High Utility Item sets From Transactional Databases with efficient Algorithms utility pattern growth (UP-Growth) and UP-Growth+

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Abstract: High utility item sets(HUIs) mining is anemerging topic in datamining, which refers to discovering all itemsets having autility meeting a user specified minimum utility threshold min_util. However, setting min_util appropriately is a difficult problem for users.Generally speaking, finding an appropriate minimum utility threshold by trial and errorisatedious process for users. If min_util is set to olow,too many HUIs will be generated, which may cause the mining process to be very inefficient. On the otherhand, if min_util is set to ohigh,it is likely that no HUIs will be found. In this paper, we address the above issues by proposing a new framework for top-k high utility item set mining, where k is the desired number of HUIs to be mined. Two types of efficient algorithms named TKU(miningTop-KUtilityitemsets) and TKO(miningTop-K utility itemsets in Onephase) are proposed formining such itemsets with out the need to setmin_util. We provide a structural comparison of the two algorithms with discussions on their advantages and limitations. Empirical evaluations on both realand synthetic datasets show that the performance of the proposed algorithms is close to that of the optimal case of state-of-the-art utility mining algorithms.

Keywords: Backup Privacy, Central Repository, Seed Block, Parity Cloud, Parity cloud service.

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I. INTRODUCTION

Frequent item set mining is a fundamental research topic in data mining. The traditional information retrieval process is valuable item set require the utility to associate the transactions. In utility mining, each item is associated with autility (e.g.unit profit) and an occurrence count in each transaction (e.g.quantity). The utility of an itemset represents its importance, which can be measured in terms of weight, value, quantity or other information depending on the user specification.

However, efficiently mining HUI sin databases is not an easy task because the downward closure property used in FIM does not hold for the utility of itemsets. In otherwords, pruning search space for HUI mining is difficult because a superset of alow utility itemset can be high util-ity.Totack let his problem, the concept of transaction-weighted utilization(TWU) model was introduced to facilitate the performance of the mining task. In this model, an item set is called high transaction-weighted utilization item-set (HTWUI) if its TWU is no less than min_util, where the TWU of an itemset represents an upperbound on its utility.Therefore, a HUI must be aH TWU Iand all the HUIs must be included in the complete set of HTWUIs. A classical TWU model-based algorithm consists of two phases. In the first phase, called phaseI, the completeset of HTWUIs are found. In these condphase, called phaseII, all HUIs are obtained by calculating the exact utilities of HTWUIs with one databases can.Although many studies have been devoted to HUImin-ing, it is difficult for users to choose an appropriatemini-mum utility threshold in practice. Depending on the threshold, the output size can be very small or very large. Besides, the choice of the threshold greatly influences the performance of the algorithms.If the thresholdisset too ow,toomany HUIs will be presented to the users and it is difficult for the users to comprehend theresults.AlargenumberofHUIsalsocausestheminingalgorithmstobecomeinefficientorevenrunoutofmemory,becausethemoreHUIsthealgorithmsgenerate,themoreresourcestheyconsume.Onthecontrary,ifthethresholdissettoohigh,noHUIwillbefound.Tofindanappropriatevalueforthemin_utilthreshold,usersneedtotrydifferentthresh-old sby guessing and reexecuting the algorithms over and over until being satisfiedwiththeresults.Thisprocessisbothinconvenientandtime-consuming.

Topreciselycontroltheoutputsizeanddiscovertheitemsets withthehighestutilitieswithoutsettingthethresh-olds, apromisingsolutionistoredefinethetaskofminingHUIsasmining top-khighutilityitemsets(top-kHUIs). The idea is to let the users specify k,i.e.,the number of desired itemsets,insteadofspecifyingtheminimumutilitythresh-old.Setting k is more intuitive than setting the threshold becausekrepresentsthenumberofitemsetsthattheuserswantto findwhereaschoosingthethresholddependsprimarilyondatabasecharacteristics,whichareoftenunknowntousers.

Usingaparameterkinsteadofthemin_utilthresholdisverydesirableformanyapplications.Forexample,toanalyzecustomerpurchasebehavior,top-kHUI mining serves as a promising solution for users who desire to know "Whatare thetop-k sets of products(i.e.,itemsets) that contributethehighestprofitstothecompany?"and"Howtoefficientlyfindtheseitemsetswithoutsettingthemin_utilthreshold?" .Althoughtop-kHUIminingisessentialtomanyapplications,developingefficientalgorithmsforminingsuchpatternsisnotaneasytask.Itposesfourmajorchallengesasdiscussedbelow.

II. OBJECTIVE

weproposeanefficientalgorithmnamedTKU(miningTop-kUtilityitemsets)fordiscoveringtopkHUIswithoutspecifyingmin_util.WefirstpresentitsbasicversionnamedTKU$_{Base}$andthend

escribetheTKUalgorithm,whichincludesseveralnovelstrategies.

ThebaselineapproachTKU$_{Base}$isanextensionofUP-Growth[25],atree-basedalgorithmforminingHUIs.TKU-$_{Base}$adoptstheUP-TreestructureofUP-Growth to maintain the information of transactions and top-kHUIs.TKU$_{Base}$is executed as constructing theUP-Tree, generating potentialtop-khighutilityitemsets(PKHUIs)fromtheUP-Tree,and(3)identifyingtop-kHUIsfromthesetofPKHUIs.

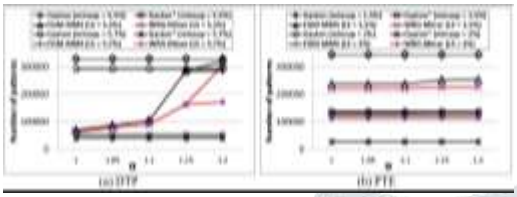
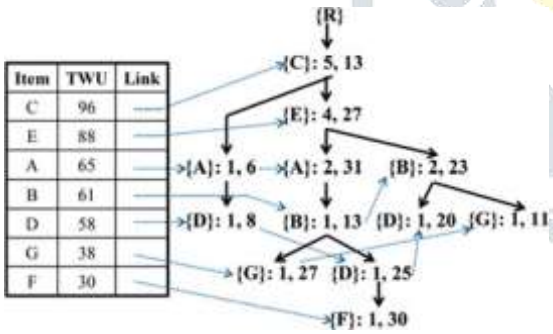


Figure:Frequent itemsets with threshold values

3.1.1 UP-TreeStructure

webrieflyintroducetheUP-Treestructure. Formore detailsaboutit, readers are referred to.EachnodeNofaUP-Treehasfiveentries:N.nameistheitemnameofN;N.countisthesupportcountofN;N.nuisthenodeutilityofN;N.parentindicatestheparentnodeofN;N.hlinkisanodelinkwhichmaypointtoanodehavingthesameitemnameasN.name.TheHeadertableisastructureemployedtofacili-tatethetraversaloftheUP-Tree.

Aheadertableentrycontainsanitemname,anestimatedutilityvalue,andalink.Thelinkpointstothefirstnodeintheup-Treehavingthesameitemnameastheentry.Thenodeswhoseitemnamesarethesamecanbetraversedefficientlybyfollowingthelinksinheadertableandthenodelinksintheup-Tree.



III. IMPLEMENTATION

TheTKU$_{Base}$algorithmusesaninternalvariablenamedborderminimumutilitythreshold(denotedasmin_util$_{Border}$)whichisinitiallysetto0andraiseddynamicallyafterasufficientnumberofitemsetswithhigherutilitieshasbeencapturedduringthegenerationofPKHUIs.Thedevelopmentoftheproposedmethodisbasedonthefollowingdefini-tionsandlemmas.

Lemma1.LetP¼hX$_1$,X$_2$,. . .,X$_M$ibeasetofitemsets(Mk),whereX$_i$istheithitemset inP andEU(X$_i$)EU(X$_j$) > 0,8 i< j.Inotherwords,X$_i$istheitemsetwiththeithhighestutilityinP.For any itemset Y, if EU(Y) < EU(X$_k$), Y isnot a top-k HUI.

Rationale.AccordingtoDefinition10,ifthereexistskitemsets whoseutilitiesarehigherthantheutilityof Y,Yisnotatop-kHUI.

Lemma2.LetP¼hX$_1$,X$_2$,. . .,X$_M$ibeasetofitemsets(Mk),whereX$_i$istheithitemsetinPandEU(X$_i$)EU(X$_j$)> 0,8i< j.Ifd$_P$¼EU(X$_k$),f$_{HUI}$(D,d)f$_{HUI}$(D,d$_P$).

Rationale.LetKHbethecompletesetoftop-kHUIs.Ifj KH j k,d¼min{EU(X) j X2KH}(byDefinition11).Becaused¼min{EU(X) j X2KH}min{EU(X$_i$) j X$_i$2P,1ik}¼EU(X$_k$)¼d$_P$,ddPandf$_{HUI}$(D,d)f$_{HUI}$(D,d$_P$).

Example3.Considerthatk¼4andabs_min_util¼0.LetPbethesetofall1-itemsets{{A}:20,{D}:20,{B}:16,{E}:15,{C}:13,G:7,F:5}inD,wherethenumberbesideeachitem-setisitsabsoluteutility.ByLemma1,{C},{G},{F}areunpromisingtobethetop-4HUIs.Thereforeabs_min_utilcanberaisedtothefourthhighestutilityvalueinP(i.e.,15)andnotop-kHUIswillbemissed.

AfterraisingabsminutilTKU$_{Base}$appliestheUP-Growthsearchprocedurewithabsminutil¼minutil$_{Border}$togeneratePKHUIs.ThoughLemma1providesawaytoraisemin_util$_{Border}$,itcannotbeapplieddurthegenerationofPKHUIsinphaseI.ThisisbecausetheutilitiesofPKHUIsareunknownduringphaseI.Asolutiontothisproblemistousealowerboundontheutilityof PKHUIsduringphaseItoraisemin_util$_{Border}$.Alowerboundontheutilityof PKHUIsisprovidedbythefollowingdefinitions.

Definition12(Minimumutilityofanitem).Theminimumutilityofanitem I2Iisdenotedasmiu(I)anddefinedasthevalueEU(I,T$_i$)forwhich: 9T$_j$2Dsuchthat0< EU(I,T$_j$)< EU(I,T$_i$).Anequivalentdefinitionisthatmiu(I)¼min{EU(I,T$_r$) j T$_r$2Dandr2g(I)}.

Lemma3.LetC¼hX$_1$,X$_2$,. . .,X$_M$ibeasetofitemsets(Mk),whereX$_i$istheithitemsetinCandMIU(X$_i$)MIU(X$_j$)> 0,8i< j.Inotherwords,X$_i$istheitemsetwiththeithhighestMUIvalueinC.ForanyitemsetY,ifTWU(Y)< d$_{MC}$¼min{MIU(X$_i$) j X$_i$2C,1ik},thenYisnotatop-kHUI.

Rationale.AccordingtoDefinition8,EU(Y)TWU(Y).IfTWU(Y) < d$_{MC}$,wehaveEU(Y)<d$_{MC}$.Besides,0< EU(Y)< MIU(X$_i$)EU(X$_i$),8X$_i$2C,1ik.AccordingtoDefinition10,ifthereexistkitemsetswhoseutilitiesarehigherthantheutil-ityofY,Yisnotatop-kHUI.

Lemma4.LetC¼hX$_1$,X$_2$,. . .,X$_M$ibeasetofitemsets(Mk),whereX$_i$istheithitemsetinCandMIU(X$_i$)MIU(X$_j$)> 0,8i< j.Ifd$_{MC}$¼MIU(X$_k$),f$_{HUI}$(D,d)f$_{HUI}$(D,d$_{MC}$).Rationale.LetKHbethecompletesetoftopkHUIs.Ifj KH jk,d¼min{EU(X) j X2KH}(byDefinition11).Becaused¼min{EU(X) j X2KH}min{EU(X$_i$) j X$_i$2C,1ik}min communication ability to backup locations in order to increase data integration.

Resource storage allocation:

Heterogeneous clouds consist many different hardware and software such as hybrid storage and diverse disks. In cloud-based enterprises, entire business data are stored in the cloud storage. So, data protection, safety and recovery are critical in these environments.Using fastest disk technology in the event of a disaster for replication of data in storage location.

min_util$_{Border}$couldberaisedbeforetheconstructionoftheUP Treeandprunemoreunpromisingitemsintransactions,thenumberofnodesmaintainedinmemorycouldbereducedandtheminingalgorithmcouldachievebetterperformance.Basedonthisidea,weproposeastrategynamedPE(PreevaluationStep)toraisemin_util$_{Border}$duringthefirstscanofthedatabase.

Strategy2(PE:PreEvaluation).ThestrategyPEusesastructurenamedPreEvaluationMatrix(PEM)tostorelowerboundsoftheut

ilitiesofcertain2itemsets.EachentryinPEMisdenotedasPEM[x][y]andcorrespondstothelowerboundofEU({x,y}),wherex,y2I. Initially,eachvalueinPEMissetto0.WhenatransactionT$_r$¼{I$_1$,I$_2$,...,I$_M$}(I$_j$2I,1iM)isretrieveduringthefirstdatabasescan,theutilityof{I$_1$}[{I$_i$}(1< iM)inT$_r$isaddedtothevalueofthecorrespondingentryofPEM[I$_1$][I$_i$]inPEM.Afterscanningallthetransactions,ifthekthhighestvalueinPEMishigherthanmin_util$_{Border}$,min_util$_{Border}$canberaisedtothekthhighestvalueinPEM.Thespacecomplexityofthestrategyis$O(j Ij^2/2)$,wherej Ijisthenumberofdistinctitemsinthedatabase.

Example5.ConsiderthedatabaseofTable1.WhenT$_1$¼{(A,1),(C,1),(D,1)}isretrieved,thecorrespondingentriesPEM[A][C],PEM[A][D]areaccumulatedwithEU({AC},T$_1$)¼6andEU({AD},T$_1$)¼7.Theremainingtransactionsinthedatabaseareprocessedbythesameprocedure.Afterthat,ifmin_util$_{Border}$islowerthanthekthhighestvalueinPEM,min_util$_{Border}$issettothekthhighestvalueinPEM.3showsthevalueofeachentryinPEMafterscanningthedatabase.Ifk¼4,thefourthhighestvalueinPEMisPEM[B][E]¼18.Ifmin_util$_{Border}$islessthanthisvalue,min_util$_{Border}$israisedto18.

NoticethatinTKU$_{Base}$,thestrategyDGUproposedin[25]cannotbeapplied,becausemin_util$_{Border}$issetto0beforetheconstructionoftheUPTree.However,ifweapplythestrategyPEtoraisemin_util$_{Border}$duringthefirstdatabasescan,DGUcanbefurtherappliedtopruneitemswhoseTWUarelessthanmin_util$_{Border}$,whichreducesthesizeoftheUPTreeandthenumberofcandidatesproducedinphaseI.

WealsoproposeastrategycalledNU(raisingthethresholdbyNodeUtilities),whichisappliedduringtheconstructionoftheUP-Tree.ThestrategyNUisdevelopedbasedonthefollowinglemmas.Lemma8.LetPATH¼hN$_1$,N$_2$,...,N$_M$,Ribeapathfromanode N$_1$totherootRinUPreeandI$_i$2Ibetheitemnameof N$_i$,1iM.PATH¼hN$_1$,N$_2$,...,N$_M$,Rirepresentsauniqueitemset X¼{I$_1$,I$_2$,...,I$_M$}inthedatabase.Besides,thenodeutilityof N$_1$isalowerboundontheutilityofX.Rationale.TheUPTreeisconstructedbyapplyingthestrategyDGN[25].Accordingtotherationaledescribedin[25],theutilityoftheitemsetX¼{I$_1$,I$_2$,...,I$_M$}isguaranteedtobehigherthanthenodeutilityof N$_1$.Therefore,N$_1$.nuEU({I$_1$,I$_2$,...,I$_M$}).

Lemma9.IftherearemnodesintheUPTree,thereareatleastMdistinctitemsetswhoseutilitiesarehigherthan0.

Rationale.ByLemma8,eachpathfromanodeintheUPTreetotherootformsauniquepath,whichrepresentsauniqueitemsetwhoseutilityishigherthanzerointhedatabase.Therefore,Mdistinctnodesin theUPTreeyieldMdistinctitemsetswhoseutilitiesarehigherthanzero.

Lemma10.LetSetNode¼hN$_1$,N$_2$,...,N$_M$ibeanorderedsetcontainingallnodesintheUPTree(Mk).LetN$_i$betheithnodeinSetNodeandN$_i$.nuN$_j$.nu> 0,8i< j.Ifd$_{NU}$¼N$_k$.nu,thenf$_{HUI}$(D,d)f$_{HUI}$(D,d$_{NU}$).

Rationale.ByLemma8,eachpathfromanodeN$_i$2SetNodetotherootRrepresentsauniqueitemsetN$_i$,1iM.LetSetItemset¼hX$_1$,X$_2$,...,X$_M$ibeanorderedsetofitemsetsthatarerepresentedbythenodesinSetNode,whereEU(X$_i$)EU(X$_j$)> 0,8i< j.LetKHbethecompletesetoftopkHUIsinthedatabaseD.Ifj KH jk,thend¼min{EU(X)j X2KH}

Definition11).Becaused¼min{EU(X)j X2KH}min{EU(X$_i$)j X$_i$2SetItemset,1ik}min{N$_i$.nujN$_i$2NodeSet,1ik}¼d$_{NU}$,wehaveddand f$_{HUI}$(D,d)f$_{HUI}$(D,d$_{NU}$).

ByLemma8,9and10,iftherearenolessthanknodesintheUPTreeduringitsconstructionandthekthhighestnodeutilityintheUPTreeishigherthanthecurrentmin_util$_{Border}$,min_util$_{Border}$canbesafelyraisedtothekthhighestnodeutilityintheUP-Tree.

Example6.LetthenotationN$_a$representsanodeoftheUP-Treesuchthatais theitemstoredinN$_a$.Ifk¼4,whenthefirstreorganizedtransactionT$_1$0¼{(C,1),(A,1),(D,1)}isinsertedintotheUP-Tree,thenodes N$_{\{C\}}$,N$_{\{A\}}$andN$_{\{D\}}$arecreatedwithnodeutilities1,6and8,whicharerespectivelylowerboundsontheutilitiesofitemsets{C},{AC}and{DAC}.Whenthesecondreorganizedtransaction T$_2$'¼{(C,6),(E,2),(A,2),(G,5)}isinsertedintotheUP-Tree,therearemorethanfournodesinthetree.ByLemma10,min_util$_{Border}$canberaisedtothefourthhighestnodeutilityinthecurrentUP-Tree.

Strategy3(NU:raisingthethresholdbyNodeUtilities).ThestrategyNUisappliedduringtheconstructionoftheUPTree(duringtheseconddatabasescan).Iftherearemorethanknodesinthecurrent UP-Treeandthek-thhighestnodeutilityvalueNU$_{k-th}$ishigherthanmin_util$_{Border}$,min_util$_{Border}$canberaisedtoNU$_{k-th}$.Afterinsertingallreorganizedtransactions,thesizeoftheconstructedUPTreecanbefurtherreducedbypruningitemswhoseTWUvaluesarelessthanmin_util$_{Border}$intheUP-Tree.

Iv. CONCLUSION

Inthispaper,wehavestudiedtheproblemoftopkhighutilityitemsetsmining,wherekisthedesirednumberofhighutilityitemsetstobemined.TwoefficientalgorithmsTKU(miningTop-KUtilityitemsets)andTKO(miningTopKutilityitemsetsinOnephase)areproposedforminingsuchitemsetswithoutsettingminimumutilitythresholds.TKUisthefirsttwophasealgorithmforminingtopkhighutilityitemsets,whichincorporatesfivestrategiesPE,NU,MD,MCandSEtoeffectivelyraisethebordermimumutilitythresholdsandfurtherprunethesearchspace.Ontheotherhand,TKOisthefirstonephasealgorithmdevelopedfortopkHUImining,whichintegratesthenovelstrategiesRUC,RUZandEPBtogreatlyimproveitsperformance.Empiricalevaluationsondifferenttypesofrealandsyntheticdatasetsshowthattheproposedalgorithmshavegoodscalabilityonlargedatasetsandtheperformanceoftheproposedalgorithmsisclosetotheoptimalcaseofthestate-ofthearttwophaseandonephaseutilityminingalgorithms.

Althoughwehaveproposedanewframeworkfortopk HUImining,ithasnotyetbeenincorporatedwithotherutilityminingtaskstodiscoverdifferenttypesoftopkhighutilitypatternssuchastopkhighutilityepisodes,topkclosedphighutilityitemsets,top-khighutilitywebaccesspatternsandtopkmobilehighutilitysequentialpatterns.Theseleavewideroomsforexplorationasfuturework.

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