Assignment 2

Krishna Kumar Bais (241110038)
Rohan (241110057)

1 GitHub Link:

2 Dataset Overview

2.1 Dataset Characteristics

The Absenteeism at Work dataset contains:

- **Total Records**: 740 observations
- **Features**: 21 attributes including demographic, behavioral, and workplace factors
- **Target Variable**: Absenteeism time in hours (range: 0-120 hours, mean: 6.92 hours)
- **Data Quality**: No missing values, 34 duplicate records identified
- **Employees**: 36 unique employees across multiple time periods

2.2 Key Features

- **Demographic**: Age, Education, Service time
- **Behavioral**: Social drinker, Social smoker, Pet ownership
- **Workplace**: Transportation expense, Distance to work, Work load, Hit target
- **Health**: Weight, Height, Body mass index
- **Temporal**: Month of absence, Day of the week, Seasons

3 Model Selection and Evaluation

3.1 Model Choice: Linear Regression

We selected Linear Regression as our primary model for the following reasons:

- **Interpretability**: Coefficients provide clear feature importance
- **Baseline Performance**: Establishes a strong baseline for comparison
- **Fairness Analysis**: Enables detailed group-wise performance evaluation
- **Computational Efficiency**: Fast training and prediction suitable for bias analysis

3.2 Evaluation Metrics

We employed multiple regression metrics to assess model performance:

- **RMSE (Root Mean Square Error)**: Overall prediction accuracy
- **MAE (Mean Absolute Error)**: Average prediction error
- **R^2 Score**: Proportion of variance explained
- **Bias**: Mean difference between predicted and actual values

4 Bias Evaluation

4.1 Representation Bias

Education Distribution Bias:

- Education Level 1: 611 records (82.6%) - **Severely over-represented**
- Education Level 2: 46 records (6.2%) - Under-represented
- Education Level 3: 79 records (10.7%) - Under-represented
- Education Level 4: 4 records (0.5%) - **Extremely under-represented**

Age Distribution Bias:

- 18-30 years: 177 samples (23.9%) - Balanced
- 31-40 years: 422 samples (57.0%) - **Over-represented**
- 41-50 years: 132 samples (17.8%) - Balanced
- 50+ years: 9 samples (1.2%) - **Under-represented**

Service Time Distribution:

- 0-5 years: 47 samples (6.4%) - Under-represented
- 6-10 years: 208 samples (28.1%) - Balanced
- 11-15 years: 273 samples (36.9%) - Over-represented
- 15+ years: 212 samples (28.6%) - Balanced

4.2 Disproportionate Effects Analysis

Age-based Absenteeism Patterns:

- 18-30 years: 5.44 hours (below average by 1.49 hours)
- 31-40 years: 7.06 hours (above average by 0.14 hours)
- 41-50 years: 6.96 hours (above average by 0.04 hours)
- 50+ years: 29.11 hours (**above average by 22.19 hours**)

Education-based Absenteeism Patterns:

- Education Level 1: 7.19 hours (above average by 0.27 hours)
- Education Level 2: 6.39 hours (below average by 0.53 hours)
- Education Level 3: 5.27 hours (below average by 1.66 hours)
- Education Level 4: 5.25 hours (below average by 1.67 hours)

4.3 Bias Sources Identified

1. **Sampling Bias**: Single organization (courier company) limits generalizability
2. **Historical Bias**: Past discriminatory practices embedded in data patterns
3. **Measurement Bias**: Inconsistent absence recording across departments
4. **Labeler Bias**: Subjective assignment of absence reason codes

5 Corrective Measures Implementation

5.1 Applied Mitigation Strategies

5.1.1 Feature Elimination

Removed proxy features that could encode sensitive attributes:

- **Height**: Potential proxy for gender/age
- **Weight**: Potential proxy for gender/age
- **Body Mass Index**: Derived from height/weight
- **ID**: Non-meaningful identifier

5.1.2 Age Group Balancing

Implemented resampling to balance age group representation:

- **Target**: Equal representation across all age groups
- **Method**: Downsampling majority groups, upsampling minority groups
- **Result**: All age groups balanced to 9 samples each

5.1.3 Education Level Balancing

Applied targeted resampling for education levels:

- **Target Count**: 17 samples per education level
- **Method**: Strategic downsampling and upsampling
- **Result**: Balanced representation across education levels 1 and 3

5.2 Dataset Transformation Results

- **Original Dataset**: 740 samples × 21 features
- **Balanced Dataset**: 34 samples × 17 features
- **After Encoding**: 34 samples × 51 features
- **Training Set**: 27 samples
- **Test Set**: 7 samples

6 Performance and Fairness Analysis

6.1 Model Performance Comparison

Table 1: Model Performance Comparison

Metric	Baseline Model	Bias-Mitigated Model	Change
RMSE	11.4292	43.1228	+277.4%
MAE	6.4389	16.5046	+156.3%
R^2 Score	-0.1987	-0.0875	+55.9%

6.2 Fairness Analysis Results

6.2.1 Baseline Model Fairness

Age Group Fairness (Baseline):

- MAE Gap: 20.78 hours
- RMSE Gap: 18.72 hours
- Bias Gap: 26.64 hours
- Average Prediction Gap: 27.51 hours

Education Level Fairness (Baseline):

- MAE Gap: 13.36 hours
- RMSE Gap: 11.60 hours

- Bias Gap: 22.20 hours
- Average Prediction Gap: 15.41 hours

Service Time Group Fairness (Baseline):

- MAE Gap: 3.76 hours
- RMSE Gap: 9.12 hours
- Bias Gap: 2.72 hours
- Average Prediction Gap: 6.47 hours

6.2.2 Bias-Mitigated Model Fairness

Age Group Fairness (Mitigated):

- MAE Gap: 0.00 hours (perfect equality)
- RMSE Gap: 0.00 hours (perfect equality)
- Bias Gap: 0.00 hours (perfect equality)
- Average Prediction Gap: 0.00 hours (perfect equality)

Education Level Fairness (Mitigated):

- MAE Gap: 17.56 hours
- RMSE Gap: 45.13 hours
- Bias Gap: 20.46 hours
- Average Prediction Gap: 0.20 hours

Service Time Group Fairness (Mitigated):

- MAE Gap: 0.00 hours (perfect equality)
- RMSE Gap: 0.00 hours (perfect equality)
- Bias Gap: 0.00 hours (perfect equality)
- Average Prediction Gap: 0.00 hours (perfect equality)

7 Impact of Corrective Measures

7.1 Performance Trade-offs

The implementation of bias mitigation measures resulted in significant trade-offs:

1. **Performance Degradation**:
   - RMSE increased from 11.43 to 43.12 hours (+277.4%)
   - MAE increased from 6.44 to 16.50 hours (+156.3%)
   - R^2 improved from -0.20 to -0.09 (+55.9%)
2. **Fairness Improvements**:
   - Age group fairness achieved perfect equality (0.00 gaps)
   - Service time group fairness achieved perfect equality (0.00 gaps)
   - Education level fairness showed mixed results (gaps increased)
3. **Dataset Size Impact**:
   - Drastic reduction from 740 to 34 samples
   - Limited training data affecting model generalization
   - Small test set (7 samples) limiting statistical significance

7.2 Detailed Fairness Comparison

Table 2: Fairness Metrics Comparison

Attribute	Metric	Baseline	Mitigated	Change
Age Group	MAE Gap	20.78	0.00	-100.0%
	RMSE Gap	18.72	0.00	-100.0%
	Bias Gap	26.64	0.00	-100.0%
	Pred Gap	27.51	0.00	-100.0%
Education	MAE Gap	13.36	17.56	+31.4%
	RMSE Gap	11.60	45.13	+289.1%
	Bias Gap	22.20	20.46	-7.8%
	Pred Gap	15.41	0.20	-98.7%
Service Time	MAE Gap	3.76	0.00	-100.0%
	RMSE Gap	9.12	0.00	-100.0%
	Bias Gap	2.72	0.00	-100.0%
	Pred Gap	6.47	0.00	-100.0%

8 Contributions

8.1 Krishna Kumar Bais (241110038)

- **Bias Evaluation Framework**: Designed and implemented comprehensive bias detection algorithms

- **Fairness Metrics Development**: Created robust fairness evaluation functions for regression tasks
- **Data Analysis**: Conducted detailed statistical analysis of demographic distributions
- **Corrective Measures Design**: Developed age and education balancing strategies
- **Performance Analysis**: Analyzed model performance trade-offs and fairness improvements

8.2 Rohan (241110057)

- **Model Implementation**: Developed and optimized linear regression pipeline
- **Data Preprocessing**: Implemented feature engineering and encoding strategies
- **Evaluation Framework**: Created comprehensive model evaluation and comparison system
- **Visualization and Reporting**: Designed analysis output formatting and result presentation
- **Code Integration**: Ensured seamless integration of all analysis components

9 Conclusions and Recommendations

9.1 Key Findings

1. The original dataset exhibits significant representation bias, particularly in education and age distributions
2. Bias mitigation techniques successfully improved fairness metrics for age and service time groups but at the cost of model performance
3. Extreme dataset balancing (740→34 samples) may be too aggressive for practical applications
4. Linear regression provides interpretable results suitable for bias analysis
5. Education-based fairness requires different mitigation strategies than age-based fairness

9.2 Performance vs. Fairness Analysis

Our results demonstrate a complex relationship between performance and fairness:

- **Perfect Fairness Achieved**: Age and service time groups achieved 0.00 gaps across all metrics
- **Performance Cost**: RMSE increased by 277.4% and MAE by 156.3%

- **Education Challenge**: Education fairness actually worsened, suggesting this attribute needs specialized treatment
- **Sample Size Impact**: The dramatic reduction in dataset size (740→34) significantly affected model reliability