DATA TRACER STUDY ANALYSIS IN HIGHER EDUCATION USING THE FP-GROWTH ALGORITHM

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ABSTRACT

Knowing the distribution of alumni from a tertiary institution is very useful as evaluation material and benchmarks for teaching and learning activities in the tertiary institution concerned. XYZ College alumni distribution data by carrying out tracer studies. Tracer study data can be used by tertiary institutions for decision making and as input in curriculum development or other academic support facilities. Data mining is used to extract information on large-scale data. The method used is the fp-growth algorithm which is part of the association rule technique which aims to find and determine a data set that often appears in a data mine. Attribute data used in this study are field of study, GPA, year of admission, year of graduation, gender, waiting period, field of work, salary, position. The purpose of this study is to examine the pattern of alignment between data on alumni work using the fp-growth algorithm. The results of this study are in the form of information on patterns of alignment of the relationship between fields of study and GPA, year of entry, year of graduation, waiting period, field of work, salary, gender, position on alumni work in tracer study data in Higher Education using the fp-growth algorithm which will make it easier for tertiary institutions to gain deeper insight into alumni, as well as gain new knowledge about graduates and can be used to improve the quality of higher education.

KEYWORDS	*Data Mining, Fp-Growth, Tracer Study*

INTRODUCTION

Tracer study is an important activity for a university to track graduates who have been produced in terms of measuring the relationship between educational goals and processes and the current condition of graduates, Dewi *et al*. (2021). This is evidenced by the existence of a graduate tracing component (tracer study) in the Higher Education Institution Accreditation (AIPT) assessment. The existence of a tracer study can provide a variety of information that is useful for the purpose of evaluating the success of learning that has been implemented in higher education and can then be used to improve and ensure the quality of XYZ College. Tracer studies are also useful in providing important information about the alignment of the relationship between the curriculum and the needs and expectations of the world of work, assessing the relevance of higher education, information for stakeholders in a college.

XYZ College is one of the universities located in DKI Jakarta Province and has produced many graduates since it was founded in 1949. The tracer study program at XYZ College is carried out to find out the work of alumni in the community. The purpose of implementing a tracer study at XYZ College is to trace the educational process through the absorption process and the position of graduates in the world of work. But until now the process of analyzing tracer study data is still using manuals, and has not been optimized and has not been done comprehensively.

Previous research related to tracer study data analysis in higher education such as research conducted by Indriyawati *et al*. (2021) analyzing tracer study data using a priori algorithm on the alignment of how closely the relationship between the field of study and the work of alumni is, the analysis results show that there is still a mismatch (not at all = 1.6%, less = 19.2%. And quite large = 27.5%) the ability of graduates with stakeholders. This is a special concern for universities to fix / set strategies so that the percentage of data is reduced. Further research in the same field was conducted by Fauzi *et al*. (2018) analyzed tracer study data using the apriori algorithm to obtain new information or knowledge related to the correlation of majors with GPA to employment. Other research in the same field was conducted by Andika *et al*. (2022) analyzed tracer study data using the fp-growth algorithm to determine the employability of graduates and also retrospective assessments, such as what services were obtained during the study period, and to obtain meaningful correlation or relationship patterns. Researchers took several patterns with antecedents in the form of ipk, waiting period, field of work, salary, first job, gender to be interpreted. Other research in the same field was conducted by Yani *et al*. (2022) aims to analyze tracer study data using the a priori algorithm to obtain new knowledge such as the first job of graduates with a waiting period of less than 6 months is as a contract or honorary employee with a salary between 3-5 million and has an ipk between 3-3.5. Other research in the same field was conducted by Abdulloh *et al*. (2017) analyzed tracer study data using the apriori algorithm with the aim of displaying information on the relationship patterns between attributes in the tracer study to facilitate campus management and gain deeper insight into alumni. Like those who have a GPA above 3, they graduate on time, have a tendency to work according to their majors.

From this background, to find out the pattern of relationships between attributes on tracer study data in Higher Education. The selection of the fp-growth algorithm in this study is because fp-growth is one of several frequently influential pattern mining methodologies, where patterns (sets of items, sequences, substructures) are frequent if their frequency of occurrence in the database is not less than the specified minimum support threshold.

This study aims to provide information on analyzing the relationship pattern between the field of study with ipk, year of entry, year of graduation, waiting period, field of work, salary, gender, position towards alumni employment on tracer study data in Higher Education using the fp-growth algorithm, so that in the future it can be used as an evaluation of the learning process as a whole for mapping and aligning graduate competencies with work needs.

RESEARCH METHOD

This research was carried out by going through four stages including: data collection, data transformation, algorithm implementation, which is the process of exploring and analyzing large amounts of data to obtain something new and useful, and a correlation pattern can be found in the data.

Research Steps

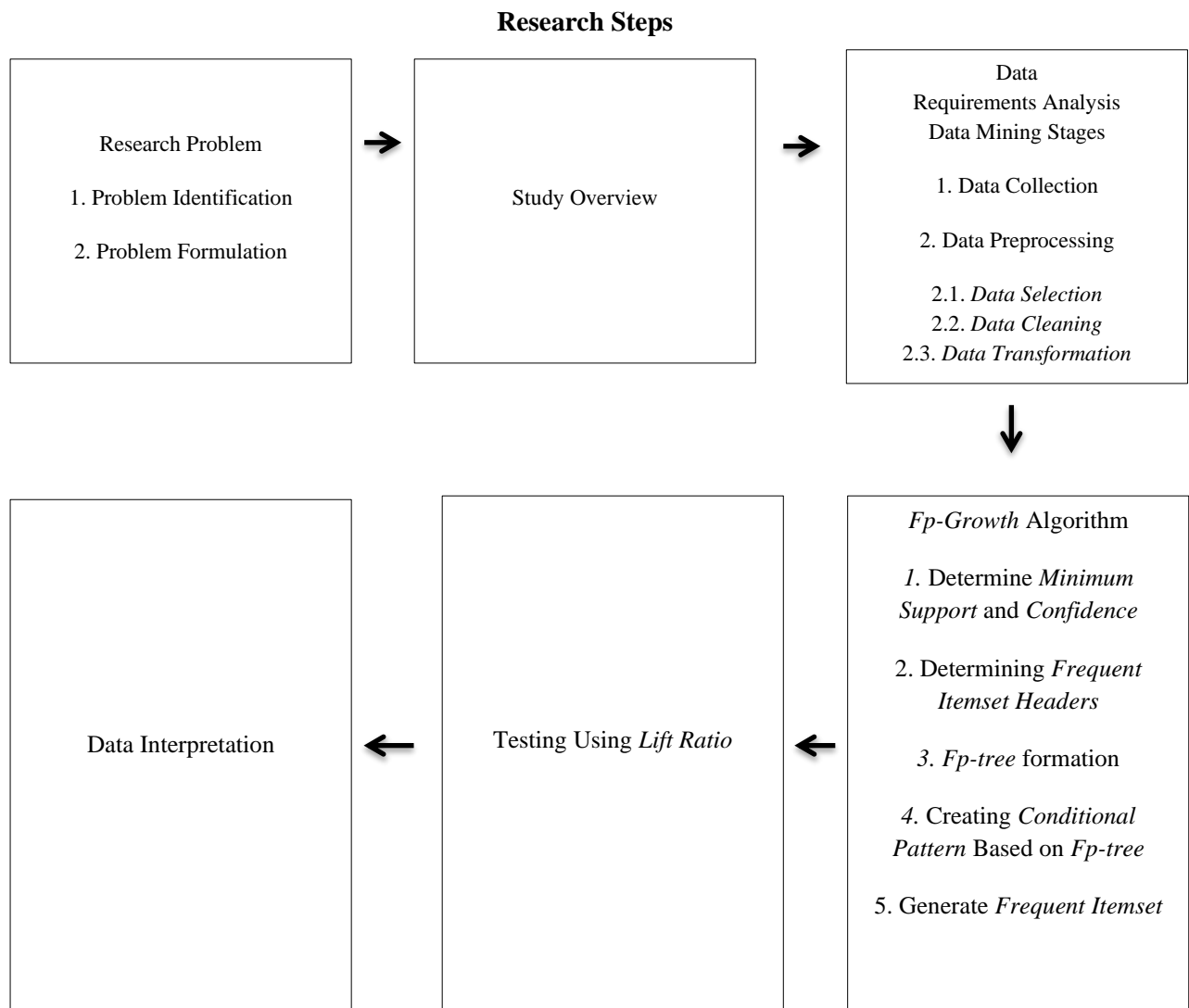| Research Problem 1. Problem Identification 2. Problem Formulation	→	Study Overview	→	Data Requirements Analysis Data Mining Stages 1. Data Collection 2. Data Preprocessing 2.1. *Data Selection* 2.2. *Data Cleaning* 2.3. *Data Transformation*
Data Interpretation	←	Testing Using *Lift Ratio*	←	*Fp-Growth* Algorithm *1.* Determine *Minimum Support* and *Confidence* 2. Determining *Frequent Itemset Headers* *3. Fp-tree* formation *4.* Creating *Conditional Pattern* Based on *Fp-tree* 5. Generate *Frequent Itemset*

Figure 1. Displaying the Research Steps

The following is an explanation of the research flowchart:
1. Research Problem
At this stage, the topic of the problem is determined by examining existing problems, in order to understand and get solutions to these problems. The formulation of the problem on this topic is how to analyze the pattern of alignment of the relationship between the field of study with ipk, year of entry, year of graduation, waiting period, field of work, salary, gender, position towards alumni employment on tracer study data in Higher Education.
2. Study Overview
At this stage, researchers will collect reading materials such as journals, books and papers so that researchers can collect information that is relevant to the research they want to do. This needs to be done so that the research can take place in a directed and structured manner in accordance with the theories obtained to produce the expected output.
3. Data Collection
This stage is the process of collecting data or how to get data. This research uses primary data from the College tracer study questionnaire that graduated in 2016-2020.
4. Data Preprocessing
Data preprocessing, data preprocessing consists of three stages: data selection, data cleaning, and data transformation.

a. Data selection, at this stage the selection of attributes that will be used in this study is carried out. The attributes used are, year of entry, ipk, year graduated, gender, type of first job, suitability of job relationship with major, waiting period to get first job, position.

Table 1. Attribute Data Used

No.	Attribute Name	Description
1.	Study Program	Alumni Study Program
2.	Field of Work	Appropriate Job or Not
3.	Waiting Period	Time lag between graduation and employment
4.	Position	Position Status at Work
5.	Gender	Male/Female
6.	Type of Work	Alumni Employment Type
7.	Year of Entry	Year of Enrollment
8.	Year Graduated	Year Completed
9.	Salary	Salary Amount
10.	GPA	< 3, 3 -3.5, > 3

b. Data cleaning, a stage of cleaning data that contains missing values, inconsistent data, and data discrepancies (outliers).
c. Data transformation, data that has gone through the stages of the data cleaning process is then transformed by determining the frequency of occurrence of the largest to the smallest, then stored into a form that can be applied to the algorithm that will be used later.

Table 2. Data Transformation

Code	Itemset	Frequency	Initials
1	a1	8	11
1	b1	6	12
1	c1	5	13
1	d1	4	14
1	e1	2	15

In Table 1. Determining the initials in the attribute data with the name of the item in the attribute data, as well as determining the attribute ranking of the frequency of occurrence.

5. Fp-Growth Algorithm

This stage discusses how to find frequent itemsets using the FP-Growth algorithm. FP-Tree is used in conjunction with the FP-Growth algorithm to determine frequent itemsets from a dataset.

Input:

1. Tracer study dataset, where each transaction is a set of items. The dataset contains a list of tracer study data attributes, which consists of data on field of study with

ipk, year of entry, year of graduation, waiting period, field of work, salary, gender, position, type of work

Table 3. Tracer Study Dataset

Code	Initials	Itemset
1	11	a1
2	21	b1
3	33	c3
4	42	d2
5	51	e1

2. Determine the desired Minimum Support and Minimum Confidence values. Minimum Support and Minimum Confidence are the minimum thresholdthe number of itemsets allowed, if the number of items is below the threshold then the item will be eliminated.

Process

1. Calculate List Header Support:
   - For each item in the dataset, count the number of occurrences of that item in all transactions.
   - Item support is the number of item occurrences divided by the total transactions.

2. Creating a Header List Support Table
   - Sort the items based on their support in descending order to form a support table.
   - Remove items that do not meet the support threshold from the support table.

Table 4. Header List of Tracer Study Dataset

Itemset	Qty	Support
a1	39	100%
b1	26	66,67%
c3	19	48.72%

Creating a Conditional Pattern Base:
   - For each item in the header list support table, construct the conditional pattern base associated with that item.
   - Conditional pattern base is the set of all interconnected paths of the FP-Tree containing the item.

Table 5. Conditional Pattern Base

Itemset	Conditional Pattern Base
e1	{d2},{c3,d2},{b1,c3,d2},{a1,c3,d2},{b1,d2},{a1,b2,d2},{a1,d2}
d2	{c3},{b1,c3},{a1,b1,c3},{a1,c3}
c3	{b1},{a1,b1}
b1	{a1}
a1	{e1},{d2,e1},{a1,d2,e1},{c3,e1},{a1,e1}

1. Creating a Conditional FP-Tree
   Create a Conditional FP-Tree by forming a top node (root) which is the item with the highest support and a leaf node (leaf) which is the item with the lowest support.

Table 6. Conditional FP-Tree

Itemse	Conditional FP-Tree
e1	{d2:2},{c3,d2:2},{b1,c3,d2:2},{a1,c3,d2:2},{b1,d2:3},{a1,b2,d2:2},{a1,d2:2}
d2	{c3:2},{b1,c3:2},{a1,b1,c3:3},{a1,c3:2}
c3	{b1:1},{a1,b1:2}
b1	{a1:3}
a1	{e1:2},{d2,e1:2},{a1,d2,e1:2},{c3,e1:2},{a1,e1:2}

2. Creating Frequency Patern:
   Frequent Pattern describes the relationship between items in tracer study data attributes that often occur together.

Table 6. Frequency Patern

Itemset	Frequency Patern
e1	d2, c3, b1, a1
d2	c3, b1, a1
c3	b1, a1
b1	a1
a1	e1, d2, a1, e1, c3

Output

3. Association Rules
   Association rules are data analysis used to identify relationships or patterns in data that appear simultaneously in tracer study data. The goal is to find relationships between attributes in the tracer study data.

Table 7. Association Rules

No.	Description	Support	Confidence	Lift Ratio
1.	If e1, d2, c3, b1, then a1	23%	39%	1
2.	If d2, c3, b1, then a1	34%	38%	1
3.	If c3, b1, then a1	43%	43%	1
4.	If b1 then a1	66%	68%	1
5.	If e1, d2, a1, e1, then c3	74%	74%	1

4. Testing Using Lift Ratio
    The patterns generated from the mining process will be tested using the lift ratio, this lift ratio test is carried out to determine whether the associative rules formed are suitable for information. Rules that meet the minimum support and minimum confidence that have been determined will be tested on the lift ratio to measure the validity or invalidity of the data that has been obtained.

5. Interpretation
    The pattern that has been formed from the processing results using the fp-growth algorithm is then translated into meaningful information that is easier to understand.

RESULT AND DISCUSSION

The data that has been obtained from the questionnaire results in 2016-2019 amounted to 6841 tracer study data, then selected according to research needs. The following is selection data using 10 attributes, consisting of study program, ipk, year of entry, year of graduation, waiting period, job, field, salary, position.

Figure 2. Selected data

Data Cleaning
At this stage data cleaning is carried out, such as deleting unnecessary data, or correcting data that has errors in writing, and others. At this stage, researchers used tracer study data at universities in 2016-2019.

Data Transformation

This stage is the process of changing the form of data format that is suitable for data mining processing. In this process, researchers use web applications and postgresql databases for the data transformation process. Data that has been cleaned, will then be transformed so that the mining process can be carried out.

Data Mining Process

Input

Tracer Study Dataset

Tracer study dataset, where each transaction is a set of items. The dataset contains a list of tracer study data attributes, which consists of data on field of study, field of work, waiting period, position, gender, type of work, year of entry, year of graduation, ipk. The following dataset has been transformed into one column, shown in Figure 13, as follows:

1	Informatika
1	Sesuai
1	< 3 Bulan
1	Pegawai Kontrak
1	Laki-Laki
1	Pegawai Swasta
1	Tahun Masuk 2015
1	Tahun Lulus 2019
1	> 3000000 - 1500000
1	IPK 3.0-3.5

Figure 13. Tracer Study Dataset

Determining Support and Confidence Values

Determine the desired Minimum Support and Minimum Confidence values. Minimum Support and Minimum Confidence are the minimum thresholdthe number of itemsets allowed, if the number of items is below the threshold then the item will be eliminated, by finding the minimum support and minimum confidence value of 50%, shown in Figure 18, as follows:

Figure 14. Displaying Support and Confidence Value Input

Process:

- **Header List**

  Determining the Header List (a collection of items that appear simultaneously) on the tracer study data, by taking itemsets that have the largest to smallest frequency of itemsets, shown in Figure 15, as follows:

Figure 15. Header List Result

- **Conditional Pattern Base**

Establishing a Conditional Pattern Base serves as a database that stores high-frequency patterns found in the tracer study dataset. The FP-growth algorithm efficiently extracts association rules from the tracer study data. The database allows FP-growth to avoid rebuilding the search tree that often occurs in association rule mining algorithms such as Apriori, shown in Figure 16, as follows:

No	Keterangan	Conditional Patern Base
	Conditional Patern Base	
1	> 6 bulan	{laki-laki,ipk 3.5-4.0,> 3000000 - 1500000,tidak sesuai,tahun lulus 2019,wirausaha}, {ipk 3.0-3.5,laki-laki,> 3000000 - 1500000,tidak sesuai,tahun lulus 2020,wirausaha,ilmu administrasi publik}
2	ilmu komunikasi	{pegawai swasta,< 3 bulan,sesuai,> 5000000,ipk 3.0-3.5,perempuan,tahun lulus 2019}, {< 3 bulan,> 5000000,ipk 3.0-3.5,perempuan,tidak sesuai,tahun lulus 2019,wirausaha}
3	keperawatan	{pegawai swasta,< 3 bulan,sesuai,> 5000000,ipk 3.0-3.5,perempuan,tahun lulus 2017}, {< 3 bulan,laki-laki,ipk 3.5-4.0,> 3000000 - 1500000,tidak sesuai,tahun lulus 2021,wirausaha}
4	fisika	{pegawai swasta,< 3 bulan,sesuai,ipk 3.0-3.5,laki-laki,> 3000000 - 1500000,tahun lulus 2017}, {pegawai swasta,sesuai,ipk 3.0-3.5,perempuan,> 3000000 - 1500000,< 6 bulan,tahun lulus 2017}
5	hubungan internasional	{pegawai swasta,< 3 bulan,sesuai,> 5000000,ipk 3.0-3.5,perempuan,tahun lulus 2017}, {pegawai swasta,sesuai,> 5000000,perempuan,ipk 3.5-4.0,< 6 bulan,tahun lulus 2017}
6	instansi pemerintah	{< 3 bulan,sesuai,> 5000000,laki-laki,ipk 3.5-4.0,tahun lulus 2021,kebidanan}, {sesuai,> 5000000,laki-laki,ipk 3.5-4.0,tahun lulus 2021,< 6 bulan,kebidanan}
7	ilmu administrasi publik	{< 3 bulan,> 5000000,ipk 3.0-3.5,laki-laki,tidak sesuai,tahun lulus 2020,wirausaha}, {ipk 3.0-3.5,laki-laki,> 3000000 - 1500000,tidak sesuai,tahun lulus 2020,wirausaha}
8	biologi	{pegawai swasta,< 3 bulan,sesuai,> 5000000,perempuan,ipk 3.5-4.0,tahun lulus 2020}, {pegawai swasta,< 3 bulan,sesuai,> 5000000,ipk 3.0-3.5,perempuan,tahun lulus 2020}, {pegawai swasta,< 3 bulan,laki-laki,ipk 3.5-4.0,> 3000000 - 1500000,tidak sesuai,tahun lulus 2020}
9	kebidanan	{pegawai swasta,< 3 bulan,sesuai,ipk 3.0-3.5,perempuan,> 3000000 - 1500000,tahun lulus 2020}, {< 3 bulan,sesuai,> 5000000,laki-laki,ipk 3.5-4.0,tahun lulus 2021}, {sesuai,> 5000000,laki-laki,ipk 3.5-4.0,tahun lulus 2021,< 6 bulan}
10	sistem informasi	{pegawai swasta,< 3 bulan,sesuai,> 5000000,ipk 3.0-3.5,perempuan,tahun lulus 2021}, {pegawai swasta,< 3 bulan,sesuai,perempuan,ipk 3.5-4.0,> 3000000 - 1500000,tahun lulus 2021}, {pegawai swasta,sesuai,> 5000000,perempuan,ipk 3.5-4.0,tahun lulus 2020,< 6 bulan}

Figure 16. Conditional Pattern Base Result

- **Conditional FP-Tree**

Conditional FP-tree on the tracer study data by forming the top node (root) which is the item with the highest support and the leaf node (leaf) which is the item with the lowest support, shown in Figure 21, as follows:

No	Keterangan	Conditional Fp Tree
	Conditional Fp Tree	
1	> 6 bulan	{laki-laki,> 3000000 - 1500000,tidak sesuai,wirausaha}, {laki-laki,> 3000000 - 1500000,tidak sesuai}, {laki-laki,> 3000000 - 1500000,wirausaha}, {laki-laki,tidak sesuai,wirausaha}, {> 3000000 - 1500000,tidak sesuai,wirausaha}, {laki-laki,> 3000000 - 1500000}, {laki-laki,tidak sesuai}, {laki-laki,wirausaha}, {> 3000000 - 1500000,tidak sesuai}, {> 3000000 - 1500000,wirausaha}, {tidak sesuai,wirausaha}, {laki-laki}, {> 3000000 - 1500000}, {tidak sesuai}, {wirausaha}
2	ilmu komunikasi	{< 3 bulan,> 5000000,ipk 3.0-3.5,perempuan,tahun lulus 2019}, {< 3 bulan,> 5000000,ipk 3.0-3.5,perempuan}, {< 3 bulan,> 5000000,ipk 3.0-3.5,tahun lulus 2019}, {< 3 bulan,> 5000000,perempuan,tahun lulus 2019}, {< 3 bulan,ipk 3.0-3.5,perempuan,tahun lulus 2019}, {> 5000000,ipk 3.0-3.5,perempuan,tahun lulus 2019}, {< 3 bulan,> 5000000,ipk 3.0-3.5}, {< 3 bulan,> 5000000,perempuan}, {< 3 bulan,> 5000000,tahun lulus 2019}, {< 3 bulan,ipk 3.0-3.5,perempuan}, {< 3 bulan,ipk 3.0-3.5,tahun lulus 2019}, {< 3 bulan,perempuan,tahun lulus 2019}, {> 5000000,ipk 3.0-3.5,perempuan}, {> 5000000,ipk 3.0-3.5,tahun lulus 2019}, {> 5000000,perempuan,tahun lulus 2019}, {ipk 3.0-3.5,perempuan,tahun lulus 2019}, {< 3 bulan,> 5000000}, {< 3 bulan,ipk 3.0-3.5}, {< 3 bulan,perempuan}, {< 3 bulan,tahun lulus 2019}, {> 5000000,ipk 3.0-3.5}, {> 5000000,perempuan}, {> 5000000,tahun lulus 2019}, {ipk 3.0-3.5,perempuan}, {ipk 3.0-3.5,tahun lulus 2019}, {perempuan,tahun lulus 2019}, {< 3 bulan}, {> 5000000}, {ipk 3.0-3.5}, {perempuan}, {tahun lulus 2019}
3	keperawatan	{< 3 bulan}
4	fisika	{pegawai swasta,sesuai,ipk 3.0-3.5,> 3000000 - 1500000,tahun lulus 2017}, {pegawai swasta,sesuai,ipk 3.0-3.5,> 3000000 - 1500000}, {pegawai swasta,sesuai,ipk 3.0-3.5,tahun lulus 2017}, {pegawai swasta,sesuai,> 3000000 - 1500000,tahun lulus 2017}, {pegawai swasta,ipk 3.0-3.5,> 3000000 - 1500000,tahun lulus 2017}, {sesuai,ipk 3.0-3.5,> 3000000 - 1500000,tahun lulus 2017}, {pegawai swasta,sesuai,ipk 3.0-3.5}, {pegawai swasta,sesuai,> 3000000 - 1500000}, {pegawai swasta,sesuai,tahun lulus 2017}, {pegawai swasta,ipk 3.0-3.5,> 3000000 - 1500000}, {pegawai swasta,ipk 3.0-3.5,tahun lulus 2017}, {pegawai swasta,> 3000000 - 1500000,tahun lulus 2017}, {sesuai,ipk 3.0-3.5,> 3000000 - 1500000}, {sesuai,ipk 3.0-3.5,tahun lulus 2017}, {sesuai,> 3000000 - 1500000,tahun lulus 2017}, {ipk 3.0-3.5,> 3000000 - 1500000,tahun lulus 2017}, {pegawai swasta,sesuai}, {pegawai swasta,ipk 3.0-3.5}, {pegawai swasta,> 3000000 - 1500000}, {pegawai swasta,tahun lulus 2017}, {sesuai,ipk 3.0-3.5}, {sesuai,> 3000000 - 1500000}, {sesuai,tahun lulus 2017}, {ipk 3.0-3.5,> 3000000 - 1500000}, {ipk 3.0-3.5,tahun lulus 2017}, {> 3000000 - 1500000,tahun lulus 2017}, {pegawai swasta}, {sesuai}, {ipk 3.0-3.5}, {> 3000000 - 1500000}, {tahun lulus 2017}
5	hubungan internasional	{pegawai swasta,sesuai,> 5000000,perempuan,tahun lulus 2017}, {pegawai swasta,sesuai,> 5000000,perempuan}, {pegawai swasta,sesuai,> 5000000,tahun lulus 2017}, {pegawai swasta,sesuai,perempuan,tahun lulus 2017}, {pegawai swasta,> 5000000,perempuan,tahun lulus 2017}, {sesuai,> 5000000,perempuan,tahun lulus 2017}, {pegawai swasta,sesuai,> 5000000}, {pegawai swasta,sesuai,perempuan}, {pegawai swasta,sesuai,tahun lulus 2017}, {pegawai swasta,> 5000000,perempuan}, {pegawai swasta,> 5000000,tahun lulus 2017}, {pegawai swasta,perempuan,tahun lulus 2017}, {sesuai,> 5000000,perempuan}, {sesuai,> 5000000,tahun lulus 2017}, {sesuai,perempuan,tahun lulus 2017}, {> 5000000,perempuan,tahun lulus 2017}, {pegawai swasta,sesuai}, {pegawai swasta,> 5000000}, {pegawai swasta,perempuan}, {pegawai swasta,tahun lulus 2017}, {sesuai,> 5000000}, {sesuai,perempuan}, {sesuai,tahun lulus 2017}, {> 5000000,perempuan}, {> 5000000,tahun lulus 2017}, {perempuan,tahun lulus 2017}, {pegawai swasta}, {sesuai}, {> 5000000}, {perempuan}, {tahun lulus 2017}

Figure 17. Conditional FP-tree result

- **Frequency Patern**

Frequent Pattern forms a relationship between items in the tracer study data attributes that often occur together, shown in Figure 22, as follows:

No	Keterangan	Frequent Patern
1	> 6 bulan	laki-laki, > 3000000 - 1500000, tidak sesuai, wirausaha, > 6 bulan
2	ilmu komunikasi	< 3 bulan, > 5000000, ipk 3.0-3.5, perempuan, tahun lulus 2019, ilmu komunikasi
3	fisika	pegawai swasta, sesuai, ipk 3.0-3.5, > 3000000 - 1500000, fisika
4	hubungan internasional	pegawai swasta, sesuai, > 5000000, perempuan, hubungan internasional
5	instansi pemerintah	sesuai, > 5000000, laki-laki, ipk 3.5-4.0, tahun lulus 2021, instansi pemerintah
6	ilmu administrasi publik	ipk 3.0-3.5, laki-laki, tahun lulus 2020, wirausaha, ilmu administrasi publik
7	biologi	pegawai swasta, < 3 bulan, sesuai, perempuan, tahun lulus 2020, biologi
8	kebidanan	> 5000000, laki-laki, ipk 3.5-4.0, tahun lulus 2021, kebidanan
9	sistem informasi	pegawai swasta, < 3 bulan, perempuan, tahun lulus 2021, sistem informasi
10	manajemen	pegawai swasta, < 3 bulan, sesuai, > 5000000, manajemen

Figure 18. Frequency Pattern Results

Output

- **Association Rule Result**

The results of association rules on the tracer study data by forming a set of rules found in the process of mining association rules from the dataset using an algorithm such as FP-growth, are shown in Figure 23, as follows:

Hasil Asosiasi Fp-Growth

Show 10 entries

No	Rule
1	Jika laki-laki, > 3000000 - 5000000, tidak sesuai, wirausaha maka > 6 bulan
2	Jika laki-laki, > 3000000 - 5000000, tidak sesuai, > 6 bulan maka wirausaha
3	Jika < 3 bulan, perempuan, ilmu komunikasi maka > 5000000, ipk 3.0-3.5
4	Jika > 5000000, ipk 3.0-3.5, perempuan maka < 3 bulan, ilmu komunikasi
5	Jika > 5000000, ipk 3.0-3.5, ilmu komunikasi maka < 3 bulan, perempuan
6	Jika pegawai swasta, sesuai, > 5000000, tahun lulus 2017 maka perempuan, hubungan internasional
7	Jika pegawai swasta, sesuai, > 5000000, hubungan internasional maka perempuan, tahun lulus 2017
8	Jika pegawai swasta, sesuai, > 3000000 - 5000000, tahun lulus 2017 maka ipk 3.0-3.5, fisika
9	Jika pegawai swasta, sesuai, > 3000000 - 5000000, fisika maka ipk 3.0-3.5, tahun lulus 2017
10	Jika pegawai swasta, sesuai, tahun lulus 2017, fisika maka ipk 3.0-3.5, > 3000000 - 5000000

Figure 18. Association Rule Results

CONCLUSION

Based on the results of research in analyzing tracer study data using data mining fp-growth associations exclusively in extracting hidden information from tracer study data to find out patterns of alignment of the relationship between fields of study with ipk, year of entry, year of graduation, waiting period, type of work, salary, gender, position, field of work of alumni, The following conclusions can be drawn from the above research are Patterns generated by the fp-growth algorithm with minimum support and minimum confidence can produce several patterns of attendents in the form of fields of study, ipk, year of entry, year of graduation, waiting period, field of work, salary, gender, position.

Interpretation of some interesting patterns: 1. If the GPA is 3-3.5 and the gender is female, then there is a 56% tendency to get a job less than 3 months after graduating with a Communication Science study program, and get a salary of more than Rp. 5,000,000. 2. If the GPA is 3-3.5 and the physics study program then it has a tendency of 67% with the type of work as a private employee, and get a salary of Rp. 3,000,000 to 5,000,000. 3. If the GPA is 3-3.5 and the gender is female, the international relations study program then has a 69% tendency with the type of work as a private employee, and get a salary of more than more than Rp. 5,000,000. 4. If the GPA is 3.5-4.0 and the midwifery study program, with the appropriate field of work, then it has a 72% tendency with the type of work in government agencies, and getting a salary of more than Rp. 5,000,000. 5. If the GPA is 3.5-4.0 and the study program is information systems, with the appropriate field of work, it has a tendency of 78% with the type of work as a private employee, and get a salary of more than Rp. 5,000,000.

From several patterns taken, it can be a proposal for the study program in making future policies, namely: 1. From the patterns obtained, it can be concluded that students with female gender who have ipk 3-3.5 tend to get jobs quickly. This can be a consideration for related parties by emphasizing learning to male students both in theory and practice. 2. Students who have ipk more than 3.5, get a job less than 6 months after graduation, and the appropriate field of work. From this data, it can be a consideration for study programs in educating and implementing curriculum in accordance with current work needs for students so that they can get jobs that are in accordance with their field of study. Future research is expected to use the latest research data and use more complete attribute data needed

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