Valence Case: Labelling User-System Conversations

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Task:

To label and score the user-system conversations using LLM and Non-LLM based techniques

Dataset Used:

User Satisfaction Simulation - Conversational Dataset (https://github.com/sunnweiwei/user-satisfaction-simulation)
In particular, I used a subset of the **Schema Guided Dialogue (SGD)** dataset which contained annotated task-oriented conversations between humans and a virtual assistant across different domains.

Evaluation Metrics:

The metrics used were taken from the paper "Simulating User Satisfaction for the Evaluation of Task-oriented Dialogue Systems"

- **Unweighted Average Recall:** UAR is the arithmetic average of all class-wise recalls.
- **Kappa Score:** It is used to check the inter-annotator agreement, but it can be modified to judge the predictions by evaluating how well the predicted labels agree with the true labels across all classes.
- **Spearman Rho Coefficient:** Spearman's rank is used to find the relationship between two variables. It can be modified similarly to suit our task.

Data Preparation:

Analysis of the dataset:

1) The dataset was heavily imbalanced towards an average rating of 3
2) Voting which is essentially the mode was used as a tiebreaker between annotators which might not be correct always.
3) Statistical Analysis:
    - Mean of gold labels: 3.09
    - Median of gold labels: 3
    - Mode of gold labels: 3
    - Standard deviation of gold labels: 0.44
    - Minimum score: 1
    - Maximum score: 5

Preprocessing and Cleaning:

The code used in the repository was mostly used to preprocess and clean the dataset.
Steps involved:

1) Extracting turn-by-turn conversation from the input SGD.txt
2) Calculating the mode of every annotation by different annotators

Non-LLM Based:

Preprocessing for Non-LLM based:

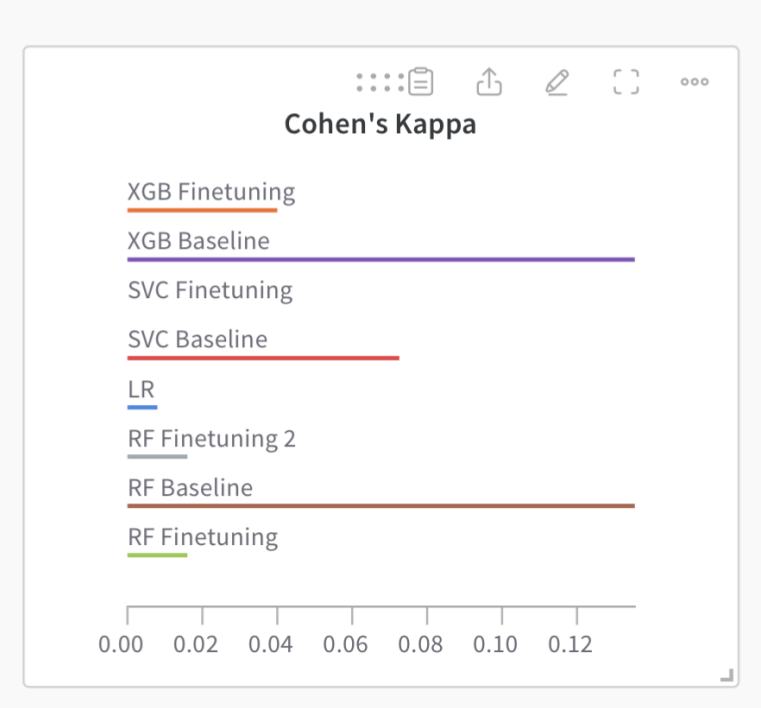
- Conversion of the text into numerical values using TF-IDF which provides insight into how the words are spread across individual data points as well as across different documents.
- The length of the input text was also stored as a feature.

Models Used:

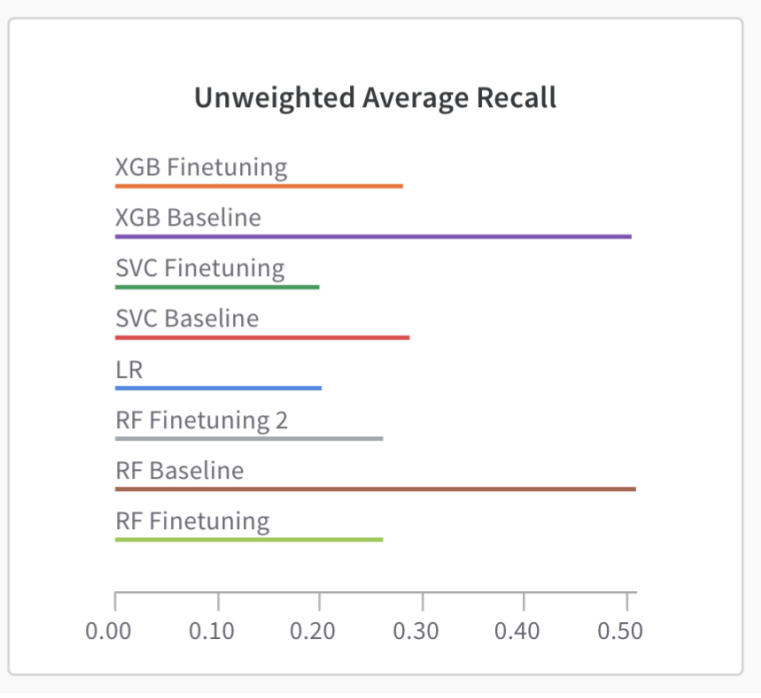
- Logistic Regression: LR was used as the most basic model to find the baseline of classification.
- Support Vector Classifier: This kernel-based approach is used a lot due to its ability to generalize using kernels that represent the input data in higher dimensions to make it linearly separable.
    - HyperParameters tuned:
        - Gamma
        - C
        - Kernel
- Random Forest: RF was used since it takes advantage of Decision Trees ability to segregate the dataset based on the features and also experiment with different weights and different architectures.
    - HyperParameters tuned:
        - Number of estimators (trees)
        - Depth of trees
        - Splits per node
        - Samples per leaf node
- XGBoost: XGBoost is used in the industry due to its feature to quickly adjust to the data points by weighing them based on misclassification.
    - HyperParameters tuned:
        - Number of estimators
        - Maximum Depth
        - Learning Rate
        - Gamma

Results:

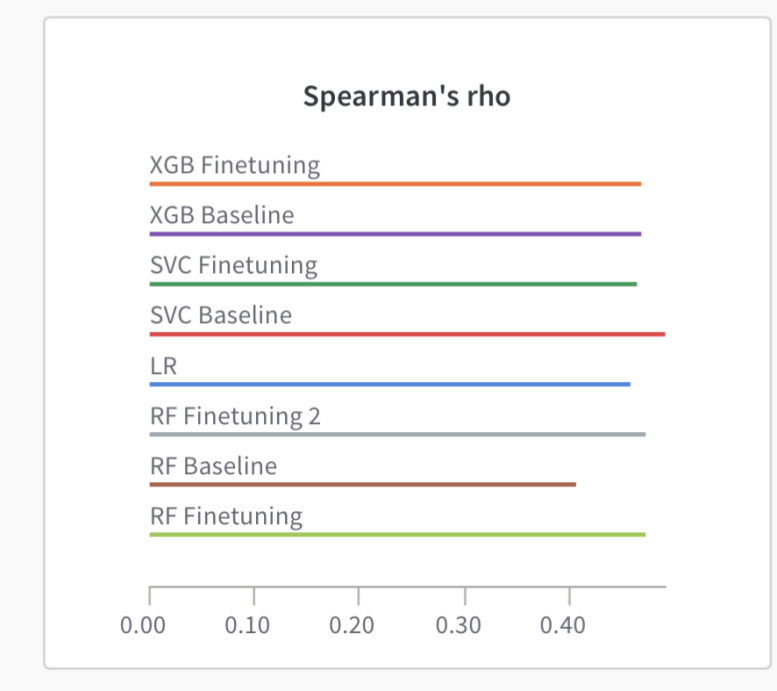
1) Visual Representation of the experiments and fine tuning. (https://wandb.ai/milindc02-university-of-texas-at-dallas/valence?nw=nwusermilindc02)
2) Final Results
    a. UAR



    b. Kappa



c. Spearmans Rho



LLM Based:

Preprocessing for LLM based:

- Converting the dataset into a json file to feed the OpenAI-based models.
- Functions to randomly select demonstrations to be provided to the GPT models
- Prompts made:

  P1 (0 shot first prompt):

  """You are an expert linguistic assistant.
  Your task is to label and give a score to conversations for user satisfaction. The score for the user satisfaction are based on a 5-level satisfaction scale.
  The scale is as follows:
  (1) Very dissatisfied (the system fails to understand and fulfill users request);
  (2) Dissatisfied (the system understands the request but fails to satisfy it in any way);
  (3) Normal (the system understands users request and either partially satisfies the request or provides information on how the request can be fulfilled);
  (4) Satisfied (the system understands and satisfies the user request, but provides more information than what the user requested or takes extra turns before meeting the request); and
  (5) Very satisfied (the system understands and satisfies the user request completely and efficiently).
  You should predict only the score which is a number and print it as Score.
  """

P2 (0 shot statistical input)

"""You are an expert linguistic assistant.
Your task is to label and give a score to conversations for user satisfaction. The score for the user satisfaction are based on a 5-level satisfaction scale.
The scale is as follows:
(1) Very dissatisfied (the system fails to understand and fulfill users request);
(2) Dissatisfied (the system understands the request but fails to satisfy it in any way);
(3) Normal (the system understands users request and either partially satisfies the request or provides information on how the request can be fulfilled);
(4) Satisfied (the system understands and satisfies the user request, but provides more information than what the user requested or takes extra turns before meeting the request); and
(5) Very satisfied (the system understands and satisfies the user request completely and efficiently).
You should predict **only the score** and print it as `Score:` followed by the appropriate number.

Additionally, here is the statistical information from a dataset of labeled conversations to help you make informed judgments on how scores are distributed:

- **Mean of gold labels**: 3.09
- **Median of gold labels**: 3
- **Mode of gold labels**: 3
- **Standard deviation of gold labels**: 0.44
- **Minimum score**: 1
- **Maximum score**: 5

These statistics indicate that most of the conversations are labeled as **3 (Normal)**, with some variability. You should consider this when labeling satisfaction, but still make your score based on the specific conversation at hand.
"""

P3 (shortened statistical)

"""You are an expert linguistic assistant.
Your task is to label and give a score to conversations for user satisfaction. The score for the user satisfaction are based on a 5-level satisfaction scale.
The scale is as follows:
(1) Very dissatisfied (the system fails to understand and fulfill users request);
(2) Dissatisfied (the system understands the request but fails to satisfy it in any way);
(3) Normal (the system understands users request and either partially satisfies the request or provides information on how the request can be fulfilled);
(4) Satisfied (the system understands and satisfies the user request, but provides more information than what the user requested or takes extra turns before meeting the request); and

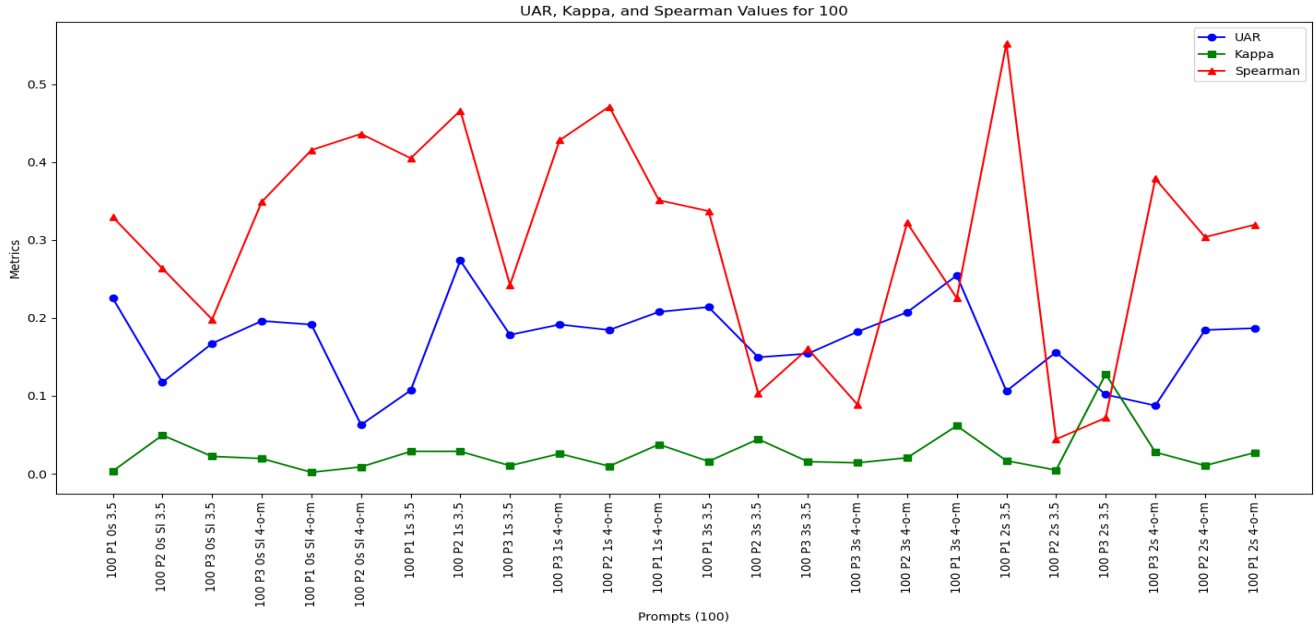
(5) Very satisfied (the system understands and satisfies the user request completely and efficiently).
You should predict **only the score** and print it as `Score:` followed by the appropriate number.
Most of the scores are 3 and the minimum value is 1 while the maximum value is 5. The scores have a standard deviation of 0.44 from the mean which is 3. Use this statistical information but do not be biased by it.
"""

Models Used:

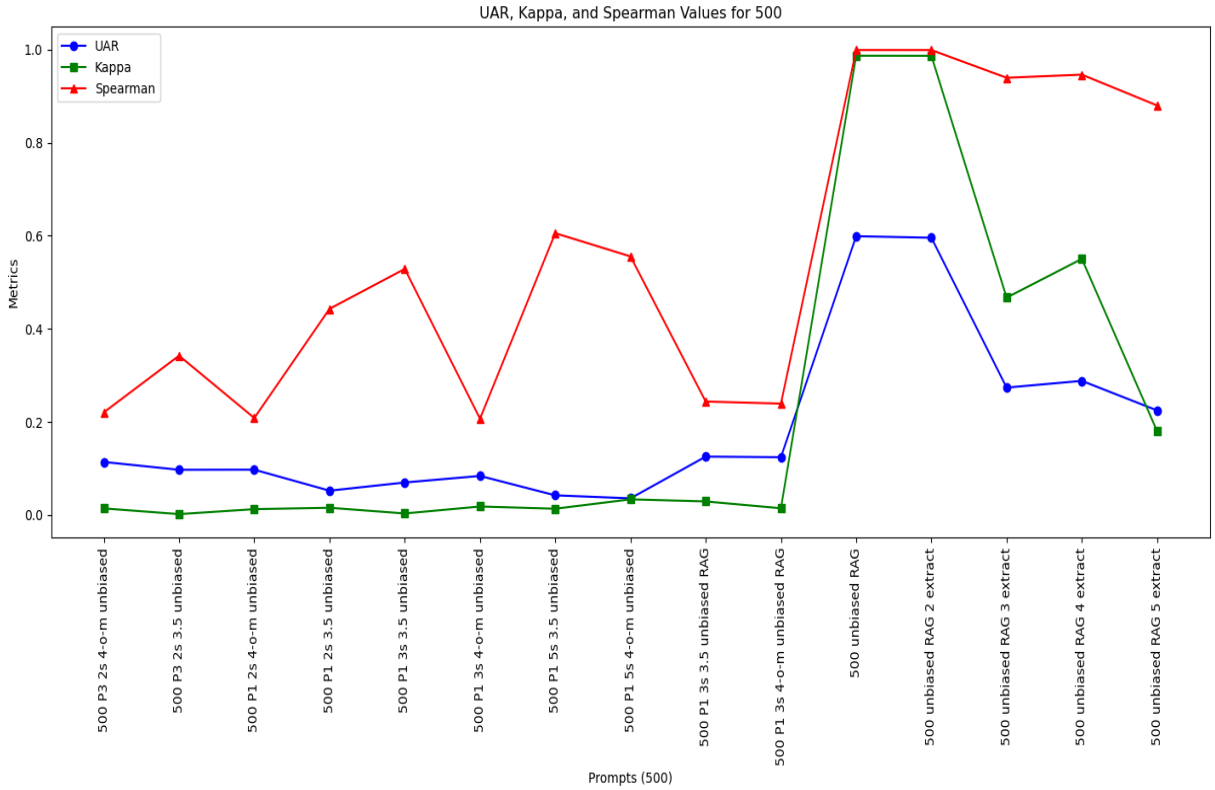
- GPT 3.5 ($0.5/1M tokens)
- GPT 4o mini ($0.15/1M tokens)

Results:

1) Preliminary Testing:



2) Main Subset Dataset:



RAG Based:

Preprocessing for LLM based:

- Converting the dataset into a json file to feed the OpenAI-based models.
- Using **Milvus** to create a vector store (Code attached)

Sentence Embeddings used:

1) Open AI embeddings
2) Sentence Transformers

Results:

- Results are in the graph attached with LLM-based
- RAG generalizes to the dataset quickly, but LLM has to be finetuned for better performance since it overfits.