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Analysis of Traffic Accident Patterns Using Association Rule Mining

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Abstract

This study analyzed the levels of minor, moderate, and severe traffic accidents in the Palembang Police area from 2015 to 2020 using association rule mining and the apriori algorithm. The study established valuable insights into accident trends and contributing factors by leveraging traffic accident data and determining variable relationships. With a minimum support threshold of 0.05 and a confidence value of 0.5, the processed data revealed 349 total incidents, categorized as follows: 58 minor accidents (16.62%), 168 moderate accidents (48.14%), and 123 severe accidents (35.24%). The findings highlight that moderate-level accidents form the majority, underlining the need for targeted interventions in this category. The application of the apriori algorithm facilitated the identification of frequent itemsets and rules that reveal patterns across accident variables, such as road conditions, road functions, accident types, weather conditions, and victim statuses. This study also demonstrated the practicality of the apriori algorithm in analyzing extensive datasets to extract actionable insights. The processed rules can be a foundation for developing predictive models or decision-making tools to mitigate accident risks. For example, analyzing variables at different accident levels allows policymakers to identify critical factors contributing to accidents, implement tailored safety measures, and prioritize infrastructure improvements. Furthermore, the study emphasizes the potential of data-driven traffic management and accident prevention approaches. By incorporating modern data mining techniques, stakeholders can transition from traditional data recapitulation to predictive analytics, enabling proactive measures for public safety. Future research can build upon this work by integrating real-time data sources, such as IoT-based traffic monitoring systems, to enhance the prediction accuracy and scope of analysis. Further exploration of mid- and low-confidence rules may provide insights into rare but critical patterns, offering a more comprehensive understanding of accident dynamics. Overall, this research is crucial to leveraging advanced computational methods for public safety and traffic accident reduction, aligning with global efforts to improve road safety and minimize fatalities.

Keywords

Apriori, Association Rule, Accident, Accident Rate

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Introduction

Technology has progressed and developed based on the needs and activities carried out by humans, as stated by Riduan and Dedy (Riduan & Dedy, 2020), explaining that the progress of technology will undoubtedly change the behavior of human activities that increasingly tend to use it. In its use, technology will undoubtedly provide convenience and comfort for users (Mamusung, 2020; Damsir, 2019). This aligns with research conducted by Arianty et al. (2020). Technology has a role and benefits in its activities and can be felt by everyone (Aulia et al., 2021 & Retnawiyati, 2021).

Technology is created in various fields, such as shipping technology and medicine, and one of them is technology in the automotive sector, both two-wheeled and four-wheeled. Technological advances in vehicles and the increasing number of mobility of road users for vehicle owners certainly have an impact on road users (Saragih, 2018; Utari & Hasugian, 2021); data from the World Health Organization (WHO) quoted in the research of Alimuddin et al. (2016), that every year around 1,300,000 people die due to traffic accidents. The highest incidence and deaths caused by traffic accidents occurred among 26-30-year-olds who rode motorbikes (Anshori, 2020; Fisu, 2019; Handayani et al., 2017; Djaja et al., 2016).

Several factors cause the source of traffic accidents. As quoted in the research of Irwanto et al. (2019) and Intari et al. (2019), accidents can be caused by the density of motorized vehicles operating on the streets, human negligence, road conditions, weather conditions, vehicle eligibility, and also the suboptimal enforcement of traffic laws. Law no. 22 of 2019 concerning traffic, article 1 point 24 quoted from research (Suryani & Mashdurohatun, 2016; Doly, 2016; Republik Indonesia, 2009) traffic accidents are incidents/events that occur on the road and are unexpected and unintentional and involve vehicles with or without other road users which can result in human casualties and property losses. Traffic accidents can be classified into 3 (three) classifications, namely: light, moderate, and severe (Fitria et al., 2017),

Accident data, such as victims of accidents by the police, are recorded and made into a stored file, which can be used for the benefit of the Republic of Indonesia Police. Irwanto et al. (2019) explain that traffic accident data is only used as material for recapitulation and publication for the police or related parties, as research conducted by Soderi (2019) explains that traffic accident data is processed into information for the benefit of the Indonesian Police. A data mining technique is needed to process the data into information using association rules to find patterns between items (Ransi & Winarko, 2014; Geurts et al., 2005; Fauzy & Asror, 2016).

The apriori algorithm can find a frequent itemset from an extensive database (Hakim & Fauzy, 2015; Utari & Hasugian, 2020). By using apriori, pairs of items that often appear can be obtained to form a pattern of association (Saragih, 2017).

Based on the level of traffic accident data, analyzing traffic accident patterns using the apriori method in the Palembang Police environment can help overcome the number of traffic accidents (Depaire et al., 2008; Chong et al., 2010; Pakgohar et al., 2011; Wardiman et al., 2016).

Methodology

Analysis Method is the analysis stage of the results of the program trial using traffic accident data on variables related to traffic accidents in the Palembang City Police area, starting from the data collection stage and determining variables—pre-processing data to the data processing stage. The data pre-processing stages include collecting data, variable determination, and variable grouping, after which the researcher's next stage is data processing, which provides for frequent itemset analysis and the formation of rules from associations using the Python programming language. The next stage is the mining process, the frequent item/item set process, and the candidate generation item, which are carried out in stages to produce support values and confidence values using the apriori algorithm, as shown in Figure 1 below:

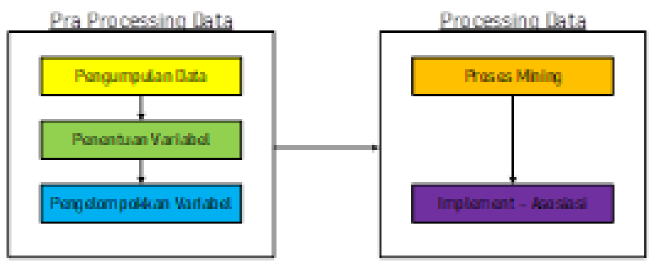

Figure 1. Preprocessing to processing chart

Figure 1 shows the flow of the pre-processing process of data-to-data processing using the apriori algorithm, which is one of the algorithms in the association rule method. Next, the process flow of the apriori algorithm is explained, as shown in Figure 2.

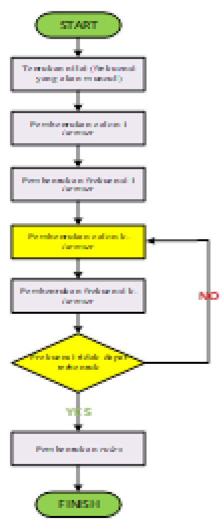

Figure 2. Flowchart Apriori Algorithm

Figure 2 above shows the process flow of each stage carried out by the apriori algorithm until the results are obtained as patterns of the most frequently occurring data.

Next, the grouping and selecting variables for this study are explained. Variables are the objects of research or what is a point of attention of the survey quoted from research (Khasan et al., 2012; Swandayani & Kusumaningtias, 2012; Sukarni, 2012; Hamdi et al., 2019; Mukhlas, 2018; Soemantri et al., 2017). Several data variables will be used in this study, namely: prominent accidents, road status, road type, road class, road function, traffic accident victims (minor injuries, serious injuries, and death), accident rate, speed limit, accident type, weather, light conditions, road surface conditions, road geometry, road slope, as shown in Figure 3 below.

Figure 3. Research Variables

Data processing is carried out before the data is processed into data mining with tools; all the data that have been collected, not all data records can be used in this study because they have to go through several stages of initial data processing or data processing.

Results and Discussion

Source code for pre-processing data by displaying activities by researchers to process initial data to the results stage of minor, moderate, and severe accidents for the variables used, as shown in Figure 4.

	0	1	2	3	4	5	6	7	8
0	tingkat_ringan	meninggal_tidak_ada	luka_berat_tidak_ada	luka_ringan_1	tipe_kecelakaan_tabrakan_depan_belakang	cahaya_redup_samar	cuaca_cerah	menonjol_tidak	fungsi_arteri
1	tingkat_ringan	meninggal_tidak_ada	luka_berat_tidak_ada	luka_ringan_1	tipe_kecelakaan_kendaraan_out_of_control_kelua...	cahaya_terang_jelas	cuaca_hujan_gerimis	menonjol_tidak	fungsi_tol
2	tingkat_berat	meninggal_2	luka_berat_1	luka_ringan_tidak_ada	tipe_kecelakaan_tabrakan_saat_menyalip	cahaya_terang_jelas	cuaca_cerah	menonjol_tidak	fungsi_arteri
3	tingkat_berat	meninggal_1	luka_berat_tidak_ada	luka_ringan_tidak_ada	tipe_kecelakaan_tabrakan_dengan_kendaraan_park...	cahaya_terang_jelas	cuaca_cerah	menonjol_tidak	fungsi_arteri
4	tingkat_berat	meninggal_1	luka_berat_tidak_ada	luka_ringan_1	tipe_kecelakaan_tabrakan_depan_belakang	menonjol_tidak	fungsi_arteri	kelas_i	tipe_jalan_22_tb
...	...	...	...	...	...	...	...	...	...
7624	tingkat_berat	meninggal_1	luka_berat_tidak_ada	luka_ringan_tidak_ada	tipe_kecelakaan_tabrakan_samping	cahaya_terang_jelas	cuaca_cerah	fungsi_tol	kelas_i
7625	tingkat_berat	meninggal_1	luka_berat_tidak_ada	luka_ringan_1	tipe_kecelakaan_tabrakan_saat_menyalip_dari_kanan	cahaya_redup_samar	cuaca_cerah	fungsi_kolektor	kelas_ii
7626	tingkat_berat	meninggal_1	luka_berat_tidak_ada	luka_ringan_1	tipe_kecelakaan_tabrakan_depan_depan	cahaya_gelap_sulit_terlihat	cuaca_tidak_diketahui	fungsi_arteri	kelas_i
7627	meninggal_tidak_ada	luka_berat_tidak_ada	luka_ringan_tidak_ada	batas_kecepatan_tidak_ada	NaN	NaN	NaN	NaN	NaN
7628	meninggal_tidak_ada	luka_berat_tidak_ada	luka_ringan_tidak_ada	batas_kecepatan_tidak_ada	NaN	NaN	NaN	NaN	NaN

8	9	10	11	12	13	14	15
fungsi_arteri	kelas_i	tipe_jalan_22_tb	bentuk_lurus	kondisi_baik	batas_kecepatan_30	kemiringan_datar	status_jalan_nasional
fungsi_tol	kelas_i	tipe_jalan_42_b	bentuk_lurus	kondisi_baik	batas_kecepatan_40	status_jalan_kota_kabupaten	NaN
fungsi_arteri	kelas_i	tipe_jalan_22_tb	bentuk_lurus	kondisi_baik	batas_kecepatan_40	kemiringan_datar	status_jalan_propinsi
fungsi_arteri	kelas_i	tipe_jalan_42_b	bentuk_lurus	kondisi_baik	batas_kecepatan_tidak_ada	kemiringan_datar	status_jalan_nasional
tipe_jalan_22_tb	batas_kecepatan_20	status_jalan_nasional	NaN	NaN	NaN	NaN	NaN
...	...	...	...	...	...	...	...
kelas_i	tipe_jalan_22_tb	bentuk_lurus	kondisi_baik	batas_kecepatan_tidak_ada	NaN	NaN	NaN
kelas_ii	tipe_jalan_42_b	bentuk_lurus	kondisi_baik	batas_kecepatan_tidak_ada	status_jalan_kota_kabupaten	NaN	NaN
kelas_i	tipe_jalan_22_tb	bentuk_tikungan	kondisi_baik	batas_kecepatan_tidak_ada	status_jalan_propinsi	NaN	NaN
NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Figure 4. Data Selection Results

In the association rules algorithm process, the variables used at the light accident level are six (6) variables; for the moderate accident level, there are twelve (12) variables, and the severe accident level has five (5) variables. Association rules are used to find patterns of relationships with light, moderate, and severe accident levels. using min_support=0.05, min_confidence=0.5, min_lift=3, min_length=3.

After the data is processed using the application and based on data owned by researchers sourced from data from the Republic of Indonesia Police, Palembang City Police, in clusters as in Table 1 below:

Table 1. Data Processing Results

No	Accident	Case	Condition	Criteria
1	Mild Level	6	Local Environmental Function	Road Function
			Class III	Road Class
			Good Condition	Road Condition
			No Serious Injuries	Victims
			Road Type 22 tb	Road Type
			Type of accident vehicle out of control exit to the left side of the road	Accident Type
2	Medium Level	12	Speed limit 20	Speed
			Straight shape	Road Shape
			Clear weather	Weather Conditions
			Arterial function	Road Function
			Class II	Road Class
			Flat slope	Road Gradient
			Good condition	Road Conditions
			Serious injury 1	Victims
			Minor injury none	Victims
			Fatalities none	Victims
			Road type 22 tb	Road Type
			Accident type out of control vehicle exits to the right side of the road.	Accident Type
			Good condition	Road Condition

			No minor injuries	Victims
3	Heavy Level	5	City/district road status	Road Status
			Provincial road status	Road Status
			Road type 22 tb	Road Type

At the level of minor accidents, there are six factors; for moderate accidents, there are 12 factors; and for severe accidents, there are five factors, with a total of 23 rules. Table 3 shows the number of incidents that occurred during the period 2015-2020, with the following details: for minor accidents, there were 58 incidents with the number of factors that occurred as many as six factors with a percentage of 16.62 percent; for moderate accidents with 168 incidents with a total of 12 factors with a percentage of 48.14 percent that occurred and for severe accidents with a total of 123 incidents with a total of 5 factors with a percentage of 35.24 percent.

Table 2. Data Processing Results

No	Conclusion	Incident	Factor	Percent (%)
1	Mild Level	58 Incident	6	16,62
2	Medium Level	168 Incident	12	48,14
3	Heavy Level	123 Incident	5	35,24
		349 Incident	23	100

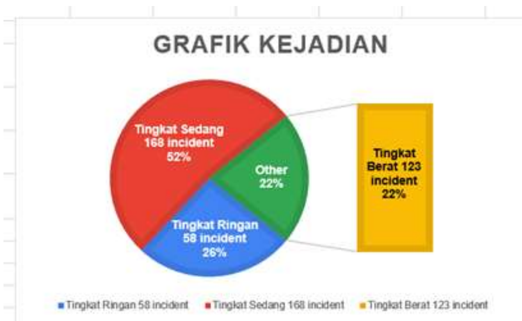

Figure 5. Event Graph

The criteria can be grouped with the following details: there are two road functions at light and medium levels, there are two road classes at light and medium levels, and there are three road conditions at light, medium, and heavy levels for victims there are five which are at one at light level; 3 at medium level; and one at heavy level, there are three road types with each level having 1, there are two accident types at light and medium levels, there is one speed at medium level, there is one road shape at medium level, there is one weather condition at medium level, there is one road slope at medium level, and there are two road statuses at heavy level. This can be seen in the following table 3:

Table 3. Number of Rules

No	Criteria	Number	Level
1	Road Function	2	1 light; 1 medium
2	Road Class	2	1 light; 1 medium
3	Road Condition	3	1 light; 1 medium;1 heavy
4	Accident Victims	5	1 light; 3 medium; 1 heavy

5	Road Type	3	1 light; 1 medium;1 heavy
6	Accident Type	2	1 light; 1 medium
7	Vehicle Speed	1	1 medium
8	Road Shape	1	1 medium
9	Weather Condition	1	1 medium
10	Road Gradient	1	2 heavy
11	Road Status	2	1 light; 1 medium
		23	

From the fp-growth processing, serious accident data is produced. In contrast, minor and moderate accidents are not displayed because the minimum confidence value limit is <0.5 or below 50 percent, with 521 factors with confidence values from 1 to 0.51, where the level of severe accidents with confidence 1 is 48.37 percent. In comparison, for the lowest confidence achievement value with a percentage of 0.38 percent, there are four incidents, so the results can be seen in Table 4 below:

Table 4. Percentage of Weight Level

No	Conclusion	Confidence	Rule	Percent (%)
1	Weight Level	1	252	48,37
2	Weight Level	0.81	2	0,38
3	Weight Level	0.80	6	1,15
4	Weight Level	0.79	2	0,38
5	Weight Level	0.78	8	1,54
6	Weight Level	0.76	2	0,38
7	Weight Level	0.75	13	2,50
8	Weight Level	0.74	6	1,15
9	Weight Level	0.73	16	3,07
10	Weight Level	0.72	4	0,77
11	Weight Level	0.71	16	3,07
12	Weight Level	0.70	11	2,11
13	Weight Level	0.69	16	3,07
14	Weight Level	0.68	16	3,07
15	Weight Level	0.67	15	2,88
16	Weight Level	0.66	12	2,30
17	Weight Level	0.65	11	2,11
18	Weight Level	0.64	19	3,65
19	Weight Level	0.63	9	1,73
20	Weight Level	0.62	11	2,11
21	Weight Level	0.61	11	2,11
22	Weight Level	0.60	11	2,11
23	Weight Level	0.59	7	1,34
24	Weight Level	0.58	10	1,92
25	Weight Level	0.57	13	2,50
26	Weight Level	0.56	3	0,58
27	Weight Level	0.55	7	1,34
28	Weight Level	0.54	4	0,77

29	Weight Level	0.53	2	0,38
30	Weight Level	0.52	3	0,58
31	Weight Level	0.51	3	0,58
			521	100

The table titled "Percentage of Weight Level" provides an insightful breakdown of the contributions of 521 rules based on their confidence levels, ranging from 0.51 to 1. It is immediately apparent that rules with the highest confidence level (1) dominate the dataset, contributing 48.37%. This suggests a strong presence of highly reliable or frequent patterns within the dataset, likely critical for the system's overall functionality or decision-making process. Such dominance also indicates the potential for over-reliance on specific patterns, which may require further analysis to avoid redundancy.

A notable observation is the consistency of contributions from mid-range confidence levels (0.70 to 0.65). These levels account for a substantial portion of the dataset, with individual percentages ranging between 2% and 3%. This balanced contribution highlights the importance of moderately strong patterns, which likely represent significant yet less dominant relationships within the data. These rules could be worth exploring in detail to uncover additional insights or emergent trends that may support the system's objectives.

In contrast, the lower confidence levels (<0.60) have a relatively minor contribution, with individual percentages mostly under 2%. While these rules may represent weaker or less frequent patterns, they are valuable for understanding outliers or less common associations. However, evaluating whether these rules contribute meaningfully to the system or introduce noise is essential. Filtering or refining these lower-confidence rules could improve the model's efficiency and focus on significant patterns.

Overall, the data indicates a clear trend where higher confidence levels contribute more significantly while lower confidence levels gradually decline in importance. This distribution is typical in systems where strong associations dominate the data, but it also points to potential areas for improvement. A detailed analysis of the middle-range and low-confidence rules may uncover opportunities to optimize the system. Visualizing this distribution, such as through a histogram or pie chart, could provide a clearer perspective and help identify clusters of interest.

In conclusion, while the dominance of high-confidence rules provides a strong foundation for the dataset, the balanced contribution of mid-range confidence levels and low-confidence patterns offer opportunities for deeper exploration and refinement. By focusing on these aspects, the system can achieve a more robust and balanced representation of patterns, ultimately enhancing its overall performance.

Conclusions

This study highlights the application of the Apriori algorithm in analyzing traffic accident patterns within the Palembang City Police jurisdiction. By utilizing historical traffic accident data and processing it through association rules, the study identified significant patterns associated with varying levels of accidents (mild, moderate, and severe). Key variables such as road conditions, accident victims, road types, weather conditions, and road statuses contributed significantly to the occurrence and severity of traffic accidents.

The analysis revealed that moderate accidents are the most prevalent, accounting for 48.14% of total incidents, severe accidents at 35.24%, and mild accidents at 16.62%. Using association rules, the study generated 23 significant rules that provide valuable insights into accident factors, such as vehicle speed, road geometry, weather conditions, and accident types. These findings underscore the potential of data mining techniques like Apriori in uncovering hidden relationships within complex datasets.

The results indicate that higher confidence levels (e.g., confidence = 1) dominate the dataset, contributing nearly half (48.37%) of the patterns, which suggests the existence of highly reliable and frequent associations. However, moderate and low-confidence patterns are critical in capturing less dominant but meaningful trends. This layered approach to confidence levels allows for a nuanced understanding of accident patterns and factors.

The findings of this study hold practical implications for traffic management and accident prevention. By identifying critical patterns, policymakers and traffic authorities can implement targeted interventions, such as improving road conditions, enforcing speed limits, and enhancing awareness of traffic laws. Moreover, this research demonstrates the utility of data mining in addressing real-world challenges, supporting the argument for adopting similar techniques in other domains.

Future research could extend this study by incorporating additional variables, such as driver behavior, vehicle type, and socio-demographic factors, to develop a more comprehensive understanding of traffic accidents. Furthermore, integrating advanced algorithms like FP-Growth or machine learning models could provide a comparative analysis and improve prediction accuracy. With continued refinement and application, data mining techniques hold promise for enhancing road safety and minimizing traffic-related fatalities.

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