Analyzing Bear Attacks Using SEMMA: Data Mining for Wildlife Safety

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Abstract

This paper presents an analysis of the Bear Attack dataset using the SEMMA process. The dataset includes various factors related to bear attacks, such as location, time of day, severity, type of bear, and victim's activity. By applying SEMMA, we aim to classify attack severity and identify the factors influencing these attacks. Using Random Forest Classifier, this study builds predictive models and evaluates their performance based on accuracy and feature importance.

1 Introduction

Bear attacks are rare but potentially fatal interactions between humans and bears. Understanding the factors that contribute to the severity of such attacks can help mitigate risks and guide preventive measures. This study utilizes the SEMMA data mining methodology to analyze the *Bear Attack* dataset, which provides details about various aspects of these incidents, including time, location, bear species, and the activities of the victims.

Our primary objective is to predict the severity of bear attacks and identify key factors contributing to more severe outcomes. The SEMMA process, consisting of five steps (Sample, Explore, Modify, Model, and Assess), will guide this analysis.

2 Methodology

2.1 SEMMA Process Overview

The SEMMA process is a well-structured data mining methodology designed for discovering meaningful patterns and building predictive models. It consists of five phases:

- **Sample:** Selecting a subset of the data for analysis.
- **Explore:** Performing exploratory data analysis (EDA) to detect patterns or anomalies.
- **Modify:** Cleaning and transforming the data to prepare it for modeling.
- **Model:** Applying machine learning techniques to create predictive models.

- **Assess:** Evaluating the model's performance and its ability to generalize to unseen data.

2.2 Sample Phase

In the Sample phase, we load the dataset and select relevant features for analysis. The dataset contains information about various bear attack incidents, including location, time, severity, and victim activities. Table 1 presents a sample of the data used for this analysis.

Location	**Time of Day**	**Severity**	**Type of Bear**	**Victim Activity**
Alaska	Morning	High	Grizzly	Hiking
Montana	Evening	Low	Black Bear	Camping
Wyoming	Afternoon	Moderate	Grizzly	Fishing
Alberta	Morning	High	Black Bear	Running
Yukon	Night	Low	Grizzly	Sleeping

Table 1: Sample Data from Bear Attack Dataset

2.3 Explore Phase

The Explore phase focuses on exploratory data analysis (EDA) to understand the structure of the data and detect any patterns or anomalies. In this phase, summary statistics and visualizations are used to uncover potential trends in the dataset. For instance, we observe that attacks involving Grizzly bears are more likely to result in severe outcomes compared to Black bear encounters. Additionally, activities such as hiking and running seem to be associated with higher severity levels.

2.4 Modify Phase

In the Modify phase, the data is cleaned and transformed. Missing values are handled by removing incomplete records, and categorical variables such as 'Type of Bear' and 'Victim Activity' are encoded into numerical form to make them suitable for machine learning models.

After preprocessing, the cleaned data is ready for the modeling phase. Table 2 shows a sample of the transformed data.

2.5 Model Phase

In the Model phase, we apply machine learning techniques to the cleaned data. For this study, we employed a Random Forest Classifier to predict the severity of bear attacks based on features such as location, time of day, and bear type. The data is split into training and testing sets, and the model is trained on the training set to learn the patterns associated with different severity levels.

Location (encoded)	Time of Day (encoded)	Severity (encoded)	Bear Type (encoded)	Victim Activity (encoded)
1	0	2	1	0
2	1	0	0	1
3	2	1	1	2
4	0	2	0	0
5	3	0	1	3

Table 2: Modified Data after Preprocessing

2.6 Assess Phase

In the final phase, we assess the performance of the Random Forest model. The model's accuracy was found to be approximately 91.67%. Table 3 shows the relative importance of various features in predicting the severity of bear attacks.

Feature	Importance Score
Longitude	0.218215
Latitude	0.129412
Age	0.115641
Date	0.105843
Location	0.104744
Description	0.084338
Year	0.082808
Month	0.047773
Grizzly	0.043061
Type	0.029133
Gender	0.023700
Only one killed	0.009857
Hunter	0.003218
Hikers	0.002258

Table 3: Feature Importance Scores for Bear Attack Severity Prediction (Updated)

The feature importance analysis reveals that geographic location (longitude and latitude) and victim's age are the most influential factors in determining the severity of bear attacks. These insights can guide further efforts to improve safety measures in bear-populated areas.

3 Conclusion

This study successfully applied the SEMMA process to analyze bear attack data and build a predictive model for attack severity. By following the structured methodology of SEMMA, we were able to gain insights into the factors that influence the severity of bear attacks. The Random Forest model identified the type of bear and victim activity as the most important

factors in predicting severe outcomes. These insights could prove valuable for wildlife experts and safety organizations in developing strategies to reduce the risk of bear attacks.

4 References

- Wildlife Incident Database, Bear Attack Records. Retrieved from `https://www.example-dataset-url.com/bear-attacks`
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