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Recommendation System for Major University Determination Based on Student's Profile and Interest

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Abstract - Failure study on university students is one of the serious problems we face today. Data from the Centre for Education Statistics Research and Development of the Ministry of the National Education Republic of Indonesia showed that the percentage of students graduate on time from 2001 to 2011 only reached 51.97%. In addition, cases of students dropping out at the beginning of the semester are also quite significant. One of the causes of failure of this study was the selection of major's errors when applying to university. This study offers a selection subject recommendation system that builds on the profile data and student's interest using the technique of Association Rule. Results of the rules of the relationship will then be matched with prospective students using questionnaires dynamic, so expect new students get recommendations more valid subject fit the profile and interest respectively.
The system built on this research utilizes student data stored on the academic system of Dian Nuswantoro University. This model, however, can be adapted by all the universities that have a system of academic information. At the end of this system is expected to be used to minimize failures caused students study majors election mistakes

Keywords - recommendation system, student profile, major determination

1. INTRODUCTION

The percentage of the number of university students graduating on time is one of the factors that determine the quality of higher education (PP No. 66 of 2010). Based on data from the Centre for Education Statistics Research and Development of the Ministry of National Education Republic of Indonesia, from 3011 the number of universities in Indonesia, in 2001 to 2010 the universities receives an average of 868.050 students and just graduated an average of 451.168 students annually or only reached 51.97% of the number of new students [1]. Meanwhile, in Central Java, 250 organizing institutions and private universities recorded 73.656 new students by the number of students (student body) 325.358 and the number of graduates only 53.307.

Even for major universities such as Tenth of November of Institute of Technology (ITS), the inadequate number of graduates is also a problem, as revealed in the study [2]. The study showed that of the 434 students of ITS, the majority of students drop out in the second and fourth semester with an average value of grade point average (GPA) and TPB students drop out each is 1.7908. A total of 49.8% of students drop out was 18 years old in which 338 of the 434 students who dropped out came from East Java. The percentage of students drop out coming from public schools amounted to 77% with the work of parents most are civil servants with the majority earning between 500.000-2.500.000. Of the 434 students, 281 people entered through SNMPTN.

One of the factors of failure of students in the academic field is because majors are selected not according to the interests and abilities of the students. The tendency of prospective students to enroll because they follow trends or coercion of parents that have a negative impact on students' academic performance. Students who choose the wrong department cannot follow the lectures delivered resulting in lower self-esteem, and ultimately resulted in the failure of his studies. Although no further research on the impact of one of the major's election, but some news from media such as [3] and [4] found a tendency for students to drop out at the beginning of the semester because failed to choose majors.

Prospective new students require a recommendation electoral college majors or courses that suit their interests and abilities, not only based on the recommendation of friends or family who may have different interests and talents. Recommendations will be valid if it is based on data and experience of other students who had entered the previous lectures.

Dian University Nuswantoro (Udinus) has academic information system which is referred to as SiAdin. It stores the profile data of students and students' academic history from the first entrance until graduation. Information stored on the SiAdin can be used as knowledge [5] majors determination recommendation system using data mining techniques [6]. However, no one has utilized that data to be a recommendation system. One reason for the data stored in SiAdin still not sufficient to be a recommendation system.

This study seeks to develop a recommendation system by utilizing data mining techniques to data SiAdin, then use a questionnaire to fill the shortage of necessary data.

2. LITERATURE REVIEW

2.1. Recommendation System

The recommendation system is an application program that is used to give a suggestion of a product, service, and information of an object to the potential consumers [7]. This system is commonly used in electronic shopping business to offer certain products to consumers based on their own liking. Besides being used in online trading, recommendation system is also widely used in social networking applications [8] to give suggestions to the user, on the other users who may be known, or have an affinity with that user.

Association rule data mining techniques are usually used to build systems of this recommendation, as in [9], [10], and [11]. So that the recommendations given not merely based on conjecture, but is derived from empirical facts that exist. Besides the excess use of data mining as a tool to make the recommendation is a rule or recommendation knowledge can be updated based on the new facts that might emerge and affect the outcome.

2.2. Recommendation Systemin Education

Some studies addressing the use in the education system recommendations include [12] which uses a procedural approach, translating the results of interviews with education experts to the tree rules used as an engine to choose the right direction. Disadvantages of this system are the use of must perform a series of Academic Potential Test (TPA) in advance to get a recommendation. Besides the decision tree is made certain, may not automatically change even though there are new facts or new knowledge from other experts.

Another study using a recommendation system in education is [13]. In that research, using association rule mining the data to determine student thesis topic selection is based on academic performance while studying in college. Although using the same technique, the implementation of these studies differs with this research, especially on the implementation and processing of data.

2.3. Data Mining in Education

Data mining in education known as the Educational Data Mining (EDM) [14]. Educational Data Mining appears to be related to the development of methods to explore the educational data to better understand the behavior of students. By understanding the behavior of students, it can be predicted that potential students fail academically.

Research on the classification of data mining algorithms for the prediction of potential students who have dropped outdone by [15] using the 354 students of Hellenic Open University as a data set. In [15] classifying two groups of attributes, namely: based curriculum and student performance. Attribute groups consist of a curriculum based on gender, age, marital status, the number of children, employment, computer capabilities, and relationships with computer work. As for student performance attributes in the group consisting of face-1, the task of the 1st, 2nd face to face, and the task of the 2nd. The implementation used is Weka. In [15] using six algorithms are decision tree, neural network, naïve Bayes, instance-based learning, logistic regression, and support vector machine.

Research by [16] investigated the socio-demographic background of the students by using attributes (age, sex, ethnicity, education, employment status and shortcomings) and the study environment (courses and course block). Data were analyzed using SPSS Statistics 17 and 8. 6.

The study was conducted to determine the factors that affect the smooth or drop out students at the Open Polytechnic of New Zealand by using a data set of 450 students used the CART algorithm.

3. RESULTS AND DISCUSSION

At the time of writing, the process of new admissions in 2016 in UDINUS still running. Thus, the authors use data on students of the Faculty of Computer Science in 2014 and 2015 as an example and sampling. Interview and literature review are conducted to collect data.

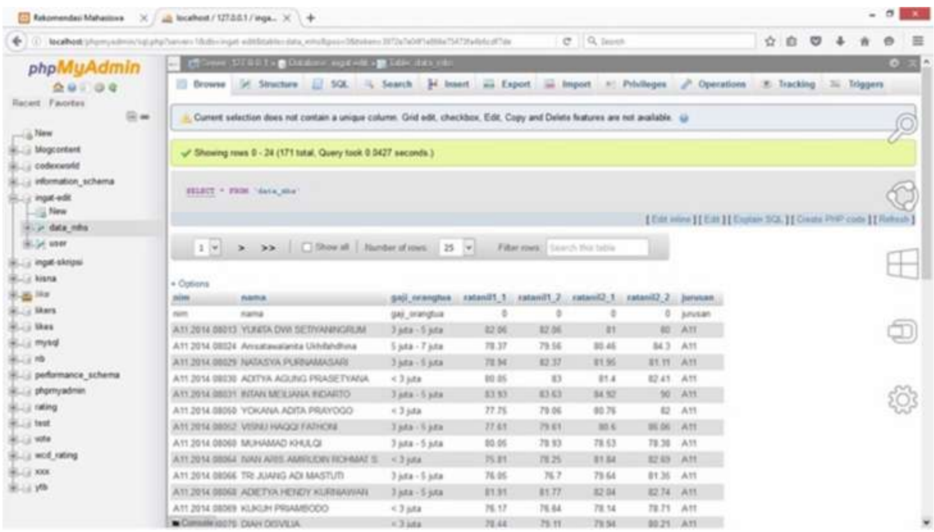

Figure 1. Database Configuration

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This recommendation system is structured on two separate but interrelated parts. The first part, called the back-end system is the part that refers to programs and scripts that work on the server behind the scenes to create a dynamic display. Some of the tasks that usually takes place on the back-end are:

1. Design of information, such as how information is organized on the server
2. Form processing
3. Connection to database

Some tasks of back-end systems are presented in the following figures.

index.php

```php
<?php
/*    error_reporting(1);
    @session_start();
    include "inc/konneksi.php";




if(@$_SESSION['admin']) {
    header("location: admin/indexAdmin.php");
} else if(@$_SESSION['user']) { */
?>
<!DOCTYPE html>


<html lang="en">

<head>

    <meta charset="utf-8">
    <meta http-equiv="X-UA-Compatible" content="IE=edge">
    <meta name="viewport" content="width=device-width, initial-scale=1">
    <meta name="description" content="">
    <meta name="author" content="">

    <title>Rekomendasi Mahasiswa</title>

    <!-- Bootstrap Core CSS -->
    <link href="css/bootstrap.min.css" rel="stylesheet">
    <link href="style/style.css" rel="stylesheet" type="text/css">

    <!-- Custom CSS -->
    <link href="css/shop-homepage.css" rel="stylesheet">


    <!-- HTML5 Shim and Respond.js IE8 support of HTML5 elements and media queries -->
    <!-- WARNING: Respond.js doesn't work if you view the page via file:// -->
    <!--[if lt IE 9]>
        <script src="https://oss.maxcdn.com/libs/html5shiv/3.7.0/html5shiv.js"></script>
        <script src="https://oss.maxcdn.com/libs/respond.js/1.4.2/respond.min.js"></script>
    <![endif]-->
<?php
```

```php
<?php
    class NaiveBayes{
    static function classify($table,$features,$category){
        $db=new pdo('mysql:host=localhost;dbname=ingat-edit',"root","");
        $db->setAttribute(PDO::ATTR_DEFAULT_FETCH_MODE,PDO::FETCH_ASSOC);
        $sql="select distinct($category) from $table";

        $arg=array();
        foreach($db->query($sql)->fetchAll() as $row){
            $ck=key($row);
            $cv=current($row);
            $arg[$cv]=1;
            $fs='';
            foreach($features as $fk=>$fv){
                $fs.=" ,sum($ck='$cv' and $fk='$fv') ";
            }
            $sql="select sum($ck='$cv') $fs from $table";
            foreach($db->query($sql)->fetchAll()  as $count_row){
                //print_r($count_row);
                $category_count=array_shift($count_row);

                $exp=0;

                foreach($count_row as $count){
                    if(!$count){
                        $count=0.00001;
                    }
                    $arg[$cv]*=$count;
                    $exp++;

                }
                $arg[$cv]=$arg[$cv]/pow($category_count,$exp-1);
            }
        }
         return current(array_keys($arg,max($arg)));

    }
}
?>
```

Figure 2. Back-end system tasks.

```sql
CREATE TABLE `data_mhs` (
  `nim` varchar(15) NOT NULL,
  `nama` varchar(100) NOT NULL,
  `gaji_orangtua` varchar(20) NOT NULL,
  `ratanil1_1` float NOT NULL,
  `ratanil1_2` float NOT NULL,
  `ratanil2_1` float NOT NULL,
  `ratanil2_2` float NOT NULL,
  `jurusan` varchar(10) NOT NULL
) ENGINE=InnoDB DEFAULT CHARSET=latin1;

--
-- Dumping data for table `data_mhs`
--

INSERT INTO `data_mhs` (`nim`, `nama`, `gaji_orangtua`, `ratanil1_1`, `ratanil1_2`, `ratanil2_1`, `ratanil2_2`, `jurusan`) VALUES
('nim', 'nama', 'gaji_orangtua', 0, 0, 0, 0, 'jurusan'),
('A11.2014.08013', 'YUNITA DWI SETIYANINGRUM', '3 juta - 5 juta', 82.06, 82.06, 81, 80, 'A11'),
('A11.2014.08024', 'Anisatawalanita Ukhifahdhina', '5 juta - 7 juta', 78.37, 79.56, 80.46, 84.3, 'A11'),
('A11.2014.08029', 'NATASYA PURNAMASARI', '3 juta - 5 juta', 78.94, 82.37, 81.95, 81.11, 'A11'),
('A11.2014.08030', 'ADITYA AGUNG PRASETYANA', '< 3 juta', 80.05, 83, 81.4, 82.41, 'A11'),
('A11.2014.08031', 'INTAN MEILIANA INDARTO', '3 juta - 5 juta', 83.93, 83.63, 84.92, 90, 'A11'),
('A11.2014.08050', 'YOKANA ADITA PRAYOGO', '< 3 juta', 77.75, 79.06, 80.76, 82, 'A11'),
('A11.2014.08052', 'VISNU HAQQI FATHONI', '3 juta - 5 juta', 77.61, 79.61, 80.6, 86.06, 'A11'),
('A11.2014.08060', 'MUHAMAD KHULQI', '3 juta - 5 juta', 80.05, 78.93, 78.53, 78.38, 'A11'),
('A11.2014.08064', 'IVAN ARIS AMIRUDIN ROHMAT S.', '< 3 juta', 75.81, 78.25, 81.84, 82.69, 'A11'),
('A11.2014.08066', 'TRI JUANG ADI MASTUTI', '3 juta - 5 juta', 76.05, 76.7, 79.64, 81.35, 'A11'),
('A11.2014.08068', 'ADIETYA HENDY KURNIAWAN', '3 juta - 5 juta', 81.91, 81.77, 82.04, 82.74, 'A11'),
('A11.2014.08069', 'KUKUH PRIAMBODO', '< 3 juta', 76.17, 76.64, 78.14, 78.71, 'A11'),
('A11.2014.08070', 'DIAH DISVILIA', '< 3 juta', 78.44, 79.11, 79.94, 80.21, 'A11'),
('A11.2014.08071', 'GUFIANDRE SETYO IRAWAN', '3 juta - 5 juta', 77, 78, 77, 77, 'A11'),
('A11.2014.08077', 'IRHAM FERDIANSYAH KATILI', '3 juta - 5 juta', 79.56, 79.31, 79.46, 79.15, 'A11'),
('A11.2014.08084', 'DIAN RIZKI WAHYUNINGRUM', '3 juta - 5 juta', 78.41, 79.23, 78.92, 80.57, 'A11'),
('A11.2014.08086', 'MICHAEL ALEXANDRO PUTRA', '< 3 juta', 68.45, 68.94, 74.23, 74.82, 'A11'),
('A11.2014.08088', 'MUKHAMMAD IKHSAN ERLANSYA', '5 juta - 7 juta', 75.59, 76.88, 77.45, 77, 'A11'),
('A11.2014.08091', 'YAFIE MUHAMMAD NOER', '5 juta - 7 juta', 77, 77.87, 75.92, 76.69, 'A11'),
('A11.2014.08094', 'ABID MACHASIN', '< 3 juta', 80, 82.42, 81.18, 81.13, 'A11'),
('A11.2014.08095', 'SYAHRUL YUDA ADI WIJAYA', '3 juta - 5 juta', 79.13, 80.32, 80.14, 82.47, 'A11'),
('A11.2014.08096', 'STEVEN THEO HATMA', '< 3 juta', 70, 73.38, 78.62, 79.23, 'A11'),
('A11.2014.08098', 'MUHAMMAD ABID HAFIZHUDDIN', '< 3 juta', 80.05, 82.52, 82.05, 81.13, 'A11'),
('A11.2014.08102', 'YUDIT ARUM MEKARSARI', '< 3 juta', 83.47, 83.95, 83.42, 83.77, 'A11'),
('A11.2014.08110', 'DIMAS AULIA FADHIL', '3 juta - 5 juta', 75.56, 75.81, 76.77, 79.15, 'A11'),
('A11.2014.08111', 'IBNU YASIN', '3 juta - 5 juta', 80.9, 82.3, 83.7, 83.7, 'A11'),
('A11.2014.08115', 'NUR KHOLIS MAJID', '3 juta - 5 juta', 76.93, 77.06, 78.38, 79.07, 'A11'),
('A11.2014.08117', 'HICO PURWANTO', '3 juta - 5 juta', 78.5, 80, 79.9, 81, 'A11'),
('A11.2014.08119', 'ENDJELIS HILMA LOVITA', '< 3 juta', 81.23, 83.31, 84.56, 85.89, 'A11'),
('A11.2014.08121', 'KOO, YUSTIAN KURNIAWAN', '< 3 juta', 71, 79.24, 74.65, 78.32, 'A11'),
('A11.2014.08122', 'DHIA AYU SHARITA', '3 juta - 5 juta', 79.13, 82.25, 80.99, 82, 'A11'),
('A11.2014.08123', 'DELANGGA GEOFANA', '3 juta - 5 juta', 77.56, 78.56, 78.62, 78.31, 'A11'),
('A11.2014.08124', 'NUR LAELATUL ROHMAH', '3 juta - 5 juta', 81.89, 83.22, 82.59, 83.3, 'A11'),
('A11.2014.08125', 'WIDMA INKA APRIASTI', '3 juta - 5 juta', 81.69, 85.68, 84, 81.43, 'A11'),
('A11.2014.08129', 'FADYLLAH FARHAN', '3 juta - 5 juta', 80.25, 79.43, 81.23, 81.38, 'A11'),
('A11.2014.08136', 'SATRIA BINTANG PERKASA', '5 juta - 7 juta', 78.12, 77.75, 79.77, 81.09, 'A11'),
('A11.2014.08140', 'DENY SETIAJI', '3 juta - 5 juta', 86.1, 85.25, 81.7, 83.47, 'A11'),
('A11.2014.08142', 'IVANDA HALIMAWAN DANISWARA', '3 juta - 5 juta', 77.53, 76.87, 79.76, 78.76, 'A11'),

CREATE TABLE `user` (
  `id_user` int(11) NOT NULL,
  `email` varchar(40) NOT NULL,
  `password` varchar(40) NOT NULL,
  `level` enum('admin','user') NOT NULL
) ENGINE=MyISAM DEFAULT CHARSET=latin1;

--
-- Dumping data for table `user`
--

INSERT INTO `user` (`id_user`, `email`, `password`, `level`) VALUES
(1, 'admin', '21232f297a57a5a743894a0e4a801fc3', 'admin'),
(2, 'user1', 'ee11cbb19052e40b07aac0ca060c23ee', 'user'),
(3, 'user2', 'ee11cbb19052e40b07aac0ca060c23ee', 'user');

--
-- Indexes for dumped tables
--

--
-- Indexes for table `user`
--
ALTER TABLE `user`
  ADD PRIMARY KEY (`id_user`);

--
-- AUTO_INCREMENT for dumped tables
--

--
-- AUTO_INCREMENT for table `user`
--
ALTER TABLE `user`
  MODIFY `id_user` int(11) NOT NULL AUTO_INCREMENT, AUTO_INCREMENT=4;
/*!40101 SET CHARACTER_SET_CLIENT=@OLD_CHARACTER_SET_CLIENT */;
/*!40101 SET CHARACTER_SET_RESULTS=@OLD_CHARACTER_SET_RESULTS */;
/*!40101 SET COLLATION_CONNECTION=@OLD_COLLATION_CONNECTION */;
```

Figure 3: Representation of the data in the back-end.

1	nim	nama	gaji_orangtua	ratanil1_1	ratanil1_2	ratanil2_1	ratanil2_2	jurusan
2	A11.2014.08013	YUNITA DWI SETIYANINGRUM	3 juta - 5 juta	82.06	82.06	81	80	A11
3	A11.2014.08024	Anisatawalanita Ukhifahdhina	5 juta - 7 juta	78.37	79.56	80.46	84.3	A11
4	A11.2014.08029	NATASYA PURNAMASARI	3 juta - 5 juta	78.94	82.37	81.95	81.11	A11
5	A11.2014.08030	ADITYA AGUNG PRASETYANA	< 3 juta	80.05	83	81.4	82.41	A11
6	A11.2014.08031	INTAN MEILIANA INDARTO	3 juta - 5 juta	83.93	83.63	84.92	90	A11
7	A11.2014.08050	YOKANA ADITA PRAYOGO	< 3 juta	77.75	79.06	80.76	82	A11
8	A11.2014.08052	VISNU HAQQI FATHONI	3 juta - 5 juta	77.61	79.61	80.6	86.06	A11
9	A11.2014.08060	MUHAMAD KHULQI	3 juta - 5 juta	80.05	78.93	78.53	78.38	A11
10	A11.2014.08064	IVAN ARIS AMIRUDIN ROHMAT S.	< 3 juta	75.81	78.25	81.84	82.69	A11
11	A11.2014.08066	TRI JUANG ADI MASTUTI	3 juta - 5 juta	76.05	76.7	79.64	81.35	A11
12	A11.2014.08068	ADIETYA HENDY KURNIAWAN	3 juta - 5 juta	81.91	81.77	82.04	82.74	A11
13	A11.2014.08069	KUKUH PRIAMBODO	< 3 juta	76.17	76.64	78.14	78.71	A11
14	A11.2014.08070	DIAH DISVILIA	< 3 juta	78.44	79.11	79.94	80.21	A11
15	A11.2014.08071	GUFIANDRE SETYO IRAWAN	3 juta - 5 juta	77	78	77	77	A11
16	A11.2014.08077	IRHAM FERDIANSYAH KATILI	3 juta - 5 juta	79.56	79.31	79.46	79.15	A11
17	A11.2014.08084	DIAN RIZKI WAHYUNINGRUM	3 juta - 5 juta	78.41	79.23	78.92	80.57	A11
18	A11.2014.08086	MICHAEL ALEXANDRO PUTRA	< 3 juta	68.45	68.94	74.23	74.82	A11
19	A11.2014.08088	MUKHAMMAD IKHSAN ERLANSYA	5 juta - 7 juta	75.59	76.88	77.45	77	A11
20	A11.2014.08091	YAFIE MUHAMMAD NOER	5 juta - 7 juta	77	77.87	75.92	76.69	A11
21	A11.2014.08094	ABID MACHASIN	< 3 juta	80	82.42	81.18	81.13	A11
22	A11.2014.08095	SYAHRUL YUDA ADI WIJAYA	3 juta - 5 juta	79.13	80.32	80.14	82.47	A11
23	A11.2014.08096	STEVEN THEO HATMA	< 3 juta	70	73.38	78.62	79.23	A11
24	A11.2014.08098	MUHAMMAD ABID HAFIZHUDDIN	< 3 juta	80.05	82.52	82.05	81.13	A11
25	A11.2014.08102	YUDIT ARUM MEKARSARI	< 3 juta	83.47	83.95	83.42	83.77	A11
26	A11.2014.08110	DIMAS AULIA FADHIL	3 juta - 5 juta	75.56	75.81	76.77	79.15	A11
27	A11.2014.08111	IBNU YASIN	3 juta - 5 juta	80.9	82.3	83.7	83.7	A11
28	A11.2014.08115	NUR KHOLIS MAJID	3 juta - 5 juta	76.93	77.06	78.38	79.07	A11
29	A11.2014.08117	HICO PURWANTO	3 juta - 5 juta	78.5	80	79.9	81	A11
30	A11.2014.08119	ENDJELIS HILMA LOVITA	< 3 juta	81.23	83.31	84.56	85.89	A11
31	A11.2014.08121	KOO, YUSTIAN KURNIAWAN	< 3 juta	71	79.24	74.65	78.32	A11

Figure 4: Representation of the data in real number

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Vol. 2 No. 1, April 2017, pp. 21 – 28

The second part is called front-end system. This section refers to all sectors ranging from the design process to the system recommendation interface. In general, several tasks at the front-end are:

1. Graphic design and image creation
2. Interface design
3. The design of information related to the ease of users utilizing the system.

Figure 5: Main view of the recommendation system.

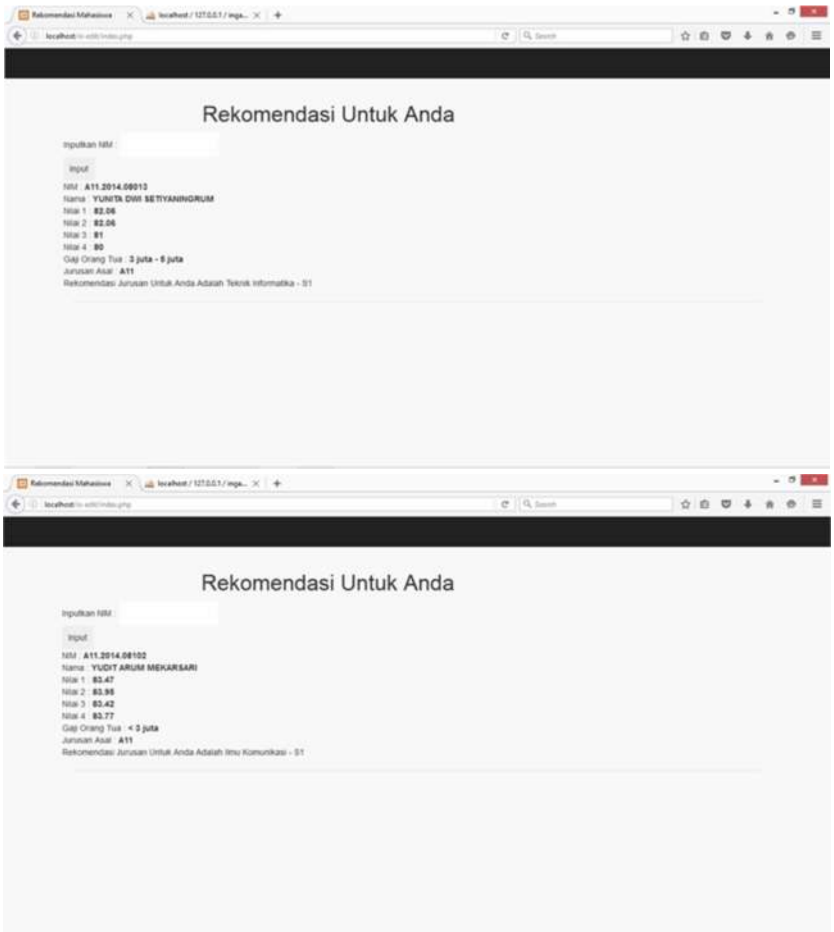

Figure 6: Student’s major recommendation result

4. CONCLUSION

This study offers a selection subject recommendation system that builds on the profile data and student interest, using the technique of Association Rule. Prospective new students get recommendations more valid, to fit the profile and interest respectively.

The system built on this research was utilizing student data stored on SiAdin. Due to the use of Data Mining techniques, rules of relationships created can be updated quickly when getting new facts that effect, without having to dismantle the system.

Although the case studies used are in University of Dian Nuswantoro, a model built can be adapted by all the universities that have a system of academic information, to minimize failures on student's major's election

REFERENCES

[1] Hastuti, K., 2012. Analisis Komparasi Algoritma Klasifikasi Data Mining until Prediksi Mahasiswa Notif. Seminar Nasional Teknologi Informasi & Komunikasi Terapan (Semantic) 2012

[2] Khoirunnisak, M., 2011. Pemodelan Faktor-Faktor yang Mempengaruhi Mahasiswa Berhenti Studi (Drop Out) di Institut Teknologi Sepuluh Nopember Surabaya Menggunakan Analisis Bayesian Mixture Survival. Skripsi S1 Statistika Institut Teknologi Sepuluh November

[3] DO Akibat Salah Jurusan, 2013, dikes pada 10 Juni 2013, http://edukasi.kompas.com/read/2010/11/10/05360848/DO.akibat.Salah.Jurusan

[4] Awas, Salah Jurusan Fatal Akibatnya!, 2013, accessed on 11 Juni 2013 http://campuslifemagz.beritasatu.com/landing.php?kategori=study&id=388

[5] El-Haley, A., 2008. Mining Students Data to Analyze Learning Behavior: A Case Study. In Proceeding of The 2008 International Arab Conference on Information Technology (ACIT2008)

[6] Witten, I. H., Frank, E., & Hall, M. A., 2011. Data Mining: Practical Machine Learning Tools and Techniques. Morgan Kaufmann

[7] Huang, Z., Zeng, D., & Chen, H., 2006. A Comparative Study of Recommendation Algorithms for E-Commerce Applications. IEEE Intelligent Systems

[8] Özseyha, C., Badur, B., & Darcan, O. N., 2012. An Association Rule-Based Recommendation Engine for an Online Dating Site. Communications of the IBIMA

[9] Mican, D., & Tomai, N., 2010. Association-Rules-Based Recommender System for Personalization in Adaptive Web-Based Applications, 10th International Conference on Web Engineering ICWE. Springer-Verlag

[10] Smith, B., McCarthy, K., Reilly, J., O'Sullivan, D., McGinty, L., & Wilson, D. C., 2005. Case Studies in Association Rule Mining for Recommender Systems. In Proc. of International Conference on Artificial Intelligence (ICAI'05)

[11] Lin, W., Alvarez, S. A., & Ruiz, C., 2000. Collaborative Recommendation via Adaptive Association Rule Mining. In Proceedings of the International Workshop on Web Mining for E-Commerce (WEBKDD)

[12] Nurfitriana, N., Darmawan, I., & Akbar, R. E., 2012. Rancang Bangun Aplikasi Sistem Pakar Berbasis Web untuk Rekomendasi Pemilihan 12 Jurusan di Universitas Siliwangi. Jurnal e-Informatika Siliwangi vol. 1, no. 1, 2012

[13] Diahpangastuti, N., 2012. Sistem Rekomendasi Bidang Minat Siswa dengan Metode Association Rule dan Algoritma Apriori. Skripsi S1 Teknik Informatika FTIF Institut Teknologi Sepuluh November

[14] Marquez-Vera, C., Romero, C., & Ventura, S., 2011. Predicting School Failure using Data Mining. In Proceedings of the 4th International Conference on Educational Data Mining (pp. 271-276)

[15] Kotsiantis, S., 2010. Educational Data Mining: A Case Study for Predicting Dropout-Prone Students. Int. J. of Knowledge Engineering and Soft Data Paradigms, (pp 101-111)

[16] Kovacic, Z. J., 2010. Early Prediction of Student Success: Mining Students Enrolment Data. In Proceedings of Informing Science & IT Education Conference (InSITE) (pp. 647-665)