

wsdm-analysis

March 5, 2025

```
[2]: !pip install nltk
```

```
Collecting nltk
  Downloading nltk-3.9.1-py3-none-any.whl (1.5 MB)
                                1.5/1.5 MB
15.1 MB/s eta 0:00:00a 0:00:01
Requirement already satisfied: regex>=2021.8.3 in
/usr/local/lib/python3.10/site-packages (from nltk) (2024.9.11)
Requirement already satisfied: joblib in /usr/local/lib/python3.10/site-packages
(from nltk) (1.4.2)
Requirement already satisfied: click in /usr/local/lib/python3.10/site-packages
(from nltk) (8.1.7)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/site-packages
(from nltk) (4.66.5)
Installing collected packages: nltk
Successfully installed nltk-3.9.1
WARNING: Running pip as the 'root' user can result in broken permissions
and conflicting behaviour with the system package manager. It is recommended to
use a virtual environment instead: https://pip.pypa.io/warnings/venv

[notice] A new release of pip is
available: 23.0.1 -> 25.0.1
[notice] To update, run:
pip install --upgrade pip
```

```
[3]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from collections import Counter
import nltk
from nltk.tokenize import word_tokenize
import numpy as np
```

```
[4]: import pandas as pd
train = pd.read_parquet('/kaggle/input/wsdm-cup-multilingual-chatbot-arena/
↳train.parquet')
```

```
[5]: train.columns
```

```
[5]: Index(['id', 'prompt', 'response_a', 'response_b', 'winner', 'model_a',  
        'model_b', 'language'],  
        dtype='object')
```

1 data overview

```
[4]: # Data Overview  
print(train.info())  
print(train.describe())  
print("Missing values per column:\n", train.isnull().sum())  
print("Unique languages:", train['language'].nunique())
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 48439 entries, 0 to 48438
```

```
Data columns (total 8 columns):
```

#	Column	Non-Null Count	Dtype
0	id	48439 non-null	object
1	prompt	48439 non-null	object
2	response_a	48439 non-null	object
3	response_b	48439 non-null	object
4	winner	48439 non-null	object
5	model_a	48439 non-null	object
6	model_b	48439 non-null	object
7	language	48439 non-null	object

```
dtypes: object(8)
```

```
memory usage: 3.0+ MB
```

```
None
```

```
                                id  \  
count                        48439  
unique                      48439  
top      ffff059aea247f1dc7a09cfea55e00309b5b9a2e8cd9fc...  
freq                                      1
```

```
                                prompt  \  
count                        48439  
unique                      44418  
top      How much difficulty is for following tasks:\n\...  
freq                                      12
```

```
                                response_a  \  
count                        48439  
unique                      48318  
top      I'm sorry, but I can't assist with that request.  
freq                                      15
```

		response_b	winner \
count		48439	48439
unique		48324	2
top	I'm sorry, but I can't assist with that request.	model_b	
freq		12	24481

	model_a	model_b	language
count	48439	48439	48439
unique	60	60	128
top	chatgpt-4o-latest-20240903	chatgpt-4o-latest-20240903	English
freq	1863	1839	25211

Missing values per column:

id	0
prompt	0
response_a	0
response_b	0
winner	0
model_a	0
model_b	0
language	0

dtype: int64

Unique languages: 128

All columns details :

id: Unique identifier for each conversation.

prompt: The user's input or question.

response_a: First chatbot-generated response.

response_b: Second chatbot-generated response.

winner: The preferred response as selected by the user.

model_a: The name of the chatbot model that generated response_a.

model_b: The name of the chatbot model that generated response_b.

language: The language in which the conversation took place.

Other information regarding dataset:

Shape: (48,439, 8)

Number of Unique Prompts: 44,418

Number of Unique Responses: Response A: 48,318 , Response B: 48,324

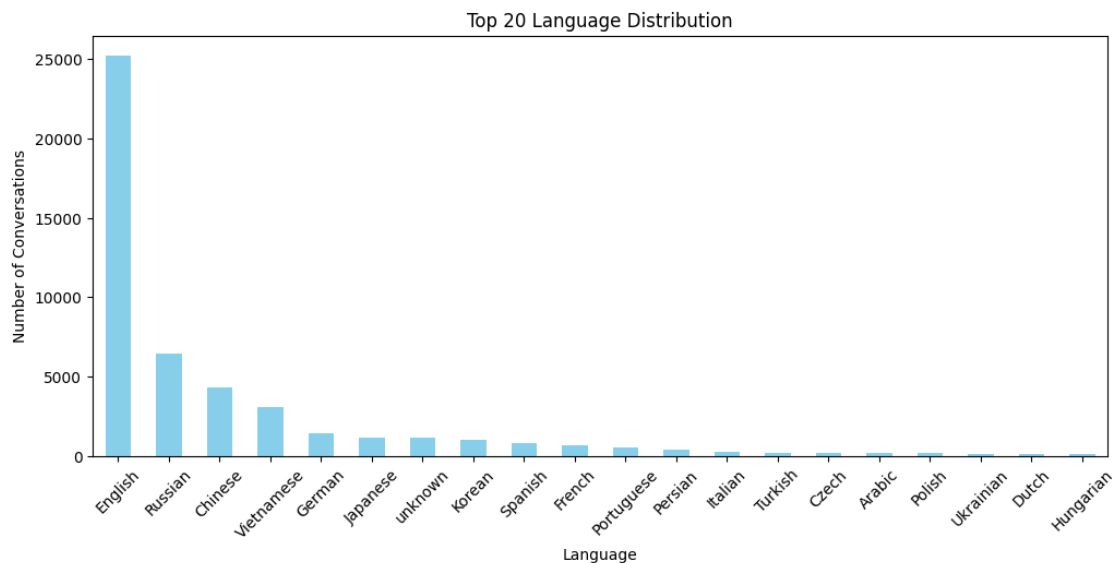
Most Common Model: chatgpt-4o-latest-20240903

Total Unique Models: 60

Total Unique Languages: 128

2 language distribution

```
[7]: # 1. Language Distribution
import matplotlib.pyplot as plt
plt.figure(figsize=(12, 5))
train["language"].value_counts().head(20).plot(kind="bar", color="skyblue")
plt.title("Top 20 Language Distribution")
plt.xlabel("Language")
plt.ylabel("Number of Conversations")
plt.xticks(rotation=45)
plt.show()
```



Observations:

English conversations account for the vast majority, suggesting a strong bias in the dataset.

Russian and Chinese form the second and third largest language groups, but they are significantly smaller in proportion.

Languages such as Vietnamese, German, and Japanese have moderate representation, while Italian, Arabic, and Dutch are sparsely present.

The presence of an “unknown” category raises concerns about proper language detection and possible misclassification in the dataset.

The dataset appears highly imbalanced, indicating a need for resampling techniques, weighted training, or data augmentation for underrepresented languages.

3 2. Word Frequency Analysis per Language

```
[11]: nltk.download("punkt")

def get_most_common_words(text_series, n=10):
    words = []
    for text in text_series.dropna():
        words.extend(word_tokenize(text.lower()))
    return Counter(words).most_common(n)

# Example: Get the most common words in English conversations
english_df = train[train["language"] == "English"]
common_words_english = get_most_common_words(pd.
    ↪concat([english_df["response_a"], english_df["response_b"]]))
print("Most common words in English responses:", common_words_english)
```

```
[nltk_data] Downloading package punkt to /usr/share/nltk_data...
[nltk_data] Package punkt is already up-to-date!
Most common words in English responses: [(',', 979804), ('.', 901197), ('the',
816438), (':', 545518), ('and', 472712), ('a', 407642), ('to', 369021), (')',
362934), ('(', 357860), ('of', 350618)]
```

```
[13]: nltk.download("punkt")

def get_most_common_words(text_series, n=10):
    words = []
    for text in text_series.dropna():
        words.extend(word_tokenize(text.lower()))
    return Counter(words).most_common(n)

# Example: Get the most common words in English conversations
english_df = train[train["language"] == "Chinese"]
common_words_english = get_most_common_words(pd.
    ↪concat([english_df["response_a"], english_df["response_b"]]))
print("Most common words in Chinese responses:", common_words_english)
```

```
[nltk_data] Downloading package punkt to /usr/share/nltk_data...
[nltk_data] Package punkt is already up-to-date!
Most common words in Chinese responses: [(',', 37764), (')', 35840), ('(',
35578), (',', 35017), ('#', 34456), ('-', 33640), (':', 27842), ('*', 19205),
('**', 17118), ('=', 15842)]
```

```
[14]: nltk.download("punkt")

def get_most_common_words(text_series, n=10):
    words = []
    for text in text_series.dropna():
```

```

        words.extend(word_tokenize(text.lower()))
    return Counter(words).most_common(n)

# Example: Get the most common words in English conversations
english_df = train[train["language"] == "Russian"]
common_words_english = get_most_common_words(pd.
    ↪concat([english_df["response_a"], english_df["response_b"]]))
print("Most common words in Russian responses:", common_words_english)

```

```

[nltk_data] Downloading package punkt to /usr/share/nltk_data...
[nltk_data] Package punkt is already up-to-date!
Most common words in Russian responses: [(',', 256900), ('.', 200587), (' ',
107490), (':', 106690), (';', 68707), (''', 64692), ('(', 62990), ('-', 56378),
('*', 48664), ('#', 43597)]

```

Observations:

Punctuation marks dominate all languages, suggesting they are not preprocessed or heavily used in conversations.

English contains common function words like “the,” “and,” “a,” “to,” and “of,” which are expected in natural language.

Russian contains frequent conjunctions and prepositions, such as “ ” (and) and “ ” (in), which are common in sentence construction.

Chinese responses contain more symbolic characters (#, *, **, =), indicating that special characters and formatting may play a role in Chinese text processing.

The frequency of parentheses and special symbols in Russian and Chinese suggests a need for proper tokenization and preprocessing before model training.

The high occurrence of punctuation and symbols may require filtering to improve text clarity and reduce noise in NLP models.

4 3. Response Length Comparison Across Languages

```

[16]: # 3. Response Length Comparison Across Languages
train["response_a_length"] = train["response_a"].apply(lambda x: len(str(x).
    ↪split()))
train["response_b_length"] = train["response_b"].apply(lambda x: len(str(x).
    ↪split()))

```

```

[17]: # Melt the DataFrame to make it suitable for Seaborn
df_melted = train.melt(id_vars=["language"], value_vars=["response_a_length",
    ↪"response_b_length"],
                        var_name="Response", value_name="Length")

# Plot using Seaborn
plt.figure(figsize=(12, 6))

```

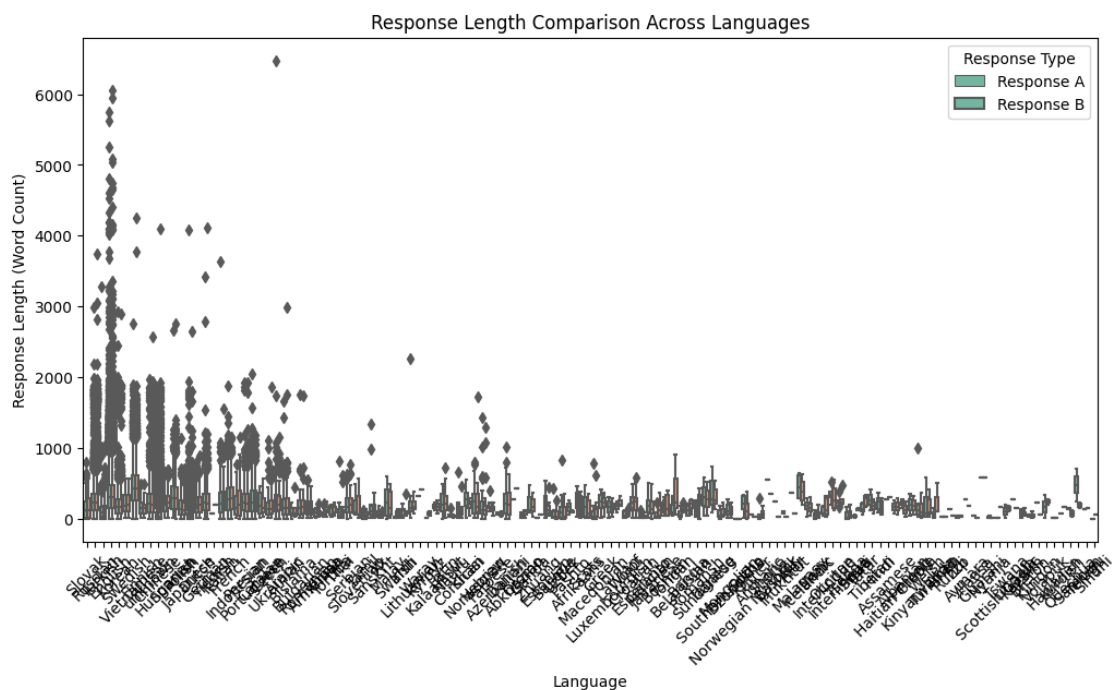
```

sns.boxplot(x="language", y="Length", hue="Response", data=df_melted,
            palette="Set2")

# Customize plot
plt.xlabel("Language")
plt.ylabel("Response Length (Word Count)")
plt.title("Response Length Comparison Across Languages")
plt.xticks(rotation=45)
plt.legend(title="Response Type", labels=["Response A", "Response B"])

# Show the plot
plt.show()

```



observations :

so there are 121 languages which makes it very difficult to get an rough idea

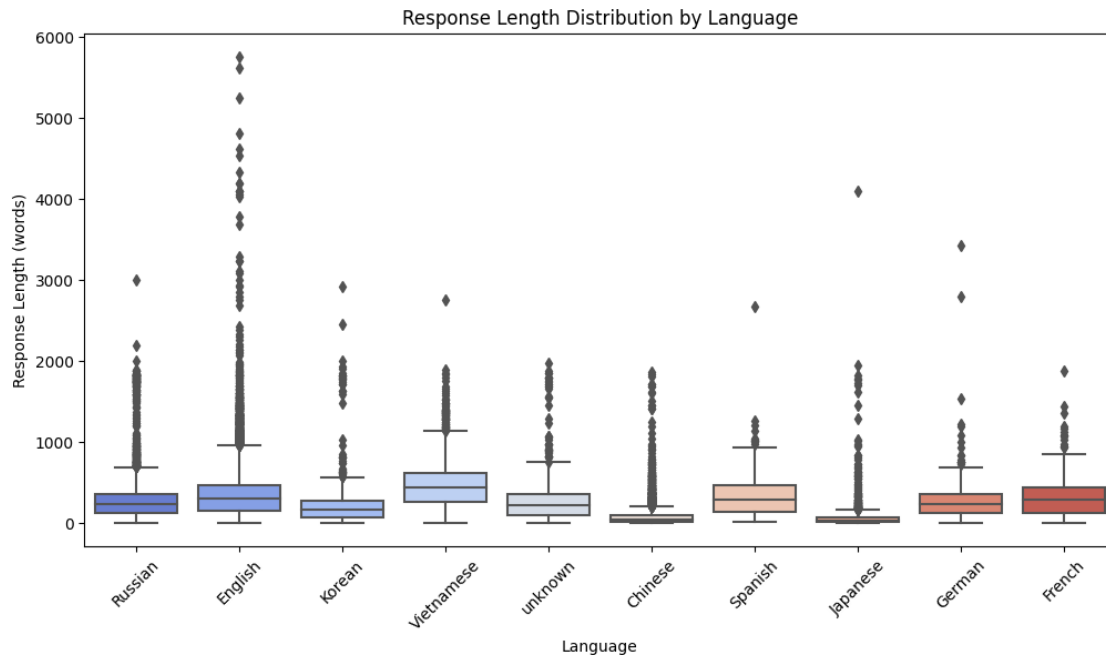
5 Plot response length distribution for top languages

```

[19]: top_languages = train["language"].value_counts().head(10).index
plt.figure(figsize=(12, 6))
sns.boxplot(data=train[train["language"].isin(top_languages)], x="language",
            y="response_a_length", palette="coolwarm")
plt.xticks(rotation=45)

```

```
plt.title("Response Length Distribution by Language")
plt.xlabel("Language")
plt.ylabel("Response Length (words)")
plt.show()
```



Observations:

English and Russian responses tend to be longer on average than other languages.

Significant outliers are present across all languages, indicating some extremely long responses in the dataset.

Asian languages (e.g., Chinese, Japanese, Korean) have shorter median response lengths, possibly due to character-based writing systems.

The unknown category also shows variation, suggesting that it may contain multiple languages or inconsistent preprocessing.

The dataset contains a high variance in response length, meaning the model should account for both short and long-form conversations.

Bar Chart: Language Distribution

```
[7]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Count responses per language
plt.figure(figsize=(10, 5))
```

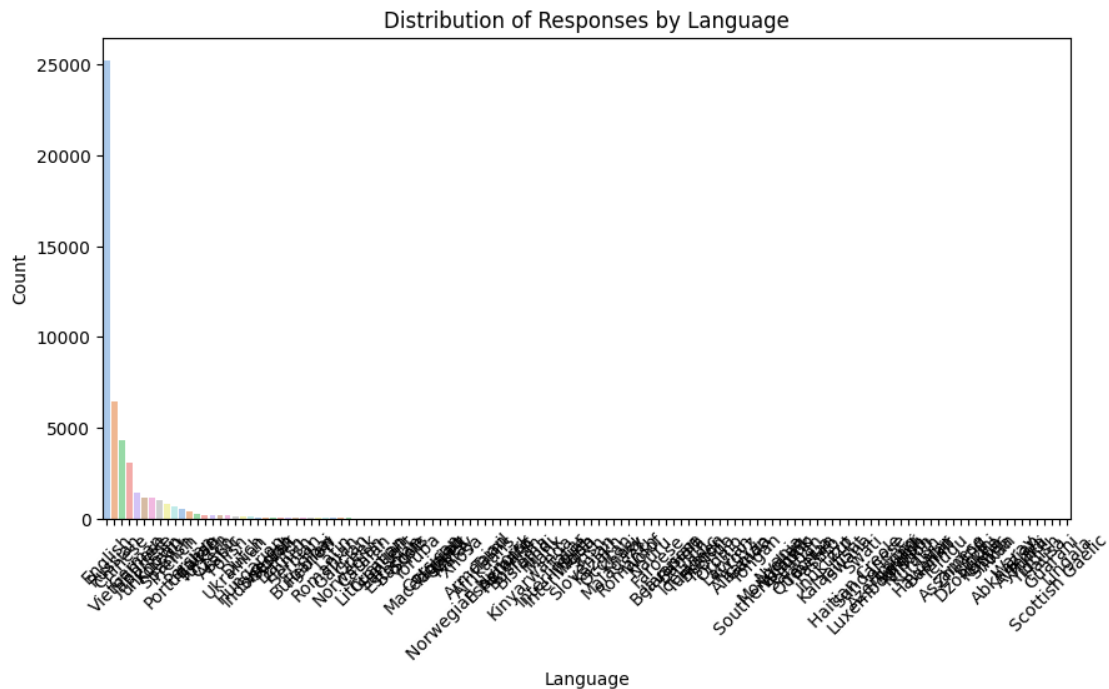


```
sns.countplot(x="language", data=train, palette="pastel",
               order=train["language"].value_counts().index)
plt.xticks(rotation=45)
plt.xlabel("Language")
plt.ylabel("Count")
plt.title("Distribution of Responses by Language")
plt.show()
```

/tmp/ipykernel_13/1165560796.py:7: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

```
sns.countplot(x="language", data=train, palette="pastel",
               order=train["language"].value_counts().index)
```



```
[9]: import numpy as np

# Compute win rates per language
win_loss_matrix = train.pivot_table(index="language", columns="winner",
                                     aggfunc="size", fill_value=0)

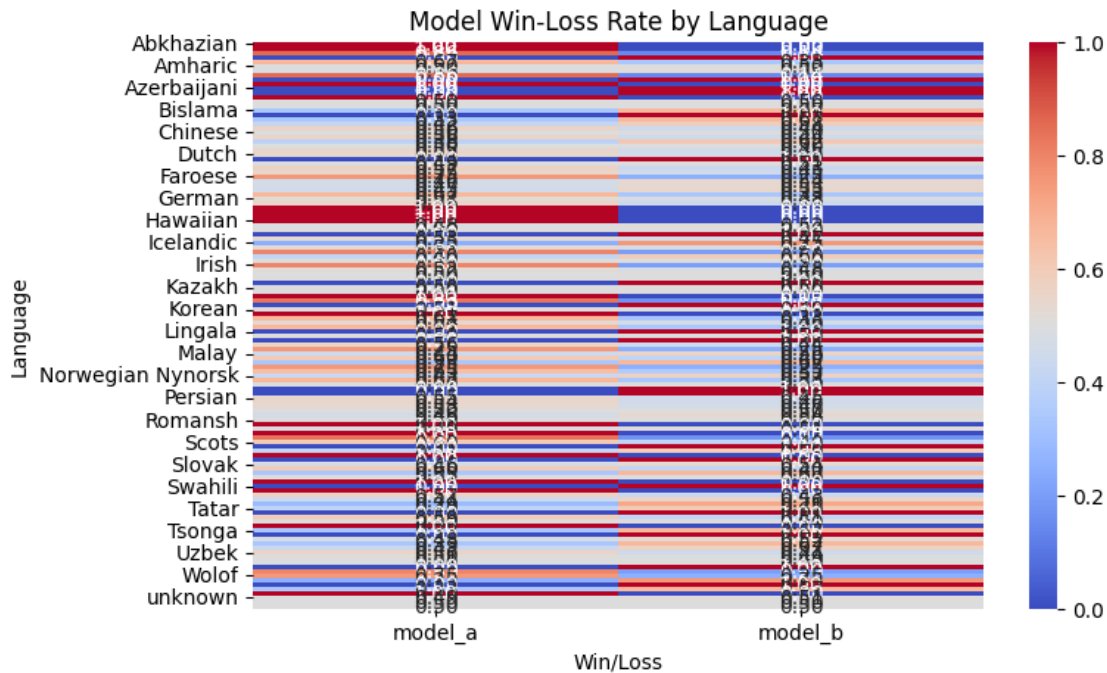
# Normalize win rates
```

```

win_loss_matrix = win_loss_matrix.div(win_loss_matrix.sum(axis=1), axis=0)

# Plot heatmap
plt.figure(figsize=(8, 5))
sns.heatmap(win_loss_matrix, annot=True, cmap="coolwarm", fmt=".2f")
plt.xlabel("Win/Loss")
plt.ylabel("Language")
plt.title("Model Win-Loss Rate by Language")
plt.show()

```



Observation:

The heatmap illustrates the win-loss rates of two chatbot models across various languages. Red indicates a high win rate, while blue represents a low win rate. Some languages show a clear dominance by one model, while others exhibit a more balanced performance. The clustering of colors suggests that certain languages may favor one model over the other, potentially due to differences in training data, language proficiency, or contextual understanding. The presence of highly mixed regions also indicates inconsistency in performance across languages.

```
[15]: !pip install umap
```

Requirement already satisfied: umap in /usr/local/lib/python3.10/site-packages (0.1.1)

WARNING: Running pip as the 'root' user can result in broken permissions and conflicting behaviour with the system package manager. It is recommended to use a virtual environment instead: <https://pip.pypa.io/warnings/venv>

[notice] A new release of pip is available: 23.0.1 -> 25.0.1
[notice] To update, run:
pip install --upgrade pip

```
[16]: train.columns
```

```
[16]: Index(['id', 'prompt', 'response_a', 'response_b', 'winner', 'model_a',  
          'model_b', 'language', 'jaccard_similarity', 'cosine_similarity',  
          'combined_response'],  
         dtype='object')
```

```
[18]: pip install umap-learn
```

```
Collecting umap-learn  
  Downloading umap_learn-0.5.7-py3-none-any.whl (88 kB)  
      88.8/88.8 kB  
4.3 MB/s eta 0:00:00  
Collecting pynndescent>=0.5  
  Downloading pynndescent-0.5.13-py3-none-any.whl (56 kB)  
      56.9/56.9 kB  
7.2 MB/s eta 0:00:00  
Requirement already satisfied: scipy>=1.3.1 in  
/usr/local/lib/python3.10/site-packages (from umap-learn) (1.14.1)  
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.10/site-  
packages (from umap-learn) (1.26.4)  
Requirement already satisfied: numba>=0.51.2 in /usr/local/lib/python3.10/site-  
packages (from umap-learn) (0.60.0)  
Requirement already satisfied: scikit-learn>=0.22 in  
/usr/local/lib/python3.10/site-packages (from umap-learn) (1.5.2)  
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/site-packages  
(from umap-learn) (4.66.5)  
Requirement already satisfied: llvmlite<0.44,>=0.43.0dev0 in  
/usr/local/lib/python3.10/site-packages (from numba>=0.51.2->umap-learn)  
(0.43.0)  
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.10/site-  
packages (from pynndescent>=0.5->umap-learn) (1.4.2)  
Requirement already satisfied: threadpoolctl>=3.1.0 in  
/usr/local/lib/python3.10/site-packages (from scikit-learn>=0.22->umap-learn)  
(3.5.0)  
Installing collected packages: pynndescent, umap-learn  
Successfully installed pynndescent-0.5.13 umap-learn-0.5.7
```

WARNING: Running pip as the 'root' user can result in broken permissions and conflicting behaviour with the system package manager. It is recommended to use a virtual environment instead: <https://pip.pypa.io/warnings/venv>

[notice] A new release of pip is available: 23.0.1 -> 25.0.1
[notice] To update, run:
`pip install --upgrade pip`
Note: you may need to restart the kernel to use updated packages.

6 Comparing Chatbot Response Clustering using t-SNE and UMAP

```
[19]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.manifold import TSNE
#import umap
import umap.umap_ as umap

# Combine response_a and response_b into a single text column
train["combined_response"] = train["response_a"] + " " + train["response_b"]

# Convert responses to TF-IDF vectors
vectorizer = TfidfVectorizer(max_features=500)
X = vectorizer.fit_transform(train["combined_response"])

# Reduce dimensions using t-SNE
tsne = TSNE(n_components=2, perplexity=30, random_state=42)
X_tsne = tsne.fit_transform(X.toarray())

# Reduce dimensions using UMAP
umap_model = umap.UMAP(n_components=2, random_state=42)
X_umap = umap_model.fit_transform(X.toarray())

# Define a color mapping based on the winner column
train["winner_label"] = train["winner"].astype(str) # Ensure categorical
↳ coloring

# Plot t-SNE
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
```

```

sns.scatterplot(x=X_tsne[:, 0], y=X_tsne[:, 1], hue=train["winner_label"],
               palette="coolwarm", alpha=0.6)
plt.title("t-SNE Chatbot Response Clustering")
plt.xlabel("t-SNE 1")
plt.ylabel("t-SNE 2")
plt.legend(title="Winner")

# Plot UMAP
plt.subplot(1, 2, 2)
sns.scatterplot(x=X_umap[:, 0], y=X_umap[:, 1], hue=train["winner_label"],
               palette="coolwarm", alpha=0.6)
plt.title("UMAP Chatbot Response Clustering")
plt.xlabel("UMAP 1")
plt.ylabel("UMAP 2")
plt.legend(title="Winner")

plt.tight_layout()
plt.show()

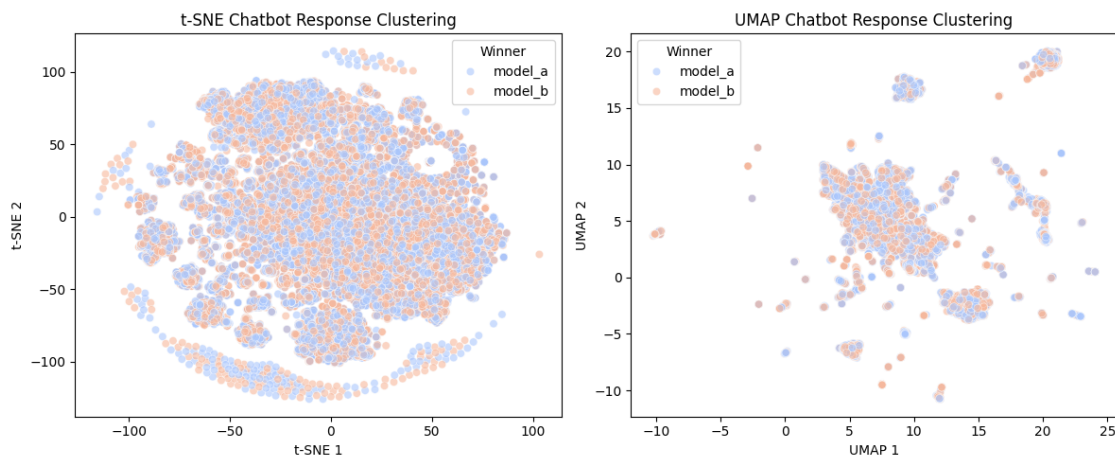
```

/usr/local/lib/python3.10/site-packages/tqdm/auto.py:21: TqdmWarning: IProgress not found. Please update jupyter and ipywidgets. See https://ipywidgets.readthedocs.io/en/stable/user_install.html

```
from .autonotebook import tqdm as notebook_tqdm
```

/usr/local/lib/python3.10/site-packages/umap/umap_.py:1952: UserWarning: n_jobs value 1 overridden to 1 by setting random_state. Use no seed for parallelism.

```
warn(
```



1. t-SNE Clustering (Left Plot)

The points are densely packed and form complex structures, including circular and elongated clusters.

There is significant overlap between responses from model_a (blue) and model_b (orange), indicating that both models generate responses with similar feature distributions.

Some outliers are present, which may indicate unique response patterns from one model.

3. UMAP Clustering (Right Plot)

The clusters are more distinct and loosely spread, highlighting key differences between chatbot responses.

Unlike t-SNE, UMAP appears to form tighter clusters, suggesting that it captures global structures more effectively.

Some isolated points suggest unique responses that differ significantly from the main clusters.

[]:

