Part III – LLM Dialogue-Act Annotation with Qwen (Ollama)

This notebook:

- Loads my mini-corpus of utterances.
- Uses a local LLM (Qwen via Ollama) to annotate dialogue acts.
- Performs iterative prompt refinement (multiple prompt versions).
- Annotates the full dataset with the best prompt.
- Computes inter-annotator agreement (Cohen's κ) between humans and the LLM.

Note: This template assumes you have Ollama installed and a `qwen` model available. You may need to adjust file paths and model names to match your setup.

In [1]:
```
import pandas as pd
import json
import ollama
from sklearn.metrics import cohen_kappa_score, confusion_matrix
import matplotlib.pyplot as plt
import numpy as np

pd.set_option('display.max_colwidth', 200)
```

1. Load data

This cell loads the utterances exported from ELAN.

It assumes the file is a tab-delimited text file with the following columns:

1. tier speaker name
2. participant name
3. start time (string)
4. start time (seconds)
5. end time (string)
6. end time (seconds)
7. duration (string)
8. duration (seconds)
9. utterance text

If you later add human annotation labels (e.g. `human1_label`, `human2_label`), you can merge them into this DataFrame or load a different file.

In [2]:
```
utter_path = 'shared_memory_transcript_updated.txt'

df = pd.read_csv(
    utter_path,
    sep='\t',
    header=None,
    names=['tier_speaker', 'speaker', 'start_str', 'start_sec', 'end_str', 'end_sec', 'dur_
    engine='python'
)

print(df.head())
print('Total utterances:', len(df))
```

```
  tier_speaker speaker     start_str  start_sec       end_str  end_sec  \
0        Manar   Manar  00:01:05.149     65.149  00:01:09.920   69.920   
1        Manar   Manar  00:01:11.620     71.620  00:01:12.083   72.083   
2        Manar   Manar  00:01:15.412     75.412  00:01:16.640   76.640   
3        Manar   Manar  00:01:18.100     78.100  00:01:20.040   80.040   
4        Manar   Manar  00:01:21.726     81.726  00:01:22.527   82.527   

        dur_str  dur_sec  \
0  00:00:04.771    4.771   
1  00:00:00.463    0.463   
2  00:00:01.228    1.228   
3  00:00:01.940    1.940   
4  00:00:00.801    0.801   

                                                                utterance  
0  Yeah man you(.) do you remember like that day we traveled also(.) to: germany.  
1                                                                    yeah.  
2                                                        =I think more! Man.  
3                                      Two and halve years, something like that.  
4                                                                   =Maybe.  
Total utterances: 96
```

Optional: Add human label columns

If you already have human annotations in a separate file, you can merge them here. For now, we create placeholder columns `human1_label` and `human2_label` that you can fill externally (e.g. in Excel) and re-load later.

In [3]:

```python
if 'human1_label' not in df.columns:
    df['human1_label'] = pd.NA
if 'human2_label' not in df.columns:
    df['human2_label'] = pd.NA

df.head()
```

Out[3]:

	tier_speaker	speaker	start_str	start_sec	end_str	end_sec	dur_str	dur_sec	utterai
0	Manar	Manar	00:01:05.149	65.149	00:01:09.920	69.920	00:00:04.771	4.771	Yeah n you(.)) remem like t day trave also(.) germa
1	Manar	Manar	00:01:11.620	71.620	00:01:12.083	72.083	00:00:00.463	0.463	ye
2	Manar	Manar	00:01:15.412	75.412	00:01:16.640	76.640	00:00:01.228	1.228	=I th mc M
3	Manar	Manar	00:01:18.100	78.100	00:01:20.040	80.040	00:00:01.940	1.940	Two a ha ye someth like tl
4	Manar	Manar	00:01:21.726	81.726	00:01:22.527	82.527	00:00:00.801	0.801	=May

2. Define dialogue-act labels

These are the labels we will use for annotation, based on your scheme.

In [27]:
```
DA_LABELS = [
    'STATEMENT',
    'QUESTION',
    'ANSWER',
    'ACKNOWLEDGEMENT',
    'BACKCHANNEL',
    'DIRECTIVE',
    'REQUEST',
    'REPAIR',
    'CLARIFICATION',
    'EXPRESSIVE',
    'EMOTIVE',
    'APOLOGY',
    'GREETING',
    'GOODBYE/CLOSING',
    'OTHER'
]
DA_LABELS
```

Out[27]:
```
['STATEMENT',
 'QUESTION',
 'ANSWER',
 'ACKNOWLEDGEMENT',
 'BACKCHANNEL',
 'DIRECTIVE',
 'REQUEST',
 'REPAIR',
 'CLARIFICATION',
 'EXPRESSIVE',
 'EMOTIVE',
 'APOLOGY',
 'GREETING',
 'GOODBYE/CLOSING',
 'OTHER']
```

3. Helper: call Qwen via Ollama

This function sends a batch of utterances to the model with a given prompt and expects JSON output of the form:

```
[{"index": 1, "label": "STATEMENT"}, ...]
```

In [28]:
```
def annotate_batch_with_llm(utterances, prompt, temperature=0.3, model_name='qwen3:0.6b'):
    joined = '\n'.join([f"{i+1}. {u}" for i, u in enumerate(utterances)])

    full_prompt = f"""{prompt}

Here are the utterances to annotate:
{joined}

Return ONLY valid JSON as a list of objects:
[
  {{"index": 1, "label": "STATEMENT"}},
  ...
]
"""

    response = ollama.chat(
        model=model_name,
        messages=[{'role': 'user', 'content': full_prompt}],
        options={'temperature': temperature}
    )
```

```
    text = response['message']['content'].strip()

    try:
        annotations = json.loads(text)
    except json.JSONDecodeError as e:
        print('Failed to parse JSON from model output:')
        print(text)
        raise e

    return annotations
```

4. Prompt Version 1 – initial instructions

This is the base prompt that defines your labels and how the model should respond. You will refine it over several versions.

In [29]:

```
prompt_v1 = '''
You are annotating dialogue acts in a conversation.

Use EXACTLY ONE label per utterance, chosen from:
STATEMENT, QUESTION, ANSWER, ACKNOWLEDGEMENT, BACKCHANNEL,
DIRECTIVE, REQUEST, REPAIR, CLARIFICATION,
EXPRESSIVE, EMOTIVE, APOLOGY, GREETING,
GOODBYE/CLOSING, OTHER.

Definitions:
- STATEMENT: provides information, description, or opinion.
- QUESTION: requests information or clarification.
- ANSWER: directly responds to a question or confirmation request.
- ACKNOWLEDGEMENT/BACKCHANNEL: signals attention, understanding, or agreement
  without adding new content (e.g. "yeah", "mm-hmm", "right").
- DIRECTIVE/REQUEST: asks the other speaker to do something or to clarify something.
- REPAIR/CLARIFICATION: corrects or reformulates previous speech, or asks for clarification
  (e.g. "No, I meant last week", "Wait, who was there?").
- EXPRESSIVE/EMOTIVE: conveys emotional stance, evaluation, or affective reaction
  (e.g. "That was amazing!", "Ugh, I hated that part").
- APOLOGY: acknowledges fault or expresses regret.
- GREETING: opens the interaction or marks social connection.
- GOODBYE/CLOSING: signals the end of the interaction or closing the topic.
- OTHER: does not fit the categories above (e.g. laughter, filler noises, unintelligible sp

Rules:
- Assign EXACTLY ONE label per utterance.
- Only use labels from the set given above.
- If unsure, choose the best fitting category and do NOT invent new labels.
'''
print(prompt_v1)
```

```
You are annotating dialogue acts in a conversation.

Use EXACTLY ONE label per utterance, chosen from:
STATEMENT, QUESTION, ANSWER, ACKNOWLEDGEMENT, BACKCHANNEL,
DIRECTIVE, REQUEST, REPAIR, CLARIFICATION,
EXPRESSIVE, EMOTIVE, APOLOGY, GREETING,
GOODBYE/CLOSING, OTHER.

Definitions:
- STATEMENT: provides information, description, or opinion.
- QUESTION: requests information or clarification.
- ANSWER: directly responds to a question or confirmation request.
- ACKNOWLEDGEMENT/BACKCHANNEL: signals attention, understanding, or agreement
  without adding new content (e.g. "yeah", "mm-hmm", "right").
- DIRECTIVE/REQUEST: asks the other speaker to do something or to clarify something.
- REPAIR/CLARIFICATION: corrects or reformulates previous speech, or asks for clarification
  (e.g. "No, I meant last week", "Wait, who was there?").
- EXPRESSIVE/EMOTIVE: conveys emotional stance, evaluation, or affective reaction
  (e.g. "That was amazing!", "Ugh, I hated that part").
- APOLOGY: acknowledges fault or expresses regret.
- GREETING: opens the interaction or marks social connection.
- GOODBYE/CLOSING: signals the end of the interaction or closing the topic.
- OTHER: does not fit the categories above (e.g. laughter, filler noises, unintelligible spe
ech).

Rules:
- Assign EXACTLY ONE label per utterance.
- Only use labels from the set given above.
- If unsure, choose the best fitting category and do NOT invent new labels.
```

5. Test Prompt V1 on a small subset

We start with 10 utterances to see how well the model follows the instructions.

In [30]:
```python
test_df = df.iloc[:10].copy()
test_utterances = test_df['utterance'].tolist()

annotations_v1 = annotate_batch_with_llm(
    utterances=test_utterances,
    prompt=prompt_v1,
    temperature=0.3,
    model_name='qwen3:0.6b'
)

annotations_v1
```

Out[30]:
```
[{'index': 1, 'label': 'STATEMENT'},
 {'index': 2, 'label': 'ACKNOWLEDGEMENT'},
 {'index': 3, 'label': 'STATEMENT'},
 {'index': 4, 'label': 'STATEMENT'},
 {'index': 5, 'label': 'STATEMENT'},
 {'index': 6, 'label': 'STATEMENT'},
 {'index': 7, 'label': 'STATEMENT'},
 {'index': 8, 'label': 'QUESTION'},
 {'index': 9, 'label': 'STATEMENT'},
 {'index': 10, 'label': 'STATEMENT'}]
```

In [31]:
```python
# Attach V1 annotations to the test DataFrame for inspection
idx_to_label_v1 = {ann['index']: ann['label'] for ann in annotations_v1}

test_df['llm_v1_label'] = [idx_to_label_v1[i+1] for i in range(len(test_df))]
test_df[['utterance', 'human1_label', 'human2_label', 'llm_v1_label']]
```

Out[31]:

	utterance	human1_label	human2_label	llm_v1_label
0	Yeah man you(.) do you remember like that day we traveled also(.) to: germany.	<NA>	<NA>	STATEMENT
1	yeah.	<NA>	<NA>	ACKNOWLEDGEMENT
2	=I think more! Man.	<NA>	<NA>	STATEMENT
3	Two and halve years, something like that.	<NA>	<NA>	STATEMENT
4	=Maybe.	<NA>	<NA>	STATEMENT
5	yeah true↓ ↓ true man.	<NA>	<NA>	STATEMENT
6	But we [did like so mcuh].	<NA>	<NA>	STATEMENT
7	What did you post=?	<NA>	<NA>	QUESTION
8	oh yea yea the[vlog].	<NA>	<NA>	STATEMENT
9	=the vlog thing	<NA>	<NA>	STATEMENT

Prompt Version 2

In [32]:

```
prompt_v2 = prompt_v1 + '''

Additional rules:
- If an utterance consists only of very short tokens like "yeah", "mm-hmm", "uh-huh", "righ
  and does not add new information, ALWAYS label it as ACKNOWLEDGEMENT or BACKCHANNEL.
- If an utterance clearly asks for information or ends with a question mark,
  label it as QUESTION, not STATEMENT.
'''
print(prompt_v2)
```

```
You are annotating dialogue acts in a conversation.

Use EXACTLY ONE label per utterance, chosen from:
STATEMENT, QUESTION, ANSWER, ACKNOWLEDGEMENT, BACKCHANNEL,
DIRECTIVE, REQUEST, REPAIR, CLARIFICATION,
EXPRESSIVE, EMOTIVE, APOLOGY, GREETING,
GOODBYE/CLOSING, OTHER.

Definitions:
- STATEMENT: provides information, description, or opinion.
- QUESTION: requests information or clarification.
- ANSWER: directly responds to a question or confirmation request.
- ACKNOWLEDGEMENT/BACKCHANNEL: signals attention, understanding, or agreement
  without adding new content (e.g. "yeah", "mm-hmm", "right").
- DIRECTIVE/REQUEST: asks the other speaker to do something or to clarify something.
- REPAIR/CLARIFICATION: corrects or reformulates previous speech, or asks for clarification
  (e.g. "No, I meant last week", "Wait, who was there?").
- EXPRESSIVE/EMOTIVE: conveys emotional stance, evaluation, or affective reaction
  (e.g. "That was amazing!", "Ugh, I hated that part").
- APOLOGY: acknowledges fault or expresses regret.
- GREETING: opens the interaction or marks social connection.
- GOODBYE/CLOSING: signals the end of the interaction or closing the topic.
- OTHER: does not fit the categories above (e.g. laughter, filler noises, unintelligible spe
ech).

Rules:
- Assign EXACTLY ONE label per utterance.
- Only use labels from the set given above.
- If unsure, choose the best fitting category and do NOT invent new labels.


Additional rules:
- If an utterance consists only of very short tokens like "yeah", "mm-hmm", "uh-huh", "righ
t",
  and does not add new information, ALWAYS label it as ACKNOWLEDGEMENT or BACKCHANNEL.
- If an utterance clearly asks for information or ends with a question mark,
  label it as QUESTION, not STATEMENT.
```

In [90]:

```
prompt_v3 = prompt_v2 + '''

 IMPORTANT RULES

- Label ALL utterances you are given.
- Number them sequentially starting at 1.
- Assign exactly ONE label per utterance.
- Do NOT skip or invent indices.
- Do NOT explain your reasoning.

 DISAMBIGUATION RULES

- If an utterance like “yeah true man” adds a stance or an evaluation, label it STATEMENT,
- If a question form asks someone to do something (“What did you post?”), label it DIRECTIV
- If the utterance conveys emotion or evaluation (“It was nice feelings, I swear”), label i
- Short non-informative responses are ACKNOWLEDGEMENTS unless they introduce new content.
- If the utterance answers a question, label it ANSWER regardless of length.
'''
print(prompt_v3)
```

```
You are annotating dialogue acts in a conversation.

Use EXACTLY ONE label per utterance, chosen from:
STATEMENT, QUESTION, ANSWER, ACKNOWLEDGEMENT, BACKCHANNEL,
DIRECTIVE, REQUEST, REPAIR, CLARIFICATION,
EXPRESSIVE, EMOTIVE, APOLOGY, GREETING,
GOODBYE/CLOSING, OTHER.

Definitions:
- STATEMENT: provides information, description, or opinion.
- QUESTION: requests information or clarification.
- ANSWER: directly responds to a question or confirmation request.
- ACKNOWLEDGEMENT/BACKCHANNEL: signals attention, understanding, or agreement
  without adding new content (e.g. "yeah", "mm-hmm", "right").
- DIRECTIVE/REQUEST: asks the other speaker to do something or to clarify something.
- REPAIR/CLARIFICATION: corrects or reformulates previous speech, or asks for clarification
  (e.g. "No, I meant last week", "Wait, who was there?").
- EXPRESSIVE/EMOTIVE: conveys emotional stance, evaluation, or affective reaction
  (e.g. "That was amazing!", "Ugh, I hated that part").
- APOLOGY: acknowledges fault or expresses regret.
- GREETING: opens the interaction or marks social connection.
- GOODBYE/CLOSING: signals the end of the interaction or closing the topic.
- OTHER: does not fit the categories above (e.g. laughter, filler noises, unintelligible spe
ech).

Rules:
- Assign EXACTLY ONE label per utterance.
- Only use labels from the set given above.
- If unsure, choose the best fitting category and do NOT invent new labels.


Additional rules:
- If an utterance consists only of very short tokens like "yeah", "mm-hmm", "uh-huh", "righ
t",
  and does not add new information, ALWAYS label it as ACKNOWLEDGEMENT or BACKCHANNEL.
- If an utterance clearly asks for information or ends with a question mark,
  label it as QUESTION, not STATEMENT.


 IMPORTANT RULES

- Label ALL utterances you are given.
- Number them sequentially starting at 1.
- Assign exactly ONE label per utterance.
- Do NOT skip or invent indices.
- Do NOT explain your reasoning.

 DISAMBIGUATION RULES

- If an utterance like “yeah true man” adds a stance or an evaluation, label it STATEMENT, n
ot ACKNOWLEDGEMENT.
- If a question form asks someone to do something (“What did you post?”), label it DIRECTIV
E, not QUESTION.
- If the utterance conveys emotion or evaluation (“It was nice feelings, I swear”), label it
EXPRESSIVE, even if declarative.
- Short non-informative responses are ACKNOWLEDGEMENTS unless they introduce new content.
- If the utterance answers a question, label it ANSWER regardless of length.
```

In [33]:
```
annotations_v2 = annotate_batch_with_llm(
    utterances=test_utterances,
    prompt=prompt_v2,
    temperature=0.2,
    model_name='qwen3:0.6b'
)

idx_to_label_v2 = {ann['index']: ann['label'] for ann in annotations_v2}
```

```
test_df['llm_v2_label'] = [idx_to_label_v2[i+1] for i in range(len(test_df))]

test_df[['utterance', 'human1_label', 'human2_label', 'llm_v1_label', 'llm_v2_label']]
```

Out[33]:

	utterance	human1_label	human2_label	llm_v1_label	llm_v2_label
0	Yeah man you(.) do you remember like that day we traveled also(.) to: germany.	<NA>	<NA>	STATEMENT	QUESTION
1	yeah.	<NA>	<NA>	ACKNOWLEDGEMENT	ACKNOWLEDGEMENT
2	=I think more! Man.	<NA>	<NA>	STATEMENT	STATEMENT
3	Two and halve years, something like that.	<NA>	<NA>	STATEMENT	STATEMENT
4	=Maybe.	<NA>	<NA>	STATEMENT	STATEMENT
5	yeah true↓ ↓ true man.	<NA>	<NA>	STATEMENT	REPAIR
6	But we [did like so mcuh].	<NA>	<NA>	STATEMENT	STATEMENT
7	What did you post=?	<NA>	<NA>	QUESTION	QUESTION
8	oh yea yea the[vlog].	<NA>	<NA>	STATEMENT	STATEMENT
9	=the vlog thing	<NA>	<NA>	STATEMENT	STATEMENT

7. Choose a final prompt

After trying at least 5 prompt versions, assign your best-performing one to `final_prompt`.

In [91]:

```
final_prompt = prompt_v3  # replace with your best prompt, e.g., prompt_v5
print(final_prompt[:500])
```

```
You are annotating dialogue acts in a conversation.

Use EXACTLY ONE label per utterance, chosen from:
STATEMENT, QUESTION, ANSWER, ACKNOWLEDGEMENT, BACKCHANNEL,
DIRECTIVE, REQUEST, REPAIR, CLARIFICATION,
EXPRESSIVE, EMOTIVE, APOLOGY, GREETING,
GOODBYE/CLOSING, OTHER.

Definitions:
- STATEMENT: provides information, description, or opinion.
- QUESTION: requests information or clarification.
- ANSWER: directly responds to a question or confirmation request.
- ACKNOWLEDGEMENT/BACKCHANNEL: signals
```

8. Annotate the full dataset with the final prompt

This function runs the LLM over the entire dataset in batches and stores the predicted label in a new column `llm_label`.

In [77]:

```
def annotate_full_df_with_llm(df, prompt, batch_size=20, temperature=0.2, model_name="qwen3
    llm_labels = []
    n = len(df)

    for start in range(0, n, batch_size):
        end = min(start + batch_size, n)
```

```
        batch_utts = df["utterance"].iloc[start:end].tolist()

        annotations = annotate_batch_with_llm(
            utterances=batch_utts,
            prompt=prompt,
            temperature=temperature,
            model_name=model_name
        )

        # Debug: show if length or indices look suspicious
        if len(annotations) != len(batch_utts):
            print(f"⚠️ Warning: batch {start}-{end} has {len(annotations)} annotations for
            print("Annotations returned:", annotations)

        # Build a mapping index -> label (if index is present)
        idx_to_label = {}
        for ann in annotations:
            idx = ann.get("index")
            lab = ann.get("label")
            if idx is not None and lab is not None:
                idx_to_label[idx] = lab

        batch_labels = []
        for i in range(len(batch_utts)):
            idx = i + 1  # we asked the model to use 1-based indices
            if idx in idx_to_label:
                batch_labels.append(idx_to_label[idx])
            else:
                # Fallback: if model skipped this index, assign OTHER and warn
                print(f"⚠️ Missing label for utterance index {idx} in batch {start}-{end},
                batch_labels.append("OTHER")

        llm_labels.extend(batch_labels)
        print(f"Annotated {end}/{n} utterances")

    return llm_labels
```

In [78]:
```
df["llm_label"] = annotate_full_df_with_llm(
    df=df,
    prompt=final_prompt,
    batch_size=20,
    temperature=0.2,
    model_name="qwen3:0.6b"
)
```

```
Annotated 20/96 utterances
Annotated 40/96 utterances
Annotated 60/96 utterances
Annotated 80/96 utterances
Annotated 96/96 utterances
```

9. Save LLM-annotated data

Save the DataFrame with the new `llm_label` column for later analysis.

In [79]:
```
out_path = 'AttarA2_with_llm_labels.csv'
df.to_csv(out_path, index=False)
print('Saved:', out_path)
```

```
Saved: AttarA2_with_llm_labels.csv
```

10. Compute Cohen's κ

This section computes agreement between:

- Human 1 vs Human 2
- Human 1 vs LLM
- Human 2 vs LLM

Make sure you have filled in `human1_label` and `human2_label` before running this. If they are still empty, κ will not be meaningful.

In [80]:
```
import pandas as pd

raw_path = "AttarA2_with_human_annotation.txt"

df_raw = pd.read_csv(
    raw_path,
    sep="\t",
    header=None,
    names=[
        "tier",         # e.g. Manar, Raihan, Manar_label, DiscourseAct_Manar
        "speaker",      # Manar / Raihan
        "start_str",
        "start_sec",
        "end_str",
        "end_sec",
        "dur_str",
        "dur_sec",
        "text"          # utterance OR label, depending on tier
    ],
    engine="python"
)

df_raw.head(20)
```

Out[80]:

	tier	speaker	start_str	start_sec	end_str	end_sec	dur_str	dur_sec	text
0	Manar	Manar	00:01:05.149	65.149	00:01:09.920	69.920	00:00:04.771	4.771	Yeah man you(.) do you remember like that day we traveled also(.) to: germany.
1	Manar	Manar	00:01:11.620	71.620	00:01:12.083	72.083	00:00:00.463	0.463	yeah.
2	Manar	Manar	00:01:15.412	75.412	00:01:16.640	76.640	00:00:01.228	1.228	=I think more! Man.
3	Manar	Manar	00:01:18.100	78.100	00:01:20.040	80.040	00:00:01.940	1.940	Two and halve years, something like that.
4	Manar	Manar	00:01:21.726	81.726	00:01:22.527	82.527	00:00:00.801	0.801	=Maybe.
5	Manar	Manar	00:01:30.030	90.030	00:01:32.300	92.300	00:00:02.270	2.270	yeah true↓ ↓ true man.
6	Manar	Manar	00:01:32.675	92.675	00:01:34.523	94.523	00:00:01.848	1.848	But we [did like so mcuh].
7	Manar	Manar	00:01:35.830	95.830	00:01:37.060	97.060	00:00:01.230	1.230	What did you post=?
8	Manar	Manar	00:01:40.046	100.046	00:01:42.230	102.230	00:00:02.184	2.184	oh yea yea the[vlog].
9	Manar	Manar	00:01:42.337	102.337	00:01:43.842	103.842	00:00:01.505	1.505	=the vlog thing
10	Manar	Manar	00:01:43.870	103.870	00:01:48.185	108.185	00:00:04.315	4.315	you are trying to do the youtube one.(.)↓ you didn't do it=
11	Manar	Manar	00:01:54.960	114.960	00:01:55.675	115.675	00:00:00.715	0.715	Yeah ↓true
12	Manar	Manar	00:01:55.768	115.768	00:01:58.730	118.730	00:00:02.962	2.962	[but you].. ↑you have all the recodings, ↓no?
13	Manar	Manar	00:02:08.004	128.004	00:02:08.907	128.907	00:00:00.903	0.903	yess=
14	Manar	Manar	00:02:13.217	133.217	00:02:13.907	133.907	00:00:00.690	0.690	[okay]
15	Manar	Manar	00:02:14.490	134.490	00:02:17.880	137.880	00:00:03.390	3.390	[But how how is] there is(.)like how is

	tier	speaker	start_str	start_sec	end_str	end_sec	dur_str	dur_sec	text
16	Manar	Manar	00:02:17.940	137.940	00:02:19.400	139.400	00:00:01.460	1.460	the issue with ↓the memory then.
17	Manar	Manar	00:02:27.050	147.050	00:02:27.340	147.340	00:00:00.290	0.290	[yes]
18	Manar	Manar	00:02:45.337	165.337	00:02:46.277	166.277	00:00:00.940	0.940	[ohh:]
19	Manar	Manar	00:02:46.900	166.900	00:02:47.440	167.440	00:00:00.540	0.540	okay

In [81]:
```
mask = df['human1_label'].notna() & df['human2_label'].notna() & df['llm_label'].notna()
eval_df = df[mask].copy()

if len(eval_df) == 0:
    print('No rows with all three labels present yet. Fill human1_label and human2_label fi
else:
    h1 = eval_df['human1_label']
    h2 = eval_df['human2_label']
    llm_labs = eval_df['llm_label']

    kappa_h1_h2 = cohen_kappa_score(h1, h2)
    kappa_h1_llm = cohen_kappa_score(h1, llm_labs)
    kappa_h2_llm = cohen_kappa_score(h2, llm_labs)

    print("Cohen's κ (Human1 vs Human2):", kappa_h1_h2)
    print("Cohen's κ (Human1 vs LLM):   ", kappa_h1_llm)
    print("Cohen's κ (Human2 vs LLM):   ", kappa_h2_llm)
```

```
No rows with all three labels present yet. Fill human1_label and human2_label first.
```

In [82]:
```
# 1) Utterances: tiers where tier == speaker ("Manar" or "Raihan")
utter_df = df_raw[df_raw["tier"].isin(["Manar", "Raihan"])].copy()

# 2) Human annotator 1: the *_label tiers (Manar_label, Raihan_label)
h1_df = df_raw[df_raw["tier"].isin(["Manar_label", "Raihan_label"])].copy()
h1_df = h1_df.rename(columns={"text": "human1_label"})

# 3) Human annotator 2: the DiscourseAct_* tiers
h2_df = df_raw[df_raw["tier"].isin(["DiscourseAct_Manar", "DiscourseAcr_Raihan"])].copy()
h2_df = h2_df.rename(columns={"text": "human2_label"})
```

In [83]:
```
# Keep only the keys + labels for h1 and h2
h1_df = h1_df[["speaker", "start_sec", "end_sec", "human1_label"]]
h2_df = h2_df[["speaker", "start_sec", "end_sec", "human2_label"]]

# For utterances, keep relevant columns
utter_df = utter_df[[
    "speaker", "start_str", "start_sec", "end_str", "end_sec", "dur_str", "dur_sec", "text"
]].rename(columns={"text": "utterance"})
```

In [84]:
```
# Merge human1 labels
merged_df = utter_df.merge(
    h1_df,
    on=["speaker", "start_sec", "end_sec"],
    how="left"
)

# Merge human2 labels
merged_df = merged_df.merge(
    h2_df,
    on=["speaker", "start_sec", "end_sec"],
    how="left"
)
```

```
merged_df.head(20)
```

Out[84]:

	speaker	start_str	start_sec	end_str	end_sec	dur_str	dur_sec	utterance	h
0	Manar	00:01:05.149	65.149	00:01:09.920	69.920	00:00:04.771	4.771	Yeah man you(.) do you remember like that day we traveled also(.) to: germany.	
1	Manar	00:01:11.620	71.620	00:01:12.083	72.083	00:00:00.463	0.463	yeah.	ACKNOV
2	Manar	00:01:15.412	75.412	00:01:16.640	76.640	00:00:01.228	1.228	=I think more! Man.	
3	Manar	00:01:18.100	78.100	00:01:20.040	80.040	00:00:01.940	1.940	Two and halve years, something like that.	
4	Manar	00:01:21.726	81.726	00:01:22.527	82.527	00:00:00.801	0.801	=Maybe.	B.
5	Manar	00:01:30.030	90.030	00:01:32.300	92.300	00:00:02.270	2.270	yeah true↓ ↓ true man.	ACKNOV
6	Manar	00:01:32.675	92.675	00:01:34.523	94.523	00:00:01.848	1.848	But we [did like so mcuh].	
7	Manar	00:01:35.830	95.830	00:01:37.060	97.060	00:00:01.230	1.230	What did you post=?	
8	Manar	00:01:40.046	100.046	00:01:42.230	102.230	00:00:02.184	2.184	oh yea yea the[vlog].	ACKNOV
9	Manar	00:01:42.337	102.337	00:01:43.842	103.842	00:00:01.505	1.505	=the vlog thing	
10	Manar	00:01:43.870	103.870	00:01:48.185	108.185	00:00:04.315	4.315	you are trying to do the youtube one.(.)↓ you didn't do it=	
11	Manar	00:01:54.960	114.960	00:01:55.675	115.675	00:00:00.715	0.715	Yeah ↓true	ACKNOV
12	Manar	00:01:55.768	115.768	00:01:58.730	118.730	00:00:02.962	2.962	[but you].. ↑you have all the recodings, ↓no?	
13	Manar	00:02:08.004	128.004	00:02:08.907	128.907	00:00:00.903	0.903	yess=	B.
14	Manar	00:02:13.217	133.217	00:02:13.907	133.907	00:00:00.690	0.690	[okay]	B.
15	Manar	00:02:14.490	134.490	00:02:17.880	137.880	00:00:03.390	3.390	[But how how is] there is(.)like how is	

	speaker	start_str	start_sec	end_str	end_sec	dur_str	dur_sec	utterance	h
16	Manar	00:02:17.940	137.940	00:02:19.400	139.400	00:00:01.460	1.460	the issue with ↓the memory then.	
17	Manar	00:02:27.050	147.050	00:02:27.340	147.340	00:00:00.290	0.290	[yes]	
18	Manar	00:02:45.337	165.337	00:02:46.277	166.277	00:00:00.940	0.940	[ohh:]	B.
19	Manar	00:02:46.900	166.900	00:02:47.440	167.440	00:00:00.540	0.540	okay	B.

In [85]:
```
df.head(20)
```

Out[85]:

	tier_speaker	speaker	start_str	start_sec	end_str	end_sec	dur_str	dur_sec	utter
0	Manar	Manar	00:01:05.149	65.149	00:01:09.920	69.920	00:00:04.771	4.771	Yeah you(remen like da trav also(germ
1	Manar	Manar	00:01:11.620	71.620	00:01:12.083	72.083	00:00:00.463	0.463	y
2	Manar	Manar	00:01:15.412	75.412	00:01:16.640	76.640	00:00:01.228	1.228	=I t m I
3	Manar	Manar	00:01:18.100	78.100	00:01:20.040	80.040	00:00:01.940	1.940	Two h y somet like
4	Manar	Manar	00:01:21.726	81.726	00:01:22.527	82.527	00:00:00.801	0.801	=Ma
5	Manar	Manar	00:01:30.030	90.030	00:01:32.300	92.300	00:00:02.270	2.270	yeah t ↓
6	Manar	Manar	00:01:32.675	92.675	00:01:34.523	94.523	00:00:01.848	1.848	Bu [dic so m
7	Manar	Manar	00:01:35.830	95.830	00:01:37.060	97.060	00:00:01.230	1.230	Wha po
8	Manar	Manar	00:01:40.046	100.046	00:01:42.230	102.230	00:00:02.184	2.184	oh yea v
9	Manar	Manar	00:01:42.337	102.337	00:01:43.842	103.842	00:00:01.505	1.505	=the t
10	Manar	Manar	00:01:43.870	103.870	00:01:48.185	108.185	00:00:04.315	4.315	you tryin do you on you d d
11	Manar	Manar	00:01:54.960	114.960	00:01:55.675	115.675	00:00:00.715	0.715	Yeah ↓
12	Manar	Manar	00:01:55.768	115.768	00:01:58.730	118.730	00:00:02.962	2.962	[but y ↑you al recod
13	Manar	Manar	00:02:08.004	128.004	00:02:08.907	128.907	00:00:00.903	0.903	y
14	Manar	Manar	00:02:13.217	133.217	00:02:13.907	133.907	00:00:00.690	0.690	[c
15	Manar	Manar	00:02:14.490	134.490	00:02:17.880	137.880	00:00:03.390	3.390	[But ho t is(ho

	tier_speaker	speaker	start_str	start_sec	end_str	end_sec	dur_str	dur_sec	uttera
16	Manar	Manar	00:02:17.940	137.940	00:02:19.400	139.400	00:00:01.460	1.460	the i with mer t
17	Manar	Manar	00:02:27.050	147.050	00:02:27.340	147.340	00:00:00.290	0.290	
18	Manar	Manar	00:02:45.337	165.337	00:02:46.277	166.277	00:00:00.940	0.940	[(
19	Manar	Manar	00:02:46.900	166.900	00:02:47.440	167.440	00:00:00.540	0.540	

In [86]:

```
# Keep only the merge keys + llm_label from the LLM dataframe
llm_df = df[["speaker", "start_sec", "end_sec", "llm_label"]]

# Merge into merged_df
merged_df = merged_df.merge(
    llm_df,
    on=["speaker", "start_sec", "end_sec"],
    how="left"
)

merged_df.head()
```

Out[86]:

	speaker	start_str	start_sec	end_str	end_sec	dur_str	dur_sec	utterance	hu
0	Manar	00:01:05.149	65.149	00:01:09.920	69.920	00:00:04.771	4.771	Yeah man you(.) do you remember like that day we traveled also(.) to: germany.	
1	Manar	00:01:11.620	71.620	00:01:12.083	72.083	00:00:00.463	0.463	yeah.	ACKNOW
2	Manar	00:01:15.412	75.412	00:01:16.640	76.640	00:00:01.228	1.228	=I think more! Man.	
3	Manar	00:01:18.100	78.100	00:01:20.040	80.040	00:00:01.940	1.940	Two and halve years, something like that.	
4	Manar	00:01:21.726	81.726	00:01:22.527	82.527	00:00:00.801	0.801	=Maybe.	BA

In [ ]:

11. Confusion matrices

If you have enough labeled data, you can visualise where the LLM disagrees with human annotators using confusion matrices.

In [87]:

```
def plot_confusion_matrix(y_true, y_pred, labels, title):
    cm = confusion_matrix(y_true, y_pred, labels=labels)
    fig, ax = plt.subplots(figsize=(8, 8))
```

```
    im = ax.imshow(cm, interpolation='nearest', cmap=plt.cm.Blues)
    ax.figure.colorbar(im, ax=ax)
    ax.set(
        xticks=np.arange(cm.shape[1]),
        yticks=np.arange(cm.shape[0]),
        xticklabels=labels,
        yticklabels=labels,
        ylabel='True label',
        xlabel='Predicted label',
        title=title
    )
    plt.setp(ax.get_xticklabels(), rotation=45, ha='right', rotation_mode='anchor')

    thresh = cm.max() / 2.0
    for i in range(cm.shape[0]):
        for j in range(cm.shape[1]):
            ax.text(j, i, cm[i, j],
                    ha='center', va='center',
                    color='white' if cm[i, j] > thresh else 'black')

    fig.tight_layout()
    plt.show()

if len(eval_df) > 0:
    plot_confusion_matrix(h1, h2, DA_LABELS, 'Human1 vs Human2')
    plot_confusion_matrix(h1, llm_labs, DA_LABELS, 'Human1 vs LLM')
    plot_confusion_matrix(h2, llm_labs, DA_LABELS, 'Human2 vs LLM')
else:
    print('Not enough labeled data to plot confusion matrices yet.')
```

```
Not enough labeled data to plot confusion matrices yet.
```

In [88]:

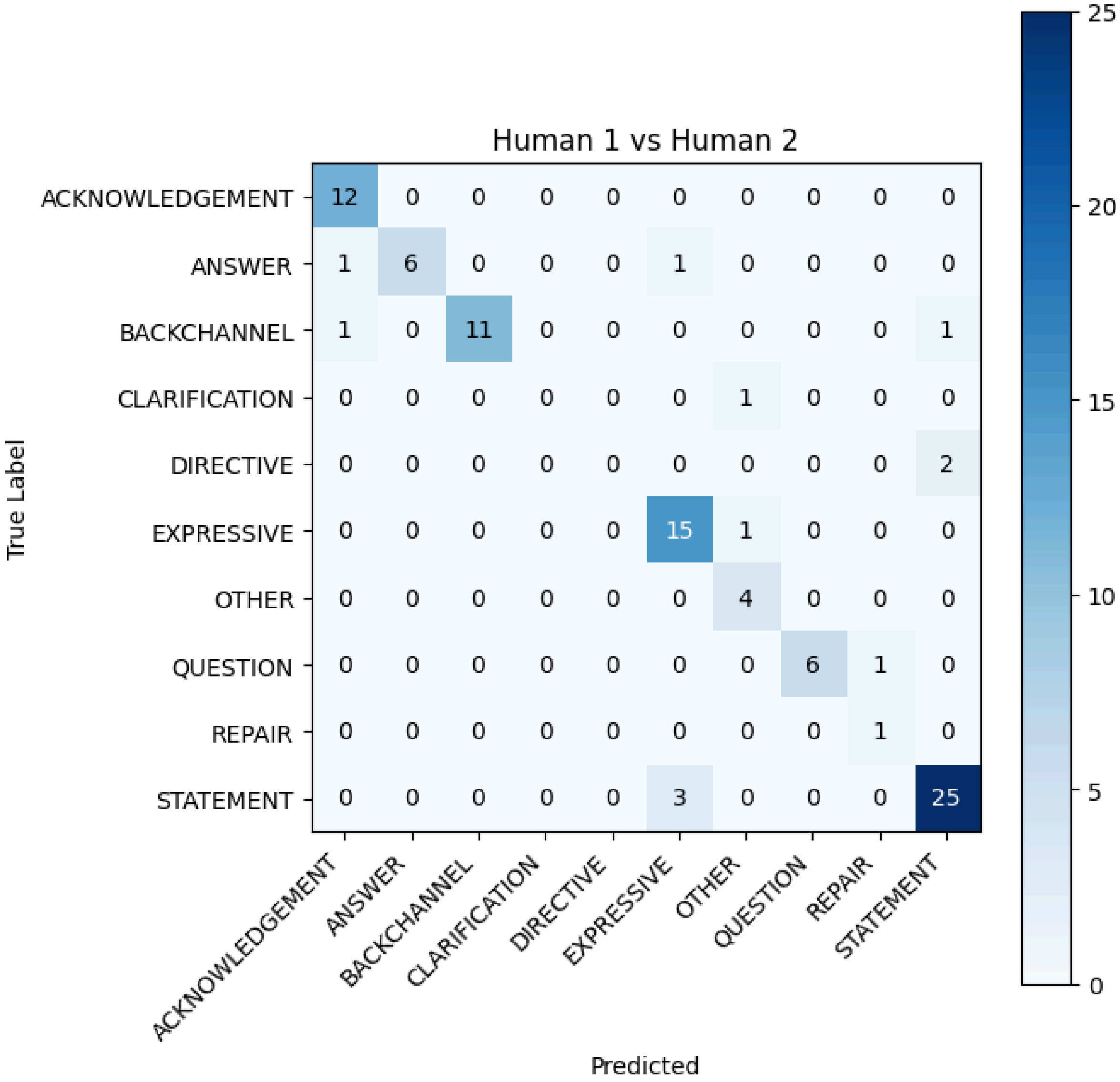
```
from sklearn.metrics import cohen_kappa_score

# Only rows where all three labels exist
eval_df = merged_df.dropna(subset=["human1_label", "human2_label", "llm_label"])

h1 = eval_df["human1_label"]
h2 = eval_df["human2_label"]
llm = eval_df["llm_label"]

k_h1_h2  = cohen_kappa_score(h1, h2)
k_h1_llm = cohen_kappa_score(h1, llm)
k_h2_llm = cohen_kappa_score(h2, llm)

print("Cohen’s κ scores:")
print("------------------")
print("Human 1 vs Human 2 :", round(k_h1_h2, 3))
print("Human 1 vs LLM     :", round(k_h1_llm, 3))
print("Human 2 vs LLM     :", round(k_h2_llm, 3))
```

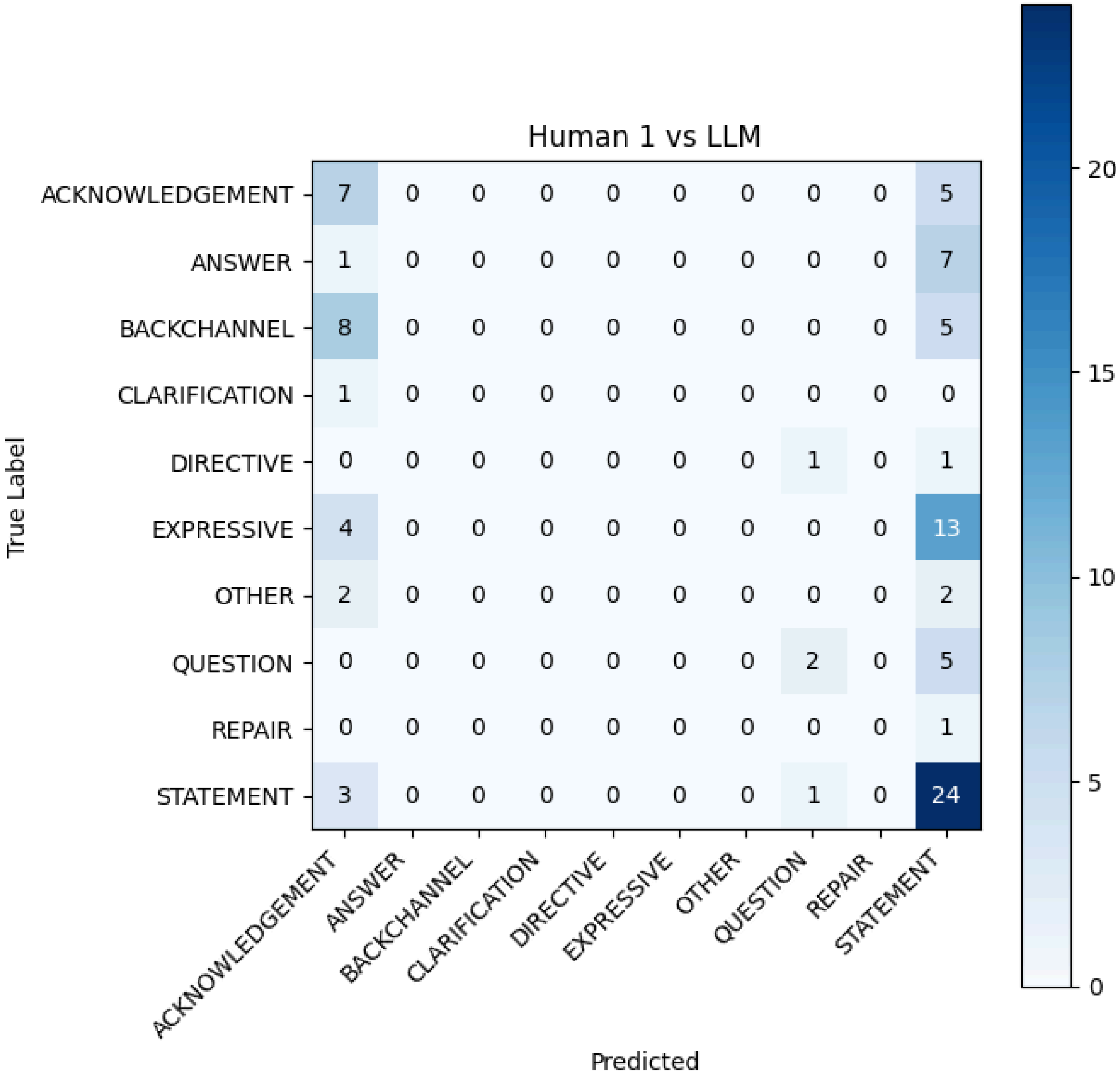
```
Cohen’s κ scores:
------------------
Human 1 vs Human 2 : 0.83
Human 1 vs LLM     : 0.147
Human 2 vs LLM     : 0.155
```

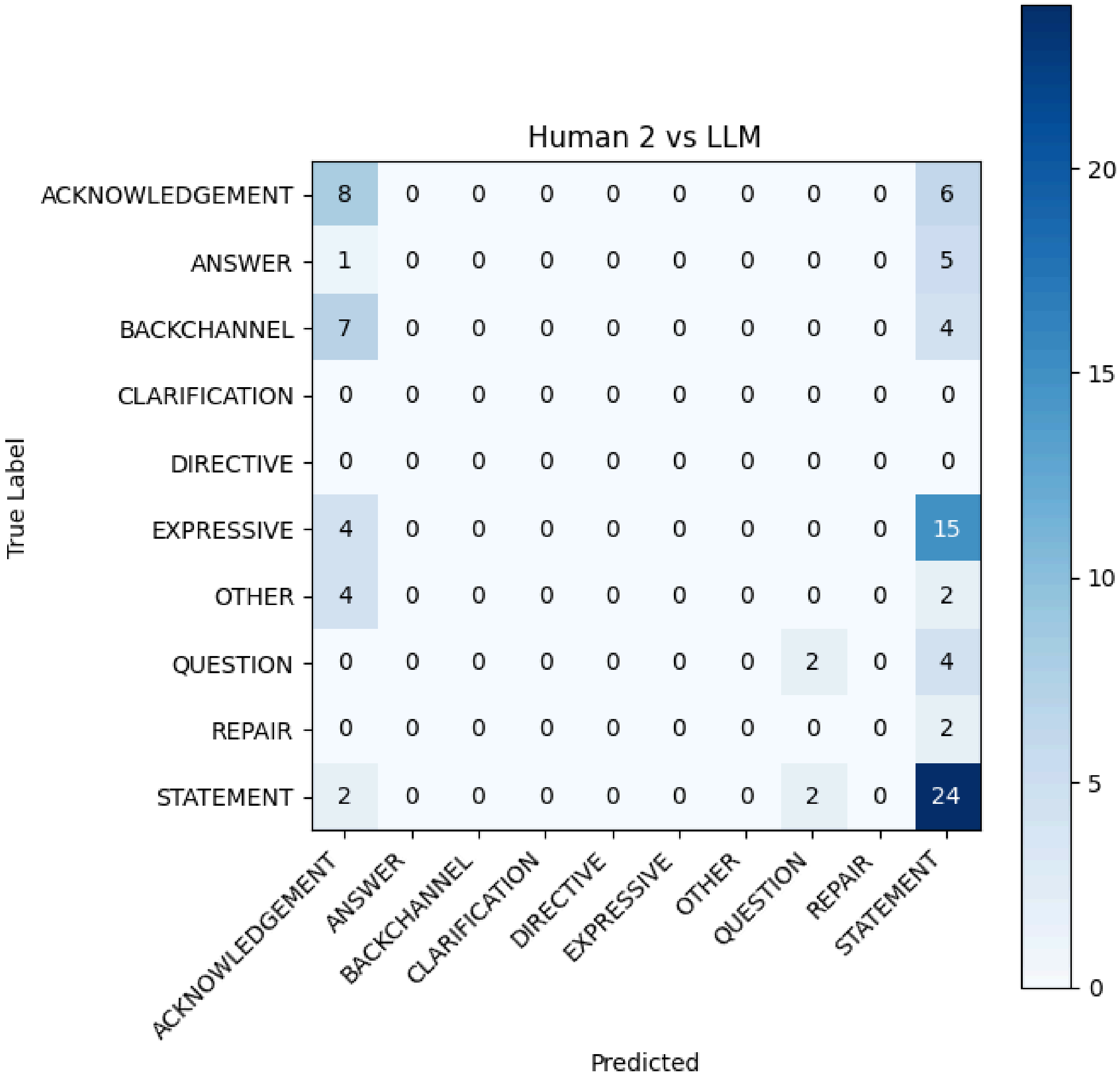
In [89]:

```
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import numpy as np

labels = sorted(eval_df["human1_label"].unique())  # adjust if needed

def plot_cm(true, pred, title):
    cm = confusion_matrix(true, pred, labels=labels)

    fig, ax = plt.subplots(figsize=(7,7))
```

```
    im = ax.imshow(cm, cmap="Blues")

    ax.set_xticks(np.arange(len(labels)))
    ax.set_yticks(np.arange(len(labels)))
    ax.set_xticklabels(labels, rotation=45, ha='right')
    ax.set_yticklabels(labels)

    ax.set_xlabel("Predicted")
    ax.set_ylabel("True Label")
    ax.set_title(title)

    for i in range(len(labels)):
        for j in range(len(labels)):
            ax.text(j, i, cm[i, j], ha="center", va="center",
                    color="white" if cm[i,j] > cm.max()/2 else "black")

    plt.colorbar(im)
    plt.tight_layout()
    plt.show()

plot_cm(h1, h2,  "Human 1 vs Human 2")
plot_cm(h1, llm, "Human 1 vs LLM")
plot_cm(h2, llm, "Human 2 vs LLM")
```




Human 1 vs LLM
True Label
Predicted
ACKNOWLEDGEMENT
ANSWER
BACKCHANNEL
CLARIFICATION
DIRECTIVE
EXPRESSIVE
OTHER
QUESTION
REPAIR
STATEMENT
7 0 0 0 0 0 0 0 0 5
1 0 0 0 0 0 0 0 0 7
8 0 0 0 0 0 0 0 0 5
1 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 1 0 1
4 0 0 0 0 0 0 0 0 13
2 0 0 0 0 0 0 0 0 2
0 0 0 0 0 0 0 2 0 5
0 0 0 0 0 0 0 0 0 1
3 0 0 0 0 0 0 1 0 24
20
15
10
5
0


Human 2 vs LLM
True Label
Predicted
ACKNOWLEDGEMENT
ANSWER
BACKCHANNEL
CLARIFICATION
DIRECTIVE
EXPRESSIVE
OTHER
QUESTION
REPAIR
STATEMENT
8 0 0 0 0 0 0 0 0 6
1 0 0 0 0 0 0 0 0 5
7 0 0 0 0 0 0 0 0 4
0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0
4 0 0 0 0 0 0 0 0 15
4 0 0 0 0 0 0 0 0 2
0 0 0 0 0 0 0 2 0 4
0 0 0 0 0 0 0 0 0 2
2 0 0 0 0 0 0 2 0 24
20
15
10
5
0

In [ ]:

In [ ]:

In [ ]: