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A Maximum Positive Flow in a Complete Weighted Bidirectional Graphs

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Abstract. In this paper we discuss a graph-theoretic definition of flow networks and define the maximum-flow problem. A flow network G=(V,E) is a bi-directional connected graph in which edge $(u,v)\in E$ has a non-negative capacity $c(u, v) \geq 0$.We consider the problem of identifying positive flow in a complete weighted bi-directional network where the flow nodes would result in variation of quantity in a given interval of time.

Keywords: Flow networks, Complete weighted bi-directional network

AMS Mathematics Subject Classification (2010): 05C21

1. Introduction

To illustrate this with an example, let us consider the problem of exchanging currency in a cylic path. Let s start the flow of cycle with the quantity A at a node X after completing one cycle with the quantity B. Depending upon the nature of the cycle, there are two possibilities that is either $A \geq B$ or $B \geq A$. Of all the possible cycles our intension is to find the cycle in which the quantity B - A is maximum. We have to find the list of possible products (quantity x capacity) by the way of forming the cycle considering 2 nodes, 3 nodes and so on for n nodes using Apriori Algorithm we can able to find the maximum positive flow.

First of all we have to form a conversion factor matrix

Consider an example conversion factor matrix for 4 countries on a particular day.

Currency names	India	United Kingdom	Canada	Dutch	Euro
India (Rupees)	1	77	38.29	24	52
United Kingdom (Pound)	0.012978	1	0.457	0.6783	0.6783
Canada (Dollar)	0.026	2.1866	1	1.4838	1.4838
Dutch (Guilder)	0.0416138	1.4732	1.484	1	2.20371
Euro	0.01892	1.4732	0.6734	0.4538	1

LEVEL 1

Consider for two nodes 1. India 2. U.K.

0.012978

India (100 Rupees) U.K.(1.2978 Pound)

99.9. Rupees

$1 \rightarrow 2$ and $2 \rightarrow 1$

{(1,2)(2,1)} No. of Products 2

0.012978 77

A 100 (India) ---------------------> 1.2978 (U.K) --------------------> 99.9. (India) B

Here B - A is minimum

Like this for level n, (i.e) 1,2,3….. n+1 countires we can find the positive flow and find the maximum by using Apriori Algorithm

The Apriori Algorithm determines the support of itemsets in a levelwise BFS (Breadth First Search) fashion. First it finds the supports of 1-itemset (the itemset with only one element) then of 2-itemsets etc:

C1 is the set of all one-item sets, k= 1

While Ck $\neq$ 0 ;

Scan data base to determine support □ (A) for all AЄ Ck

Extract frequent itemsets from Ck into Lk

Geneerate Ck+1

k : =k +1

The algorithm does not determine the supports of all possible itemsets, instead it uses a clever strategy to determine candidates for frequent itemsets i.e it finds sets Ck of k-itemsets which contain all the frequent itemsets but not much else.

Mining for association among items in a large database of sales transaction is an important database mining function. For Example, the information that a customer who purchases keyboard also tends to buy a mouse at the same time is represented in association rule below: keyboard Mouse [Support = 6%, confidence = 70%]

Itemset

- A set of items is referred to as itemset
- An item set containing k items is called k – item set.

Apriori Algorithm (1)

Apriori Algorithm is an influential algorithm for mining frequent itemsets for Boolean associates rules.

Apriori Algorithm (2)

Uses a Level - wise search, where k-itemsets (An itemset that contains k items is a k-itemset) are used to explore (k+1)- itemsets, to mine frequent itemsets from transactional database for Boolean association rules. First, the set of frequent 1-itemsets is found. This set is denoted L1. L1 is used to find L2, the set of frequent 2-itemsets, which is used to fine L3, and so on, until no more frequent k-itemsets can be found.

Using this Algorithm we can able to determine the maximum positive flow.

Level 1
Consider 2 countries, for example : 1 India & 2 U.K
Starting Rs.100
After completing 1 cyle, the Profit & Loss percentage is found below:

Tid	Net Amount	Profit%	Loss%
1 2 1	99.9	--	0.9

Result :

There is no profit among two countries
Level 2:
Let us consider 3 countries, for example 1. Inida, 2 U.K. & 3. Canada
Step 1

Tid	Net Amount	Profit%	Loss%
1 2 1	99.9	--	0.9
1 3 1	99.5	--	0.9

By joining of 2 countries, there is no profit. Proceed Step 2

Step 2:

Tid	Net Amount	Profit%	Loss%
1 2 3 1	**108.658**	**1.08**	**--**
1 3 2 1	91.49	--	0.85

Result:
So, there is a positive flow from India → U.K. → Canada → India
This cycle of conversion process makes profit.
Level 3:
Consider for countries, for example : 1. India 2. Euro 3. Dutch 4. U.K
Step 1 :

Tid (By joining of 2 countries)	Net Amount	Profit%	Loss%
1 2 1	99.9	--	0.9
1 3 1	99.8	--	0.99
1 4 1	99.1	--	0.99

There is no profit among two countries. Proceed Step 2.
Step 2.

Tid (By joining of 3 countries from a cycle)	Net Amount	Profit%	Loss%
1 2 3 1	99.8	--	0.9
1 3 4 1	215.5	2.15	--
1 4 3 1	45.8	--	0.45

1 4 2 1	98.6	--	0.98
1 2 4 1	93.2	--	0.93
1 3 2 1	98.16	--	0.98

Proceed Step 3:

Step 3.

Tid (By joining of 3 countries from a cycle)	Net Amount	Profit%	Loss%
1 2 3 4 1	**217.76**	**2.17**	**--**
1 2 4 3 1	45.3	--	0.45
1 3 4 2 1	**317.9**	**3.17**	**--**
1 3 2 4 1	98.5	--	0.98
1 4 3 2 1	44.6	--	0.44
1 4 2 3 1	**100.12**	**1.0012**	**--**

step 4.
Among this the profit are given below:

TID	Profit %
1 3 4 1	2.15
1 2 3 4 1	2.17
1 3 4 2 1	3.17
1 4 2 3 1	1.0012

Result :

India → Dutch → U.K → Euro → India.

2. Conclusion

The Apriori Algorithm and the Game of Life Process have been used the basis for predictive analysis to build a tool. In this direction, research work is processing. Oliver Magnity has contributed some valuable ideas to achieve our goal.

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