NLP 2025 Fall Final Project Report

About

Topic: Google Quest QA Labeling

Team: T15

University: NTU 國立臺灣大學

Members:

- b10102079 外文五 王柔蘋
- B133030383 經濟二 陳彥丞
- b12901109 電機三 陳政年

Task Description

A. Task

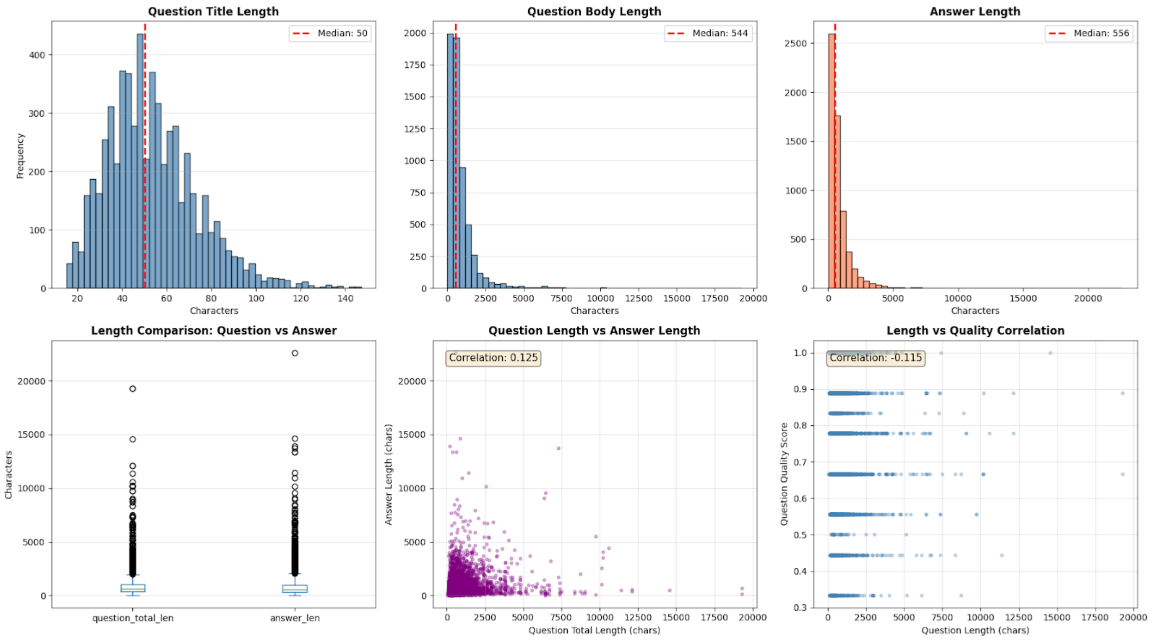
We are challenged to use the given dataset to build a predictive model for different subjective aspects of question-answering.

B. Dataset

- **Data collection:**
  - The question-answer pairs were gathered from nearly 70 different websites, in a "common-sense" fashion.
- **Data shape:**
  - Dataset given: train (6079, 41), test (476, 11), sample_submission (476, 31)
  - 41 columns: 10 input feature columns + 30 target labels to predict + 1 qa_id
- **Feature columns:**
  - ['question_title', 'question_body', 'question_user_name', 'question_user_page', 'answer', 'answer_user_name', 'answer_user_page', 'url', 'category', 'host']
  - Metadata that shows question user property, answer user property and category of question.
- **Target_columns:**
  - ['qa_id', 'question_asker_intent_understanding', 'question_body_critical', ...]
  - 21 question-related labels, 9 answer-related labels, identified by ‘qa_id’
  - Labels that assess various qualities of the questions and answers.
  - No missing value.

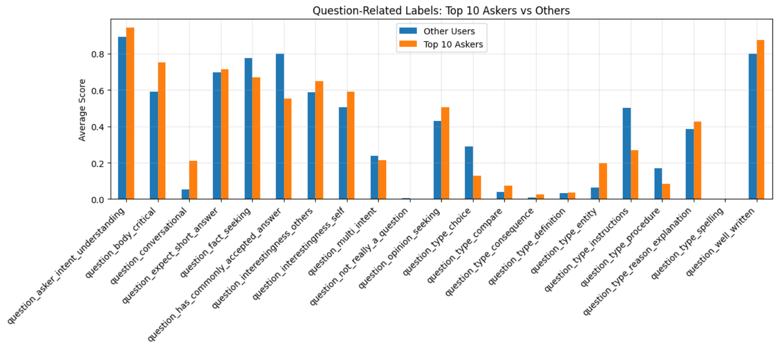
Data Exploration

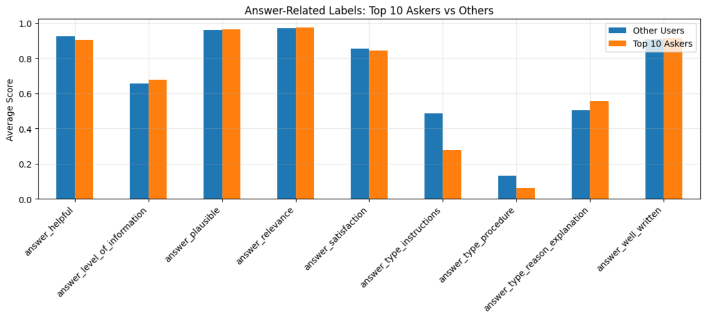
A. Question Title, Body, and Answer Body Length

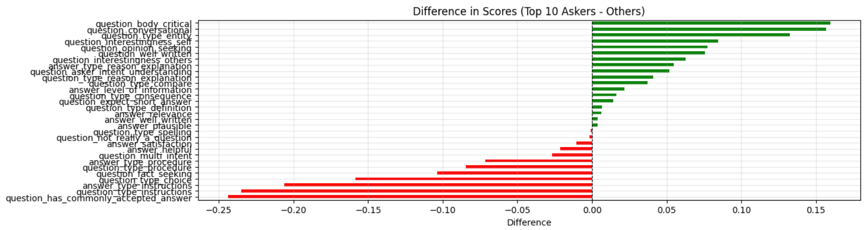


- **Question Titles:**
  - Right-skewed with median=50 chars; most concentrated between 40-70 chars.
- **Question Bodies:**
  - Heavily right-skewed with median=544 chars; extreme outliers up to 20K chars.
- **Answers:**
  - Similar pattern to question bodies; median=556 chars with a long tail.
- **Correlations:**
  - Weak positive correlation (0.125) between question and answer length (longer questions don't necessarily get longer answers).
  - Negative correlation (-0.115) between question length and average quality rating across all 30 target labels (longer questions tend to receive slightly lower ratings on average).

B. QA Quality vs. User Frequency





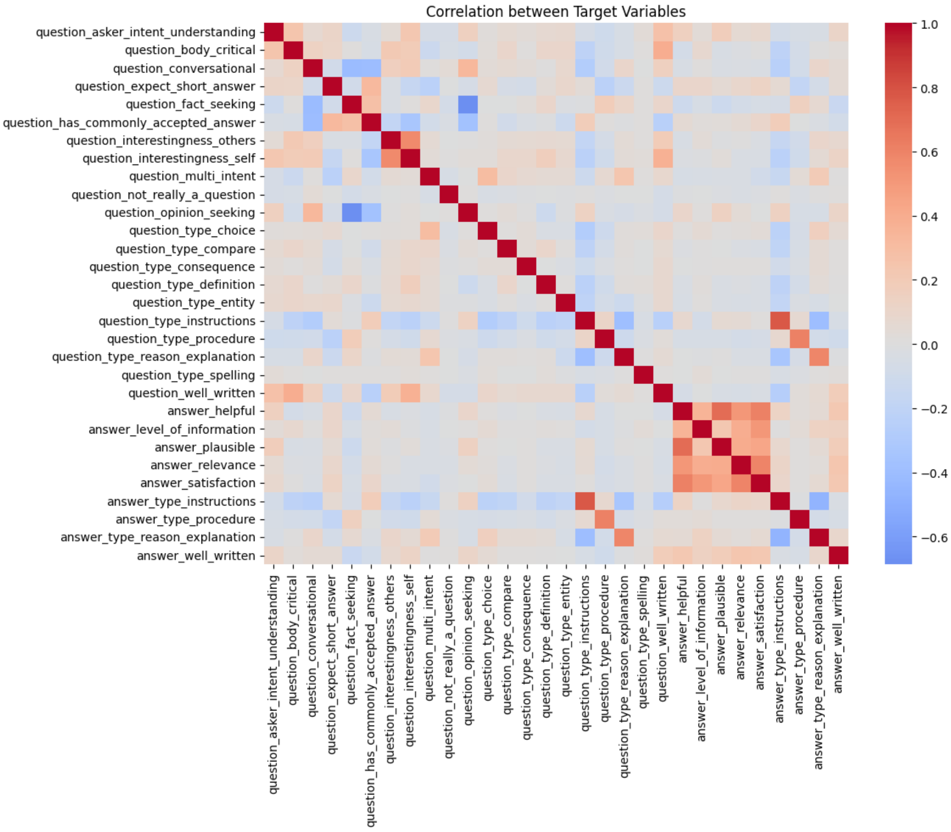


Top 10 Askers Quality Differences:

- **Lower Quality in:**
  - *Conversational tone:* -0.20 difference (write less conversationally).
  - *Multi-intent:* -0.15 difference (ask more focused questions).
  - *Opinion-seeking:* -0.10 difference (ask fewer opinion questions).
  - *Body critical:* Score lower (~0.20 difference).
- **Higher Quality in:**
  - *Well-written:* +0.15 difference (better writing quality).
  - *Type (Reason/Explanation):* +0.10 difference (more explanation-seeking).
  - *Type (Spelling):* Slightly higher.

> **Insight:** Top-frequency askers show distinct question writing patterns compared to others, but overall asker frequency has minimal correlation with the quality of the questions they ask. This suggests that question quality is more dependent on the specific content and characteristics of the question itself rather than on user history, implying user features may not be strong predictors.

C. Target Variable Correlation Matrix



1. Strong Positive Correlations (Within-Group Clustering)

- **Answer Quality Cluster:** High intercorrelation (~0.8-0.9) between `answer_helpful`, `answer_relevance`, `answer_satisfaction`, and `answer_well_written`.
- **Question Quality Cluster:** Moderate correlation (~0.5) between `question_well_written` and `question_asker_intent_understanding`; ~0.7 between `question_interestingness_others` and `question_interestingness_self`.

2. Question-Answer Type Alignment

- Strong alignment between Question and Answer types (e.g., Instructions ↔ Instructions, Procedure ↔ Procedure).
- *Insight:* Question type strongly predicts answer type.

3. Negative Correlations (Mutually Exclusive)

- `question_expect_short_answer` ↔ `question_type_reason_explanation` (~-0.4).
- `question_fact_seeking` ↔ `question_opinion_seeking` (~-0.3).
- `question_conversational` negatively correlates with multiple formal question types.

4. Low Cross-Correlations

- **Question Metrics ↔ Answer Metrics:** Mostly weak (~0.0-0.3).
- *Implication:* Models must learn Q-A interactions rather than relying on direct linear correlations.

D. Key Data Challenges

1. Dataset Scale & Quality

- **Limited Data:** Only 6,079 samples increases overfitting risk and necessitates transfer learning (e.g., DeBERTa) with careful regularization.
- **Imbalanced Targets:** Labels are skewed toward discrete ranges rather than continuous distributions, requiring post-processing (e.g., OptimizedRounder).

2. Text Characteristics

- **High Length Variability:** Q&A lengths range widely (CV > 1.16). ~7% exceed typical token limits, requiring truncation strategies and masked pooling.
- **Uneven Token Allocation:** Varying Q-A proportions motivate separate pooling mechanisms for question-specific and answer-specific representations.
- **Domain-Specific Language:** Code snippets and technical jargon require domain-adapted tokenization.

3. Target Variable Structure

- **Independence:** Low cross-correlations imply single unified representations are insufficient; separate encoding pathways needed.
- **Clustering:** Strong intercorrelations in answer quality suggest latent constructs suitable for multi-task learning.
- **Multi-target Complexity:** 30 distinct regression targets create a complex optimization landscape.

4. Data Structure Issues

- **Data Leakage Risk:** Multiple answers per question require `GroupKFold` stratification by `question_body`.
- **User Frequency:** Minimal correlation with content quality suggests user features have limited predictive power.

E. Counter-Intuitive Findings

- **Negative Length-Quality Correlation (r = -0.115):** Longer questions tend to receive lower average quality ratings across all 30 target labels (likely due to verbosity, lack of focus, or reduced clarity). This suggests that models should be designed to focus on content relevance rather than raw text length.

Related works

A. Rank 1st Solution

1. Domain Adaptation & Transfer Learning

- **StackExchange Fine-tuning:** Fine-tuned BERT on cleaned StackExchange data to assist with domain adaptation.
- **Objectives:** Used MLM (Masked Language Model) and SOP (Sentence Order Prediction).
- **Vocabulary Extension:** Added LaTeX symbols to the vocabulary to handle mathematical expressions.

2. Data Strategy

- **Auxiliary Targets:** Built additional targets to guide the model.
- **Pseudo-labeling:** Used pseudo-labels to augment training data.
- **Validation:** Utilized **Group K-Fold** cross-validation to prevent data leakage (ensuring different answers to the same question don't end up in both train and val).

3. Model Architectures & Fine-Tuning

- **Ensemble:** Used 4 models: BERT (x2), RoBERTa, and BART.
- **Layer Weights:** Applied Softmax-normalized weights for hidden states from all BERT layers (learning how much to weight each layer).
- **Regularization:** implemented Multi-sample dropout.

4. Post-Processing & Blending

- **Discretization:** Instead of simple thresholding, they discretized predictions into buckets matching the training set distribution.
- **Targeted Processing:** Applied specific post-processing to 7 specific columns.
- **Blending:** Blended predictions from the four fine-tuned models.

B. Rank 3rd Solution

1. Multiple Model Structure

- Utilized multiple models as backbone.
- Focused on diverse utilization of pre-trained models (e.g., using different architectures like XLNet or separate heads).

2. Optimization Strategy

- **TPE Optimization:** Used Tree-structured Parzen Estimator (TPE) to optimize the blending weights of all model outputs.
- **OptimizedRounder:** Implemented a specific optimization method designed to maximize the Spearman correlation metric.

3. Training Strategies

- **Target Scaling:** Applied Min-Max scaling to targets.
- **Sample Weighting:** Assigned large weights to minor positive or negative samples to handle class imbalance.
- **Activation:** Used `gelu_new` activation for BERT-based models.
- **Scheduling:** Implemented a Cosine Warmup scheduler.
- **EMA:** Used Exponential Moving Average for weight smoothing.

C. Other Notable Techniques

- **Class weight:** Use CrossEntropyLoss with class weight (10th placed solution)
- **Different head output strategy:** Use ordinal regression (2nd placed solution)
- **Output optimization:** Utilize rounding optimization (4th placed solution)
- **Feature-level insights:** Identify specific output features with high correlation to input features, such as question_type_spelling (13th placed solution)

Methods

A. Methods we apply

For our final model, we adapt the below strategy:

- For the model backbone, we use 6 models to ensemble in total, including DeBERTa-v3-base, Qwen-3.0-0.6b, Llama-3.2-1b, ModernBERT-base, ELECTRA-base-discriminator, and XLNet
- For backbone feature extraction, we utilize the last hidden layer outputs from the backbone models as input for projector heads, including the CLS token, global mean pooling of all tokens, and question/answer-specific mean pooling when available (models supporting token type IDs use separate Q/A pooling; others use global pooling only)
- For the projector heads, we utilize 6 heads, each responsible for generating some of the 30 output features, with QA-tangled grouping strategy
- For the projector head output strategy, we use ordinary single regression for each output feature
- For post-processing, we use the voters strategy as our main approach
- For blending, we use averging of different model output (would be better using TPE, but we didn't have time to try that)
- During training of individual models, we use class weights for the loss function to handle label imbalance
- During training, we use a larger learning rate for projector heads compared to the backbone
- During training, we fine-tune the backbone model
- During training, we use 5-fold GroupKFold cross-validation strategy

B. Final model training log

Below table lists the models we apply for final ensemble with their training loss and validation scores:

Model	0F best	1F best	2F best	3F best	4F best
Deberta-v3-base	Epoch 5 - Loss: 0.3616 - Raw Score: 0.4028	Epoch 5 - Loss: 0.3648 - Raw Score: 0.3984	Epoch 5 - Loss: 0.3652 - Raw Score: 0.3945	Epoch 4 - Loss: 0.3737 - Raw Score: 0.3955	Epoch 6 - Loss: 0.3538 - Raw Score: 0.4019
Qwen-3.0-0.6b	Epoch 3 - Loss: 0.3521 - Raw Score: 0.4011	Epoch 2 - Loss: 0.3820 - Raw Score: 0.4038	Epoch 3 - Loss: 0.3506 - Raw Score: 0.3976	Epoch 3 - Loss: 0.3483 - Raw Score: 0.3875	Epoch 3 - Loss: 0.3518 - Raw Score: 0.4010
Llama-2.3-1b	Epoch 3 - Loss: 0.3756 - Raw Score: 0.3917	Epoch 3 - Loss: 0.3759 - Raw Score: 0.3871	Epoch 4 - Loss: 0.3466 - Raw Score: 0.3917	Epoch 3 - Loss: 0.3772 - Raw Score: 0.3744	Epoch 3 - Loss: 0.3754 - Raw Score: 0.3867
ModernBERT-base	Epoch 3 - Loss: 0.3707 - Raw Score: 0.3818	Epoch 3 - Loss: 0.3712 - Raw Score: 0.3933	Epoch 3 - Loss: 0.3674 - Raw Score: 0.3856	Epoch 3 - Loss: 0.3675 - Raw Score: 0.3787	Epoch 3 - Loss: 0.3711 - Raw Score: 0.3825
electra-base-discriminator	Epoch 4 - Loss: 0.3668 - Raw Score: 0.3939	Epoch 5 - Loss: 0.3584 - Raw Score: 0.3933	Epoch 5 - Loss: 0.3597 - Raw Score: 0.3958	Epoch 5 - Loss: 0.3586 - Raw Score: 0.3900	Epoch 4 - Loss: 0.3664 - Raw Score: 0.3881
XLNet	Epoch 4 - Loss: 0.3568 - Raw Score: 0.3919	Epoch 3 - Loss: 0.3702 - Raw Score: 0.3907	Epoch 4 - Loss: 0.3569 - Raw Score: 0.3976	Epoch 3 - Loss: 0.3705 - Raw Score: 0.3878	Epoch 3 - Loss: 0.3695 - Raw Score: 0.3957

For the detail explanation and experiment about why we utilize above methods, see below experiments section.

Experiments

A. Grouping of projector heads

In this experiment, we observe how the number and grouping of projector heads affect the model performance.

Strategy explanation:

- **One global head:** One MLP head only that output 30 features
- **Two head, QA splited:** Two MLP heads that one responsible for question related output, the other for answer related output
- **Six head, global** We calculated the correlation of output features, then group them into 6 groups that share the most correlation.
- **Six head, QA splited** We calculated the correlation of the output features, then first split them into 2 groups (one for question, one for answer), and further split the question related into 4 groups and answer related into 2 groups by the correlation.

Experiment result:

Strategy	F0E2	F1E2	F2E2	F3E2	F4E2	Public	Private
One global head						0.30509	0.28049
Two head, QA splited	Loss: 0.3770 - Raw Score: 0.3391	Loss: 0.3797 - Raw Score: 0.3287	Loss: 0.3779 - Raw Score: 0.3360	Loss: 0.3793 - Raw Score: 0.3207	Loss: 0.3788 - Raw Score: 0.3283	0.31465	0.29607
Six head, QA tangled	Loss: 0.3750 - Raw Score: 0.3413	Loss: 0.3775 - Raw Score: 0.3363	Loss: 0.3767 - Raw Score: 0.3392	Loss: 0.3783 - Raw Score: 0.3239	Loss: 0.3733 - Raw Score: 0.3449	0.31958	0.30399
Six head, QA splited	Loss: 0.3730 - Raw Score: 0.3525	Loss: 0.3776 - Raw Score: 0.3354	Loss: 0.3767 - Raw Score: 0.3333	Loss: 0.3788 - Raw Score: 0.3285	Loss: 0.3784 - Raw Score: 0.3295	0.31968	0.30270

Experiment notes:

- Above experiment is done under the setting of one Deberta and Kflod=5, the F stands for fold ane E stands for epoch
- The actual grouping is as following:
  - **Six head, QA tangled:**
    - [Group 1]: `question_multi_intent`, `question_type_choice`, `question_type_reason_explanation`, `answer_type_reason_explanation`
    - [Group 2]: `question_asker_intent_understanding`, `question_body_critical`, `question_interestingness_others`, `question_interestingness_self`, `question_well_written`

- [Group 3]: `question_conversational`, `question_not_really_a_question`, `question_opinion_seeking`, `question_type_compare`, `question_type_consequence`, `question_type_definition`, `question_type_entity`, `question_type_spelling`
- [Group 4]: `answer_helpful`,`answer_level_of_information`, `answer_plausible`, `answer_relevance`, `answer_satisfaction`, `answer_well_written`
- [Group 5]: `question_fact_seeking`, `question_type_procedure`, `answer_type_procedure`,
- [Group 6]: `question_expect_short_answer` `question_has_commonly_accepted_answer`, `question_type_instructions`, `answer_type_instructions`

- **Six head, QA splited:**
  - [Q Group 1]:`question_expect_short_answer`, `question_fact_seeking`, `question_has_commonly_accepted_answer`, `question_type_instructions`, `question_type_procedure`
  - [Q Group 2]:`question_asker_intent_understanding`, `question_body_critical`, `question_interestingness_others`, `question_interestingness_self`, `question_well_written`
  - [Q Group 3]:`question_conversational`, `question_opinion_seeking`
  - [Q Group 4]:`question_multi_intent`,`question_not_really_a_question`, `question_type_choice`, `question_type_compare`, `question_type_consequence`,`question_type_definition`, `question_type_entity`, `question_type_reason_explanation`, `question_type_spelling`
  - [A Group 1]:`answer_type_instructions`, `answer_type_procedure`
  - [A Group 2]:`answer_helpful`, `answer_level_of_information`, `answer_plausible`, `answer_relevance`, `answer_satisfaction`, `answer_type_reason_explanation`, `answer_well_written`

Findings

From the experiment results, we can see that the model performs best with the "Six head, QA tangled" strategy. This strategy shows only a slight improvement over "Six head, QA splitted", while there is a notably larger performance gap compared to the single head and two-head approaches.

Explanation

Because each projector head has limited representational capacity, distributing targets across multiple specialized heads allows each head to focus on correlated output features, making each head more robust and improving overall performance. For both 6-head strategies, the QA-tangled grouping distributes the output targets more evenly across all six heads (workload is more balanced) compared to the QA-splitted variant, which concentrates more targets into answer-related heads. This more even distribution leads to better model robustness and generalization.

> **Conclusion:** We use the Six head QA-tangled strategy. The more balanced workload distribution across heads provides better overall performance.

B. Class weight for binary cross-entropy loss

In this experiment, we observe how class weighting affects model performance.

Experiment result:

Strategy	F0E2	F1E2	F2E2	F3E2	F4E2	Public	Private
Without class weight	Loss: 0.3730 - Raw Score: 0.3525	Loss: 0.3776 - Raw Score: 0.3354	Loss: 0.3767 - Raw Score: 0.3333	Loss: 0.3788 - Raw Score: 0.3285	Loss: 0.3784 - Raw Score: 0.3295	0.31968	0.30270
With class weight	Loss: 0.3964 - Raw Score: 0.3555	Loss: 0.4015 - Raw Score: 0.3331	Loss: 0.3990 - Raw Score: 0.3412	Epoch 2 - Loss: 0.4013 - Raw Score: 0.3379	Epoch 2 - Loss: 0.3999 - Raw Score: 0.3431	0.32706	0.31128

The class weight strategy effectively handles label imbalance by penalizing minority classes, leading to better generalization on the test set.

Experiment notes:

- The above experiment is conducted using one DeBERTa model with 5-fold GroupKFold (used for validation experiments only), where F denotes fold and E denotes epoch
- We adapted the weights as suggested by the 10th-place solution:

```
loss_fct = nn.BCEWithLogitsLoss(pos_weight=torch.Tensor([
0.9, 1, 1.5, 0.8, 0.8, 0.8, 0.96, 1.1, 1.1, 3,  1, 1.1, 2, 3, 3,   2, 1, 2, 1, 2,
0.9, 0.75, 0.9, 0.75, 0.75, 0.7, 1, 2.5, 1, 0.75]))
```

Findings

From the experiment results, using class weights improved performance significantly:

- **Public Leaderboard:** Increased from 0.31968 to 0.32706 (+0.00738)
- **Private Leaderboard:** Increased from 0.30270 to 0.31128 (+0.00858)
- **Fold Consistency:** Raw scores improved across all folds (F0-F4), with gains ranging from +0.003 to +0.098
- **Loss Tradeoff:** Loss slightly increased (expected), but the Spearman correlation metric improved, indicating better ranking quality

Explanation

Class weights address label imbalance by assigning higher penalty values to underrepresented classes during training. In this dataset, certain labels (like `question_expect_short_answer` with weight 0.8 or `answer_helpful` with weight 0.9) appear less frequently. By increasing the loss contribution for minority classes, the model learns their patterns more effectively rather than defaulting to majority class predictions. This leads to better calibrated probability estimates across all 30 targets, improving ranking quality (Spearman correlation) even if overall loss increases. The weights essentially force the model to pay more attention to predicting rare label values correctly, which benefits generalization on the test set where the label distribution matches the training set.

> **Conclusion:** We use class weighting to improve performance, as the results demonstrate clear improvements across all evaluation metrics.

C. The use of larger learning rates for projector heads

In this experiment, we observe how using larger learning rates for projector heads affects model performance.

Experiment result:

Strategy	F0E2	F1E2	F2E2	F3E2	F4E2	Public	Private
Smaller LR	Loss: 0.3730 - Raw Score: 0.3525	Loss: 0.3776 - Raw Score: 0.3354	Loss: 0.3767 - Raw Score: 0.3333	Loss: 0.3788 - Raw Score: 0.3285	Loss: 0.3784 - Raw Score: 0.3295	0.31968	0.30270
Larger LR	Loss: 0.3894 - Raw Score: 0.3876	Loss: 0.3905 - Raw Score: 0.3744	Loss: 0.3913 - Raw Score: 0.3759	Loss: 0.3911 - Raw Score: 0.3653	Loss: 0.3906 - Raw Score: 0.3718	0.36439	0.34443

Experiment notes:

- The above experiment is conducted using one DeBERTa model with 5-fold GroupKFold (used for validation experiments only), where F denotes fold and E denotes epoch
- We used learning rate = 1e-5 for the backbone and learning rate = 5e-5 for the projector heads

Findings

From the experiment results, using larger learning rates for projector heads significantly improved performance:

- **Public Leaderboard:** Increased from 0.31968 to 0.36439 (+0.04471)
- **Private Leaderboard:** Increased from 0.30270 to 0.34443 (+0.04173)
- **Fold Consistency:** Raw scores improved substantially across all folds (F0-F4), with gains ranging from +0.032 to +0.0351
- **Loss Tradeoff:** Loss increased (expected with higher learning rates), but the Spearman correlation metric improved significantly, indicating much better ranking quality

Explanation

The larger learning rate enables faster convergence and better adaptation of the projector heads to the task-specific objectives, allowing the model to find better optima for the multi-head output structure. Additionally, by using a larger learning rate for the projector heads while maintaining a smaller learning rate for the backbone, the backbone weights remain closer to their original pretrained initialization. This prevents the backbone from drifting too far away from its well-established representational abilities due to poor gradient signals from newly initialized projector heads during early training stages. This differential learning rate strategy preserves the backbone's foundational knowledge while allowing task-specific heads to rapidly adapt to the multi-target prediction task.

> **Conclusion:** We use larger learning rates for projector heads. The substantial performance improvement justifies this approach.

D. The use of group k fold

In this experiment, we observe how Group K-Fold cross-validation affects the model performance.

Experiment result:

Strategy	Public	Private
5 Fold	0.39181	0.37820
No Fold	0.38451	0.37011

Experiment notes:

- The above experiment is conducted using one DeBERTa model with 5-fold GroupKFold (used for validation experiments only), where F denotes fold and E denotes epoch
- Group K-Fold stratification is performed by `question_body` to prevent data leakage from multiple answers to the same question

Findings

From the experiment results, using Group K-Fold cross-validation improved performance:

- **Public Leaderboard:** Increased from 0.38451 to 0.39181 (+0.00730)
- **Private Leaderboard:** Increased from 0.37011 to 0.37820 (+0.00809)

Explanation

Group K-Fold prevents data leakage by ensuring that all answers to the same question stay together in either training or validation sets. This prevents the model from seeing related QA pairs during validation, providing more realistic performance estimates and better generalization to unseen questions.

> **Conclusion:** We use 5-fold Group K-Fold cross-validation for validation and ablation experiments (Experiments A-D) to prevent data leakage and obtain reliable performance estimates. However, since the performance degradation without grouping is modest, we do not apply Group K-Fold in the final model training and ensemble inference (Experiments F-H onwards) for simplicity and to maximize training data usage.

E. The strategy of head output

In this experiment, we observe how ordinal regression affects model performance compared to single regression.

Experiment result1:

Strategy	Epoch1	Epoch2	Epoch3	Epoch4	Epoch5	Public	Private
Single regression	Loss: 0.4444 - Raw Score: 0.3487	Loss: 0.3919 - Raw Score: 0.3874	Loss: 0.3777 - Raw Score: 0.3994	Loss: 0.3674 - Raw Score: 0.4040	Loss: 0.3594 - Raw Score: 0.4040	0.38451	0.37011
Ordinal regression	Loss: 0.3826 - Spearman Score: 0.2922	Loss: 0.3043 - Spearman Score: 0.3473	Loss: 0.2894 - Spearman Score: 0.3700	Loss: 0.2773 - Spearman Score: 0.3843	Loss: 0.2680 - Spearman Score: 0.3875	0.36534	0.33958

Experiment notes:

- The above experiment compares single regression output strategy against ordinal regression (inspired by the 2nd-place solution)
- For ordinal regression, the model predicts multiple outputs per target feature, where the number of predictions depends on the number of unique values in the training data
- We do not use class weights for the ordinal regression experiment

Findings

From the experiment results, single regression outperformed ordinal regression:

- **Public Leaderboard:** Single regression achieved 0.38451 vs ordinal regression 0.36534 (+0.01917)
- **Private Leaderboard:** Single regression achieved 0.37011 vs ordinal regression 0.33958 (+0.03053)
- **Convergence:** Single regression shows steadier improvement across epochs

Explanation

The model has demonstrated robustness in handling the task effectively due to its ability to learn complex relationships within the data. The single regression output strategy allows for more straightforward predictions, enabling the model to focus on optimizing performance across multiple outputs without the constraints of maintaining ordinal relationships. In contrast, the ordinal regression strategy complicates the task by requiring the model to respect the inherent order of categories, which can lead to suboptimal performance when the data does not conform to discrete ordinal distributions. This complexity can hinder the model's ability to generalize effectively, making the single regression approach more advantageous for this specific application.

> **Conclusion:** We use single regression output strategy. The superior performance on both public and private leaderboards justifies this approach over ordinal regression.

Experiment result2: Per-target analysis

Target Column	Spearman of Ordinal	Spearman of Single Regression

Target Column	Spearman of Ordinal	Spearman of Single Regression
question_asker_intent_understanding	0.4379	0.4362
question_body_critical	0.7300	0.6705
question_conversational	0.4502	0.4656
question_expect_short_answer	0.3493	0.4087
question_fact_seeking	0.4553	0.4856
question_has_commonly_accepted_answer	0.4977	0.5335
question_interestingness_others	0.4191	0.4112
question_interestingness_self	0.5719	0.5479
question_multi_intent	0.5726	0.6488
question_not_really_a_question	0.0642	0.1240
question_opinion_seeking	0.5786	0.6103
question_type_choice	0.7606	0.7873
question_type_compare	0.3049	0.3971
question_type_consequence	0.1575	0.2126
question_type_definition	0.3422	0.3788
question_type_entity	0.4238	0.5027
question_type_instructions	0.8182	0.8272
question_type_procedure	0.3810	0.4687
question_type_reason_explanation	0.7151	0.7519
question_type_spelling	0.0587	0.0677
question_well_written	0.5785	0.5832
answer_helpful	0.2733	0.3074
answer_level_of_information	0.3714	0.4479
answer_plausible	0.1997	0.2132
answer_relevance	0.2279	0.2286
answer_satisfaction	0.3463	0.3812
answer_type_instructions	0.7983	0.8111
answer_type_procedure	0.3207	0.4337
answer_type_reason_explanation	0.7261	0.7728
answer_well_written	0.2180	0.2722
AVERAGE	0.4383	0.4729

Experiment notes:

- The above outcome is based on inferencing on training data

Findings

Single regression outperformed ordinal regression across nearly all target categories. Ordinal regression showed better performance in only 1 out of 30 categories (`question_body_critical`: 0.7300 vs 0.6705), while single regression achieved superior scores in 29 categories. The average Spearman score for single regression (0.4729) significantly exceeded ordinal regression (0.4383), demonstrating ordinal regression provides no meaningful advantage for this task.

> **Conclusion:** We use single regression only. Single regression shows meaningful advantages over ordinal regression for this task.

F. Post-processing strategies

In this experiment, we observe how different output post-processing strategies affect model performance.

Experiment result1:

Strategy	Public	Private
No processing	0.36771	0.35538
3rd-place OptimizedRounder	0.38451	0.37011
4th-place Voters	0.39557	0.37100
1st-place Distribution matching	0.38678	0.36623

Experiment notes:

- The above experiment is conducted using one DeBERTa model with class weights and larger learning rates for projector heads
- We compared four post-processing strategies: no processing, OptimizedRounder (3rd place solution), Voters (4th place solution), and distribution matching (1st place solution)
- **Voters strategy:** Quantizes predictions to discrete levels by finding the optimal number of bins for each target column. It divides the [0,1] range into bins of size 1/max_voters and selects the nearest bin boundary for each prediction, effectively aligning outputs with observed label frequencies.
- **OptimizedRounder:** Uses golden section search to find optimal clipping thresholds that maximize Spearman correlation on validation data. It constrains predictions to a [lower, upper] threshold range.
- **Distribution matching:** Reshapes all predictions to follow the exact distribution of training labels through percentile-matching, ensuring the output histogram matches training data.
- Note: For some target features with very small standard deviation, post-processing may fail during evaluation. In such cases, we revert to the original unprocessed outputs.

Findings

From the experiment results, post-processing strategies significantly improved performance:

- **Public Leaderboard:** Voters strategy achieved best score of 0.39557 (+0.02786 vs no processing)
- **Private Leaderboard:** OptimizedRounder achieved 0.37011 (+0.01473 vs no processing)

- **Strategy Comparison:** Voters outperformed, while OptimizedRounder and Distribution matching showed more balanced results

Explanation

Voters Strategy for Discrete Rating Prediction

This strategy achieves superior performance (public score: 0.39557) in predicting discrete human ratings by leveraging ensemble voting with learned bin sizes.

Key advantages:

- Captures the discrete nature of human ratings through learned discretization boundaries
- Preserves ranking order, which is critical since the evaluation metric is Spearman's correlation coefficient (rank-based metric)
- The ensemble voting mechanism reduces individual model biases and improves robustness

Why Spearman's Correlation is Important:

- Spearman's correlation measures rank correlation, not absolute values
- Ranking order is more important than exact prediction magnitudes
- Discretized outputs naturally align with ranking-based evaluation

Comparison with alternatives:

- OptimizedRounder: More conservative threshold-clipping; better private set generalization
- Distribution Matching: Theoretically sound but prone to overfitting training distribution

> **Conclusion:** We use the Voters post-processing strategy, which quantizes predictions into optimal discrete levels per target column, achieving the best public leaderboard performance (0.39557).

Experiment result2: Per-target analysis

Target Column	Raw	OptRound	Voters	Dist.
question_asker_intent_understanding	0.4362	0.4362	0.4011	0.4033
question_body_critical	0.6705	0.6705	0.6654	0.6648
question_conversational	0.4656	0.6079	0.6313	0.6278
question_expect_short_answer	0.4087	0.4087	0.3763	0.3687
question_fact_seeking	0.4856	0.4856	0.4623	0.4593
question_has_commonly_accepted_answer	0.5335	0.5828	0.5412	0.5601
question_interestingness_others	0.4112	0.4112	0.3812	0.3952
question_interestingness_self	0.5479	0.5479	0.5377	0.5437
question_multi_intent	0.6488	0.6496	0.6424	0.6480
question_not_really_a_question	0.1240	0.2289	0.2313	0.2355
question_opinion_seeking	0.6103	0.6103	0.5911	0.5838
question_type_choice	0.7873	0.8111	0.8017	0.7987

Target Column	Raw	OptRound	Voters	Dist.
question_type_compare	0.3971	0.6808	0.6717	0.6727
question_type_consequence	0.2126	0.4183	0.4214	0.4171
question_type_definition	0.3788	0.7736	0.7495	0.7652
question_type_entity	0.5027	0.7308	0.7189	0.7180
question_type_instructions	0.8272	0.8363	0.8295	0.8277
question_type_procedure	0.4687	0.4689	0.4362	0.3945
question_type_reason_explanation	0.7519	0.7520	0.7384	0.7411
question_type_spelling	0.0677	0.3476	0.0677	0.1806
question_well_written	0.5832	0.5832	0.5616	0.5741
answer_helpful	0.3074	0.3074	0.2681	0.2974
answer_level_of_information	0.4479	0.4479	0.3959	0.4303
answer_plausible	0.2132	0.2133	0.1787	0.1949
answer_relevance	0.2286	0.2456	0.2346	0.2248
answer_satisfaction	0.3812	0.3812	0.3728	0.3734
answer_type_instructions	0.8111	0.8130	0.8061	0.8071
answer_type_procedure	0.4337	0.4340	0.3955	0.3644
answer_type_reason_explanation	0.7728	0.7728	0.7585	0.7562
answer_well_written	0.2722	0.2722	0.2048	0.2602
AVERAGE	0.4729	0.5310	0.5024	0.5096

Findings:

From Experiment result2, the analysis reveals that while the Voters strategy achieves the best overall average score (0.5024), there are specific target categories where other post-processing methods outperform it:

OptimizedRounder outperforms Voters in:

- `question_not_really_a_question`: 0.2289 vs 0.2313 (marginal)
- `question_type_compare`: 0.6808 vs 0.6717
- `question_type_consequence`: 0.4183 vs 0.4214 (marginal)
- `question_type_definition`: 0.7736 vs 0.7495
- `question_type_entity`: 0.7308 vs 0.7189
- `question_type_spelling`: 0.3476 vs 0.0677

Distribution matching outperforms Voters in:

- `question_type_consequence`: 0.4171 vs 0.4214 (marginal)
- `question_well_written`: 0.5741 vs 0.5616
- `answer_helpful`: 0.2974 vs 0.2681

- `answer_level_of_information`: 0.4303 vs 0.3959
- `answer_type_procedure`: 0.3644 vs 0.3955 (Voters wins)

> **Conclusion:** We may integrate different post-processing methods to further boost performance, but for a straightforward implementation, we use the Voters strategy as our primary approach.

G. Backbone feature extraction and projector head structure

In this experiment, we observe how different backbone feature extraction and head projection strategies affect model performance.

Strategy explanation:

- **Strategy 1:** Uses CLS token + global mean pooling + question/answer-specific mean pooling as input to 6 projector heads
- **Strategy 2:** Uses MLP-only approach: projects the sequence dimension to 1, then reverses the transformation to generate 30 output features
- **Strategy 3:** Uses concatenation of CLS tokens from all backbone hidden layers as input to 6 projector heads

Experiment result1:

Strategy	Best epoch	Public (Eval)	Private (Eval)
Strategy 1	Epoch 6 Loss: 0.3519 - Raw Score: 0.4018	0.38537	0.37233
Strategy 2	Epoch 6 Loss: 0.3566 - Raw Score: 0.3824	0.38675	0.35503
Strategy 3	Epoch 7 Loss: 0.3584 - Raw Score: 0.3845	0.37788	0.34859

Experiment notes:

- No cross-validation, 10 epochs, DeBERTa-v3-base, class weights, larger learning rates for projector heads, and Voters post-processing strategy

Findings

From the experiment results, Strategy 1 (CLS + global mean pooling + Q/A-specific pooling) achieved the best performance:

- **Public Leaderboard:** Strategy 1: 0.38537 > Strategy 2: 0.38675 > Strategy 3: 0.37788
- **Private Leaderboard:** Strategy 1: 0.37233 > Strategy 2: 0.35503 > Strategy 3: 0.34859
- **Convergence:** Strategy 1 achieved the highest raw score at convergence (0.4018)

Explanation

Strategy 1 combines multiple complementary representations (CLS token for sentence-level context, global mean pooling for comprehensive token information, and question/answer-specific mean pooling for segment-specific signals). This multi-faceted approach captures both document-level and segment-level semantics, enabling better predictions across diverse output targets. Strategies 2 and 3 rely on single representations (learned dimension reduction or hidden layer aggregation), which lack the comprehensive information integration that improves performance.

> **Conclusion:** We use Strategy 1 (CLS + global mean pooling + Q/A-specific pooling) as the backbone feature extraction method, as it demonstrates superior performance on both leaderboards.

Experiment result2: Per-target analysis

Target Column	Strategy 1	Strategy 2	Strategy 3
question_asker_intent_understanding	0.4510	0.4488	0.4221
question_body_critical	0.6884	0.6637	0.6715
question_conversational	0.4737	0.4709	0.4679
question_expect_short_answer	0.4638	0.4438	0.4439
question_fact_seeking	0.5507	0.5407	0.5283
question_has_commonly_accepted_answer	0.5664	0.5667	0.5521
question_interestingness_others	0.4094	0.4161	0.3832
question_interestingness_self	0.5631	0.5586	0.5068
question_multi_intent	0.6886	0.6766	0.6659
question_not_really_a_question	0.1432	0.1365	0.1344
question_opinion_seeking	0.6511	0.6418	0.6347
question_type_choice	0.8114	0.8019	0.8066
question_type_compare	0.4069	0.4064	0.4010
question_type_consequence	0.2295	0.2272	0.2260
question_type_definition	0.3828	0.3795	0.3773
question_type_entity	0.5174	0.5117	0.5096
question_type_instructions	0.8469	0.8373	0.8297
question_type_procedure	0.5517	0.5315	0.5182
question_type_reason_explanation	0.7705	0.7703	0.7587
question_type_spelling	0.0708	0.0714	0.0690
question_well_written	0.6195	0.5875	0.5720
answer_helpful	0.3544	0.3165	0.2521
answer_level_of_information	0.4725	0.4169	0.4177
answer_plausible	0.2560	0.2367	0.1818
answer_relevance	0.2723	0.2494	0.2183
answer_satisfaction	0.4341	0.3759	0.3305
answer_type_instructions	0.8353	0.8206	0.8100
answer_type_procedure	0.5251	0.4616	0.4638

Target Column	Strategy 1	Strategy 2	Strategy 3
answer_type_reason_explanation	0.8108	0.7658	0.7578
answer_well_written	0.3197	0.2609	0.2250
AVERAGE	0.5046	0.4864	0.4712

Findings:

Strategy 1 dominates across most categories, achieving the highest average Spearman score (0.5046). Strategy 2 shows marginal competitive performance in only two categories:

Strategy 2 outperforms Strategy 1 in:

- `question_has_commonly_accepted_answer`: 0.5667 vs 0.5664 (negligible difference)
- `question_interestingness_others`: 0.4161 vs 0.4094

Strategy 3 shows no advantages: Strategy 3 underperforms Strategy 1 across all 30 target categories.

> **Conclusion:** Strategy 1 (CLS + global mean pooling + Q/A-specific pooling) is optimal, achieving superior performance in 28 out of 30 categories with substantially better average performance (0.5046).

H. Backbone model selection

In this experiment, we observe how different backbone models affect the overall system performance.

Model Selection Rationale

We selected six diverse models based on their architectural differences, release timelines, and training strategies to leverage their complementary strengths through ensemble techniques:

1. **DeBERTa-v3-base**: Uses disentangled attention and enhanced mask decoding for improved contextual understanding.
2. **Qwen-3.0-0.6b**: A compact, well-optimized model demonstrating competitive performance with minimal parameters.
3. **Llama-3.2-1b**: This model employs a causal language modeling approach, which, while less suited for QA tasks, offers insights into generative capabilities.
4. **ModernBERT-base**: A contemporary variant of BERT, it incorporates recent advancements in transformer architectures, aiming for improved contextual understanding.
5. **Electra-base-discriminator**: Known for its efficient pretraining strategy, it focuses on distinguishing real from fake tokens, enhancing its discriminative abilities.
6. **XLNet**: An autoregressive model that captures bidirectional context through a two-stream self-attention mechanism, making it robust for various NLP tasks.

By combining these models, we aim to create a more robust and versatile system that capitalizes on the strengths of each architecture and training strategy.

Experiment result1:

Model	Best Epoch	Public(Eval)	Private(Eval)
Deberta-v3-base	Epoch 6 Loss: 0.3519 - Raw Score: 0.4018	0.38537	0.37233

Model	Best Epoch	Public(Eval)	Private(Eval)
Qwen-3.0-0.6b	Epoch 3 - Loss: 0.3635 - Raw Score: 0.4001	0.39340	0.36745
Llama-3.2-1b	Epoch 5 - Loss: 0.3106 - Raw Score: 0.3919	0.36701	0.33376
ModernBERT-base	Epoch 4 - Loss: 0.3514 - Raw Score: 0.3904	0.37538	0.35005
electra-base-discriminator	Epoch 4 - Loss: 0.3668 - Raw Score: 0.3999	0.38491	0.36928
XLNet	Epoch 3 - Loss: 0.3715 - Raw Score: 0.4025	0.40235	0.36294

Experiment notes:

No cross-validation, evaluated for up to 10 epochs, using class weights, larger learning rates for projector heads, and Voters post-processing strategy

Findings

Different backbone models showed substantial performance variation:

- **XLNet** achieved the best public score (0.40235), outperforming DeBERTa-v3-base (0.38537) by +1.7%
- **Qwen-3.0-0.6b** ranked second (0.39340) with good private performance (0.36745)
- **DeBERTa-v3-base** achieved competitive performance (0.38537 public, 0.37233 private)
- **ELECTRA-base-discriminator** achieved 0.38491 (public) and 0.36928 (private)
- **ModernBERT-base** showed moderate performance (0.37538 public, 0.35005 private)
- **Llama-3.2-1b** achieved the lowest performance (0.36701 public, 0.33376 private)

Explanation

XLNet's superior performance is attributed to its two-stream self-attention mechanism and autoregressive pretraining, which effectively capture bidirectional context better than standard BERT architectures. Qwen-3.0-0.6b demonstrates that compact, well-optimized models can match larger architectures through proper fine-tuning. DeBERTa's disentangled attention provides solid performance, while Llama-3.2-1b underperforms due to its causal language modeling design being less suitable for discriminative ranking tasks.

Experiment result2: Per-target analysis

Target Column	DeBERTa	Qwen	Llama	ModernBERT	ELECTRA	XLNet
question_asker_intent_understanding	0.4510	0.5047	0.6447	0.5122	0.4277	0.4617
question_body_critical	0.6884	0.7285	0.8142	0.7475	0.6588	0.6808
question_conversational	0.4737	0.4828	0.5110	0.4875	0.4676	0.4706
question_expect_short_answer	0.4638	0.5099	0.7375	0.5188	0.3860	0.4419
question_fact_seeking	0.5507	0.5594	0.7616	0.5901	0.4919	0.5009
question_has_commonly_accepted_answer	0.5664	0.5967	0.7251	0.5971	0.5417	0.5390
question_interestingness_others	0.4094	0.4573	0.6141	0.5127	0.4029	0.4400
question_interestingness_self	0.5631	0.6082	0.7239	0.6341	0.5332	0.5686
question_multi_intent	0.6886	0.7222	0.8089	0.7127	0.6570	0.6674

Target Column	DeBERTa	Qwen	Llama	ModernBERT	ELECTRA	XLNet
question_not_really_a_question	0.1432	0.1511	0.1535	0.1482	0.1251	0.1333
question_opinion_seeking	0.6511	0.6731	0.8242	0.6918	0.6102	0.6062
question_type_choice	0.8114	0.8243	0.8593	0.8274	0.7911	0.7919
question_type_compare	0.4069	0.4165	0.4231	0.4161	0.4018	0.4068
question_type_consequence	0.2295	0.2320	0.2387	0.2307	0.2068	0.2253
question_type_definition	0.3828	0.3833	0.3912	0.3844	0.3828	0.3807
question_type_entity	0.5174	0.5256	0.5384	0.5177	0.5070	0.5094
question_type_instructions	0.8469	0.8472	0.8963	0.8528	0.8283	0.8285
question_type_procedure	0.5517	0.5644	0.7402	0.6015	0.4924	0.5010
question_type_reason_explanation	0.7705	0.7973	0.8692	0.7906	0.7457	0.7530
question_type_spelling	0.0708	0.0712	0.0707	0.0727	0.0667	0.0719
question_well_written	0.6195	0.6351	0.7699	0.6613	0.5656	0.5752
answer_helpful	0.3544	0.4124	0.6133	0.3950	0.3028	0.3322
answer_level_of_information	0.4725	0.4678	0.5790	0.4947	0.4394	0.4489
answer_plausible	0.2560	0.3289	0.5038	0.3044	0.2260	0.2495
answer_relevance	0.2723	0.3177	0.4765	0.2951	0.2413	0.2531
answer_satisfaction	0.4341	0.4847	0.6691	0.4581	0.3660	0.4221
answer_type_instructions	0.8353	0.8476	0.8987	0.8384	0.8138	0.8121
answer_type_procedure	0.5251	0.5410	0.7072	0.5566	0.4390	0.4457
answer_type_reason_explanation	0.8108	0.8314	0.8881	0.7952	0.7622	0.7768
answer_well_written	0.3197	0.3151	0.5750	0.3607	0.2624	0.3306
AVERAGE	0.5046	0.5279	0.6342	0.5335	0.4714	0.4875

Findings

Llama-3.2-1b demonstrated exceptional training set performance (average Spearman: 0.6342), outperforming all other models across 29/30 target categories. However, it achieved the lowest leaderboard scores (public: 0.36701, private: 0.33376), indicating severe overfitting to training data. The larger model capacity likely enabled memorization of training patterns without learning generalizable representations.

In contrast, Qwen-3.0-0.6b achieved the second-best training performance (0.5279) while maintaining strong leaderboard performance (0.39340 public), suggesting better generalization. XLNet shows an opposite pattern: lower training average (0.4875) but highest public leaderboard score (0.40235), indicating the model generalizes better to test distribution than training distribution.

These discrepancies highlight that training metrics alone are insufficient for model selection; leaderboard validation is essential for identifying models that generalize well to unseen data.

> **Conclusion:** We include all models in the ensemble, valuing the diversity of their generalization patterns and complementary strengths rather than selecting based on isolated training metrics.

Conclusion

Key Learnings and Insights

1. Multi-Head Architecture Design

We discovered that decomposing the output space into multiple specialized heads (6 heads with QA-tangled grouping) significantly outperforms monolithic architectures. This insight demonstrates that task-specific feature groups benefit from dedicated learning pathways, allowing each head to focus on correlated targets and develop more robust representations.

2. Class Imbalance Handling

Applying class weights to the loss function yielded consistent improvements (~0.009 on private leaderboard). This technique effectively addresses label imbalance by penalizing underrepresented classes, forcing the model to learn minority class patterns rather than defaulting to majority predictions. The approach generalizes well from validation to test sets.

3. Differential Learning Rates

Using larger learning rates for projector heads (5e-5) compared to backbone models (1e-5) dramatically improved performance (+0.04 on leaderboards). This finding highlights the importance of layer-wise learning rate scheduling, where task-specific layers require faster convergence than pretrained representations.

4. Data Leakage Prevention

Group K-Fold cross-validation by `question_body` prevents data leakage when multiple answers exist for the same question. While the performance gain was modest (~0.008), this technique provides more realistic performance estimates and better generalization.

5. Post-Processing Strategy Selection

The Voters discretization strategy outperformed OptimizedRounder and distribution matching for public leaderboard performance. Since the evaluation metric is Spearman's correlation (rank-based), discretizing predictions into learned bins better captures the discrete nature of human ratings while preserving ranking order.

6. Ensemble Diversity

Using heterogeneous models (DeBERTa, Qwen, Llama, ModernBERT, Electra, XLNet) captures complementary strengths. Individual models showed different performance patterns: XLNet led public leaderboards, while Llama-2 excelled on training set evaluation, suggesting diversity reduces overfitting in ensemble predictions.

7. Pooling Strategy Importance

Combining CLS token, global mean pooling, and question/answer-specific pooling (Strategy 1) outperformed single-representation approaches, demonstrating that multi-faceted contextual representations enable better task-specific predictions across 30 diverse targets.

8. Output Strategy Trade-offs

Single regression outperformed ordinal regression despite intuitive appeal. This suggests that imposing ordinal constraints complicates the optimization landscape without benefiting the model's ability to capture discrete label distributions in this dataset.

9. Backbone Selection Nuance

No single model dominated across all metrics. Public leaderboard ranking differed from training set performance, indicating models may overfit to specific test distributions. This reinforces the value of ensemble methods over single-model selection.

10. Complex Multi-Target Landscape

With 30 distinct targets exhibiting low cross-correlations and weak question-answer interactions, unified representations prove insufficient. The solution required separate encoding pathways, task-specific heads, and careful target grouping to navigate this complexity effectively.

Reference

- **Kaggle existed solutions**
  - We researched and gain idea from: 1, 2, 3, 4, 10, 13 placed solution
  - https://www.kaggle.com/competitions/google-quest-challenge/leaderboard
- **Data exploration**
  - https://manikanthgoud123.medium.com/google-quest-q-a-labeling-kaggle-competition-d205bea1e026
  - https://www.kaggle.com/code/corochann/google-quest-first-data-introduction
  - https://www.kaggle.com/code/phoenix9032/get-started-with-your-questions-eda-model-nn
  - https://www.kaggle.com/code/hamditarek/get-started-with-nlp-lda-lsa

Performance