

# Using GPT-2, GPT-NEO, T5 to classify Explanations of Movie Recommendations as Good or Bad via a novel quality metric

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Date: 4/1

# Background: Conversational Recommender Systems

Chatbots



Recommender system



Large Language Models



CRS

# Search Vs. CRS

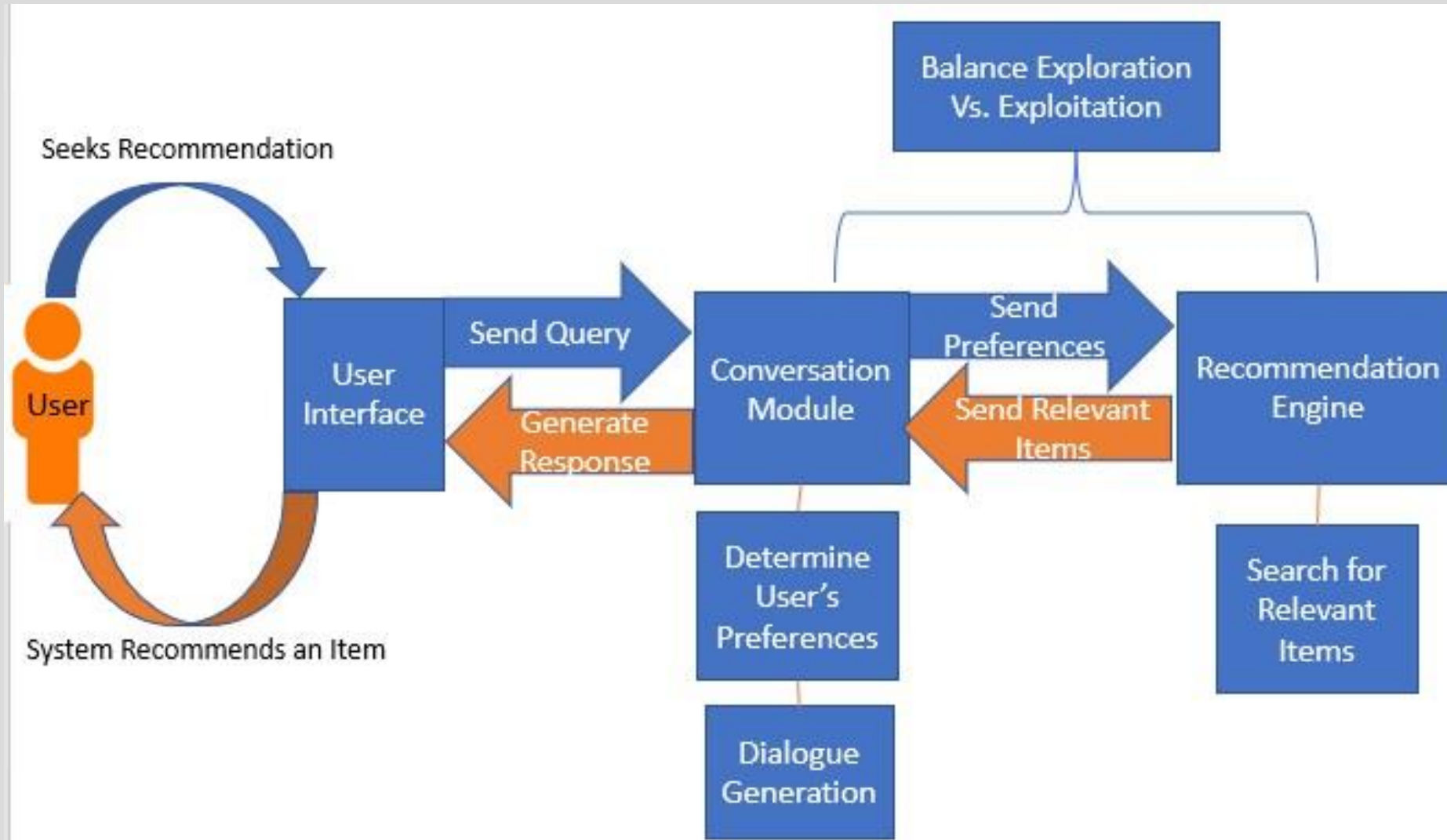
## Search

- Keywords
- Single Interaction
- Specific

## CRS

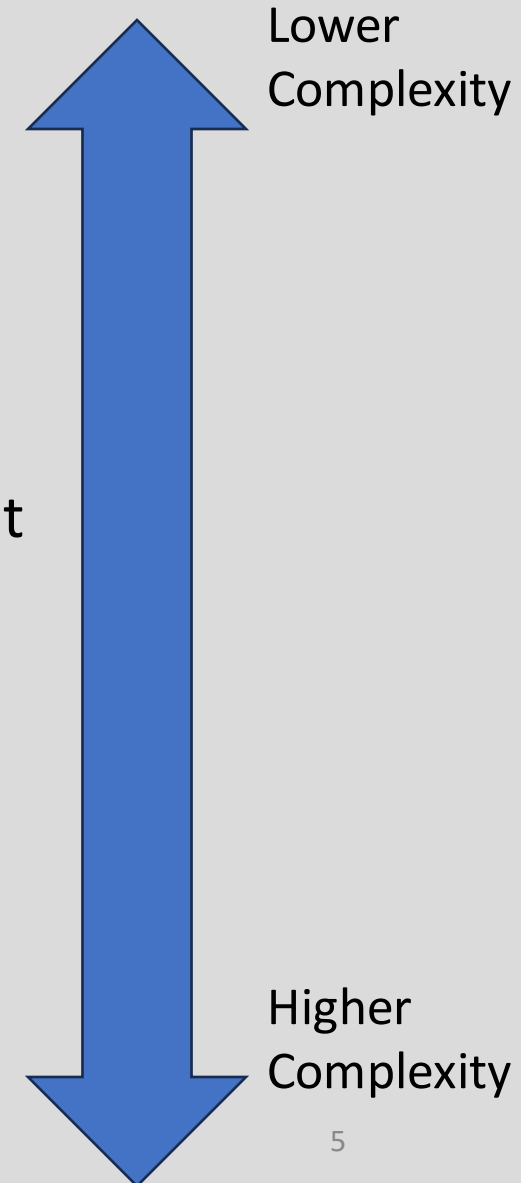
- Natural Language
- Multi-round
- Exploratory
- Feedback
- Context window
- Sidestep cold start problem
- Avoid user drift over time

# 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 may 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



# Evaluation Patterns in Other Papers

1

## Create CRS

- Recommendation Engine
- Conversation Engine
- Test and report metrics (NDCG, MRR, BLEU etc)

2

## Online user survey: Author model versus other model(s)

3

## Survey Comparison Issues

- Relativity
- Comparing restaurants

# 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

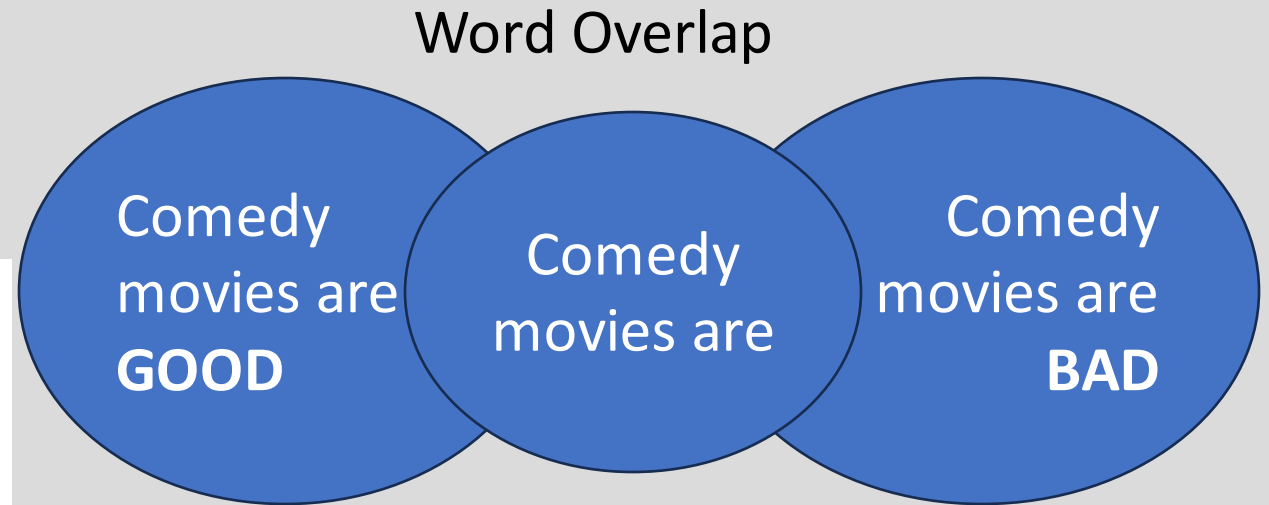
# Quality Gaps

## 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

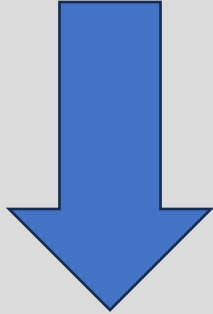


Translation Accuracy

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

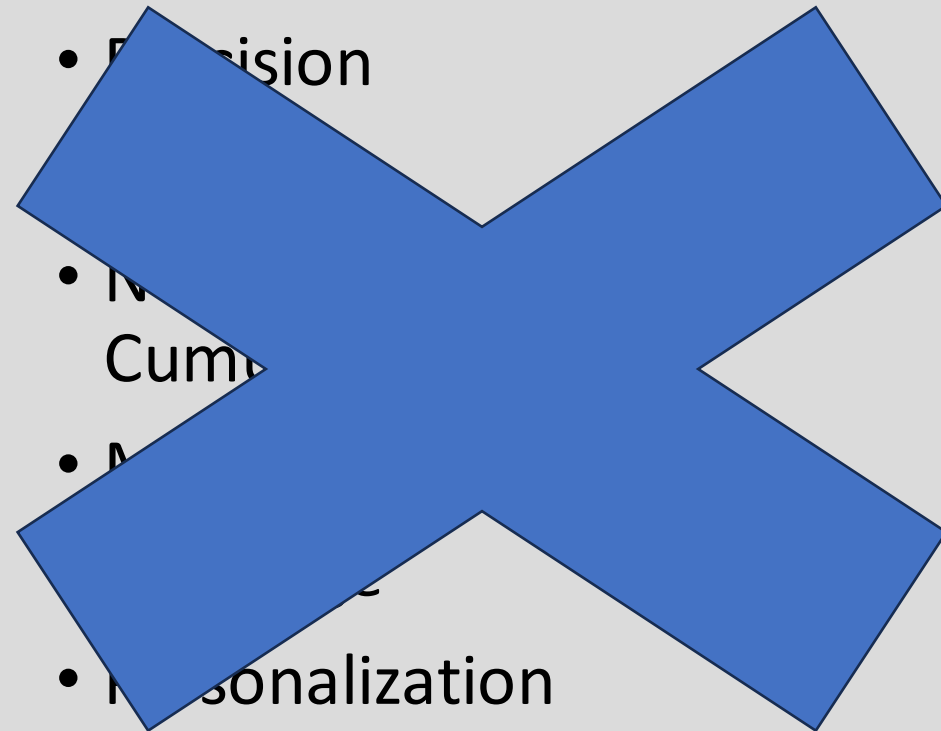
## Recommendation Quality

- Precision

- Recall
- Cumulative

- Mean

- Personalization



# What Makes A Good recommendation?

Factors of Explainability	Definition
Relevance	If the recommendation is relevant to the query
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:

SYSTEM: What kind of movies do you like?

USER: Can you find me a movie like [Pretty Woman (1990)]. An all time favorite.

SYSTEM: RECOMMENDATION REASON Of course. Since you want a movie like [Pretty Woman (1990)], I recommend MOVIE DESCRIPTION [Bridget Jones's Diary (2001)], it's also a romance comedy. It tells a story that Bridget Jones is determined to improve herself while she looks for love in a year in which she keeps a personal diary. PERSONAL OPINION & ENCOURAGEMENT I think it's one of the most charming romantic comedies in a while! I believe this movie will give you an unprecedented experience.

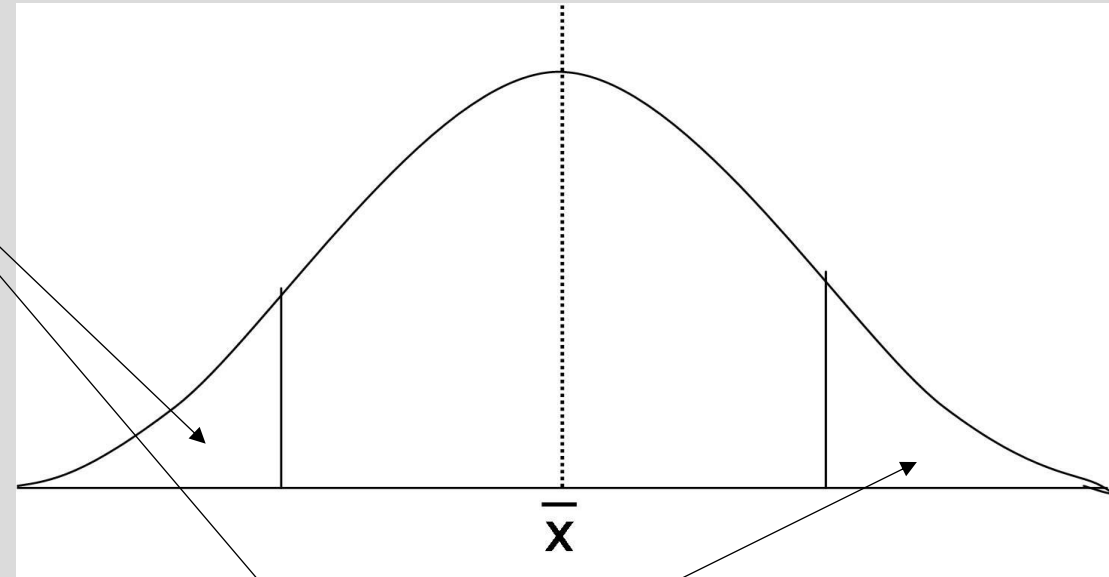
MOVIE WIKI KNOWLEDGE: ... Bridget Jones's Diary is a 2001 romantic comedy film directed by MOVIE PLOT Sharon Maguire and written by ... Bridget Jones is determined to improve herself while she looks for love in a year in which she keeps a personal diary ... MOVIE REVIEW As a huge fan of the books, I had incredibly high expectations of the movie ...

USER: Oh, I have seen that and that was good.

...

# 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

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

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

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

# Calculating Quality Factor: Repetition

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

```
#Repetition functions
def scoreRepetition(idList, wholeConv):
    repetitionScores = []
    #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
        repetitionScores.append(repeatedWords)
    return repetitionScores

#End repetition 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.

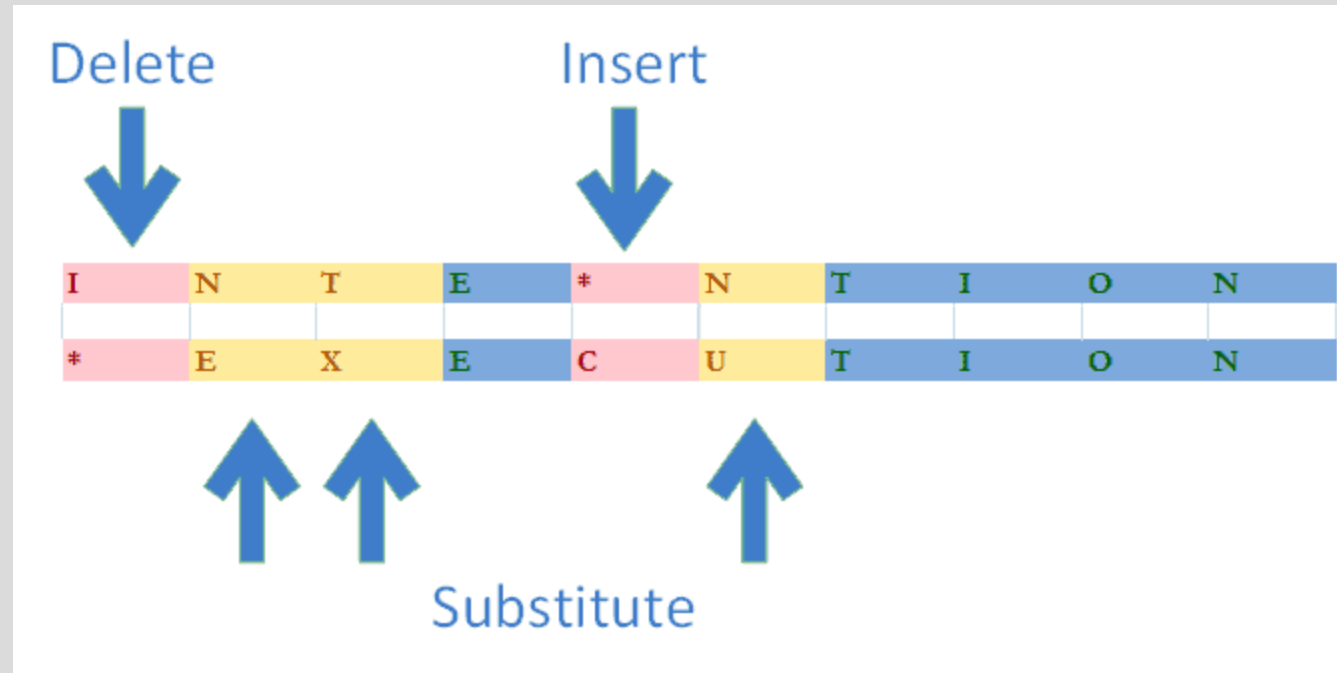
```
curString = " ".join(wholeConv[hash(id)][0])  
blob = TextBlob(curString)  
subjectivityScores.append(blob.sentiment.subjectivity)
```

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



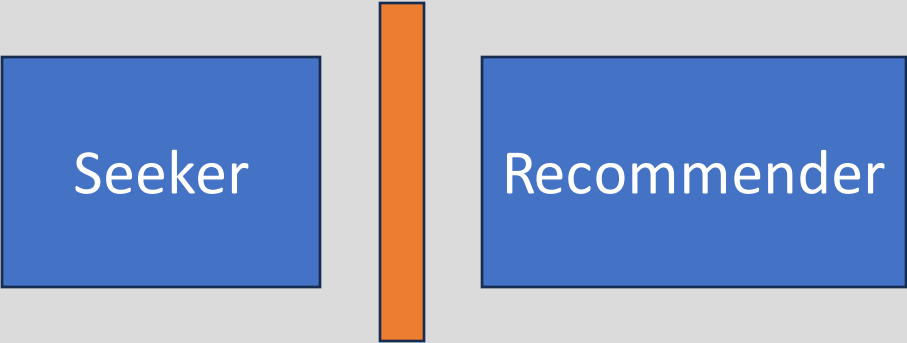
# Calculating Quality Factor: Grammar

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

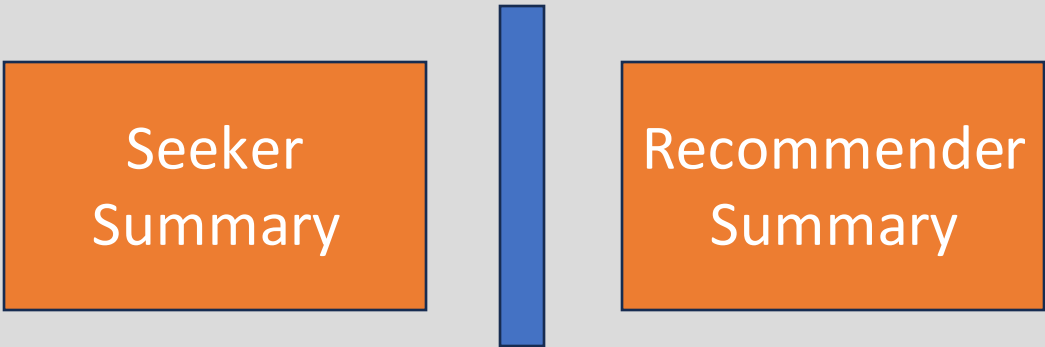


# Calculating Quality Factor: Feature Appearance

1. Divide conversation into 2 parts

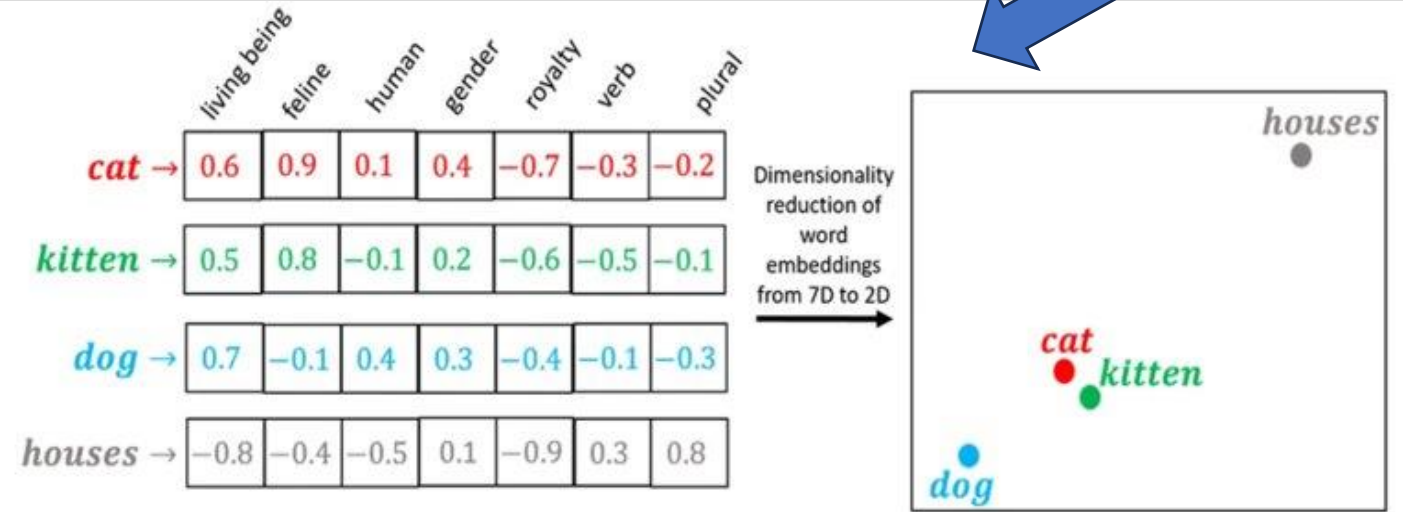
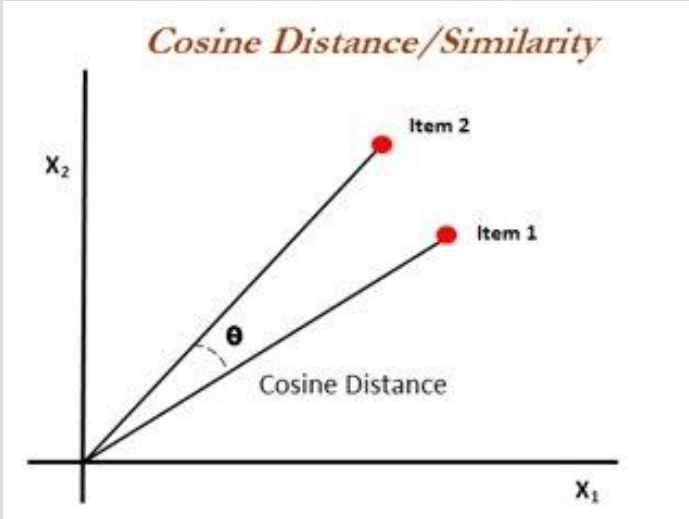


2. Use BART to summarize each half

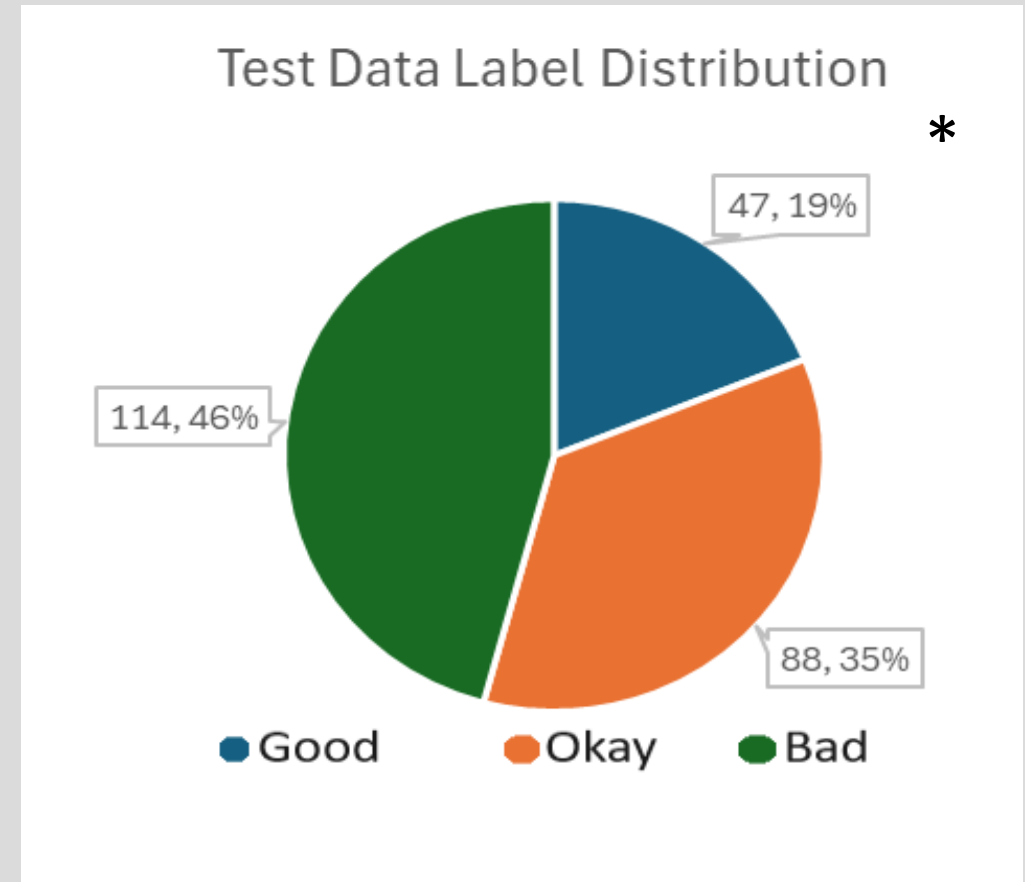
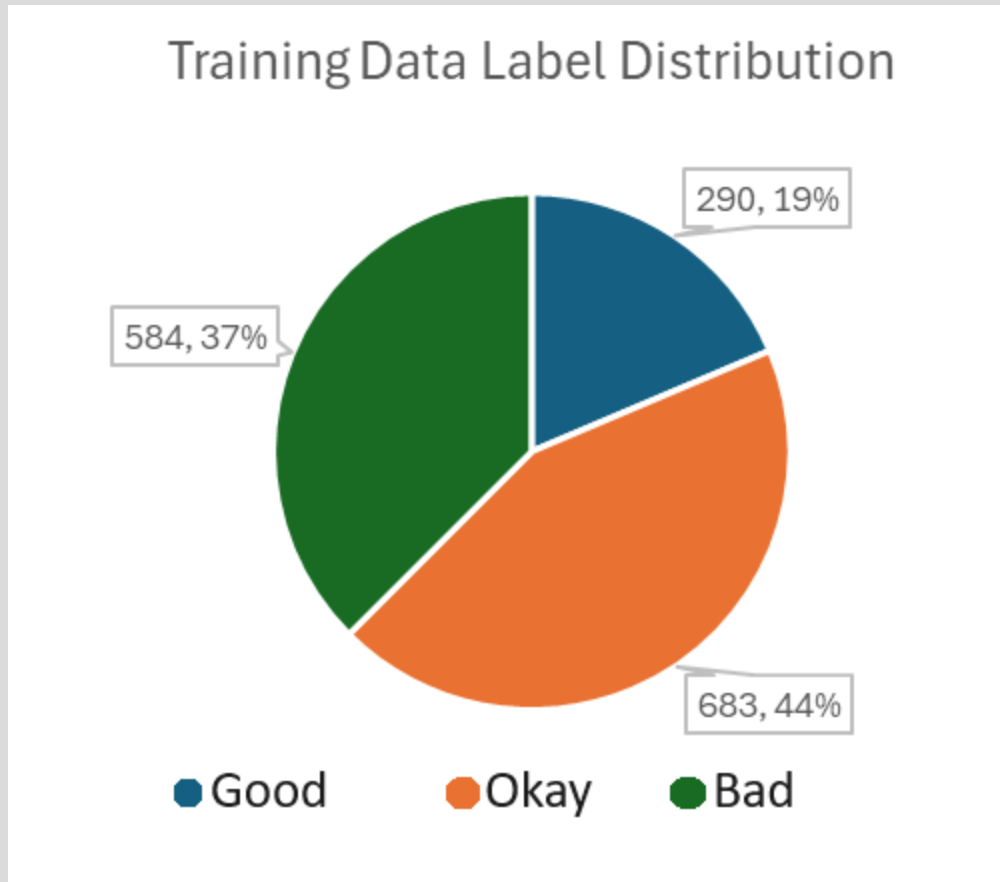


4. Calculate Cosine Similarity of Summary Embeddings

3. Embed Summaries with BERT



# Target Label Distribution:



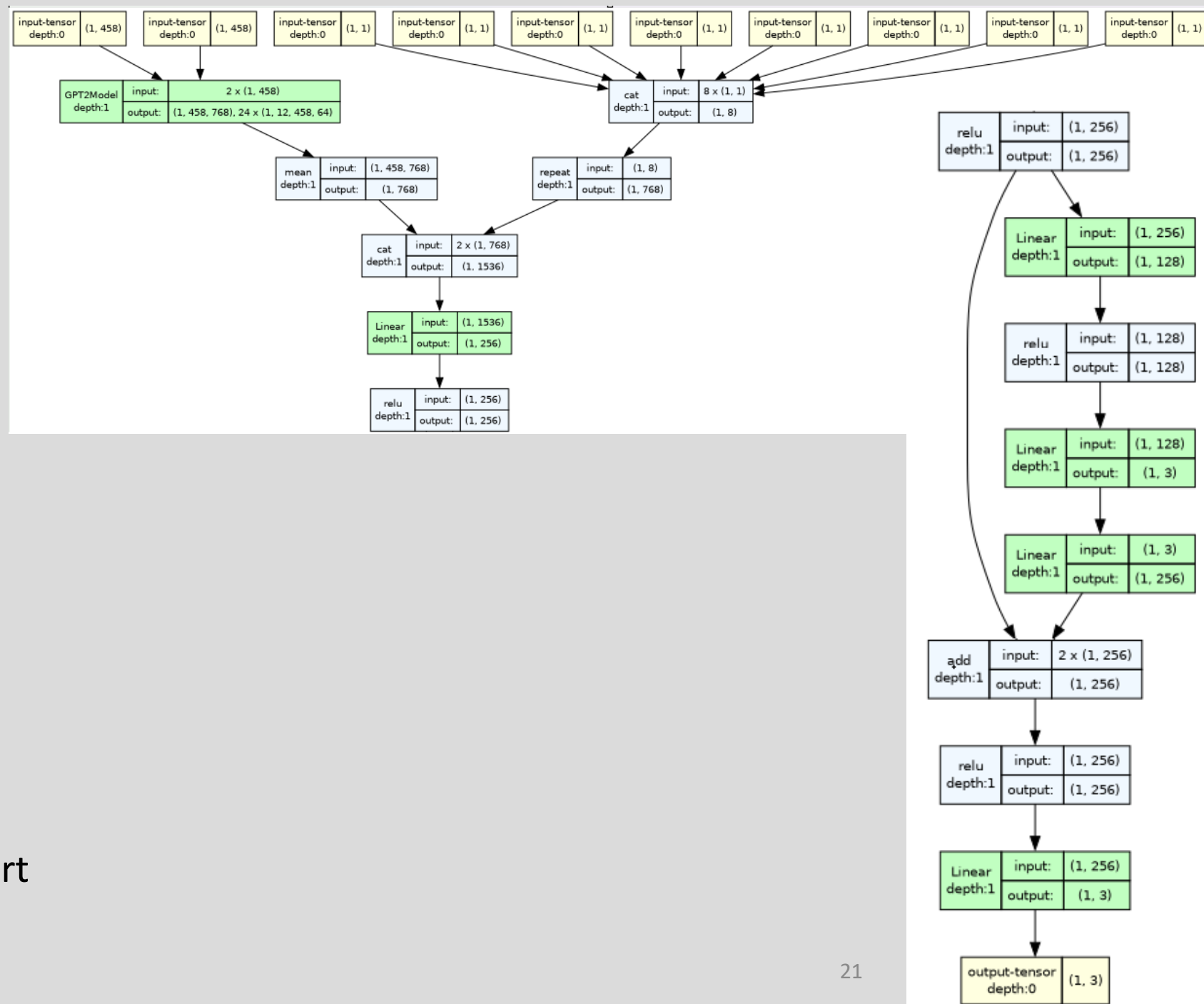
\* Imbalanced test set explicitly part of the dataset. 823 of the system responses in the E-Redial test set are idle with no movie recommendations

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

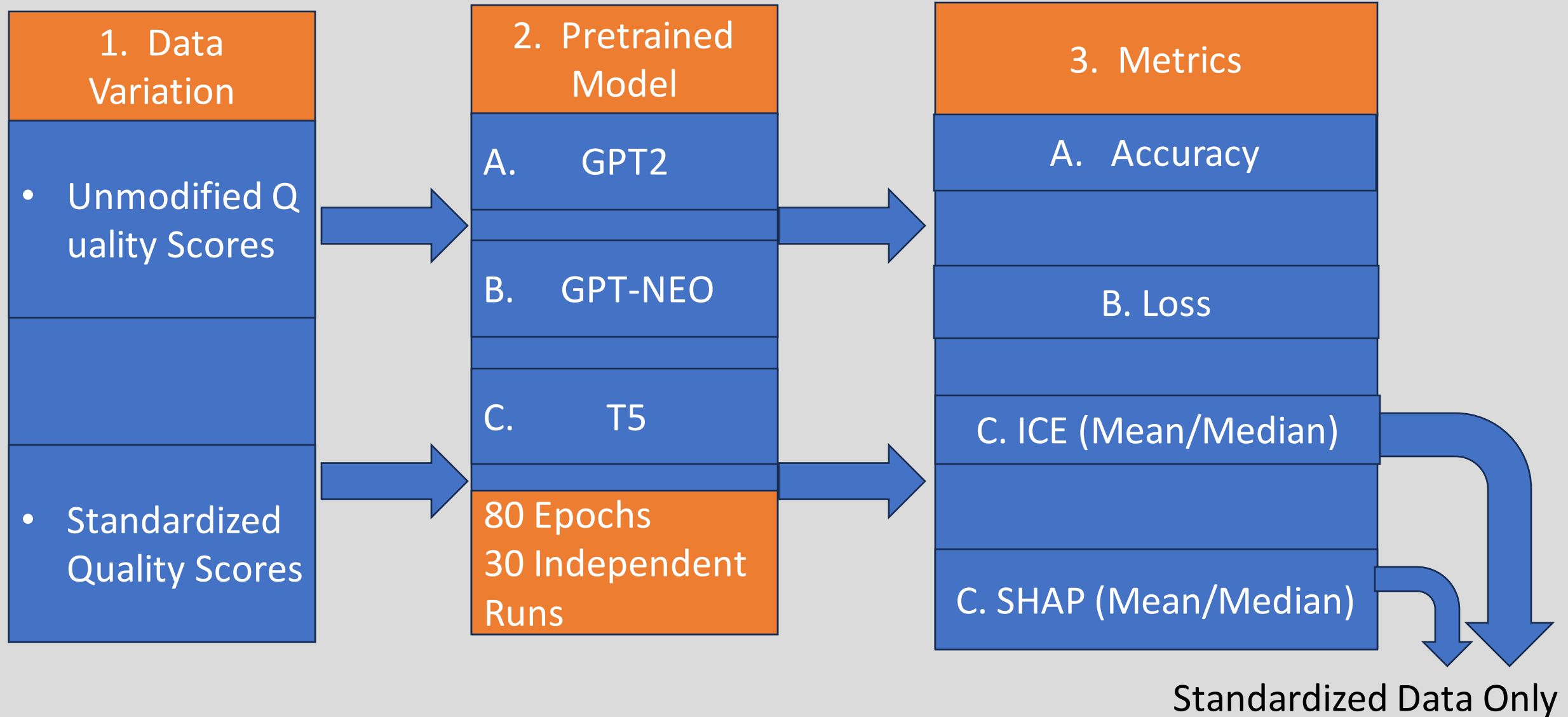
GPT2	NEO	T5
Transformer Architecture	Transformer Architecture	Transformer Architecture
Language Modelling Objective / token prediction	Language Modelling Objective / token prediction	Text-to-Text Objective
124 million parameters	125 million parameters	222 million parameters

# Model Architecture

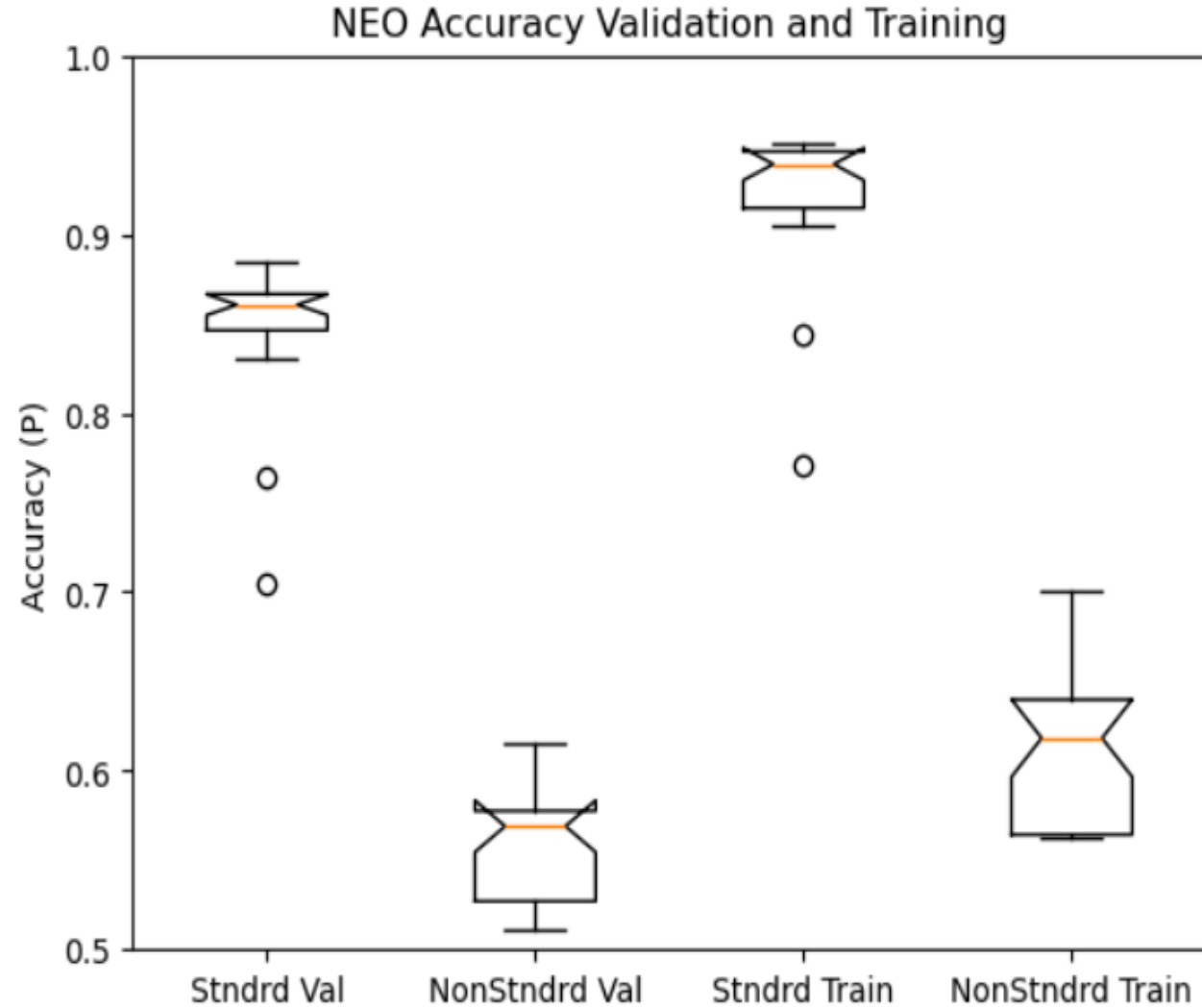
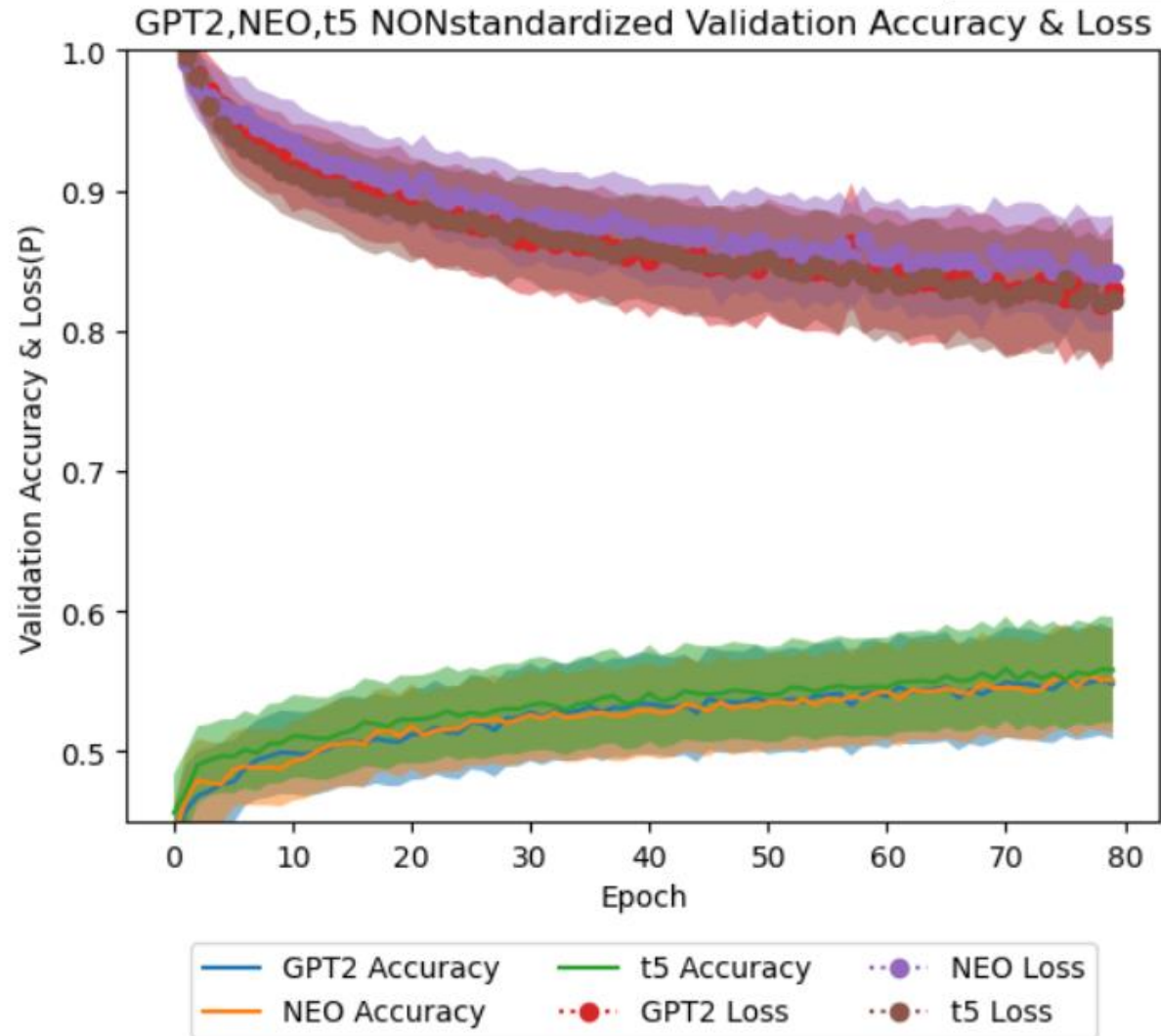
- Input:
  - Embedded Conversation
  - 8 Quality Factors for the conversation
- Output:
  - Class Label  
{Good(0), Okay(1), Bad(2)}
- Architecture:
  - Base Model (GPT2, NEO, T5)
  - 3 blocks of 3 linear layers (256,128,3) with residual connections between the start and end of the block.



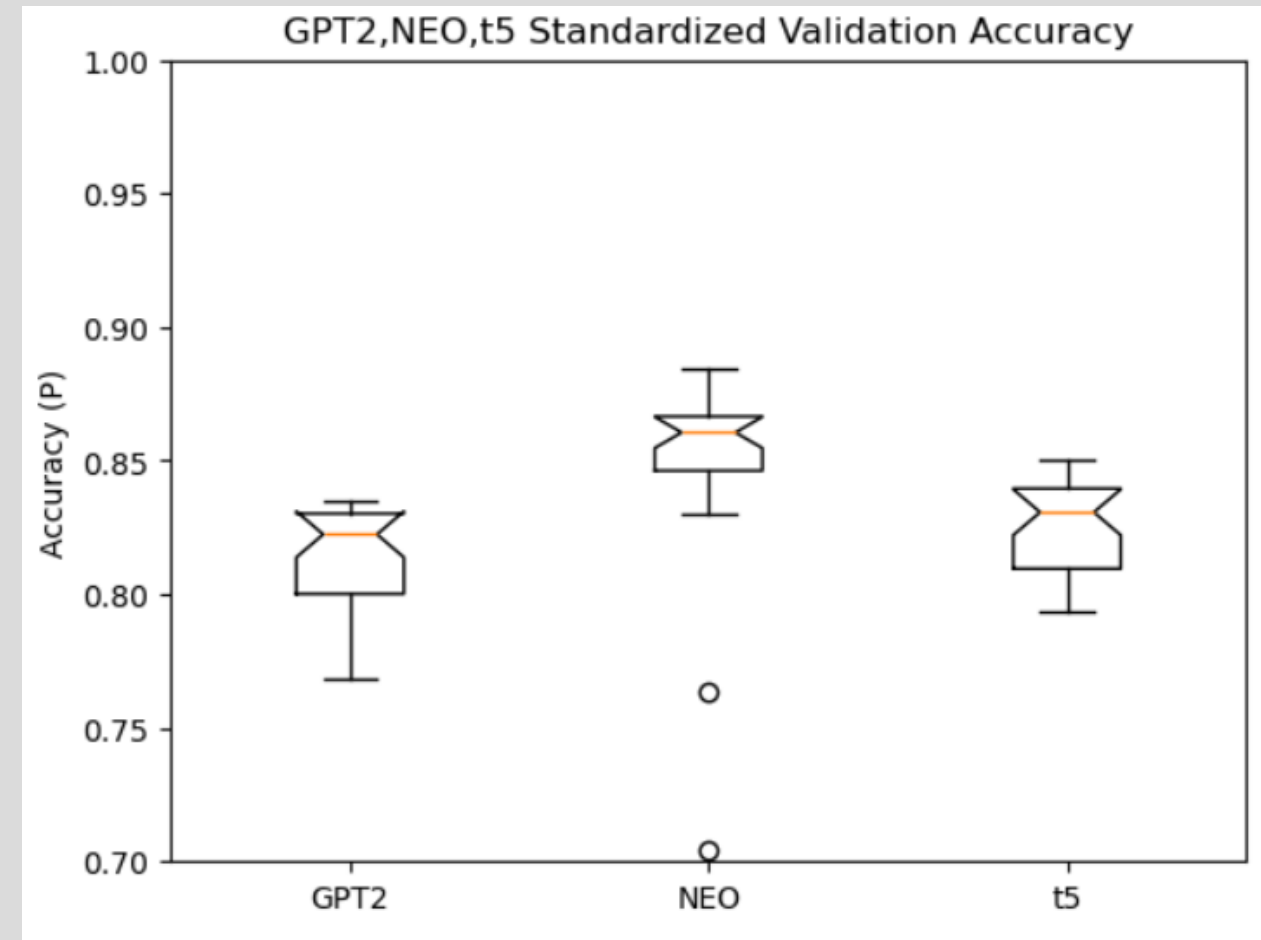
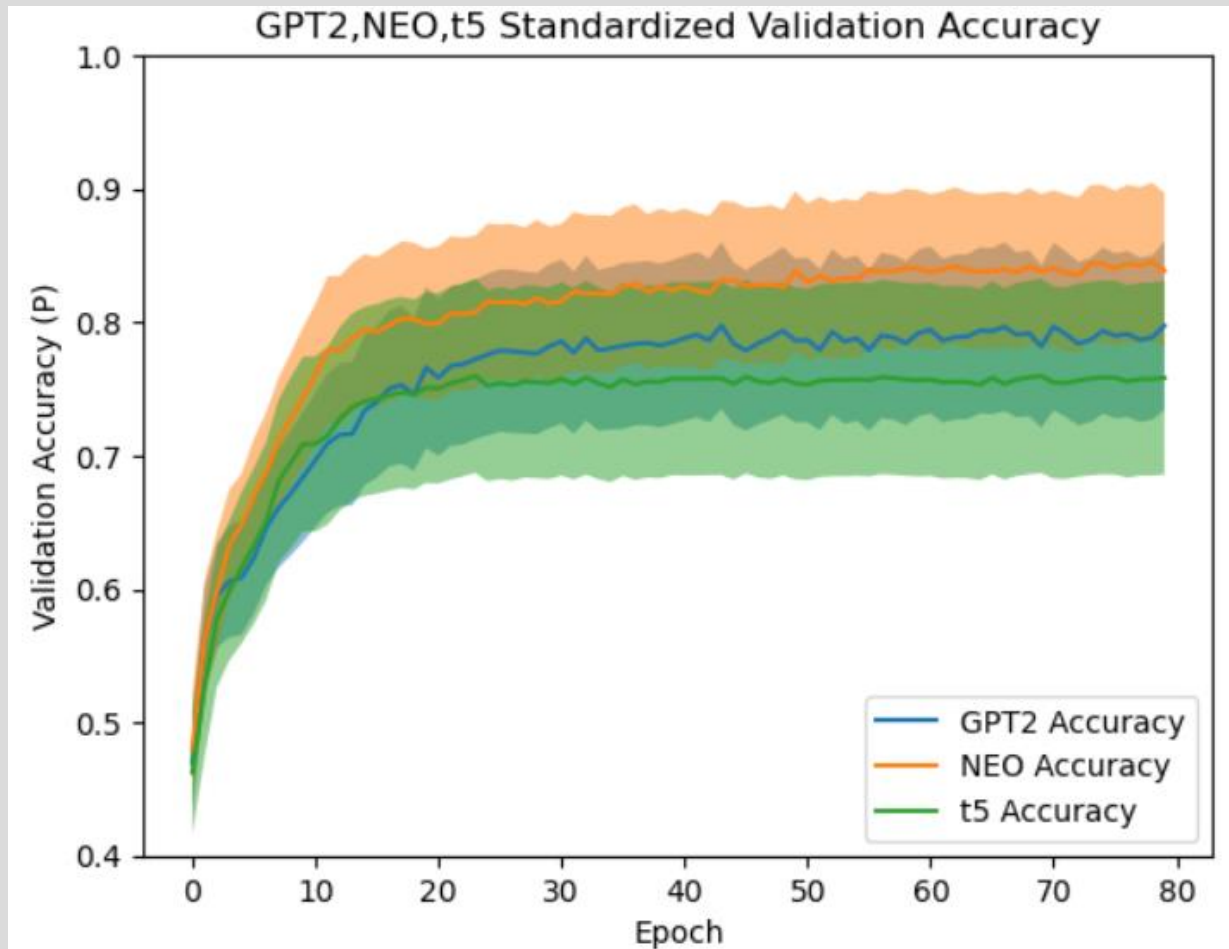
# Experiment Details



# Results: NonStandardized Validation & Training



# Results Standardized: Validation Set





# 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 conversations)
  - 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 quantifies the contribution of each feature to a prediction.

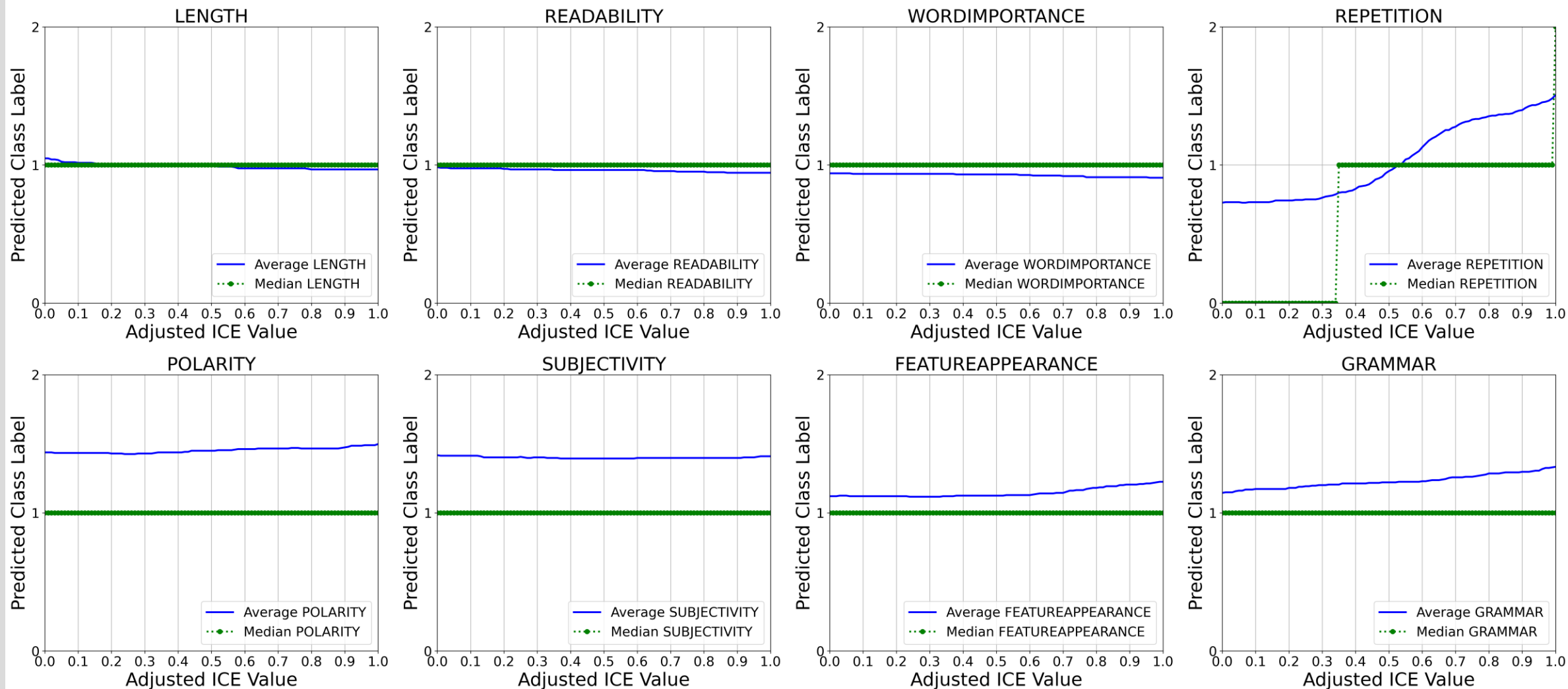
- Explains model behavior at a global level
- Big Picture explanation
- Smaller tweaks

# ICE Results: GPT2

Mean

Median

GPT2 Quality Factor ICE values

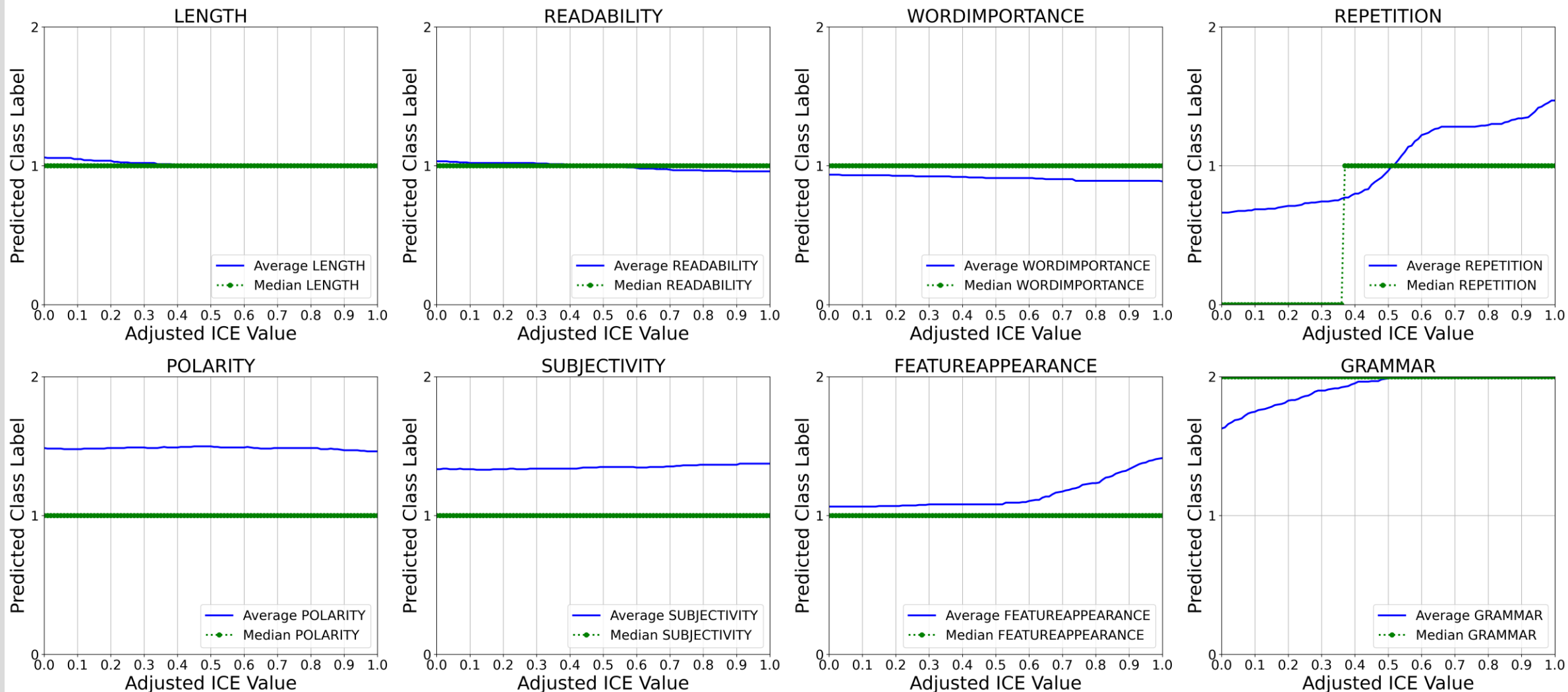


# ICE Results: T5

Mean

Median

t5 Quality Factor ICE values

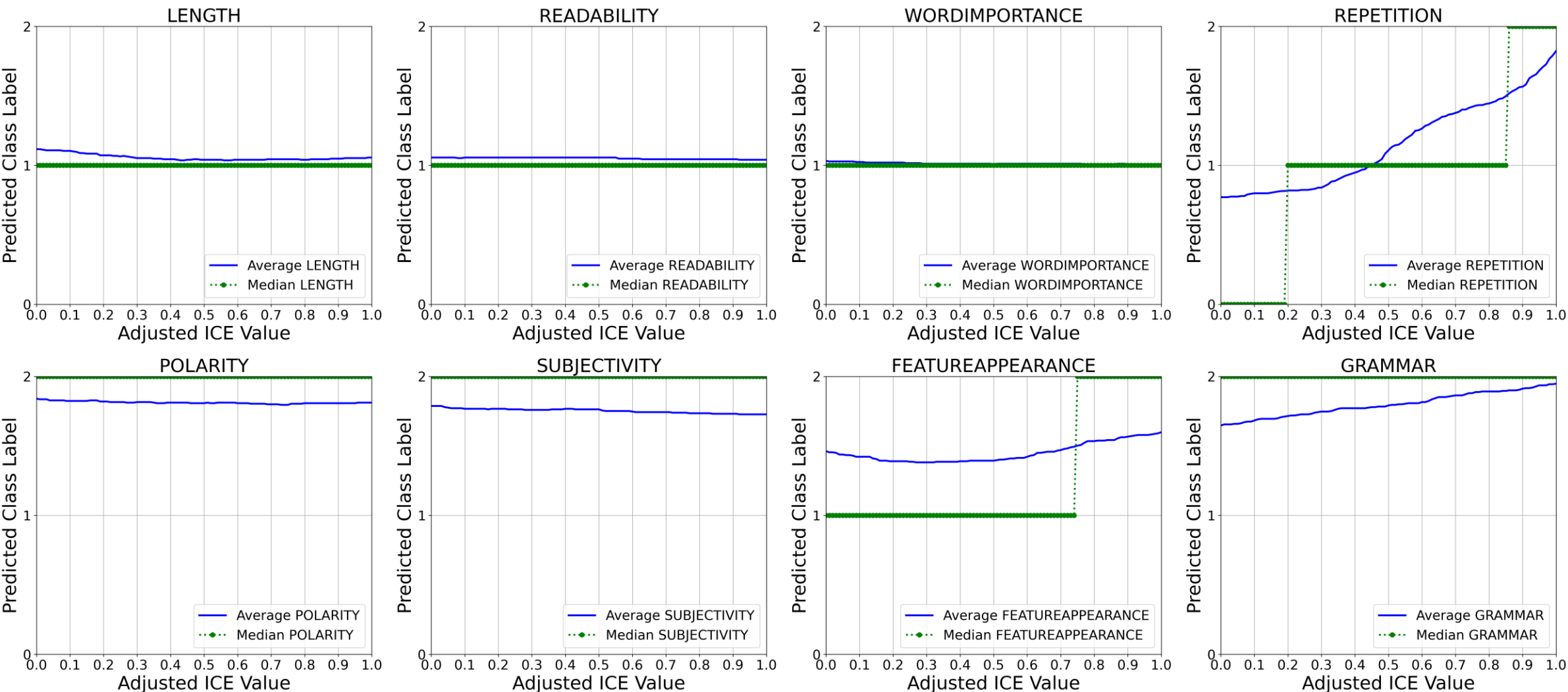


# ICE Results: NEO

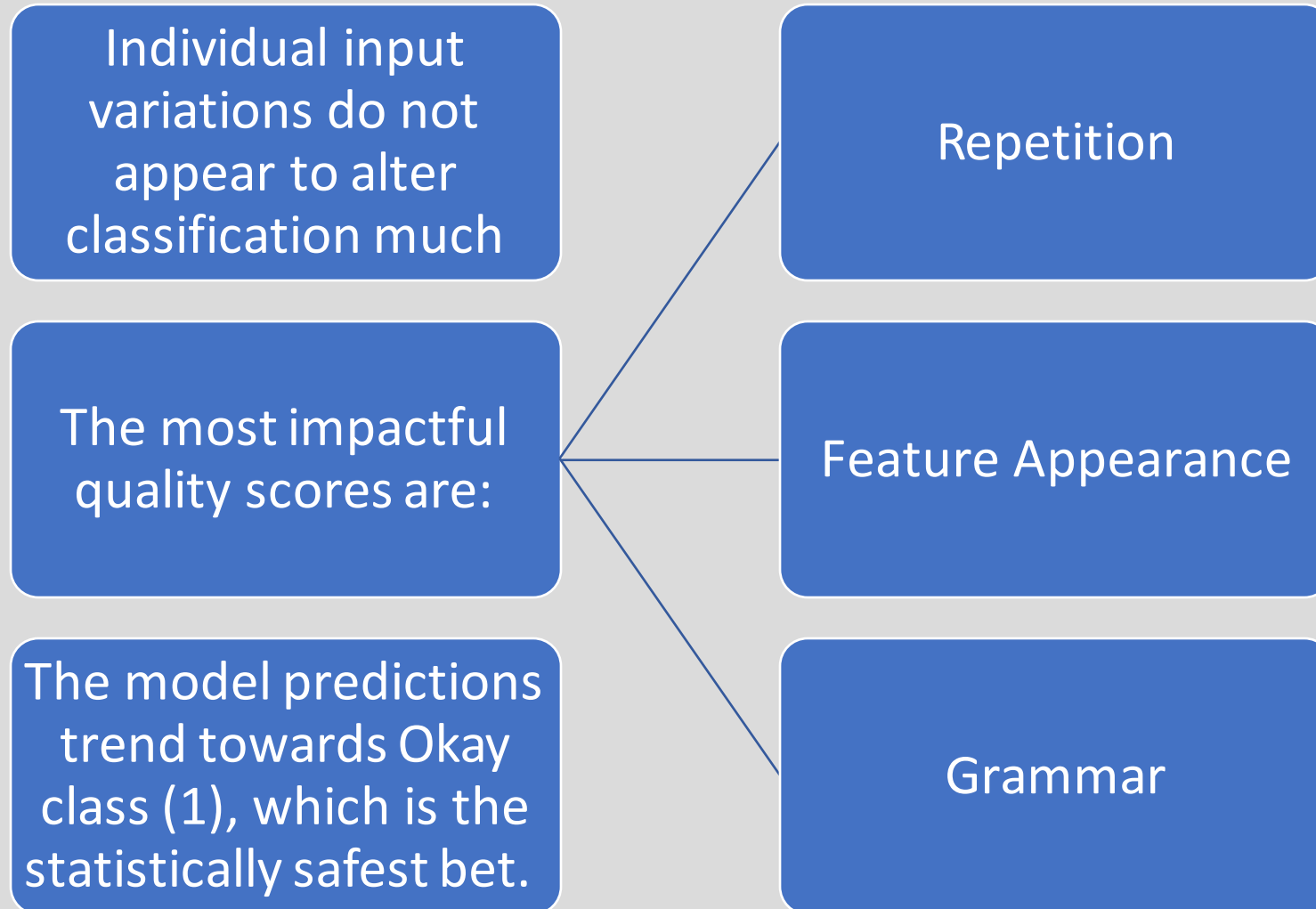
Mean

Median

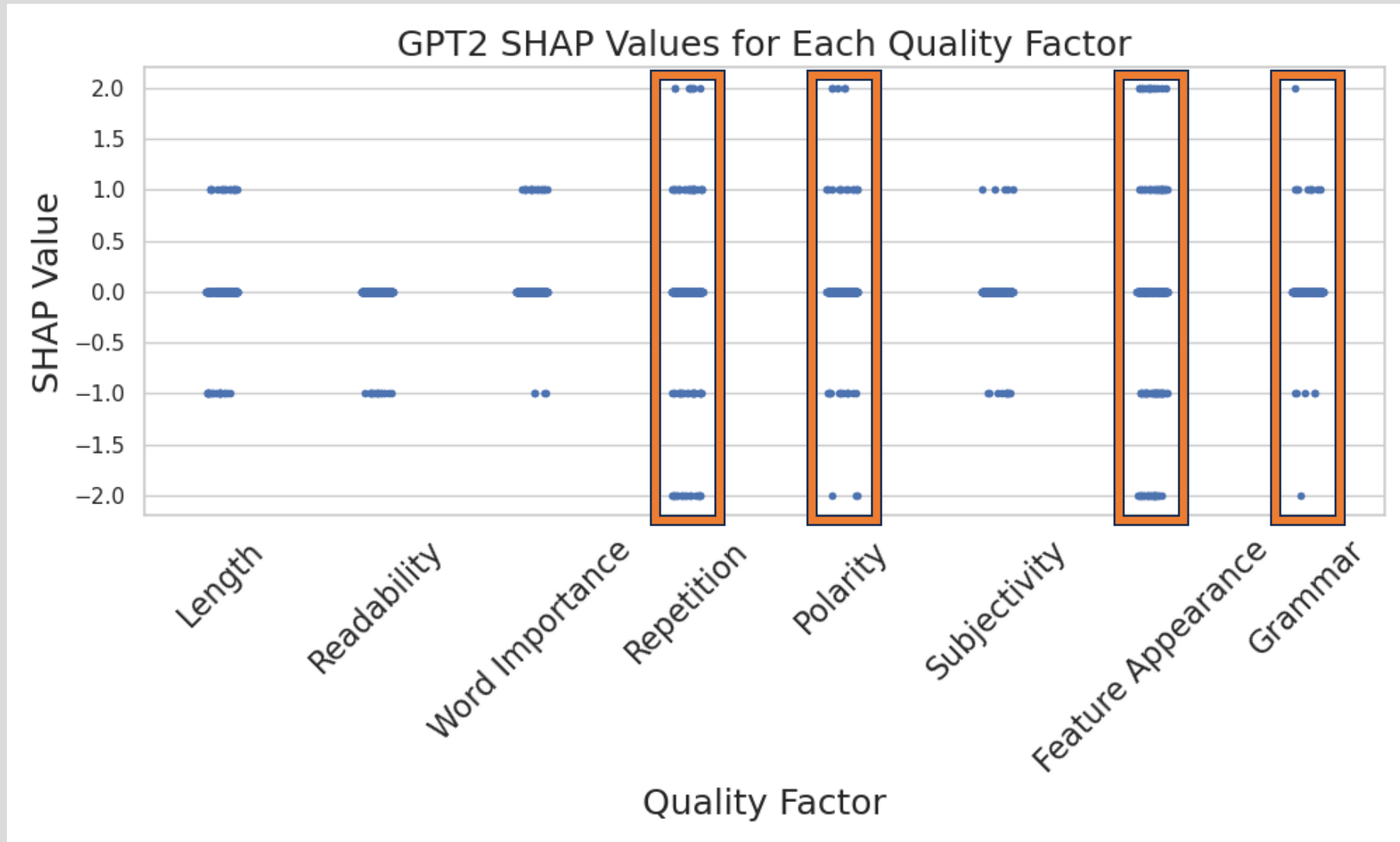
NEO Quality Factor ICE values



# ICE Results Summarized:

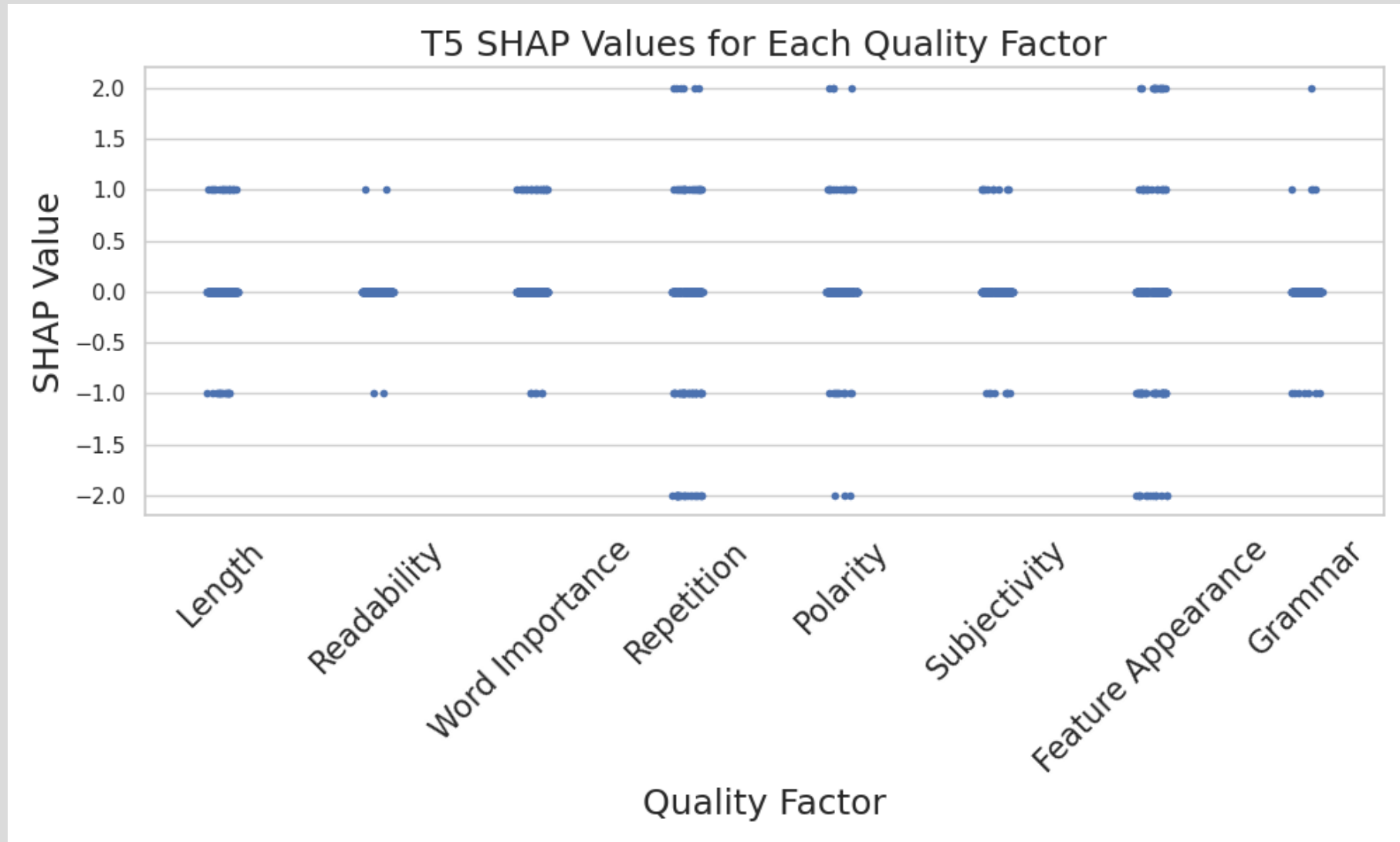


# SHAP Results: GPT2

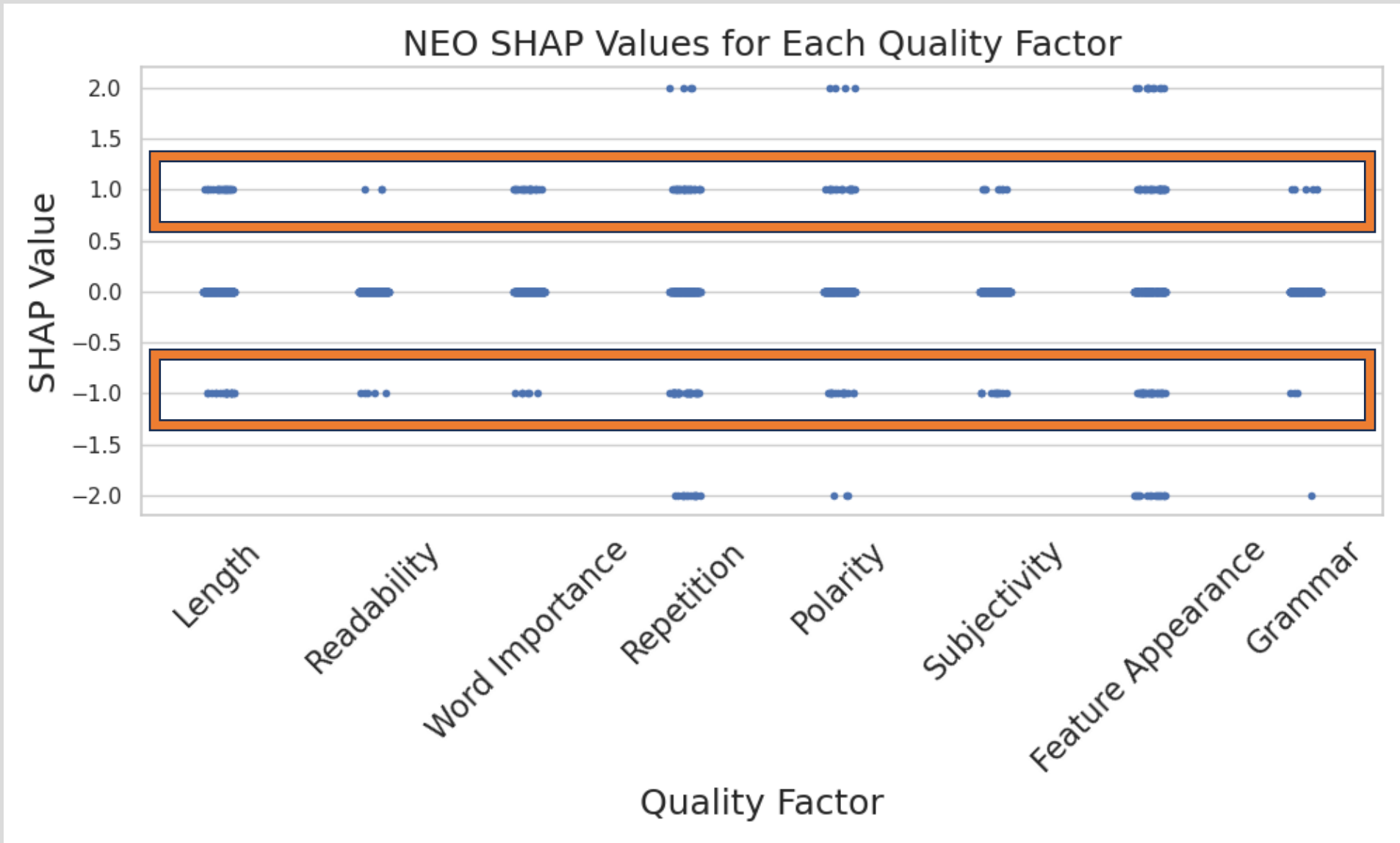




# SHAP Results: T5



# SHAP Results: NEO



# SHAP Results Summarized

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

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

Repetition, 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.

# Overall Summary:

Goal: To find a set of evaluative metrics that accurately assess how well a recommendation request has been explained.

Combine 2 CRS datasets: E-Redial and INSPIRED

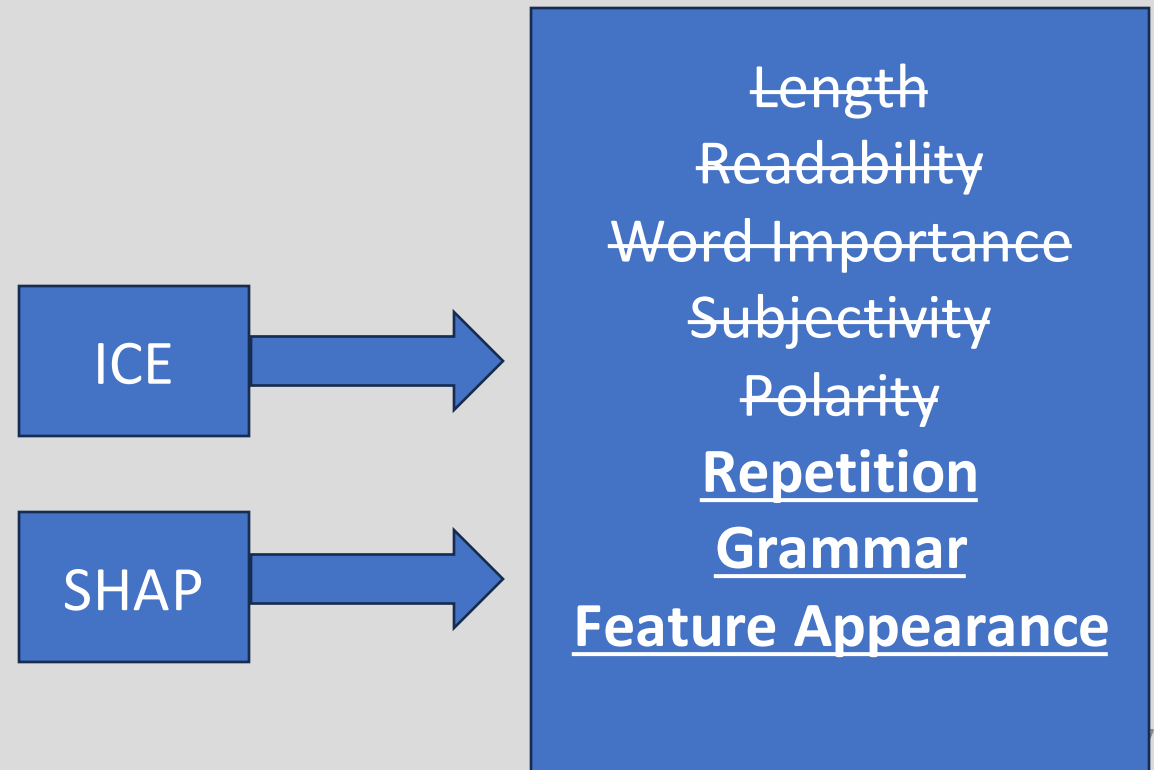
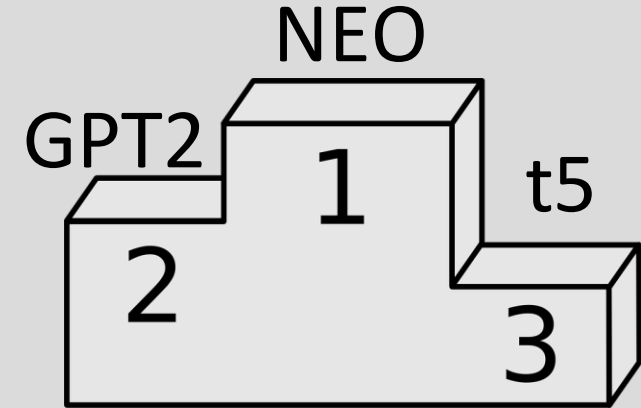
Score each conversation on 8 quality factors: Length, Readability, Repetition, Word Importance, Polarity, Subjectivity, Grammar, Feature Appearance

Based on Quality factors, assign each conversation a score {Good(0), Okay(1), Bad(2)}

Incorporate LLM / tranformer NLP base models to embed conversational data in conjunction with a residual network architecture

# 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?

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Thanks!

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