

m Deadline: 2025-10-10 23:59

Individual Assignment - Each student must submit their own work

Submission Policy

 \mathbf{X} You have a total of two extra days available for late submissions across all assignments.

 If you want to use late days for an assignment, please send an email to ml-elsalab@googlegroups.com specifying the number of late days you intend to use (in units of days).

No copying or cheating; otherwise, you will receive zero points for this assignment.

Rules

- You may use any ML algorithm (linear models, tree ensembles, etc.)
- You may use any standard packages or libraries (e.g., numpy, pandas, scikit-learn, tensorflow, pytorch, lightgbm, etc.) to implement your solution. (Only for Q5)
- The work must be your own implementation of the method, even if the algorithm or approach itself is described in a paper or other resource.
 - You are not allowed to use any open-source implementations of this task that are publicly available, such as:
 - Copying code from GitHub repositories, blogs, or other students.
 - Directly using implementations released with research papers.
 - o Otherwise, you will receive zero points for this assignment.

Go Rank Prediction

& Objective

The goal of this assignment is to implement a Machine Learning model that can predict the playing strength (rank) of a Go player from their game records. The dataset contains Go games annotated with player rank labels.

Your task is to build a model that uses extracted features from the games to accurately estimate the player's rank.

Core Challenge: Generalization Ability

- Your model should not rely on memorizing specific games.
- The training set and the test set are not identical: test samples are aggregated from different sets of games.
- Your model must demonstrate the ability to generalize to unseen game records.

▼ Task Requirements

- 1. Build a ML model (e.g. regression or classification mode) to predict the player's rank.
- 2. Evaluate your model's performance in terms of:
 - Accuracy (exact rank prediction)

Dataset

- Training Data
 - The training set consists of nine files, each corresponding to one rank (1D–9D).
 - For example: log_9D_policy_train.txt contains data from 9-dan players, log_8D_policy_train.txt from 8-dan, and so on.
 - In every game, both players belong to the same rank, ensuring clean labels.

- Each file records all moves from multiple games played at that rank.
- Each move includes several types of numerical features, such as:
 - Policy values
 - Rank model outputs
 - Strength score
 - Lead information

Test Data

- The test set consists of multiple files, each identified by a random ID (e.g., 1.txt, 2.txt) rather than rank.
- Each file contains multiple games, all from the same rank.
- In every game, both players belong to the same rank, ensuring clean labels.
- Test samples are aggregated from several games per file.
- The internal structure of each move in the test set is identical to that of the training set.
- Output Label
 - The task is to predict the correct rank for the entire file.
- Data Format

Example snippet from log_1D_policy_train.txt:

```
B[Q16]
0.149007 0.212477 0.192526 ... 0.127816
50.146% 51.0391% 49.2588% ... 48.8448%
0.0915034 0.110794 0.108707 ... 0.135415
-2.84864
41.2% -0.6 17.2
```

Each move (e.g., B[Q16], W[D4]) is represented by **six parts**:

1. Move

- The player's color and coordinate, e.g., B[Q16].
- The color (B or W) is important, since it affects how winrate and lead differences are computed (both are black's perspective).

2. Policy Probabilities (9 values)

- These come from nine different SL models, each trained on games of a specific rank (1D-9D).
- They represent the probability of this move according to each model.
- Meaning: If the probability is high for a given model, the move is highly consistent with how players of that rank tend to play.

3. Value Predictions (9 values)

 Also from the nine SL models (1D-9D), but these are the predicted winrates of the position.

4. Rank Model Outputs (9 values)

- Produced by a dedicated SL rank_model.
- The outputs are probabilities that the position belongs to each of the 1D–9D ranks.
- Reference:
 - Determining Player Skill in the Game of Go with Deep Neural Networks
 - In the paper, the outputs were "strong / median / weak."
 Here, they are expanded to nine ranks.

5. Strength Score (1 value)

A relative strength score.

- Meaning: Moves from players of similar strength will have similar values.
- Reference:
 - Strength Estimation and Human-Like Strength Adjustment in Games

6. KataGo Analysis (3 values)

These values are computed by **KataGo**, currently the **strongest open-source Go engine**, widely used in research and analysis:

- Winrate (black's perspective): The predicted winning probability for black, directly from the network's value head.
- Lead (black's perspective): The estimated territory lead (in points).
- Uncertainty: How uncertain the model is about this position;
 higher values mean the prediction is more likely to be wrong.

⚠ Both winrate and lead are given from black's perspective. For moves played by white, the signs must be inverted.

Evaluation

Your submission will be scored based on:

 Exact Rank Accuracy: fraction of test samples where predicted rank matches true rank.

What You Need to Implement

- You are only responsible for submitting the predicted results of your model.
- Summit Rule
 - Team Name
 - Please use your student ID as the team name.
 - If you are an auditor, add _a after your student ID (e.g., b12345678_a).
 - Submission Limit
 - Each team may submit up to 10 times per day.

Grading Policy (25 Points + Up to 20 Bonus Points)

- ***** Base Score (based on private leaderboard accuracy)
 - $\geq 70\% \rightarrow 5$ points
 - ≥ 73% → 10 points
 - ≥ 77% → 15 points
 - ≥ 80% → 20 points
 - ≥ 83% → 25 points
 - ≥ 85% → eligible for leaderboard bonus (see below)

- Only participants with private leaderboard accuracy ≥ 85% are eligible for extra bonus points.
- Bonus is based on private leaderboard ranking:
 - Top 5%: +20 points
 - Next 5%: +19 points
 - Next 5%: +18 points
 - $_{\circ}$ $\,$ $\,$... decreasing by 1 point for every additional 5%
 - Until bonus reaches 0

Note:

- The private leaderboard will be revealed on 2025/10/17.
- <u>M</u> If you do not make a Kaggle submission, you will receive 0 points
 for this question, regardless of other files you submit.

Submission Requirements (To NTU Cool)

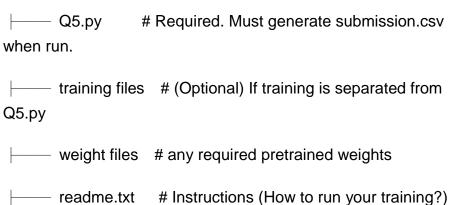
Your submission should be compressed into a .zip file named after your student ID.

 Example: If your student ID is D13922036, your submission file should be named D13922036.zip.

Submission Requirements

- Required Files:
 - Q5.py
 - Must be executable and directly produce submission.csv (in the correct Kaggle format).
 - This is to ensure that your Kaggle submission is indeed generated by your own code.
 - If Q5.py cannot generate a valid submission.csv, your score for Q5 will be 0, regardless of your Kaggle leaderboard performance.
- Training Code:
 - You must also submit your training script. This can be:
 - A separate training.py, or
 - Integrated into Q5.py (in which case, Q5.py must default to evaluation mode, and training must only be enabled via an additional switch/flag).
 - Please provide a readme.txt with instructions for running training

- Weight Files:
 - If Q5.py loads a pre-trained weight file (e.g., .pkl, .txt, .npy), you must include this file in your .zip submission.
- Important Note:
 - Do not include your Q1–Q4 .ipynb files in the .zip submission. Only files related to Q5 should be included.
- Example
 - o <student_id>.zip



⚠ Any submission format errors will result in score deductions.

