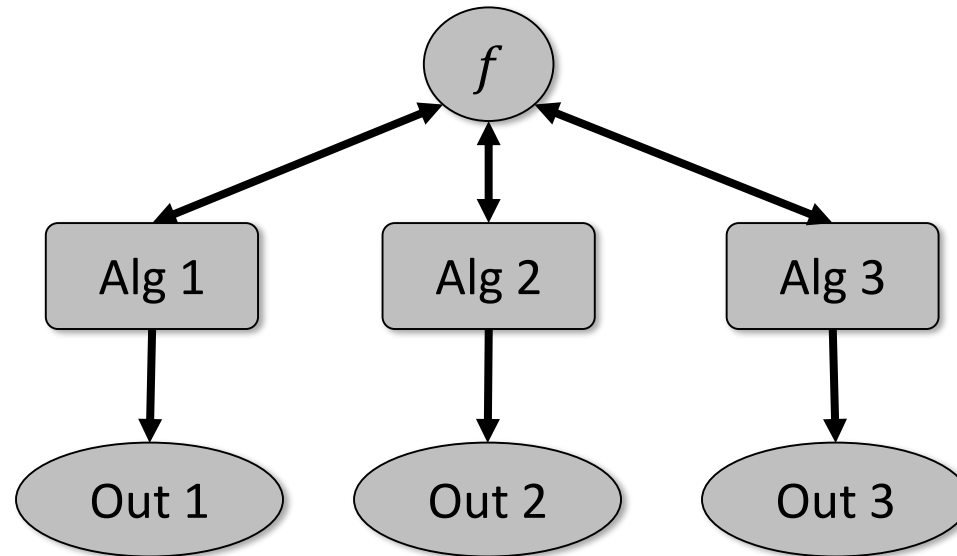
- volume
- speed
- **unkown task**
- privacy



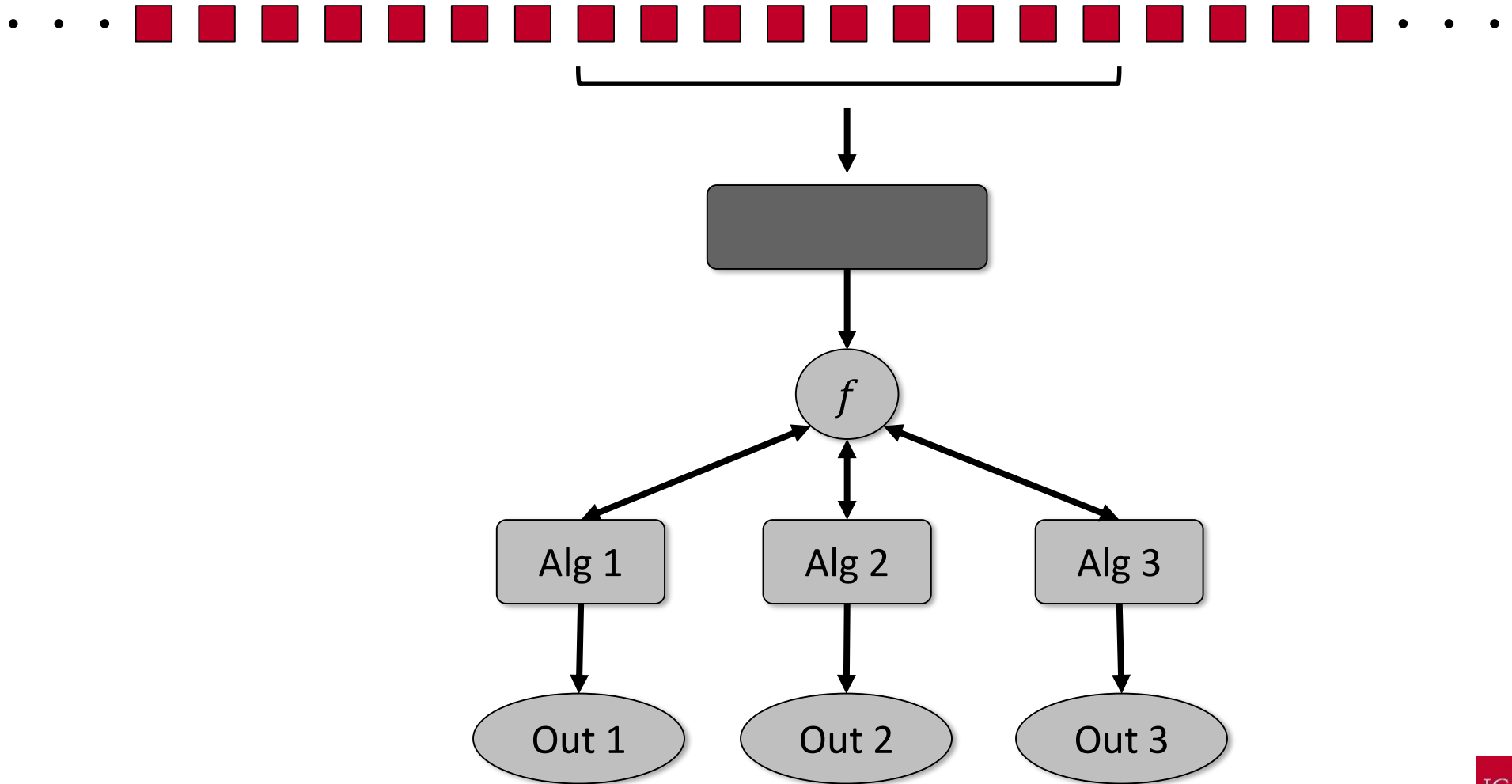
Benefits

Benefits:

- volume
- speed
- unknown task
- **privacy**



Condensed Representation



EDDO (Estimation of Discrete Densities Online)

Applying the product rule to $f(X_1, X_2, \dots, X_n)$ yields

$$f_1(X_1) \cdot f_2(X_2 \mid X_1) \cdot \dots \cdot f_n(X_n \mid X_1, X_2, \dots, X_{n-1})$$

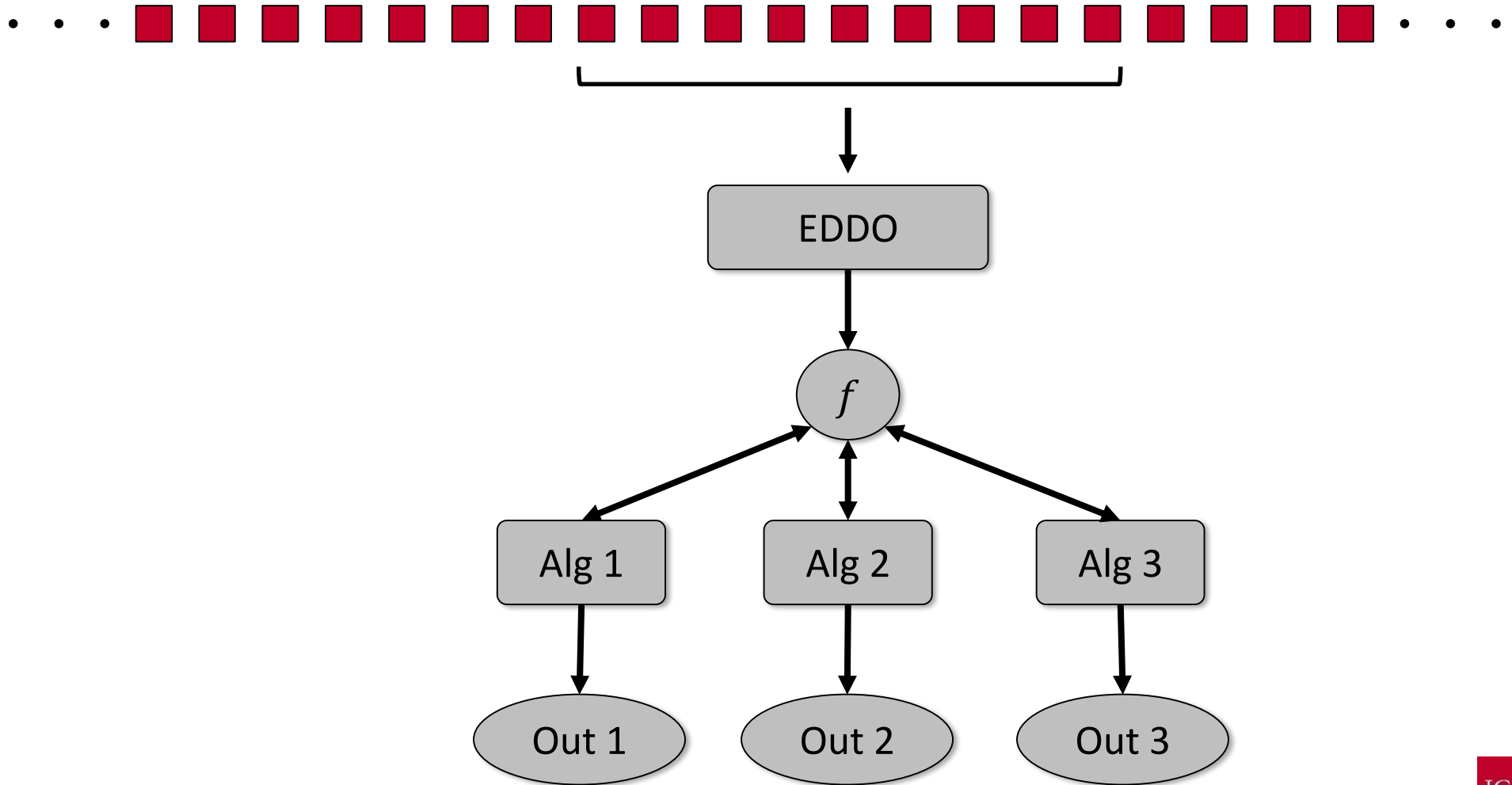
Classifier

Majority class for $f_1(X_1)$

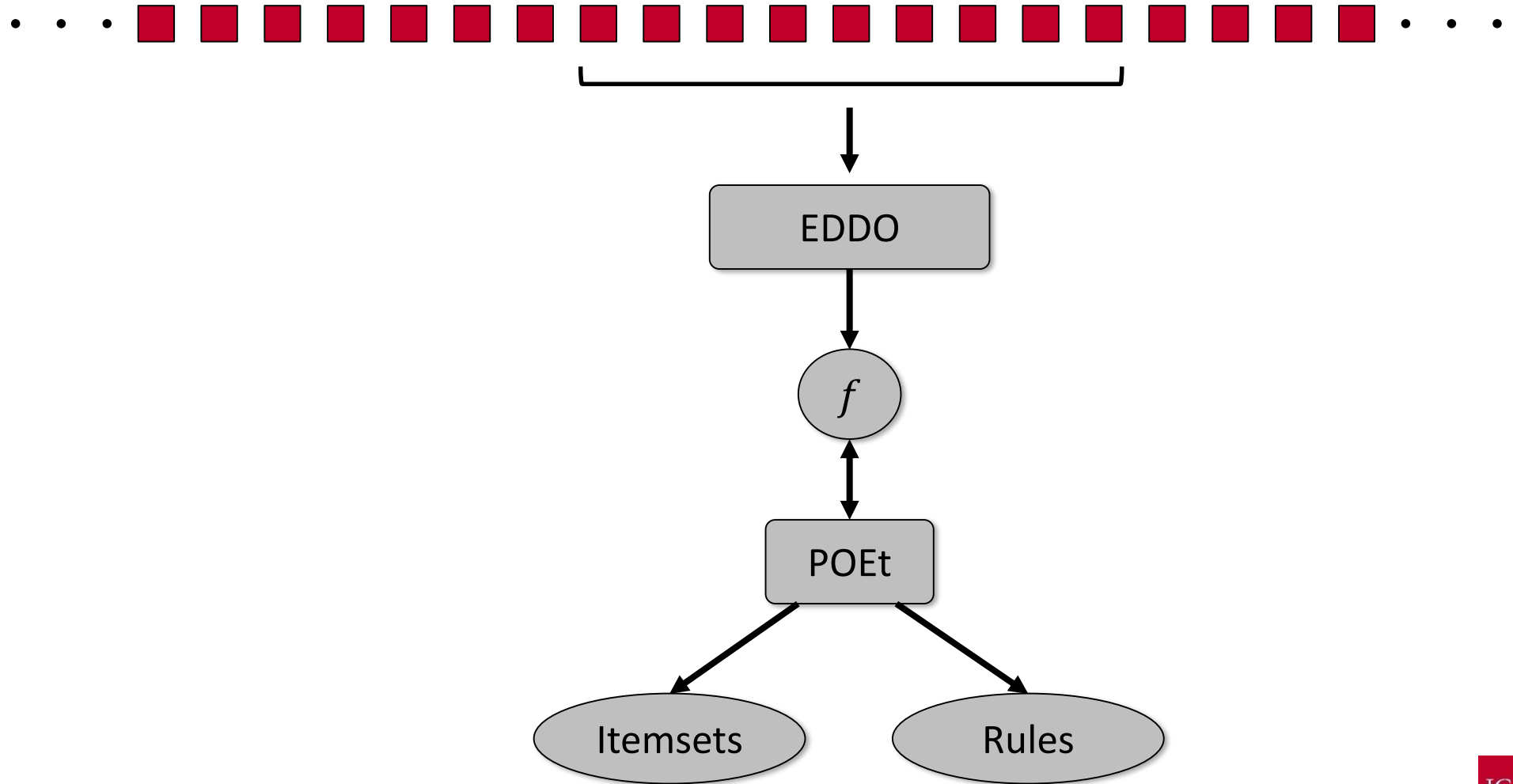
Hoeffding trees for $f_i(X_i \mid X_1, X_2, \dots, X_{i-1})$

Both enable the estimation in an online fashion.

MiDEO (Mining Density Estimates inferred Online)



Pattern Mining



Setting

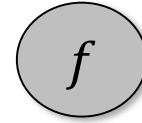
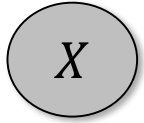
Itemsets $(X_4, v_3), (X_9, v_1), (X_1, v_5)$

Association rules $(X_4, v_3), (X_9, v_1) \Rightarrow (X_1, v_5)$

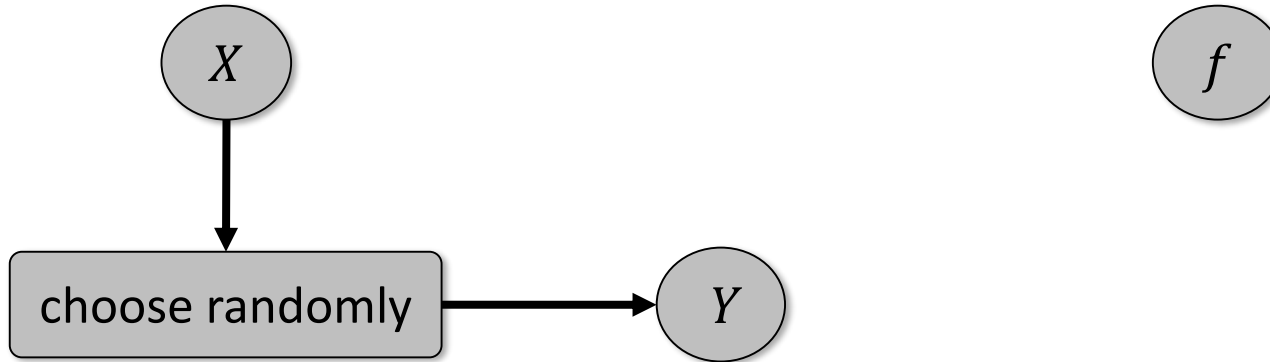
Measure of interestingness

- minimum support threshold
- confidence $f((X_1, v_5) | (X_4, v_3), (X_9, v_1))$

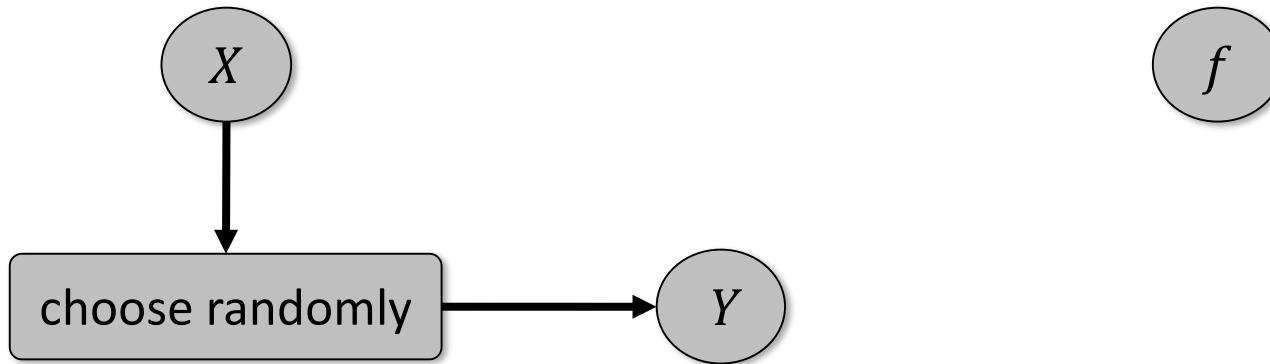
POEt – generating itemsets



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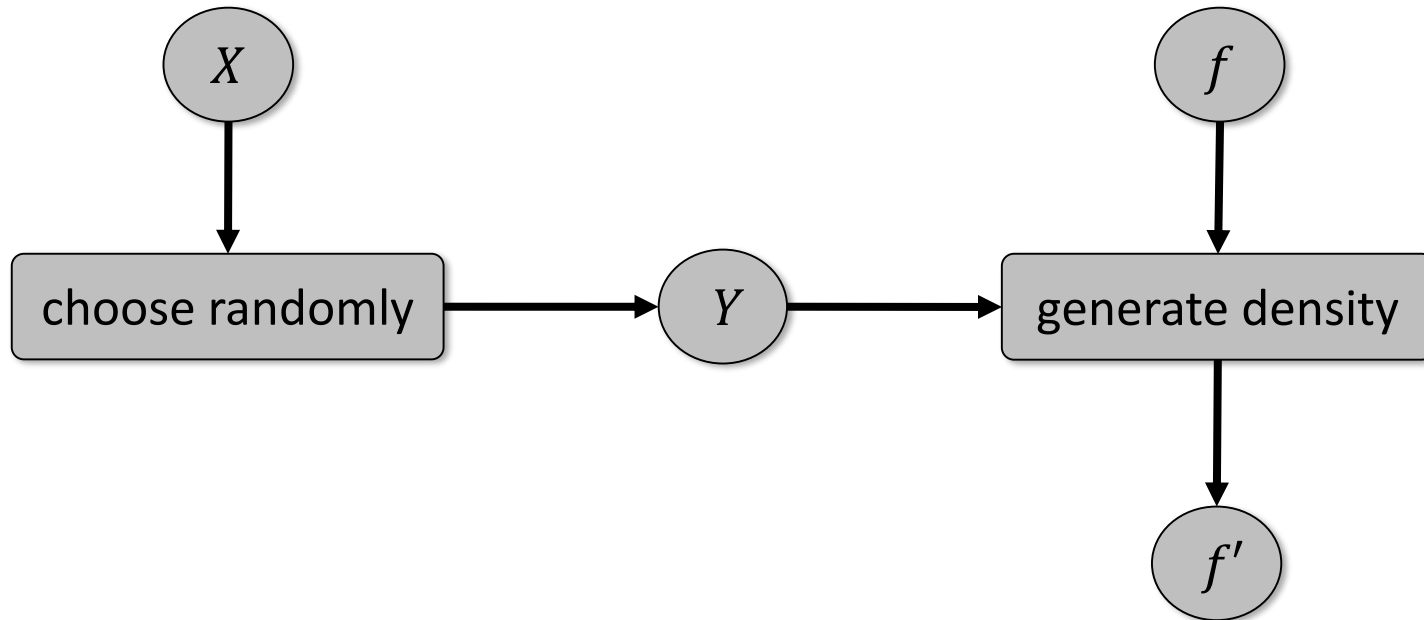


POEt – generating itemsets

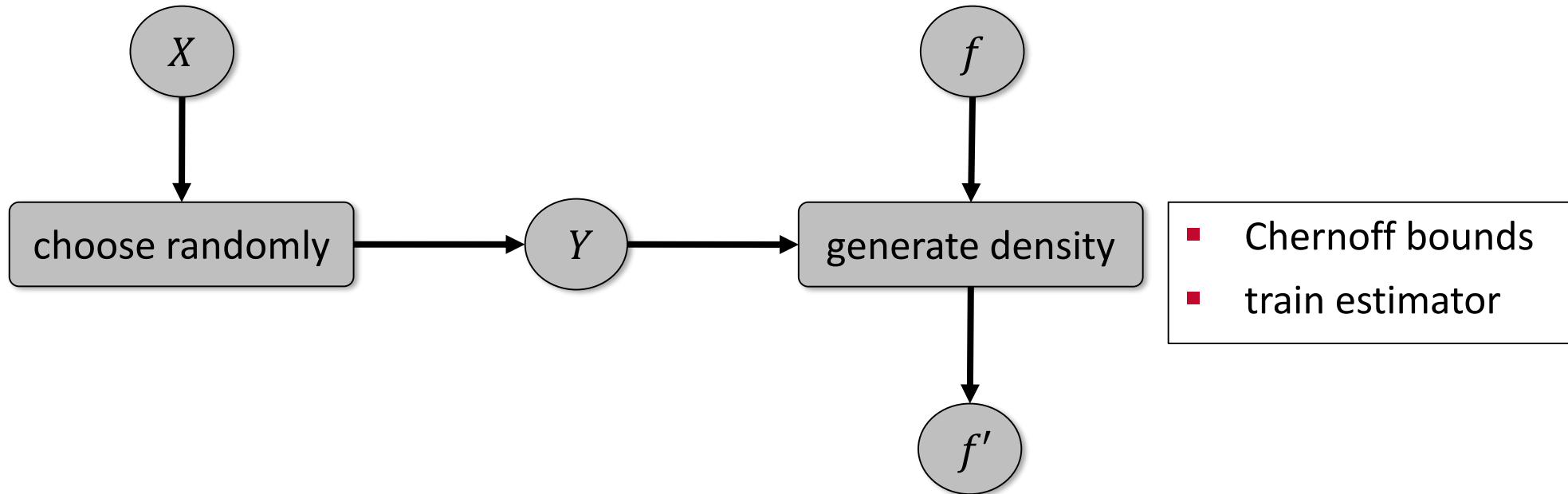


- Geometric distribution for size
- Uniformly at random for the elements

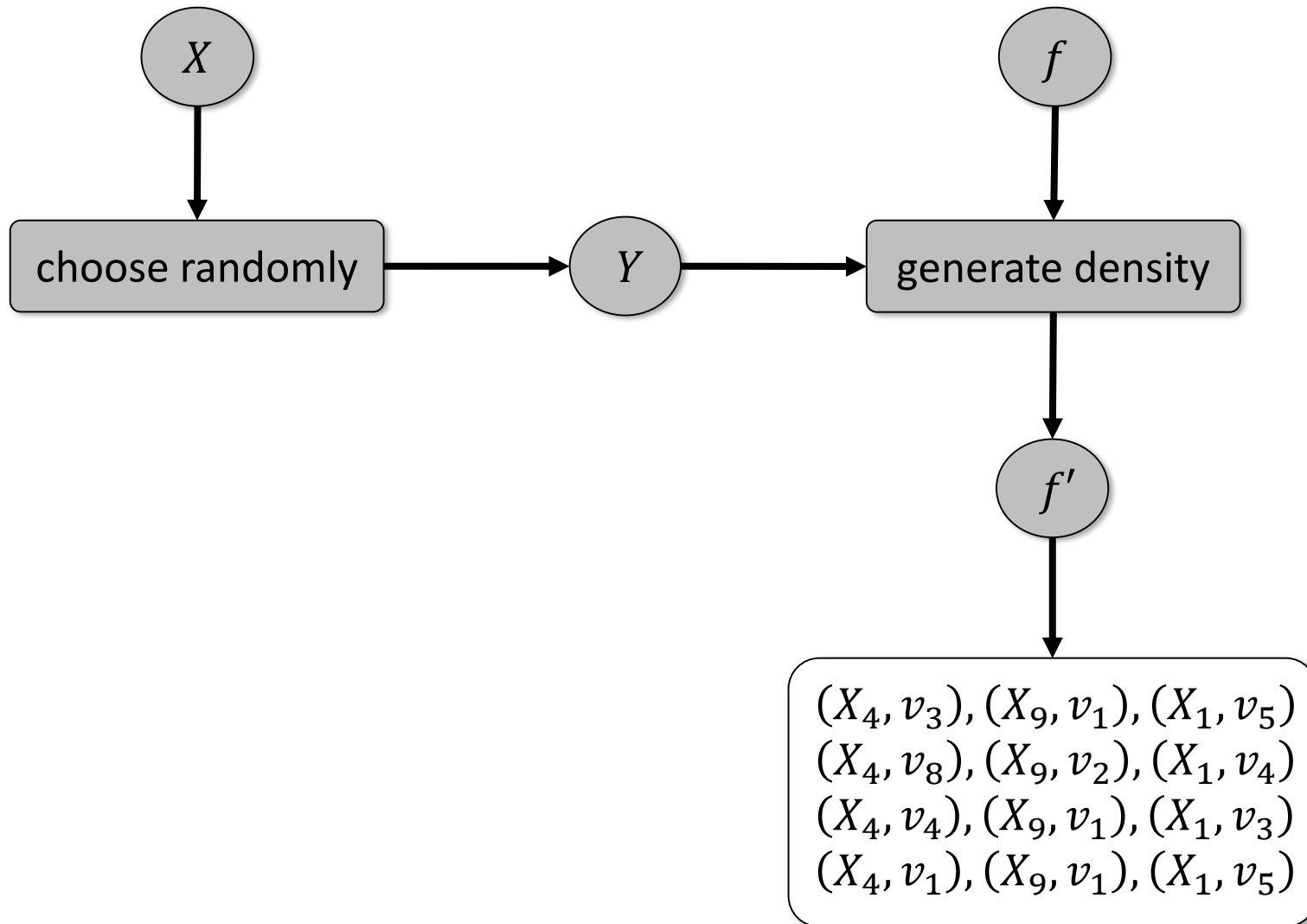
POEt – generating itemsets



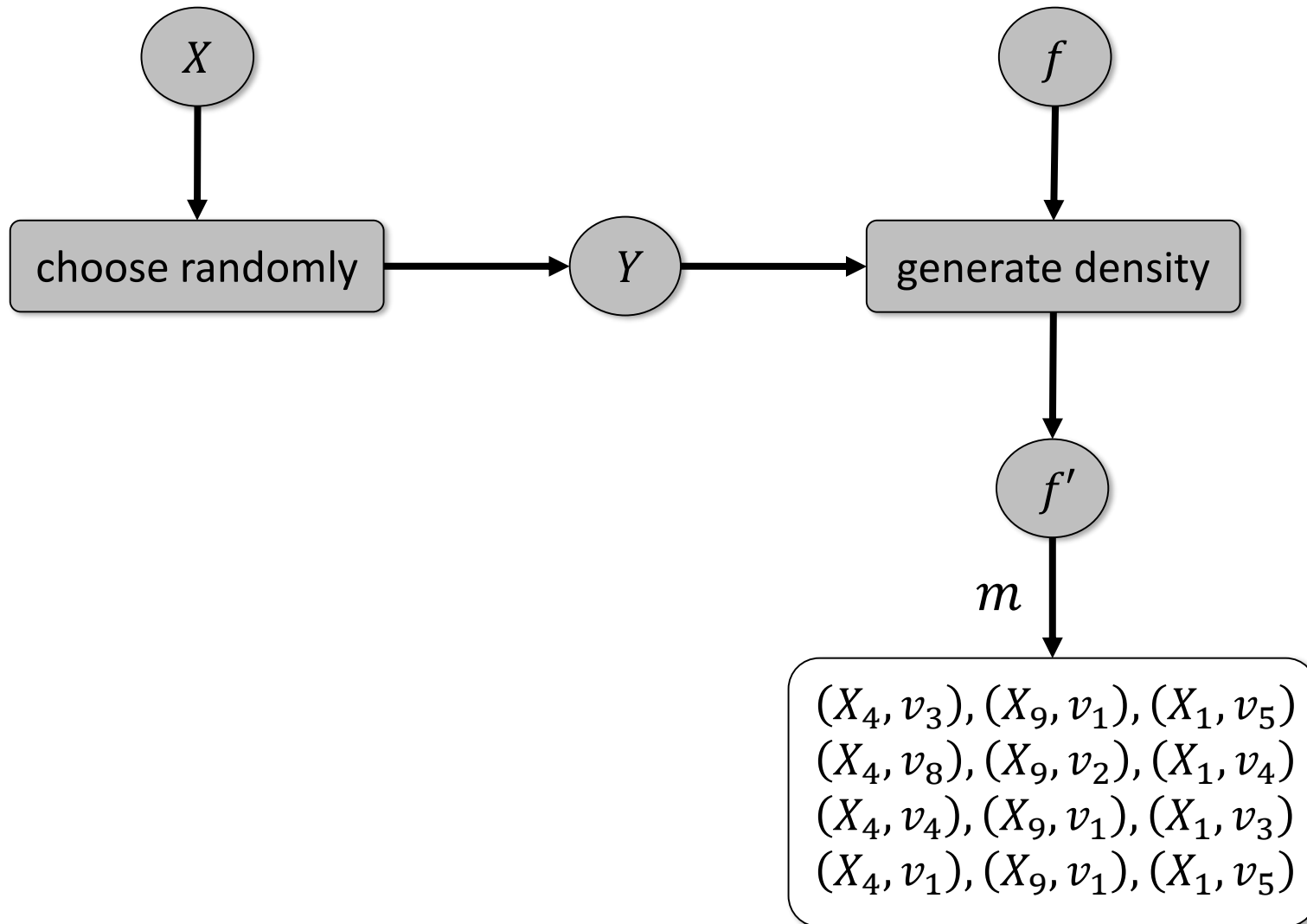
POEt – generating itemsets



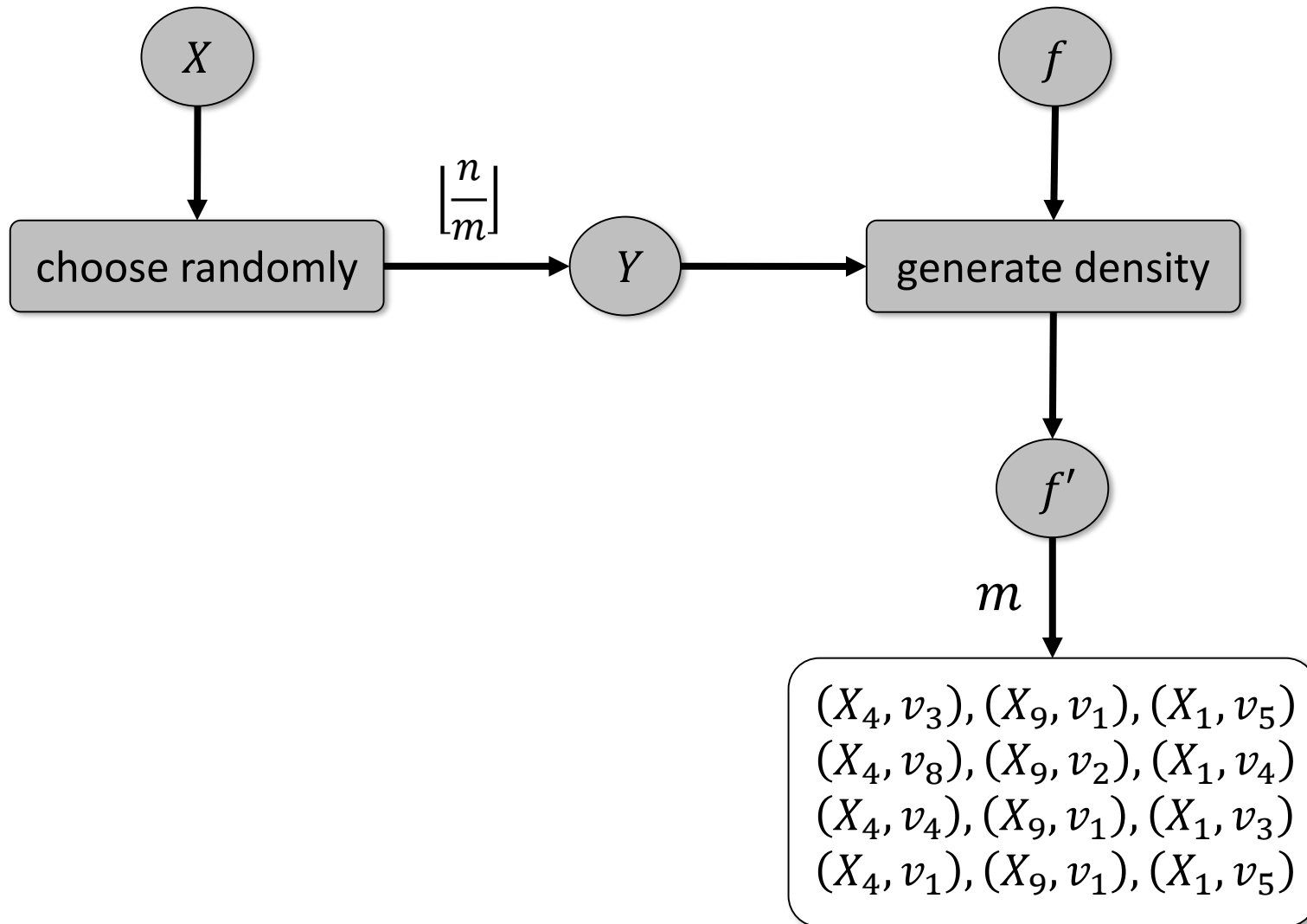
POEt – generating itemsets



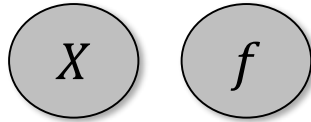
POEt – generating itemsets



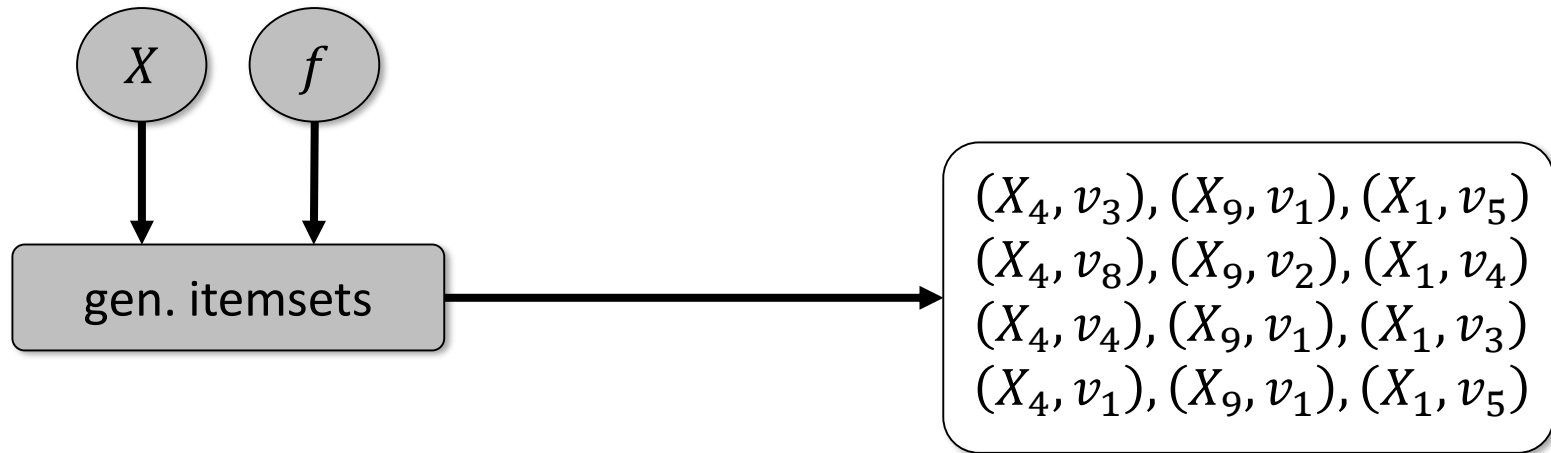
POEt – generating itemsets



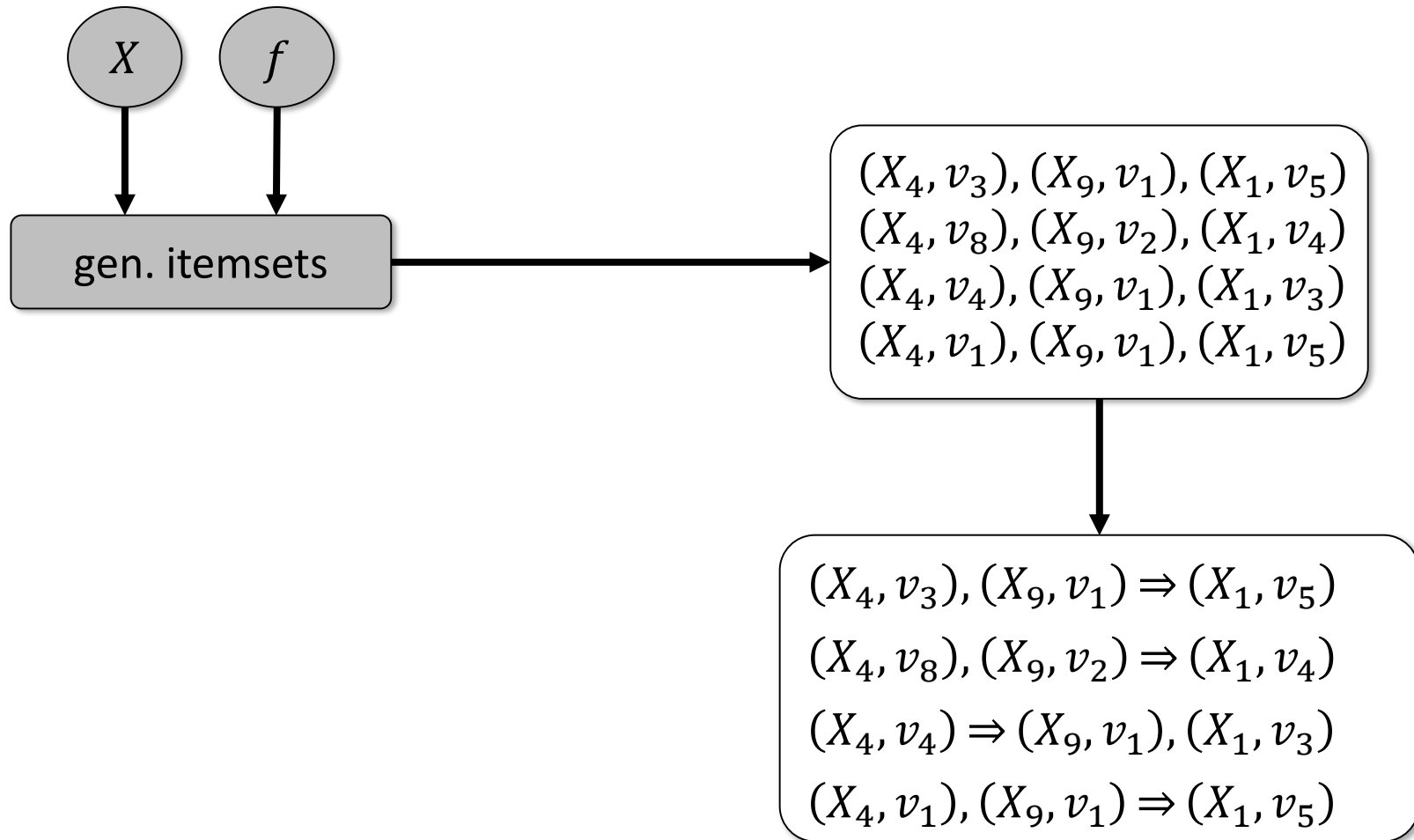
POEt – generating association rules



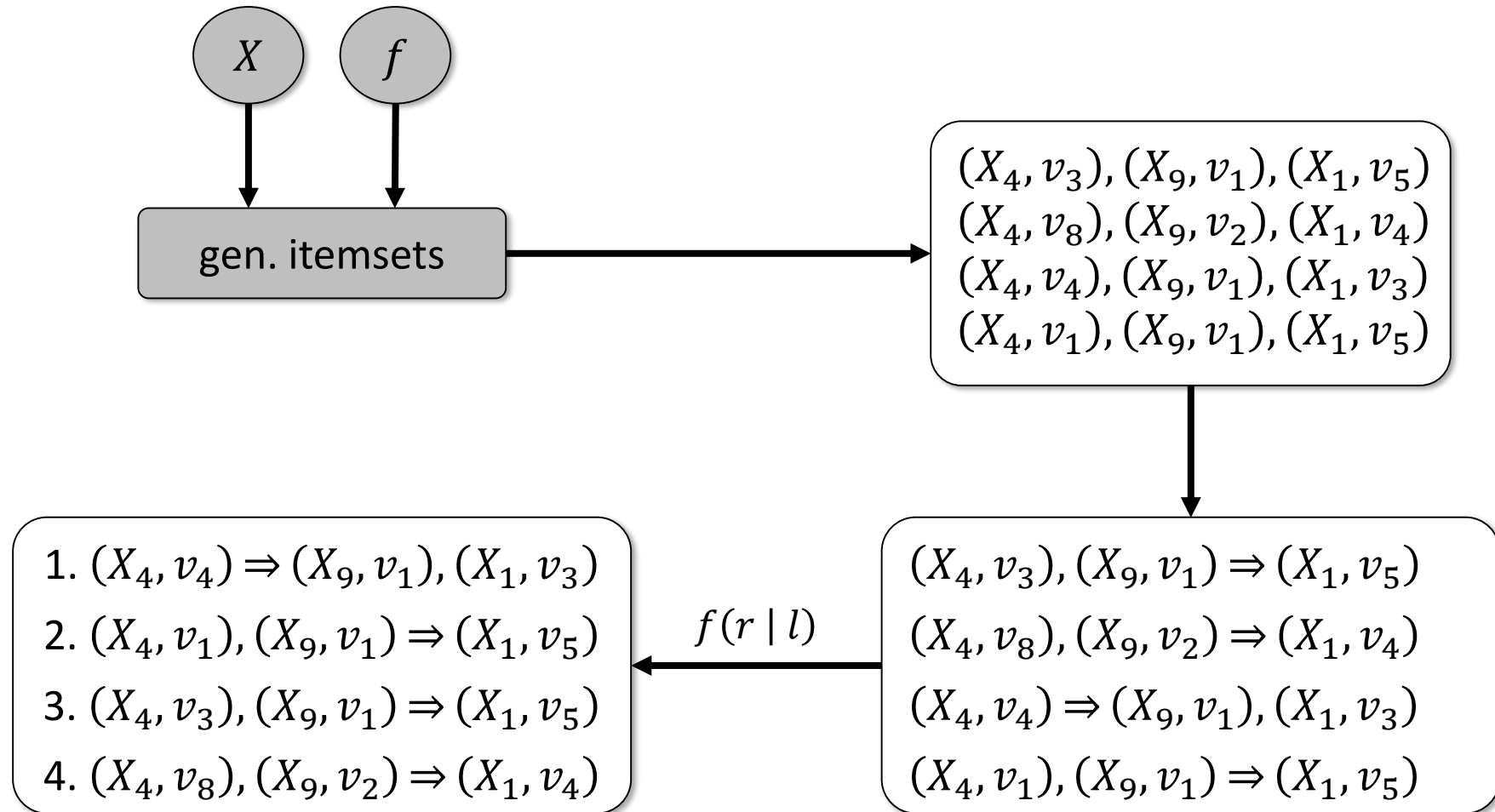
POEt – generating association rules



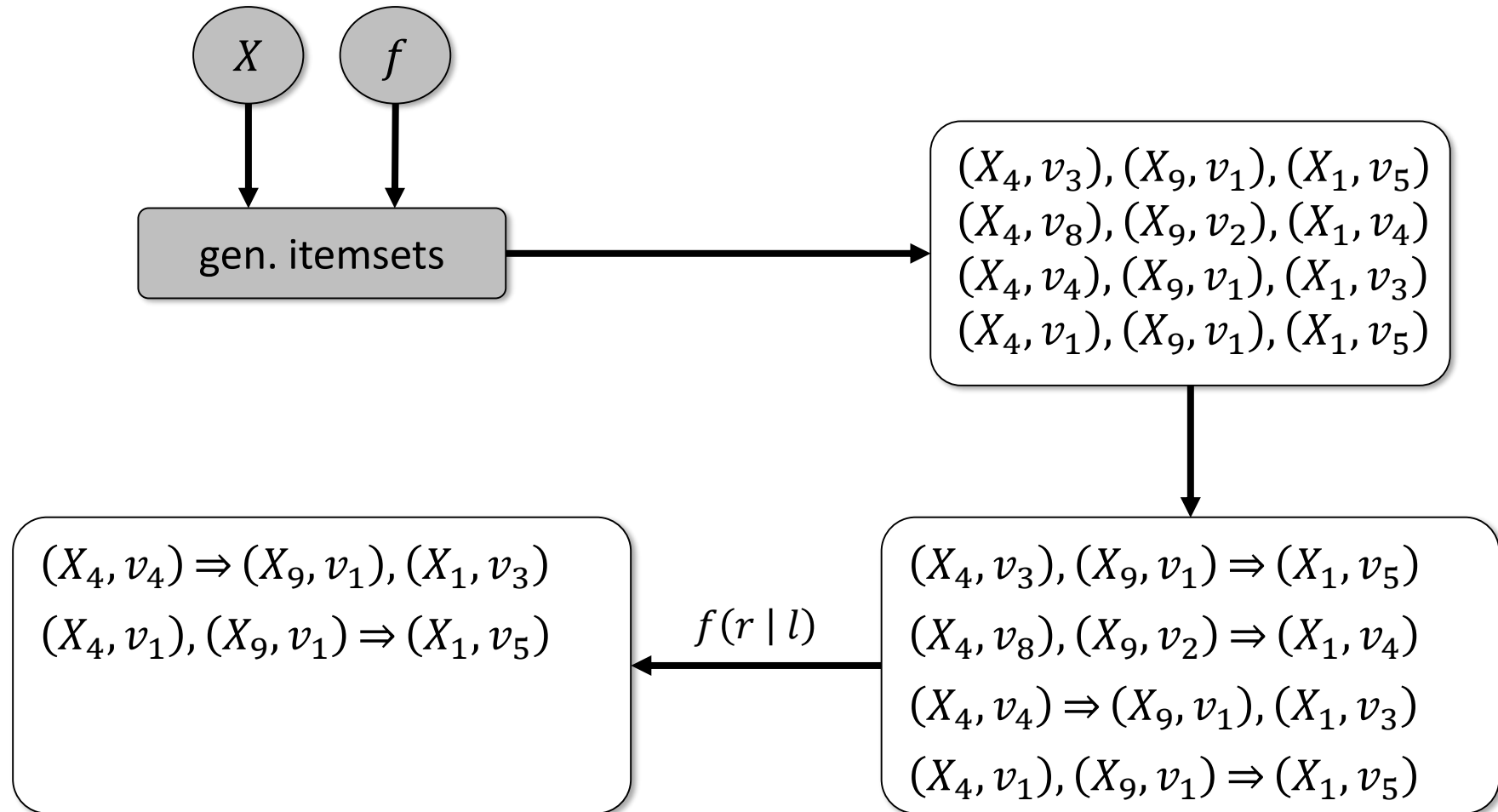
POEt – generating association rules



POEt – generating association rules



POEt – generating association rules



Evaluation

Datasets

Dataset	Instances	Attributes
IBM dataset generator	100,000	100
Bayesian networks	100,000	10
MovieLens	49,282	23

Compared to

- Apriori
- Moment

Performance measure

- percentaged overlap

$$\frac{|I_1 \cap I_2|}{|I_2|}$$

Itemsets (1)

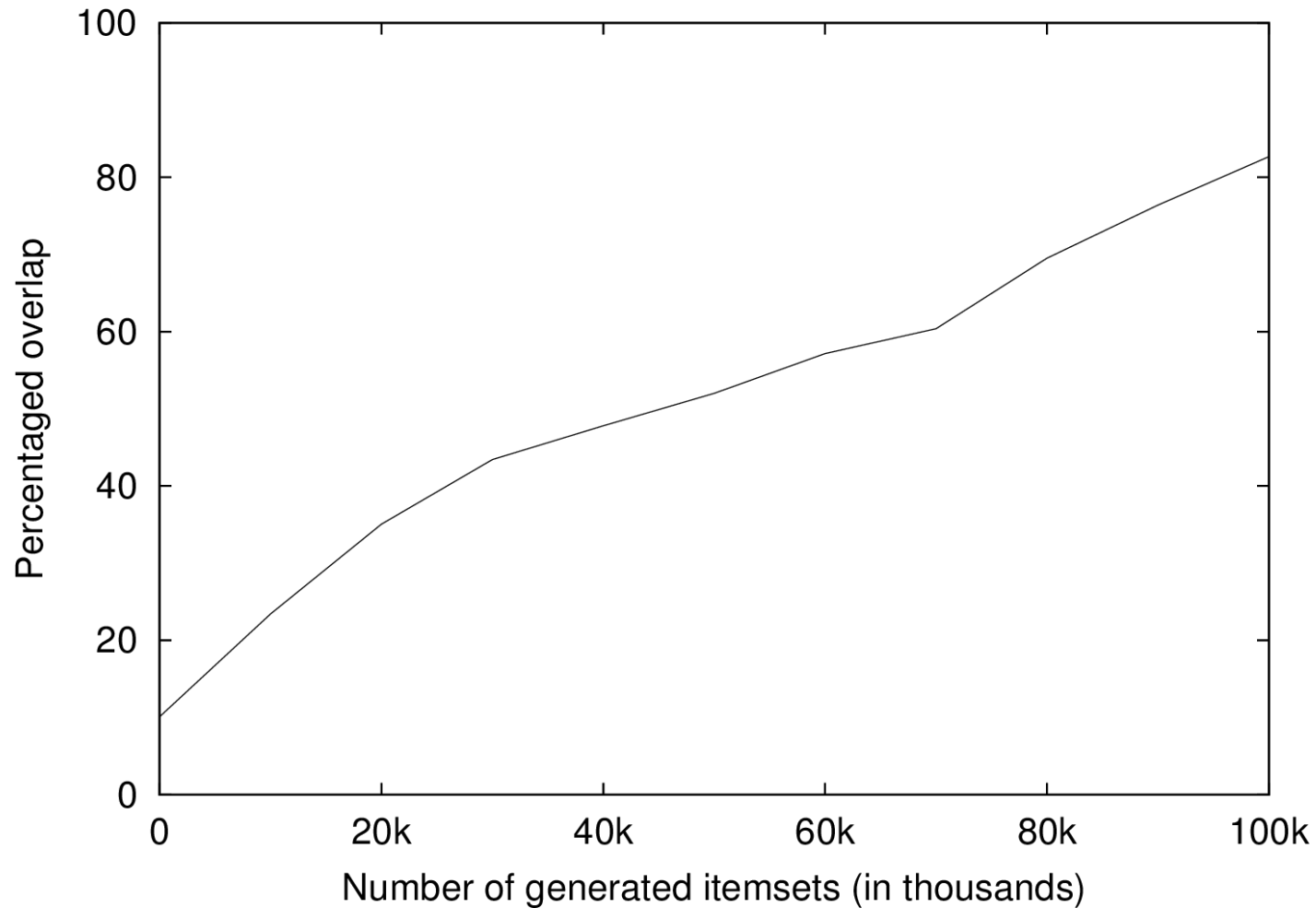
Dataset	Algorithm	Support		
		5%	10%	25%
IBM dataset generator	Apriori	0.002	0.002	0.006
	Moment	0.001	0.000	0.001
Bayesian networks	Apriori	0.384	0.487	0.524
	Moment	0.101	0.195	0.415
MovieLens	Apriori	0.133	0.111	0.333
	Moment	0.143	0.111	0.143

Evaluation - Itemsets (1)

Dataset	Algorithm	Support		
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MovieLens	Apriori	0.133	0.111	0.333
	Moment	0.143	0.111	0.143

$(X_{gender}, male), (X_{thriller}, true), (X_{comedy}, false)$

Evaluation - Itemsets (2)

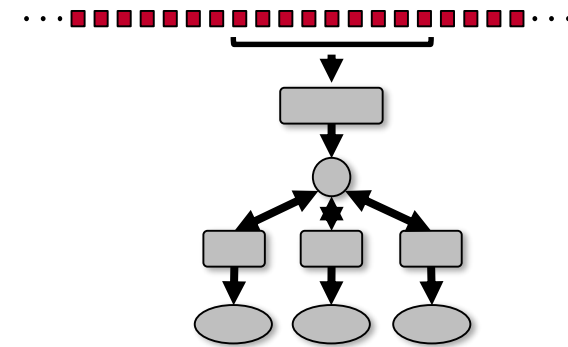


Evaluation - Association rules

Dataset	Confidence		
	0%	25%	50%
IBM dataset generator	0.000	0.000	0.000
Bayesian networks	0.389	0.345	0.210
MovieLens	0.098	0.093	0.100

Conclusions and Future Work

- framework for algorithms operating on density estimates
- a probabilistic condensed representation of data
- pattern mining on condensed representation



Future Work:

- more accurate itemset and association rule mining
- fast inference algorithm for speed-ups
- other algorithms that perform traditional data mining tasks on online density estimates

Thank you for your attention