## CSE 4502/5717 Big Data Analytics Fall 2024 Exam 3 Helpsheet

1. Association Rules Mining. An itemset is a set of items. A *k*-itemset is an itemset of size *k*. A transaction is an itemset. A rule is represented as  $X \to Y$  where  $X \neq \emptyset, Y \neq \emptyset, X \cap Y = \emptyset$ .

We are given a database DB of transactions and the number of transactions in the database is n. Let I be the set of distinct items in the database and let d = |I|.

For an itemset X, we define  $\sigma(X)$  as the number of transactions in which X occurs, i.e.  $\sigma(X) = |\{T \in DB | X \subseteq T\}|$  The **support** of any rule  $X \to Y$  is  $\frac{\sigma(X \cup Y)}{n}$ . The **confidence** of any rule  $X \to Y$  is  $\frac{\sigma(X \cup Y)}{\sigma(X)}$ .

Association Rules Mining is defined as follows.

Input: A DB of transactions and two numbers: minSupport and minConfidence.

**Output:** All rules  $X \to Y$  whose support is  $\geq \min$ Support and whose confidence is  $\geq \min$ Confidence.

An itemset is **frequent** if  $\sigma(X) \ge n \cdot \min$ Support

We discussed the Apriori algorithm for finding all the frequent itemsets. This algorithm is based on the a priori principle: If X is not frequent then no superset of X is frequent. Also, If X is frequent then every subset of X is also frequent.

The pseudocode for the Apriori algorithm is given next.

Algorithm 1: Apriori algorithm

k := 1;Compute  $F_1 = \{i \in I | \sigma(i) \ge n \cdot \text{minSupport}\};$ while  $F_k \neq \emptyset$  do k := k + 1;Generate candidates  $C_k$  from  $F_{k-1};$ for  $T \in DB$  do  $\begin{bmatrix} \text{for } C \in C_k \text{ do} \\ & \text{if } C \subseteq T \text{ then} \\ & & \text{if } C(C) := \sigma(C) + 1; \end{bmatrix}$   $F_k := \emptyset;$ for  $C \in C_k$  do  $\begin{bmatrix} \text{if } \sigma(C) \ge n \cdot minSupport \text{ then} \\ & & \text{If } F_k := F_k \cup \{C\}; \end{bmatrix}$ 

We can use a hash tree to compute the support for each candidate itemset.

We also presented a randomized Monte Carlo algorithm for identifying frequent itemsets. The idea was to pick a random sample, identify frequent itemsets in the sample (with a smaller support) and output these. We proved that the output of this algorithm will be correct with a high probability using the Chernoff bounds:

If X is B(n, p), then the following are true:

$$Prob.[X \ge (1+\epsilon)np] \le \exp(-\epsilon^2 np/3)$$
$$Prob.[X \le (1-\epsilon)np] \le \exp(-\epsilon^2 np/2),$$

for any  $0 < \epsilon < 1$ .

2. Polynomial Arithmetic. A degree-*n* polynomial can be evaluated at a given point in O(n) time. Lagrangian interpolation algorithm runs in  $O(n^3)$  time whereas Newton's interpolation algorithm takes  $O(n^2)$  time.

Two degree-*n* polynomials can be multiplied in  $O(n \log n)$  time. A degree-*n* polynomial can be evaluated at *n* given arbitrary points in  $O(n \log^2 n)$  time. Also, interpolation of a polynomial presented in value form at *n* arbitrary points can be done in  $O(n \log^3 n)$  time.