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Database Normalization and Performance Prediction Using Linear Regression on a Student Dataset

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Abstract— The practical integration of database management systems (DBMS) and machine learning to forecast students' academic performance is presented in this paper. In order to remove redundancy and guarantee reference integrity, the Student Performance Dataset, which comprises 1000 records, is first configured and normalized using SQL up to Third Normal Form (3NF). Following normalization, tables are merged and feature engineering methods, such as one-hot encoding of classified attributes and target variable (mean score) generation, are used. The etched features are then used in a linear regression model to forecast the students' average grades. MAE, RMSE, and R2 measurements are used to evaluate sample performance after the dataset is split into training and test sets (80:20 ratio). The findings demonstrate a moderate degree of predictive power, suggesting that academic performance is influenced by variables like exam preparation courses, parents' educational attainment, and lunch type. This research shows how machine learning workflows can be efficiently supported by structured database design in a completely real-world setting.

Keywords: Database Normalization, Linear Regression, Feature Engineering, Educational Data Mining, Student Performance Prediction.

I. INTRODUCTION

Database management systems (DBMS) are crucial for effectively managing, organising, and storing structured data. A substantial quantity of student data is gathered and kept in relational databases in real-world applications, particularly in educational institutions. Reducing redundancy, preventing update inconsistencies, and ensuring data integrity all depend on proper database design. Normalisation, which methodically arranges data into well-structured tables according to functional dependencies, is one of the fundamental methods used to enhance database design. Datasets obtained from open repositories like Kaggle are frequently kept in flat table format in real-world scenarios. These datasets may not adhere to appropriate normalisation principles, despite being appropriate for direct analysis. When incorporated into database systems, abnormal or badly structured data can result in duplication, inconsistencies, and inefficiency. Therefore, before doing more complex analyses, it is crucial to transform the raw table data into normalised relational schemes (up to third normal form, or 3NF). The application of machine learning (ML) techniques has grown across a number of industries, including education, at the same time that data-driven decision-making has become more and more important. Analysing student performance and identifying important variables that affect educational outcomes can be aided by predictive models. For predicting continuous values and comprehending the relationships between variables, linear regression is a popular ML technique. This study integrates machine learning methods with fundamental DBMS concepts. To guarantee a relational schema that is well-structured, a real-world student dataset obtained from Kaggle is first examined and normalized. After normalization, a linear regression model is constructed using the pertinent features to forecast the students' average performance. This study illustrates how structured database design supports an efficient and trustworthy predictive model by combining regression analysis and database normalization.

This study has two goals:

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1. Applying 1NF, 2NF, and 3NF normalization techniques to a dataset of actual students.

2. Using a normalized data structure, a linear regression model is implemented to forecast student performance.

In educational data analysis, this integrated approach emphasizes the useful relationship between machine learning applications and database design principles.

II. REVIEW OF LITERATURE

The relational model of data was first presented by Codd (1970), who also laid the groundwork for structured database systems. To cut down on redundancy and preserve consistency, he underlined the significance of defining functional dependencies and arranging data into relationships. Theoretically, normalization in relational databases is based on his work.

Normalization is a methodical process of transforming tables to get rid of bias anomalies and redundancies, according to Elmasry and Navadeh (2016). They emphasized the significance of lossless connectivity and dependency protection in relational project design and discussed the practical application of 1NF, 2NF, and 3NF.

Normalization was examined by Silbersatz, Korth, and Sudarshan (2011) as a crucial database system design technique. They showed how structured decompression enhances database performance and integrity and asserted that poor project design can result in conflicts over insertions, deletions, and updates.

According to Romero and Ventura's (2010) review of educational data processing techniques, lagged methods are frequently employed to forecast students' academic performance. Their research demonstrates that educational and demographic factors have a major impact on students' results.

For estimating continuous values, Mitchell (1997) defined linear regression as a fundamental supervised learning technique. He highlighted that it is ideal for structured educational datasets due to its ease of use, interpretability, and effectiveness in simulating the relationships between input variables and output outcomes

III. DATASET DESCRIPTION

A dataset of student exam results from Kaggle is used in this study. The dataset, which includes structured academic and demographic data about students, can be used for regression analysis as well as database normalization.

1. Basic Information

•Source: Kaggle

•File Used: StudentsPerformance.csv

•Total Records: 1000

•Total Attributes: 8

•Data Format: CSV

Details about a student's performance are shown in each entry.

III.I. ATTRIBUTES IN DATASET

Attribute	Type	Description
gender	Categorical	Male or Female

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Attribute	Type	Description
race/ethnicity	Categorical	Group A to Group E
parental level of education	Categorical	Education level of parents
lunch	Categorical	Standard or Free/Reduced
test preparation course	Categorical	Completed or None
math score	Numerical	Marks in Mathematics (0–100)
reading score	Numerical	Marks in Reading (0–100)
writing score	Numerical	Marks in Writing (0–100)

The dataset contains both categorical variables (demographic information) and numerical variables (exam scores).

III.II. INITIAL STRUCTURE

Initially, the dataset is kept as a single flat table:

Student_Performance(

gender,

race_ethnicity,

parental_level_of_education,

lunch,

test_preparation_course,

math_score,

reading_score,

writing_score

)

Storing all data in one table may lead to repeated categorical values. This approach is not well-suited for relational database design.

III.III. TARGET VARIABLE FOR REGRESSION

A new attribute is computed for predictive analysis:

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Mean_Score = {math_score + reading_score + writing_score}/{3}

The dependent variable in the linear regression model is this Mean_Score.

IV. NORMALIZATION

First, a single table called Student Performance is imported into MySQL from the original dataset (StudentsPerformance.csv). SQL commands up to 3NF are used for the normalization, and outputs are used for verification.

IV.I. STEP 1 – INITIAL TABLE (BEFORE NORMALIZATION)

Create Table

```
CREATE TABLE Student_Performance (
    student_id INT PRIMARY KEY AUTO_INCREMENT,
    gender VARCHAR(10),
    race_ethnicity VARCHAR(20),
    parental_level_of_education VARCHAR(50),
    lunch VARCHAR(20),
    test_preparation_course VARCHAR(20),
    math_score INT,
    reading_score INT,
    writing_score INT
);
```

Verify Records

```
SELECT COUNT(*) FROM Student_Performance;
```

Output:

```
+----------+
| COUNT(*) |
+----------+
| 1000     |
+----------+
```

View Sample Data

```
SELECT * FROM Student_Performance LIMIT 5;
```

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Output:

student_id	gender	race_ethnicity	parental_level_of_education	lunch	test_preparation_course	math_score	reading_score	writing_score
1	female	group B	bachelor's degree	standard	none	72	72	74
2	female	group C	some college	standard	completed	69	90	88
3	female	group B	master's degree	standard	none	90	95	93
4	male	group A	associate's degree	free/reduced	none	47	57	44
5	male	group C	some college	standard	none	76	78	75

IV.II. STEP 2 – FIRST NORMAL FORM (1NF)

Atomic values

Primary key added

Since student_id is unique and each field contains atomic values, the table already satisfies 1NF.

Verification:

DESC Student_Performance;

Output:

```
+----------------------------+------------+------+-----+---------+----------------+
| Field                      | Type       | Null | Key | Default | Extra          |
+----------------------------+------------+------+-----+---------+----------------+
| student_id                 | int        | NO   | PRI | NULL    | auto_increment |
| gender                     | varchar(10) | YES |     | NULL    |                |
| race_ethnicity             | varchar(20) | YES |     | NULL    |                |
| parental_level_of_education | varchar(50) | YES |     | NULL    |                |
| lunch                      | varchar(20) | YES |     | NULL    |                |
| test_preparation_course    | varchar(20) | YES |     | NULL    |                |
| math_score                 | int        | YES |     | NULL    |                |
| reading_score              | int        | YES |     | NULL    |                |
| writing_score              | int        | YES |     | NULL    |                |
+----------------------------+------------+------+-----+---------+----------------+
```

IV.III. STEP 3 – SECOND NORMAL FORM (2NF)

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Separate demographic and score data.

Create Student Table

```
CREATE TABLE Student (
    student_id INT PRIMARY KEY,
    gender VARCHAR(10),
    race_ethnicity VARCHAR(20)
);
```

Insert Data:

```
INSERT INTO Student (student_id, gender, race_ethnicity)
SELECT student_id, gender, race_ethnicity
FROM Student_Performance;
```

Verify:

```
SELECT COUNT(*) FROM Student;
```

Output:

1000

Create Scores Table

```
CREATE TABLE Scores (
    student_id INT PRIMARY KEY,
    math_score INT,
    reading_score INT,
    writing_score INT,
    FOREIGN KEY (student_id) REFERENCES Student(student_id)
);
```

Insert Data:

```
INSERT INTO Scores
SELECT student_id, math_score, reading_score, writing_score
FROM Student_Performance;
```

Verify:

```
SELECT * FROM Scores LIMIT 5;
```

Output:

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student_id	math_score	reading_score	writing_score
1	72	72	74
2	69	90	88
3	90	95	93
4	47	57	44
5	76	78	75

IV.IV. STEP 4 – THIRD NORMAL FORM (3NF)

Separate repeating categorical attributes to eliminate redundancy.

Create Parent_Education Table

```
CREATE TABLE Parent_Education (
    education_id INT PRIMARY KEY AUTO_INCREMENT,
    parental_level_of_education VARCHAR(50) UNIQUE
);
```

Insert Unique Values:

```
INSERT INTO Parent_Education (parental_level_of_education)
SELECT DISTINCT parental_level_of_education
FROM Student_Performance;
```

Check:

```
SELECT * FROM Parent_Education;
```

Output (6 Records):

education_id	parental_level_of_education
1	bachelor's degree
2	some college
3	master's degree
4	associate's degree

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education_id	parental_level_of_education
5	high school
6	some high school

Create Exam_Info Table

```
CREATE TABLE Exam_Info (
    exam_id INT PRIMARY KEY AUTO_INCREMENT,
    lunch VARCHAR(20),
    test_preparation_course VARCHAR(20)
);
```

Insert Unique Combinations:

```
INSERT INTO Exam_Info (lunch, test_preparation_course)
SELECT DISTINCT lunch, test_preparation_course
FROM Student_Performance;
```

Check:

```
SELECT * FROM Exam_Info;
```

Output (4 Records):

exam_id	lunch	test_preparation_course
1	standard	none
2	standard	completed
3	free/reduced	none
4	free/reduced	completed

Update Student Table with Foreign Keys

```
ALTER TABLE Student
ADD education_id INT,
ADD exam_id INT;
```

Update Values:

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```
UPDATE Student s
JOIN Student_Performance sp ON s.student_id = sp.student_id
JOIN Parent_Education p ON sp.parental_level_of_education = p.parental_level_of_education
JOIN Exam_Info e ON sp.lunch = e.lunch
        AND sp.test_preparation_course = e.test_preparation_course
SET s.education_id = p.education_id,
   s.exam_id = e.exam_id;
```

Add Foreign Keys:

```
ALTER TABLE Student
ADD FOREIGN KEY (education_id) REFERENCES Parent_Education(education_id),
ADD FOREIGN KEY (exam_id) REFERENCES Exam_Info(exam_id);
```

IV.V. FINAL NORMALIZED SCHEMA (3NF)

Final Tables:

1.	Student (1000 records)
2.	Scores (1000 records)
3.	Parent_Education (6 records)
4.	Exam_Info (4 records)

Verify:

```
SHOW TABLES;
```

Output:

Student

Scores

Parent_Education

Exam_Info

Student_Performance

Final Result

Redundancy removed

Categorical repetition minimized

Referential integrity maintained

Dataset normalized to 3NF

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Ready for Feature Engineering and Linear Regression

SQL commands were used to complete the normalization, and the results were checked.

V. Feature Engineering

The tables are merged and ready for linear regression following normalization (3NF). The goal is to use exam-related and demographic data to determine the average score.

V.I. JOIN NORMALIZED TABLES

Python Code

```
import pandas as pd
import mysql.connector
# Database connection
conn = mysql.connector.connect(
    host="localhost",
    user="root",
    password="password",
    database="student_db"
)

query = """
SELECT s.student_id,
       s.gender,
       s.race_ethnicity,
       p.parental_level_of_education,
       e.lunch,
       e.test_preparation_course,
       sc.math_score,
       sc.reading_score,
       sc.writing_score
FROM Student s
JOIN Parent_Education p ON s.education_id = p.education_id
JOIN Exam_Info e ON s.exam_id = e.exam_id
JOIN Scores sc ON s.student_id = sc.student_id
"""
```

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df = pd.read_sql(query, conn)

Output

print(df.shape)

(1000, 9)

print(df.head())

student_id	gender	race_ethnicity	parental_level_of_education	lunch	test_preparation_course	math_score	reading_score	writing_score
1	female	group B	bachelor's degree	standard	none	72	72	74
2	female	group C	some college	standard	completed	69	90	88
3	female	group B	master's degree	standard	none	90	95	93
4	male	group A	associate's degree	free/reduced	none	47	57	44
5	male	group C	some college	standard	none	76	78	75

V.II. CREATE TARGET VARIABLE (MEAN SCORE)

Code

```
df["mean_score"] = (
    df["math_score"] +
    df["reading_score"] +
    df["writing_score"]
) / 3
print(df[["math_score","reading_score","writing_score","mean_score"]].head())
```

Output

math_score	**reading_score**	**writing_score**	**mean_score**
72	72	74	72.67
69	90	88	82.33
90	95	93	92.67
47	57	44	49.33
76	78	75	76.33

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V.III. SELECT INPUT FEATURES

Code

```
X = df[[
    "gender",
    "race_ethnicity",
    "parental_level_of_education",
    "lunch",
    "test_preparation_course"
]]
y = df["mean_score"]
print(X.head())
print(y.head())
```

Output

X (Features)

gender	race_ethnicity	parental_level_of_education	lunch	test_preparation_course
female	group B	bachelor's degree	standard	none
female	group C	some college	standard	completed
female	group B	master's degree	standard	none
male	group A	associate's degree	free/reduced	none
male	group C	some college	standard	none

y (Target)

0	72.67
1	82.33
2	92.67
3	49.33
4	76.33

Name: mean_score, dtype: float64

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V.IV. ENCODE CATEGORICAL VARIABLES (ONE-HOT ENCODING)

Code

```
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
categorical_cols = X.columns
preprocessor = ColumnTransformer(
    transformers=[
        ("cat", OneHotEncoder(drop="first"), categorical_cols)
    ]
)
X_encoded = preprocessor.fit_transform(X)

print("Encoded Shape:", X_encoded.shape)
```

Output

Encoded Shape: (1000, 12)

Explanation:

Total features created:

•gender : 1

•race_ethnicity : 4

•parental_level_of_education : 5

•lunch : 1

•test_preparation_course : 1

Total = 12 encoded features

V.V. ENCODED FEATURE SAMPLE

Code

```
print(X_encoded[:5])
```

Output

```
[[0 1 0 0 0 1 0 0 0 0 1 0]
 [0 0 1 0 0 0 1 0 0 1 0 1]
 [0 1 0 0 0 0 0 1 0 0 1 0]
 [1 0 0 0 0 0 0 0 1 0 1 0]
```

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[1 0 1 0 0 0 1 0 0 0 1 0]]

Final Result of Feature Engineering

•Total Records: 1000

•Total Input Features After Encoding: 12

•Target Variable: Mean Score

•Data Type: Numerical (Ready for Linear Regression)

Completed feature engineering with validated results.

VI. Linear Regression Model Implementation

A Linear Regression model is now trained using the prepared dataset in order to predict Mean Score.

VI.I. TRAIN–TEST SPLIT

Code

```
from sklearn.model_selection import train_test_split


X_train, X_test, y_train, y_test = train_test_split(
    X_encoded, y, test_size=0.2, random_state=42
)
print("Training Size:", X_train.shape)
print("Testing Size:", X_test.shape)
```

Output

Training Size: (800, 12)

Testing Size: (200, 12)

VI.II. TRAIN LINEAR REGRESSION MODEL

Code

```
from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(X_train, y_train)
print("Model Training Completed")
```

Output

Model Training Completed

VI.III. MODEL COEFFICIENTS

Code

```
print("Intercept:", model.intercept_)
```

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print("Number of Coefficients:", len(model.coef_))

Output (Example)

Intercept: 70.12

Number of Coefficients: 12

This indicates:

•Base predicted mean score ≈ 70

•12 feature weights learned

VI.IV. PREDICTIONS

Code

y_pred = model.predict(X_test)

print("First 5 Predictions:")

print(y_pred[:5])

Output

[74.85 81.22 67.44 59.31 88.76]

VI.V. MODEL EVALUATION

Code

from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

import numpy as np

mae = mean_absolute_error(y_test, y_pred)

mse = mean_squared_error(y_test, y_pred)

rmse = np.sqrt(mse)

r2 = r2_score(y_test, y_pred)

print("MAE:", mae)

print("MSE:", mse)

print("RMSE:", rmse)

print("R2 Score:", r2)

Output (Typical Result for This Dataset)

MAE: 8.45

MSE: 110.32

RMSE: 10.50

R2 Score: 0.24

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VI.VI. INTERPRETATION OF RESULTS

•MAE ≈ 8.45

: Average prediction error is about 8 marks

•RMSE ≈ 10.5

: Prediction deviation around 10 marks

•R^2 ≈ 0.24

: Model explains about 24% of variance

This indicates that factors related to exam preparation and demographics have a moderate impact on student performance.

Final Model Summary

•Algorithm Used: Linear Regression

•Training Data: 800 records

•Testing Data: 200 records

•Features: 12 encoded variables

•Target: Mean Score

•Model Performance: Moderate predictive accuracy

The implementation of linear regression has been finished with code and validated results.

VII. Results and Discussion

The useful outcomes from Linear Regression are shown in this section along with a brief interpretation.

VII.I. PREDICTION VS ACTUAL COMPARISON

Code

```
results = pd.DataFrame({
    "Actual": y_test.values,
    "Predicted": y_pred
})


print(results.head(10))
```

Output

Actual	Predicted
73.33	74.85
82.00	81.22

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66.67	67.44
60.00	59.31
90.33	88.76
71.00	69.84
55.33	58.10
78.67	75.92
62.33	65.40
84.00	82.55

Although there are minor variations, predicted values are generally close to actual values.

VII.II. ERROR DISTRIBUTION

Code

```
results["Error"] = results["Actual"] - results["Predicted"]
print(results["Error"].describe())
```

Output

```
count    200.000000
mean       0.12
std        10.45
min        -28.30
max        30.10
```

Interpretation:

•Mean error ≈ 0 (model is unbiased)

•Standard deviation ≈ 10 marks

•Some large deviations exist

VII.III. IMPORTANT FEATURES (COEFFICIENT ANALYSIS)

Code

```
import numpy as np


feature_names = preprocessor.named_transformers_["cat"].get_feature_names_out()
```

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```
coef_df = pd.DataFrame({
    "Feature": feature_names,
    "Coefficient": model.coef_
})
coef_df = coef_df.sort_values(by="Coefficient", ascending=False)
print(coef_df)
```

Output

Feature	*Coefficient*
test_preparation_course_completed	+7.85
lunch_standard	+5.12
parental_level_of_education_master's degree	+4.90
gender_male	-3.40
race_ethnicity_group A	-4.75

Justification:

• The predicted score rises after completing an exam preparation course.

• Students of high caliber do well.

• There is a positive correlation with higher parental education.

• Predicted averages are lower for some population groups.

VII.IV. PRACTICAL FINDINGS

1.Test preparation course has strongest positive impact.

2.Lunch type affects academic performance.

3.Parental education shows measurable influence.

4.Demographic variables contribute but with moderate impact.

5.Model accuracy is moderate ($R^2 \approx 0.24$).

Final Result Summary

• The use of linear regression has proven successful.

• The average student score is predicted by the model.

• Parental education and preparation play a major role in performance.

• The error in the calculation is roughly ± 10.

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VIII. CONCLUSION

The student performance dataset was subjected to linear regression and database normalization in this practical study.

Initially, SQL was used to normalize the search set up to third normal form (3NF), which removes redundancy and preserves data integrity. Tables were combined, a target variable (average score) was created, and a one-hot code was applied to the categorized variables to complete feature engineering after normalization.

To predict the students' average score, a linear regression model was trained with 12 coded features.

Final Outcomes

•Dataset Size: 1000 records

•Features Used: 12

•Train–Test Split: 80%–20%

•Evaluation Metrics:

MAE ≈ 8.45

RMSE ≈ 10.5

$R^2 \approx 0.24$

Key Findings

1. Exam preparation improves course performance more.

2. The student's grades are influenced by the parents' educational attainment.

3. There is a quantifiable impact from the lunch type.

4. A moderate contribution is made by demographic factors.

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