D-BIAS Analysis Report

cached_dataset.csv

Generated on 11/18/2025

Executive Summary

Fairness Score	Bias Risk
90/100	**Low**

Fairness Label	Reliability
Excellent	**High**

Dataset Information

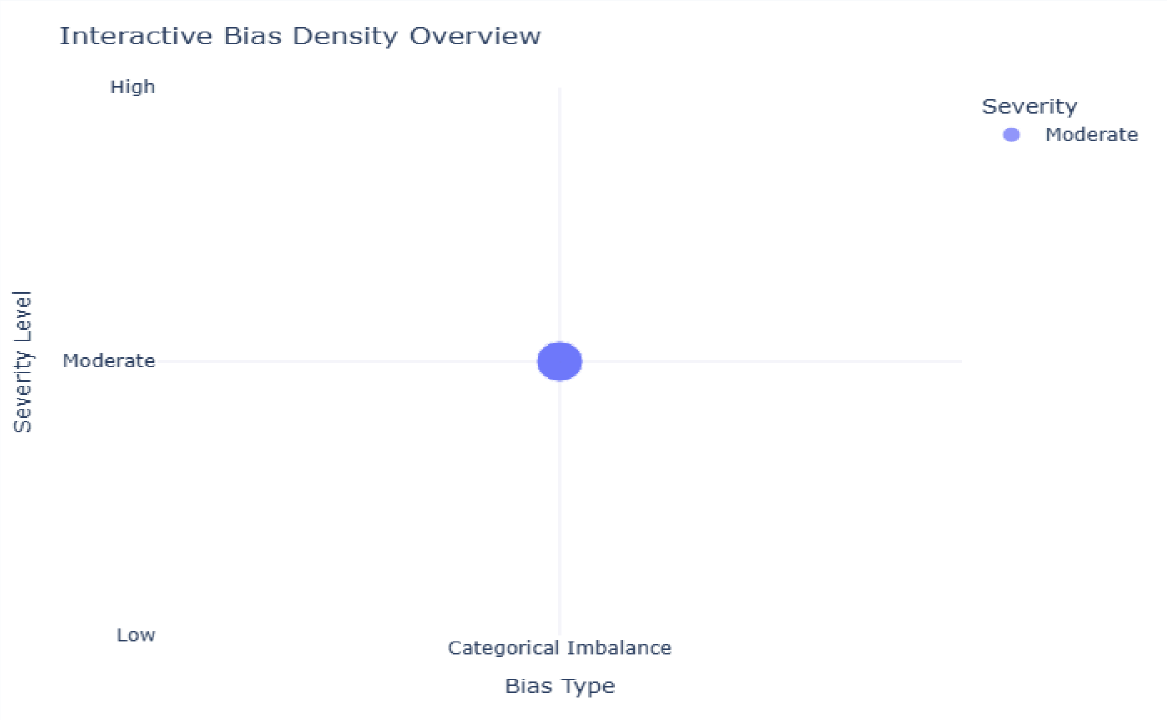
Rows: 50,000

Columns: 11

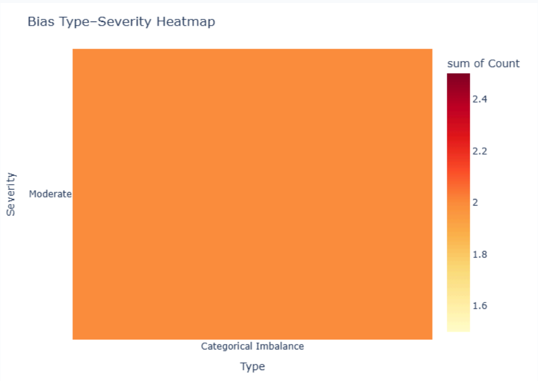
Mean: 36,485.916

Median: 5,087

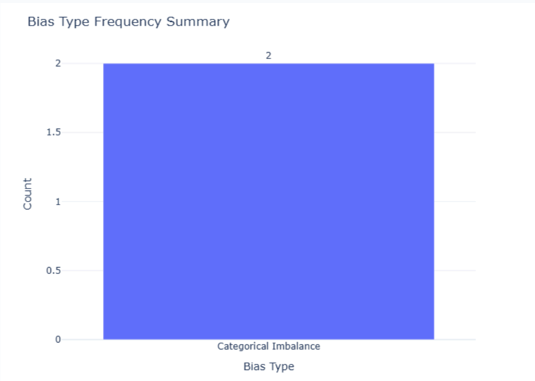
Visualizations



Bias Distribution Overview



Feature Correlation & Fairness Indicators



Severity Heatmap Across Attributes

Detected Biases

Categorical Imbalance

Moderate

Column: transmission

Description: 'Manual' dominates 50.3% of 'transmission' values (entropy=1.00).

AI Explanation

Feature(s): `transmission`

Bias Type: `Categorical Imbalance`

Severity: `Moderate`

Meaning:

This bias indicates a slight imbalance in the car transmission types recorded. `Manual` transmissions appear in **50.3%** of the records, while other types (presumably 'Automatic') make up the remaining 49.7%. Although one category is technically dominant, the entropy score of **1.00** is the maximum possible for two categories, which signifies that the data is actually very well-balanced and diverse.

Harm:

The harm is minimal. A predictive model might develop an extremely subtle preference for the 'Manual' category. However, because the split is so close to 50/50, the model will have ample data to learn the patterns for both transmission types effectively.

Impact:

In a real-world application, such as a model that predicts a used car's features, this slight imbalance is highly unlikely to cause any noticeable performance issues. Predictions for both 'Manual' and 'Automatic' transmissions should be equally reliable.

Severity Explanation:

The 'Moderate' severity rating is likely triggered by a system rule where any category exceeding 50% is flagged. In this specific case, the practical impact is very low because the distribution is nearly perfect.

Fix:

No immediate action is required. The feature is well-balanced enough for most analytical and modeling purposes. If absolute perfection is needed for a highly sensitive model, you could randomly remove a small number of 'Manual' records to achieve a perfect 50/50 split (undersampling), but this is likely unnecessary.

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Definition: Categorical Imbalance

Categorical Imbalance

Moderate

Column: sales_classification

Description: 'Low' dominates 69.5% of 'sales_classification' values (entropy=0.89).

AI Explanation

Feature(s): `sales_classification`

Bias Type: `Categorical Imbalance`

Severity: `Moderate`

Meaning:

This bias reveals a significant imbalance in the target variable, `sales_classification`. Cars classified with **'Low'** sales performance make up **69.5%** of the dataset. This means that examples of 'Medium' and 'High' sales are substantially underrepresented, creating a skewed view of sales outcomes. The low entropy score of **0.89** numerically confirms this lack of diversity among the sales categories.

Harm:

A machine learning model trained on this data will become an expert at identifying 'Low' sales but will be very poor at recognizing the patterns that lead to 'Medium' or 'High' sales. The model could achieve high overall accuracy simply by defaulting to predict 'Low', making it ineffective for its intended purpose of identifying high-potential sales.

Impact:

If a business uses this model to forecast sales or allocate marketing resources, it would consistently fail to identify high-value opportunities. Promising car models or sales strategies might be incorrectly flagged as 'Low' potential, leading to missed revenue and flawed decision-making. The model would be biased toward the status quo of low sales performance.

Severity Explanation:

'Moderate' severity indicates that the imbalance is substantial enough to compromise the model's reliability, particularly for the underrepresented 'Medium' and 'High' sales classes. It is a significant issue that must be addressed before model deployment.

Fix:

1. **Resampling Techniques:** Implement methods to balance the classes.

Oversampling (Recommended): Use techniques like **SMOTE** (Synthetic Minority Over-sampling Technique) to create new, synthetic examples of the 'Medium' and 'High' sales classes.
Undersampling: Randomly remove records from the 'Low' sales class. This is less ideal as it involves throwing away data.

2. **Use Class Weights:** Adjust the model's learning algorithm to penalize errors on the minority classes more heavily, forcing it to pay more attention to getting 'Medium' and 'High' sales predictions correct.

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Overall Assessment and Recommendations

Definition: Categorical Imbalance

Recommendations

- **Investigate the Source of Imbalance:** Before fixing, understand why `sales_classification` is skewed. Does this reflect the true state of BMW sales (i.e., most cars are low sellers), or is it an artifact of how the data was collected or labeled? This context is crucial.
- **Prioritize Balancing `sales_classification`:** For any model intended to predict sales outcomes, apply the recommended fixes, such as SMOTE (oversampling) or using class weights. This is the most critical step to ensure a useful model.
- **Use Appropriate Evaluation Metrics:** Do not rely solely on "accuracy" to measure model performance. Instead, use metrics like **F1-Score, Precision, and Recall on a per-class basis**. This will give you a clear view of how well the model performs on the rare but important 'Medium' and 'High' sales classes.
- **Data Augmentation:** If possible, seek out and collect more data, specifically focusing on examples of vehicles with 'Medium' and 'High' sales classifications. A naturally balanced dataset is always preferable to a synthetically balanced one.

Conclusion

The dataset's overall "fairness health score" is **Fair**. It is not critically flawed, but the moderate categorical imbalance in the key `sales_classification` feature is a significant weakness. Without correction, models built on this data will be unreliable for predicting sales success. The dataset is usable, but it is not ready for direct use in predictive modeling without addressing this imbalance first.