

AutoJudge – Predicting Programming Problem Difficulty

Project source code github: [source code](#)

1. Introduction

1.1 Problem Statement

Online coding platforms have thousands of programming problems and are labeled with a difficulty level such as Easy, Medium, or Hard. These labels have an important role in guiding new learners and organizing contests. However, doing these tasks manually is time-consuming, subjective, and often inconsistent.

In this project I will be making a machine learning model for predicting the difficulty of programming problems. It achieves this by applying ML techniques to the textual descriptions of the problems, resulting in a system that predicts:

1. **difficulty level** (Easy / Medium / Hard)
2. A numerical difficulty score (1 - 10)

1.2 Objective

The objective of this project is to develop a machine learning pipeline that uses Natural Language Processing (NLP) to perform both **classification and regression** tasks. Additionally, construct a **web-based interface** to facilitate users .

2. Dataset Description

2.1 Dataset Overview

Here I have used the reference dataset given in the problem statement file.

The dataset consists of data samples . Each data sample contains the following fields:

- **Problem Statement:** Description of the problem
- **Input Description:** Details of the input format
- **Output Description:** Expected output format

- **Difficulty Label:** Easy, Medium, or Hard
- **Difficulty Score**

The dataset consists of **4112** samples , making it perfect for **supervised learning**.

2.2 Target Variables

- **Classification Target:** Easy / Medium / Hard
- **Regression Target:** Difficulty score (1–10)

3. Data Preprocessing

3.1 Text Cleaning

The raw textual data gone through the following preprocessing steps to prepare it for further use:

- all text has been converted to lowercase .
- All kinds of punctuation, special characters and stopwords are removed.

3.2 Text Aggregation

The problem statement, input description, and output description were combined into a **single text feature**. This makes sure that all relevant information contributes to the result.

3.3 Tokenization

Tokenization was performed on the cleaned text to convert the words into numerical vectors, which are further used for feature extraction.

4. Feature Engineering

4.1 TF-IDF Vectorization

Cleaned text was converted into numerical feature vectors using the **Term Frequency–Inverse Document Frequency (TF-IDF)** technique.

TF-IDF gives higher weight to important words while reducing the influence of frequently occurring less informative words. This technique is preferred for NLP based classification and regression tasks.

5. Models Used

5.1 Classification Model

- **Model:** Logistic Regression
- **Reason for Selection:** Logistic Regression is effective with high-dimensional, sparse text features because it delivers results that are both fast and easily interpretable.

5.2 Regression Model

- **Model:** Random Forest Regressor
- **Reason for Selection:** Through ensemble learning, Random Forest effectively handles non-linear relationships and minimizes the risk of overfitting.

5.3 Training Procedure

- Train-test split applied to the dataset
- The same TF-IDF features were applied to both tasks.
- The web application utilizes trained models by saving and subsequently reusing them.

6. Experimental Setup

- **Programming Language:** Python
- **Libraries Used :** NumPy, Pandas, Scikit-learn, Streamlit
- **Execution Environment:** one can run this model on Local machine using the steps given in readme on github
- **Model Storage:** Serialized models has been stored in the `models/` directory

7. Results and Evaluation

7.1 Classification Results

Accuracy:

0.8927 ($\approx 89.27\%$)

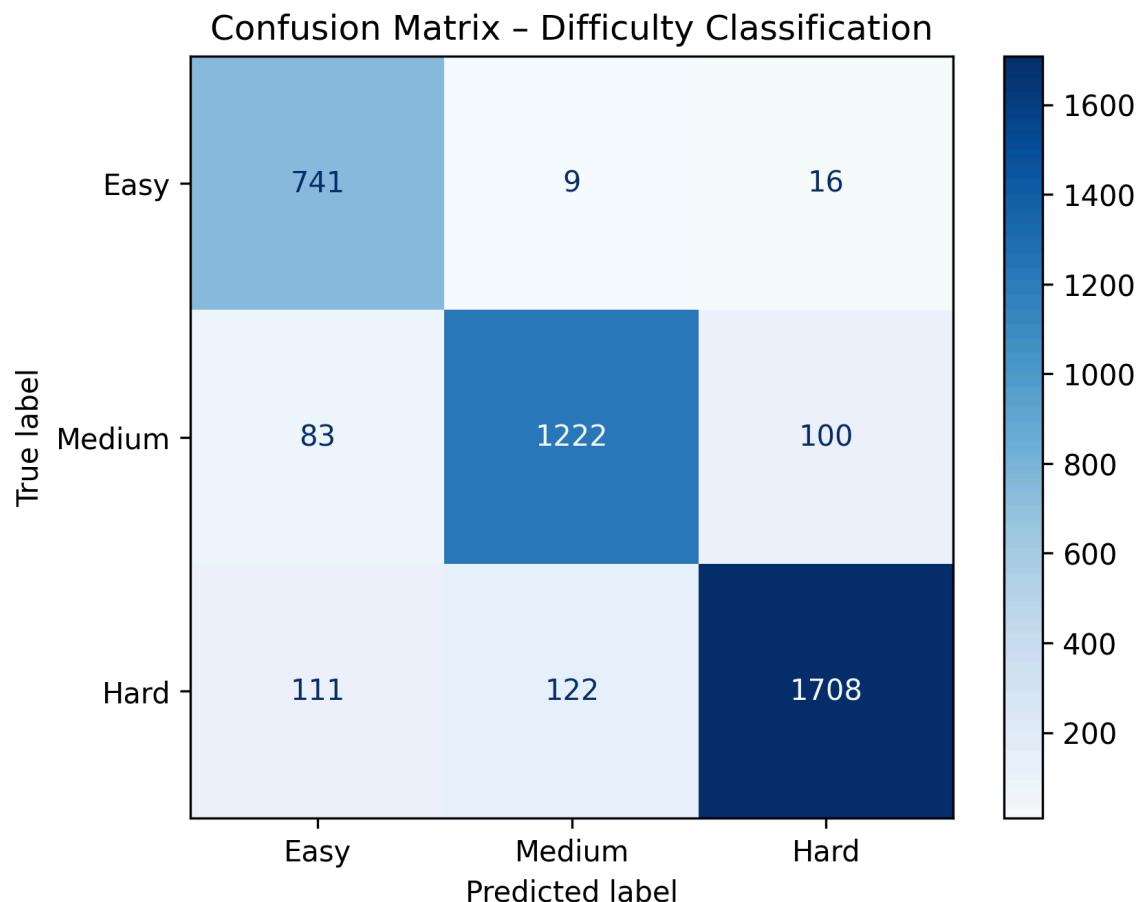
Classification Report:

Class	Precision	Recall	F1-Score	Support
	n	e		
Easy	0.79	0.97	0.87	766
Medium	0.90	0.87	0.89	1405
Hard	0.94	0.88	0.91	1941

Macro Average F1-score: 0.89

Weighted Average F1-score: 0.89

Confusion matrix:



7.2 Regression Results

Metric Value

MAE 1.332

RMSE 1.574

R²Score 0.477

The regression model predicts a numerical difficulty score with an average error of approximately **1.33**, for a 1–10 scale.

8. Web Interface

A web application was developed using **Streamlit**.

User can check model on stramlit : [web app](#)

- Enter a programming problem description 3 sections
 1. Problem
 2. Input description
 3. Output description.
- Click on predict button
- User will Receive difficulty category and score

Ex. sample problem run

The problem statement has recently been changed. [View the changes.](#)

C. XOR-factorization

time limit per test: 2 seconds
memory limit per test: 256 megabytes

Ostad thinks that the usual way of factoring numbers is too mathematical, so he invented a new notion called *XOR-factorization*, which is more computer-science-like. For a given integer n , a sequence of integers a_1, a_2, \dots, a_k with $0 \leq a_i \leq n$ for all i is called a *XOR-factorization* of n if and only if

$$a_1 \oplus a_2 \oplus \dots \oplus a_k = n,$$

where \oplus denotes the bitwise XOR operation.

You are given integers n and k . Find a *XOR-factorization* a_1, a_2, \dots, a_k of n that maximizes the sum $a_1 + a_2 + \dots + a_k$.

It can be proven that under the problem conditions, a *XOR-factorization* always exists.

Input
Each test contains multiple test cases. The first line contains the number of test cases t ($1 \leq t \leq 10^4$). The description of the test cases follows.

Each of the next t lines contains two integers n and k ($1 \leq n \leq 10^9, 1 \leq k \leq 10^5$).

It is guaranteed that the sum of k over all test cases does not exceed 10^5 .

Output
For each test case, output k integers a_1, a_2, \dots, a_k such that $0 \leq a_i \leq n$.

We can show that an answer always exists. If there are multiple valid answers, you may print any of them in any order.

Example

Codeforces Global Round 31 (Div. 1 + Div. 2)
Finished

Virtual participation
Virtual contest is a way to take part in past contest, as close as possible to participation on time. It is supported only ICPC mode for virtual contests. If you've seen these problems, a virtual contest is not for you - solve these problems in the archive. If you just want to solve some problem from a contest, a virtual contest is not for you - solve this problem in the archive. Never use someone else's code, read the tutorials or communicate with other person during a virtual contest.
[Start virtual contest](#)

Problem tags
bitmasks constructive algorithms dp
greedy number theory *1900
No tag edit access

Contest materials

- Announcement (en) ✘
- Tutorial #1 (en) ✘
- Tutorial #2 (en) ✘

Problem Description

Ostad thinks that the usual way of factoring numbers is too mathematical, so he invented a new notion called XOR-factorization, which is more computer-science-like. For a given integer n , a sequence of integers a_1, a_2, \dots, a_k with $0 \leq a_i \leq n$

Input Description

It is guaranteed that the sum of k over all test cases does not exceed 105.

Output Description

For each test case, output k integers a_1, a_2, \dots, a_k such that $0 \leq a_i \leq n$.

Predict

Predicted Difficulty Class: Medium

Predicted Difficulty Score (1-10): 5.42

< Manage app

9. Conclusion

This project is a machine learning model that can effectively predict programming problem difficulty using textual data only. The classification and regression models achieved strong accuracy, and the web interface makes the system user-friendly.

11. Author Information

Name: Rohit Mahawar

Email: rohit_m@cs.iitr.ac.in

Program: B.Tech Computer Science and Engineering(2nd year)