Towards Better Recommendation Explainability Evaluation for Conversational Recommender Systems

Thesis Defense

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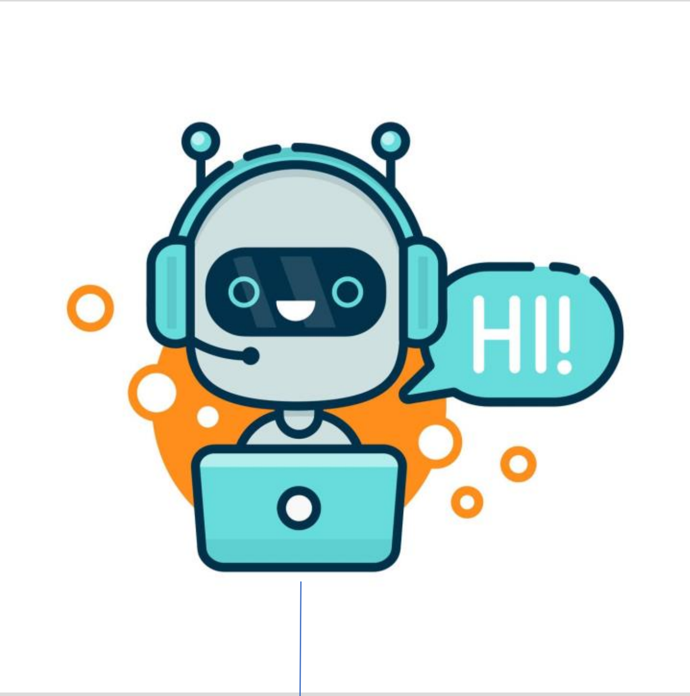
Date: 4/1

Background: Conversational Recommender Systems

<u>Chatbots</u>



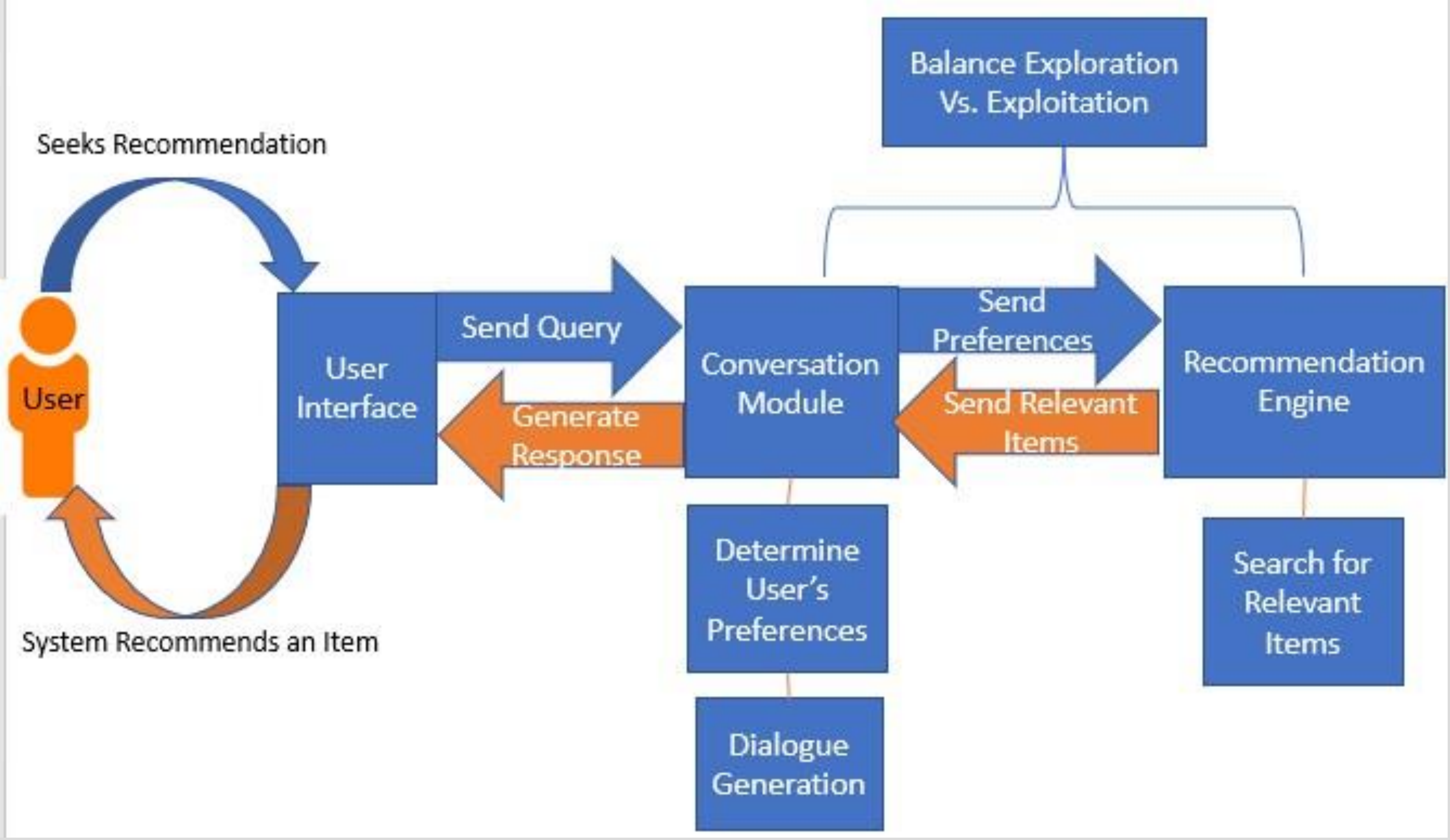
<u>Recommender system</u>

<u>Large Language Models</u>

ChatGPT

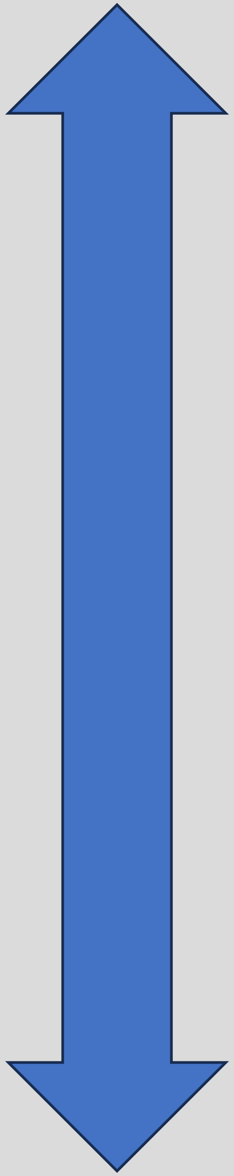
CRS

CRS: How Do They work?



Dialog Strategy: How does the Conversation Feel?

- Active User Passive System (AUPS):
  - System only responds to direct user prompts
  - Search Engine / Voice Assistant
- System Active User Passive (SAUP):
  - User responds to system, does volunteer outside of initial prompt
  - System interrogates user
- System Active User Engage (SAUE):
  - System engages user, user my chit chat and add feedback
  - Formal conversation between two humans
- System Active User Active (SAUA):
  - System engages user, user may interrupt and redirect.
  - Two humans conversing informally



How to Evaluate System Performance?

- Turn Level: Evaluate each sentence
- Dialogue Level: Evaluate the whole

Conversational Quality

- conversation
- BLEU
- ROGUE
- METEOR
- MAUDE
- Readability
- Novel Sentence Evaluation
- Perplexity

Recommendation Quality

- Precision
- Recall
- Normalized Discounted Cumulative Gain
- Mean Reciprocal Rank
- Coverage
- Personalization

Quality Gaps

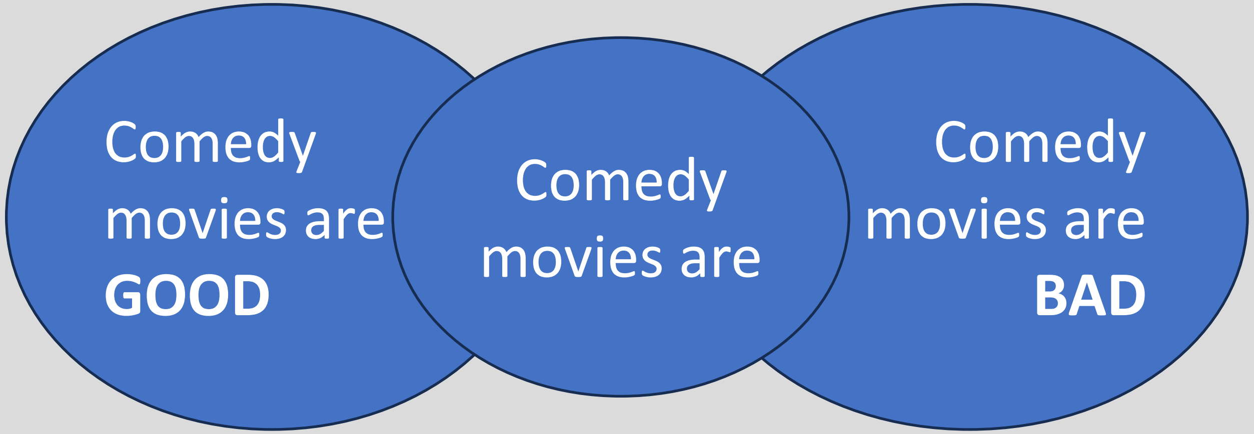
Assessment Metrics

Table 2: Conversational Evaluation Metrics Summary

Metric name	Used In
BLEU	[9],[10],[18],[19],[27],[28]
ROGUE	[12],[19],[27]
METEOR	[27]
Vector Extrema	[27]
N-gram	[12],[19],[28] [43]
Precision/Recall	[19],[28],[30],[43]
Perplexity	[10],[12],[18],[19]

- Deep Learning Regimes
  - BERT
  - ChatGPT
  - Transformers
  - Contrastive Learning
  - Word embeddings

Word Overlap



Translation Accuracy

1. The cat ran fast
2. The animal moved hastily
3. The beast moved

How to Evaluate System Performance?

Conversational Quality

- Assume the recommendation engine exists.
- Focus solely on evaluating conversation engine.
- Offline evaluations

Recommendation Quality

- ecision
- N
  Cum
- M
  e
- sonalization

What Makes A Good recommendation?

Factors of Explainability	Definition
Length	How long the explanation is
Readability	How easy the recommendation is to read
Word Importance	The importance of words in the recommendation
Repetition	How many duplicate segments are in a sentence
Subjectivity	If the recommendation includes personal opinions and emotion
Polarity	Confidence level that the recommendation is positive or negative
Grammatical Correctness	Misspelled words and incorrect usage of language
Feature Appearance	If an explanation captures item features

Quality can be subjective!

User: I'm looking for a fun movie with Samuel L. Jackson in it, or a movie with cool gadgets.

Try Captain America Winter Soldier.

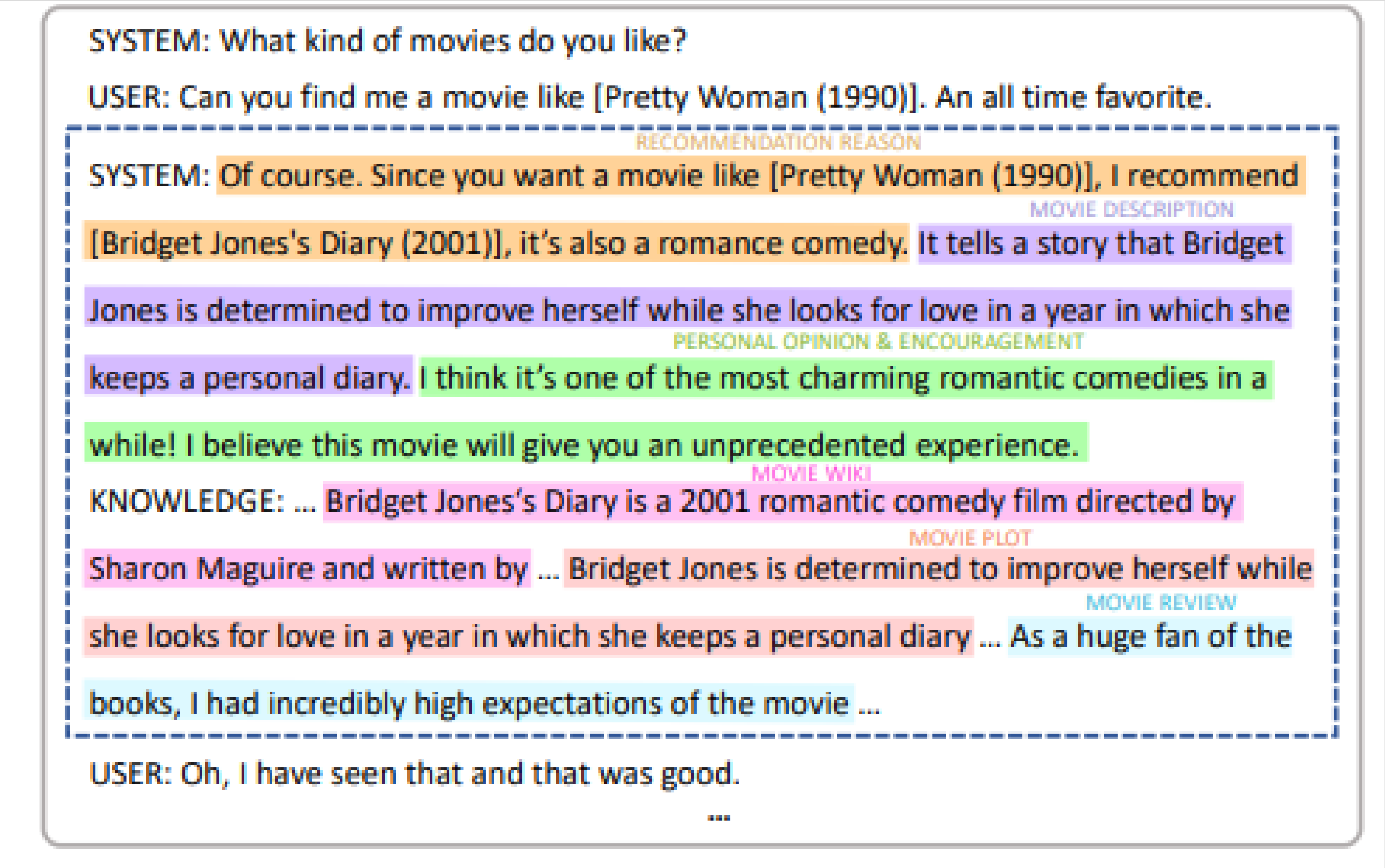
Try Spiral (Saw 9).

Dataset: E-Redial & INSPIRED

Dataset Information:

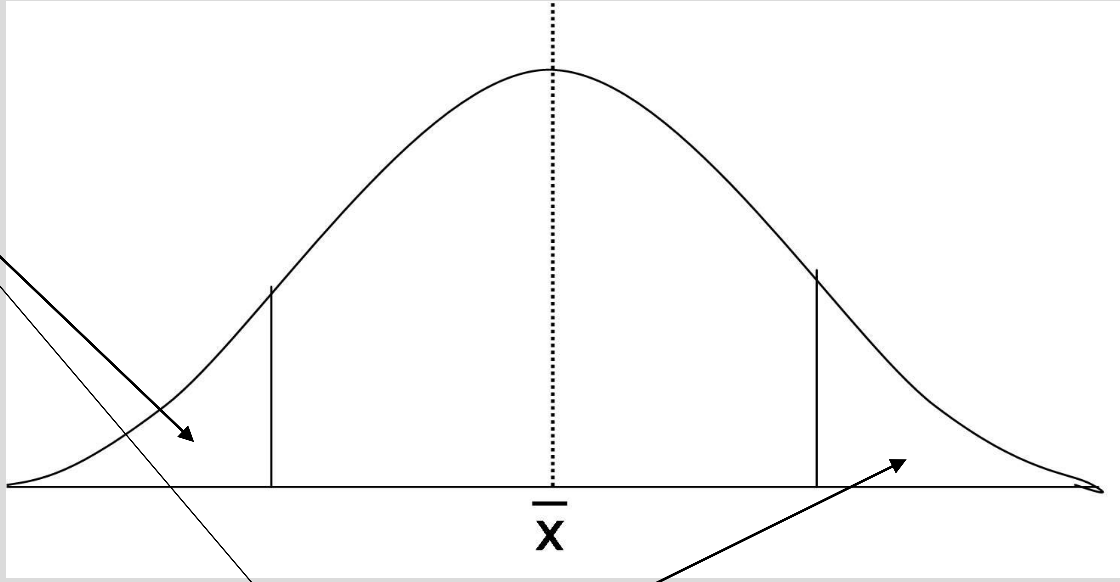
- Redial Dataset ----> Extended Redial & INSPIRED Dataset
- Recorded conversations between two humans SEEKER and RECOMMENDER talking about movies
  - Minimum conversation length
  - Minimum movies mentioned
  - Recommendation Requirements
    - Movie Description (purple)
    - Personal Opinion (green)
    - Wiki Info (pink)
    - Plot Description (peach)
    - Review (cyan)
- No turn order requirements

Sample Conversation:



Calculating Quality Factor: Length

- Defined as the number of words after removing stop words
- If z score is 2.5 deviations away, score 0
- If z score is negative, apply penalty
- If z score is positive apply smaller penalty



Conversation too long / short, score 0

Calculating Quality Factor: Readability

- How easy a conversation is to read.
  - Determined by number of words in a sentence
  - Number of syllables per word.
- Flesch Kincaid Reading Ease score
  - Reading levels (1st grade, 7th grade etc)
  - 8th grade is an average value
  - Higher values represent an easier read

```
score = 206.835 -(1.015 * (totalWords/totalSentences))
                -(84.6 * (totalSyllables/totalWords))
```

Calculating Quality Factor: Word Importance

- The sum of how impactful each word in a conversation is.
- Term-Frequency Inverse Document Frequency

$$\mathrm{TF}(t,d) = \frac{\text{Number of times term } t \text{ appears in document } d}{\text{Total number of terms in document } d}$$

$$\mathrm{IDF}(t,D) = \log\left(\frac{\text{Total number of documents in the corpus } N}{\text{Number of documents containing term } t}\right)$$

$$\text{TF-IDF}(t,d,D) = \mathrm{TF}(t,d) \times \mathrm{IDF}(t,D)$$

Calculating Quality Factor: Repetition

- How many duplicate words are in a conversation after stop words have been removed

```
#Repitition functions
def scoreRepitition(idList, wholeConv):
    repitionScores = []
    #Loop over conversations
    for id in idList:
        repeatedWords = 0
        curString = " ".join(wholeConv[hash(id)][0])

        #remove stop words
        tokenizedString = nltk.word_tokenize(curString)
        setString = set(tokenizedString)
        if STOP_WORDS.intersection(setString):
            setString -= STOP_WORDS

        #Search for repeated words
        for word in setString:
            if tokenizedString.count(word) > 1:
                repeatedWords +=1
        repitionScores.append(repeatedWords)
    return repitionScores

#End repitition function
```

Calculating Quality Factor: Subjectivity & Polarity

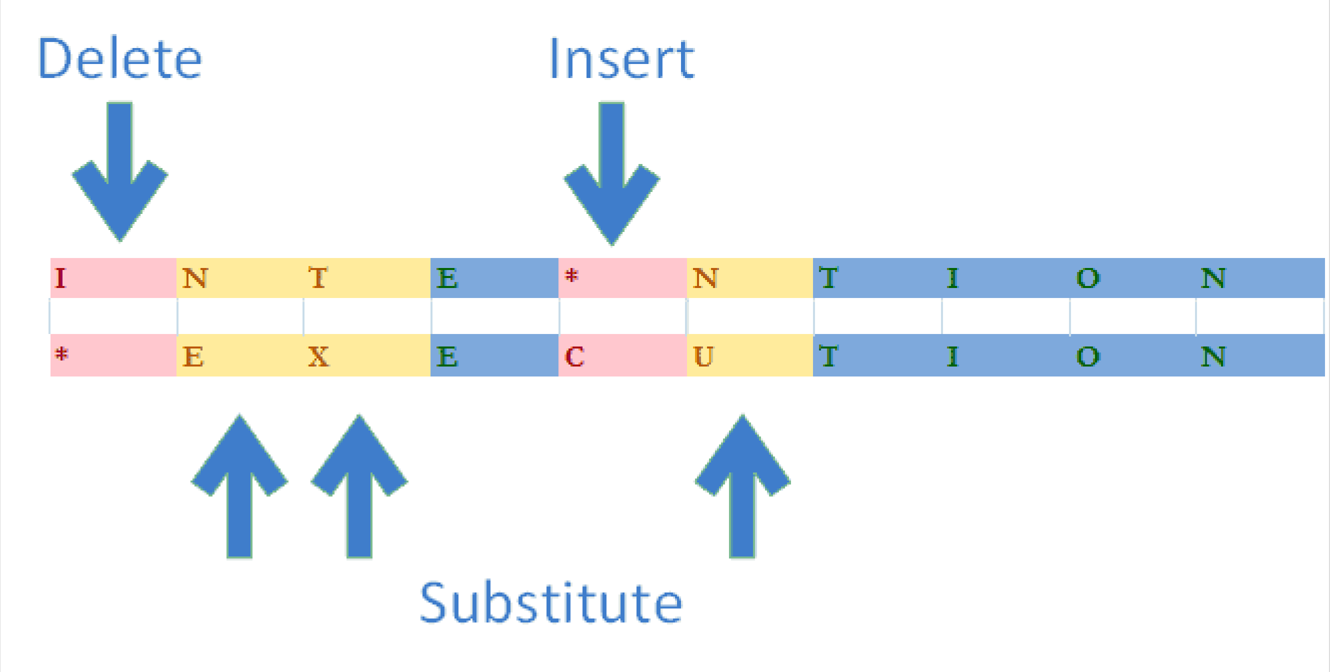
- Subjectivity measures how much a conversation contains personal opinion, emotion, and/or judgement.
- Polarity measures if the tone of a conversation is positive negative or neutral.
- Calculated by using the TextBlob python Library.

```
curString = " ".join(wholeConv[hash(id)][0])
blob = TextBlob(curString)
subjectivityScores.append(blob.sentiment.subjectivity)
```

```
curString = " ".join(wholeConv[hash(id)][0])
blob = TextBlob(curString)
polarityScores.append(blob.sentiment.polarity)
```

Calculating Quality Factor: Grammar

- Number of spelling errors after stop words and punctuation has been removed (Ignores movie titles*)
- Python spellchecker library.
  - Modified Levenshtein distance



Calculating Quality Factor: Feature Appearance

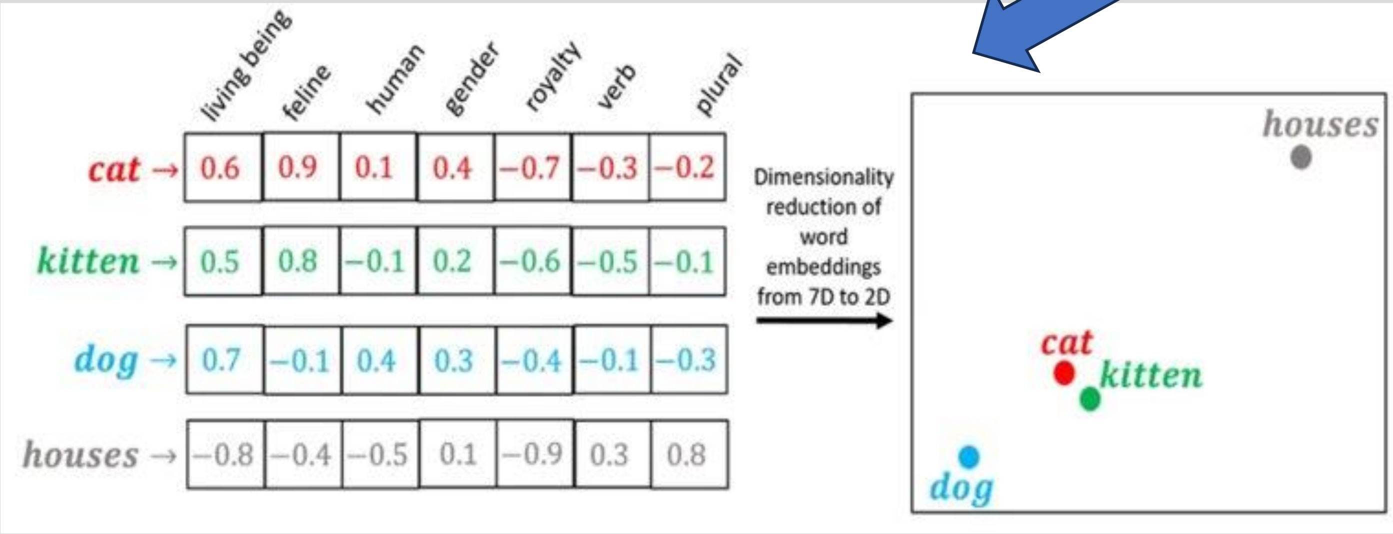
1. Divide conversation into 2 parts

Seeker | Recommender

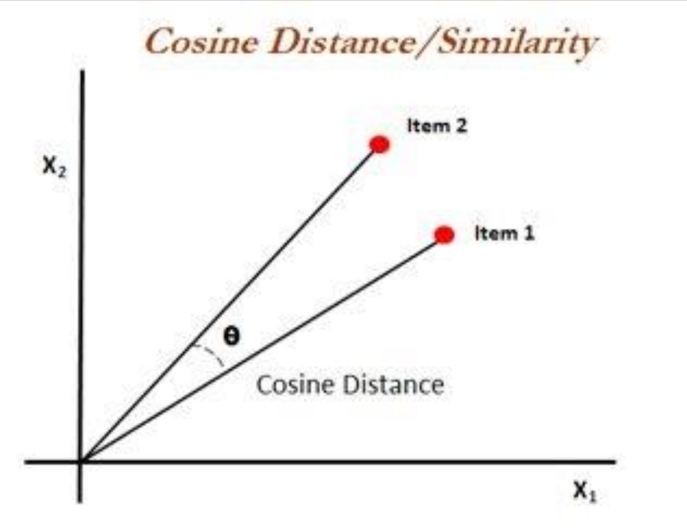
2. Use BART to summarize each half

Seeker Summary | Recommender Summary

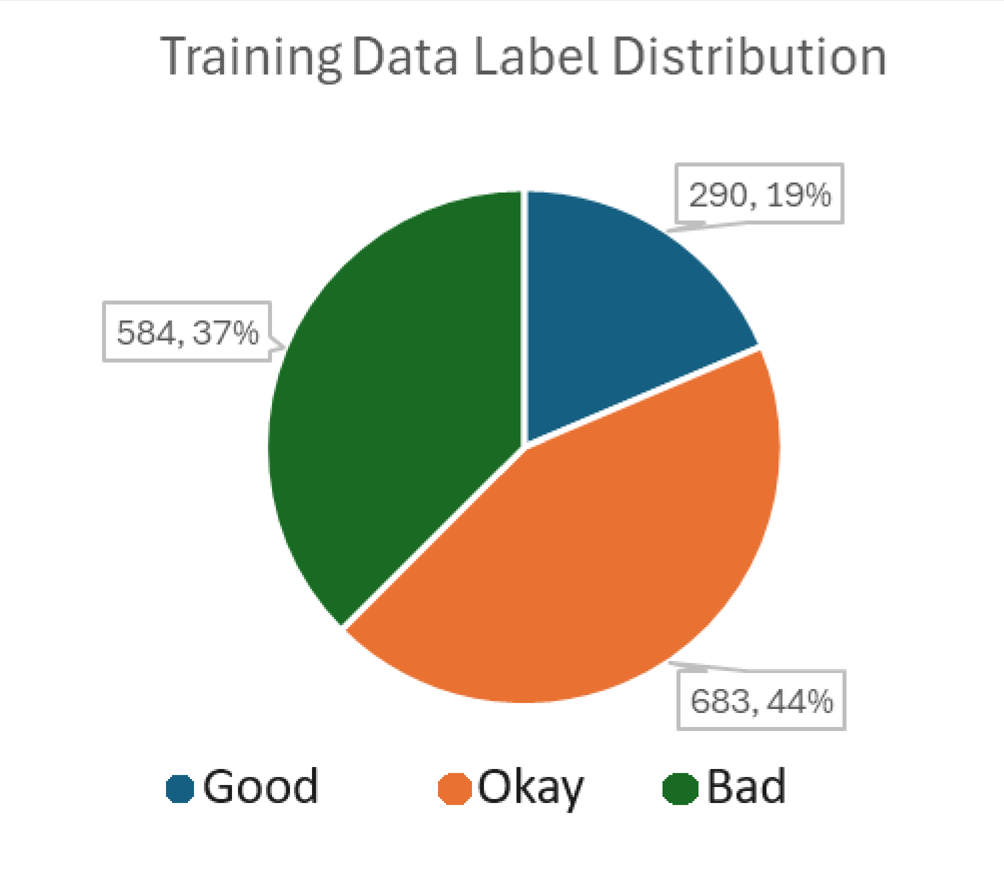
3. Embed Summaries with BERT

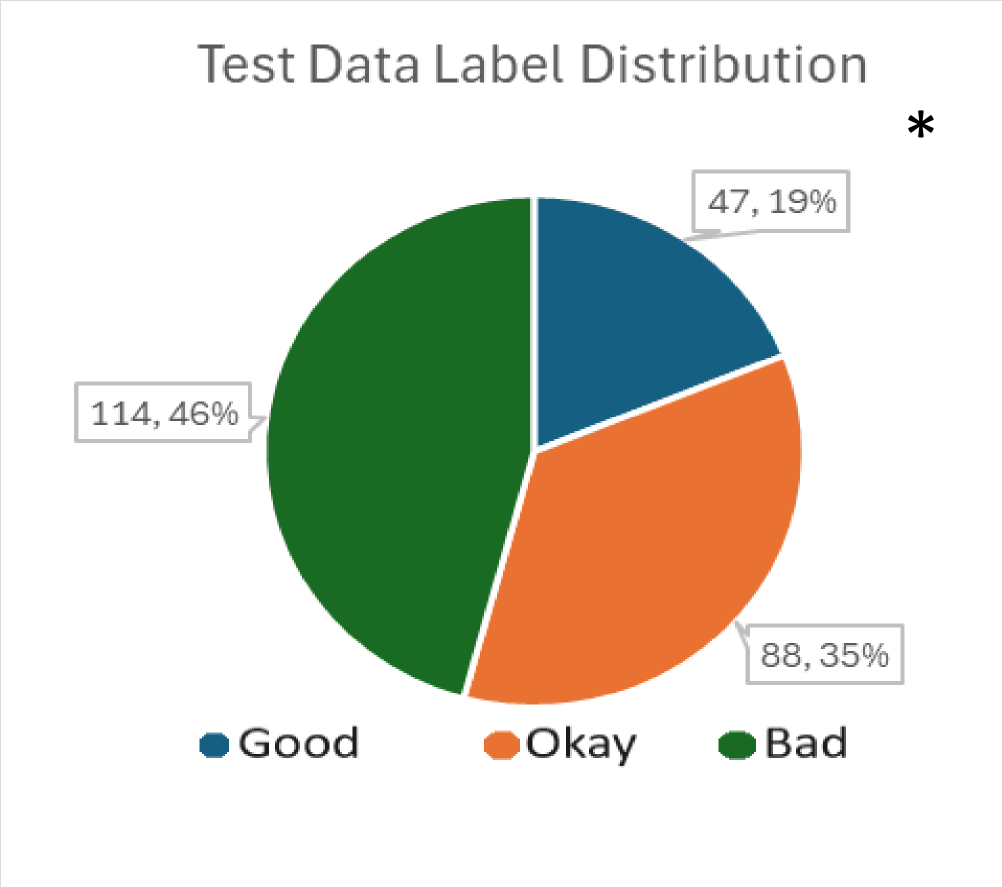


4. Calculate Cosine Similarity of Summary Embeddings



Target Label Distribution:





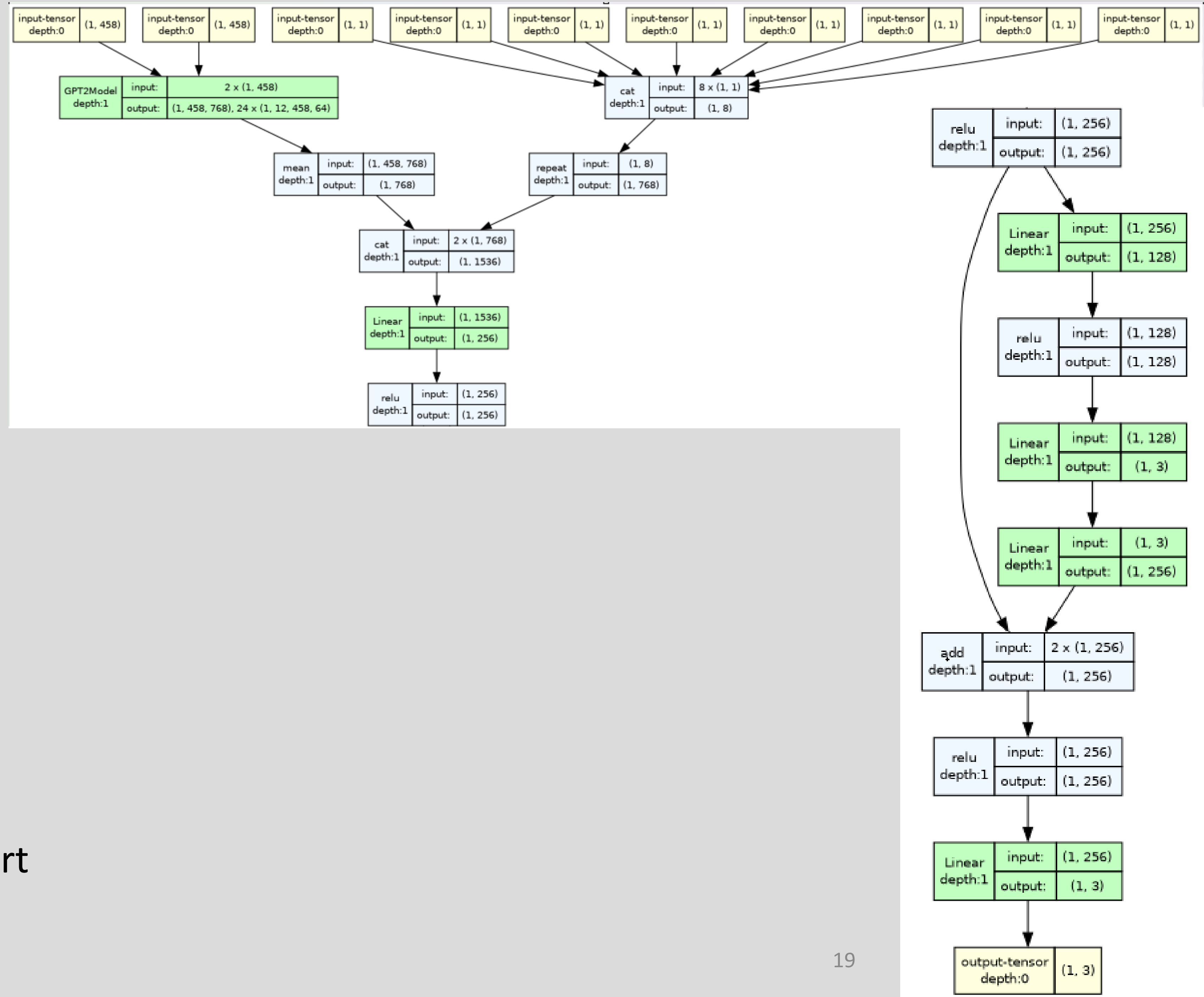
*Imbalanced test set explicitly part of the dataset. 823 of the system responses in the E-Redial test set are idle with no movie recommendations

Model Architecture: Base Models – GPT2, GPT-NEO, T5

GPT2	NEO	T5
Transformer Architecture	Transformer Architecture	Transformer Architecture
Language Modelling Objective / token prediction	Language Modelling Objective / token prediction	Text-to-Text Objective
124 million parameters	125 million parameters	222 million parameters

Model Architecture

- Input:
  - Embedded Conversation
  - 8 Quality Factors for the conversation
- Output:
  - Class Label {Good(0),Okay(1),Bad(2)}
- Architecture:
  - Base Model (GPT2, NEO, T5)
  - 3 blocks of 3 linear layers (256,128,3) with residual connections between the start and end of the block.



Experiment Details

1. Data Variation

- Unmodified Quality Scores
- Standardized Quality Scores

2. Pretrained Model

A. GPT2

B. GPT-NEO

C. T5

80 Epochs
30 Independent Runs

3. Metrics

A. Accuracy

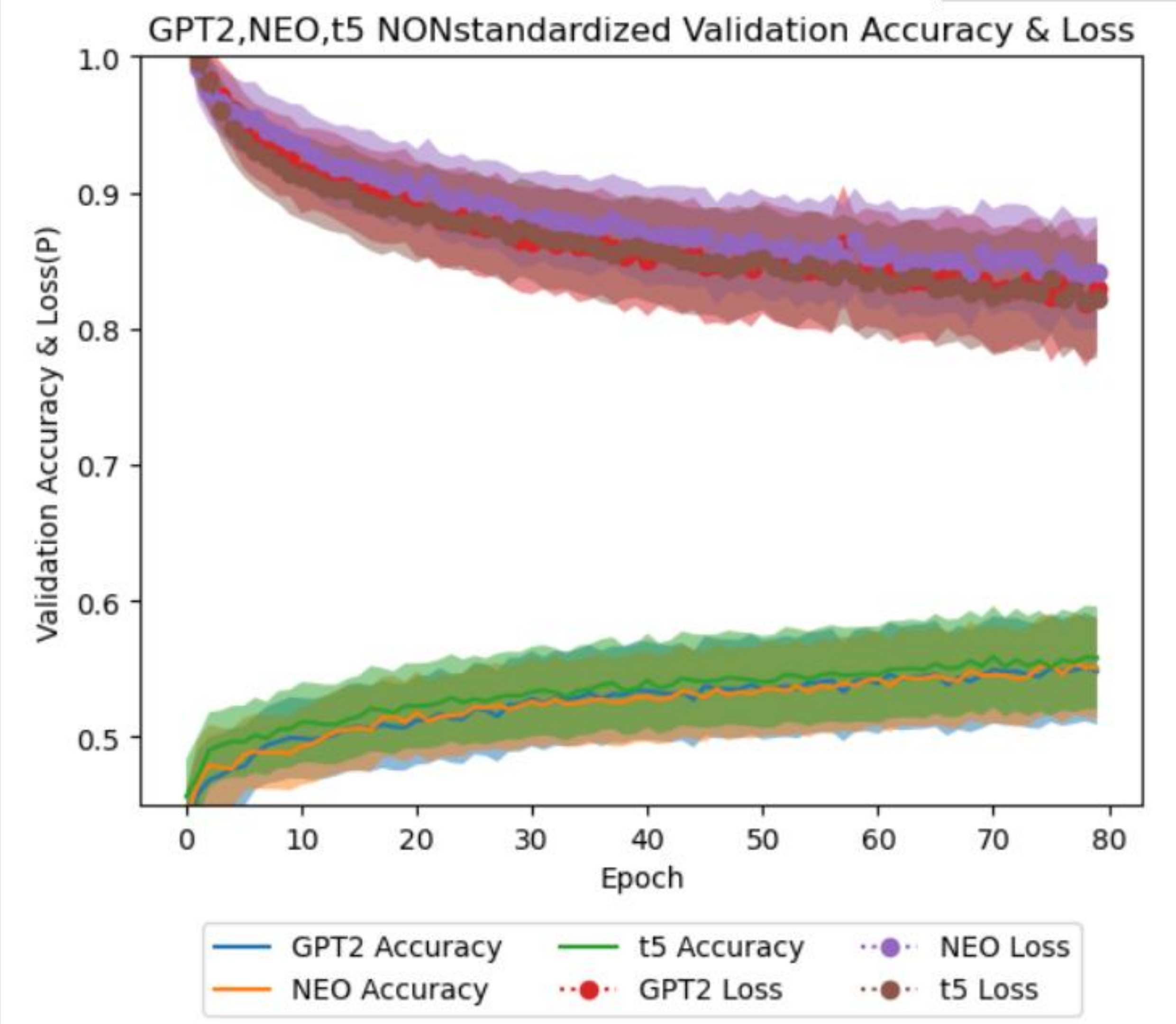
B. Loss

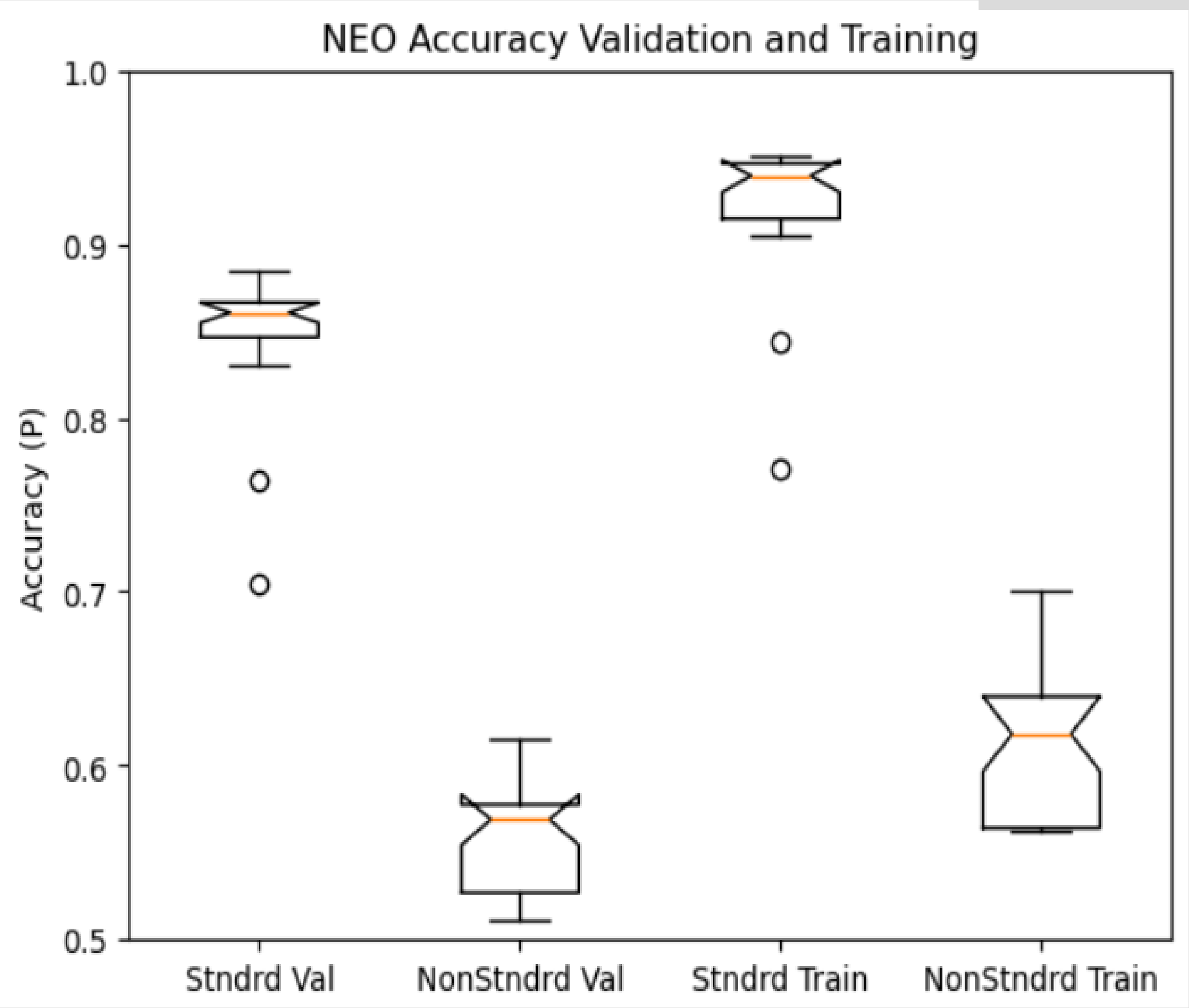
C. ICE (Mean/Median)

C. SHAP (Mean/Median)

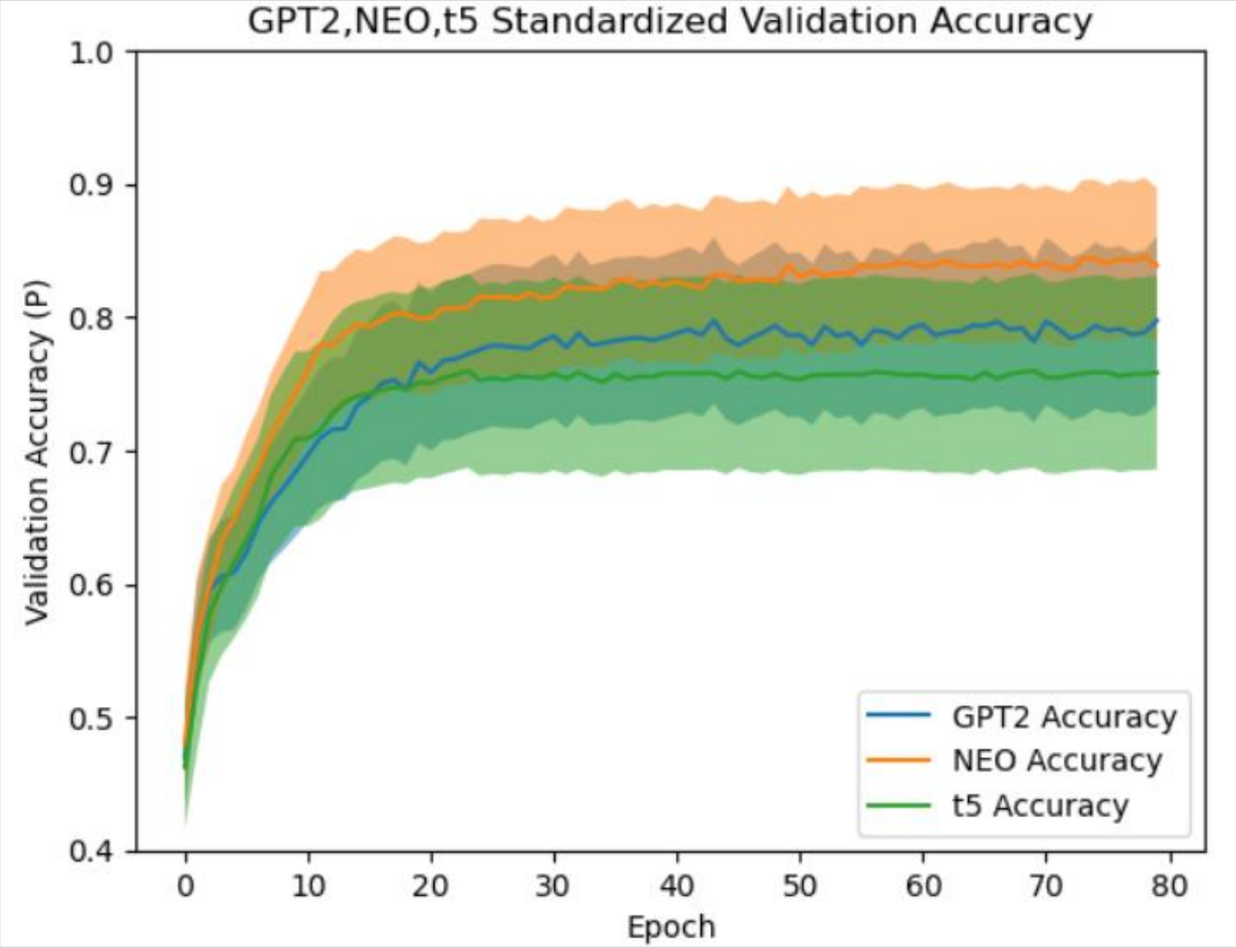
Standardized Data Only

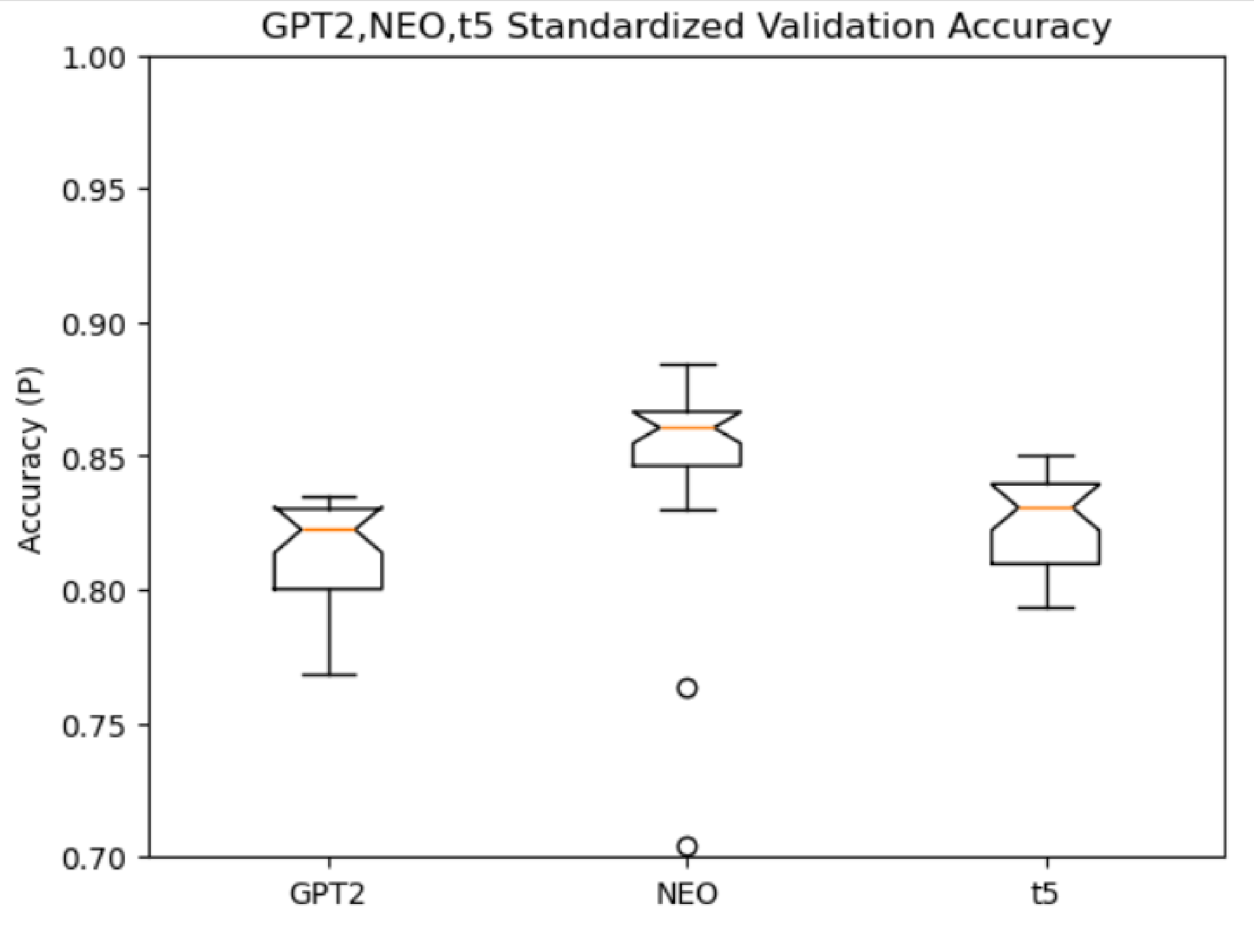
Results: NonStandardized Validation & Training





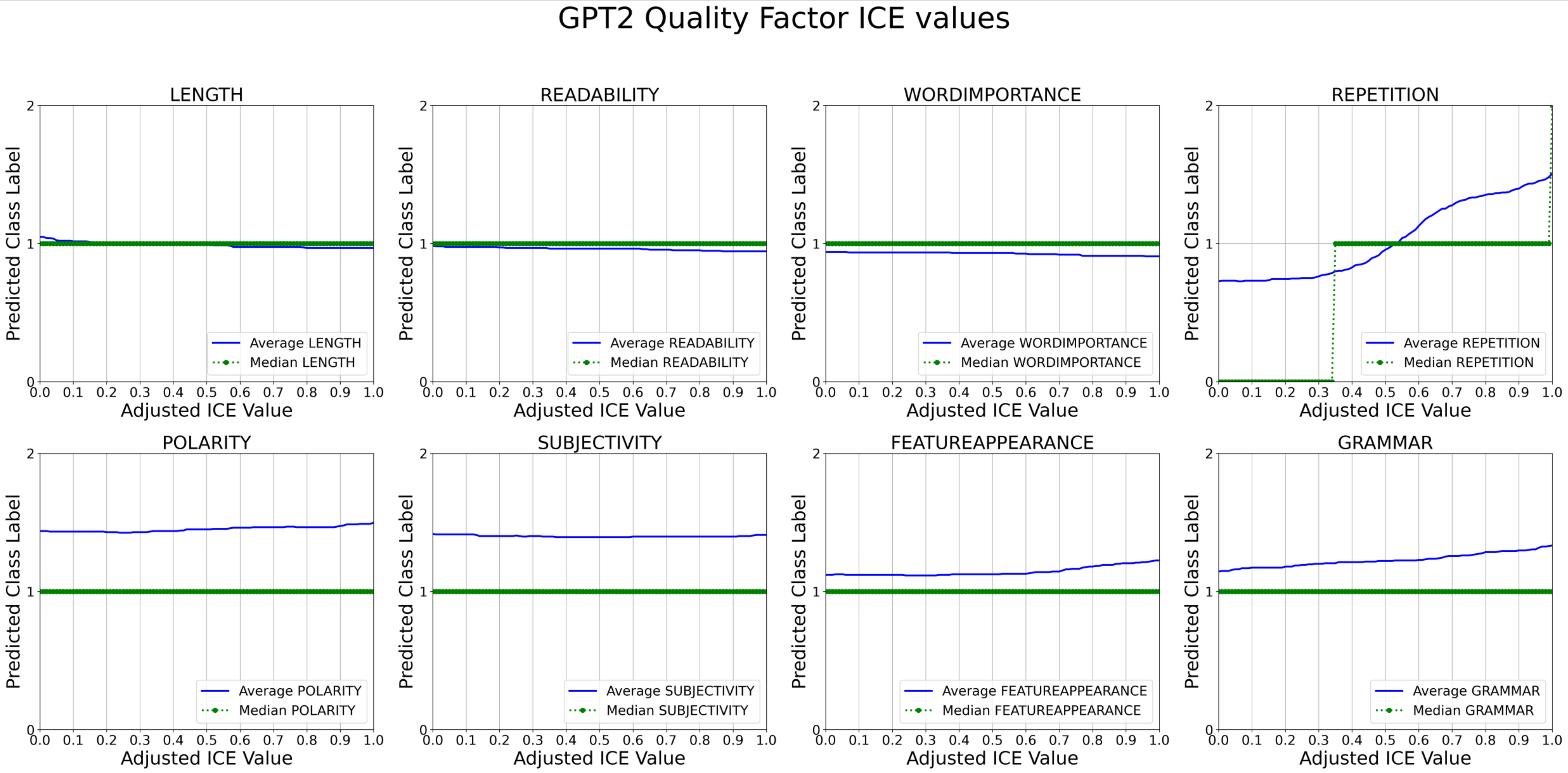
Results Standardized: Validation Set





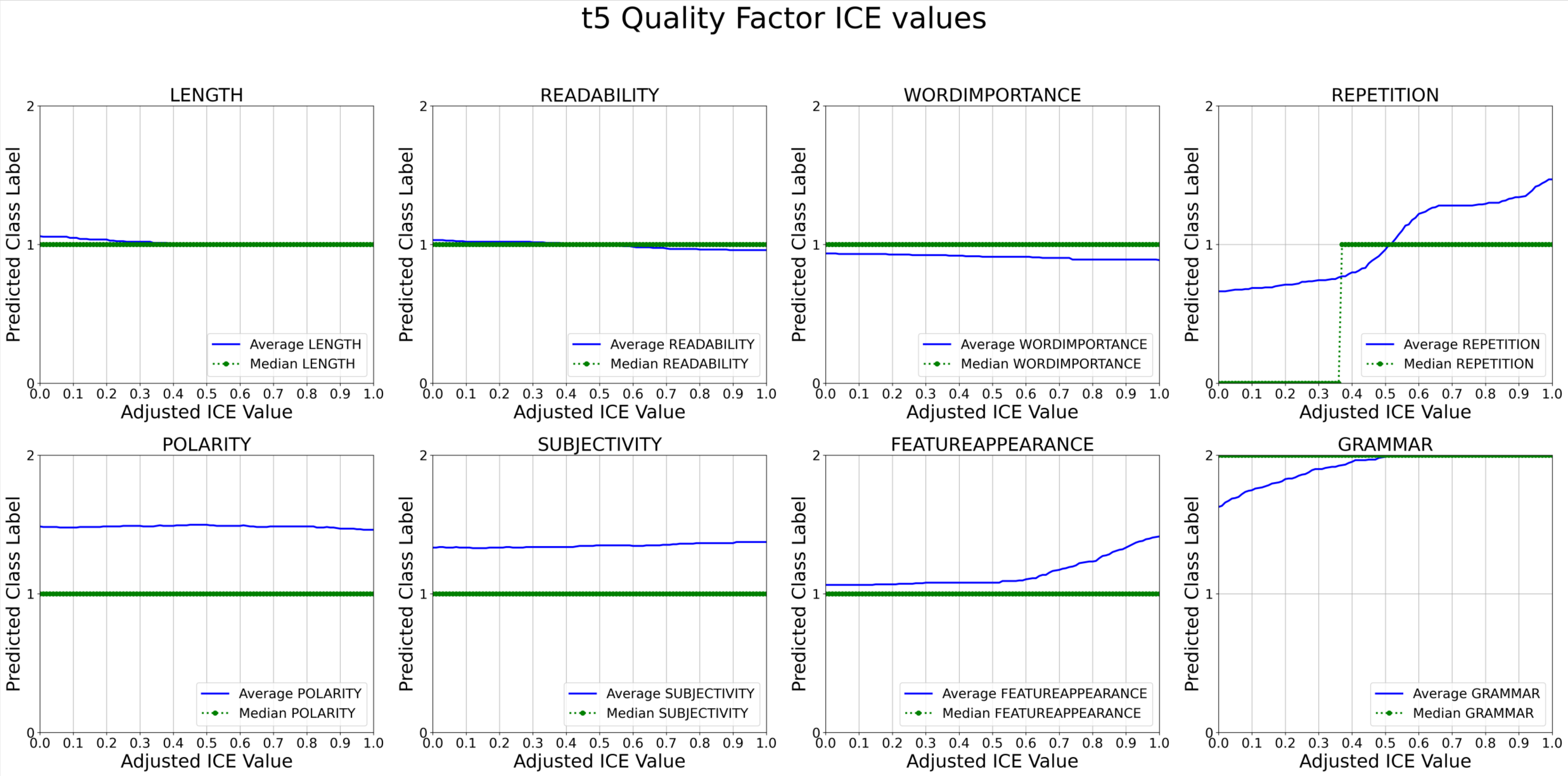
ICE Results: GPT2

Mean Median



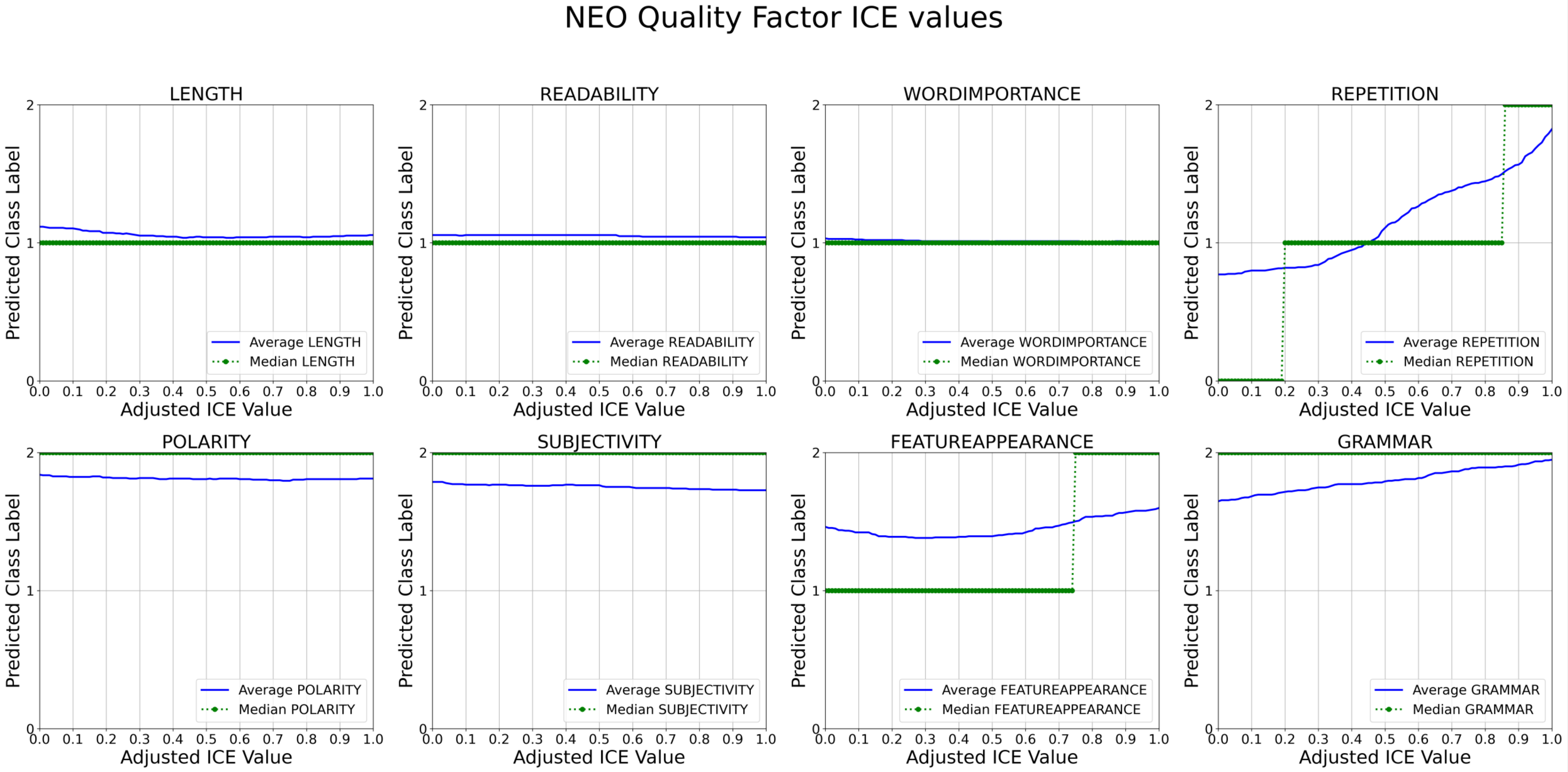
ICE Results: T5

Mean Median



ICE Results: NEO

Mean Median



ICE Results Summarized:

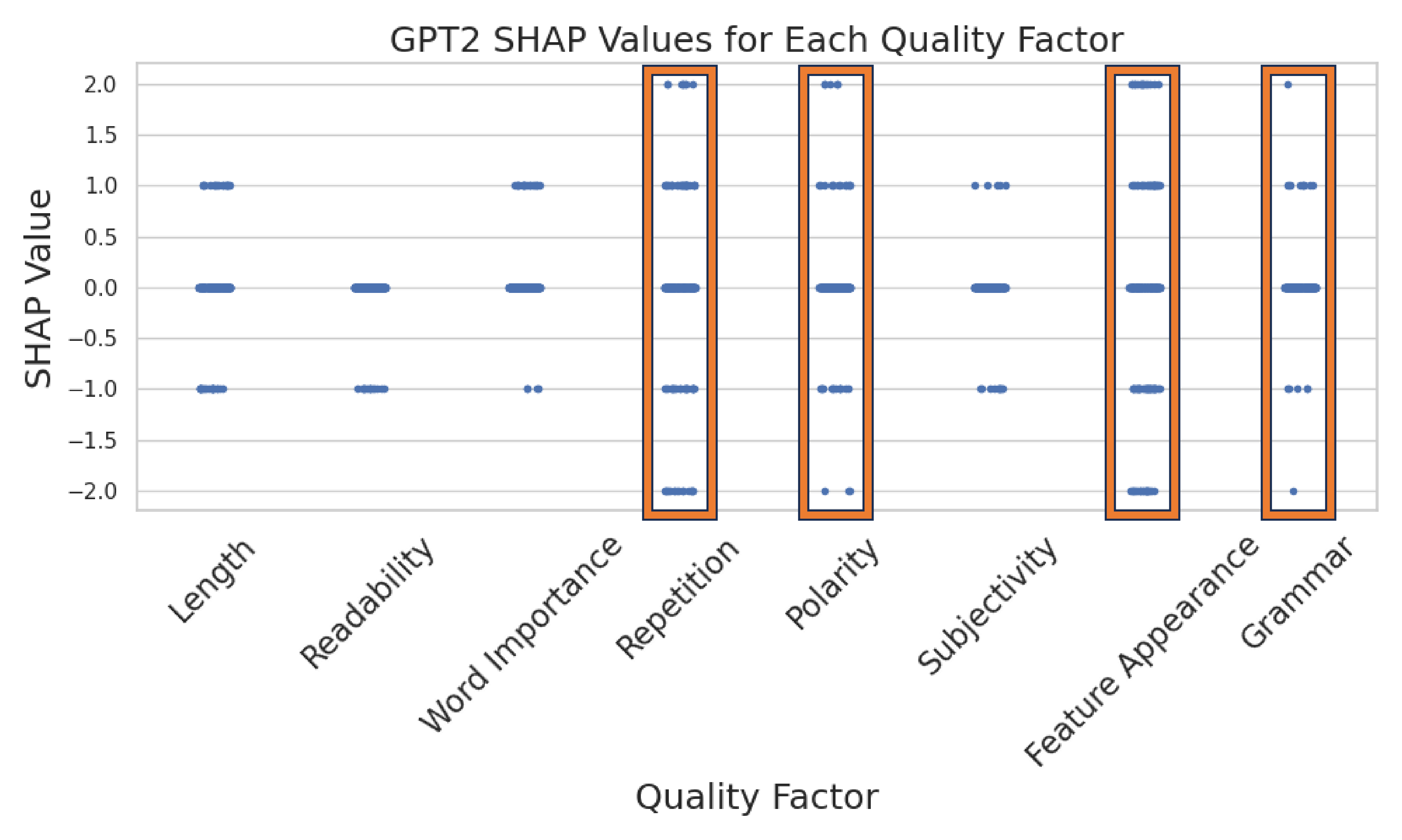
Individual input variations do not appear to alter classification much

The most impactful quality scores are:

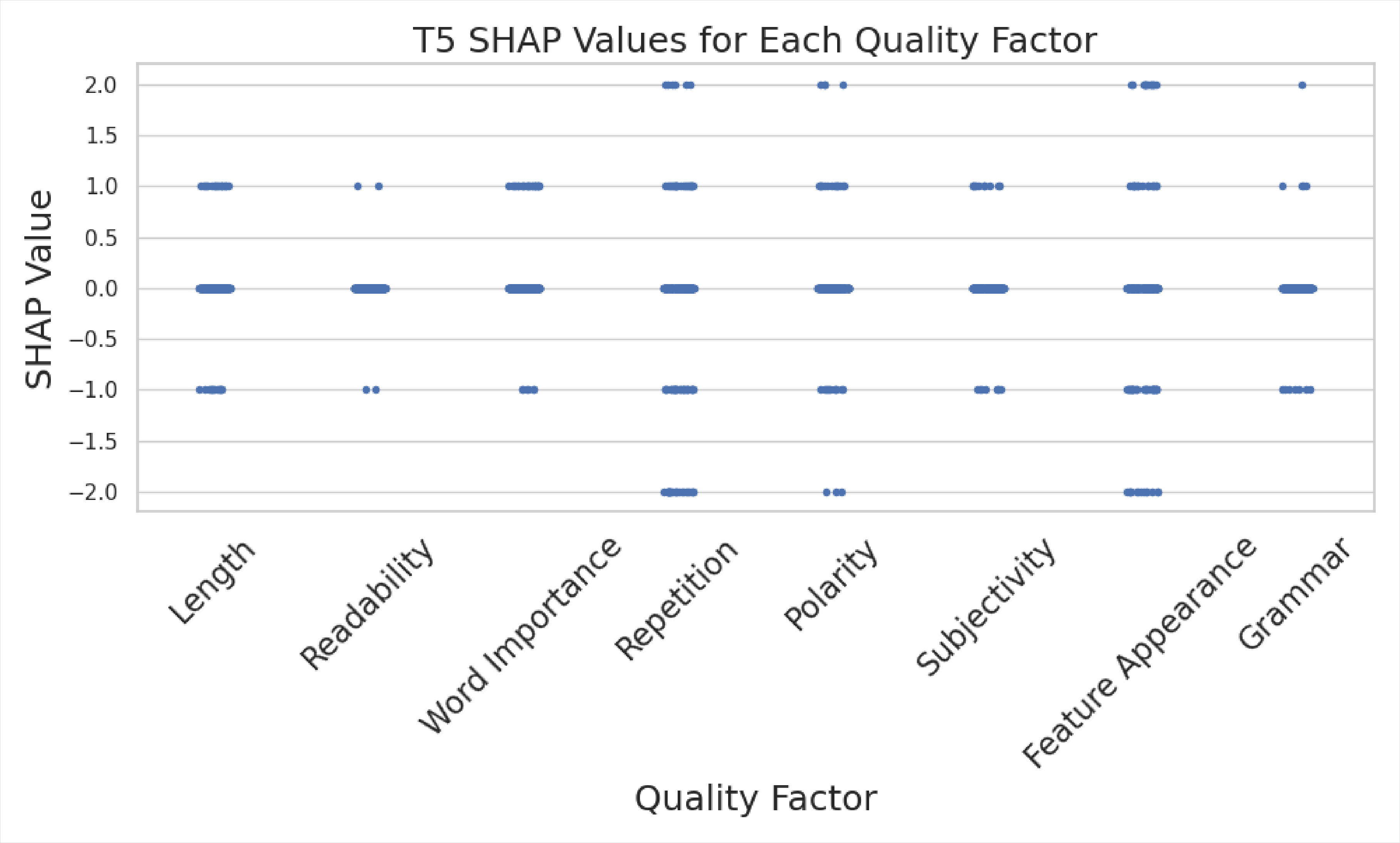
- Repetition
- Feature Appearance
- Grammar

The model predictions trend towards Okay class (1), which is the statistically safest bet.

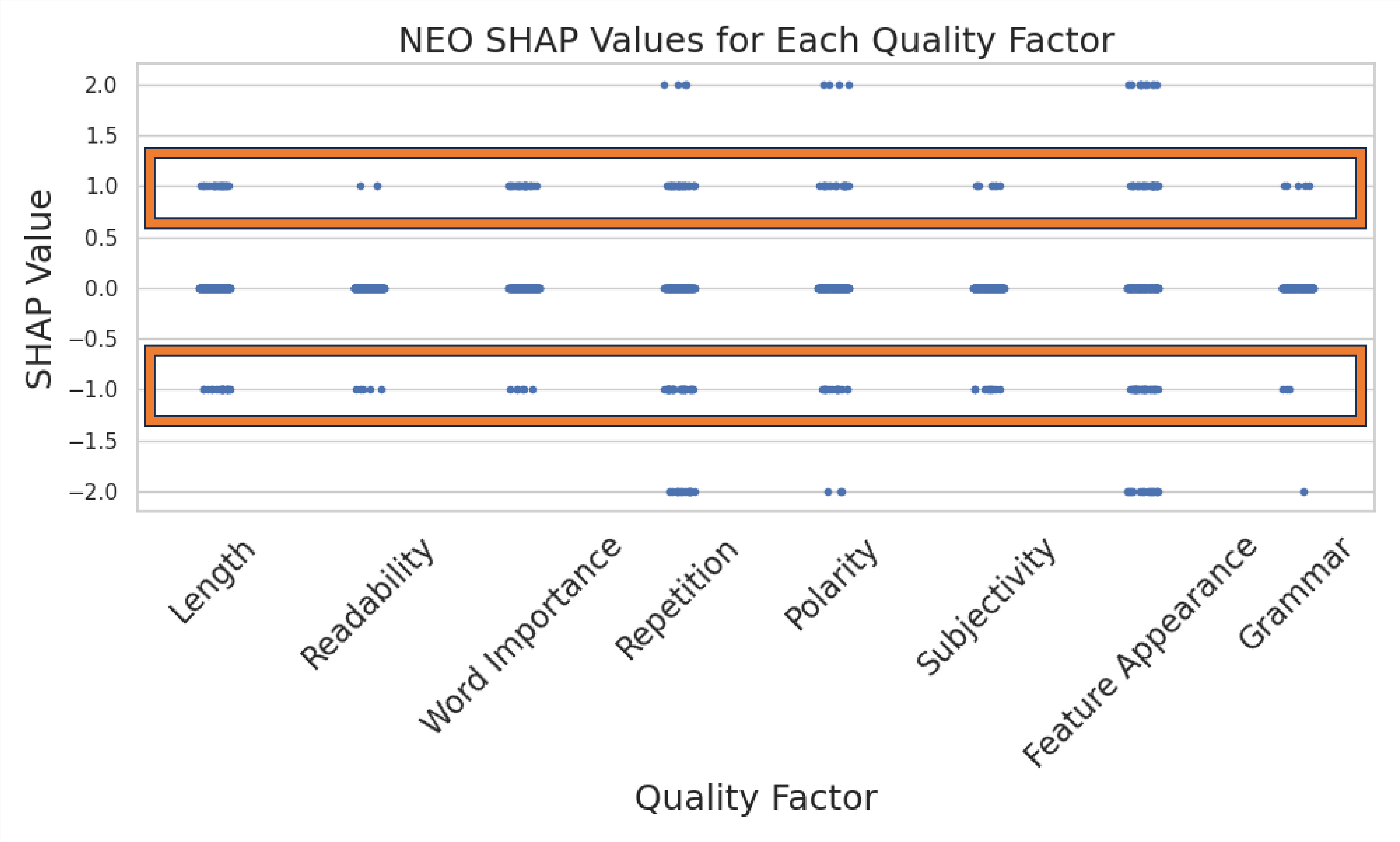
SHAP Results: GPT2



SHAP Results: T5



SHAP Results: NEO



SHAP Results Summarized

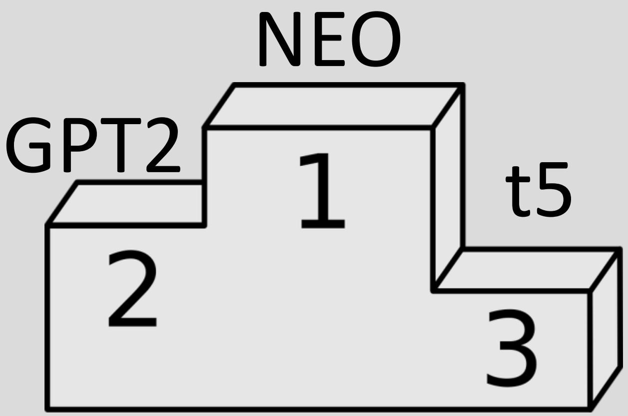
The strongest trend is for each QF value variation to not alter the predition (neutral effect)

Indicates individual factors are not as important as combinations of factors.

Repettion, Polarity, Feature Appearance, Grammar have the strongest effects on predictions, although each QF pushes predictions both positively and negatively.

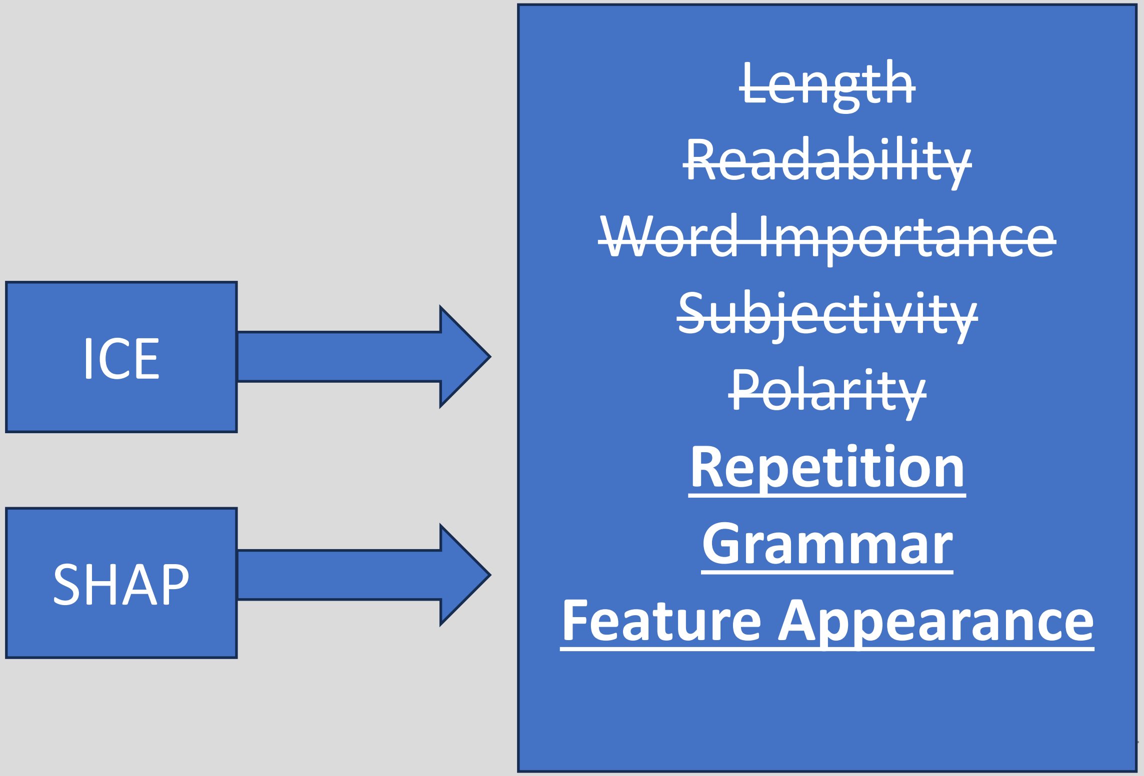
NEO shows the most reactivity to alterations in QF values, GPT2 shows the highest variety of reactivity to QF alterations.

Discussion:



- Training > Validation

- Standardization greatly improves model performance



Discussion:

- Regardless of conversation type (SAUP, SAUE, etc) the 8 quality factors appear to be robust enough and useful for classifying conversational recommendations.
- All models had similar performances across ICE and SHAP analyses, and across training and validation sets.
- GPT2 and NEO had very similar behavior.
  - NEO is an open-source version of GPT2
  - NEO uses local attention in every other layer with a window size of 256 tokens.
  - Both models generate tokens sequentially based on previous input.
- T5 performs the worst
  - Architecture
  - Training data not as diverse

Conclusion & Future Direction

- Better fine-tuning
- Move beyond standard metrics
- Incorporate more quality factors
- Focus more on dialogue improvements in CRS

Conclusion & Future Direction

Retrieval Augmented Generation

Increase explainability

Increase reliability

Mitigate hallucinations

Leverage cloud services:

More powerful LLMs

More training data

Faster prototyping

Questions?

Thanks!

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Individual Conditional Expectation (ICE)

- Plot how model predictions change for individual instances as a single input feature changes (other inputs held constant)
- Useful for understanding the relationship between a feature and the model's predictions across different instances.
- Done in 5 steps:
    - Loop over 8 quality factors as QF
    - Loop over conversations in the validation set
    - Grab input data hold everything except QF constant
    - Vary QF value from 0.0-1.0
    - Predict class label, record results

Shapley Additive explanations (SHAP)

- SHAP values quantify how much a feature impacts model predictions, and the relative importance of each feature overall
- Done in 7 steps:
    - Establish background dataset (first 82 covnersations)
    - Loop over 8 quality factors as QF
    - Loop over conversations in the validation set
    - Grab input data hold everything except QF constant
    - Swap QF value with that same QF value from a different conversation in the background dataset
    - Predict class label,
    - Calculate SHAP value by taking the difference between the model prediction, on original data versus prediction on altered data, record results

ICE and SHAP, Why Both?

ICE analysis helps in understanding how predictions vary across instances as a single feature changes.

- Explains model behavior at the individual level
- Case by case explanation
- Exhaustive
- What if scenarios

SHAP analysis quantifyies the contribution of each feature to a prediction.

- Explains model behavior at a global level
- Big Picture explanation
- Smaller tweaks