AutoJudge

Predicting Programming Problem Difficulty

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1. Problem Statement

Competitive programming platforms host a large number of problems that are manually labeled into difficulty levels such as easy, medium, and hard. This manual labeling process is subjective, time-consuming, and often inconsistent across platforms. The objective of this project is to design an automatic system that predicts the difficulty of a programming problem based solely on its textual description and related metadata.

The task is formulated in two complementary ways:

- **Regression:** Predict a continuous difficulty score representing the relative hardness of a problem.
- **Classification:** Predict a discrete difficulty label (easy / medium / hard) using the learned representations.

The final system integrates machine learning models with a web-based interface to allow real-time predictions.

2. Dataset Description

Two datasets were used to train the models.

1. **Kattis Problems Dataset**
    - Link: data_kt
    - Number of Entries: 4112
    - Columns:

```
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   title              4112 non-null   object
 1   description        4112 non-null   object
 2   input_description  4112 non-null   object
 3   output_description 4112 non-null   object
 4   sample_io          4112 non-null   object
 5   problem_class      4112 non-null   object
 6   problem_score      4112 non-null   float64
 7   url                4112 non-null   object
```

2. **Codeforces Problems Dataset**
    - Link: [data_cf]
    - Number of Entries: 10024
    - Irrelevant columns (like contest_id, contest_name, tags, time_limit etc) were removed. Only the following columns were kept.

```
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   title          10024 non-null  object
 1   description    9981 non-null   object
 2   input_format   9862 non-null   object
 3   output_format  9742 non-null   object
 4   examples       9895 non-null   object
 5   rating         9767 non-null   float64
```

3. Data Preprocessing

Data preprocessing is critical for ensuring meaningful feature extraction. The following steps were applied consistently during training and inference:

1. For the Codeforces dataset, the rows with null values in the rating column are dropped. In the remaining columns, null fields are replaced with empty strings.
2. Normalization of ‘rating’ column (in Codeforces dataset) and ‘problem_score’ column (in Kattis dataset)
3. The Codeforces dataset does not provide explicit difficulty class labels. Therefore, difficulty classes for Codeforces problems were derived by analyzing the relationship between problem scores and difficulty classes in the Kattis dataset. Based on the observed score distributions, score thresholds were

defined to map normalized problem scores to the classes easy, medium, and hard.

4. Conversion to strings of ‘examples’ column (in Codeforces dataset) and ‘sample_io’ column (in Kattis dataset)
5. Aggregation of all textual fields into a single string to represent the complete problem context:
   Combined Text = Title + Description + Input + Output + Sample_io/examples
6. Text Cleaning through removal of extra whitespace and lowercasing
7. Concatenation of both the datasets into a single dataframe. Final dataframe:

```
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   title              13879 non-null  object
 1   description        13879 non-null  object
 2   input_description  13879 non-null  object
 3   output_description 13879 non-null  object
 4   sample_io          13879 non-null  object
 5   problem_class      13879 non-null  object
 6   problem_score      13879 non-null  float64
 7   sample_io_text     13879 non-null  object
 8   score_norm         13879 non-null  float64
 9   combined_text      13879 non-null  object
```

4. Feature Engineering

The system uses a hybrid feature representation combining **textual** and **numeric** features.

4.1 TF-IDF Features

- TF-IDF vectorization is applied to the combined problem text
- Captures keyword importance and semantic structure
- Produces a high-dimensional sparse feature matrix

4.2 Numeric Features

Four handcrafted numeric features were engineered:

1. **Constraint Magnitude Feature:** Extracts numerical constraints such as 10^5, 10^9 and converts it to a logarithmic scale.

2. **Mathematical Density:** Counts LaTeX expressions, operators, and mathematical symbols
3. **Algorithmic Keyword Count:** Counts occurrences of algorithm-related terms such as dp, graph, dfs, binary search, etc.
4. **Text Length:** Character length of the main problem description

5. Models Used and Results

5.1 Regression Models (Difficulty Score Prediction)

The following regression models were evaluated:

Evaluation	**Ridge Regression**	**Random Forest Regressor**	**XGBoost Regressor**
MAE	0.1750	0.1777	0.1708
R2	0.3311	0.3216	0.3659

As observed from the table, the model with least MAE and highest R2 value is XGBoost Regressor. Hence it was used for predicting difficulty scores.

5.2 Classification Models (Difficulty Class Prediction)

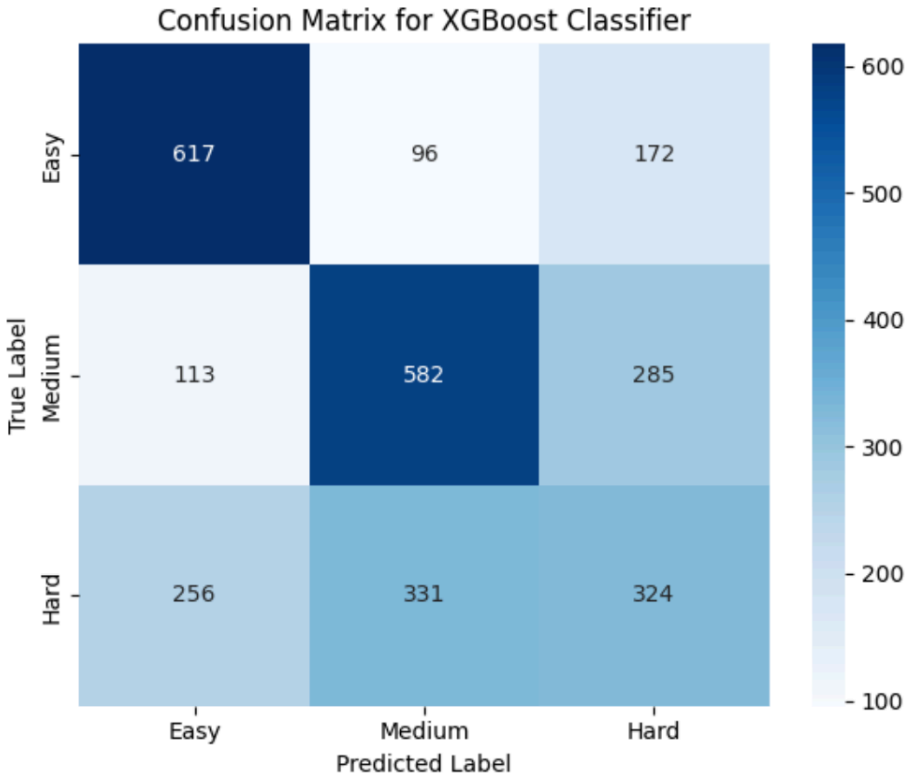
The following classification models were evaluated:

Evaluation	**Logistic Regression**	**SVM**	**XGBoost Classifier**
Accuracy	0.5345	0.5075	0.5486
F1	0.5295	0.5039	0.5426
Precision	0.5262	0.5012	0.5391
Recall	0.5347	0.5075	0.5489

The XGBoost classifier achieves the highest overall accuracy (0.5486) and macro-averaged F1 score (0.5426), indicating improved class balance and better

modeling of non-linear relationships in the feature space. Consequently, XGBoost was selected as the final classification model for deployment.

Confusion Matrix of XGBoost Classifier:



6. Experimental Setup

- Train–test split: 80% training, 20% testing
- Feature pipeline: TF-IDF + numeric features (stacked)
- Evaluation metrics:
    - Regression: MAE, R^2
    - Classification: Accuracy, Precision, Recall, F1-score, Confusion Matrix

All experiments were conducted using the same preprocessing and feature extraction pipeline to avoid train–serve skew.

8. Web Interface And Browser Extension

1. Web UI:

To demonstrate real-time difficulty prediction in a practical setting, the system was integrated with both a **web-based interface** and a **browser extension**. This allows users to obtain predictions either by manually entering problem details or by directly analyzing problems on competitive programming platforms.

• Architecture

- Backend: Flask REST API
- Frontend: HTML + JavaScript
- Models loaded using joblib

• Functionality

- User inputs problem details via a form
- Backend extracts features and runs ML models
- Output displayed: Predicted difficulty class and Difficulty score

2. Browser Extension

It was observed that copying and pasting the problem can be tedious. So tan extension was added for Codeforces website which predicted problem class without manual input.

• Architecture

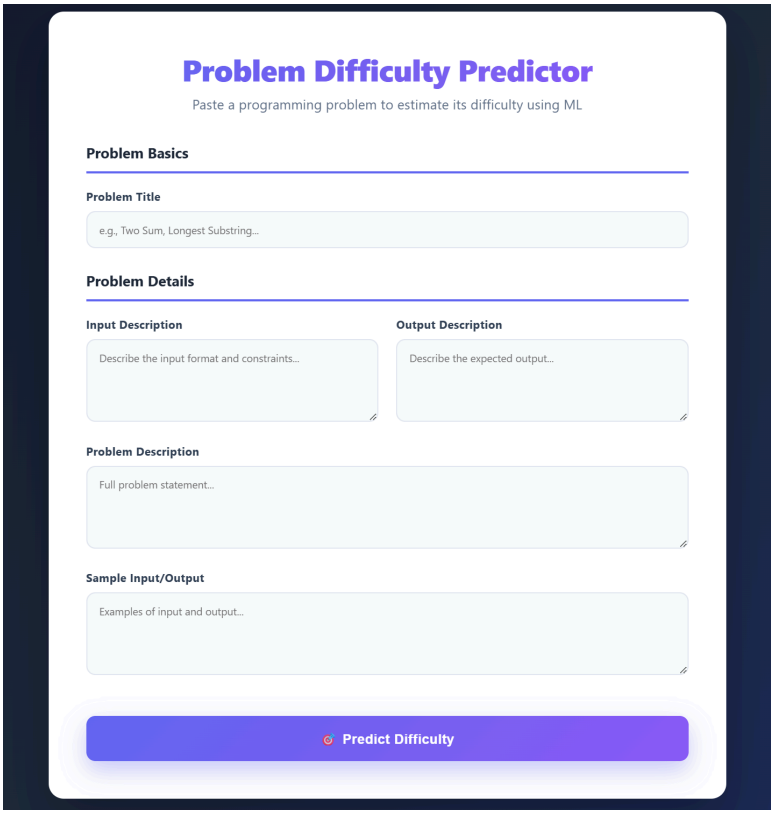
- Content Script: DOM extraction from problem webpages
- Frontend: HTML + JavaScript (Extension popup)
- Backend Communication: REST API calls to Flask server

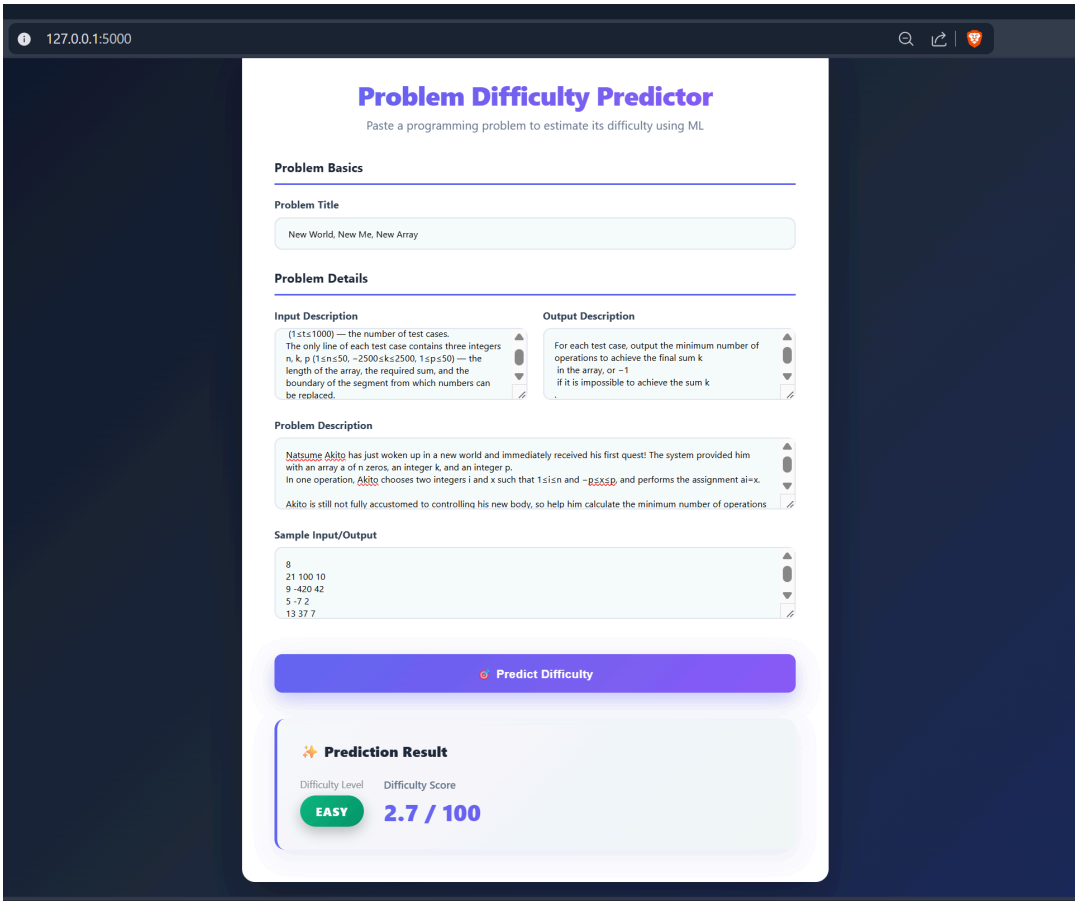
• Functionality

- Automatically extracts problem details from the active webpage
- Sends extracted data to the Flask `/predict` API endpoint
- Receives prediction results from the backend
- Output displayed in extension popup

3. Sample Prediction

- **Web UI**:
  Rating of problem shown in the web ui screenshot = 800
  Predicted Result = Easy


Problem Difficulty Predictor
Paste a programming problem to estimate its difficulty using ML
Problem Basics
Problem Title
e.g., Two Sum, Longest Substring...
Problem Details
Input Description
Describe the input format and constraints...
Output Description
Describe the expected output...
Problem Description
Full problem statement...
Sample Input/Output
Examples of input and output...
Predict Difficulty


127.0.0.1:5000
Problem Difficulty Predictor
Paste a programming problem to estimate its difficulty using ML
Problem Basics
Problem Title
New World, New Me, New Array
Problem Details
Input Description
(1≤t≤1000) — the number of test cases.
The only line of each test case contains three integers n, k, p (1≤n≤50, −2500≤k≤2500, 1≤p≤50) — the length of the array, the required sum, and the boundary of the segment from which numbers can be replaced.
Output Description
For each test case, output the minimum number of operations to achieve the final sum k in the array, or −1 if it is impossible to achieve the sum k .
Problem Description
Natsume Akito has just woken up in a new world and immediately received his first quest! The system provided him with an array a of n zeros, an integer k, and an integer p.
In one operation, Akito chooses two integers i and x such that 1≤i≤n and −p≤x≤p, and performs the assignment ai=x.
Akito is still not fully accustomed to controlling his new body, so help him calculate the minimum number of operations
Sample Input/Output
8
21 100 10
9 -420 42
5 -7 2
13 37 7
Predict Difficulty
Prediction Result
Difficulty Level
EASY
Difficulty Score
2.7 / 100

- **Extension:**
  Rating of problem shown in the web ui screenshot = 1400
  Predicted Result = Medium

9. Conclusion

This project demonstrates that text analysis can fairly predict how hard a problem is, using machine learning. Among all models tested, XGBoost did the best job against linear and tree-based models for both regression and classification tasks.

Key takeaways:

- Hybrid feature representations are crucial
- Text is best represented in models that handle sparse data
- The system generalizes well despite the subjective nature of difficulty labels

Future work may include:

- Add code submissions and editorial data
- Utilize transformer-based text representations.
- Extend to normalize difficulty across different platforms